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Workforce Analytic Approaches to Find Degrees of Freedom in the EV Transition

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Executive Summary

The Electric Vehicle (EV) transition represents a significant potential disruption to the content and location of work in the U.S. automotive industry, with ramifications for the wages and employment of hundreds of thousands of incumbent automotive workers engaged in the production of Internal Combustion Engine Vehicles (ICEVs). The workforce transitions available for affected workers will shape economic consequences for individuals and their communities, and are thus critical for achieving an economically inclusive transition that can align climate goals with the prosperity of those most directly affected by industry disruption. At the same time, the jobs created through the energy transition – both in EV manufacturing and other industries – will create skill demands that must be met by different regional labor markets: new jobs in specific occupational categories (e.g. electrician, machinist) may exhaust the available stock of occupational talent in specific regions, leading to vacancies that may constrain the performance of manufacturing capacity investments. Resolving these constraints will require novel occupational transitions by workers who do not currently work in the kinds of jobs being created, and whose skills may only be a partial match.

To support effective workforce transitions out of displaced incumbent roles or into new roles created by the energy transition, U.S. DoE and other stakeholders need analytical approaches to quantify the skill similarities of workers to alternative employment opportunities, the relative wages offered and the competitiveness of workers with alternative sources of labor supply. These insights will enable decision makers to identify key skill gaps to close in facilitation of workforce transitions, as well as choice margins such as geographic co-location and wage incentives that are vital to creating transition conditions both feasible and desirable to workers.

This report represents a 12-week effort to characterize the outlook for workforce transition pathways for incumbent workers affected by energy transition, and for workers entering new jobs. We focus on automotive production workers potentially disrupted by the transition from ICEVs to EVs. We also characterize the relative abundance of occupational skills to meet regional EV production needs, both as a source of competition with transitioning automotive workers and as an overall constraint on successful capacity-building for the EV industry.

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The methodology we apply can be extended to inform analysis of skill supply and workforce transition conditions for other critical industries in the energy transition. Such industries may compete for skills and serve as demand sources for displaced legacy industry skill sets. We leverage this cross-industry capability to consider the transition opportunities presented specifically by growth in the heat pump, solar panel manufacturing, and transformer industries (HSTs). Prior evidence available to DoE MESC has suggested that the set of occupational and skill needs for these industries overlaps significantly, and we consider a common set of needs based on extant MESC data. We further consider the competitive position of transitioning automotive workers to meet skill demands in green industries.

From the incumbent ICEV perspective, we seek to understand the feasibility of multiple special cases of transition for workers: (1) transitions within the same industry; (2) transitions in place (same geography); and (3) wage-sustaining transitions. A transition could theoretically satisfy all three, some, or none of these criteria. Our analysis focuses on empirically identifiable factors that may limit transitions on each of these dimensions: the skill similarity between disrupted occupations and occupations demanded by the EV industry and overall[6]; the quantity and location of anticipated EV labor demand necessary to absorb displaced workers in specific regions; and the prevailing wages of occupations that satisfy the previous conditions.

We also generate first-order estimates of the capacity of local labor markets to meet regional skill demands. Large transitions by incumbent workers could feed into capacity expansion, which may offer better labor supply conditions. We find evidence to suggest that, overall, incumbent automotive workers in a range of production roles have relatively high skill similarity to occupational roles demanded in EVs. Exact occupational matches between incumbent ICEV workers and demanded EV, Battery, and HST production workers include “engine and other machine assemblers” as well as “machinists, welders, cutters, solderers, and brazers”.[7] Higher-wage automotive occupations with more specialized skills appear to have better competitive positions in terms of their skill similarity versus the wage-price of other potential EV entrants, but are also more geographically concentrated and hence dependent on co-location of EV production capacity with automotive production for transition opportunities. Salient examples of this geographic concentration phenomenon in metropolitan areas include Detroit, and for some occupations, Atlanta. An example of the inverse – high representation of ICEV-related occupations but very little expected demand for EV or Battery production – would be Houston, TX. Mass displacement of workers here would not be plausibly mitigated in our analysis by EV or Battery production jobs.

We find that for HSTs, some automotive production roles overlap with occupations anticipated to be in demand, e.g “engine and other machine assemblers”. Certain automotive production

[6]The skill similarity methods deployed in this paper are adapted from methods developed by Combemale with Gonchar, Krishnan, Telang and George through the National Network for Critical Technology Assessment and the Workforce Supply Chains Initiative at Carnegie Mellon University’s Block Center for Technology and Society. A summary of the methodology is available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4671063 We extend the methods first by mirroring the skill similarity approach to evaluate *exit* as well as entry potential for occupations, second by constructing distributional comparisons of occupational wages to identify the share of potential job-matches that may be wage-sustaining or wage-improving, and third by identifying “skill missingness” for occupational transitions in terms of the domain of occupations whose candidacy improves *and* whose wage position is competitive.

[7] These and other titles in quotations are taken from the Standard Occupational Classification Taxonomy maintained by BLS

occupations in the same geography as anticipated HST production demand have promising skill similarities and enjoy competitive wage positions relative to outside occupations that could also be candidates for a skills-match with HST requirements. Example occupations include “machine tool setters, operators and tenders”, and “inspectors, testers, sorters, samplers, and weighers”. There are notable exceptions on the ICEV production side, such as “tool and die makers”, with limited potential occupations available for a transitioning ICEV worker. While the stock of exact occupational matches to meet potential HST production demand may be a constraint in some regions, we find that similar occupations have significant stocks and many are experiencing net employment declines, suggesting a possible reduction in competition for talent and a potential outflow of workers from declining occupations that could be supported into new HST roles.

Where our findings do not appear to support adequate demand or skills-match for a full transition of the ICEV manufacturing workers, this project is intended to suggest a data-driven set of candidate occupations for “soft landing” transitions. Such opportunities are identified from location, wages, current or future (projected) demand, and skill content potentially well-matched to those of transitioning ICEV workers – ideally in low carbon or decarbonizing sectors – with the goal of supporting a more detailed exploration in future work. We argue that a disrupted incumbent occupation has greater potential for a “soft landing” if there are many other occupations with high employment for which the incumbent is a strong match on skill requirements, and which have wage distributions that are comparable to or higher than the wage distribution of the incumbent occupation.

We find that strong industry-associated wage premia for higher wage occupations suggest that wage-sustaining labor market opportunities may be limited for such roles in automotive production. “First line supervisors” are an example of a high wage premium, but even median-wages for occupations such as “automotive engine assemblers” are well within the upper quartile of wages for most occupations whose skill requirements might make them plausible transition targets. This joint comparison on wage and skills suggests the potential for a “hard landing” in which displaced workers have difficulty finding work that uses their skills and offers comparable wages to their current employment. Managing these transitions may require greater support for workers, such as identifying wage-sustaining opportunities, and training to make workers more competitive with the upper end of the wage distribution for potential new occupations. Mitigating “hard landings” may also require a targeted approach to identifying opportunities for new federally-supported manufacturing capacity investments in well-paying jobs that are well matched to the skills of disrupted workers. In this report, we develop such an approach in the context of HSTs.

Our work finds examples of potential “soft landing” opportunities for some automotive occupations. Less specialized occupations with lower wages appear to have a lower industry premium, and hence a closer match with the wage distribution of alternative occupations whose skill requirements make them plausible transition candidates. “Multiple machine tool setters, operators, and tenders, metal and plastic” workers are occupations that appear best poised for a soft landing without additional support: not only are they similarly qualified to perform several EV and Battery production jobs when compared with other potentially disrupted automotive manufacturing occupations, but so too are they the most wage competitive when compared to occupations to which they are most similar.

This project is geared toward building and parametrizing models from often very limited empirical data, as well as from potentially enormous technical and economic option spaces. As such, one of its key value propositions is to identify the areas of greatest empirical uncertainty, and which areas have the greatest potential impact of estimates and actionable policy in the future. We seek to establish those facts, estimates and predictions that are supported well by the evidence available; how their limitations should affect interpretation; and to lay out repeatable methods for extensions and updates as the automotive transition and larger energy transition continue. For example, we are able to identify a set of occupations that meet a skill similarity threshold compared to a target occupation (e.g. filling an EV occupational demand). From those candidate occupations we can then identify which job requirements most often fail to meet the requirements of the target occupation, and in particular which skills – if trainable to the standard of the target occupation – would improve the skill match of candidate occupations with lower wages than the target occupation. In so doing, we can identify which skills could be targets for training programs to support wage-improving transitions.

This report identifies levers that affect the scale, content and location of EV jobs, and the relative competitiveness of automotive workers for such roles. These levers include incentives for geographic co-location with ICEV production to facilitate transitions-in-place, and market structure and vertical integration incentives to create within-firm pipelines for worker transition; both levers affect the visibility and proximity of opportunities. The quality of transition opportunities may be supported through targeted training to close key skill gaps. This then enables higher wage transition targets, incentives, and technical support to employers in designing the task and skill content of new jobs. Such employer-driven choices may include process-level decisions about breaking production into narrow tasks performed by low-wage workers, or aggregating tasks into jobs with greater skill requirements, scope of responsibility, and wages. For example, “engine and other machine assemblers” generally have lower requirements for “customer-oriented social skills” than other such occupations; however when compared to similar occupations that earn more than them, “building and construction” as well as the “use of other vehicles or heavy machinery” are more relevant skills. Lastly, informational targeting to displaced workers about specific opportunities in industries and occupations with high absorptive capacity could help direct talent to opportunities with high return for individuals and energy transition goals.

Our mixed-methods approach also reveals openings for policy development: our interviews reveal a crucial lack of information among educational institutions about job requirements and demand outlook, hindering curriculum development. Policymakers have an opportunity to coordinate between employers and educational institutions, such as through grant making and public-facing reporting requirements that incentivize partnerships and create a common base of information for planning. The time-sensitivity of policy windows for workforce transitions is especially salient: some ICEV occupations may be well-matched on wages and skills to growth occupations in HST production, but such a transition will not be feasible without proper support. This support may include incentives for geographic co-location of employment opportunities; pipelines that can mitigate worker uncertainty, such as training and advance employment commitments; and aligning the timeline between workforce disruption and job creation. Our findings illustrate the potential for a repeatable framework to develop industry- and place-based workforce transition strategies. By focusing on wage-sustaining transitions out of disrupted ICEV occupations and into EVs and HSTs, we demonstrate how this approach can support both disrupted workers and opportunities for new entrants.

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I. Background

This study explores the workforce implications of the transition from internal combustion engine vehicles (ICEVs) to non-hybrid electric vehicles (EVs, consisting primarily of Battery EVs or BEVs), with particular attention to transition pathways for different incumbent occupations employed in the automotive sector. Here we briefly explain key differences between ICEVs and EVs and provide an introduction to automotive supply chains that will frame our findings. The impact of the EV transition on automotive workers may depend on their opportunities to transition in place or within the same firm, which in turn depends on where that worker is in the supply chain, whether their company is vertically integrated or in close partnership with their battery and electronics suppliers, and whether there is co-location of EV production suited to their skills with their current site of employment.

EV vs ICEV Technologies

As shown in the diagram below by Küpper *et al*. (2020), the key manufacturing differences between EVs and ICEVs are in powertrain manufacturing: where ICEVs rely on combustion engines, EVs draw power from an electric motor (or e-drive) and battery system. There are differences in chassis assembly (due to lightweighting and changes in components), but in our industry interviews these changes are not expected to impact labor demand or the skill required for assembly. Since the other systems of the vehicle (suspension, braking, body, etc) have similar production processes and thus similar labor and skill requirements, we focus our analysis on the powertrains of the two vehicle types.

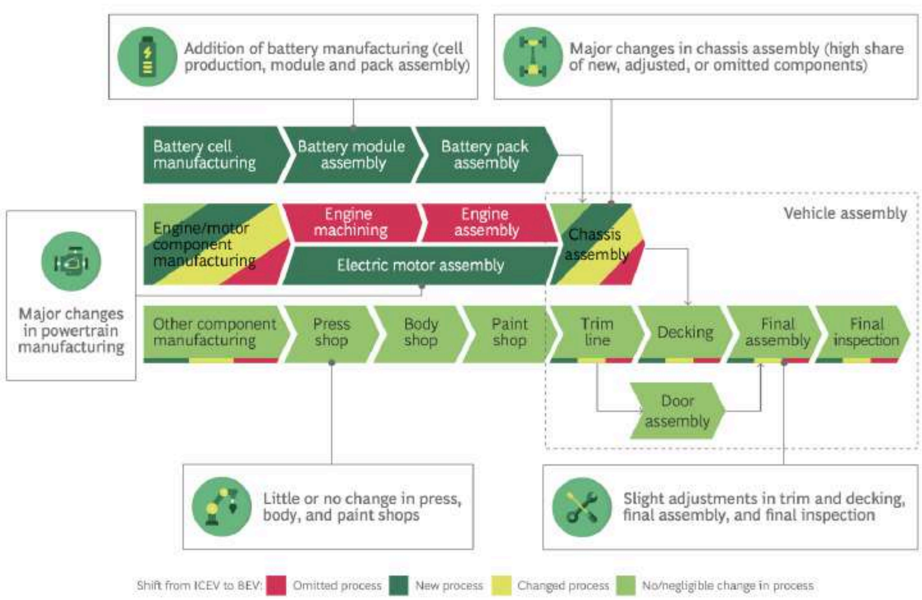


Figure 1: Küpper *et al*. 2020 highlights the key areas of difference in the manufacturing and assembly processes in the shift from ICEV to BEV.

Comparing just the powertrain components of EVs and ICEVs, early reports suggested that due to the decrease in moving parts for electric motors, EVs would require less labor. A 2017 UBS teardown comparison between the two vehicle types found that the ICE powertrain has 80% more moving parts than typical EVs (Hummel *et al.* 2017).[8] Focus on part count has been a main source of evidence for statements from original equipment manufacturers (OEMs) and the UAW that electric vehicles will require less production labor (Ford Statement, VW Statement, UAW report). However, conflicting evidence accounting for process complexity and additional production tasks related to battery fabrication and assembly suggests that there may not be a significant net change in labor intensiveness between EV and ICEV power trains (Cotterman *et al.* 2022). Therefore, understanding the battery production supply chain is critical to anticipating labor dynamics in the transition to electrification.

Although many OEMs make their own engines for ICEVs, all EV manufacturers have either partnered with or outsourced to Tier 1 and some Tier 2 suppliers for their EV batteries. Understandably, automotive firms lack the knowledge and expertise to break into the chemical engineering required for battery production. This chart by Gohlke *et al.* (2022), shown as **Figure 2** on the next page, demonstrates the three tiers of EV battery production: the manufacturing of individual cells, the manufacturing of cells into modules and then modules into packs, and the final vehicle assembly by OEMs. There is significant heterogeneity in the vertical integration structure of these supply chains. Note that some firms choose to manufacture their own packs, and some firms have entered joint-ventures to manufacture battery cells together, while other firms such as Nissan and GM are only involved in vehicle assembly (Gohlke *et al.* 2022).

[8] Considering the cost of components as a loose guideline for the labor required for manufacturing, the electrification changes to the powertrain account for only about 25-30% of the overall cost of a given automobile. Estimates provided from interviews by Hummel *et al.* suggest that the cost of an engine represents around 25% of overall costs, whereas the EV powertrain (including the battery) started out at about 30% of costs and has been decreasing. 10% of these costs derive from minerals and raw materials for mining and chemical processing (primarily abroad), 10% comes from battery cell manufacturing (primary abroad as of 2023), and 10% is the battery management system, consisting of thermal engineering, and structural engineering (which is sometimes made domestically). Hummel *et al.* also noted that for EVs, given the complexity of battery supply chains, many of these costs may be hidden or deliberately obfuscated by OEMs.

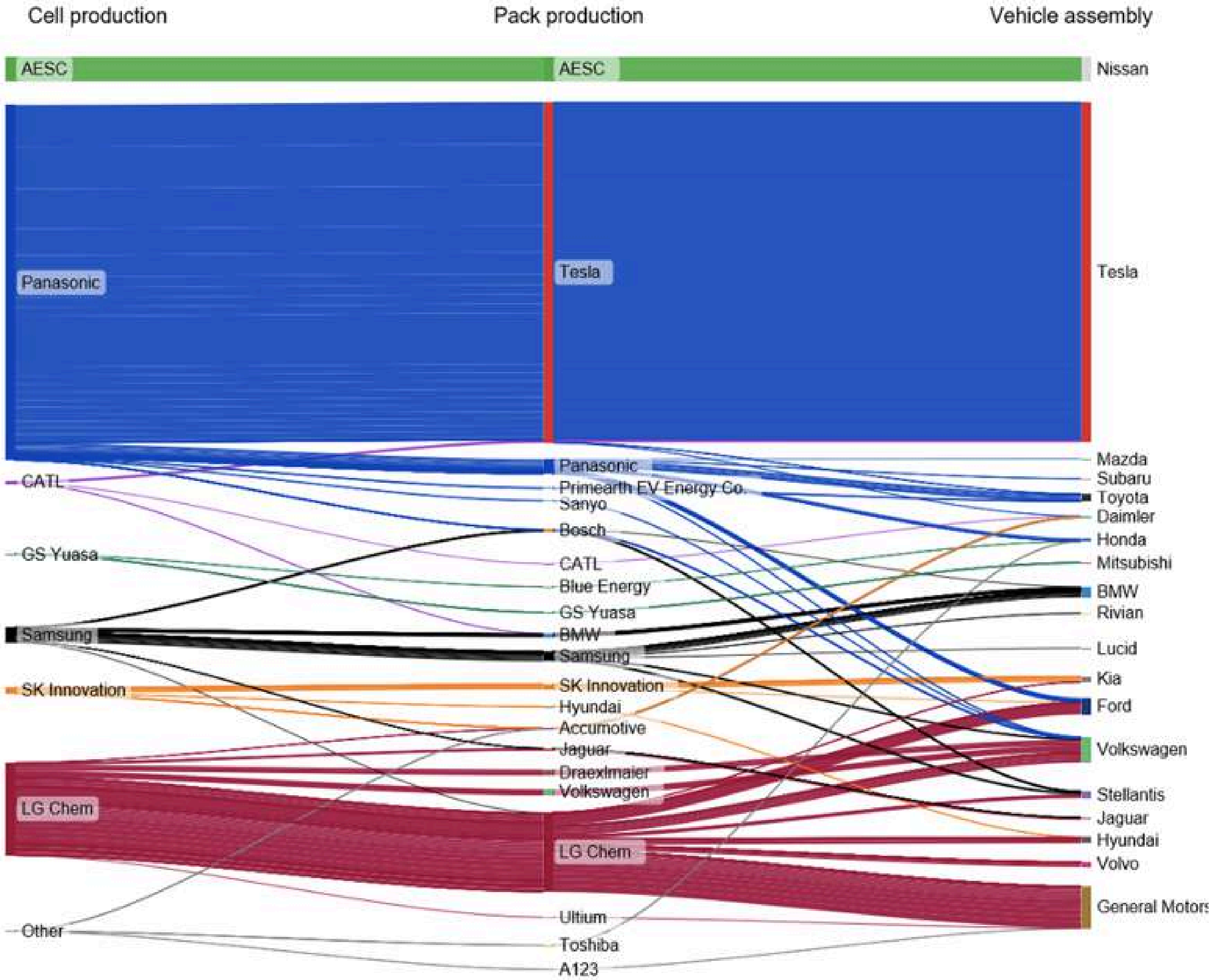


Figure 2: Gohlke *et al.* 2022 map the EV battery production supply chain for cell and pack production and final vehicle assembly.

Net Change in Production Jobs

It is important to distinguish between the potential disruption of ICEV jobs in a 'steady state' EV production scenario, and the rate at which labor-affecting production changeovers may occur. In our later analysis as part of this report, we use a snapshot approach based on the publicized capacity and labor demand associated with existing and announced plants; in the latest section of our analysis, we place this capacity in context against potential scenarios for long-run capacity demand and labor intensity. In this section, however, we deal at a high-level with past work on the timing of change as an important factor in the degrees of freedom available to manage the workforce dimension of the EV transition. We focus in our discussion on unanswered questions about how changes in predominant battery chemistry or process regimes across the industry add further uncertainty about the long-run labor and skill content of EV production.

Across European firms, Strategy and the European Association of Automobile Stampers estimate that a mixed hybrid and EV scenario would create more jobs overall across the entire automotive supply chain (including battery production), while a phase-out of ICEVs by 2040 would lead to a net reduction of at least 359,000 jobs in the ICEV domain (CLEPA, 2021).

Bauer *et al.*'s (2020) study (**Table 1**) of Volkswagen's transition to EVs modeled this, focusing on the calculations of man-hours required on the shop floor for two reference EV models, alongside estimates about productivity improvements from increased digitization and automation. They make the moderate assumption that Volkswagen will increase from 10% BEVs in 2020 to 55% by 2029. They found that the number of workers required for conventional powertrain production within Volkswagen is 70% greater than those required for the e-drive (not including battery manufacturing). Compared to the internal combustion engine, employment intensity of the electric drive is 40% lower, and that of the battery system is 60% lower. Nonetheless, the average demand for vehicle production employees at Volkswagen should decrease by only around 12% by 2029, due to process improvements in manufacturing and insourcing of battery cell manufacturing. They anticipate that Volkswagen will more-or-less maintain their current workforce numbers by increasing unit production and expanding to include new EV component production.

Through the direct calculation of the personnel requirements for each individual ICEV, plug-in hybrid EV (PHEV), and BEV component produced in 2016, Bauer *et al.* (2018) developed the table below – which does not include battery cell manufacturing, since cells are outsourced or produced in other factories across all the German OEMs surveyed.

Change in personnel requirements in relation to total requirements in 2017		Without productivity		increasesWith productivity increases	
	Support year	2025	2030	2025	2030
Scenario 1 (25 % BEV)	ICEV	-17 %	-26 %	-29 %	-43 %
	PHEV	+7 %	+10 %	+4 %	+4 %
	BEV	+3 %	+5 %	+2 %	+2 %
	Balance	-7 %	-11 %	-23 %	-37 %
Scenario 2 (40 % BEV)	ICEV	-22 %	-44 %	-33 %	-56 %
	PHEV	+8 %	+15 %	+5 %	+9 %
	BEV	+5 %	+11 %	+4 %	+7 %
	Balance	-9 %	-18 %	-24 %	-40 %
Scenario 3 (80 % BEV)	ICEV	-37 %	-65 %	-45 %	-71 %
	PHEV	+7 %	+7 %	+4 %	+3 %
	BEV	+10 %	+23 %	+8 %	+15 %
	Balance	-20 %	-35 %	-33 %	-53 %

Table 1: Bauer *et al.* 2018 highlight the labor requirements of vehicles produced in Germany with and without considering the productivity increases due to automation and digitization.

As demonstrated by the history of technologies from warships to lithium-ion batteries, production costs are likely to decrease more-or-less exponentially as firms learn how to manufacture more efficiently through "learning curves" (Wright 1936; Singh 2021). This is true of the EV market as well. Excluding battery production, Singh (2021) draws from German models by Hermann *et al.* (2018) and Bauer *et al.* (2018) to estimate US job losses based on lower anticipated EV adoption across the US, and notes that the EV powertrain effect (again, not including the battery) is dwarfed by the productivity effect of firms learning and automating their production. For a 25% BEV share by 2030, Singh (2021) finds a workforce decrease of 11% when purely accounting for the production switch from powertrain to EV, and a 37% decrease when including an estimated increase in productivity. The Volkswagen study also accounts for efficiency gains through learning and other environmental factors such as automation using Volkswagen's internal estimates.

	Decrease in Personnel Required (%) (per 1 million powertrains)	
	Excluding productivity effect	Including productivity effect
10% BEV share	**3%**	30%
25% BEV share	**11%**	37%
40% BEV share	**18%**	40%

Table 2: *Singh* 2021 estimates the reduction in required labor (not including battery manufacturing) when transitioning to BEVs.

It is easier to automate new production lines and brand-new greenfield factories than it is to automate existing facilities (Waldman-Brown 2020; Bauer *et al*. 2020). Thus, manufacturers often use technological shifts as an incentive to upgrade their technologies; Amazon, for instance, installs additional robots in each new warehouse it builds while keeping their older warehouses manual due to the cost of change-over (Waldman-Brown, 2020). Bauer *et al.* (2020) notes that the e-drive and digitization – including increased automation – are "mutually dependent", and finds that electrification is likely to accelerate the introduction of digitization and automation within the factory. This view was repeated by interviewees in both OEMs and small or medium enterprise (SME) suppliers, but interestingly one OEM suggested that this process will not lead to lower labor requirements. It was unclear if that was due to an assumed increase in demand and throughput or due to process complexity.

When including the labor required for battery cell production, Cotterman *et al.* (2022) finds that EVs today require more worker hours per vehicle overall; 4-11 worker hours per ICEV powertrain, compared to 15-24 hours for an EV powertrain including the electric motor, inverter, and battery pack (**Figure 3**, next page). This study combined industry data from multiple firms (OEMs and suppliers) with public sources and labor intensity models. Despite firms not necessarily vertically integrating battery production, this finding suggests for policy makers that the labor in total for the industry may not shrink, and may in fact grow due to electrification of automobiles.

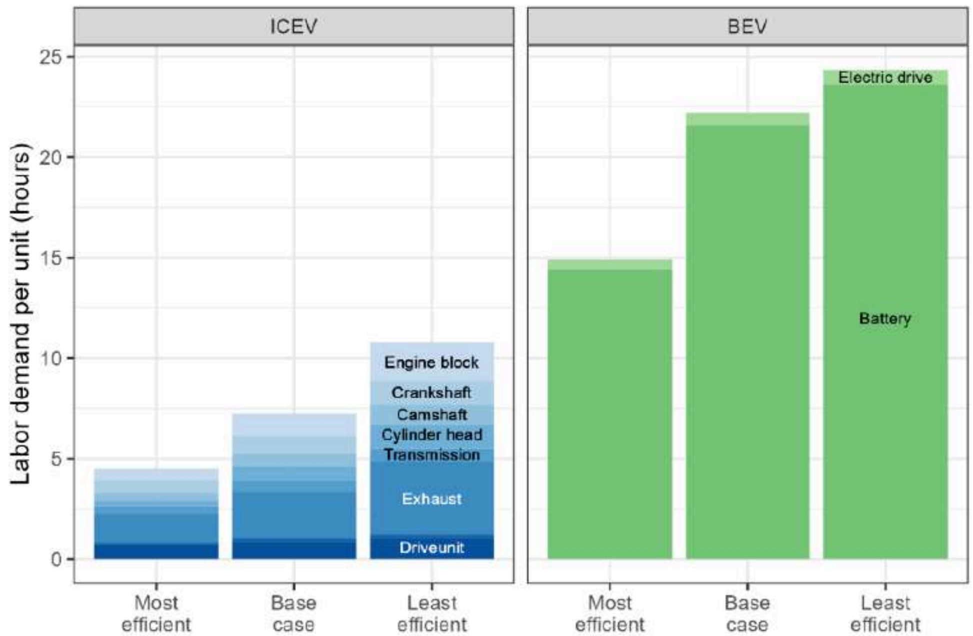


Figure 3: *Cotterman et al.* 2022 compare the powertrain labor intensity between ICEV and BEV production.

Heat Pumps, Solar Panels and Transformers

A secondary thrust of this report is to evaluate the potential stock of workers to meet occupational demand created by capacity investment in heat pump, solar panel and transformer (HST) production, and in particular to evaluate the potential of incumbent ICEV occupations to find wage-sustaining transitions in HST manufacturing. Absent detailed occupational distribution data for these industries, we use a common set of occupations derived from prior MESC research (see the analysis section for further detail).[9] We do not focus on installation or maintenance, nor on the associated infrastructure or facility construction work related to HSTs, matching our scope for EVs and ICEVs.

Workforce has been identified as a bottleneck on large power transformer production (Nguyen *et al.* 2022), noting a lack of training capacity to meet specific industry needs. This lack of training is in part connected with a lack of stable demand, which makes it difficult both to sustain training infrastructure and to incentivize workers to pursue the skills necessary to enter the industry. The need for stable demand, or at least robust employment options in similar occupations, is a salient motivation for our focus in this report on occupational similarity and identifying wage-improving transitions.

The body of research on heat pump workforce requirements and development has principally focused on installation (Branford and Roberts 2022; Karpathy *et al.* 2022)[10], similar to recent work in solar panels (Gadzanku, Kramer and Smith 2023). Our focus on manufacturing is motivated by its potential similarity to disrupted ICEV occupations, and to the place-based

[9] We do not study certain highly industry-specific occupations, such as glaziers identified in the solar power context by U.S. BLS as a narrow production occupation of interest (Hamilton 2011b).
[10] Both sources are from the UK labor context.

nature of manufacturing demand. This workforce regionality provides geographic challenges to meet skill needs and opportunities for targeted transition pipelines. Here, a major point of uncertainty, in addition to workforce availability, is the rapidity of uptake of industrial heat pumps, and hence the demand conditions for labor.

Where the focus has been on manufacturing capacity-building, past research has dealt with incentives for heat pump adoption as drivers of workforce demand and indicated a tendency for unilateral firm partnerships with training institutions – this work also notes current shortages in the industry (Joe *et al* 2021). In the solar panel context in particular, recent research calls attention to a demographic imbalance between the current workforce and nationally or regionally representative workforces, noting expected labor demand growth as a channel for hiring strategies that are more inclusive and shape the characteristics of the future workforce. Collectively, current research suggests broad uncertainties in the HST occupational demand and strong potential in the effectiveness of policy levers in influencing HST manufacturing and its workforce, thus meriting analysis.

Workforce Transitions and Skill Similarity

In order to scope the potential transition opportunities for incumbent automotive workers, we consider the skill requirements for new EV jobs and the feasibility of matching incumbent skills to the domain of new demand. We draw on existing studies and data to establish a set of occupations that will be involved in the EV transition. Hamilton (2011) identified seven occupations in the BLS database that are likely to see increased demand in EV and battery production. We also selected the top 10 production occupations in Motor Vehicle Parts Manufacturing from the BLS as a comparison for the incumbent ICEV occupations (O*NET OnLine). We then leverage the O*NET skills, knowledge, ability, and work activity (SKAW) taxonomy to obtain a basis of comparison between incumbent ICEV worker requirements and the requirements of occupational opportunities in EV production. O*NET is a database maintained by the U.S. Employment and Training Administration, and provides (among other data) detailed ratings of the importance and difficulty of a consistent set of skills, knowledge, abilities and work activities across hundreds of occupations under the Standard Occupational Classification system (maintained by U.S. BLS).[11] The O*NET taxonomy enables quantitative comparison between occupations to evaluate the potential similarity of their requirements, and to identify potentially feasible occupational transitions for workers. We use a measure of similarity between the Skills, Knowledge, Abilities, and Work Activities (SKAWs) required between occupations to identify these potential transitions. We are then able to identify the stock of workers in these occupations and the rate of transition, or flow of workers, into other occupations that meet a particular skill threshold.

We apply the methodology for generating a “skill similarity” measure across occupations, hence narrowing down the set of candidate occupations for incumbent workers to transition into. This methodology, developed by Combemale and Gonchar (Combemale *et al.* 2023), allows us to make comparisons across occupations in potentially different industry or firm contexts. Such comparisons will be necessary for scoping the potential for longer-range workforce transitions out of incumbent ICEV roles. We utilize these methods both to see which

[11] For a detailed discussion of the O*NET content model and taxonomy, please see https://www.onetcenter.org/content.html

occupations are a good fit for newly created roles in the EV industry (e.g. which occupations are good candidates to fill a future battery production mechatronics position), but also the mirror question: to see which occupations are the best transition for incumbent workers (e.g. to which occupation might a displaced ICEV working transition). See the report section “Skills Mapping with Workforce Insights Tool” for more details.

Worker knowledge can be roughly classified into general skills and job-specific skills: while an ICEV metal press worker might need to learn a completely new general skill set to produce auto body parts out of plastic instead of steel, a metal fabricator may need new job-specific skills to switch from the steel used in ICEVs to aluminum in an EV. Likewise, machine operators may have general skills in PLC operation, but would need to learn how to use different software interfaces for different types of equipment. As an example of industry- or firm-specific characteristics, the American job classification for “Welders, Cutters, Solderers, and Brazers” (O*NET 51-4121.00) varies regionally following regional manufacturing clusters: Florida is full of ship-builders requiring thick MIG/MAG welds; Massachusetts has an “aerospace alley” requiring precision aerospace parts and sheet metal fabs which require TIG welding; Colorado is primarily mining and related pipefitting, requiring thinner MIG/MAG welds; and Ohio tends to specialize in automotive and agricultural equipment, which is generally MIG/MAG but could also be TIG (Waldman-Brown 2023).

Bauer *et al.*’s 2020 study notes that ICEVs require primarily mechanical and mechatronic skills, where EVs require more knowledge of electronics, high-voltage safety, and digital IT systems because they are becoming increasingly digitized. A UBS teardown EV versus ICEV comparison notes that today’s EVs contain 6-10x more embedded semiconductor content than ICEVs (Hummel *et al.* 2017). However, a study by the Ohio Manufacturers’ Association and the Ohio Governor’s Office of Workforce Transformation (2023) is unconcerned about ICEV-related job loss due to the overlap in core competencies and the state’s overall shortage of skilled technicians. Instead, they estimate the need for around 25,400 new jobs across the state including EV manufacturing, EV battery production, EV charger manufacturing, EV maintenance, charger installation and operations, and battery recycling.

Geography and Labor Phenomena

Just as the automotive industry is highly concentrated geographically, battery production and other EV-related production capacity are likely to be concentrated in specific geographical regions, rather than uniformly distributed. This goes alongside related workforce development programs, university researchers, OEMs, suppliers, and startups. Whether the location of EV production capacity aligns with the location of existing automotive production facilities is of first-order importance for the feasibility of “transitions in place.”

Literature on the topic poses three main reasons for this agglomeration: the interconnections and business networks between firms; the creation of common-pool resources, including skilled workers; and shared experiences and affinities. A subset of the discussion on resource agglomeration focuses on the regional “ecosystems” (Reynolds & Uygun, 2017; Scaringella & Radziwon, 2018) that emerge from how nearby institutions become interconnected to mutual benefit through business networks, cultural affinities, interpersonal ties, and shared knowledge. Armstrong and Traficonte (2021) define regional manufacturing ecosystems as “constellations of market and non-market organizations that collaborate to support manufacturing competitiveness" (pg. 9). The roots of the symbiotic ecosystem concept can be found in the late 19th-century economist Alfred Marshall's "industrial district" (1890), which explained how the presence of related firms in a concentrated geographic region can create positive spillover effects for firms, institutions, and workers through the specialized knowledge that can be found "in the air." Gertler (1995) identifies "closeness" as a critical determinant in new technological adoption across SMEs, which he defines as a firm's physical proximity and cultural affinity to technology providers and other firms that have adopted the technology in question. These reinforcement effects mean that regions that demonstrate early success in EV production are likely to continue attracting related companies and talent, whereas regions that fail to adapt quickly may fall further behind over time as EV resources and firms agglomerate elsewhere.

One Michigan industrial expert gave the example of Monroe County. On the border between Detroit and Toledo, 25% of jobs in the county are tied up in primarily SME-supplier powertrain manufacturing. It is unlikely that this county will see enough battery plants come into the region to compensate for a potential 25% loss of employment. As the expert explained, the region had undergone job transitions such as coal plant closures, "but it's different for a whole community versus a sprinkling of individuals." Manufacturing worker mobility has been low in Michigan, especially compared to previous decades.

Iyer *et al.*'s (2021) study on Indiana's automotive ecosystem (**Figure 4**) found nearly twice as many firms exclusively involved in ICEV supply chains than EV supply chains, but the largest fraction of firms were either currently or could potentially be engaged in both types of vehicles.

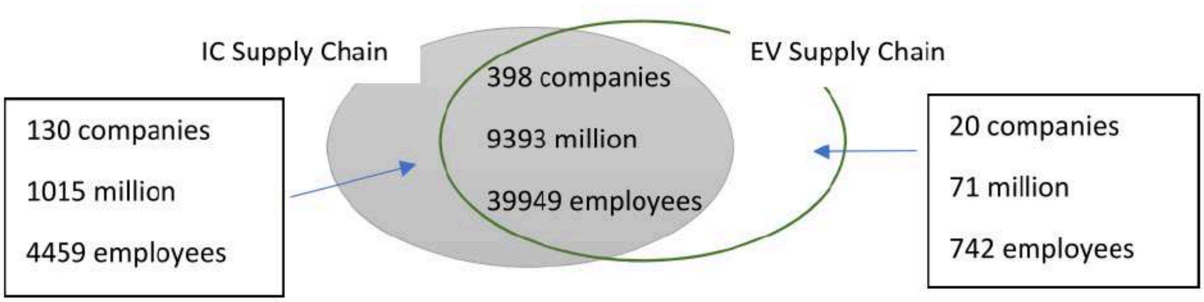


Figure 4: Iyer *et al.* 2021 measure the intersection between ICEV and EV supply chains in Indiana. In their figure reprinted here, the unit-less value listed is millions of dollars in revenue.

This agglomeration trend was evident in interviews with two battery startups who have maintained research and development arms in Northern California so they can take advantage of the local ecosystem of battery engineers and chemists developed by Tesla in Fremont. One of these California firms ended up relocating their battery production to draw from the local automotive workforce for assembly and fabrication in their new location, but retained their R&D arm in California. In contrast, the HR director of an East Coast battery startup in an old industrial district was able to readily hire experienced manufacturing workers but, struggled to find enough battery experts locally.

Project Model Roadmap

In order to measure the impacts and distribution of the changing skill landscape as we transition from ICEV to EV, we created the Model Roadmap seen in **Figure 5**. This Roadmap outlines our process for merging supply and demand of occupation-level employment information with an industry-wide interview protocol for confirming more granular skill-level information on the key occupations for employers. We separate the process into gathering data on supply and demand of ICEVs and BEVs through open data sources. We then validate both the occupations and the industry dynamics involved via interviews of OEMs, suppliers, industry organizations, educational institutions, and automotive industry unions.

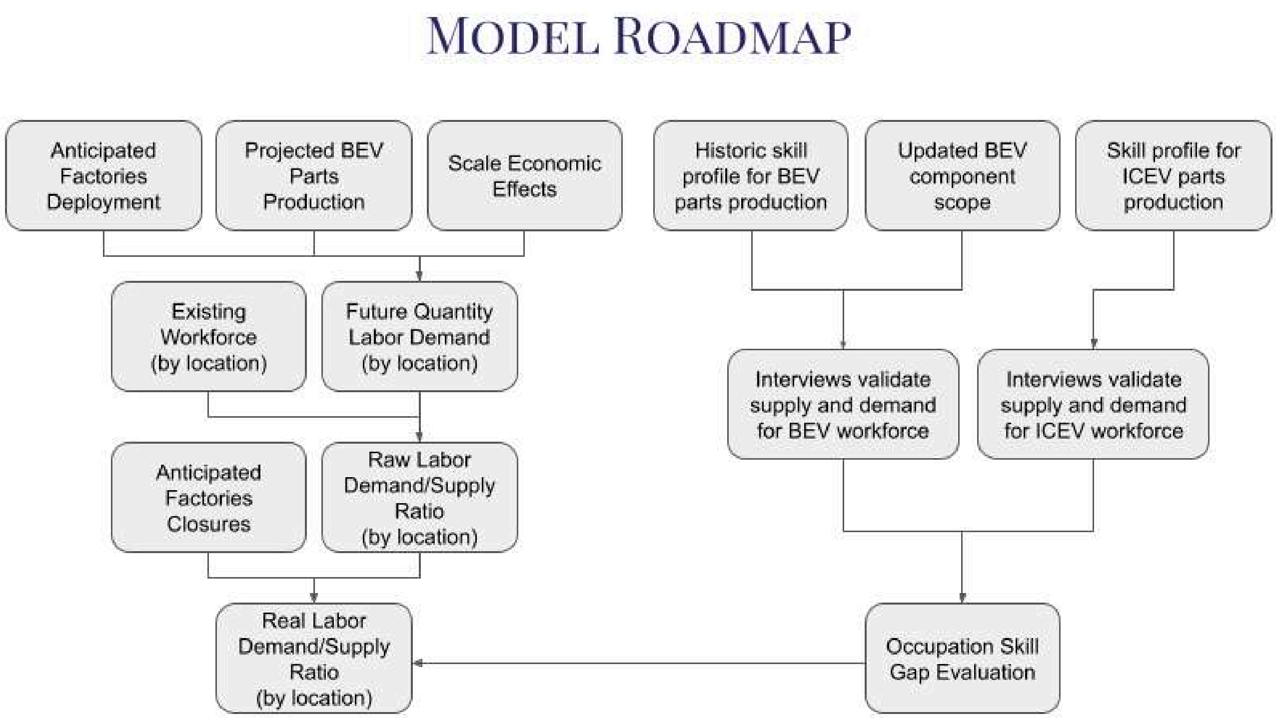


Figure 5: Model Roadmap visually demonstrating Valdos Consulting’s approach to measuring the workforce dynamics in the ICEV to EV transition

II. Methodology And Analysis

Interview Process

Overall, recent literature indicates that the EV transition in the US will lead to a negligible-to-moderate decline of jobs across internal combustion engine (ICE) drivetrain manufacturers and assembly, with a comparable or greater increase in jobs across battery production and e-drive assembly. To better understand these scenarios and estimate what skills will be needed, our interviews focused on four types of firms:

1) ICE powertrain manufacturers, who can tell us which skills required for current combustion engine components may become obsolete
2) Battery manufacturers, who can tell us what skills are required from chemical engineering and cell production to battery module production and assembly
3) OEMs that have either changed their production lines from ICEV to EV, or added new EV lines
4) ICEV automotive suppliers that have added (or considered adding) new EV production lines

As part of our interviews with these firms, we asked several categories of questions:

1) Current proportion of production that goes towards EVs, and how this might change
2) Breakdown of production steps, including the number of workers and skills required for each step
3) Educational background of current workers
4) Whether firms do internal training and partner with workforce education institutions
5) Major differences between ICEV and EV production, and differences in required skills (when relevant)

We also interviewed regional workforce institutions and manufacturing associations. These interviews allowed us to gain a better sense of the EV landscape, see what work others have done on this topic, and obtain introductions to relevant firms for further interviews.

Highlighted in **Table 3** (next page), we conducted 14 interviews with the following firms and institutions. Interviews ranged from 30-90 minutes, with an average of one hour per interview. Interviews and follow-up questions are ongoing.

Organization	People Interviewed	Number of Interviews
Automotive suppliers (SMEs)	Firm owners, factory managers	2
Automotive OEMs	Workforce development professionals, HR directors, company executives, policy experts	4
Battery companies	HR directors, policy experts,	3
Regional manufacturing associations and workforce institutions	Community college directors, chamber of commerce representatives, state manufacturing associations	5
Union institutions	Union local presidents and union-affiliated institutions	2

Table 3: Summary of the interviews conducted by Valdos Consulting during the project period

Our firm selection process was not random. Rather it was driven in part by the existing professional networks of the authors, and in turn by the follow-on networking assistance of participants who were willing to connect us to others. This selection process may have skewed our research towards more successful firms with large profiles and more connections (and indeed to firms still operating in the industry, and hence with time and interest to participate). As we mentioned up-front that our study is workforce-related, we may have also been more likely to select for firms that anticipated creating new jobs or transitioning workers.

We employed several strategies to identify and contact interviewees:

1) Contacting firms already known to the team: we conducted 10 interviews with firms with whom we already had relationships, contacting prior interviewees and contacts of the researchers
2) NatBatt listing of EV battery companies: we sent 47 cold emails to firms and followed up with phone calls to request interviews; we conducted 1 interview out of these initial contacts.
3) Snowball sampling: we conducted 3 interviews following introductions from other interviewees or contacts.

Our questions were open-ended with a semi-structured interview format, as shown in **Appendix G**. We conducted most of these interviews with at least two researchers from Valdos, and several firm interviews were also joined by DOE staff members.

Labor Supply and Demand Modeling

Incumbent ICEV Labor Supply and Mobility

To estimate the relative standing and mobility of existing labor supply related to Internal Combustion Engine Vehicle (ICEV) production, we proceeded through the following framework. First, we collected U.S. Bureau of Labor and Statistics (BLS) data on Occupational Employment and Wage Statistics Estimates (the "BLS dataset") to represent existing labor supplies and their distribution across the mainland at the spatial resolution of metropolitan statistical areas (MSAs). We filtered this dataset to the top ten occupation codes within the most represented production occupation code for the ICEV industry; this subset of BLS data serves as our approximation of the incumbent ICEV workforce most likely to be displaced by changes in the technology being manufactured. From here, we mapped ICEV labor supply concomitant to these occupation codes. Next, we mapped labor competition by employing the Workforce Insights Tool to identify alternative occupations that incumbent ICEV workers may be suited for given their skill set. These alternative occupations compose the possible opportunity space, should a given ICEV worker need to find a new occupation.

As a convention, we use a handful of focal occupations for our analysis, particularly "Engine and other Machine Assemblers" for incumbent automotive workers, to play out each methodological layer and its implications. We include results for all other occupations of interest in the Appendices.

We conducted the next two analyses to compare the average wage of ICEV workers to workers holding similar occupations in the same MSA. First, we mapped the ratio of workers in similar occupations who are paid more than ICEV workers to total workers in similar occupations. This analysis approximates the strategic position of ICEV workers to comparable workers in their area. Second, we plotted histograms of how workers with similar skills are being paid in their area in order to better illustrate the wage distribution of alternative occupations for a given ICEV worker seeking new local employment. From these analyses we gained significant insights on the possibility space of ICEV workers: what occupations are available to them, what wage percentile they would need to occupy when entering a new position in order to maintain their standard of living.[12]

Data Collection & Cleaning: BLS Dataset

The BLS dataset provides detailed information about employment and wages across different occupations and industries within the United States. It is a survey-based source that reports the number of people employed in various occupations, their average earnings, and the distribution of wages within specific industries. This dataset includes employment data on 147,886,000 workers.

One limitation of the BLS dataset is that some data are available at coarse spatial resolution (e.g., national, state/territory), and others are available at finer spatial resolution (e.g., Metropolitan Statistical Area (MSA), or nonmetropolitan area). Employment information by

[12] see discussion of the relative distribution of wages for candidate transition occupations versus incumbent wage distributions in our Results section

industry (i.e., using North American Industry Classification System, or NAICS codes) is only available at the national level. However, occupational data (i.e., using Standard Occupational Classification (SOC) codes) is available at the MSA level. For this analysis, we focused on MSA-resolved occupational data, as this is the most granular level of geographic information available. At the MSA level, within each occupational SOC code, the BLS dataset reports estimated total employment ("TOT_EMP") and mean annual wage ("A_MEAN"). It also reports five wage percentiles across the reported employment: 10th percentile ("A_PCT10"), 25th percentile ("A_PCT25"), 50th percentile or annual median wage ("A_MEDIAN"), 75th percentile ("A_PCT75"), and 90th percentile ("A_PCT90"). Later on, these wage distributions help us compare relative wages across comparable occupations.

For the appropriate ICEV industry code (i.e., NAICS 336300 - "Motor Vehicle Parts Manufacturing"), the production occupation code [51-0000] comprises the greatest share of the industry code's total employment. This production occupation code represents 64.51% of total employment; we focused here on the ten most highly represented specific occupations therein, which are summarized in **Table 4**. Together, these ten occupation codes comprise 85.27% of total employment reported in the production occupation. These represent a significant part of the industry workforce, including those facing displacement from production related jobs due to changes in product type, and those whose skills are least "generic" when with other industries. They do not represent certain highly mobile workers like accountants or other back-office staff.

Occupation Code	Occupation Name	% Total Emp	% Production Occ
51-2090	Miscellaneous Assemblers and Fabricators	23.25%	36.04%
51-4031	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	5.68%	8.80%
51-2031	Engine and Other Machine Assemblers	5.12%	7.94%
51-1011	First-Line Supervisors of Production and Operating Workers	4.21%	6.53%
51-9061	Inspectors, Testers, Sorters, Samplers, and Weighers	4.11%	6.37%
51-4081	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	3.01%	4.67%
51-4041	Machinists	2.77%	4.29%
51-2028	Electrical, Electronic, and Electromechanical Assemblers, Except Coil Winders, Tapers, and Finishers	2.49%	3.86%
51-4121	Welders, Cutters, Solderers, and Brazers	2.35%	3.64%
51-4111	Tool and Die Makers	2.02%	3.13%
Total	**-**	**55.01%**	**85.27%**

Table 4: The ten most highly represented occupations within the motor vehicle parts manufacturing industry. The occupation code's share of total employment and share of the production occupational total are also tabulated. Note that the SOC 2-digit category "51" comprises 64% of total automotive employment, and 85% of that employment is represented in the following top 10 occupations, hence 55% of total employment.

Mapping Labor Supply to Metropolitan Statistical Areas

For each occupation code, we mapped the labor supply reported at the MSA level. Specifically, we used the “Tot Emp” column from the BLS “all_data_M_2022” data set, filtered per occupation code, and mapped those values to MSAs using the “Area Title” column as the common value in a crosswalk. **Figure 6** offers an example map for one occupation code (51-2031); the full labor supply map set is compiled in **Appendix A**.

Number of “Engine and Other Machine Assemblers” (51-2031) by MSA

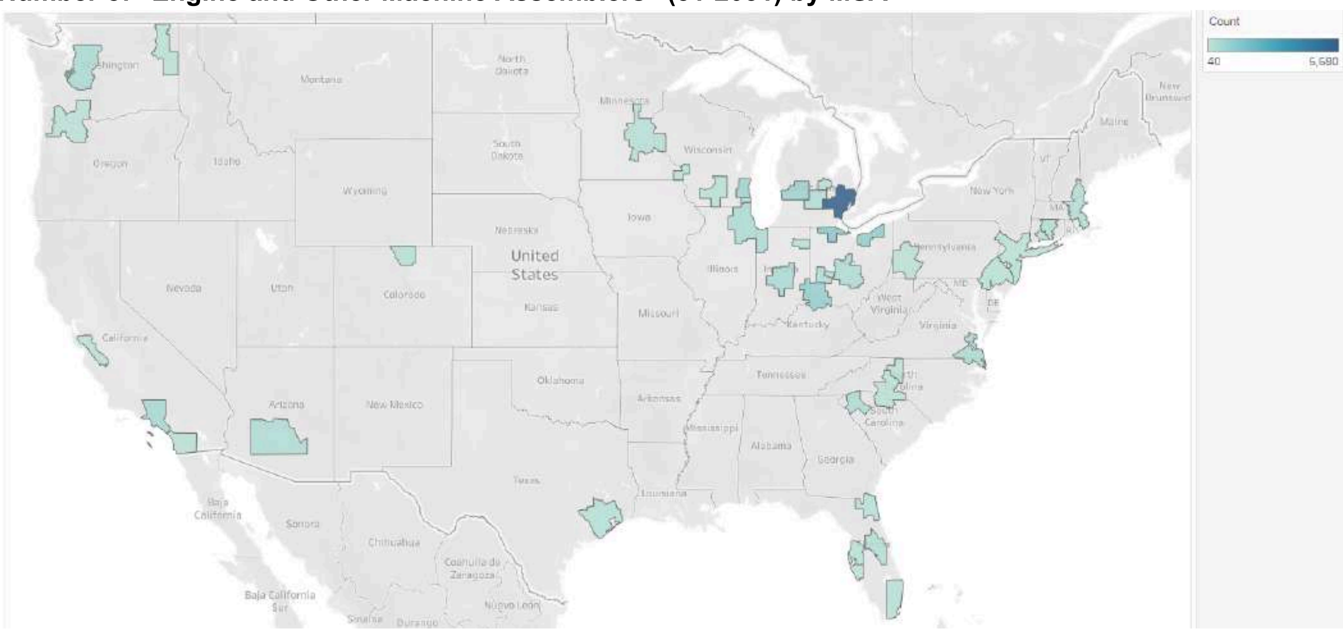


Figure 6: Map of labor supply for “Engine and Other Machine Assemblers” by MSA. Dark blue indicates a larger labor supply.

The most recent year with available data is 2022. Here we compare it to data going back to 2012, 2017, and 2021. **Figures 7**, **8**, and **9** on the following pages show changes to the available labor supply over 10 years, 5 years, and 1 year respectively. The MSAs represented year to year are not consistent in the available data. The BLS does not publish data for each MSA every year. This leads to inconsistencies in which MSAs are included from one map to the next. Changes to the labor supply are highly variable from one MSA to the next. This reflects heterogeneity in labor demand depending on geographic location. The full set of changes in labor supply figures may be found in **Appendix J**.

Change in Number of "Engine and Other Machine Assemblers" (51-2031) Over 10 Years by MSA

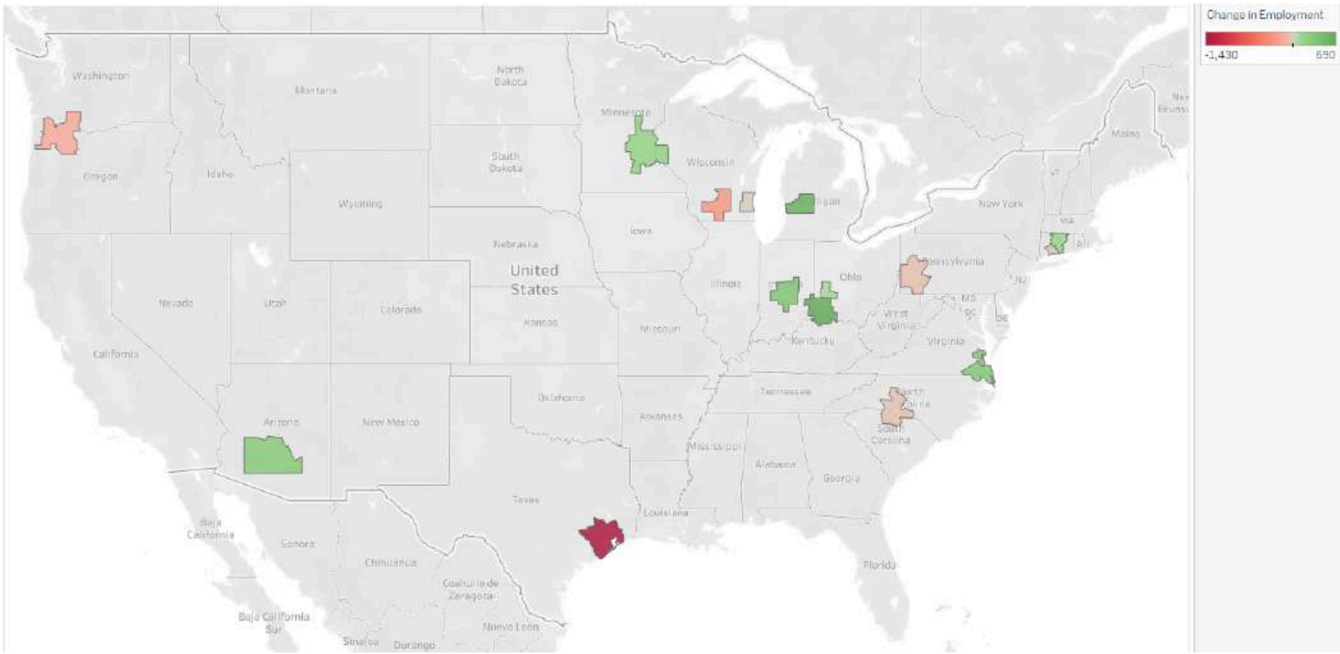


Figure 7: Map of labor change over 10 years for "Engine and Other Machine Assemblers" by MSA. Green indicates an increase in the available labor supply. Red indicates a decrease.

Change in Number of "Engine and Other Machine Assemblers" (51-2031) Over 5 Years by MSA

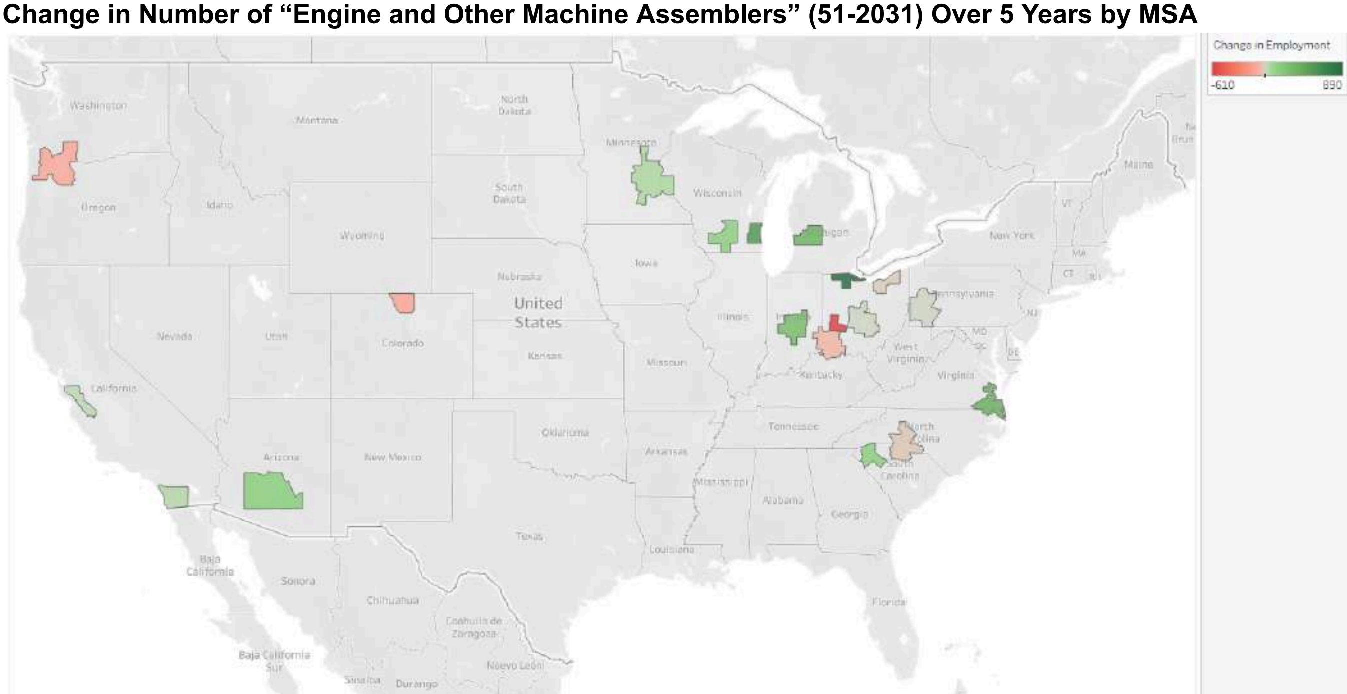


Figure 8: Map of labor change over 5 years for "Engine and Other Machine Assemblers" by MSA. Green indicates an increase in the available labor supply. Red indicates a decrease.

Change in Number of "Engine and Other Machine Assemblers" (51-2031) Over 1 Year by MSA

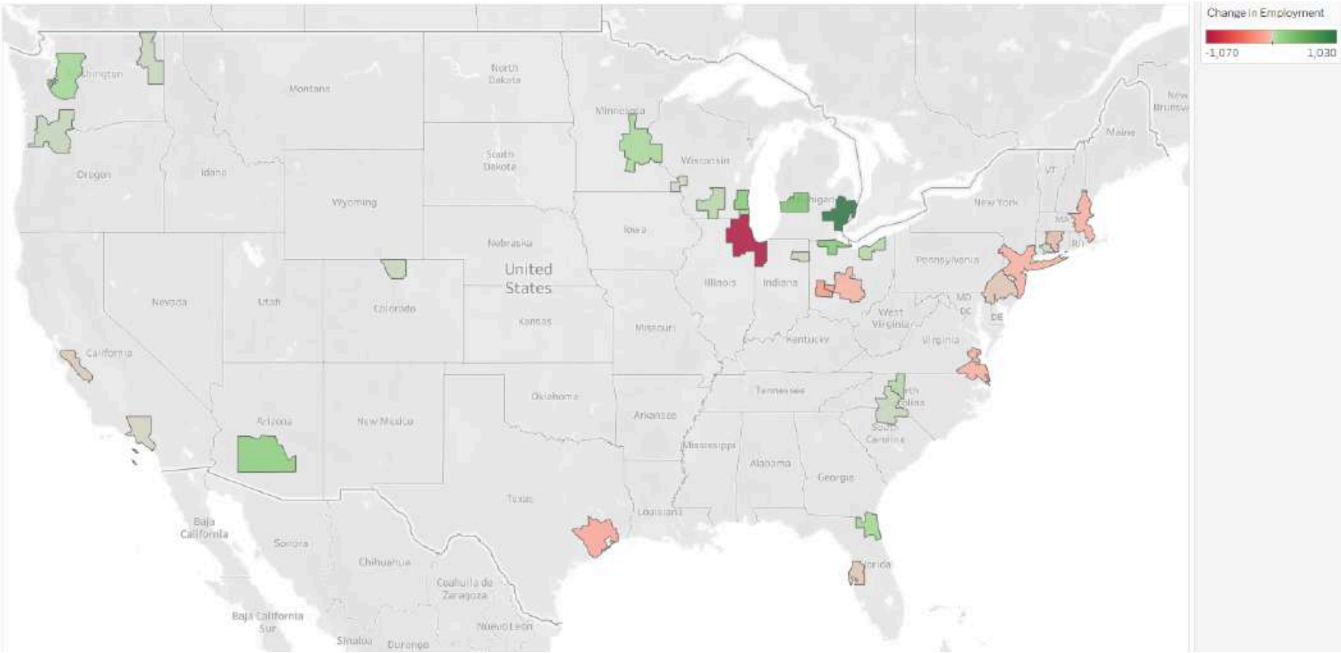


Figure 9: Map of labor change over 1 year for "Engine and Other Machine Assemblers" by MSA. Green indicates an increase in the available labor supply. Red indicates a decrease.

Skills Mapping with Workforce Insights

In order to determine labor competition for the selected occupation codes, we employed the Workforce Insights Tool (Combemale *et al.* 2023). For further details on the method, contact the corresponding author, Christophe Combemale.

For each occupation in the O*NET database, they have collected data on Skills, Abilities, Knowledge, and Work Activities (SKAWs) requirements. Each of these 4 categories has multiple subcategories so each individual occupation has 161 SKAWs that describe the occupation. For each of these SKAWs, there are two elements: Level, and Importance. Level is a measure of the degree of expertise needed in a given attribute to complete the requirements of the occupation. Importance is the emphasis placed on that attribute relative to other attributes within the occupation. The full methods report by Gonchar and Combemale describes the computation for Skills, while the same process is applied to Skills, Abilities, Knowledge, and Work Activities to measure overall occupational similarity.[13]

The percentage match between Levels of all occupations and a test occupation is then modified by the vector of Importance values. Specifically, a cosine similarity is calculated between all occupations and the test occupation using the method from Blair *et al.* 2021. This cosine similarity measures the angle between the Importance vectors of each occupation in the comparison. This method accounts for differences in how different occupations scale Importance. See **Appendix K** for details and a simplified example similarity comparison.

[13]The methods report prepared for the National Network of Critical Technology is available on SSRN at this address: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4671063
Please contact corresponding author Christophe Combemale for the latest materials from the Workforce Supply Chains initiative.

Mapping Labor Competition

The Tool's weighted comparisons method ranks cross-occupation similarity scores from 0 (no fit) to 1 (perfect fit). Here, we use the weighted comparisons feature to determine (a) what alternative occupations could fill the role of a given occupation and, inversed, (b) what alternative occupations can be filled by a given occupation. We define these as "similar occupations" - occupations to which workers within our occupation of interest may be able to transition, given their current skill set. We employed different minimum similarity score thresholds, varying between 0.7 and 0.9. **Figure 10** maps the ratio of employees within one occupation of interest ("Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic") to those employed in "similar occupations" at the MSA resolution using a similarity score threshold of 0.7; the full labor competition map set is compiled in **Appendix B**. While these labor competition heatmaps are somewhat informative, they have notable limitations. Wage differentials across occupations are not yet represented; we address this in the following section. These figures do not capture turnover or occupation change frictions, e.g., cost to retrain workers.

Number of "Engine and Other Machine Assemblers" (51-2031) divided by Number of Jobs with Skill Similarity>=0.7 by MSA

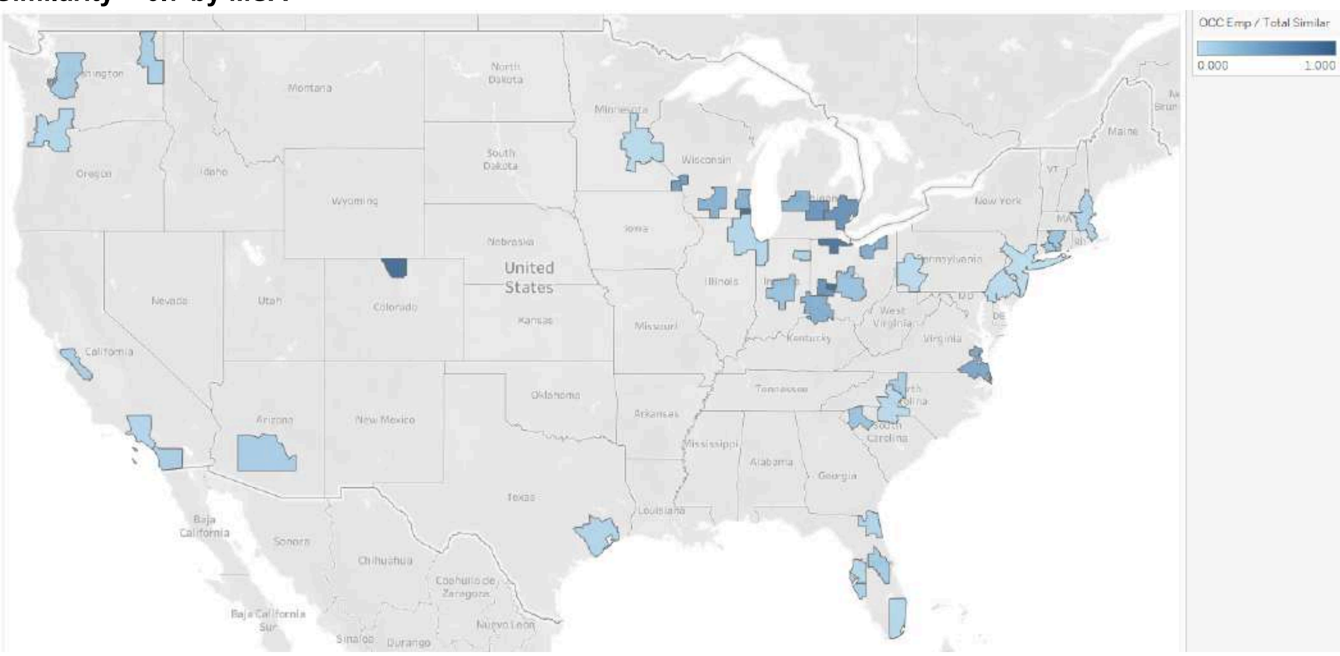


Figure 10: Quantity of "Engine and Other Machine Assemblers" as a fraction of workers in similar occupations (with a similarity measure of 0.7 or greater). This figure depicts how much competition exists in each MSA. Lighter blue represents more competition. Darker blue represents less competition, meaning less opportunity for an employer to replace a given worker, but also fewer potential opportunities for said worker to transition into when leaving their position.

Mapping Relative Wages of Similar Occupations to the ICEV Labor Supply

The previous section presented ratios representing the relative ease or difficulty of finding a similar job within the same MSA. However, a more important question to ask is: how likely is a worker to maintain or improve their wages by transitioning to a similar occupation? We approached this question using the percentile wage distributions (10th, 25th, 50th, 75th, & 90th) for each occupation and comparing them to annual wages of similar, alternative occupations in the MSA. For example, if the 10th percentile for the 'machinist' occupation is lower than the annual wages of an alternative occupation, then 90% of the total employment of that occupation is considered viable for transition. We repeated this process at ascending percentiles until a viable percentile is found, or until all percentiles available have been compared. For this methodological description, we use occupation 51-2031 "Engine and Other Machine Assemblers" to depict examples, but these methods are generalizable to any of the occupations in the previously shown **Table 4**. **Appendix C** contains the specific logic employed for this exercise in Tableau.

This analysis yields, per occupation of interest, MSA-resolved ratios of the sum of viable alternative occupation workers over the sum of all alternative occupation workers. **Figure 11** maps the ratio of viable to total alternative occupations for one occupation of interest, "Engine and Other Machine Assemblers", to total workers in similar occupations at the MSA resolution using **(a)** 0.7 and **(b)** 0.8 as the similarity score threshold. Additional example mappings from this analysis are compiled in **Appendix C**. Lower ratios for a given occupation and threshold can be interpreted as a riskier position for a worker because in the event of job loss, comparable occupations are paid less than their current wage. In short, we approximate the strategic position of ICEV workers to comparable workers in their area in this analysis. The threshold parameter is a key parameter for interpreting these maps: a higher threshold tightens the alternative occupation domain, but what remains are occupations that are a better fit for the given occupation.

a) Relative Wage Position of "Engine and Other Machine Assemblers" (51-2031) When Comparing Jobs with Skill Similarity >= 0.7 to 50th Percentile by MSA

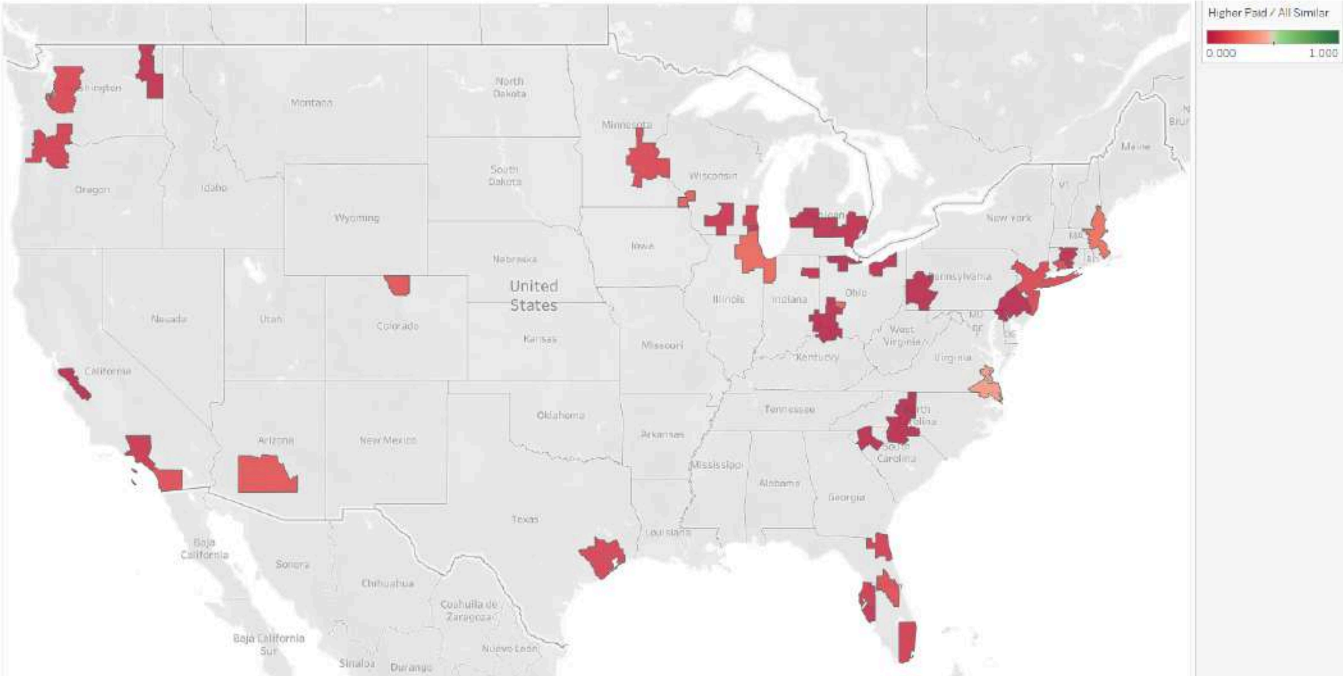


Figure 11: Quantity of workers earning equal or more than the average worker in occupation 51-2031 "Engine and Other Machine Assemblers" as a fraction of the total number of workers in similar occupations, using **(a)** 0.7 and **(b)** 0.8 as the similarity thresholds (next page).

b) Relative Wage Position of "Engine and Other Machine Assemblers" (51-2031) When Comparing Jobs with Skill Similarity >= 0.8 to 50th Percentile by MSA

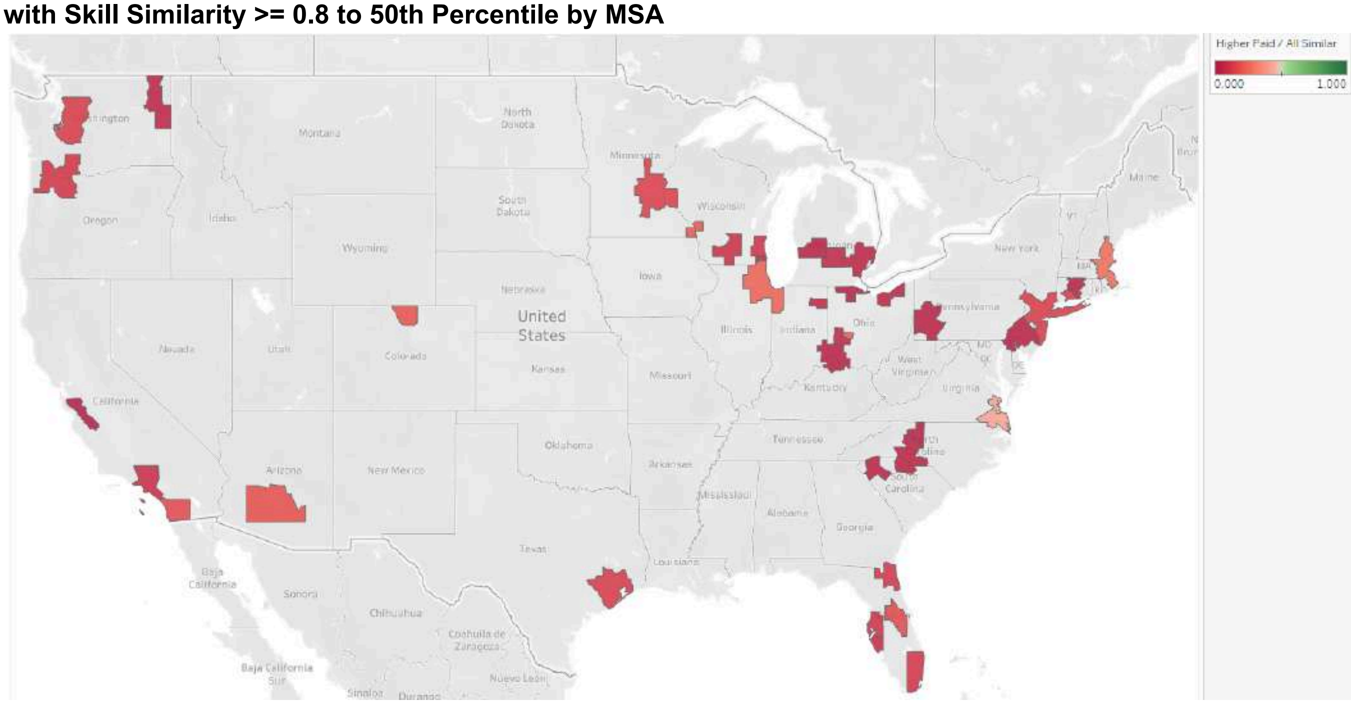
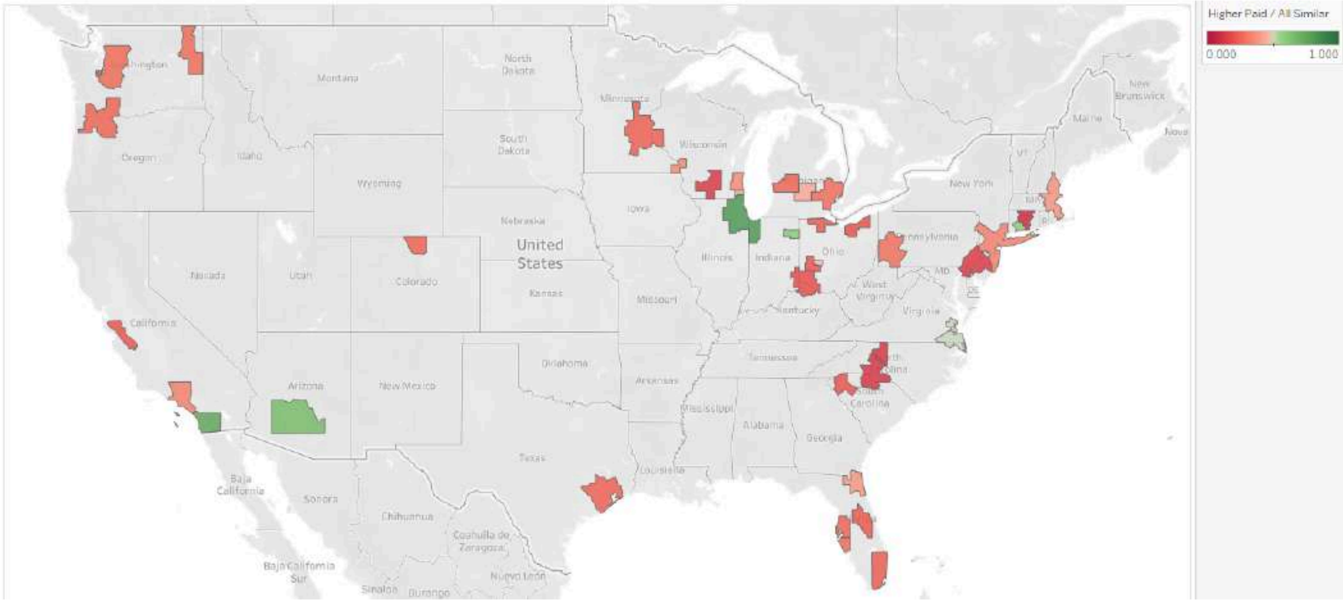


Figure 11: Quantity of workers earning equal or more than the average worker in occupation 51-2031 'Engine and Other Machine Assemblers" as a fraction of the total number of workers in similar occupations, using **(a)** 0.7 and (previous page) **(b)** 0.8 as the similarity thresholds (this page).

The above **Figure 11** depicts prospects from the position of the worker making the mean salary (i.e., 50th percentile). Employees within the worker's occupation are generally paid better than those in similar occupations in MSAs colored along the red gradient, while compensation for workers in similar occupations is higher than studied occupation for those MSAs along the green gradient. One can interpret red MSAs as those where it is difficult for a worker in the studied occupation to change to a similar occupation and maintain a similar standard of living. While mean salary is an appropriate first estimate of relative wage comparisons, it does not take advantage of and account for the distributional salary data available in the BLS dataset.

We repeat the analysis from the perspective of employees at varying percentiles of earners within the same occupation; **Figure 12,** on the next page, shows these results. This set of results represents a sensitivity analysis depicting how a worker's prospects can vary within an occupation depending on their earnings. Consider, for example, the Chicago and Houston MSAs. The prospects for 51-2031 “Engine and Other Machine Assemblers” workers at the 10th percentile of earnings have significantly more opportunities to increase earnings than their counterparts in higher percentiles in Chicago, compared to Houston where there is little opportunity to increase earnings for workers at any percentile.

a) Relative Wage Position of "Engine and Other Machine Assemblers" (51-2031) When Comparing Jobs with Skill Similarity>=0.7 to 10th Percentile by MSA



b) Relative Wage Position of "Engine and Other Machine Assemblers" (51-2031) When Comparing Jobs with Skill Similarity>=0.7 to 25th Percentile by MSA

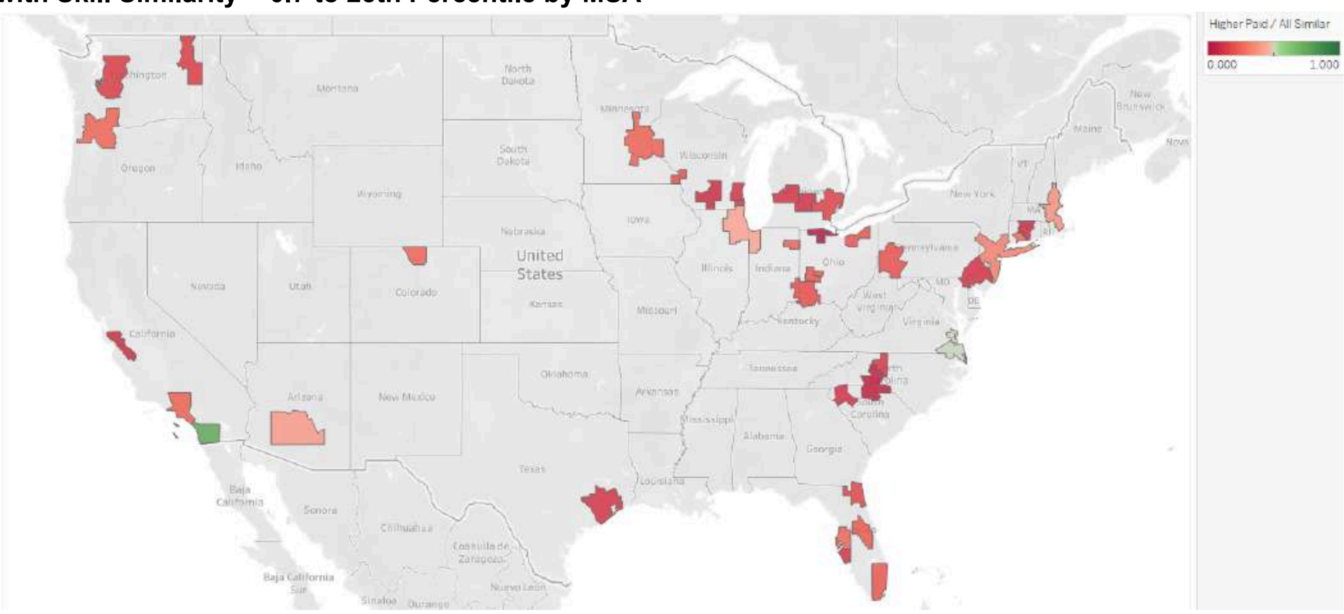
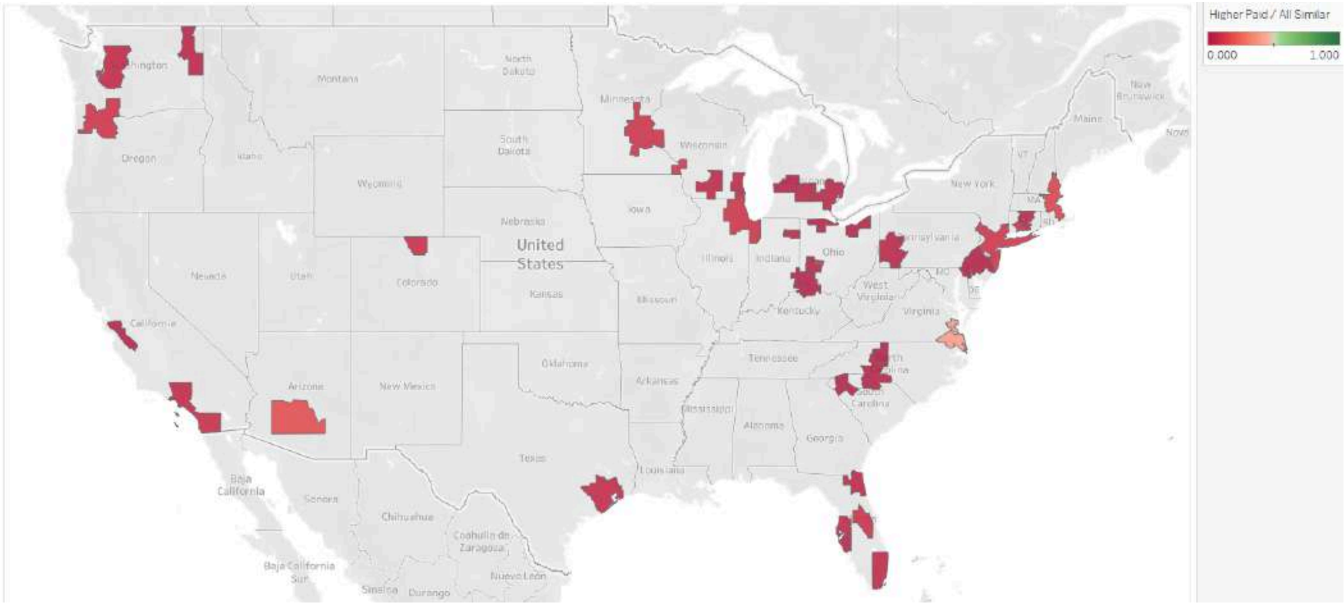


Figure 12: Quantity of workers earning equal or more than the 10th, 25th, 75th, and 90th percentile worker in occupation 51-2031 "Engine and Other Machine Assemblers" over the total number of workers in similar occupations, with **(a)** 10th percentile, **(b)** 25th percentile, **(c)** 75th percentile, and **(d)** 90th percentile of earners respectively (continued on next page).

Figure 12 (continued)

c) Relative Wage Position of "Engine and Other Machine Assemblers" (51-2031) When Comparing Jobs with Skill Similarity>=0.7 to 75th Percentile by MSA



d) Relative Wage Position of "Engine and Other Machine Assemblers" (51-2031) When Comparing Jobs with Skill Similarity>=0.7 to 90th Percentile by MSA

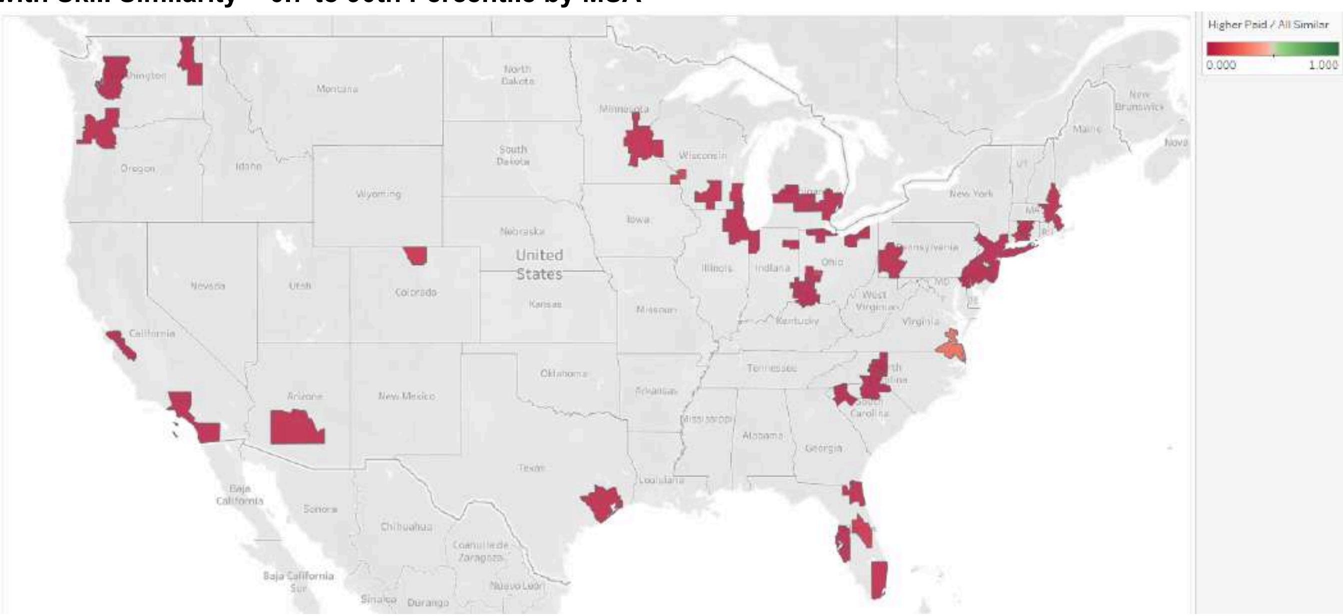


Figure 12: Quantity of workers earning equal or more than the 10th, 25th, 75th, and 90th percentile in occupation 51-2031 "Engine and Other Machine Assemblers" as a fraction of the total workers in similar occupations, with **(a)** 10th percentile, **(b)** 25th percentile, **(c)** 75th percentile, and **(d)** 90th percentile of earners respectively.

As expected, lower wage percentile workers have more opportunities to increase earnings, while higher wage percentile workers are less likely to be able to maintain their earnings when changing occupations. A limitation of this analysis is that it treats all workers within an occupation as equally qualified for alternative positions. Realistically we expect that there is a relationship, however big or small it may be, between competency and earnings, but this analysis does not capture that relationship.

Next, we combine **Figures 11** and **12** to produce a weighted composite **Figure 13**. The ratio values from **Figures 11** and **12** are weighted by the size of each percentile bin to produce a single estimate of an occupations earning potential across the full distribution of wages. This method of generating different calculations for each percentile group, then taking the weighted average of their results, incorporates the 'spread' of wages in an MSA and allows us to account for the potential of skewed distributions of wages within the occupation. The composite ratio map is similar to its first-order approximation as depicted by **Figure 12**'s median (50th percentile) ratio. There are slight differences; for example, the San Diego MSA has better alternatives for transitioning ICEV workers (0.2684 vs 0.1388) depicted in the composite estimate. Overall, the 50th percentile approach is a reliable approximation of the weighted average of percentiles.

Relative Wage Position of "Engine and Other Machine Assemblers" (51-2031) When Comparing Jobs with Skill Similarity>=0.7 Weighted by Quantity of Workers within Percentiles, by MSA

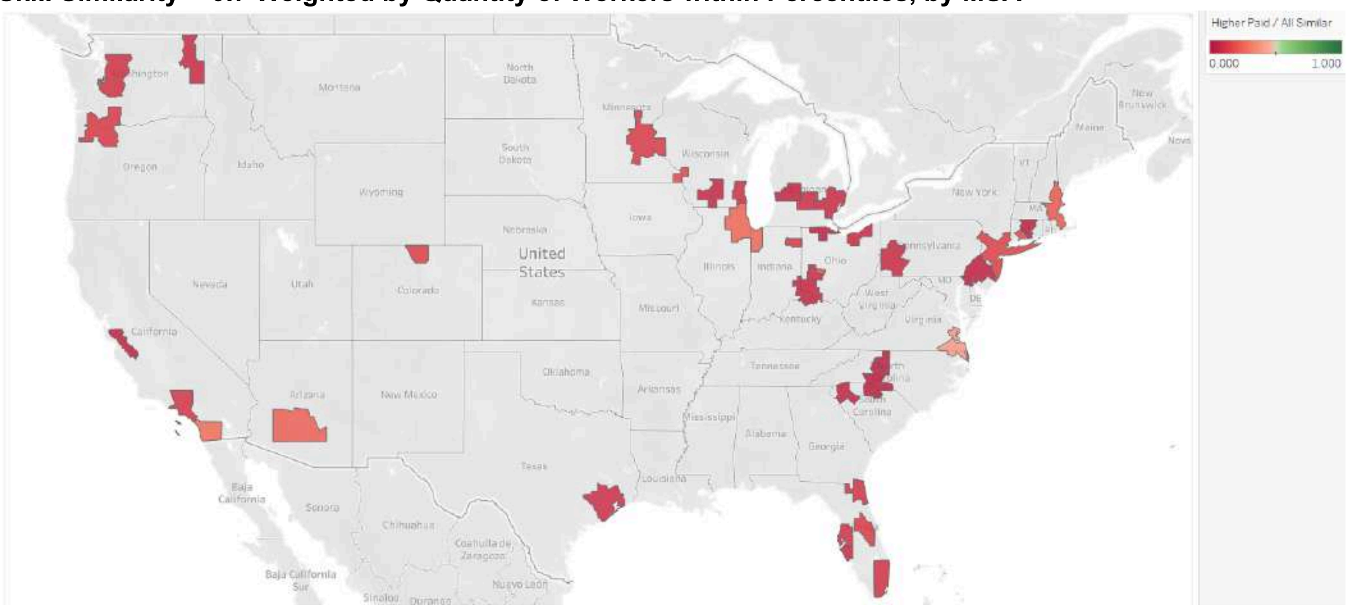


Figure 13: Weighted average of the number of workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile workers in occupation 51-2031 "Engine and Other Machine Assemblers" over the total number of workers in similar occupations. This figure is similar to **Figure 11** but offers a more accurate account of any skew in the distribution of wages within the occupation.

While the relative wage position maps are informative when looking at labor supply, they do not capture the effects of changing labor demand over time. To capture the effects of demand change, we filter our dataset to only include occupations with an increasing supply in their MSA from 2021 to 2022. This is done with the assumption that it will be more difficult for a worker to change from their current occupation to a *contracting* occupation. Next, we use the same logic used to produce **Figure 13**, replacing all references to 'total employment' with the corresponding 'change in employment'. This results in **Figure 14**. This allows us to estimate the probability of an exiting ICEV worker landing a job that has a higher or lower salary. The full set of figures depicting relative wage positions of occupations based on change in supply (rather than static supply) can be found in **Appendix J**.

Relative Wage Position of "Engine and Other Machine Assemblers" (51-2031) When Comparing Jobs with Skill Similarity>=0.7 Weighted by Change in Labor Supply within Percentiles, by MSA

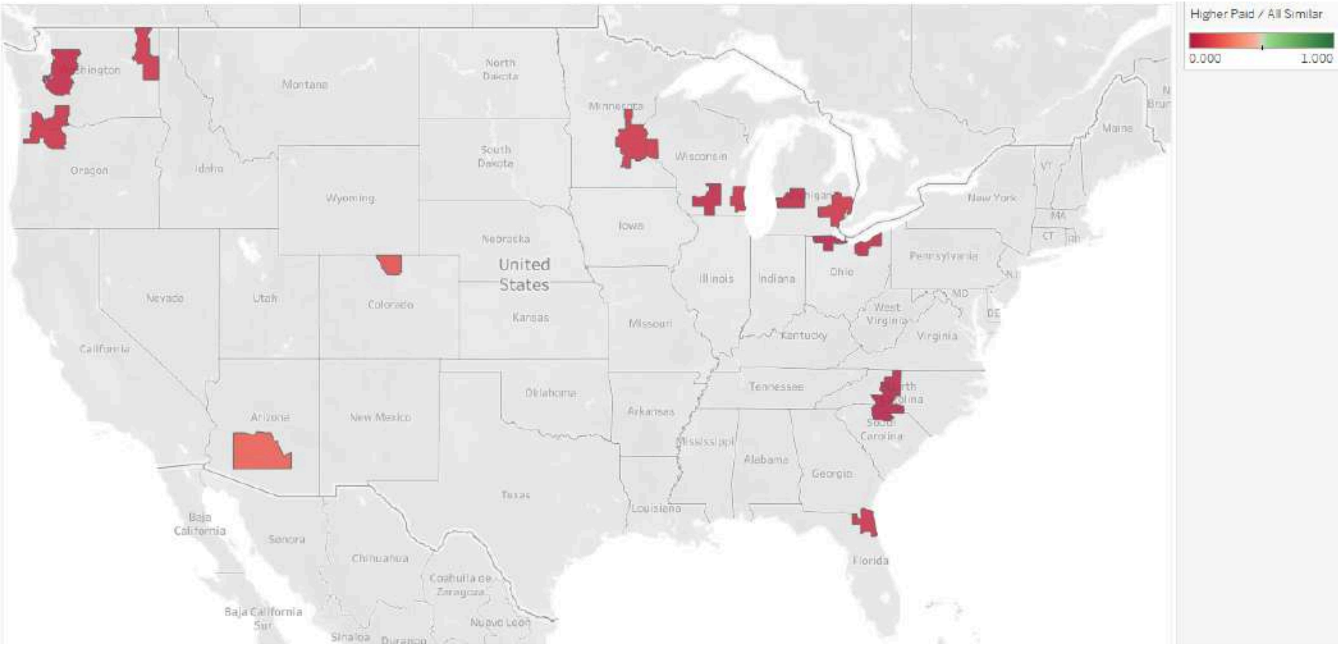


Figure 14: Weighted average of the change in workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile workers in occupation 51-2031 "Engine and Other Machine Assemblers' as a fraction of the total number of change in workers in similar occupations. This figure excludes occupations that had a decrease in total employees in their MSA.

We quantify the gap between earnings comparing an occupation to its alternatives. We use a skill similarity of 0.7 to calculate and map the wage premium demanded by the occupation, as compared to occupations to which a current worker could reasonably transition (**Figure 15**, next page). Specifically, we calculate the weighted average using total employment within each occupation, then subtract that value from the mean wage of our occupation of interest, divide that by the mean wage of said occupation, and plot the resulting percentage difference. This figure shows that 51-2031 workers command a wage premium in almost every location where they are found, sometimes nearing +50% when compared to those in alternative occupations. The only MSA for which 51-2031 workers do not command a wage premium, Virginia Beach, may be explained by heavy right tails in wages for similar occupations specific to the region. Overall, the prevailing trend indicates that it will be difficult to maintain or improve earnings when transitioning out of this occupation.

Percentage Wage Premium Demanded by Engine and Other Machine Assemblers (51-2031) When Compared to Jobs with Skill Similarity>=0.7

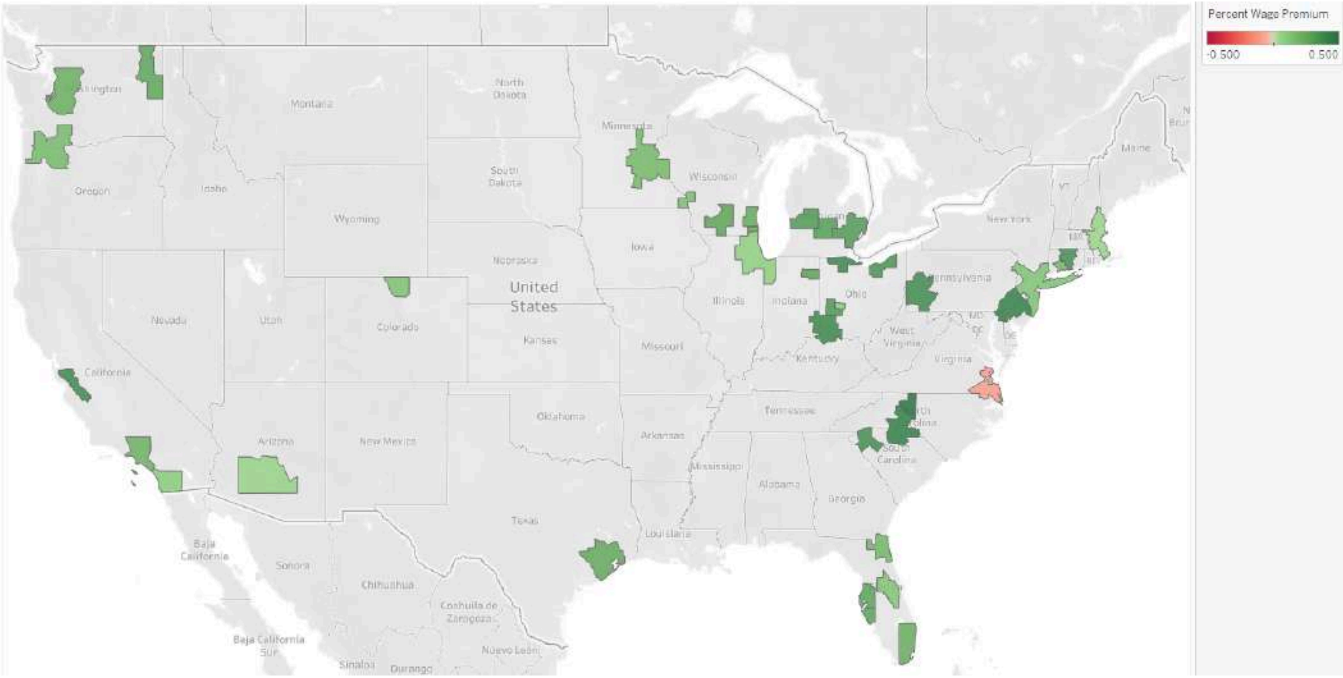


Figure 15: Local wage premium demanded by workers in occupation 51-2031 “Engine and Other Machine Assemblers" when compared to workers in alternative occupations.

Finally, we summarize our wage premium comparison analyses by aggregating wage premium comparisons at the MSA resolution to the national scale. **Figure 16** illustrates the national aggregation as parallel box plots for an occupation of interest compared to its alternative occupations. Each point in the box plot represents an average annual wage within an MSA. The values of alternative occupations were weighted by the total employment of those occupations. Despite having more geographic variance, 51-2031 wages are higher on average than wages of other similar occupations.

National Distribution of Wage Premiums Demanded by "Engine and Other Machine Assemblers" Compared to Jobs with Similarity>=0.7

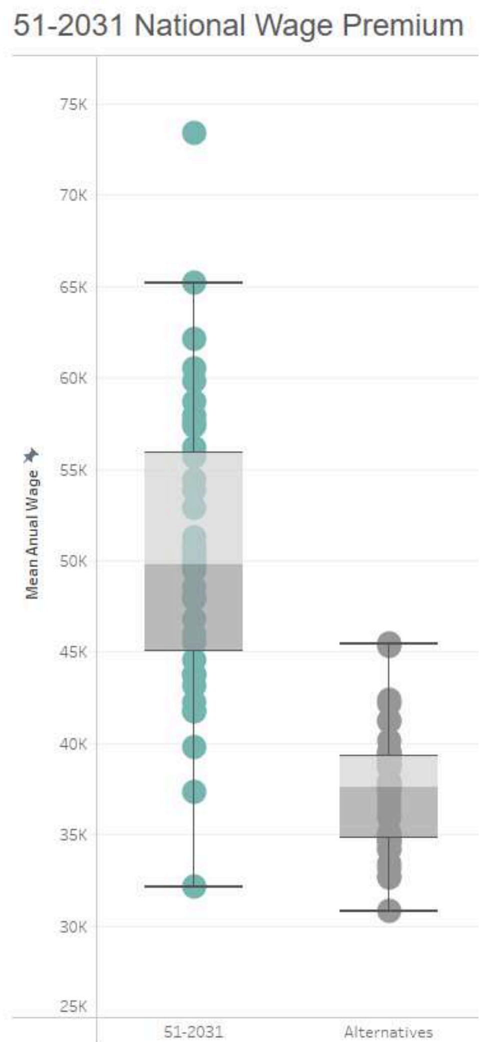


Figure 16: Wage distributions of workers in occupation 51-2031 "Engine and Other Machine Assemblers" when compared to workers in alternative occupations. Each point in the box plots represents an average annual wage within an MSA. The values of alternative occupations were weighted by the total employment per occupation.

Relative Alternative Wage Analysis

In the last section, we explored where the wages of an occupation sit relative to similar occupations on average or by a specific percentile. Here, we offer greater detail by plotting the distribution of wages in similar occupations. For each percentile entry for each alternative occupation, a portion of the total employment represented by that occupation (in the specified geography) is assigned to a corresponding bin to compose a combined histogram. The portion of the total employment allocated to a bin depends on the percentile that the data was pulled from (e.g., 10th to 25th percentile yields 15 percent in-bin). **Appendix D** contains the specific logic employed for this exercise in Tableau.

Overlaying the 10th, 25th, 50th, 75th, and 90th percentiles of our occupation of interest on top of the histogram of alternative occupation wages allows us to compare the distributions. **Figure 17** shows the distribution of wages in alternative occupations for one occupation's (51-2031 "Engine and Other Machine Assemblers") wage percentiles at varying minimum thresholds for skill similarity to the alternative occupations. Additional example figures from this analysis are compiled in **Appendix D**. These figures have multiple, color-coded, stacked histograms, each one representing a percentile for a particular alternative occupation. The black points are the percentiles of the occupation of interest in **Figure 17**,"Engine and Other Machine Assemblers". Note that the black dots are exact values whereas the values for similar occupations are binned. The occupation of interest (black dots) is also included in the color bars of the histogram. This is because the roles are not industry specific, and the distribution of wage even within an occupation represents meaningful information for potential job transitions.

Distribution of Annual Wages of "Engine and Other Machine Assemblers" (51-2031) and Jobs with Similarity>=0.7, >=0.8, and >=0.9 in the Detroit MSA

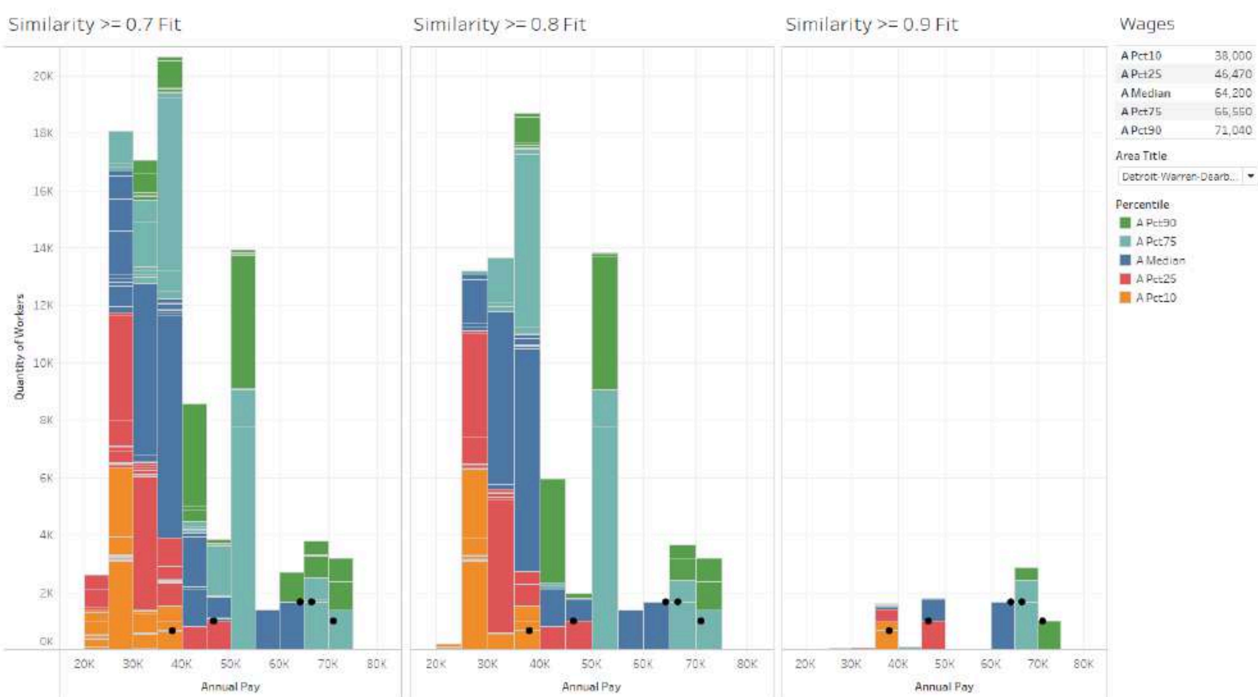


Figure 17: Histogram of distribution of wages in alternative occupations to 51-2031 "Engine and Other Machine Assemblers" by occupation percentile wages, color-coded by percentile, in the Detroit MSA, when specifying **(a)** 0.7, **(b)** 0.8, and **(c)** 0.9 as the minimum threshold for occupational skill similarity. The black circles indicate the 10th, 25th, 50th, 75th, and 90th percentile of 51-2031 pay respectively.

By observing the distributions at, and to the right of, a given 51-2031 percentile, we can determine what occupations will allow them to maintain or improve their current earnings, as well as determine into what percentile of earners they will need to be hired when transitioning occupations. The three histograms represent the opportunity space when considering occupations with varying skill similarities. A lower skill similarity reflects a higher need for additional training in order to fulfill the needs of the target occupation. These figures allow us to more precisely visualize the prospects of workers in an occupation, custom tailored to their geographic area. This can allow for data-driven targeted policy decisions at the local, state, and federal levels by identifying where workers' prospects are unique to a specific location, and where they have regional or national commonality.

In isolation **Figure 17** paints an imperfect picture. The existence of workers in other occupations in an area does not necessarily mean that there are job openings for workers looking to fill that occupation, though it does suggest a background level of job openings due to ordinary attrition and labor market turnover. While **Figure 17** looks at the *stock* of similar jobs, we also need to consider the *flow* into and out of those jobs.

The existing BLS data lacks the detail to determine turnover within an occupation. The closest approximation with the available public data is found in the net change in jobs in an occupation over a period of time. Analyzing this informs us about the potential number of net new jobs that could be filled by a net influx of displaced automotive workers, noting that the background turnover of an occupation may provide some opportunities for individual new workers to enter even if net growth is negative. We implement this in **Figure 18** (next page), with all similar figures plotting other occupations and MSAs found in **Appendix D**. This allows us to visualize a change in employment over time (though negative changes could be driven by a combination of both decreasing employment and aging or exiting workers). By using this net change in employment in place of total employment to calculate the size of our histogram bins, we can avoid comparing our occupation of interest to occupations that will have limited employment opportunities while simultaneously indicating which other (shrinking) occupations the workers within our occupation of interest may need to compete with when looking for a new job.

Distribution of Annual Wages of "Engine and Other Machine Assemblers" (51-2031) and Jobs with Similarity>=0.7 in the Detroit MSA Weighted by Change in Labor Supply

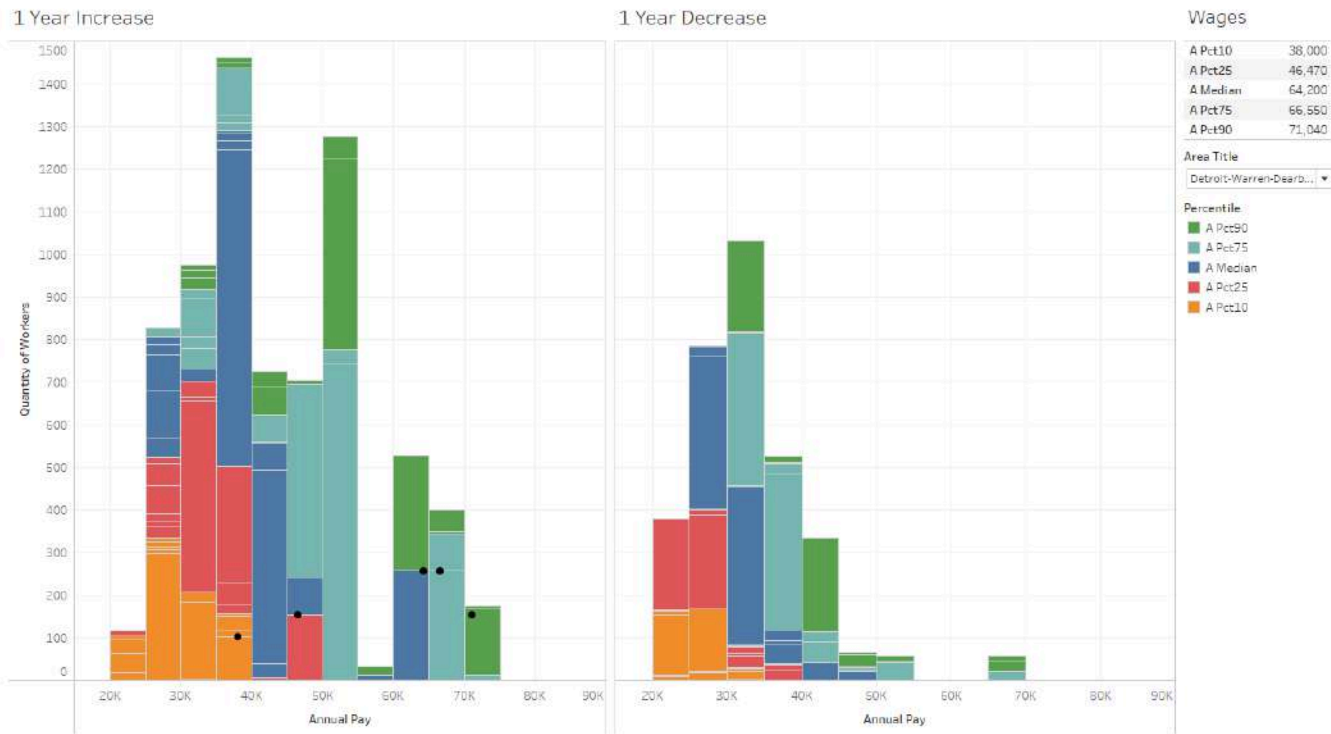


Figure 18: Histogram of distribution of wages in alternative occupations to 51-2031 "Engine and Other Machine Assemblers" by occupation percentile wages weighted by the change in labor supply for the same occupation, color-coded by percentile, in the Detroit MSA, when specifying 0.7 as the minimum threshold for occupational skill similarity. The black circles indicate the 10th, 25th, 50th, 75th, and 90th percentile of 51-2031 pay respectively.

The histogram to the left indicates an increase in the labor supply in those occupations. If the employment for those occupations continues with the same upward trend, this figure indicates the possible transition options available to 51-2031 workers. The histogram to the right indicates a decrease in the labor supply in those occupations. If this is reflective of a continued pattern of decreasing employment for these occupations, workers exiting 51-2031 may find themselves competing with these workers for new positions. If this is the case, 51-2031 workers will be forced to take positions with approximately half the annual salary on average.

Age Distribution of Incumbent ICEV Workforce

While some portion of displaced ICEV workers may transition to new occupations, we can anticipate that other workers will simply move on to an early retirement, exiting the workforce. Indeed, if there is a left sufficient skew in the age of the workforce, then worker attrition over time due to retirement (assuming fewer new hires to backfill the attrition) could mean that the number of disrupted workers in need of transition could be ameliorated by delays in the timing of ICEV disruption, or phased reductions in incumbent labor demand.[14] In order to understand the ratio between these groups, as well as how each occupation is impacted individually, we plot the age distribution of each occupation. The following figure (**Figure 19**) uses publically available US Census data on age distribution by occupation. Not all occupation names match one-to-one with our list of ICEV SOC codes, but they are close enough to provide an informative picture.

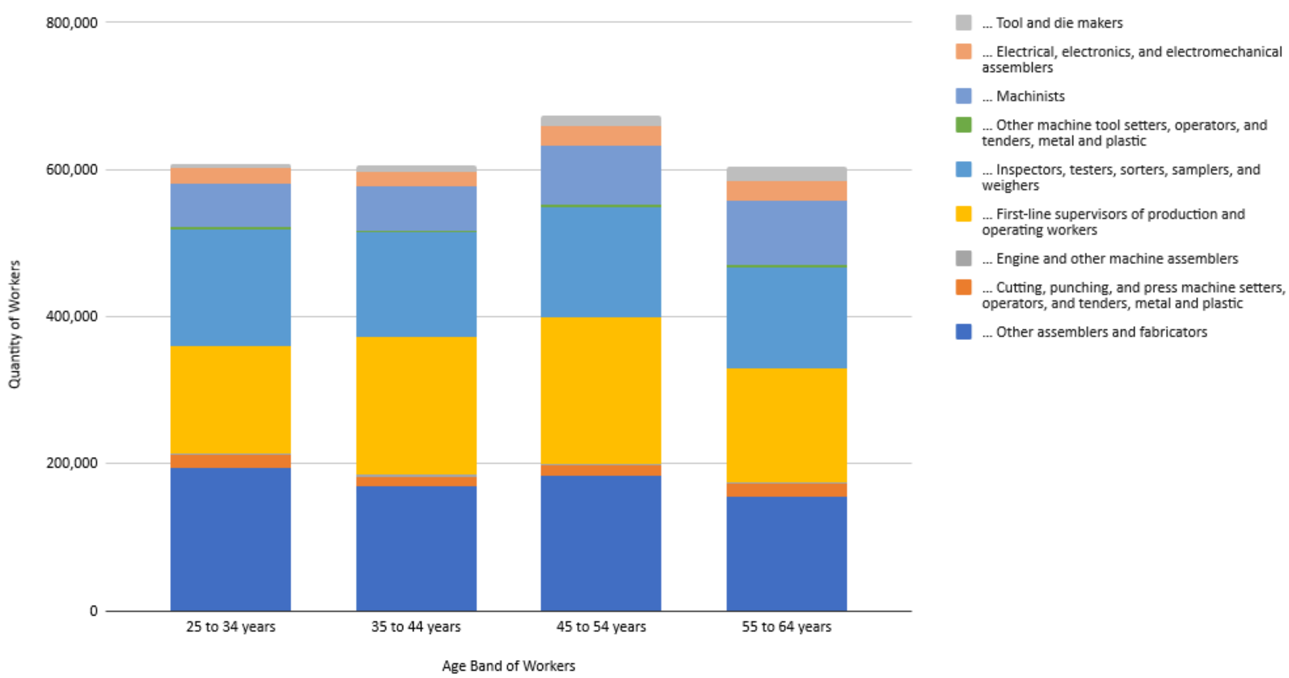


Figure 19: *Age distribution of workers in the top ICEV occupations.* These stacked bar charts show the quantity of workers represented in each of the four age groups.

When all occupations are combined, the distribution seems roughly even, with the 45 to 54 age group having the highest representation. Next, we look at the percent distribution of workers for each occupation individually (**Figure 20**, next page). When observing age distributions at this level of detail, we see several occupations exhibit skewed distributions. Of note, over 40% of “Tool and Die Makers” are between the ages of 55 and 64, making them the occupation with the greatest percentage of near-retirement workers. Even if only a quarter of these move into early retirement, that would still represent more than a 10% drop in the number of “Tool and Die Makers” in the affected area.

[14]Further work is needed to validate whether the age of workers in our production occupations of interest is correlated with higher wages (e.g. due to greater experience), but if so, a left-skewed age distribution could present opportunities to further manage the transition – older, high-wage workers may have the narrowest options for wage-sustaining transitions, but may also be more prepared to transition out of the labor market into earlier retirement.

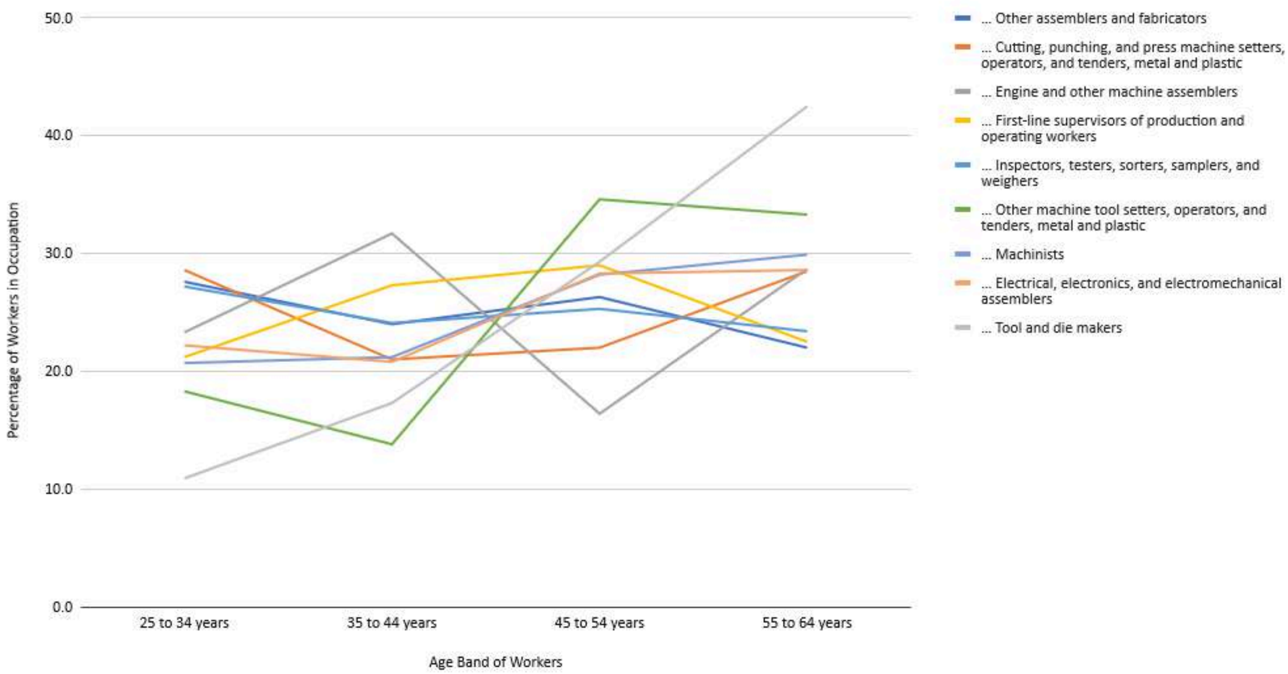


Figure 20: *Percentage age distribution of workers in the top ICEV occupations.* Each line is made up of four points, one for each group represented in the Census data used by BLS.

Emerging EV and Battery Labor Demand

To estimate labor demand for electric vehicles and batteries, we proceed through the following modeling framework. First, we clean data on new factory announcements in clean energy from private sector manufacturing as compiled by Argonne National Laboratory ("Argonne dataset")[Energy.gov 2023], filtering these announcements into two technology categories: (i) Batteries and (ii) Electric Vehicles. Reported jobs were available for 76.1% of the announcements in these two categories. For announcements without reported jobs data, we fit a linear model of the invested dollars to jobs reported for the two technology categories. We further increase the granularity of the linear regression categories by splitting the Battery technology category into two product sets: (i) Cells, Packs, and Cells & Packs and (ii) Battery Components and Constituent Materials. We impute missing reported jobs data using the most specific regression available, as shown in **Table 5**. Finally, we map coordinate data to geographic metropolitan statistical areas (MSA) to enable cross-comparison with the best available labor data.

Technology Category	Product Sub-Category	Reported Jobs Available	Reported Jobs Imputed with Regression
Batteries	Cells, Packs, and Cells & Packs	60197 (66 factories)	18142 (26 factories)
Batteries	Battery Components and Constituent Materials	16155 (68 factories)	4852 (21 factories)
Electric Vehicles	(n/a)	52713 (86 factories)	10544 (22 factories)
Total		129,065 (220 factories)	33,538 (69 factories)

Table 5: Summary of reported jobs data present and imputed via linear regression in the Argonne dataset

Data Collection & Cleaning: Argonne Dataset

The Argonne dataset provides investment, jobs, and location data for announced factories across four technologies; Batteries, Electric Vehicles, Offshore Wind, and Solar (Energy.gov 2023). We focus solely on factories intended for the production of Battery and Electric Vehicle products. **Table 6** summarizes the total data counts from the original file and through the data cleaning and filtering process.

Not all announced factories include details regarding reported investment (“reported_investment”), reported jobs (“reported_jobs”), or location (“latitude” and “longitude”). We filter out points missing location data, then we filter out points missing reported jobs or investments. Next, we manually check any two points whose locations match with a two-tenths degree tolerance, and confirm that these are not duplicate points belonging to the same factory announcement.

Step	Batteries	EVs	Total
Original	245	146	391
Points including reported investment and/or reported jobs	178	108	286
Remaining points mappable to MSA	166	105	271

Table 6: Argonne data summary pre- and post-data cleaning and assignment to unit of analysis (MSAs).

Imputing Missing Jobs Estimates in the Argonne Dataset

Not all anticipated factories in the remaining dataset included values for reported jobs (**Table 5**). In order to impute these missing data, we fit linear regression models to impute reported jobs as a function of reported investment. Model choice and estimation for all regressions are detailed in **Appendix E**. The missing reported jobs data points do not appear to have a spatial bias (**Figure E.1**).

The first set of linear regressions are segmented by technology type: Batteries & Electric Vehicles, for which 71.8% and 74.4% of the variance in reported jobs could be explained by reported investment (**Table 7**).

Technology	N	Reported Investment Estimated Coefficient	Estimated Intercept	Standard Error	R^2
Batteries	109	0.6514	113.35	479.7652	0.7176
Electric Vehicles	71	1.0868	181.39	590.9882	0.7439

Table 7: Summary of linear regression coefficient estimations and standard errors when modeling reported jobs as a function of reported investment.

We conduct the second set of linear regressions by product subtype. All three Electric Vehicle subtypes had fewer than 30 data points (limiting the reliability of a linear model), but the five battery subtypes could be grouped into two sets of similar subtypes which had sufficient data for estimating a model. Set 1 contained (a) Cells, (b), Packs, and (c) Cell & Packs product subtypes. Set 2 contained (a) Battery Components and (b) Constituent Materials. For Set 1 and Set 2 of Battery subtypes, 75.8% and 57.7% of the variance in reported jobs could be explained by reported investment (**Table 8**).

Set of Battery Product Subtypes	**N**	**Reported Investment Estimated Coefficient**	**Estimated Intercept**	**Standard Error**	**R^2**
Set 1	54	0.6983	219.40	536.0863	0.7584
Set 2	55	0.3355	108.23	230.9518	0.5768

Table 8: Summary of linear regression coefficient estimations and standard errors when modeling reported jobs as a function of reported investment.

We use the regressions detailed above to impute reported jobs for the 29% of our the dataset for which this information was missing. We impute missing reported jobs data using the most specific regression available, as shown in **Table 5**. By imputing these missing data we increased the usable dataset size from 210 to 217 announcements.

Aggregating Labor Demand to Metropolitan Statistical Areas

The Argonne dataset is our approximation of labor demand. We pair this with labor supply data from the Bureau of Labor Statistics (BLS), which reports at the unit of MSA. Thus, we aggregated the Argonne dataset's point data into MSAs for more direct comparison. **Appendix F** offers technical details on this aggregation method. We also construct a buffer around each MSA polygon of two-tenths of a degree, and manually check Argonne points in the buffer zone to determine whether they should be grouped into an MSA.

In sum, 271 of the 296 points are aggregated into 74 unique MSAs, representing a total labor demand of 153,220 employees. When we filter down to MSAs for which labor supply data was available from BLS (as not all MSAs have jobs data within BLS), we are left with a total labor demand of 139,058 employees. **Figure 21** (following page) maps this labor demand. This figure captures 85% of the total labor demand reported or imputed in the Argonne dataset, and is compatible with BLS data for further analysis of labor supply and demand.

Battery & EV Jobs - Total Mappable Demand

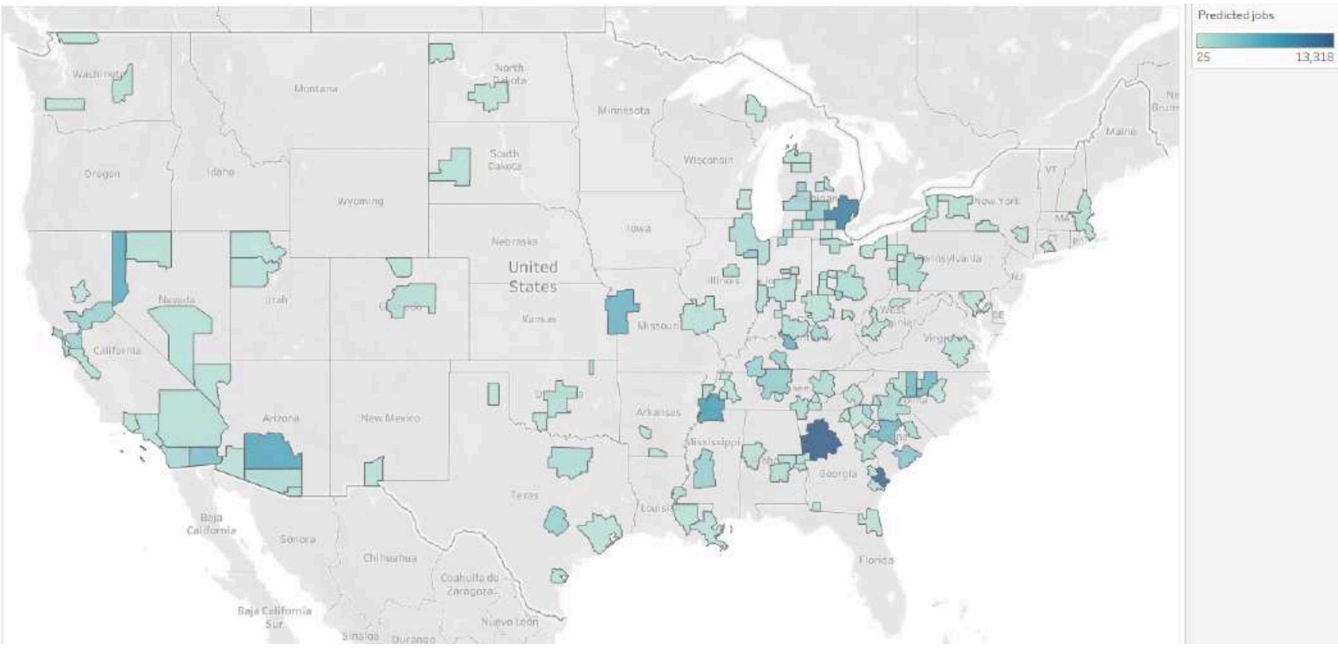


Figure 21: Argonne factory announcement data aggregated to MSAs, for those MSAs that also have labor supply data available in the BLS dataset. The heatmap shows the total jobs either reported or imputed via the most technology-specific linear regression.

Comparing EV and Battery Labor Demand with Current Labor Supply

Here we evaluate if local labor supply can meet the demand of announced Battery and EV factories. Specifically, we combine MSA-aggregated data on new factory announcements and thus labor demand from the Argonne dataset with current employment in related occupations from the BLS dataset. The occupations we focus on for fulfilling the new labor demand created by these factories were informed by Careers in Electric Vehicles (Hamilton 2011) and interviews conducted during the project. Hamilton outlines manufacturing occupations that are vital for the growing EV and Battery production industries, and are likely to make up the majority of the labor demand forecasted in the factory announcements:

51-2022 Electrical and Electronic Equipment Assemblers
51-2023 Electromechanical Equipment Assemblers
51-2031 Engine and Other Machine Assemblers
51-2092 Team Assemblers
51-9161 Computer Numerically Controlled Tool Operators
51-4041 Machinists
11-3051 Industrial Production Managers

We made three minor adjustments to this manufacturing occupations list in order to marry Hamilton's concepts with the available BLS dataset. (1) We combined 51-2022 and 51-2023 and calculated it as 51-2028. (2) We elevated 51-2092 to 51-2090. (3) Since "computer controlled machine tool operators" (Hamilton 2011) do not exist in the BLS dataset, we used 51-9161 in its place.

We subtracted labor demand in the Argonne dataset from the available labor supply reported by the BLS dataset for each MSA and mapped these in **Figure 22**. For MSAs reporting values greater than one, the current labor supply can be interpreted as exceeding the predicted labor demand from the factory announcements. Many 'outlier' red MSAs shown in this figure occur when large factories were announced in MSAs with relatively small population and limited auto industry representation at present. There are, of course, limitations to this first-order analysis. First, all occupations in Batteries and Electric Vehicles are grouped together, so we lack details on the distribution of occupations demanded compared to labor supply occupations. We do not have data on the turnover rate of workers – voluntary or involuntary separations creating job openings for transitioning workers to enter – or the rate of growth of net job opportunities. We also do not know how many people will want to change jobs due to wage competition or other factors. Nonetheless, this method offers a first-order analysis of which locations are at the highest risk of not being able to fulfill their factory announcement goals, resulting from an inability to staff all anticipated positions.

Anticipated Battery & EV Job Demand / Total Workers In Desired Occupations (Hamilton 2011)

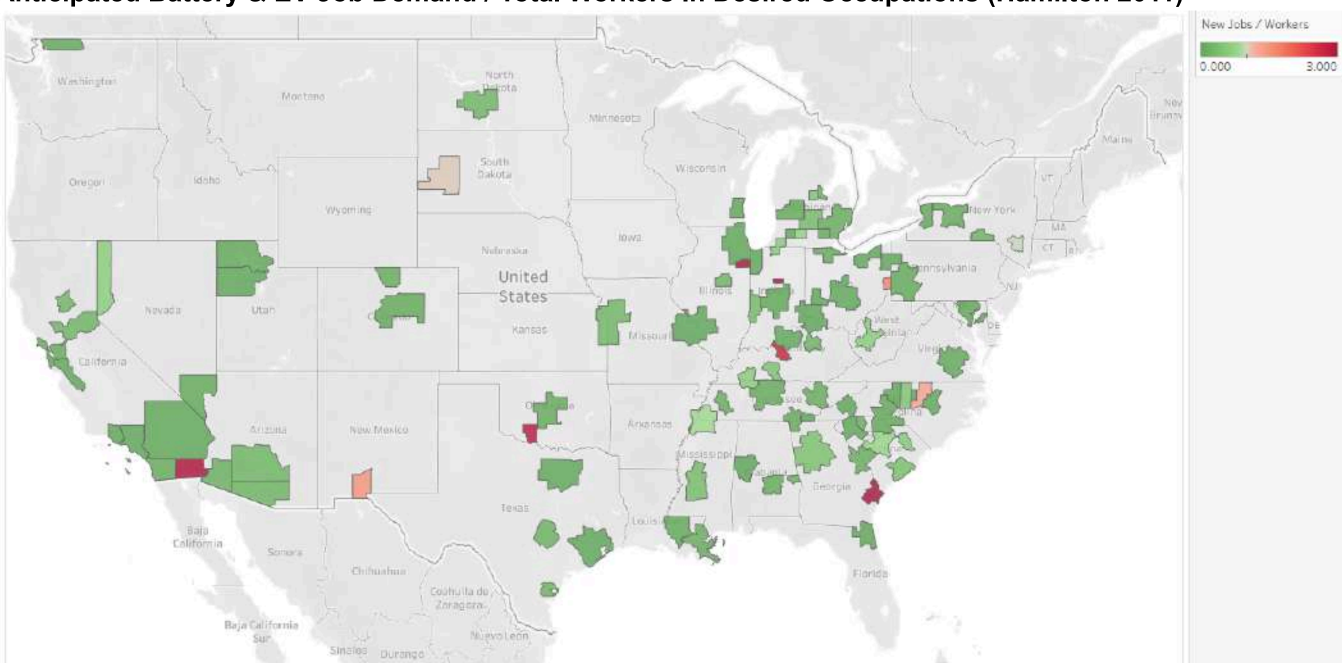


Figure 22: Labor demand for Battery and EV factory announcements over available labor stock filling critical occupations (Hamilton 2011). A 1:1 ratio indicates that the new labor demand matches the total existing labor supply. Red indicates that demand exceeds total supply. Green is not necessarily sufficient to guarantee a labor pool size because we cannot assume that all available laborers will be willing to switch jobs. Additionally, for the purpose of this figure, all critical occupations are treated as equally desired, but in reality, the quantity demanded for each occupation will vary.

Steady State Battery Capacity Supply and Demand Constraints

In order to identify policy levers in the battery production market, we need an estimate of demand for battery production capacity in relation to supply. In this section we take a first-order approach to identify the range of potential battery production capacity demand and supply,we discuss sources of uncertainty and their implications for interpretation, and identify additional needed empirical evidence to resolve unanswered or uncertain questions. Given the uncertainty about the timing of demand and supply dynamics, we take a steady-state view to focus on long-run transition opportunities and compare it to the currently announced capacity supply (Kogod School of Business 2023).

We estimate steady state demand for battery production capacity from annual vehicle sales, and expected battery capacity per electric vehicle and vehicle life. Domestic versus foreign-manufactured content of vehicles sold in the U.S. varies significantly across the models on the market. This affects how the implications of EV displacement on powertrain manufacturing will be distributed between domestic and foreign workers, but as a starting point for comparative analysis we assume that domestic battery demand will be met by domestic supply. The implication of greater reliance on offshore capacity is that there will be a reduced transition pipeline for workers, and still less optionality on the geographic location of domestic capacity.

In the United States, there were 15.1 million vehicles sold annually on average between 1976 and 2023, with variation over the period (e.g. peak sales of 21.7 million in 2001 and record low sales of 8.5 million in 2020) (BEA 2023). The Biden Administration has set a goal of having 50% of all new vehicle sales be electric by 2030 (White House 2023). The US Energy Information Administration estimates that by 2050 EVs (both BEV and PHEV) will make up a maximum of 28% of the US vehicle market (Energy Information Administration, 2023). BCG estimates this proportion could be as high as 64% as soon as 2035 (Arora *et al.* 2021). Using these three estimates of the percent of vehicles sold as EVs gives total EVs sold as 4.2, 7.6, and 9.7 million EVs sold in the US annually.

EVs currently on the global market have available battery capacities of 21.3kWh to 123kWh, with an unweighted average of 68.6kWh (EVdatabase.org 2023). Given the typical US vehicle is larger than the global average (requiring larger battery capacity), we expect this average to be a reasonable estimate of battery capacity in the future, despite it being weighted towards more expensive vehicles currently. With the average vehicle life in the US being 12.2 years (Bureau of Transportation Statistics, 2023) and EV batteries lasting between 8 and 15 years on average (depending on climate and use) (Alternative Fuels Data Center, 2023), the average EV will use between 1 and 1.5 battery packs in its lifetime. To find the total annual battery production capacity required we multiply vehicles sold, average battery capacity, and the average number of battery packs required for the lifetime of the vehicle.

Then for a low estimate of battery capacity demand we find 290GWh/yr, using 4.2 million vehicles, 6.86kWh capacity per vehicle, and 1 battery pack per vehicle lifetime. Our middle case estimate of battery capacity demand is ~650GWh/yr, using 7.6 million vehicles, 6.86kWh capacity per vehicle, and 1.25 battery packs per vehicle lifetime. The high estimate is ~1000GWh/yr, using 9.7 million vehicles, 6.86kWh capacity per vehicle, and 1.5 battery packs per vehicle lifetime.

The NAATBatt dataset assembled by the National Renewable Energy Laboratory "is a directory of North American companies in the li-ion supply chain: manufacturing, research and development, services, end of life management, and product distributors" (NREL 2023). We use this as a proxy for future steady state battery production supply. The listed details from announcements in the database include future openings and experimental battery technologies so it is likely an overestimate of the true supply of battery production capacity. The current database has 1344GWh/yr of capacity announced.

The expected national battery production capacity provides a basis for evaluating the freedom to incentivize or choose the location of production (e.g. to enable transition in place for incumbent workers). If the committed capacity – announced, under construction, or operational – is a large proportion of the expected steady-state capacity demand, then the geographic distribution of future labor demand may be more difficult to alter. Contrastingly, if steady-state capacity demand significantly exceeds expectations of currently announced supply, it may be possible to facilitate incumbent worker transitions within geographic clusters by incentivizing co-location of EV and ICEV capacity.

Emerging Heat Pump, Solar, and Transformer (HST) Labor Demand

We pivot our analysis here to examine three growing sectors of manufacturing demand that may provide transition opportunities for ICEV workers in addition to the EV market: Heat Pumps, Solar Panels, and Transformers (HSTs). Of these three technology types, only solar panel production has workforce data at the time of this report (updated November 2023). This dataset has 98 factory announcements. 65 of those include reported investments and/or reported jobs; 41 have both. 60 of those 65 were mappable to MSAs using the method described for EV and Battery jobs announcements.

We expand the dataset of 41 Solar factory announcements that included both reported investments and reported jobs using the same linear regression process we use to expand the EV and Battery datasets. This increases the number of factories that we include in our analysis by seven (six mappable) and increases the number of workers demanded in this analysis by 2,841 (2,515 mappable) for a total of 28,682 jobs. Details on the regression analysis can be found in **Appendix E**. **Figure 23** shows the resulting map of anticipated labor demand for solar panel production.

Solar Jobs - Total Mappable Demand

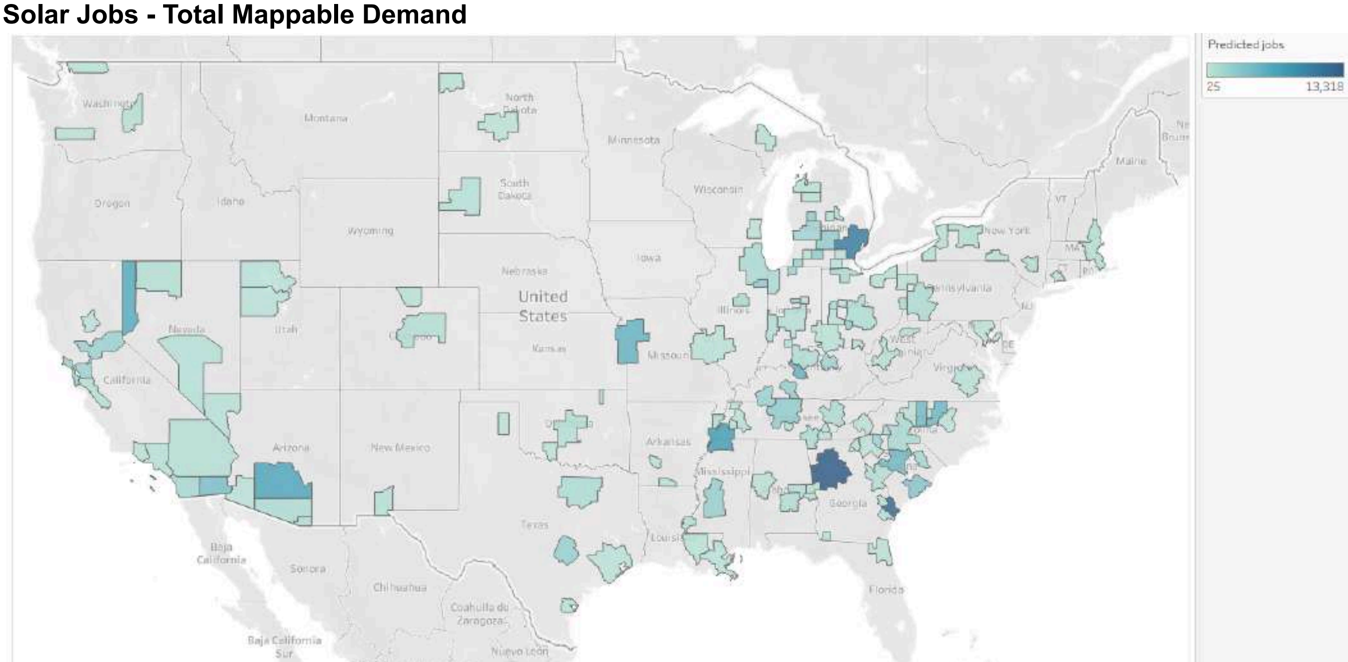


Figure 23: Argonne factory announcement data aggregated to MSAs, for those MSAs that also have labor supply data available in the BLS dataset. The heatmap shows the total jobs either reported or imputed via the most granular available linear regression.

The National Solar Jobs Census 2022 reports 33,473 current jobs at manufacturing firms, accounting for 12.7% of what is collectively termed the solar workforce (IREC 2023). Since our solar factory announcements dataset cumulatively estimates 28,682 jobs, the labor demand we account for effectively doubles total projected jobs in solar manufacturing. While this labor demand appears significant relative to current solar manufacturing jobs, it is a fraction of the labor that would be required to meet net solar manufacturing demands domestically. Installed solar capacity in 2022 was approximately 153 GW and a record 32 GW capacity was added in 2023, and the SEIA and Wood Mackenzie estimated total operating solar capacity in 2028 reaching 375 GW (i.e., 38 GW year-over-year capacity growth, net 190 GW growth) (SEIA 2023). The announced $20 billion committed for domestic PV manufacturing that SEIA tracks accounts for only about 128 GW of solar capacity (S&P Global 2023), meeting two-thirds of the required capacity in the 2028 projection.

The current announcements in solar manufacturing are not on track to meet solar capacity with domestic production in the short-term as currently projected, and we are ev further pale in comparison to longer-term projections. The EIA's projection of solar capacity in 2050 ranges from 600 to 1600 GW across various scenarios (Energy Information Administration 2023), so meeting their mid-range projection would further require about 38 GW year-over-year growth in solar capacity. And in the upper range, the DOE Solar Futures study projects that solar capacity should be ~1600 GW to achieve a decarbonized grid, requiring about 56 GW year-over-year growth in solar capacity (SETO 2021). Given the gap between current installed solar capacity and projected capacity requirements, and despite projected solar deployment announcements, there is significant policy potential to boost domestic solar production.

Comparing Labor Demand for HST Production with Current Labor Supply

As in the previous section Comparing EV Labor Demand with Current Labor Supply, here we explore the ability of existing labor supply to meet emerging demand. The following essential occupations for HST production were identified using expert elicitation:

- CNC Programmer / CNC Machinist
- Electromechanical Technician / Mechatronics Technician
- Industrial Machinery Mechanic
- Industrial Maintenance Technician
- Machinists (non-CNC)
- Robotics Technician
- Welder / Fabricator

Note, that these only capture the HST production, not installation. We coded these occupations to the following SOC codes:

- 17-3024 Electro-Mechanical and Mechatronics Technologists and Technicians
- 49-9041 Industrial Machinery Mechanics
- 51-4041 Machinists
- 51-4121 Welders, Cutters, Solderers, and Brazers
- 51-9161 Computer Numerically Controlled Tool Operators

Not all occupations have one-to-one matches with existing SOC codes. As a result, Electromechanical Technician / Mechatronics Technician & Robotics technician were both coded to 17-3024. Similarly, Industrial Machinery Mechanic & Industrial Maintenance Technician were both coded to 49-9041.

As in *Comparing EV and Battery Labor Demand with Current Labor Supply*, we map anticipated demand over the available supply of workers in the desired occupation (**Figure 24**). This is a conservative labor supply estimate, as it does not reflect the availability of similar occupations that may act as alternative sourcing options.

Anticipated Solar Job Demand / Total Workers In Desired Occupations

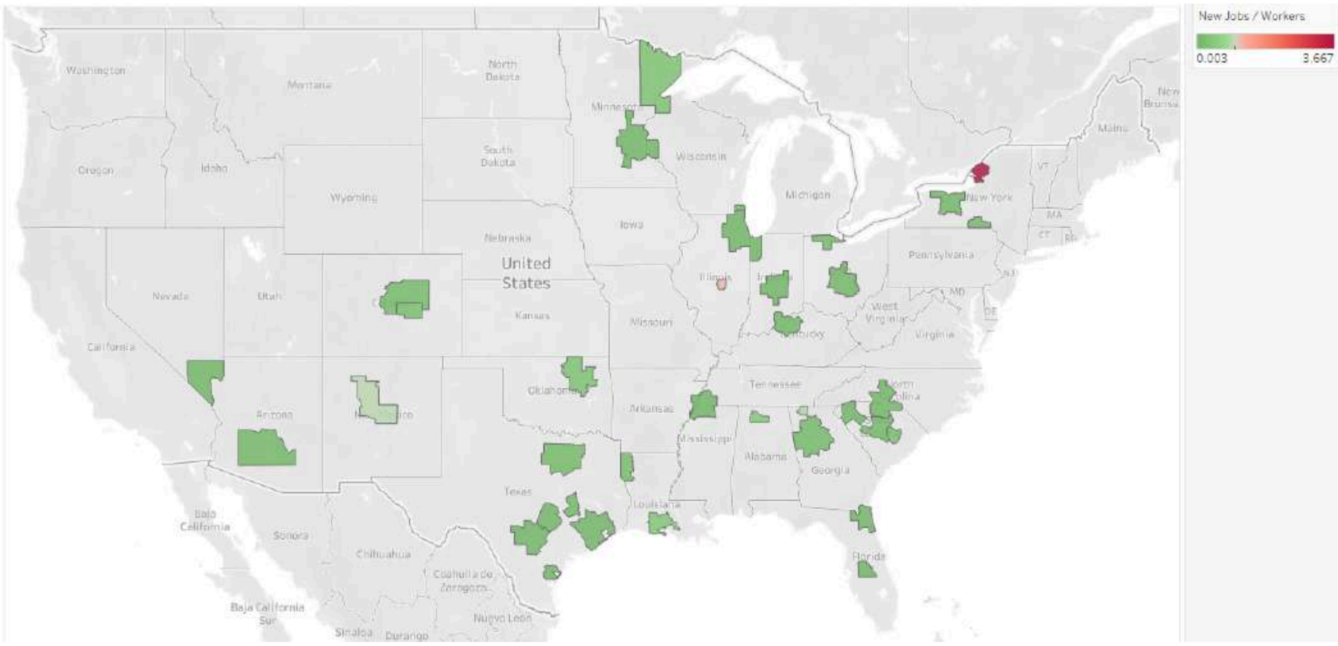


Figure 24: Labor demand for Solar factory announcements over available labor stock filling critical occupations. A 1:1 ratio (white) indicates that the new labor demand matches the total existing labor supply. Red indicates that demand exceeds total supply. Green indicates labor stock will fill announced factory occupations, but we cannot assume that all available laborers will be willing to switch jobs.Additionally, for the purpose of this figure, all critical occupations are treated as equally desired, but in reality, the quantity demanded for each occupation will vary.

Workforce Transition from ICEV to EV, Battery, and HST Production

In order to understand if and how the existing ICEV workforce can transition into new EV, battery, and HST jobs, we first need to see how incumbent occupations compare to transition options. In order to make these comparisons we first combine the list of essential occupations from EV, battery, and HST production to form the following list of occupations:

- 11-3051 Industrial Production Managers
- 17-3024 Electro-Mechanical and Mechatronics Technologists and Technicians
- 49-9041 Industrial Machinery Mechanics
- 51-2028 Electrical, Electronic, and Electromechanical Assemblers, Except Coil Winders, Tapers, and Finishers
- 51-2031 Engine and Other Machine Assemblers
- 51-2090 Miscellaneous Assemblers and Fabricators
- 51-4041 Machinists
- 51-4121 Welders, Cutters, Solderers, and Brazers
- 51-9161 Computer Numerically Controlled Tool Operators

As before, we use the Workforce Insights Tool (Combemale *et al.* 2023) to evaluate the skill gap between incumbent ICEV workers and the jobs to which they may be able to transition. We only include transition occupations with similarity greater than or equal to 0.7, as any lower falls below our baseline similarity threshold.

Similarity Ratings of ICEV Workers Transitioning to EV, Battery, and HST Production Occupations

	Source OCC							
	51-1011	51-2031	51-4031	51-4041	51-4081	51-4111	51-4121	51-9061
49-9041					0.8049			
51-2031	0.8293	1.0000		0.7805	0.9512	0.7073		0.7561
51-4041				1.0000	0.8780			
51-4121	0.9512	0.8537	0.9512	0.9512	1.0000	0.9024	1.0000	1.0000
51-9161					0.9268			

Table 9: Similarity ratings for ICEV Source Occupations transitioning to new occupations, excluding those below the 0.7 similarity threshold. Note that no incumbent ICEV jobs were a match for 17-3024, 51-2090, 11-3051, or 51-2028. No similarity results were available for 51-2090 and 51-2028 (see Limitations). 51-4041, 51-4121, 51-2090, and 51-2028 appear in both ICEV and EV, battery, and HST production occupations, meaning that some number of them may be able to find one-to-one transitions in areas where there is geographic alignment of supply and demand.

Once we identify the workers who have the skills required to fill these HST jobs, we estimate the potential pay gap between these occupations. For each combination of ICEV occupation and EV, battery, and HST production occupation that has a skill similarity of 0.7 or above (see Table 9), we subtract the ICEV job's average annual wage from the alternative's average annual wage (see Table 10). This difference in average earnings between occupations gives a first order approximation of the relative wage premium for ICEVs compared with HST roles, and the possible wage sustainment or losses from transition.

Difference in Mean Annual Wages for ICEV Workers Transitioning to EV, Battery, and HST Production Occupations

	51-1011	51-2031	51-4031	51-4041	51-4081	51-4111	51-4121	51-9061	51-2090	51-2028
49-9041					$18,950.00				$20,740.00	$19,220.00
51-2031	$(17,120.00)	$ -		$ 550.00	$ 9,940.00	$ (7,410.00)		$ 4,690.00	$11,730.00	$10,210.00
51-4041				$ -	$ 9,390.00				$11,180.00	$ 9,660.00
51-4121	$(18,640.00)	$ (1,520.00)	$ 8,220.00	$ (970.00)	$ 8,420.00	$ (8,930.00)	$ -	$ 3,170.00	$10,210.00	$ 8,690.00
51-9161					$ 5,900.00				$ 7,690.00	$ 6,170.00
17-3024	$ (3,180.00)	$ 13,940.00	$23,680.00	$ 14,490.00	$23,880.00	$ 6,530.00	$ 15,460.00	$18,630.00	$25,670.00	$24,150.00
51-2090	$(28,850.00)	$(11,730.00)	$ (1,990.00)	$(11,180.00)	$ (1,790.00)	$(19,140.00)	$(10,210.00)	$ (7,040.00)	$ -	$ (1,520.00)
11-3051	$ 51,800.00	$ 68,920.00	$78,660.00	$ 69,470.00	$78,860.00	$ 61,510.00	$ 70,440.00	$73,610.00	$80,650.00	$79,130.00
51-2028	$(27,330.00)	$(10,210.00)	$ (470.00)	$ (9,660.00)	$ (270.00)	$(17,620.00)	$ (8,690.00)	$ (5,520.00)	$ 1,520.00	$ -

Table 10: Mean annual wage of EV, battery, and HST production occupations (columns) minus the mean annual wages of ICEV occupations (rows). Green (positive) numbers indicate positive potential change in earnings resulting from a change in occupation. Red (negative) numbers indicate a decrease in earnings if the ICEV worker changes occupations. From the employer's perspective, none of the ICEV occupations met the SKAW similarity threshold for 17-3024, 51-2090, 11-3051, or 51-2028. Wage comparisons were included for reference only. Similarly, no similarity results were available for 51-2090 and 51-2028 (see Limitations). These wage comparisons are included for reference only. 51-4081 (Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic) are a notable outlier, as they may be able to transition to five different desired occupations in the EV, Battery, and HST production environment, and they would receive in increase in average annual earnings in all cases. This indicates that they should be competitive when pursuing any of these occupations.

It is important to keep in mind that earnings exist across a distribution, meaning that in cases where the average net change in earnings is negative, there may still be some portion of incumbent workers that could see a positive wage change by changing occupations. Additionally, 11-3051 “Industrial Production Managers”, which appear to have a large positive earnings advantage, represent a career progression that will not be possible for the majority of employees in the other occupations listed.

SKAWs Gaps Between Similar Occupations

In this section we use publicly available O*NET data, in combination with outputs from the Workforce Insights Tool, to identify Skills, Knowledge, Abilities, and Work Activities (SKAWs) that are most frequently missing between our occupation of interest and occupations with similarity scores greater than or equal to 0.7, 0.8, and 0.9. The O*NET datasets include Level values (1 to 7 scale) and Importance values (1 to 5 scale) for 35 Skills, 33 Knowledge categories, 52 Abilities, and 41 Work Activities for a total of 161 comparison SKAWs. We combine these data into one dataset that includes the Level and Importance of each SKAW. Next, we compare the SKAW values associated with each occupation to that of our occupation of interest. A SKAW requirement is considered in deficit depending on directionality: the question is whether we are looking at our occupation of interest’s ability to transition to a new occupation, or at other occupations transitioning to our occupation of interest. We define a deficit as when the source occupation’s SKAW is less than that of the target occupation.

In the following sections, we analyze (1) SKAW gaps between ICEV occupations and similar target occupations and (2) SKAW gaps between similar source occupations and EV, battery, and HST occupations. Since similarity is directional, these sections produce distinct results. We produce two visualizations of occupational SKAW gaps: one weighted on higher frequency of a SKAW’s gap, and the other weighted on the average magnitude of the SKAW gap. Combined these analyses show what the common deficiencies in an occupation’s skill requirements are, relative to candidate destination occupations, and how much training may be required to overcome those deficits.

SKAWs Gaps Between Incumbent ICEV and Similar Target Occupations

Figure 25 shows the SKAWs most frequently insufficient for “Engine and Other Machine Assemblers” to transition to new occupations, as well as the average scale of the gap when looking at all potential transitions. This information highlights key areas limiting “Engine and Other Machine Assemblers” from making successful occupation transitions.

Most Frequently Deficient SKAW Level Requirement Between “Engine and Other Machine Assemblers” (51-2031) and Workers in Similar Occupations to Which They May Transition

Figure 25: The proportion of potential transition occupations where “Engine and Other Machine Assemblers” (51-2031) have a high degree of similarity, but are missing critical SKAWs for the similar occupations. The number of deficit SKAWs is capped at five if more exist. Relevance is determined by the Importance score of that skill in the similar occupation. Importance scores measure the relevance of the SKAW with cutoffs of 3 or 4 out of 5 on the Importance scale. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for identifying similar occupations.

The most frequent deficits relate to communication skill, physical strength, and vision. Strength and vision vary person to person, and this figure indicates that many of the options available to “Engine and Other Machine Assemblers” will require more physical effort and visual attention. This may be problematic for older workers, but should not disqualify most workers looking to make the switch. A more significant challenge to transition will be the gaps in communication skills, both in terms of current expectations and opportunities to develop new skills.

Next we visualize the SKAWs that have the largest magnitude deficits. The following **Figure 26** shows that the largest deficit tends to be “Performing for or Working Directly with the Public.” This is not a surprise, as “Engine and Other Machine Assemblers” rarely need to work with the public while potential target occupations like “Postal Service Mail Carriers” do. Depending on the amount and type of communication required, this may be a pain point for employers and transitioning employees. Other differences in importance tend to be much smaller in magnitude (less than 0.4 on the 7-point difficulty level scale), suggesting that an employer looking to make a hire may be more willing to overlook deficits to fill an empty position.

SKAW Gaps Between "Engine and Other Machine Assemblers" (51-2031) and Workers in Similar Occupations to Which They Can Transition

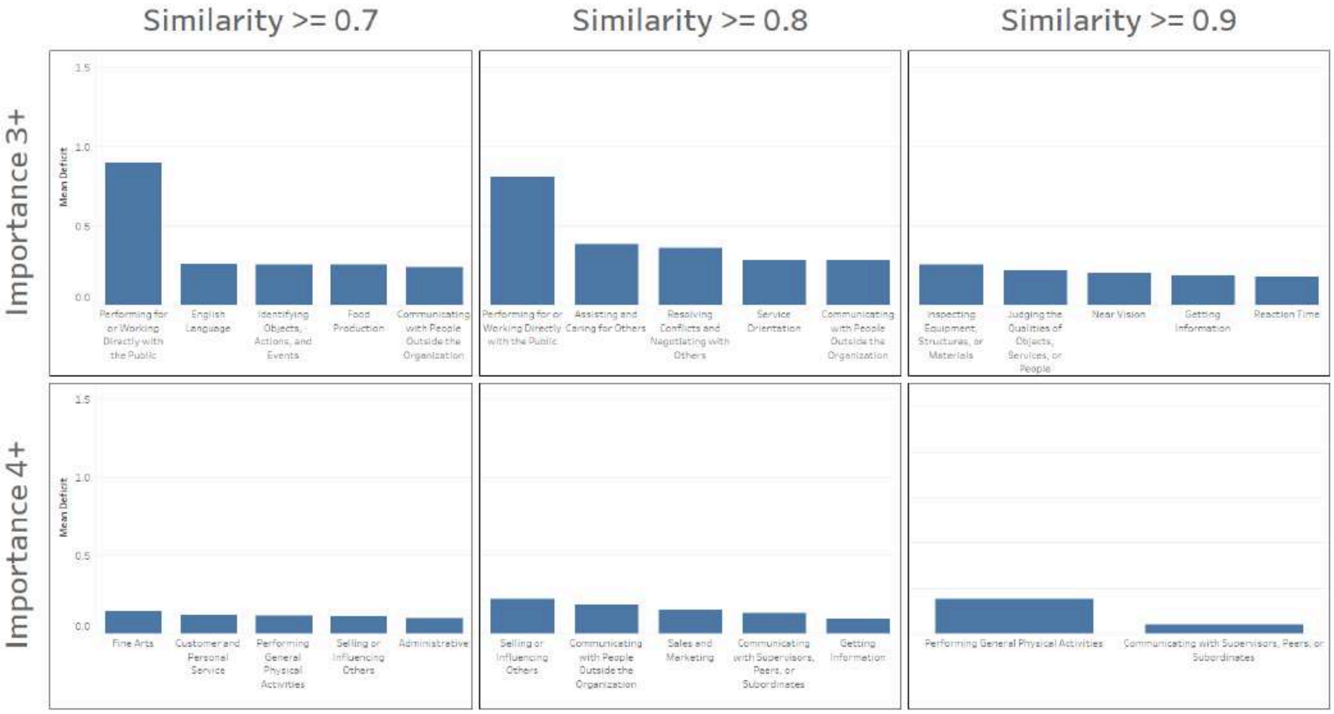


Figure 26: Average disparity between "Engine and Other Machine Assemblers" (51-2031) and Workers in Similar Occupations where SKAW deficits are relevant (capped at top 5 SKAWs if more exist). Relevance is determined by the Importance score of that skill in the similar occupation. Cutoffs of 3 and 4 were used for Importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

SKAW deficits are an additional tool to understand how wages are impacted by job transitions. While "Engine and Other Machine Assemblers" (51-2031) have dozens of similar occupations to which they may potentially transition, not all such occupations will allow them to maintain earnings. When comparing the median annual wage of "Engine and Other Machine Assemblers" within the Motor Vehicle Parts Manufacturing industry in 2022 ($62,270) to the the median annual wage for similar occupations (cross-industry) at the same time, we see that only one occupation ("Tapers" 47-2082) is greater than or equal to "Engine and Other Machine Assemblers" in median annual earnings.

The implications of this are not consistent across all MSAs, or even within the "Engine and Other Machine Assemblers" occupation itself. Workers who are earning below the median annual wage may still find suitable jobs elsewhere, but those individuals earning more than the median annual wage will struggle to maintain their level of income if they are forced to change occupations. The most relevant SKAW missing to allow for "Engine and Other Machine Assemblers" to make the transition to "Tapers" is Building and Construction. All other deficits are less important (than a level of 4) and are smaller in magnitude (less than 0.5 deficit).This narrow opportunity space for "Engine and Other Machine Assemblers" is not consistent for all ICEV workers. For example, the same analysis shows that "Machinists" (51-4041) within the same industry have 24 wage-sustaining occupations to consider.

Skill Gaps Between EV, Battery and HST, and Similar Origin Occupations

"Engine and Other Machine Assemblers" are also important for EV and Battery production (Hamilton 2011). In cases where there is a geographical mismatch between new jobs and the existing labor supply of "Engine and Other Machine Assemblers", it is worth our time to see what other occupations may act as alternative sourcing options when staffing new factories. The following figures (**Figures 27**, **28**, **29**, and **30**) show the most frequent SKAW deficits between prospective hires and the "Engine and Other Machine Assemblers" occupation, as well as the average magnitude of the SKAW deficits with the greatest average disparity.

Most Frequently Missing Skills Between "Engine and Other Machine Assemblers" (51-2031) and Workers in Similar Occupations That are Alternative Hiring Sources

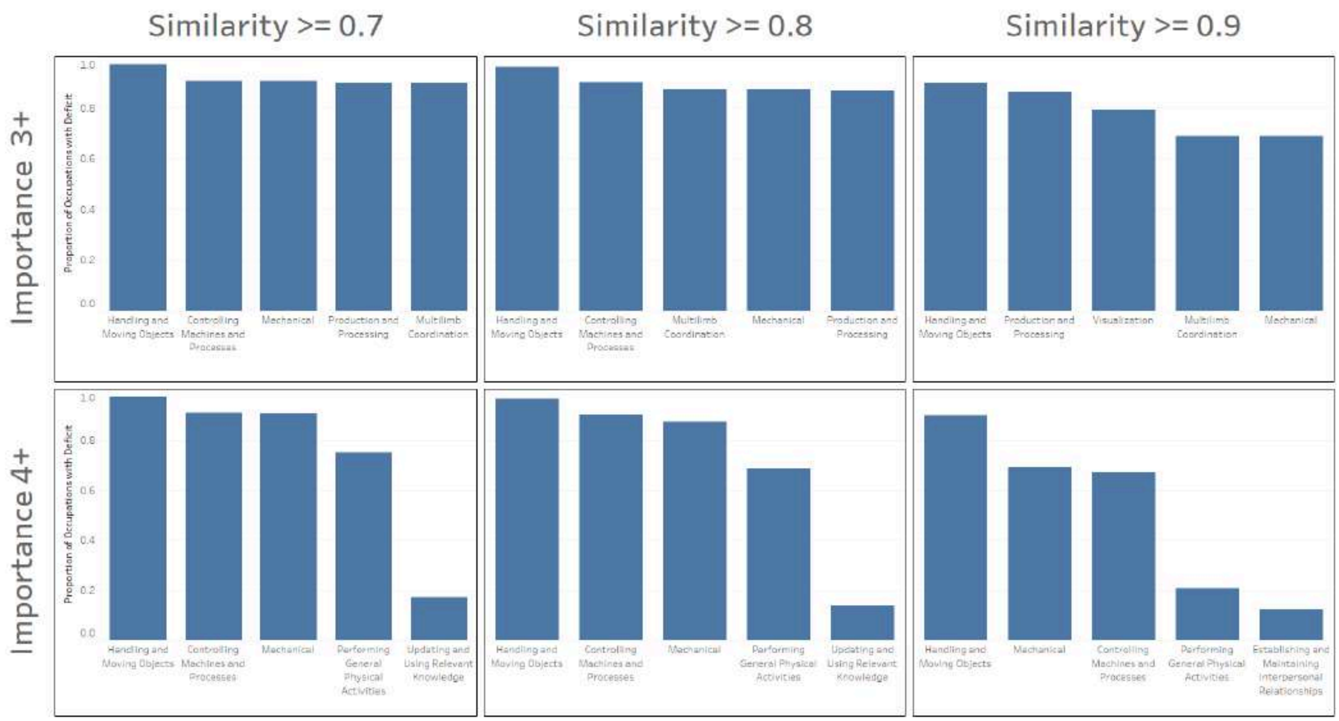


Figure 27: Most frequently appearing relevant SKAW deficits when comparing "Engine and Other Machine Assemblers" (51-2031) to workers in similar occupations where SKAW deficits are relevant (capped at top 5 SKAWs if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the Importance score of that skill in the similar occupation. Cutoffs of 3 and 4 were used for Importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Here we see that almost all occupations that can be used as alternative sourcing options have the same deficits. These deficits conceptually cluster into two categories: those that may be resolved with training – identifying objects, actions, and events, making decisions and solving problems, etc.; and those that may be mitigated with factory process improvements – organizing, planning, and prioritizing work, getting information, etc. The following figure shows that these deficits are not just frequent, but also large. This means that these deficits must be addressed in order to expand the available labor supply. Fortunately, the same SKAWs are required to make the job accessible for most similar occupations, meaning training and process improvements may be generalizable.

SKAW Gaps Between "Engine and Other Machine Assemblers" (51-2031) and Workers in Similar Occupations That are Alternative Hiring Sources

Figure 28: Average skill disparity between "Engine and Other Machine Assemblers" (51-2031) and workers in similar occupations where SKAW deficits are relevant (capped at top 5 SKAWs if more exist). Relevant SKAWs are determined by the element's Importance score in a similar occupation. Cutoffs of 3 and 4 were used for Importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Similar to the analysis in the previous section, we can filter these results to only include occupations with a median annual wage that is less than the median annual wage of "Engine and Other Machine Assemblers" (industry agnostic). Doing this results in 131 occupations with a similarity rating of 0.7 or greater. The following figures show the SKAW deficits associated with those 131 occupations. Several of the SKAW deficits are the same, but their magnitude and rank order have changed to match the gaps in the updated pool of workers who may see a positive change in wages by transitioning to this occupation.

Most Frequently Missing SKAWs Between "Engine and Other Machine Assemblers" (51-2031) and Workers in Similar Occupations That are Alternative Hiring Sources with Median Annual Earnings Less Than the Median Annual Earnings of "Engine and Other Machine Assemblers"

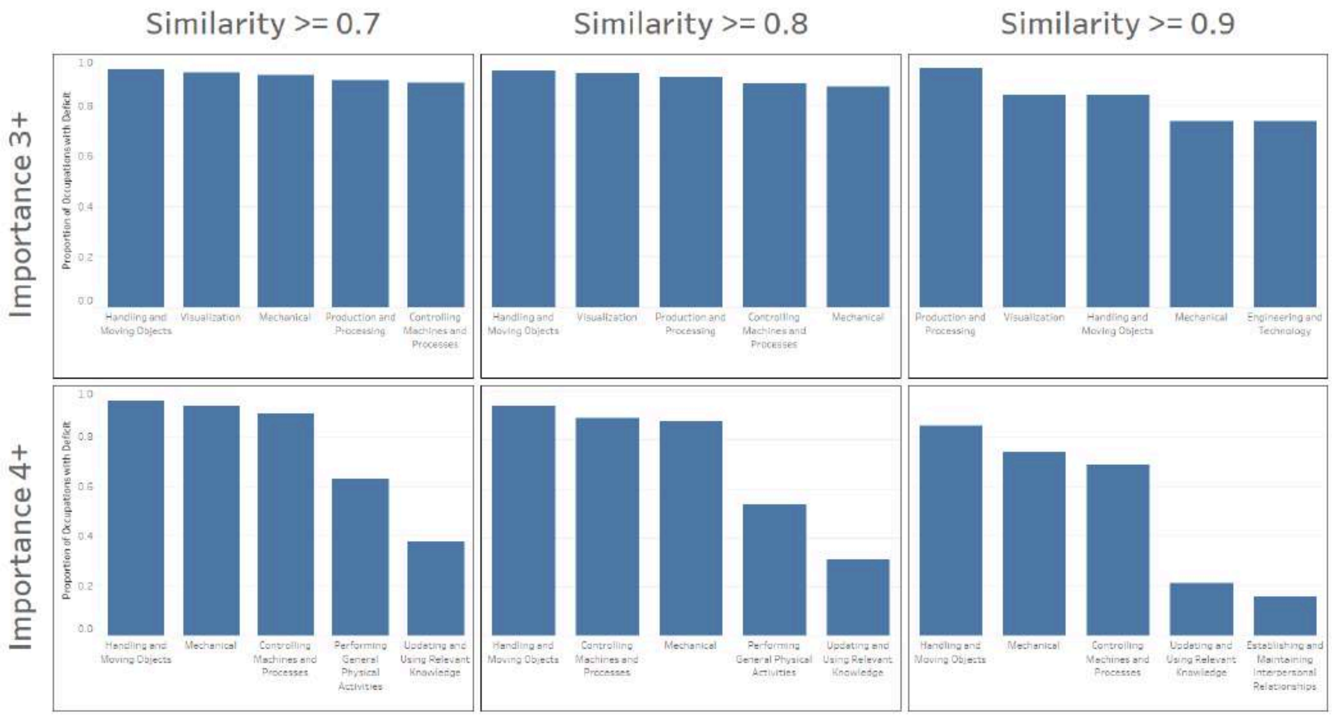


Figure 29: Most frequently appearing relevant SKAW deficits when comparing "Engine and Other Machine Assemblers" (51-2031) to workers in similar occupations with lower median annual earnings where SKAW deficits are relevant (capped at top 5 SKAW if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the Importance score of that skill in the similar occupation. Cutoffs of 3 and 4 were used for Importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

SKAW Gaps Between "Engine and Other Machine Assemblers" (51-2031) and Workers in Similar Occupations with Lower Median Annual Earnings

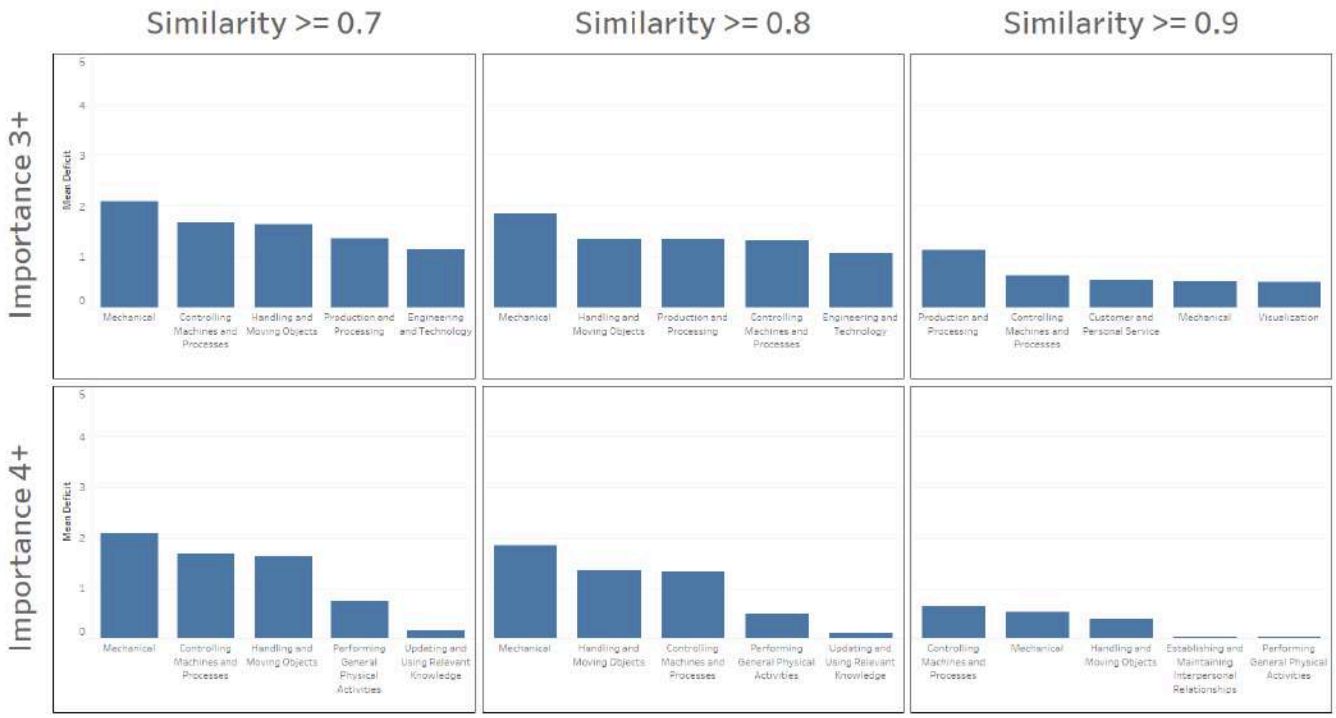


Figure 30: Average SKAW disparity between "Engine and Other Machine Assemblers" (51-2031) and workers in similar occupations with lower median annual earnings where SKAW deficits are relevant (capped at top 5 SKAWs if more exist). Relevant SKAWs are determined by the element's Importance score in a similar occupation. Cutoffs of 3 and 4 were used for Importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

When looking at this subset of similar occupations, we see an increase in the consistency of SKAW gaps, meaning that a greater percentage of occupations fail to meet any given SKAW. This homogeneity allows for employers and educators to develop training programs that are generalizable across similar occupations for workers that may find this transition financially beneficial. Additionally, we see that the average magnitude of SKAW deficits decreases when looking at this subset of occupations, indicating that less training will likely be necessary to bring new employees from external occupations up to the necessary SKAW requirements.

III. Results and Discussion

Scoping Transition Prospects for Displaced Workers

To step through the nuances and implications of our analysis, we look at two occupations side by side: 51-4031, “Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic” - “Machine Setters”; and 51-2031, “Engine and Other Machine Assemblers” - “Engine Assemblers”. First, a side-by-side comparison of labor supply in **Figure 31** shows critical distinctions. “Machine Setters” appear in many more MSAs than “Engine Assemblers”. This output is driven by two main factors. First, these labor supply figures are not specific to a single industry. As “Machine Setters” are required in industries beyond the automotive industry, we see them represented in more geographic areas. Second, within the automotive industry, the engine is one element of a car, while the car itself is made up of many more components facilitated by “Machine Setters”. We can expect that there are factories that include “Machine Setters” but have no “Engine Assemblers”.

These differences also highlight the idea that displaced workers (like “Machine Setters”) in one industry may be able to find a job in the same occupation in a different industry, while other more specialized workers like “Engine Assemblers” are more likely to need to change occupations altogether if they are displaced.

Number of “Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic” (51-4031) by MSA

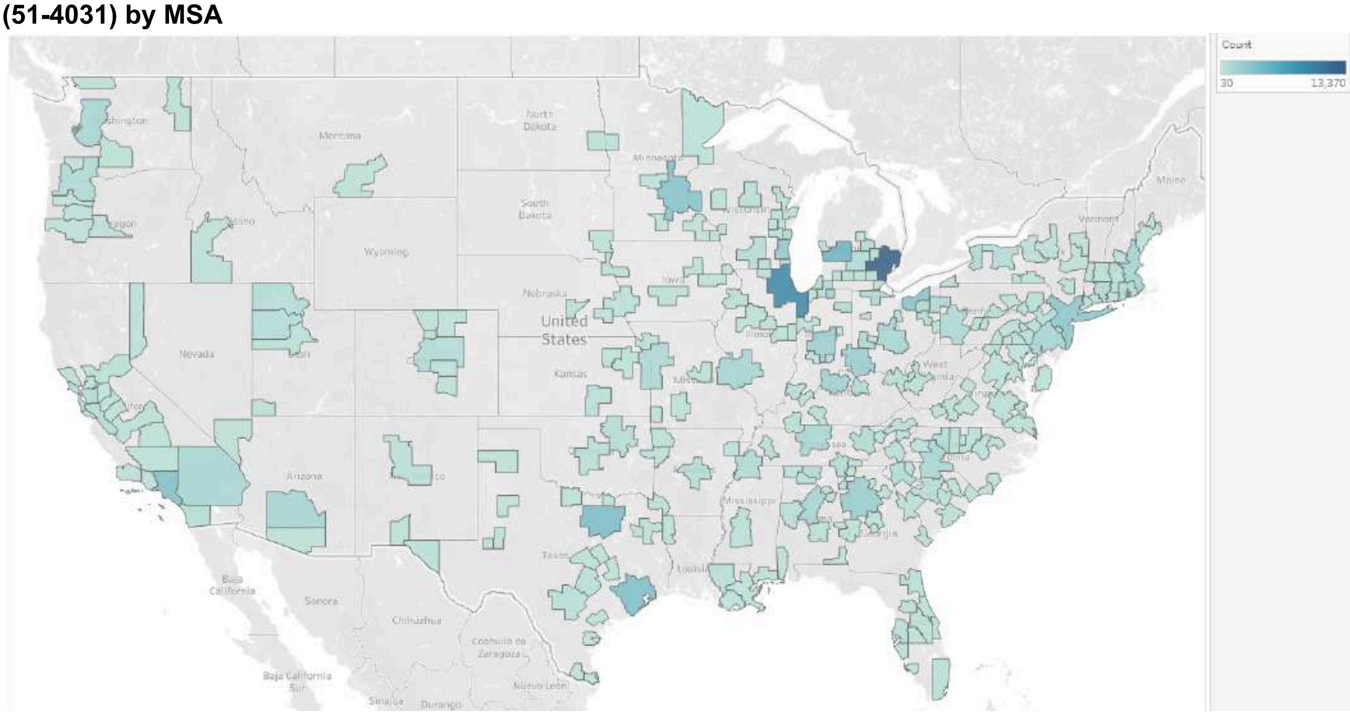


Figure 31: Side-by-side comparison of labor supply of 51-4031 “Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic” and 51-2031 “Engine and Other Machine Assemblers”.

Figure 31 (continued)
Number of "Engine and Other Machine Assemblers" (51-2031) by MSA

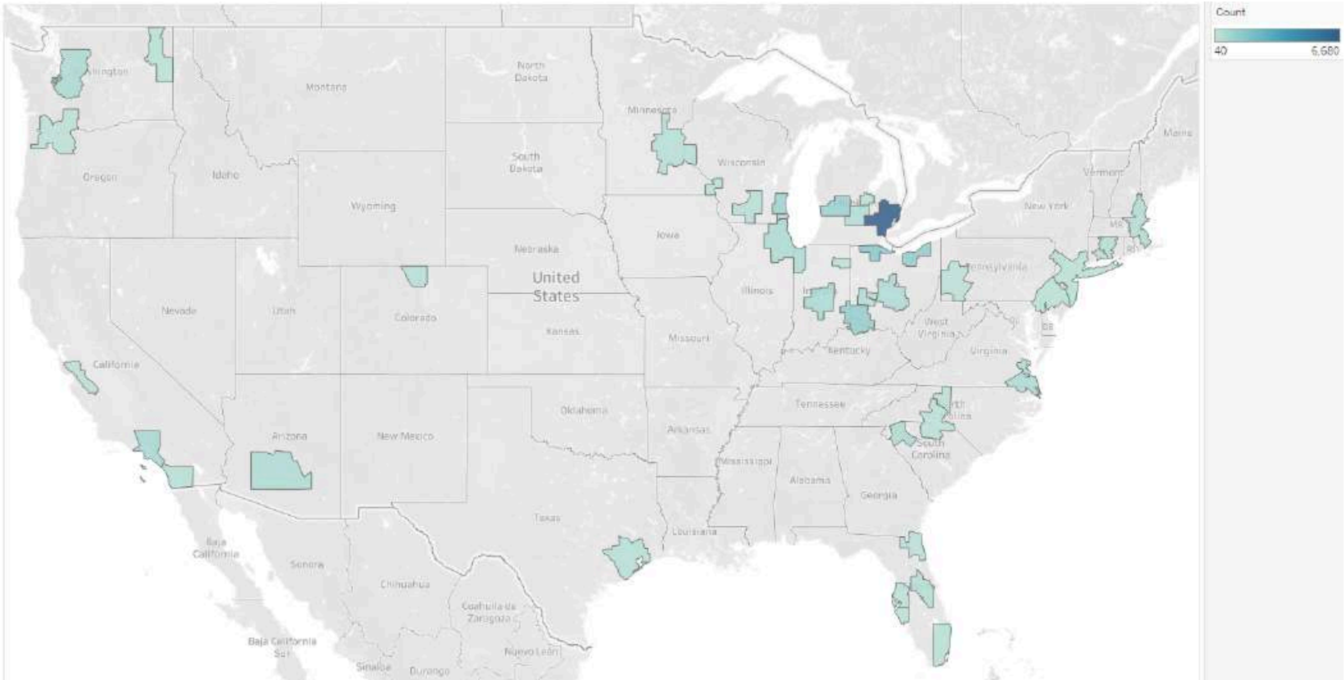
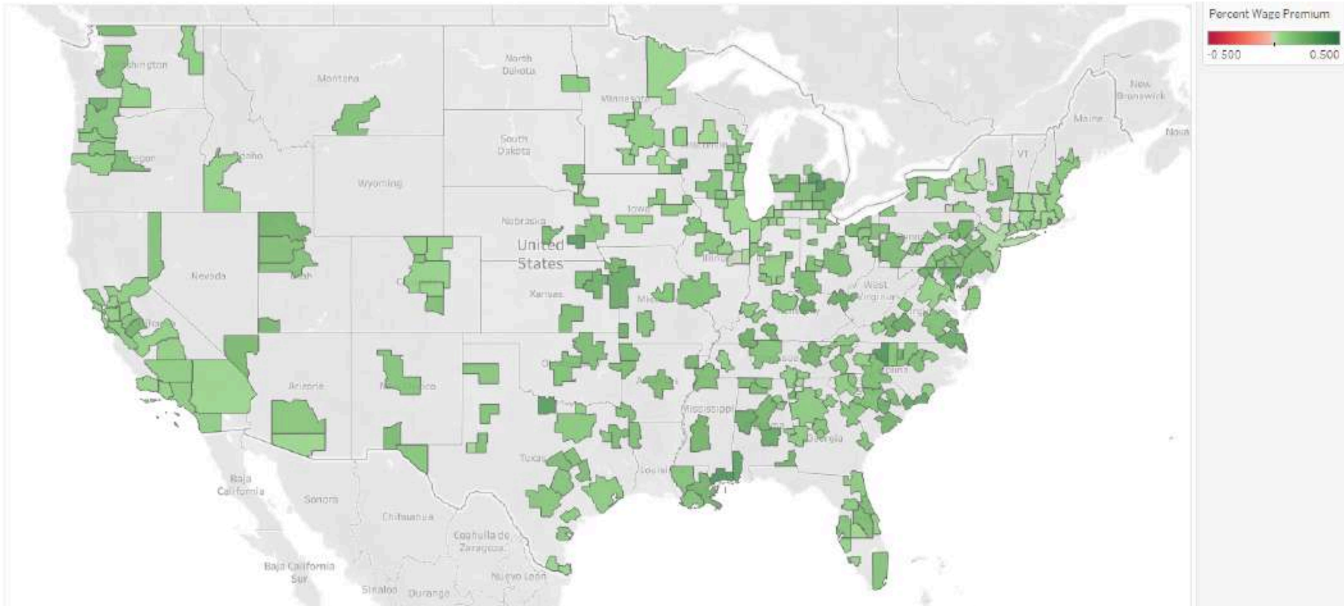


Figure 31: Side-by-side comparison of labor supply of 51-4031 "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" and 51-2031 "Engine and Other Machine Assemblers".

Another important factor to consider when anticipating the outcomes of displaced workers is how well they are paid compared to workers in similar occupations which represent transition opportunities. A comparatively well-paid worker who finds themselves changing occupations is far less likely to maintain that wage premium. Conversely, comparatively low-paid workers may find that changing occupations is a good way to increase their earnings. In **Figure 32** (next page), we see that both "Machine Setters" and "Engine Assemblers" almost universally command a wage premium. However, as described above, this has very different implications for each of them. Because "Engine Assemblers" are highly specialized and highly paid, high volume worker displacement will lead to the majority of displaced "Engine Assemblers" decreasing their earnings, sometimes by more than 40%. This will have significant personal and economy-wide knock-on effects in the impacted regions. On the other hand, "Machine Setters" are less specialized and may be able to shift industries instead of occupations, maintaining their earnings.

Percentage Wage Premium Demanded by "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic' (51-4031) When Compared to Jobs with Skill Similarity>=0.7



Percentage Wage Premium Demanded by "Engine and Other Machine Assemblers" (51-2031) When Compared to Jobs with Skill Similarity>=0.7

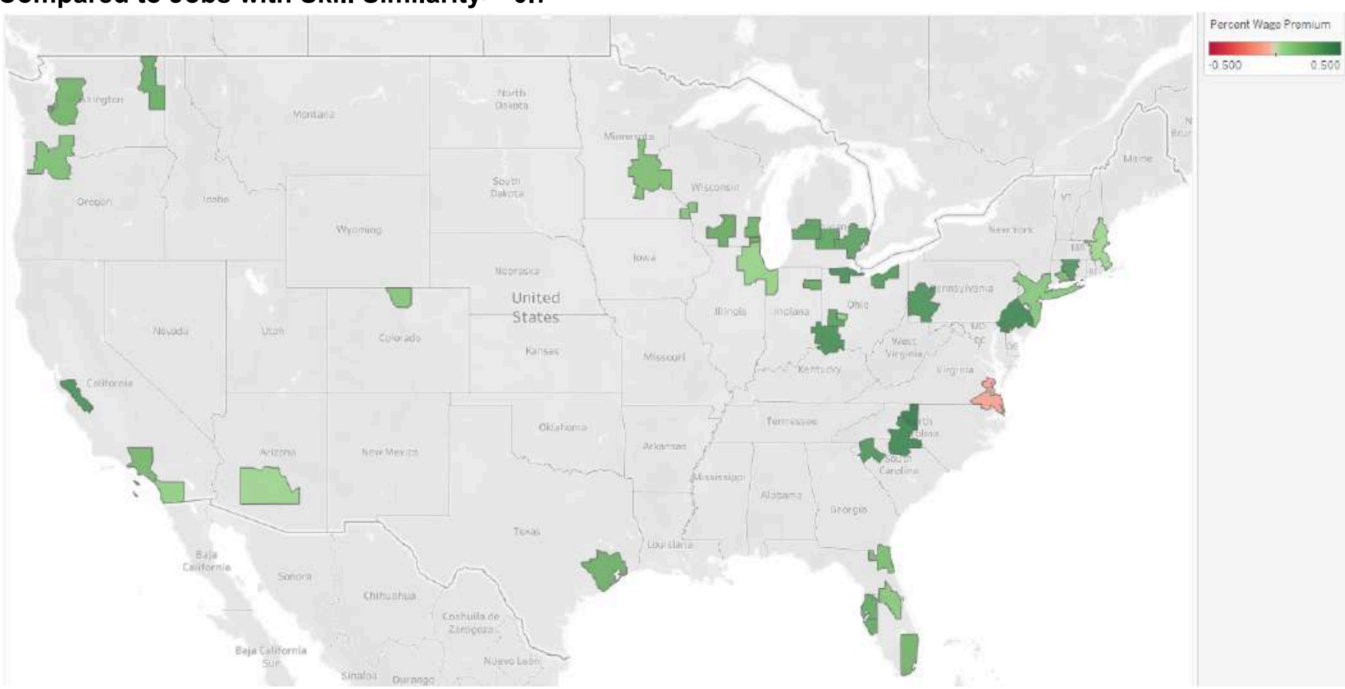


Figure 32: Side-by-side comparison of local wage premium demanded by workers in occupations 51-4031 "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" and 51-2031 "Engine and Other Machine Assemblers" when compared to workers in alternative occupations. Note the scale bar represents a +/- 50% change in wages.

When we aggregate the information in **Figure 32** to represent the national level (see **Figure 33**), we see the same story; both occupations tend to command a wage premium when compared to their peers. While it appears that "Engine Assemblers" may need to take nearly double the pay cut of their “Machine Setters” counterparts (-$12,138 vs -$6,127 when comparing median to median), the percentage drop in pay is closer (-24% vs -15%).

National Distribution of Wage Premiums Demanded by “Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic” (51-4031) and “Engine and Other Machine Assemblers” Compared to Jobs with Similarity>=0.7

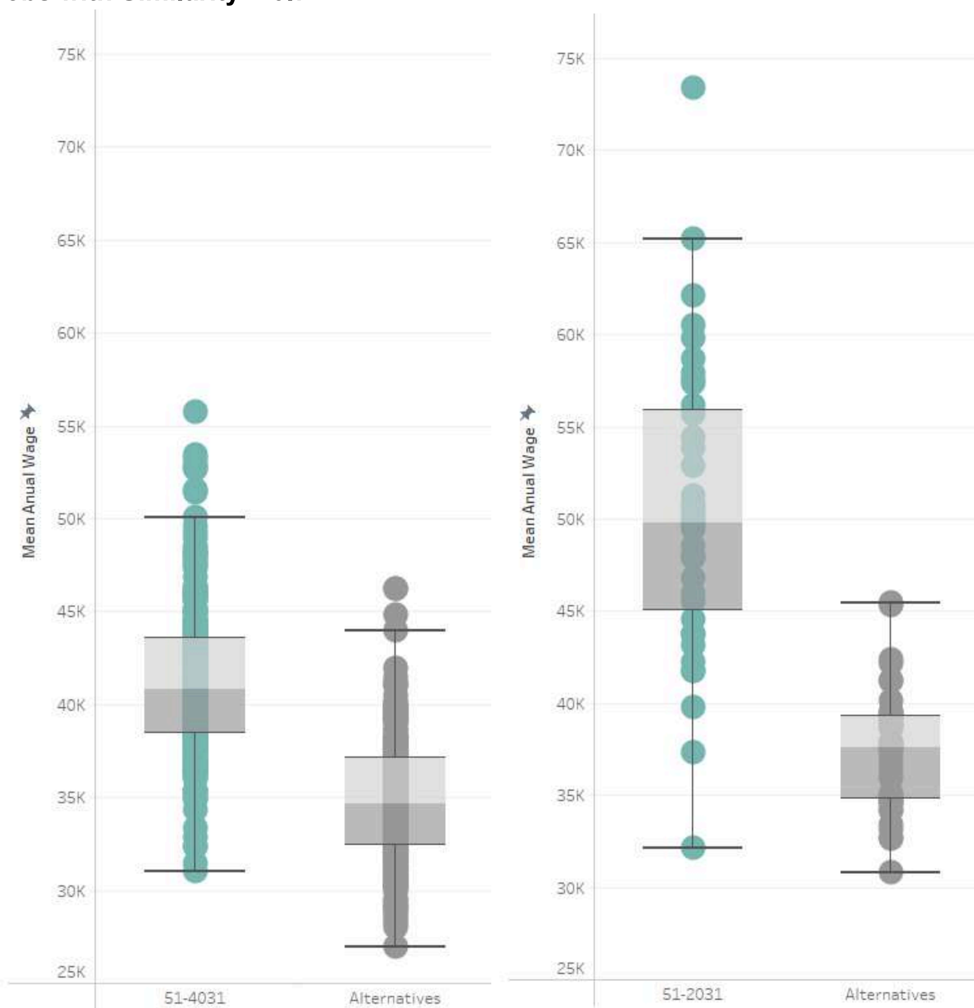
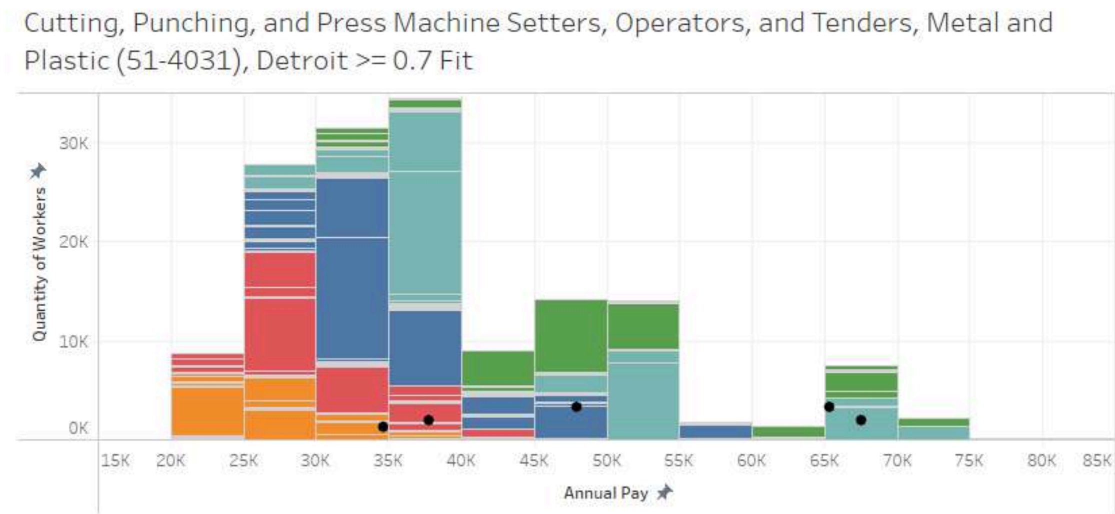


Figure 33: Side-by-side comparison of wage distributions of workers in occupations 51-4031 “Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic” and 51-2031 “Engine and Other Machine Assemblers” when compared to workers in alternative occupations.

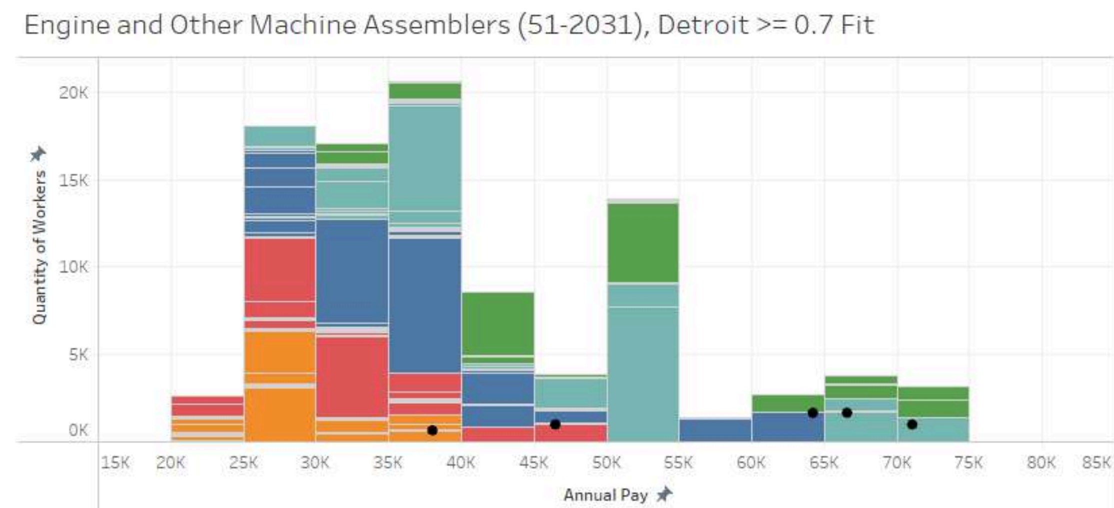
We can make more specific comparisons and predictions regarding worker outcomes when we look closely at a specific geographic area. Figure A.2 and Figure A.3 indicate that Detroit has the highest concentration of “Machine Setters” and “Engine Assemblers”, so we look there as a first case. By looking at **Figure 34** (next page), we can see that workers in the 50th percentile or higher of Machine Setters will need to be in the 75th percentile or higher of workers in their new occupation if they want to maintain earnings. “Engine Assemblers” in the 50th percentile or higher will almost certainly need to be in the 90th percentile of earners in their new occupation if they are to maintain their earnings. This is an unlikely outcome, as workers changing occupations can be expected to require additional training, a dynamic that we would expect to push them towards the lower end of earners in their new occupation, not the higher.

For both occupations, workers in the lower 25th percentile will find a change in occupation less impactful. The distinction between high and low earners within “Engine Assemblers” is particularly notable, as the wage distribution of those workers has a prominent left skew. This means that a larger portion of “Engine Assemblers” can be expected to take enormous pay cuts, some losing more than 50% of their current earnings if they cannot at least earn the median wage of their new occupation; Large pay cuts are a plausible outcome for any worker transitioning to an occupation with a skill similarity of only 0.7.



51-4031 Wages (Detroit)

A Pct10	34,600
A Pct25	37,730
A Median	47,910
A Pct75	65,300
A Pct90	67,490



51-2031 Wages (Detroit)

A Pct10	38,000
A Pct25	46,470
A Median	64,200
A Pct75	66,550
A Pct90	71,040

Percentile
- A Pct90
- A Pct75
- A Median
- A Pct25
- A Pct10

Figure 34: Histogram of distribution of wages in alternative occupations to 51-4031 “Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic” and 51-2031 “Engine and Other Machine Assemblers” by occupation percentile wages, color-coded by percentile, in the Detroit MSA.

Labor Demand In New Factories

Our analysis utilizes data sets listing estimated or announced jobs created by new factories in EV, battery, and solar production; there is not a comprehensive basis for evaluating the accuracy of these estimates relative to actual employment over time. The same data does not currently exist for heat-pumps or transformer labor demand. Nonetheless, the following insights demonstrate ways in which this analysis can be used to understand the labor market today, and ways in which further analysis supported by additional data is likely beneficial.

Figure 22, from the prior section, is an optimistic view of labor stock meeting labor demand. It depicts a ratio of demand for workers over the total employment of workers in a given occupation, but does not examine outside factors. Not all workers in an area will transition into new job openings, especially if doing so will require the challenges of learning a new occupation. A worker may also require a higher wage to transition occupations, representing a possible premium over the price of their skills in the existing labor market. Large transitions could put pressure on labor supply to meet demand in other sectors – e.g. overlapping skill demands in battery versus transformer production – creating workforce bottlenecks for existing industries and competing for talent with other capacity investments.

Consider key MSAs where labor demand significantly outpaces supply: there are 11,902 anticipated battery production jobs in Savannah, GA, but there are only net 7,000 workers either in the required occupations or in occupations with at least a 0.9 similarity rating. The potential workforce expands to 49,440 when allowing for a skill similarity of 0.7, but these lower similarity ratings suggest significant training requirements for new workers. Even with said training, it is an open question whether or not ~12,000 workers can be sourced from the regional labor pool. These factories will either need to be highly automated, such that skill demand, labor demand, or both are reduced, or they will need to source many workers from outside of their MSA.

An MSA of significant note for solar production is Watertown-Fort Drum, NY, where new jobs (550) exceed total labor supply (150) by 267%. While the ratio of demand vs supply appears unfavorable, a labor deficit of only 400 may be pulled from similar occupations or surrounding MSAs. The following figure (**Figure 35**, next page) shows the demand for new jobs divided by the available workers in all similar occupations with a similarity of at least 0.7, and it suggests this labor deficit may be manageable. In this case, Watertown-Fort Drum, NY only needs to pull on 2.6% of the available workforce. This does mean that the majority of workers who will fill the factory jobs opening in that MSA will likely be transitioning occupations, a consideration for the employer and policy makers in that region.

Anticipated Solar Job Demand / Total Workers In Desired Occupations or Occupations of Similarity >= 0.7 by MSA

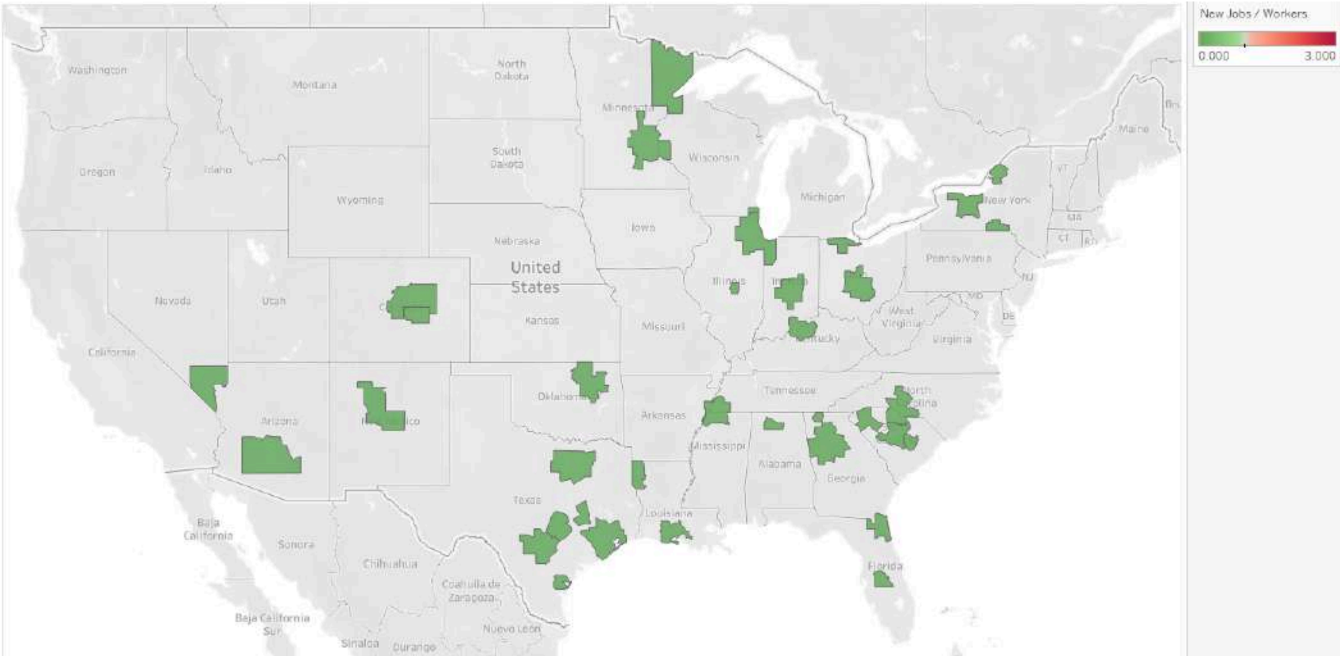


Figure 35: Anticipated number of jobs demanded by new solar factories divided by the number of existing workers in similar occupations, where similarity is greater than or equal to 0.7. The color transition point for this figure is 1:1, meaning that MSAs will transition to red when the new demand exceeds the existing labor force. In this case, no MSAs have a projected demand exceeding the available supply.

Using the change in labor supply technique described in the **Relative Alternative Wage Analysis** section of this document, we can take a more detailed view of the labor situation in Watertown-Fort Drum, NY. The following **Figure 36** (next page) shows the wage distribution of occupations similar to Welders, Cutters, Solderers, and Brazers. The left histogram reflects occupations that have grown from 2021 to 2022, while the right histogram shows occupations that have decreased in employment over the same time. Assuming that this trend continues, and a meaningful percentage of workers in the right histogram would like to remain in the workforce, these positions can be filled so long as the employer is willing to provide the necessary on-the-job training required to get transitioning workers up to speed in their new occupation. Depending on the competition for labor, the average wages for these occupations may increase. This would incentivize more workers to move to the area until wages normalize.

Distribution of Annual Wages of "Welders, Cutters, Solderers, and Brazers" (51-4121) and Jobs with Similarity>=0.7 in the Watertown-Fort Drum, NY MSA Weighted by Change in Labor Supply

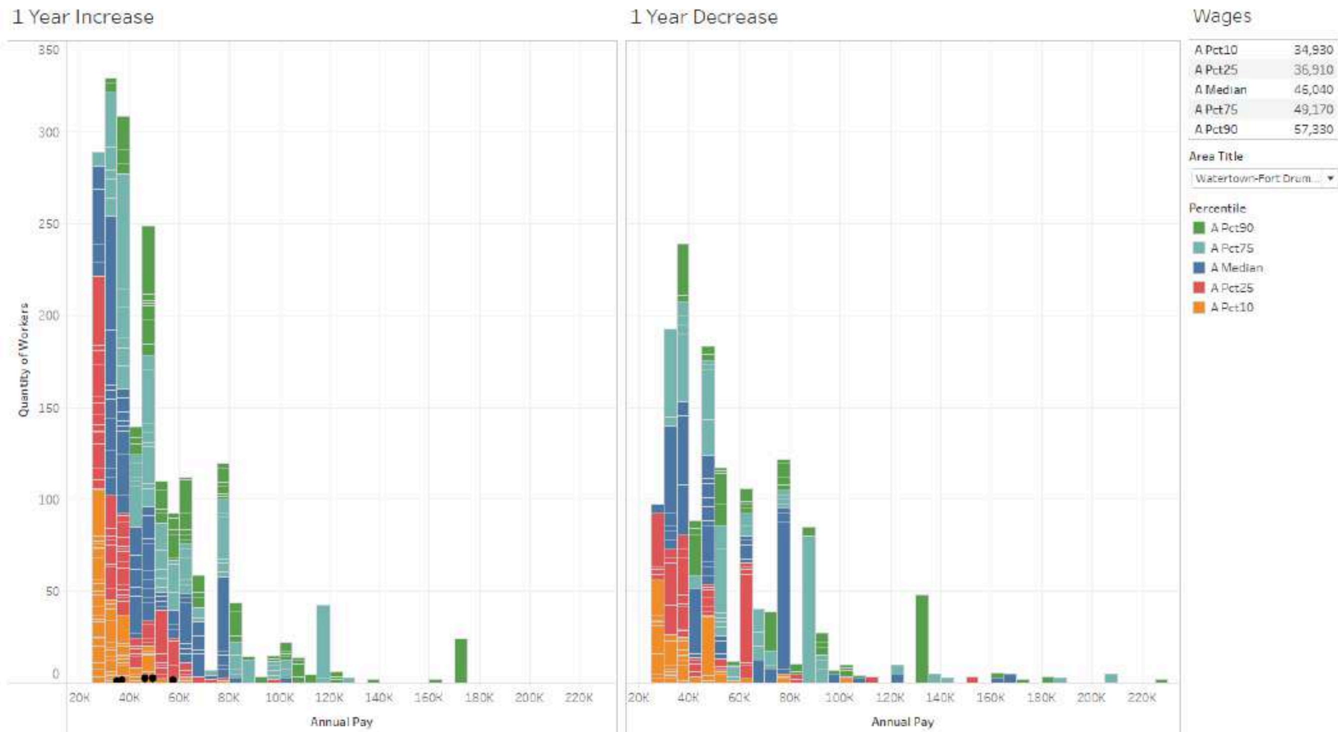


Figure 36: Histogram of distribution of wages in similar occupations to 51-4121 "Welders, Cutters, Solderers, and Brazers" by wage percentile, weighted by the change in labor supply for the same occupation, color-coded by percentile, in the Watertown-Fort Drum, NY MSA, when specifying 0.7 as the minimum threshold for similarity. The black circles indicate the 10th, 25th, 50th, 75th, and 90th percentile of 51-2031 pay respectively.

Steady State Demand versus Capacity and Geographic Degrees of Freedom

Our comparison of steady state supply and demand estimates suggests that even if EV production increases significantly – approaching the BCG market share estimates previously described – there is already enough battery capacity announced to meet future demand, leaving little room for policy levers to shift location or other parameters of new production. If stronger demand is expected, there may be more opportunity for influencing locational choices, but it will also rely on further refinement of the capacity estimates from NAATBatt and Argonne or an alternative data source on battery production.

The expected labor demand (derived from firm announcements) associated with different levels of capacity supply offers another margin of interest for workforce transitions. The level of labor demand indicates the upper bound of the ability of EV production to absorb ICEV production workers through intra-industry and potentially intra-firm transitions. Any estimated shortfall in demand relative to the potential scale of displacement indicates the extent to which the ICEV workforce will depend on alternative transition pathways like HSTs and other energy transition industries, or to the wider labor market[15].

[15] see Cotterman *et al*. 2023 for an operations-based treatment: further work is needed to quantify the magnitude of labor displacement from affected ICEV production tasks in order to provide a basis of comparison for EV labor demand in this analysis

There are several important uncertainties behind this comparison, however. Firstly, the NAATBatt and Argonne data we use to estimate the volume of announced capacity has some potential multiple-entry errors, though our interim report lays out the efforts our team has taken to identify and correct duplication using site addresses and other identifying information. The battery chemistry and form factor are also unknown in some cases – some production sites are for solid state and other novel technology – which raises the uncertainty that all announced capacities will reach mature production and serve the steady-state needs of the EV market. Our evaluation of the NAATBatt and Argonne Data also included spot-checks of whether announced sites from prior years were still under development or had been discontinued: while we found that most sites remained active, some had been shut down or pivoted to serving other industries, such as large-scale storage for renewables. Instances of both were confirmed by our interviews.

The currency of the announcement data and the overall rate of attrition of announced capacity remain unknown. We expect that these cumulative sources of error and uncertainty would likely lead us to revise our estimate of the share of future capacity needs that have been committed. Conversely, there may be missing data that could undercount the expected capacity; note that there appears to be random missingness between the NAATBatt and Argonne coverage. Once announced, it is possible that established sites will be scaled to meet demand rather than new facilities being built; the distribution of sites may limit geographic flexibility for the transition even if there is still apparent room to grow the capacity supply.

EV, Battery, and HST Jobs as Transition Opportunities for ICEV Workers

Previously, we explored the skill matches between ICEV workers and EV, battery, and HST occupations, as well as the difference in mean annual earnings between them to determine which occupations may act as potential wage-sustaining transition opportunities for ICEV workers (see **Table 9** and **Table 10** for HSTs). While the distribution of emerging occupational demand is unknown, and wage premiums vary from MSA to MSA, at the national level we find three potential trajectory categories that ICEV workers may exhibit.

The first are those whose exact occupations are demanded by EV, Battery, and HST production industries. These occupations include 51-2031 “Engine and Other Machine Assemblers”, 51-4041 “Machinists”, 51-4121 “Welders, Cutters, Solderers, and Brazers”, 51-2090 “Miscellaneous Assemblers and Fabricators”, and 51-2028 “Electrical, Electronic, and Electromechanical Assemblers, Except Coil Winders, Tapers, and Finishers”. Wage competitiveness may vary, but these workers might have a competitive edge against alternative occupations based on their work experience.

The second group is those who have multiple occupations for which they have a high degree of similarity and for which the mean annual wage of the new target occupation is greater than their current mean annual wage. These ICEV occupations include 51-4031 “Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic”, 51-4081 “Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic”, and 51-9061 “Inspectors, Testers, Sorters, Samplers, and Weigher”, with 51-4081 having the best prospects for finding a wage-sustaining transition into the EV, Battery, or HST production space.

The remaining group is ICEV workers in occupations that either are not qualified to transition to EV, Battery, or HST production occupations, or that are qualified but would not be competitive when pursuing a wage-sustaining transition. These occupations are 51-1011 “First-Line Supervisors of Production and Operating Workers” and 51-4111 “Tool and Die Makers”.

“First-Line Supervisors of Production and Operating Workers” are not a good SKAW fit for the production occupations identified for EV, Battery, or HST production, but we can expect that some number of production supervisors will be needed in those factories. It is unclear what the demand for those will be, or how wage-competitive these workers will be when competing for those positions.

In the *Age Distribution of Incumbent ICEV Workforce* section of this document, we see “Tool and Die Makers” have an older population of workers. The over-40% who are approaching retirement age may not be interested in transitioning occupations, and may instead simply exit the workforce. For those in that age bracket who do want to stay in the workforce, transitioning occupations may not be a wage-sustaining option. Our SKAW evaluations do not find any occupations that will allow for such a transition at scale. Fortunately, “Tool and Die Makers” are in demand in more industries than ICEV, so displaced ICEV “Tool and Die Makers” may find success in replacing their peers who are entering retirement.

Interview Insights

Table 11 below shows a summary of skill changes highlighted in our interview process focused on ICEV and EVs. We were not able to complete interviews with heat exchanger, solar, or transformer manufacturers in the time available. Overall respondents believe that there is a significant skill crossover between producing ICEV and EV drivetrains, but that there is a need for more employees with those skills. Particular occupations highlighted as difficult-to-find employees are “Tool and Die Fabrication”, “Mechatronics Operators and Technicians”, and “Battery Engineers”. Below the table are some highlights from the interview process from different areas of the supply chain.

EV Production Stage	Shift from ICEV	New skills needed for EVs
Battery production	New component	Chemical engineering; flow operation
Fabricated metal components: chassis, battery pans, frames, etc	Need for increased robustness; heavier steel breaks dies	More tool and die fabrication; experience with heavier steels
Other component manufacturing	More digitization and computerization	Component integration; programming skills
Autobody manufacturing and painting	Need for reduced weight	Aluminum expertise; plastic molding
Vehicle assembly and inspection	Integrating e-drive, more electrical connections, more computerization	Electrical integration; wiring; high voltage safety; e-drive familiarity; programming

Table 11: High-level takeaways from interviews on the labor and skills impacts of transitioning from ICEVs to EVs.

Battery Manufacturing

A state manufacturing expert estimated that about 70-75% of manufacturing technician skills translate across industries, although several Midwestern states note a chronic shortfall of regional skilled technicians. As a highly automated, flow production environment, battery manufacturing is very similar to semiconductor production and somewhat similar to plastics or food and beverage, but this requires different skills from the discrete metal fabrication factories engaged in ICEV drivetrain production.

One battery startup was seeking a similarly educated set of operators, technicians, and degreed engineers. They explained that they used a “really generic flow process” for manufacturing so their operators typically didn’t need any degrees, and only needed to “show up on time.” They would rather hire technicians with associate’s degrees and some familiarity with manufacturing equipment, but they might settle for workers who have at least a high school degree. They anticipated a need for 40-70 shop floor workers per gigawatt-hour produced, with 30-40% having an associate’s degree or lower and the majority of the firm being engineers with at least bachelor’s degrees and researchers with PhDs. Another battery startup estimated a need for about 200 shop floor workers per gigawatt-hour; perhaps 40% would be engineers and the other 60% would be technicians and operators, about half of whom might need associate’s degrees. Instead of worrying about technicians, two battery startups on opposite coasts were more concerned about finding battery engineers who were capable of designing their battery cells and fine-tuning the chemistry and production steps.

Vehicle Assembly and Inspection

Several interviewees mentioned “high-voltage safety” as the most critical new skill for EVs. According to representatives from a state industry and training initiative, this is the “biggest short-term training required.” The safe handling and shipping of EV batteries, maintenance and service, battery discharging at a mechanic shop, and the first responders to EV crashes will all need to know how to mitigate the risks of thermal runaway when EV batteries get damaged and catch fire. A representative from a locomotive factory pushing for electrification noted that their firm had all the necessary skillsets on hand, except for battery safety.

Compared to ICEV assembly, one interviewee noted that EV assembly requires more engineers, more licensed electricians to deal with EV components and wiring, as well as Industrial Maintenance and Integrated Automation (IMIA) as factories become more automated. An OEM workforce representative said that his firm doesn’t see ICEV and EV jobs as separate from each other, since EVs have the same setup within their old ICEV plants: painting, vinyl, stamping, etc. with mostly minor process changes. Installing a battery is a similar process to installing an engine, although EVs require more understanding of systems and data management and more knowledge of the theory of operation. The biggest shifts, they explained, are new materials, more wires, and more plastics rather than metal parts– “but you’ll always need screws.”

OEM Transitions

OEMs did not foresee noticeable job losses from the ICEV business in the next few years, and possibly not even into the future given their need to build up battery manufacturing workforces through new international partnerships. OEMs deliberately build up new plants close to their existing plants to retain talent, under the assumption that workers are unlikely to relocate. When considering which ICEV factories to transition to EVs, they have several different buckets for consideration: the existing workforce, the location of the facility, the existence of state or local incentives, the age of the facility, and the ease of retooling the plants. The layout and age of the plant is one of the most important criteria, as well as the timing of when ICEVs currently produced on that line will reach the end of their product cycle.

Shifts in OEM-Supplier Relations

During COVID, the automotive industry “learned some hard lessons” about the fragility of their supply chains and their lack of transparency across suppliers. They decided to pay more attention across the board, and to go deeper. They hired new supply chain experts and supplier relations personnel, and built up more internal support for engineering, collaboration, and incentive structures across their supply chains – this included doing a lot of work with their challenged suppliers to bring them up to higher standards. The industry is now building up visibility across their entire supply chain to work with lower tiers of suppliers directly. This new approach is also tied to their digitization strategy, which goes hand-in-hand with the electromobility transition and developing software and data as a core competency. They are thinking about vertical integration in new ways for the first time in over 20 years. To quote a workforce expert from an OEM, who recently met with all the suppliers in their state to ensure that they had the right resources and connections to state and regional workforce grants: “if [our suppliers] don’t succeed, we don’t succeed.”

Data-Driven Policy Opportunities

The findings in this report suggest significant policy opportunities. These include shaping wage-sustaining workforce transitions within automotive electrification, and supporting wage-improving transitions from the wider labor market into new job roles created by EV and HST manufacturing capacity development.

We find that some ICEV occupations, especially those with the most specialized skills and highest wages, may have the most challenging options for wage-sustaining transitions. In general, the methods used in this report provide a framework for narrowing in on the areas of greatest risk: in the interest of wage-sustaining transition, policy interventions such as training or incentives to co-locate well-matched new sources of skill demand could have the highest returns. This may be accomplished by focusing on specific occupations, such as “Engine and Other Machine Assemblers”, that have the narrowest outlook for occupational destinations that match their skills, wages, and geography.

Our extensive interviews with stakeholders in the training and transition apparatus for ICEV workers found that educational institutions did not feel well informed about job requirements, or on the timing and demand outlook for jobs with specific skill requirements. These constraints make it challenging to invest confidently in new curriculum development, and to engage workers whose incentive to participate in training depends in large part on their confidence that there are available jobs at desirable wages. Workers want to know there are job opportunities in their region, and that they can enter these jobs quickly following training. Reciprocally, small and medium employers (SMEs) we interviewed generally indicated that they had difficulty training at scale in-house, especially on the time scales needed to achieve rapid scale-up and performance on capital investments. This suggests that industry-wide training capabilities have an important role both for scale economies, and to create a pipeline that produces ready talent in time to meet demand rather than lagging behind it.

This joint problem indicates a high potential cost from uncertainty about timing and skill content, but also reveals an opportunity for policymakers to take a coordinating function. By incentivizing employers to pair with educational institutions, policymakers can guide the co-creation of clear training objectives, and as much as possible facilitate timelines that orient the scale and cycle time of training programs. Such linkages could also provide credible signals to trainers – who would be engaged in earlier stages of site selection and development – that they can expect a favorable demand outlook for the skills they provide to students. Our analysis found that workforce considerations often entered discussion after critical locational and capital allocation decisions had already been made. Indeed, some funding sources for workforce development may not coincide perfectly with the timing of funds available for other employer priorities, suggesting value from broadening the scope of government support (e.g. loans) that could be linked to employer-trainer pairing mandates.

As detailed in our results section, some incumbent ICEV occupations have promising skill similarities to the anticipated domain of occupations demanded for HST production. HST occupational demand seems unlikely to be satisfied without some occupational transitions, and these ICEV occupations appear to have competitive wage positions relative to other outside candidate occupations. Moreover, and in contrast to EV production capacity announcements, the available data does not suggest that the needed level of HST capacity to meet different steady-state demand scenarios has been geographically committed.[16] While the composition of HST occupational demand remains uncertain, these insights suggest a policy window to link outflows from ICEV occupations into new jobs created by HST demand. As geographic degrees of freedom remain open for HST capacity siting, policymakers may have leverage to co-locate production and hence demand growth alongside automotive communities affected by the transition. This is especially true for communities which do not have a co-located EV, Battery, or similar site announcement.

A managed transition for workers from ICEVs to HSTs could include focused training programs tailored to the skill gaps between automotive and HST production requirements. Such programs might involve a structured pipeline into specific new jobs with known wages and employment opportunities. Critical to the success of such a pipeline would be the timing of demand opening up near or shortly after the moment of supply disruption: linking the timing of occupational outflows and the growth of transition opportunities would require a careful coordination effort with employers in both industries. Organized labor groups could serve important functions, not only in designing training, but in the credible communication of these pipeline opportunities to workers faced with an uncertain labor market.

Our findings indicate that skill similarity has the potential to be binding on successful transition potential for disrupted or entrant workers. While the scope of this report has focused on skill supply, we also highlight the importance of demand-side levers such as technology and site-selection in better matching the available or trainable skill supply. We identify a policy opportunity to incorporate the supply-outlook methods in this report into both the decision making process of employers, and in the evaluation procedures of government agencies deciding on investment and other support decisions.[17] Decision makers interested in the workforce outcomes of new industrial capacity development can refer to capabilities like those in this report to gain a first-order indication of the feasibility of labor markets meeting new skill demand. While more work is needed to develop a mirror capability to evaluate how choices affect skill demand, a data-driven evaluation approach can highlight areas of concern or rapidly down-select a large possibility space to a set of credible options for closer analysis.

In summary, the methods deployed in this report offer a repeatable framework for identifying policy opportunities, and placing an actionable focus on skill requirements, geography, and wages. Our skill-gap approach can be used to identify occupational differentials for training programs to close. Our corresponding skills-similarity based wage-distribution-comparison approach can quickly identify the transition outlook for disrupted workers. These approaches enable a prioritization of those occupations that may require the most structured transition support to sustain employment and wages. We further identify opportunities to match declining with growing occupations, and those growth occupations where skill supply may present the greatest bottleneck for capacity expansion and performance on industrial investment.

[16] While we note considerable uncertainty about transformer and heat pump capacity, evidence from solar panel production suggests significant room to increase capacity to meet demand (rather than an artifact of undercounted data).
[17] see “Technical Assistance” in our limitations and future work subsection

Limitations and Future Work

Current Limitations

The currently available data imposes several limitations on our analysis. Some of these can be overcome with creative measures, but others will remain until new data can be developed, and this analysis can be updated to reflect it. Limitations include:

Unknown Distribution of Skill Demand - Through our processing of the Argonne data, we have reasonable estimates of the total quantity of labor demand, but we do not know the distribution of skill demand. This means that we cannot break down total demand into demand for specific occupations. Rough estimates can be extrapolated from our interview process, but the sample size for these interviews is not enough to confidently state skill demand distributions, especially not with the specificity required to identify different skill demands for the distinct technology types included in this analysis.

Unknown Upper-Bound of Labor Demand - The current data ecosystem lacks robust information on the current or future labor demand. Factory announcements that include worker counts are useful estimates, but the reliability of those projections is unknown. Organizations making those announcements have incentives to overestimate the number of jobs that their factory will create because higher job counts create a positive image of what the factory will bring to the area where it will be built. This can lead to more favorable tax deals, construction permits, and rezoning of real estate (if needed).

Job posting data are available, and trends can be drawn over time but this has its limitations as well. The largest issue with using job posting data is that it is not always clear which jobs are real; companies fill or close positions and forget to take postings down, and other companies post the same job multiple times for different geographic locations but only intend to fill one position. This means that job posting data is naturally an overestimation of demand, but it is unclear how large that overestimation is, or if that overestimation is uniform across geographies or industries. Even without those challenges relating to quantity, there is also the problem of mapping job postings to occupations. Companies aren't required to list their jobs with SOC codes or any other naming standard for occupations. When job listings do overlap with existing conventions, they may have misalignments in the job description.

Lack of Mappability - The majority of announced factories in this analysis are mappable to MSAs, but not all of them. This means that the total labor demand will be slightly higher than anticipated in these areas. Our figures are limited to the MSAs we have data for in the BLS so this is not captured in our figures.

Incompatibility of Datasets - During our analysis we found several points of data incompatibility. The Argonne dataset's use of coordinates was not mapped to MSAs as in the BLS dataset, but that was overcome by mapping coordinates to MSAs. Once this was done, we found an additional incompatibility; the BLS data does not contain data on every MSA in the U.S. This meant that some MSAs with new factory announcements did not have corresponding labor data. This limitation cannot be overcome with the current dataset, so our analysis is limited to those MSAs where the datasets were compatible.

Additional incompatibility was found between the BLS data and the Workforce Insights Tool. There is not 100% parity between occupations represented in these datasets. There are cases where occupations are missing from either the Workforce Insights Tool or the BLS data. Typically this is a result of the Workforce Insights Tool's tendency to use the most granular level of detail when referencing occupations (all six digits of an SOC code). At the same time, BLS tends to only go down to the five-digit SOC code. Because SOC codes are hierarchical (each additional digit referencing a subset of the shorter code), we were able to find equivalents between the tools, but this does lead to a minor loss in precision.

Labor Stock & Flow - At this point, our labor supply mapping has used current stock and changes in stock over time to project available workforce availability and transition options. A limitation of this method is that it is missing internal turnover and replacement within occupations. In our analysis, occupations with high turnover but unchanging total labor stock would appear no different from occupations with low turnover and unchanging labor stock. In reality, those two occupation scenarios are different, with the high turnover occupation representing a greater quantity of transition options for exiting ICEV workers as well as a more abundant sourcing opportunity for emerging EV, battery, and HST production jobs.

Modeling and Resolving Uncertainty

In the following figure (**Figure 37**, next page), we diagram the potential relationships among sources of uncertainty – some addressed by our analysis, others requiring future work – and their implications for two key parameters of interest: the need for retraining of incumbent workers, based on the match of their skills to alternative or emerging opportunities to achieve wage-sustaining transitions in place; and the quantity of demand for labor that mirrors the demand-shock to incumbent labor demand. Positive anticipated relationships are indicated by a (+) and negative by a (-). The posited direction of causality within the model is indicated by the orientation of the arrows. We then model a two-stage relationship from first outputs to conditions for workforce transitions.

We also consider some systematic drivers of technical uncertainty, which will require further research to parametrize for specific chemistry families or process regimes. We lay out these potential drivers in a table in **Appendix H**, which summarizes distinct categories of uncertainties and describes possible implications for high and low values on each dimension.

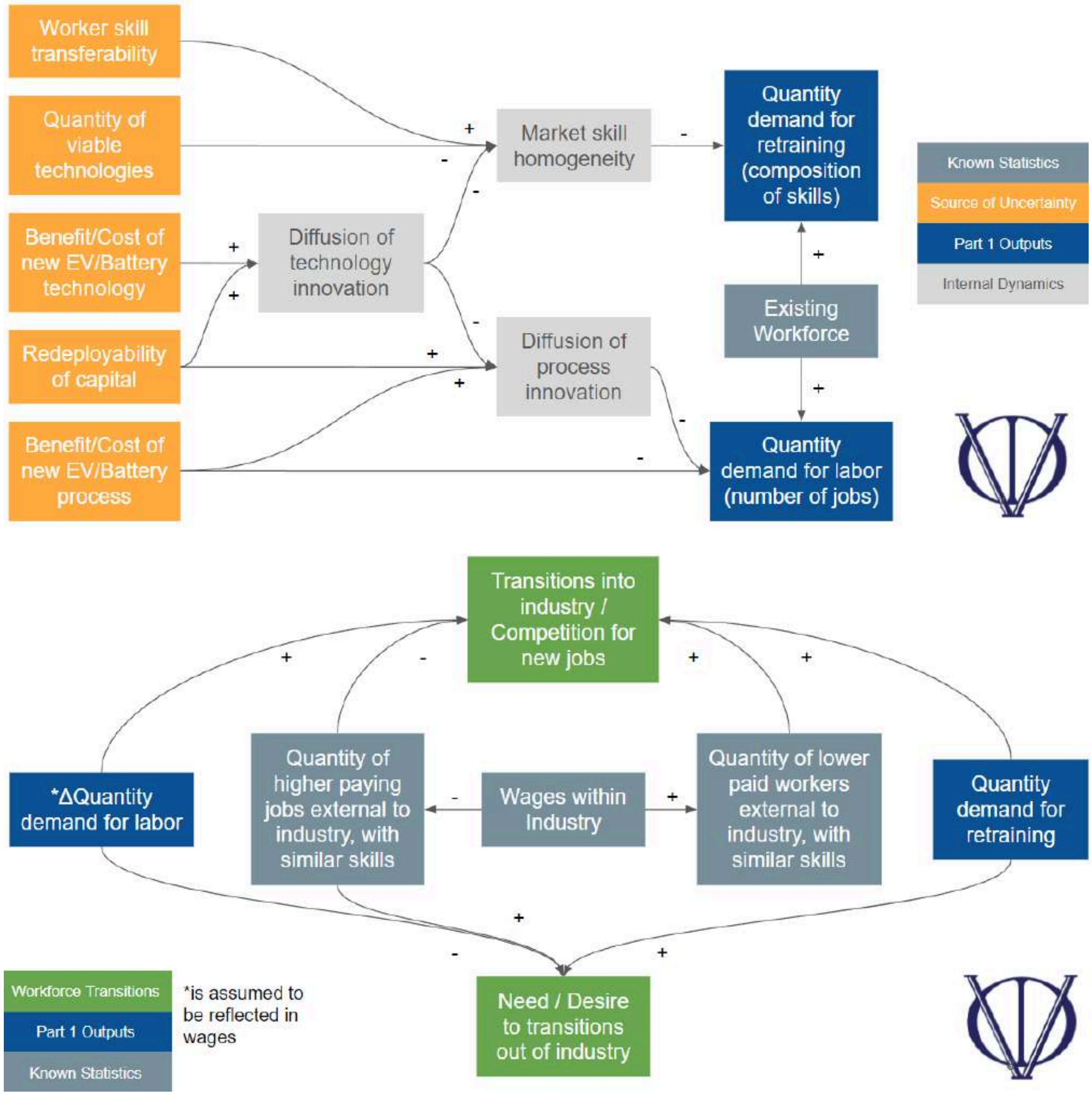


Figure 37: Interpretation of Model Drivers and Sources of Uncertainty in Workforce Transitions Opportunities and Predictions

Not all uncertainties detailed in this section are of equal relevance for different policy considerations. Below, we detail opportunities for resolving uncertainty and furthering key analyses that we believe may have the greatest impact on the useability or implications of our findings, and questions about the workforce implications of automotive electrification and HST expansion that our work is unable to address given current limitations.

1. **Leveraging Grant Applications and Reporting Requirements**

Many of the sources of uncertainty in this report could be resolved with firm-level data. For example, firms are likely to have more detailed information on the breakdown of occupations that they expect to hire, relative to the single-dimensional job creation announcements that populate current government datasets. As we found in our interviews, there is also meaningful heterogeneity among firms in the breakdown of occupational employment depending on their workforce strategy.

Introducing or expanding existing protocols of information gathering could yield useful details for understanding the frequency and direction of occupational transitions. DoE and other government agencies could make simple enhancements to grant applications and/or reporting requirements for recipients of federal assistance by including detailed labor demand questionnaires in the required application or reporting materials. For instance, requirements for applying for and receiving federal support in capacity development could include reporting occupational breakdowns on new job estimates, whether directly workforce related or not. If funded, firms could then be required to report employment and wage distribution in detail at the establishment level, as well as the occupational background of new employees and occupational destinations of exiting employees if known. Said data could serve as a basis for validating the occupational transitions predicted from skill similarity alone.

Such protocols for reporting requirements and the resulting data could create a consistent basis for evaluating skill demand in a way that credibly signals non-government stakeholders, like organized labor and training institutions. Thus, policymakers can encourage forward-looking curriculum design and targeted training offerings to the hardest-to-place target occupations, improving the robustness of transition options for workers.

2. **Technical Assistance and Creating Incentive-Compatible Data Collection**

A significant challenge for many firms investing in new or expanded manufacturing capacity is a lack of resources to develop systematic predictions of their own labor needs, which can in turn limit the validity of prospective estimates of the match between demand and supply. While out of the scope of this report, technical assistance to firms in developing credible workforce strategies presents two opportunities. First, it can offer an analytical basis for firms to develop pathways to align capacity-development objectives with workforce strategies that meet policy objectives around wages and inclusion, hence becoming more competitive for certain sources of government support. Second, technical assistance is an opportunity to harmonize data collection and analytics across firms, and between industry and government.

DoE and other agencies can develop a standard of data collection to be used in technical support to firms on workforce strategy, enabling the continual reporting of skills and occupational needs. Doing so could further reduce uncertainty over time and provide the data foundations for a situational awareness capacity that reapplies the methods in this report at regular intervals. This framework would also enable analytics around firm- and policy-levers on skill demand: tracking SKAWS at the process task level makes it possible to map the possibility space for how jobs and their associated skill demand might be recombined.

3. **Additional Interviews and Post-Hoc Data Collection**

Based on high uncertainty and information missingness, we note the high priority of investigating HST occupational demand. Across the HST domain, we only found labor demand estimates for a fraction of solar capacity expansion, and no clear labor demand estimates for heat pumps or transformers. Given the significant relative demand for these industries, we may be missing a significant part of the greater story of workforce dynamics across the broader EV transition.

For all the analysis categories, but particularly for HSTs where none were conducted, conducting further interviews or industry listening sessions will improve on the validity of this analysis for the target industries in three ways. First, it will confirm or adjust the occupations that are most critical for production. Second, it will inform the distribution of SKAWs within those occupations, as the specifics of one industry's production needs may vary from the overall occupation. Lastly, it would allow us to identify the distribution of wages within the occupations, as wages may differ across industries within a single occupation.

4. **Examining Heterogeneity in Wage Comparisons**

Appendix C contains a wealth of wage-based similarity comparisons for the ICEV and other occupations we examine in this analysis. We identify broad trends in these analyses, but each individual occupation has uncertainty in the specific factors at play. These factors may include demographic variation, individual firm behavior/size, geographic heterogeneity, and industry heterogeneity, among others.

Figure C.21 shows a general national trend for Machinists but with a small selection of MSAs that counter the trend. The red MSA in Wyoming could be a case where the population size of the region means market dynamics are dictated by a relatively small number of employers. Identifying outlier MSAs and the market dynamics within them will be a critical next step to making national policy work at the local scale.

Figure C.28 shows a mixed wage premium for Machine Tool Setters at the 0.7 similarity score cut point, but a significantly improved picture at the 0.9 cut point. This change in similarity score is likely capturing a change in the composition of occupations in the comparison pool. The nuances of that change in composition are still uncertain. With additional resources, we could use industry data within BLS to tease out where these differences are related to cost of living (and thus wages) or similar occupations being employed in different industries (aerospace vs automotive for example). Using a policy lever to incentivize behavior will look different if geography is the driver versus when industry premiums are the cause.

Extending Methods and Cases

This report represents a starting point for building and deploying an analytical capability that appraises the workforce implications of manufacturing and infrastructure capacity-building and transformation on a national scale but with attention to regional and occupational specificity. The 12-week timeline of this project has been a demonstration that these methods can keep pace with the rate of capacity development needed for timely achievement of energy transition and other industrial policy goals.

In addition to resolving limitations, there are extensive opportunities for further work to refine the insights and broaden the scope of this research. Given sufficient data on occupational requirements, future work could characterize the skill stock and flow outlook for other industries affected by the energy transition. Each industry will have its own technical, operational and market levers to change the content and location of skill demand: guided by insights like those in this report, future work can target specific workforce bottlenecks that may require a demand-side approach to resolve. Deeper operational studies can leverage shop-floor data and expert insights into the technical options space to find skill demand choices (e.g. Combemale, Whitefoot, Fuchs and Ales 2021) that act on supply-side insights.

There is a clear need for cross-industry and cross-application comparison at a systems level. Different dimensions of the energy transition may require similar skills, hence drawing on a common pool of talent as would any other positive labor demand shock. While in some instances this commonality can produce opportunities to connect workers from occupation-industry contexts with declining employment to sources of anticipated job creation, it can also put different aspects of the energy transition in competition with each other for talent. This has the potential to produce workforce bottlenecks that would not be apparent from industry-specific studies alone.

Future work could also connect component supply chain mechanisms, such as co-location incentives and supply chain risk, with the supply chain perspective on labor. Such work would add to the systems-level perspective by quantifying how workforce constraints compare with other risks, and hence the value proposition of investments in training and other levers that improve the robustness of labor markets. In an interconnected production environment, talent shortages may drive vulnerability.

Appendix A: Supporting Figures, Mapping Labor Supply to Metropolitan Statistical Areas

Number of "Miscellaneous Assemblers and Fabricators" (51-2090) by MSA

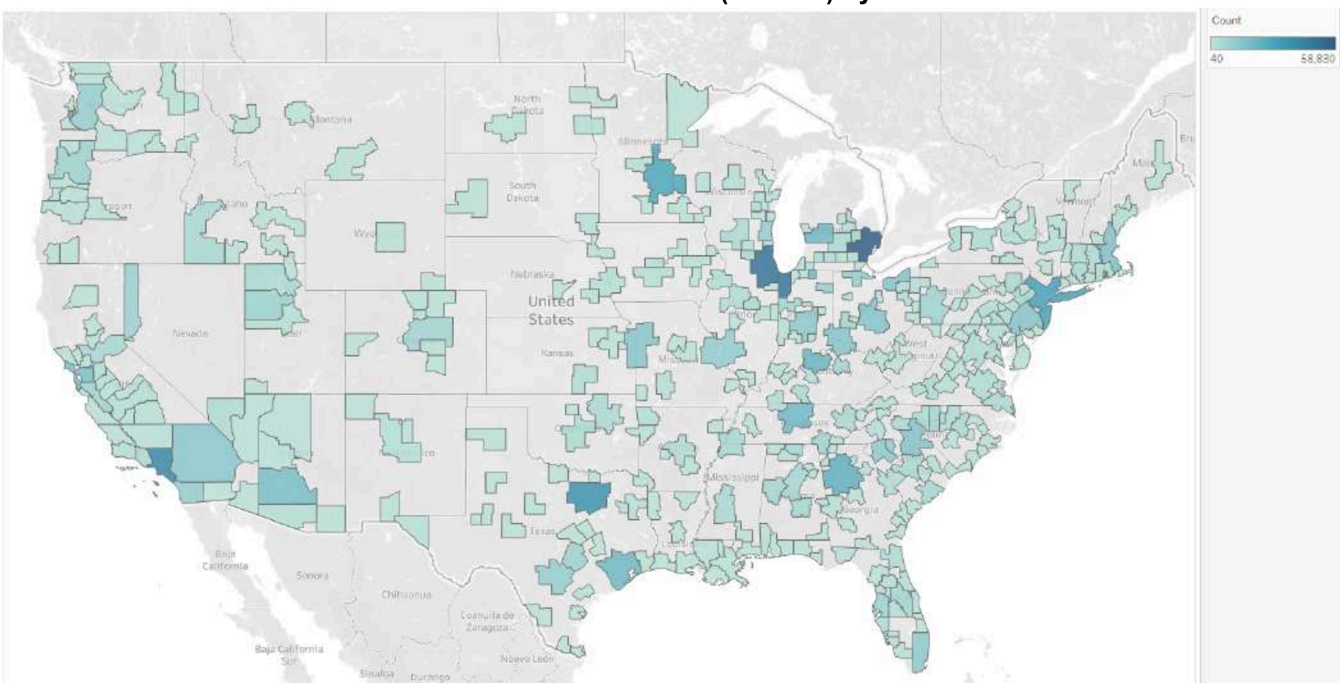


Figure A.1: Map of labor supply for "Miscellaneous Assemblers and Fabricators" by MSA. Dark blue indicates a larger labor supply.

Number of "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) by MSA

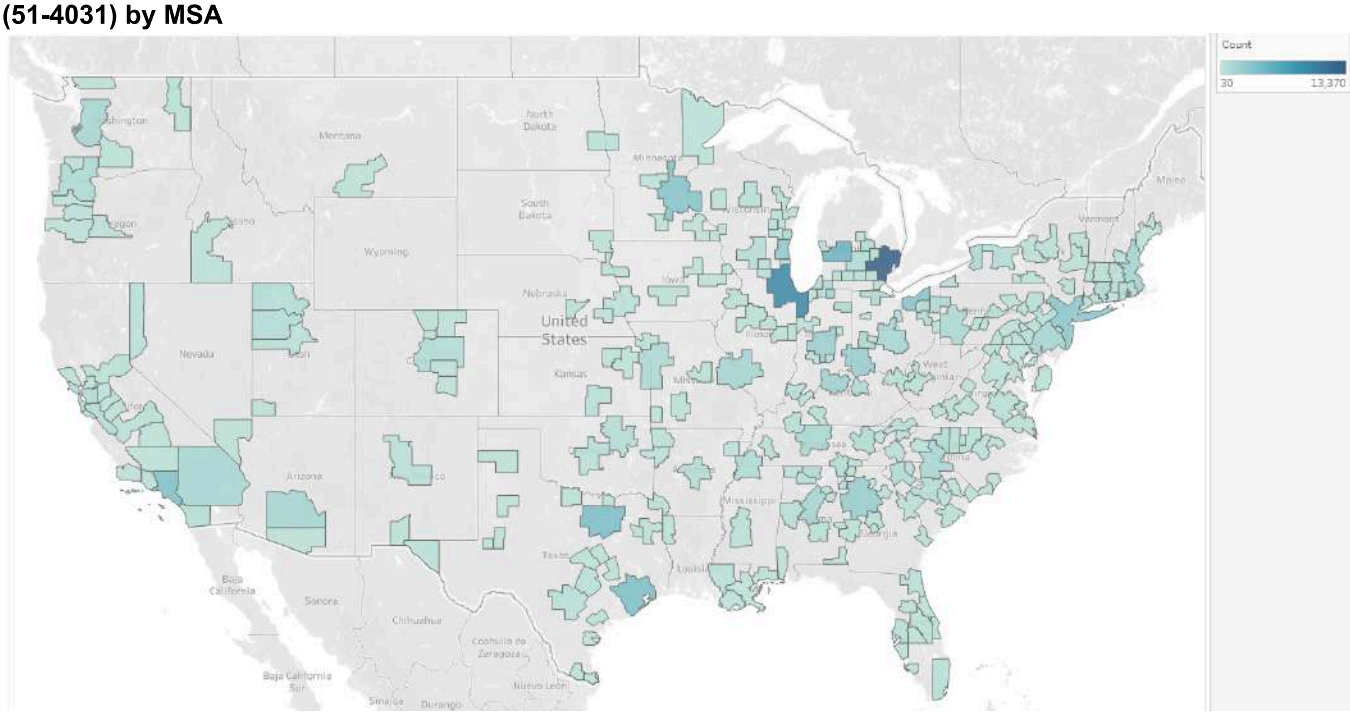


Figure A.2: Map of labor supply for "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" by MSA.

Number of "Engine and Other Machine Assemblers" (51-2031) by MSA

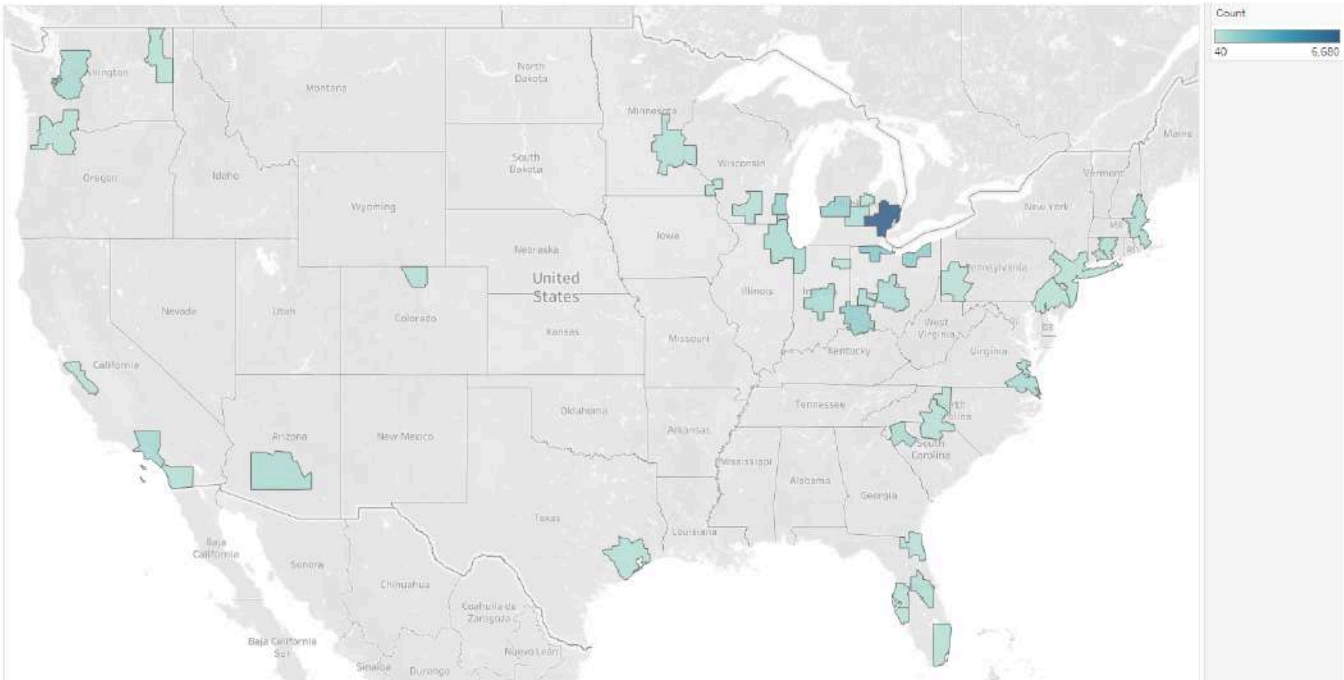


Figure A.3: Map of labor supply for "Engine and Other Machine Assemblers" by MSA.

Number of "First-Line Supervisors of Production and Operating Workers" (51-1011) by MSA

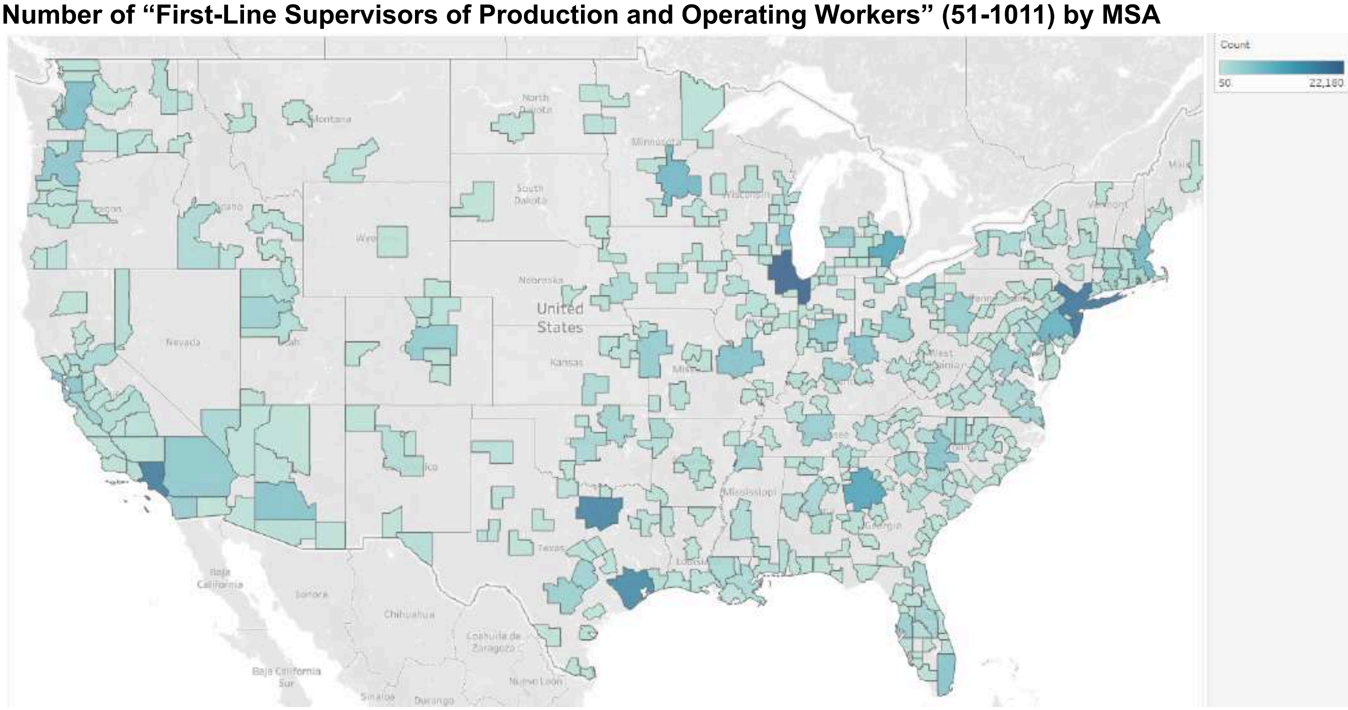


Figure A.4: Map of labor supply for "First-Line Supervisors of Production and Operating Workers" by MSA.

Number of “Inspectors, Testers, Sorters, Samplers, and Weighers” (51-9061) by MSA

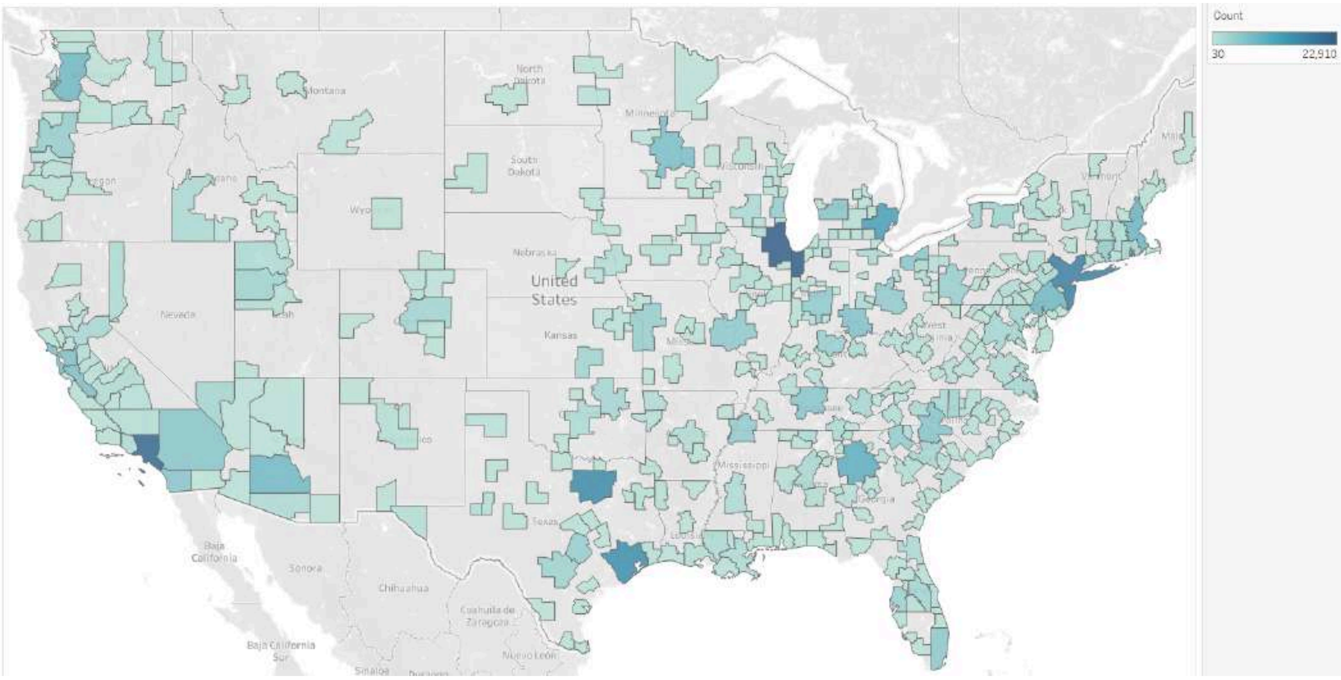


Figure A.5: Map of labor supply for “Inspectors, Testers, Sorters, Samplers, and Weighers” by MSA.

Number of “Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic” (51-4081) by MSA

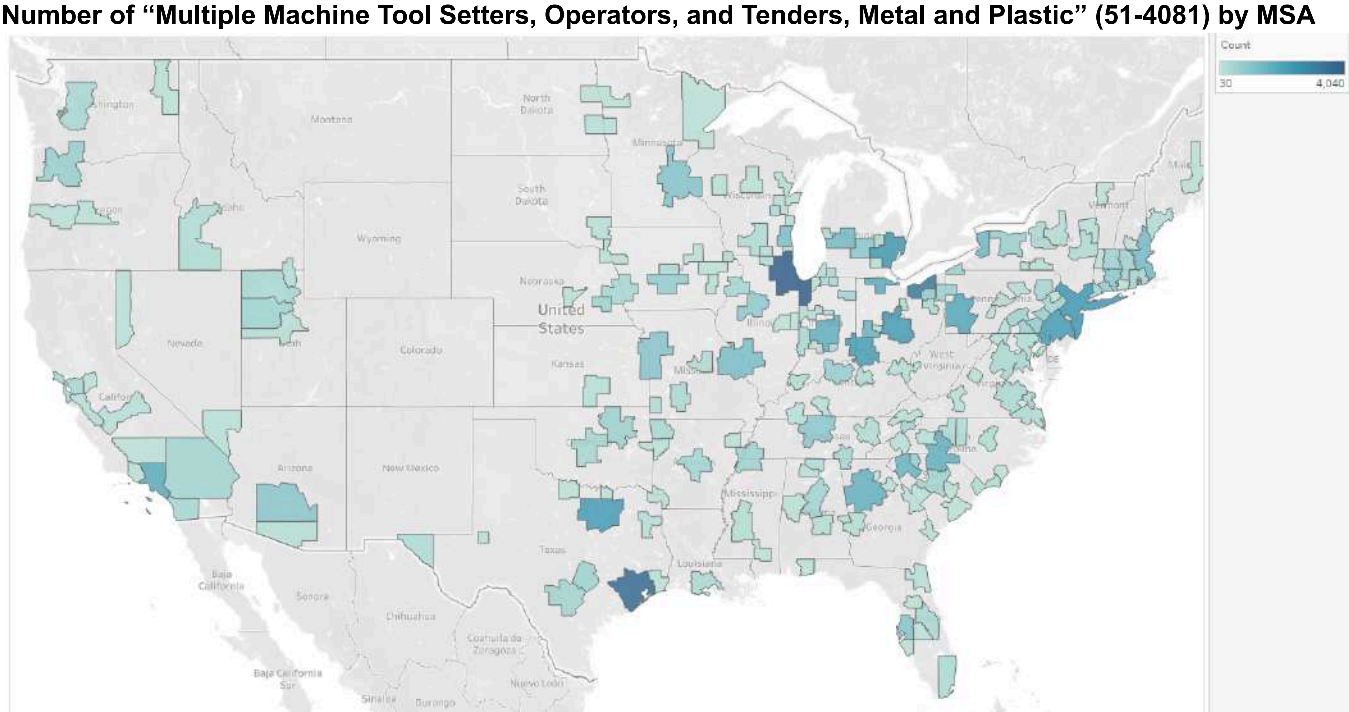


Figure A.6: Map of labor supply for “Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic” by MSA.

Number of "Machinists" (51-4041) by MSA

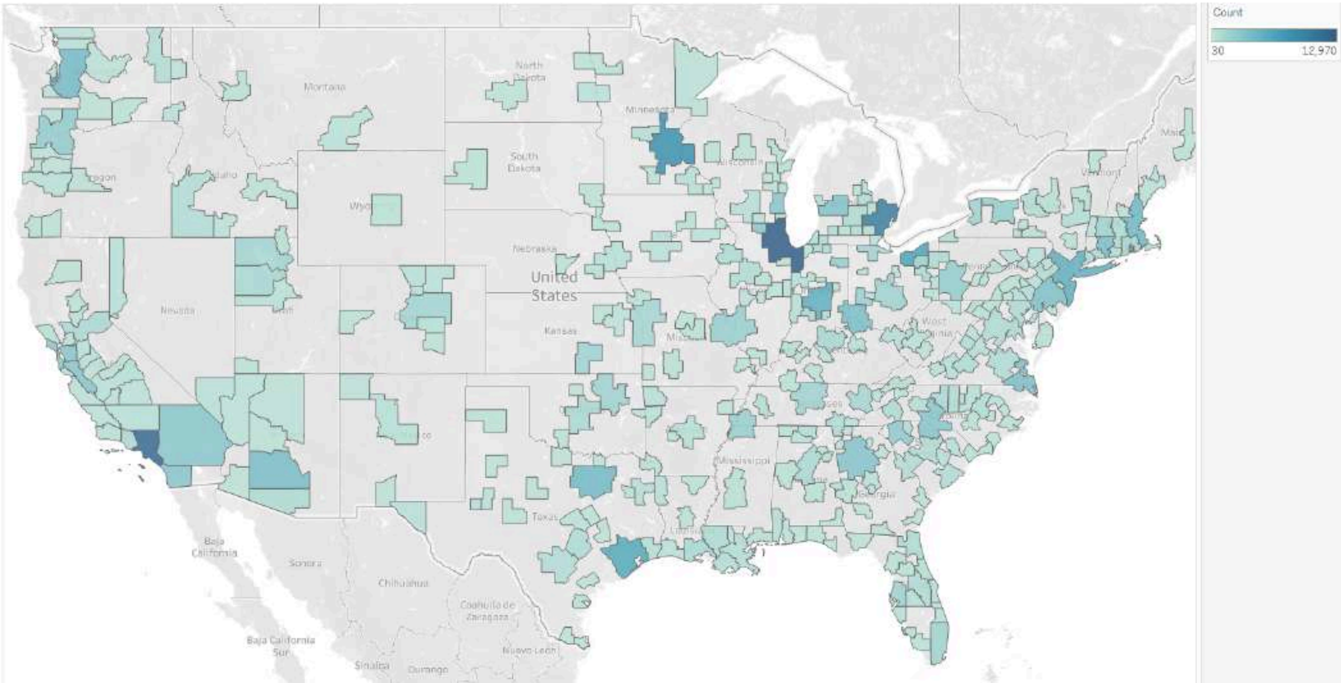


Figure A.7: Map of labor supply for "Machinists" by MSA.

Number of "Electrical, Electronic, and Electromechanical Assemblers, Except Coil Winders, Tapers, and Finishers" (51-2028) by MSA

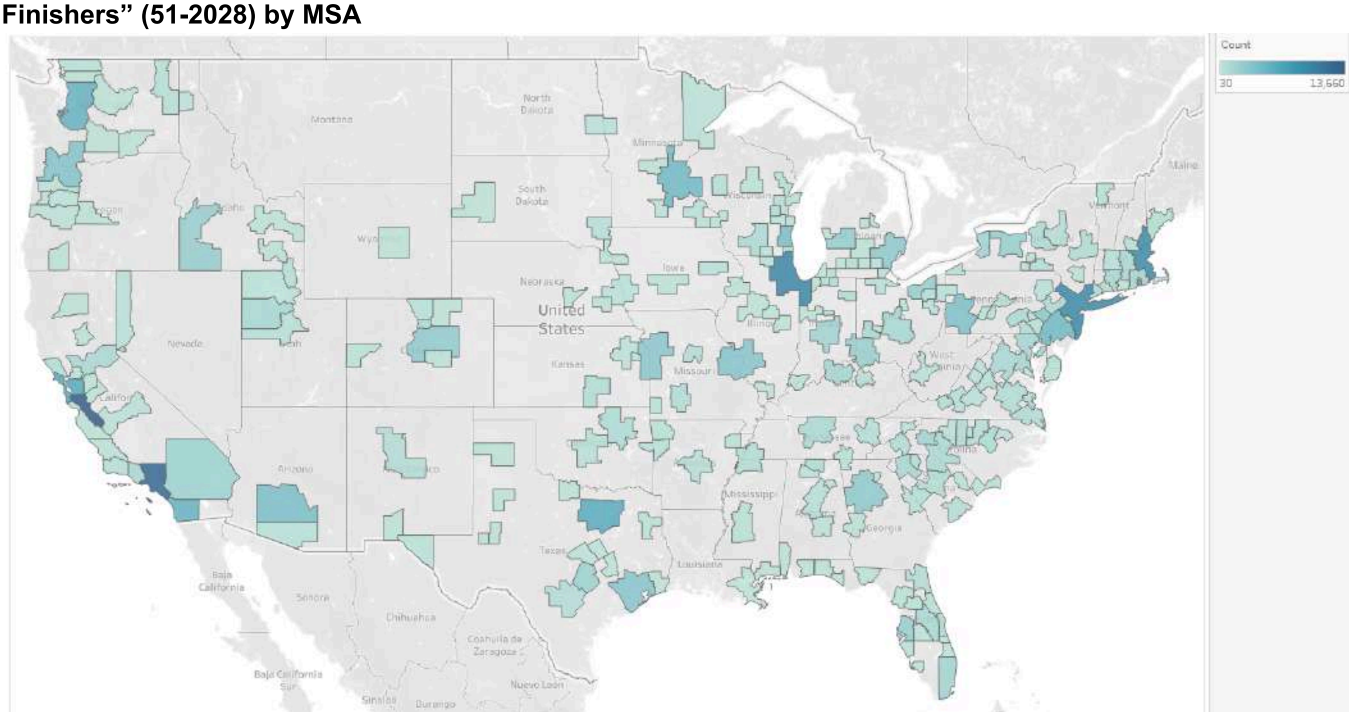


Figure A.8: Map of labor supply for "Electrical, Electronic, and Electromechanical Assemblers, Except Coil Winders, Tapers, and Finishers" by MSA.

Number of "Welders, Cutters, Solderers, and Brazers" (51-4121) by MSA

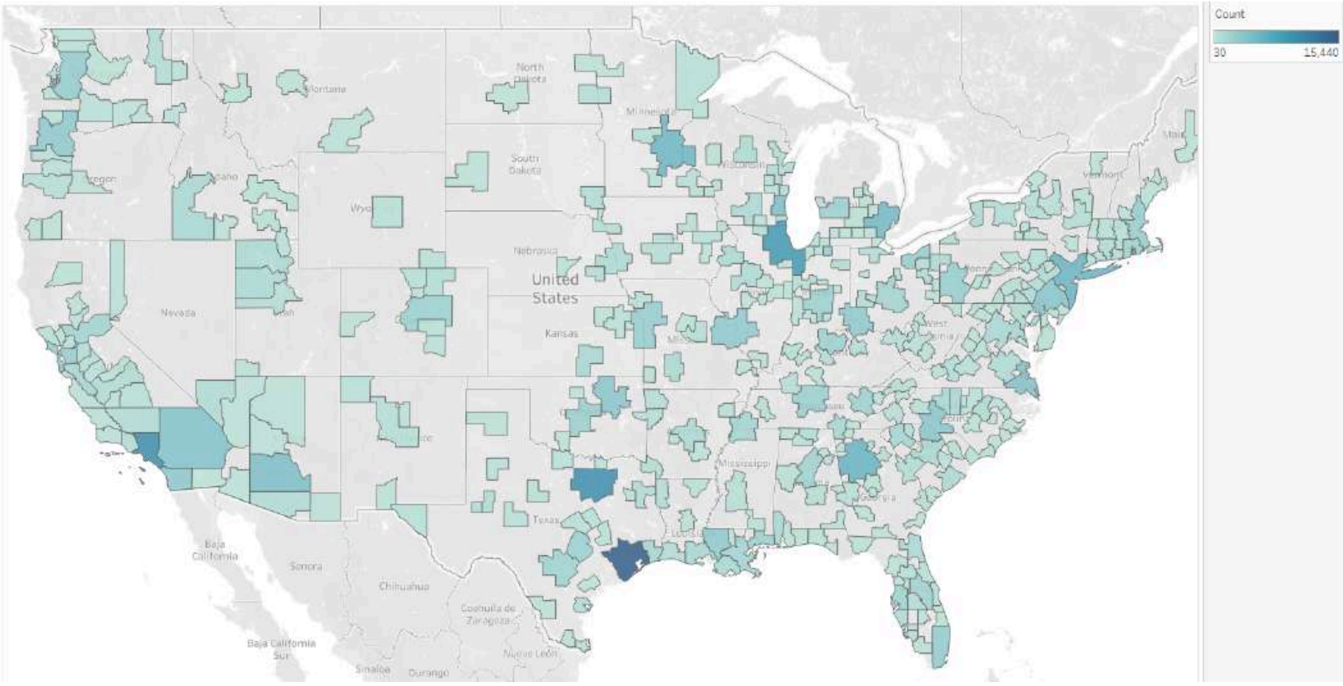


Figure A.9: Map of labor supply for "Welders, Cutters, Solderers, and Brazers" by MSA.

Number of "Tool and Die Makers" (51-4111) by MSA

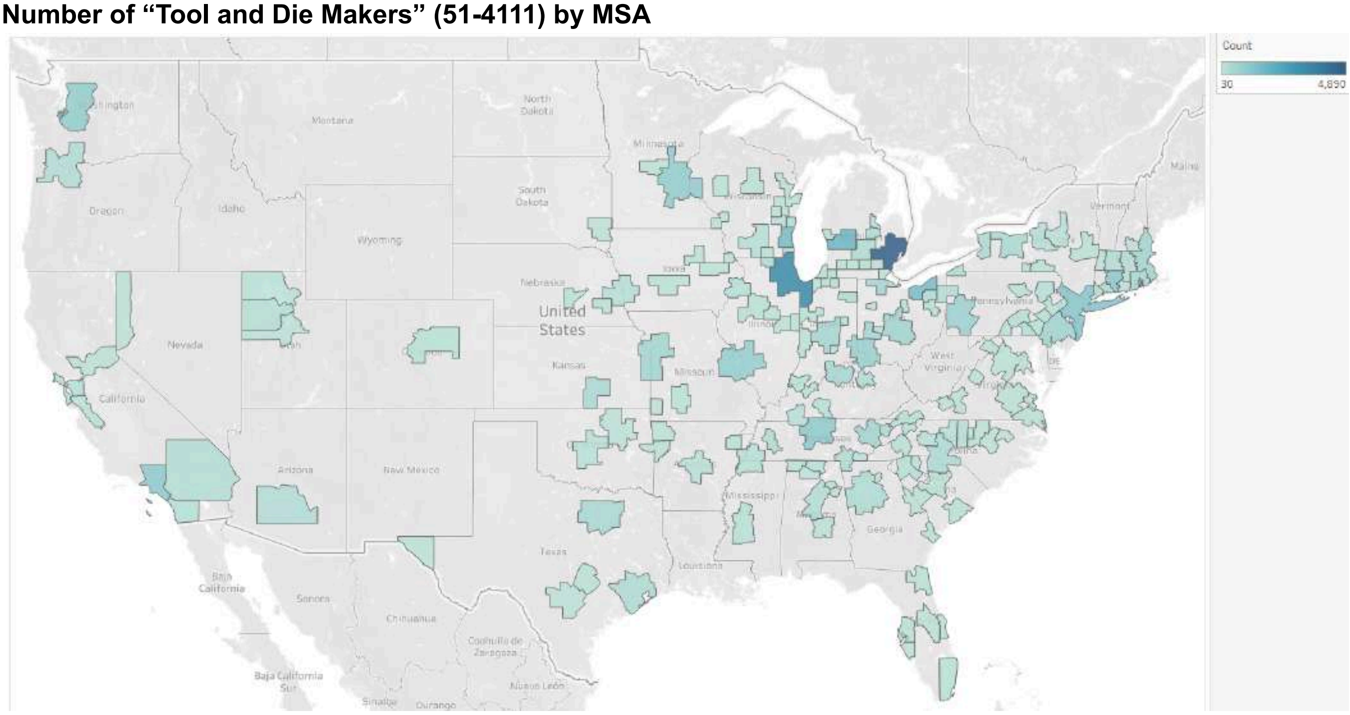


Figure A.10: Map of labor supply for "Tool and Die Makers" by MSA.

Number of "Electro-Mechanical and Mechatronics Technologists and Technicians" (17-3024) by MSA

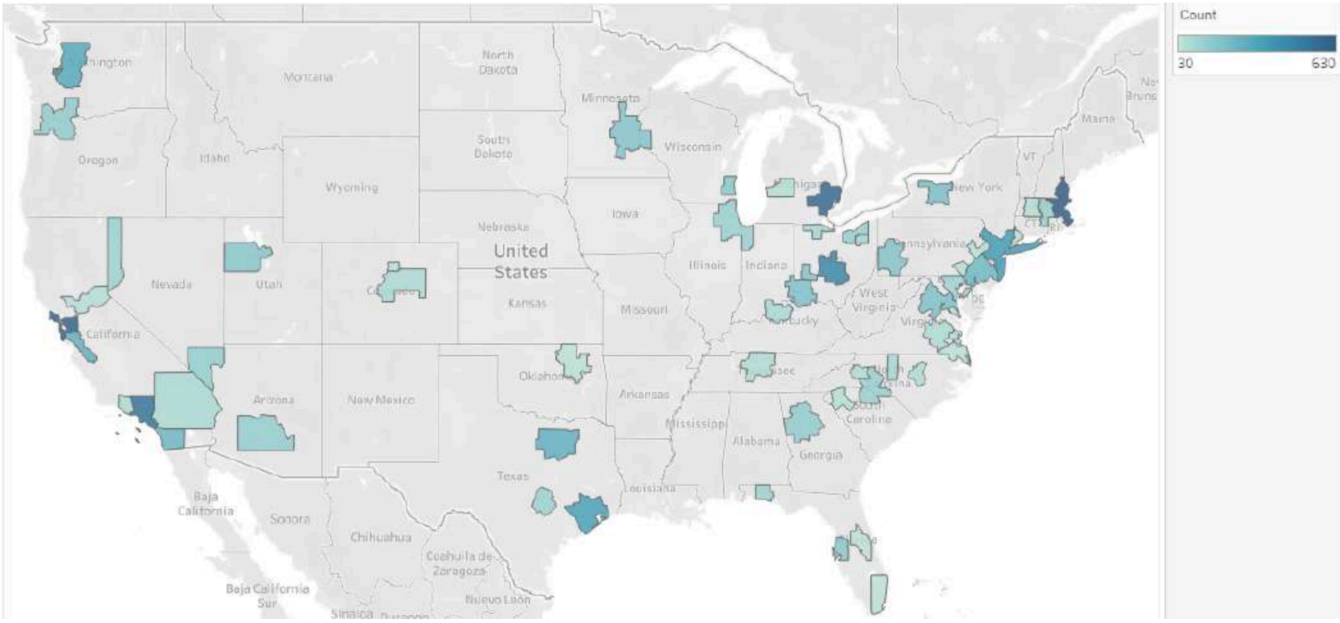


Figure A.11: Map of labor supply for "Electro-Mechanical and Mechatronics Technologists and Technicians" by MSA.

Number of "Industrial Production Managers" (11-3051) by MSA

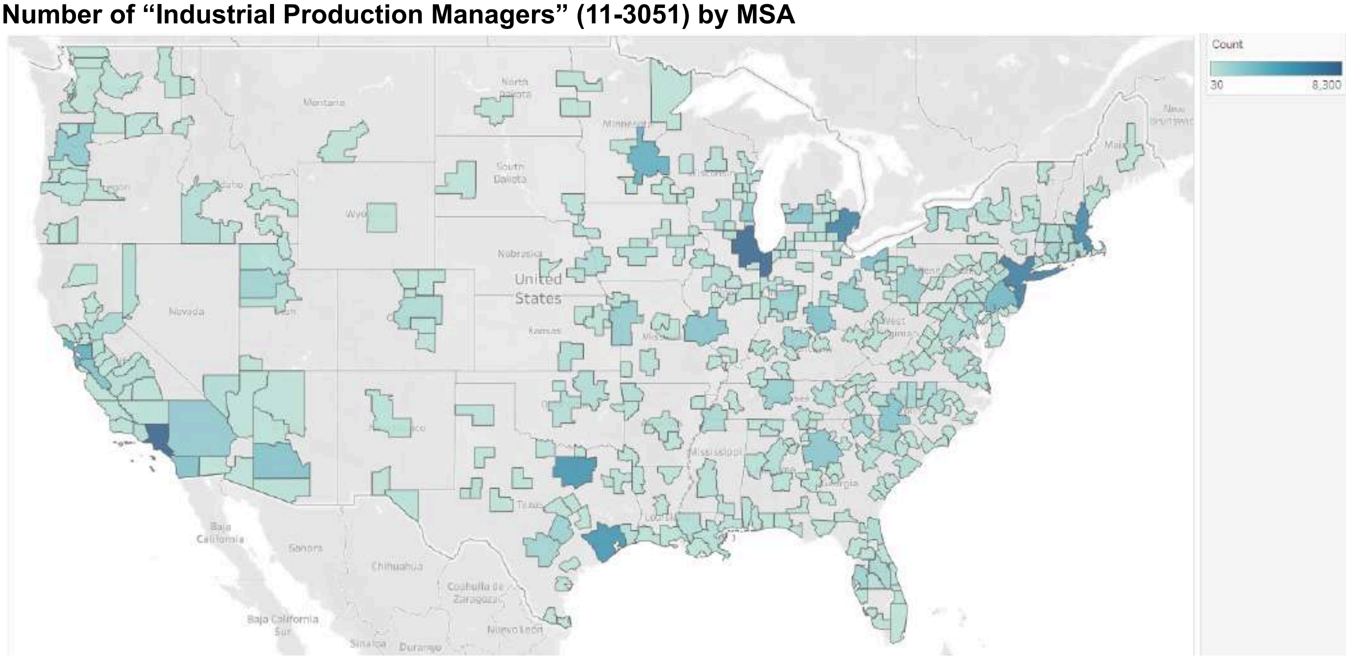


Figure A.12: Map of labor supply for "Industrial Production Managers" by MSA.

Number of “Industrial Machinery Mechanics” (49-9041) by MSA

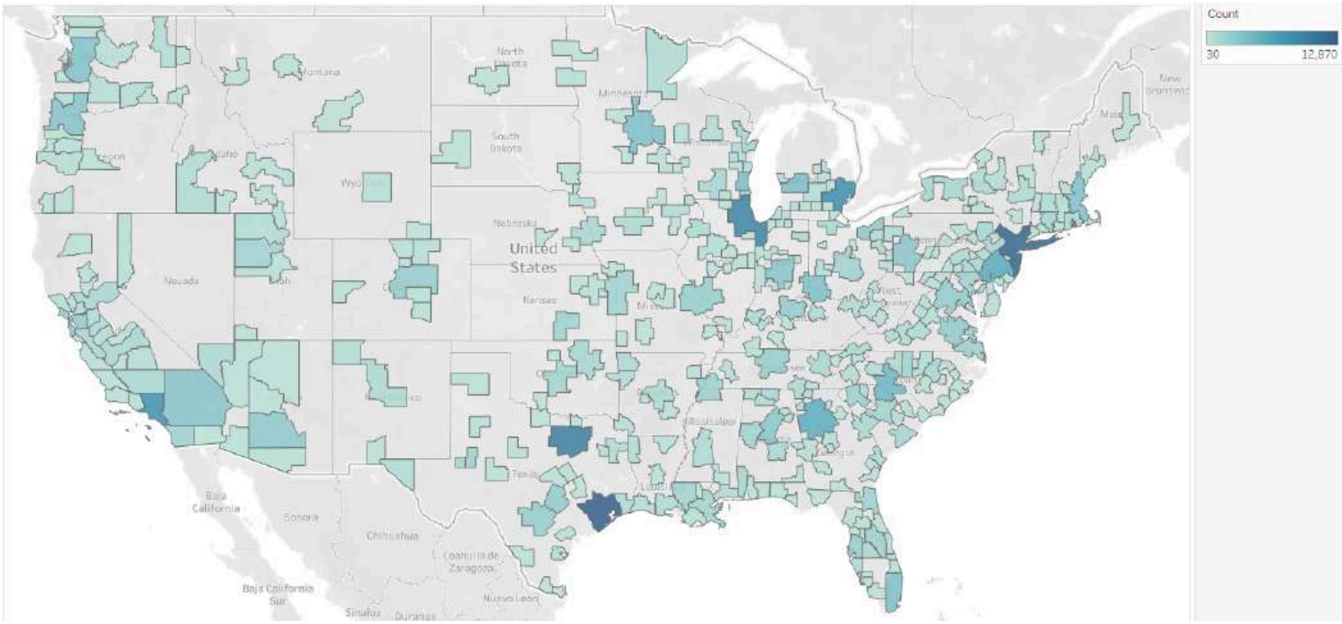


Figure A.13: Map of labor supply for “Industrial Machinery Mechanics” by MSA.

Appendix B: Supporting Figures, Mapping Labor Competition

This appendix comprises two sections: (1) ratio of ICEV workers to workers in occupations they can transition to, and (2) ratio of EV, battery, and HST workers to workers in occupations that can transition into. Similarity is directional, so these sections are distinct.

Ratio of ICEV Workers to Workers in Candidate Destination Occupations

This section includes figures for an occupation of interest divided by the number of similar jobs. Similarity is directional, and for these figures that direction goes from our occupation of interest to the similar occupations.

Number of "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) divided by Number of Jobs with Skill Similarity>=0.7 by MSA

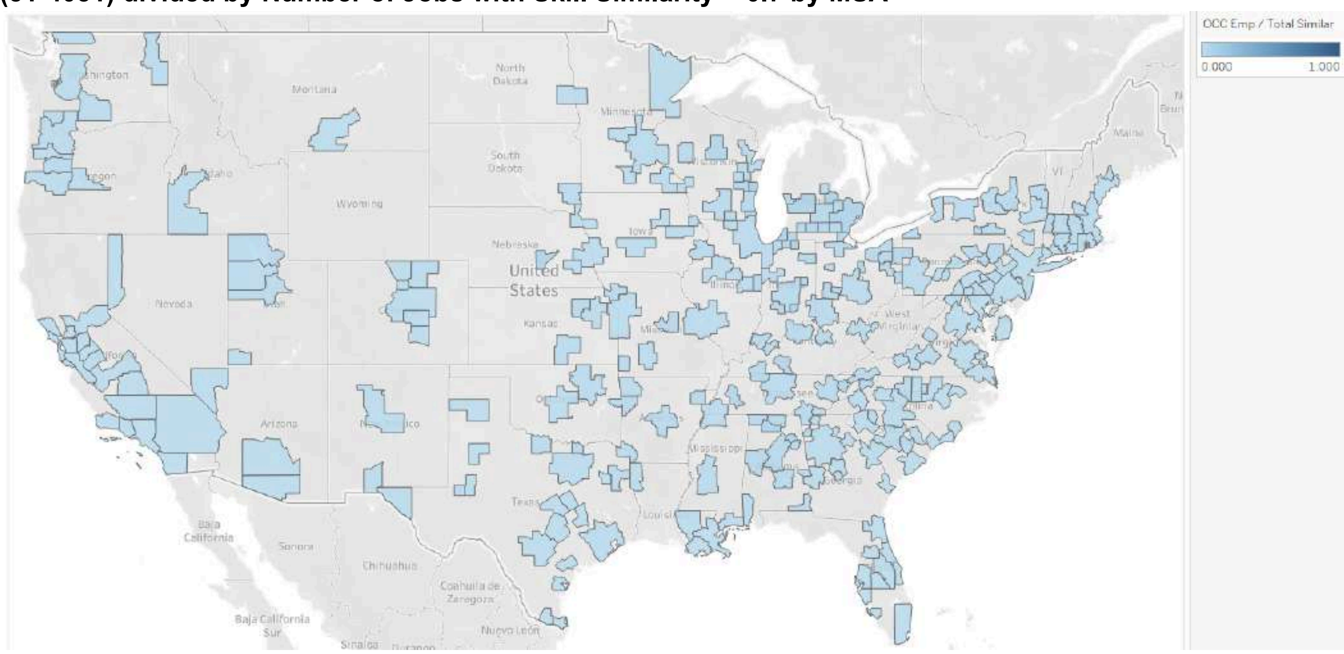


Figure B.1: Quantity of 51-4031 "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" workers over quantity of workers in similar occupations, with a similarity rate of 0.7 or greater.

Number of "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) divided by Number of Jobs with Skill Similarity>=0.8 by MSA

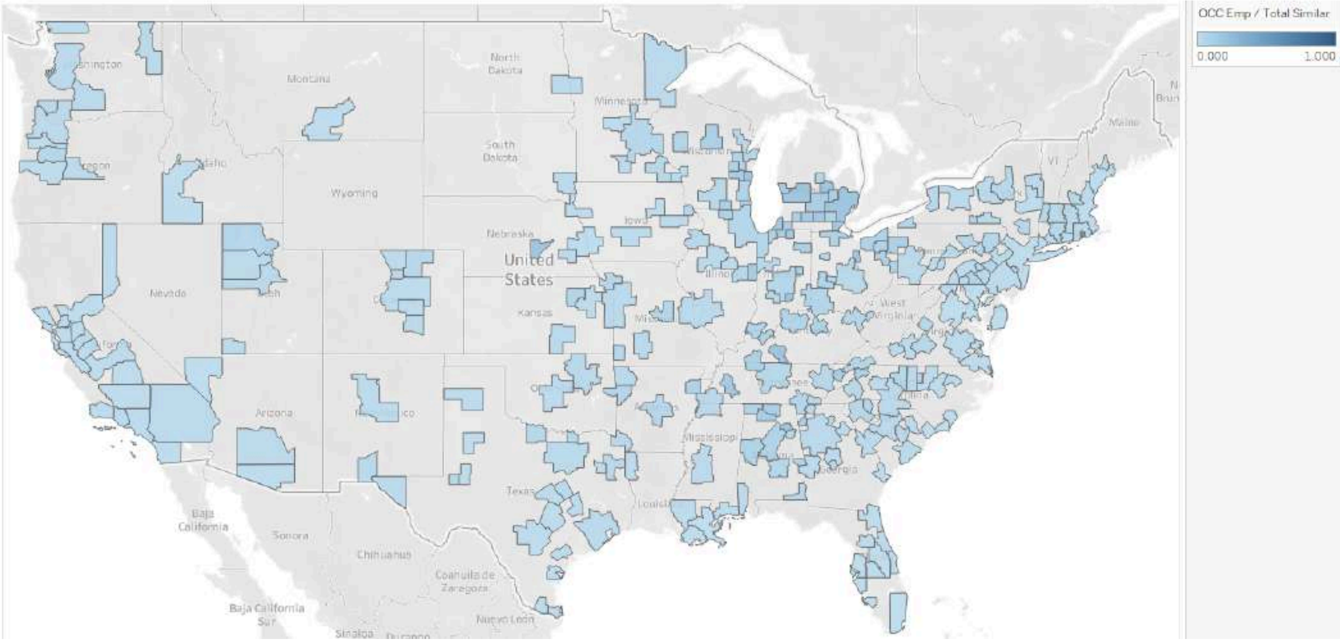


Figure B.2: Quantity of 51-4031 "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" workers over quantity of workers in similar occupations, with a similarity rate of 0.8 or greater.

Number of "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) divided by Number of Jobs with Skill Similarity>=0.9 by MSA

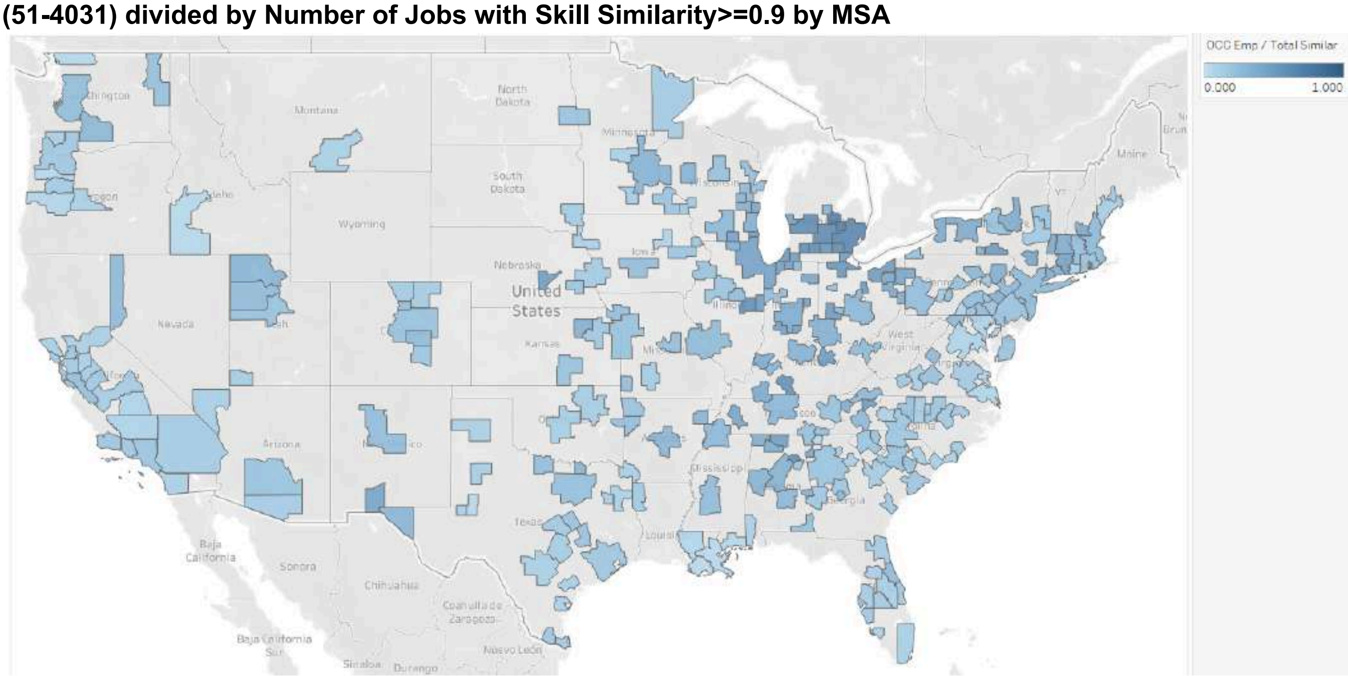


Figure B.3: Quantity of 51-4031 "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" workers over quantity of workers in similar occupations, with a similarity rate of 0.9 or greater.

Number of "Engine and Other Machine Assemblers" (51-2031) divided by Number of Jobs with Skill Similarity>=0.7 by MSA

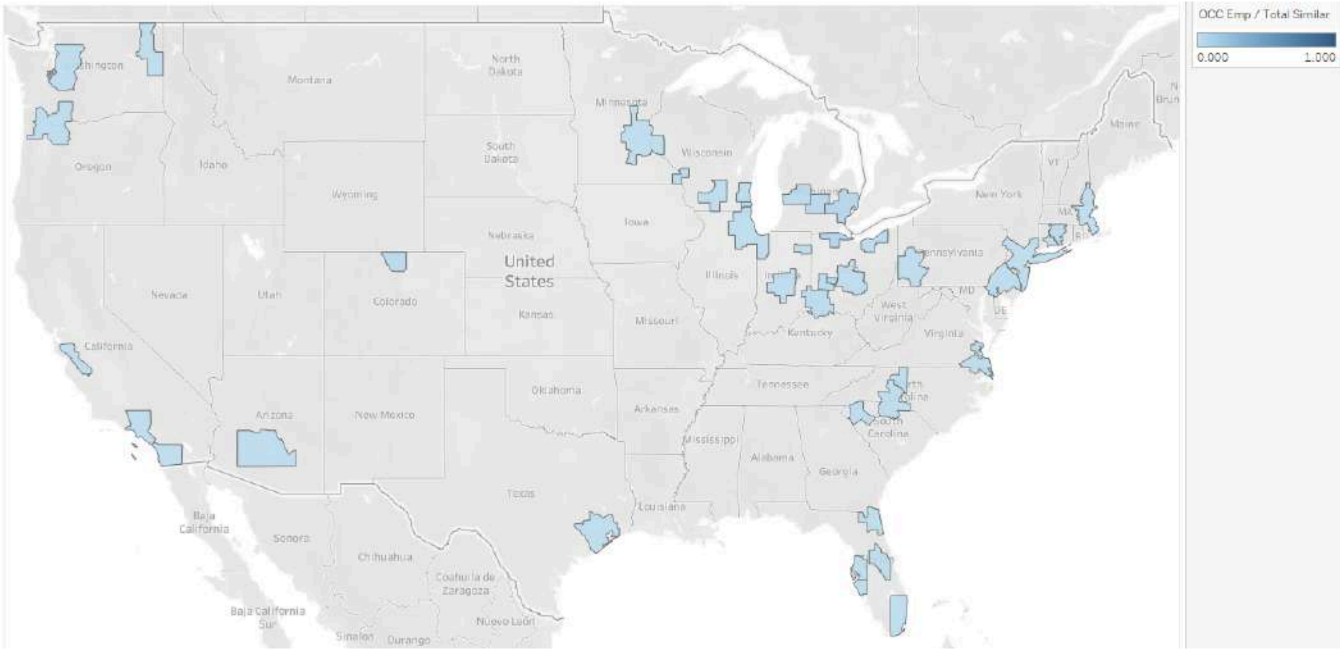


Figure B.4: Quantity of 51-2031 "Engine and Other Machine Assemblers" workers over quantity of workers in similar occupations, with a similarity rate of 0.7 or greater.

Number of "Engine and Other Machine Assemblers" (51-2031) divided by Number of Jobs with Skill Similarity>=0.8 by MSA

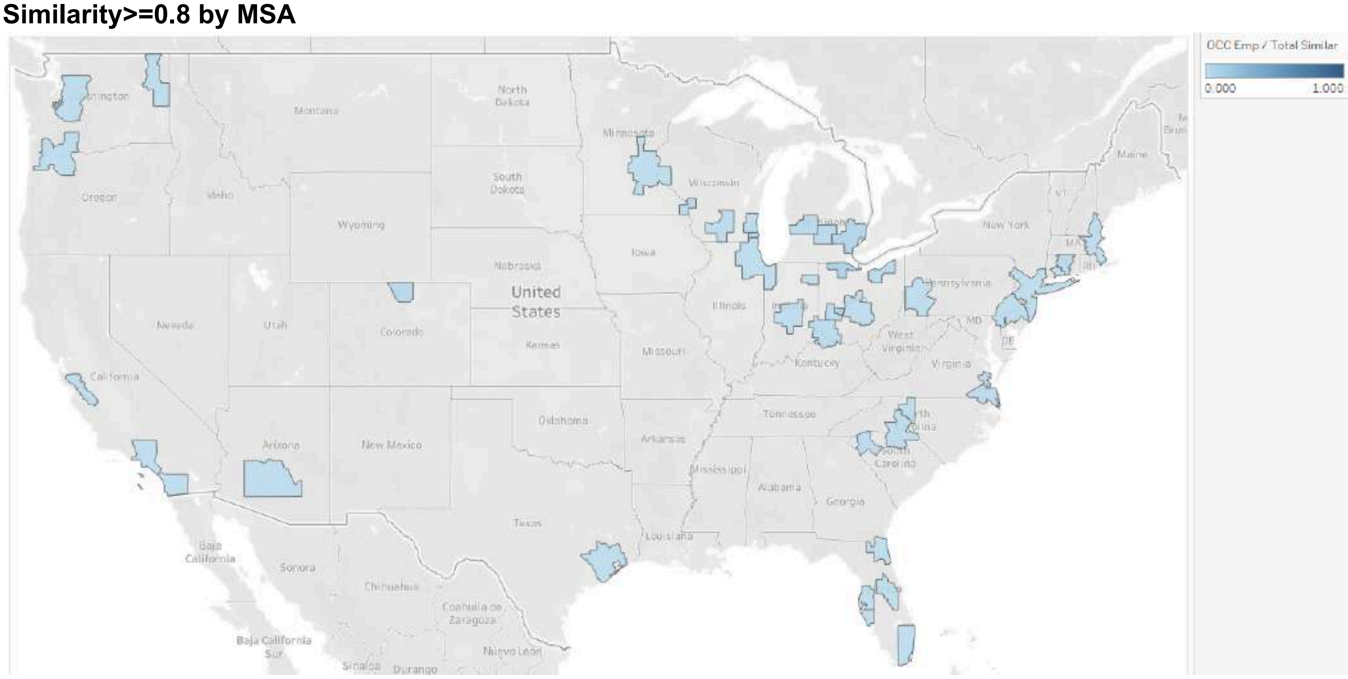


Figure B.5: Quantity of 51-2031 "Engine and Other Machine Assemblers" workers over quantity of workers in similar occupations, with a similarity rate of 0.8 or greater.

Number of "Engine and Other Machine Assemblers" (51-2031) divided by Number of Jobs with Skill Similarity>=0.9 by MSA

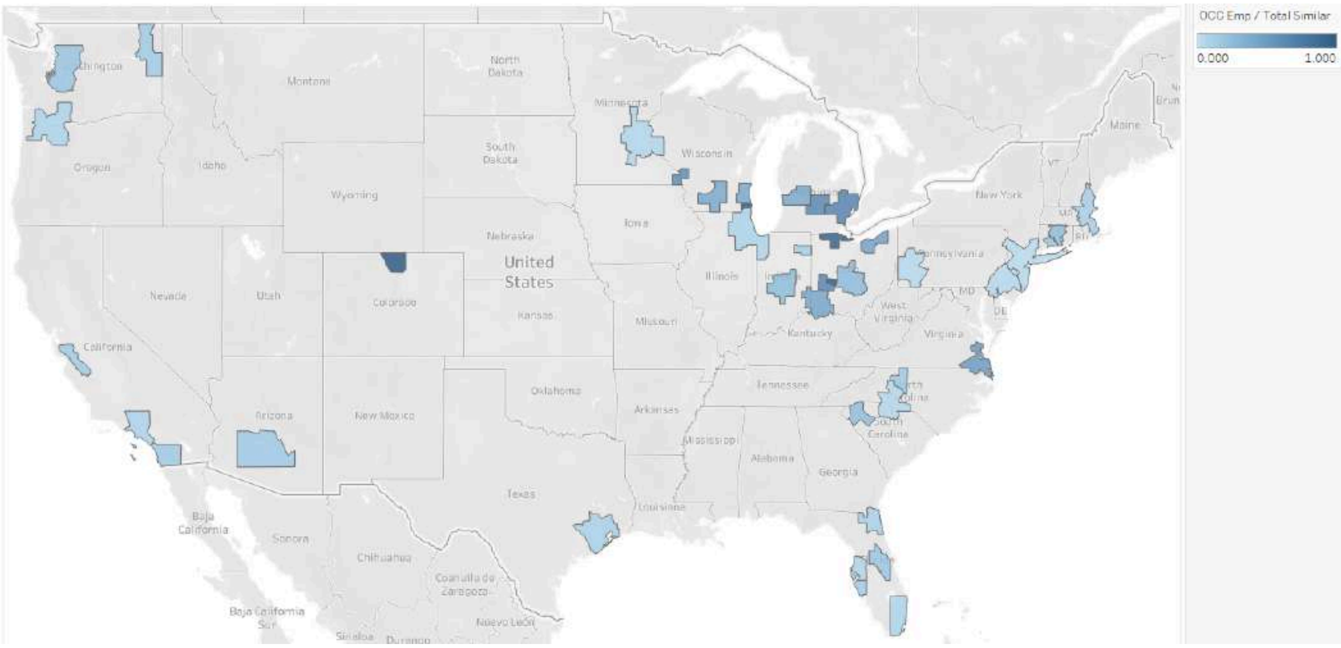


Figure B.6: Quantity of 51-2031 "Engine and Other Machine Assemblers" workers over quantity of workers in similar occupations, with a similarity rate of 0.9 or greater.

Number of 51-4041 "Machinists" divided by Number of Jobs with Skill Similarity>=0.7 by MSA

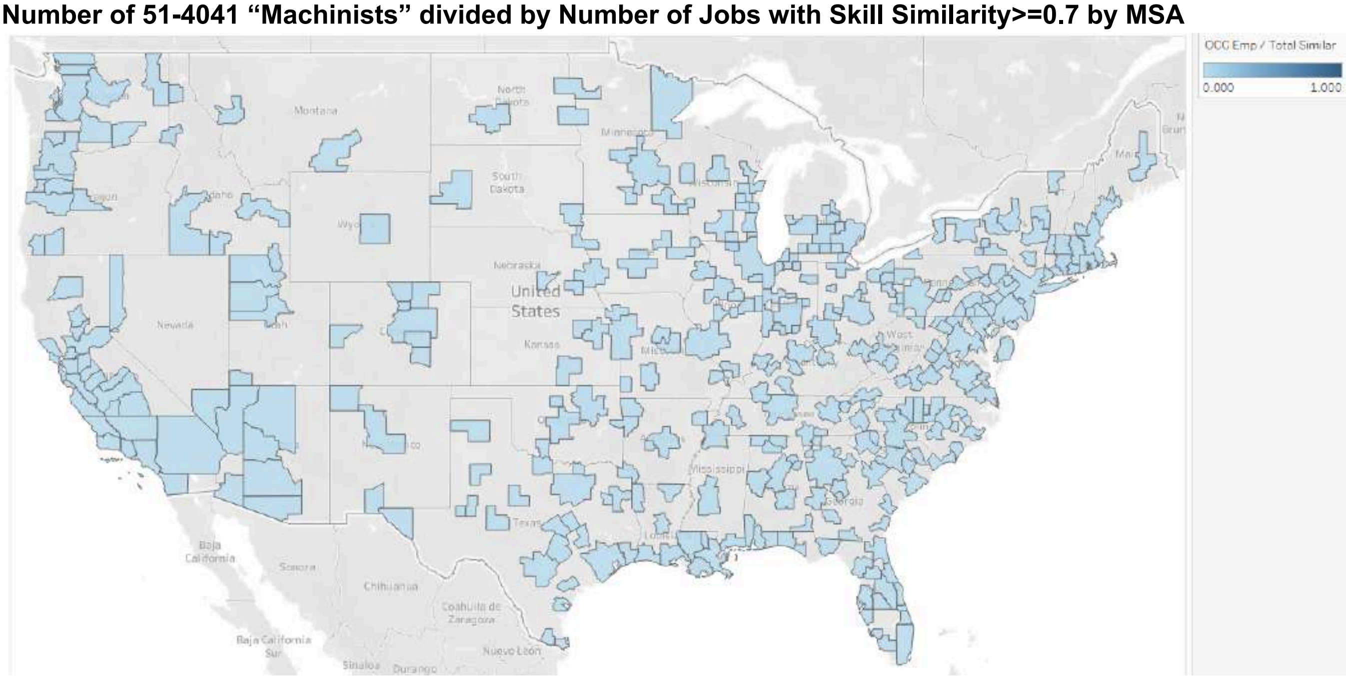


Figure B.7: Quantity of 51-4041 "Machinists" workers over quantity of workers in similar occupations, with a similarity rate of 0.7 or greater.

Number of 51-4041 “Machinists” divided by Number of Jobs with Skill Similarity>=0.8 by MSA

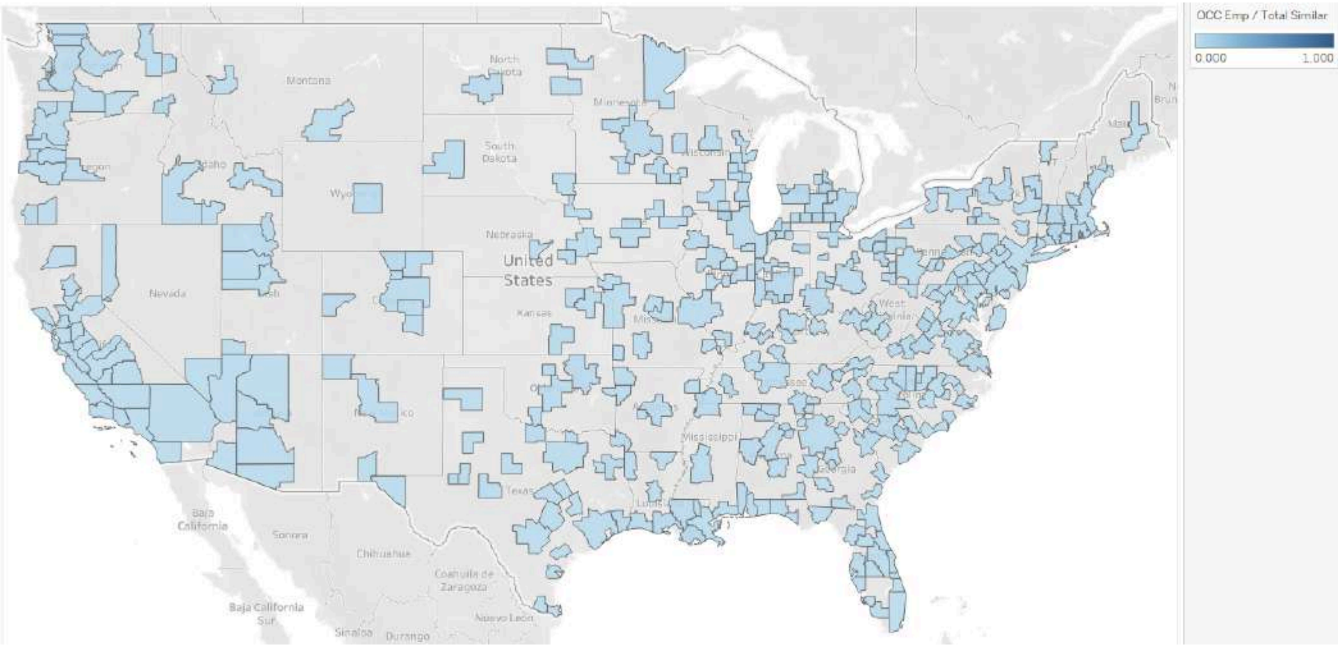


Figure B.8: Quantity of 51-4041 “Machinists” workers over quantity of workers in similar occupations, with a similarity rate of 0.8 or greater.

Number of 51-4041 “Machinists” divided by Number of Jobs with Skill Similarity>=0.9 by MSA

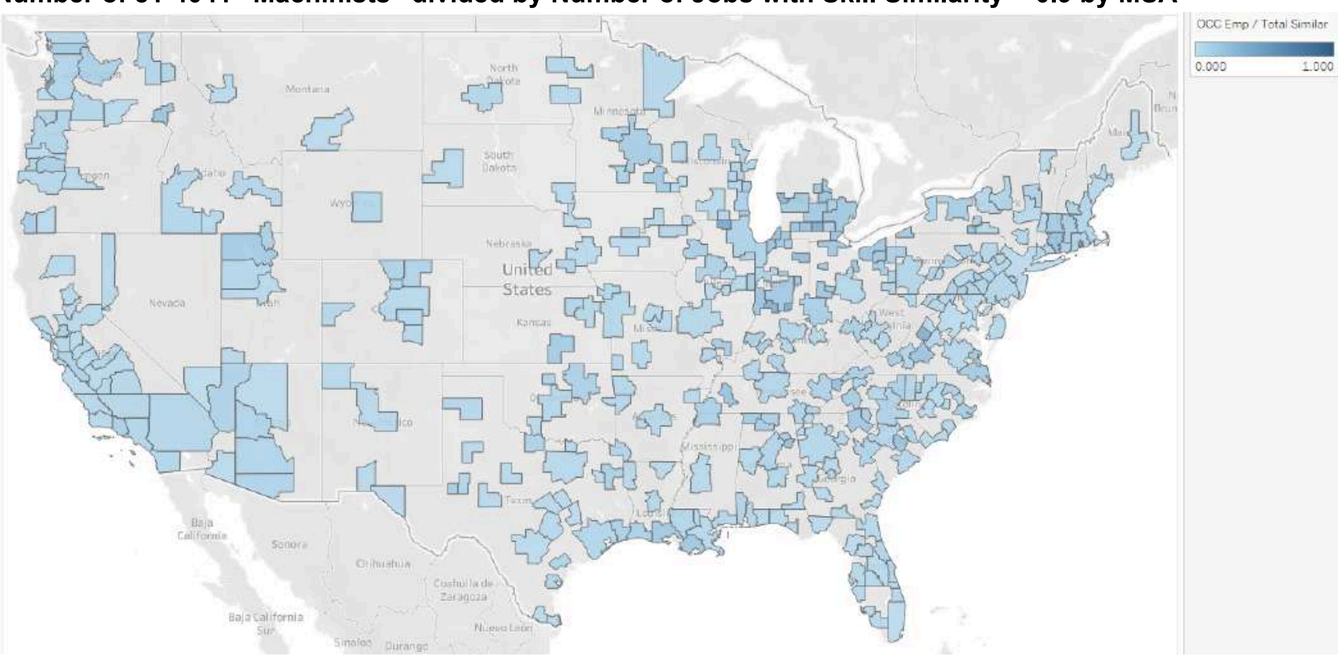


Figure B.9: Quantity of 51-4041 “Machinists” workers over quantity of workers in similar occupations, with a similarity rate of 0.9 or greater.

Number of "First-Line Supervisors of Production and Operating Workers" (51-1011) divided by Number of Jobs with Skill Similarity>=0.7 by MSA

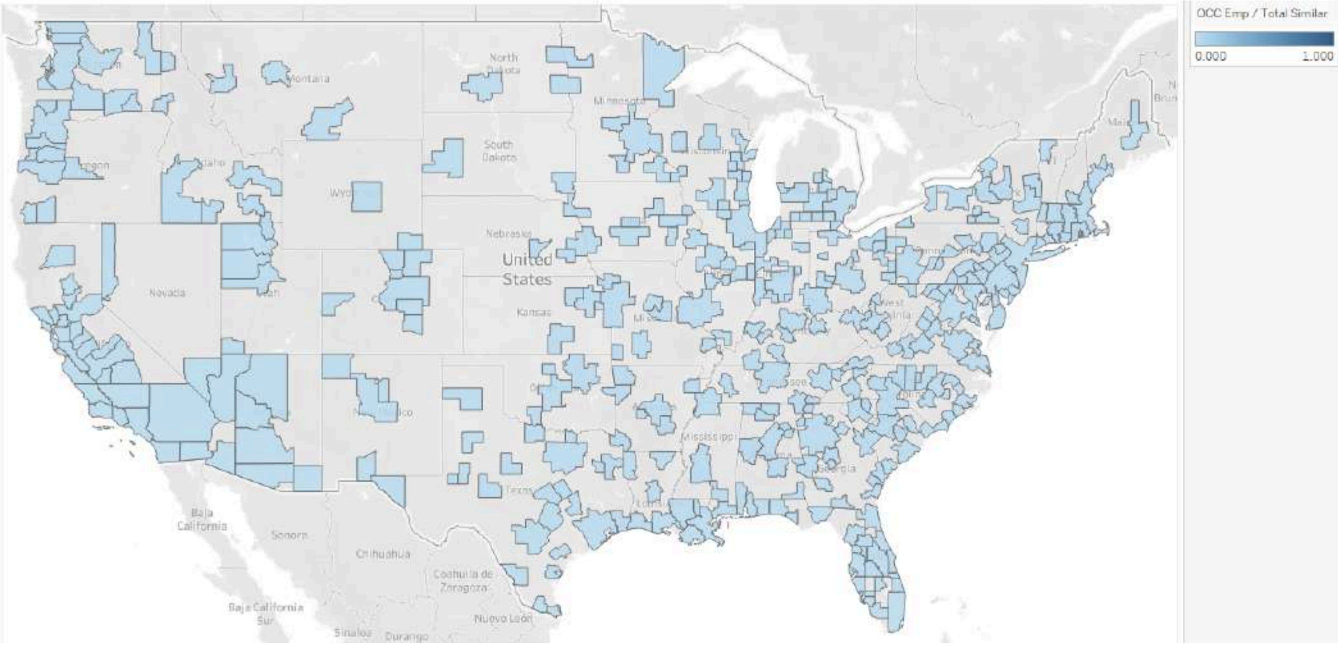


Figure B.10: Quantity of 51-1011 "First-Line Supervisors of Production and Operating Workers" workers over quantity of workers in similar occupations, with a similarity rate of 0.7 or greater.

Number of "First-Line Supervisors of Production and Operating Workers" (51-1011) divided by Number of Jobs with Skill Similarity>=0.8 by MSA

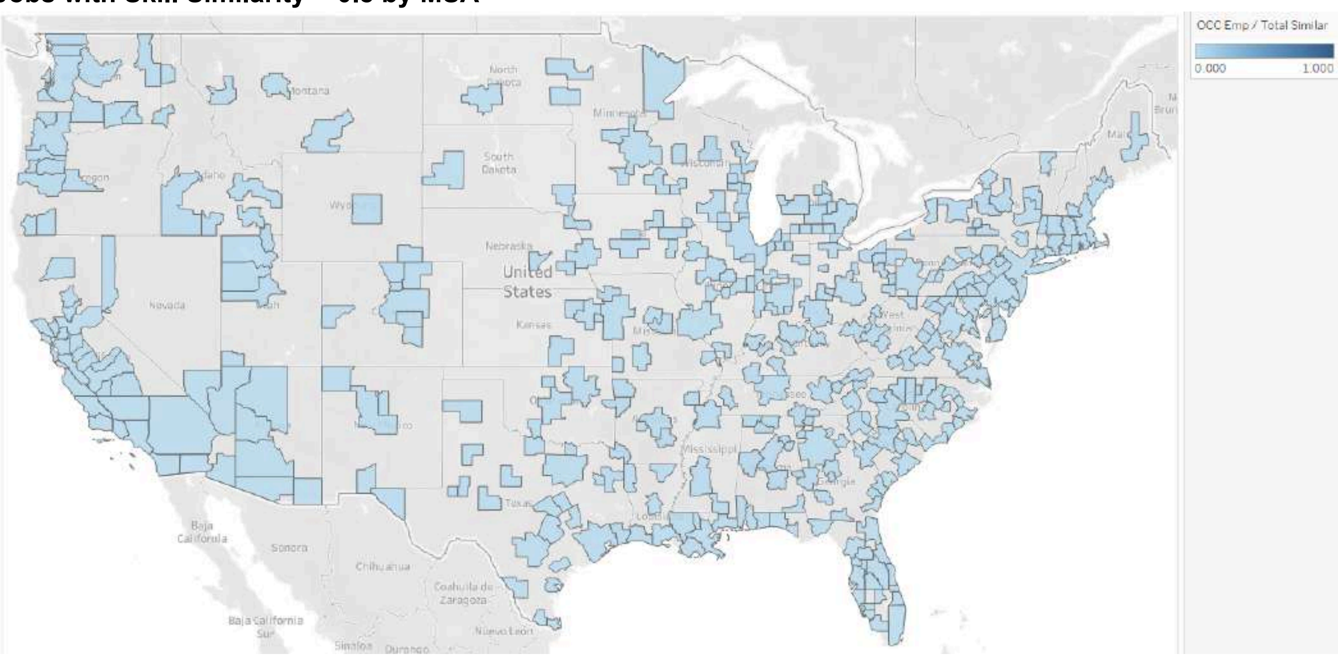


Figure B.11: Quantity of 51-1011 "First-Line Supervisors of Production and Operating Workers" workers over quantity of workers in similar occupations, with a similarity rate of 0.8 or greater.

Number of "First-Line Supervisors of Production and Operating Workers" (51-1011) divided by Number of Jobs with Skill Similarity>=0.9 by MSA

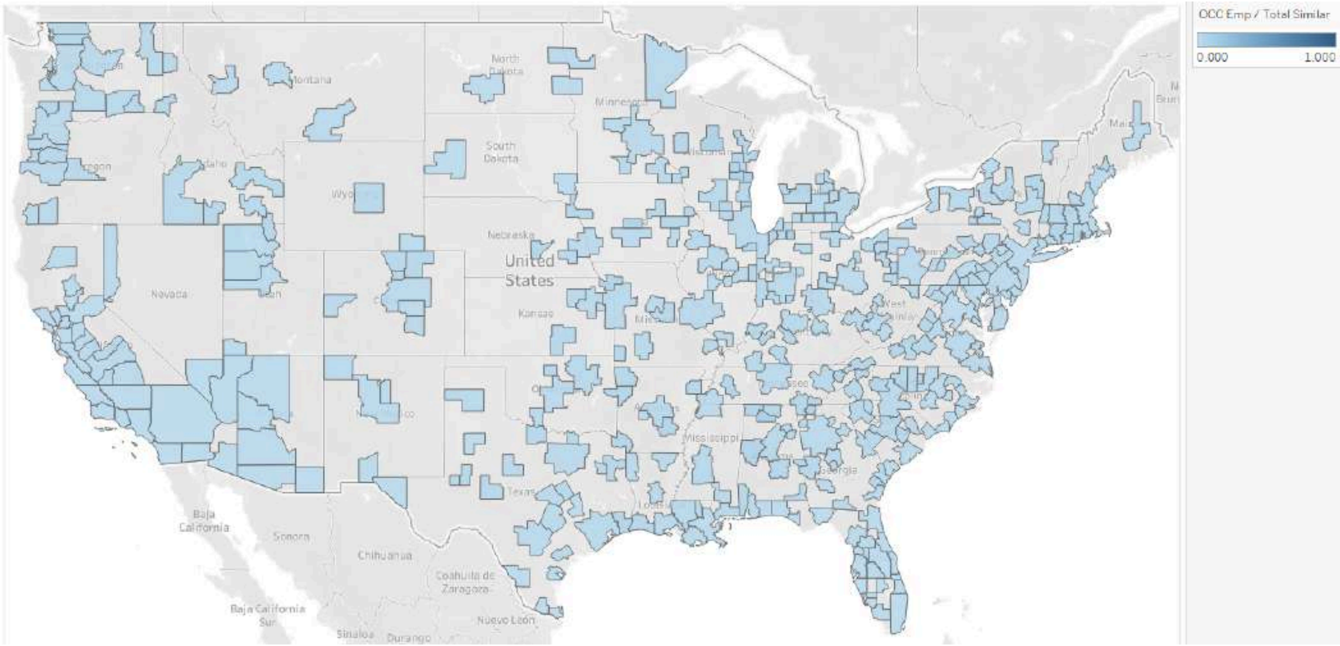


Figure B.12: Quantity of 51-1011 "First-Line Supervisors of Production and Operating Workers" workers over quantity of workers in similar occupations, with a similarity rate of 0.9 or greater.

Number of "Inspectors, Testers, Sorters, Samplers, and Weighers" (51-9061) divided by Number of Jobs with Skill Similarity>=0.7 by MSA

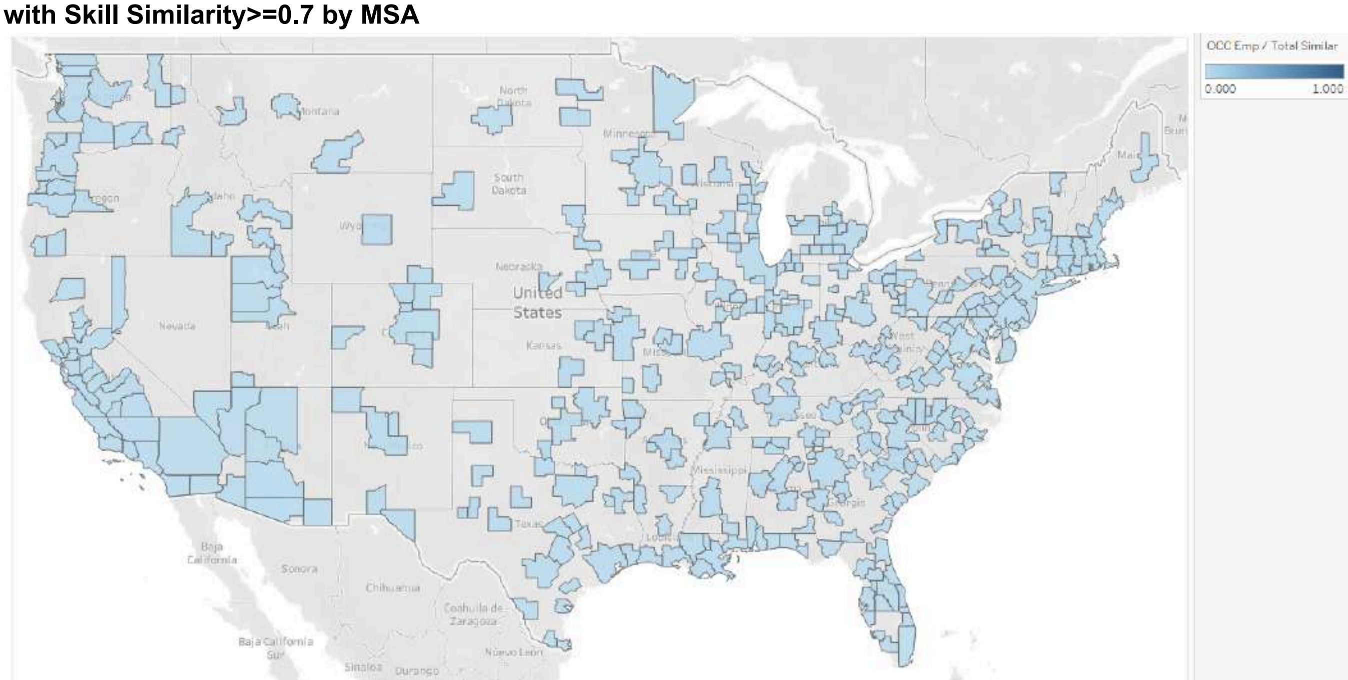


Figure B.13: Quantity of 51-9061 "Inspectors, Testers, Sorters, Samplers, and Weighers" workers over quantity of workers in similar occupations, with a similarity rate of 0.7 or greater.

Number of "Inspectors, Testers, Sorters, Samplers, and Weighers" (51-9061) divided by Number of Jobs with Skill Similarity>=0.8 by MSA

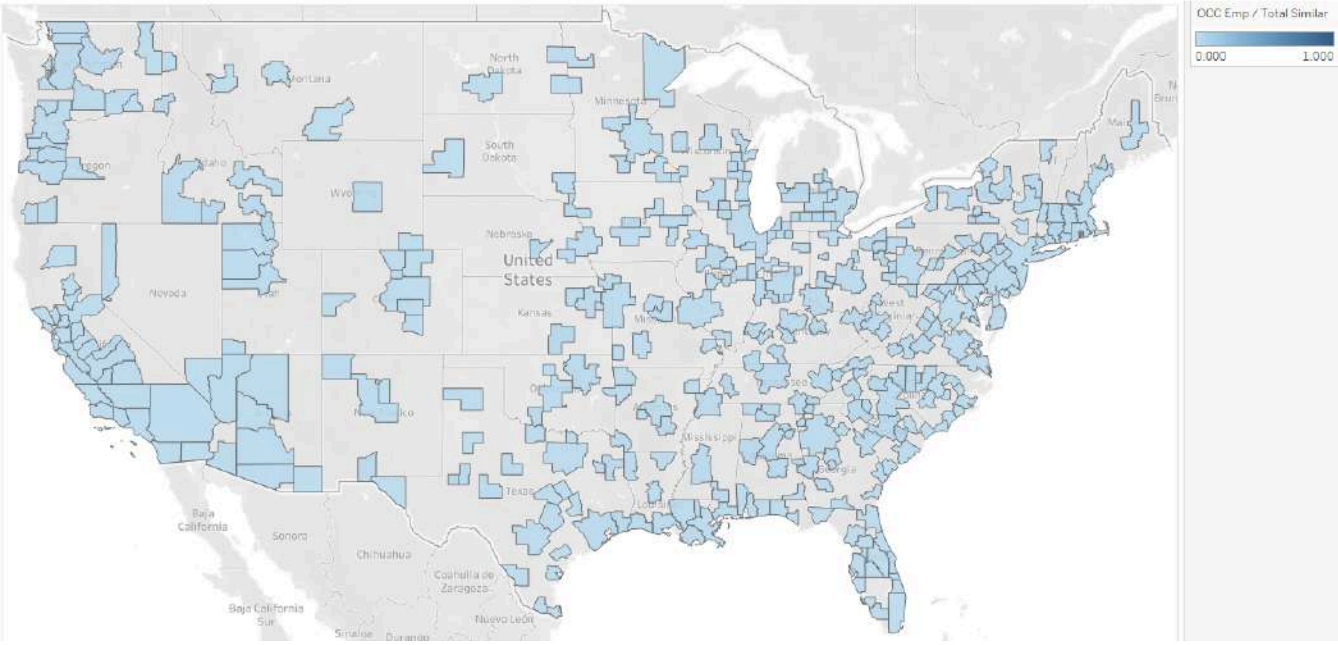


Figure B.14: Quantity of 51-9061 "Inspectors, Testers, Sorters, Samplers, and Weighers" workers over quantity of workers in similar occupations, with a similarity rate of 0.8 or greater.

Number of "Inspectors, Testers, Sorters, Samplers, and Weighers" (51-9061) divided by Number of Jobs with Skill Similarity>=0.9 by MSA

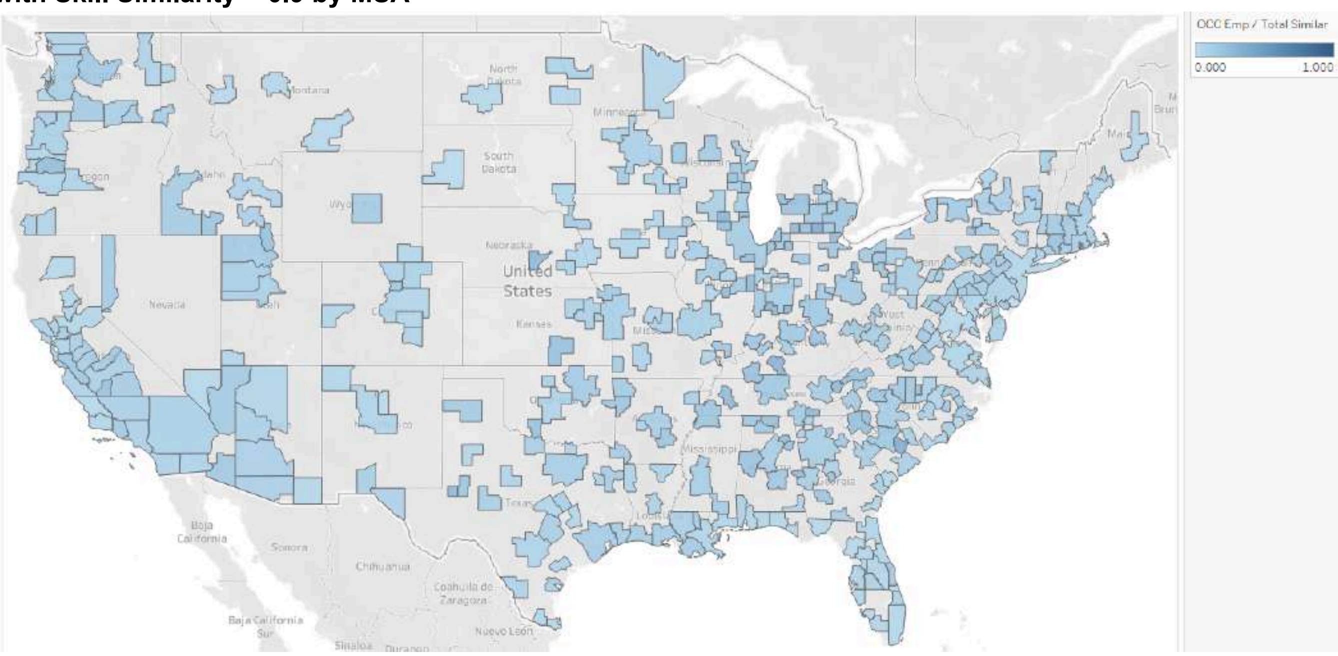


Figure B.15: Quantity of 51-9061 "Inspectors, Testers, Sorters, Samplers, and Weighers" workers over quantity of workers in similar occupations, with a similarity rate of 0.9 or greater.

Number of "Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic" (51-4081) divided by Number of Jobs with Skill Similarity>=0.7 by MSA

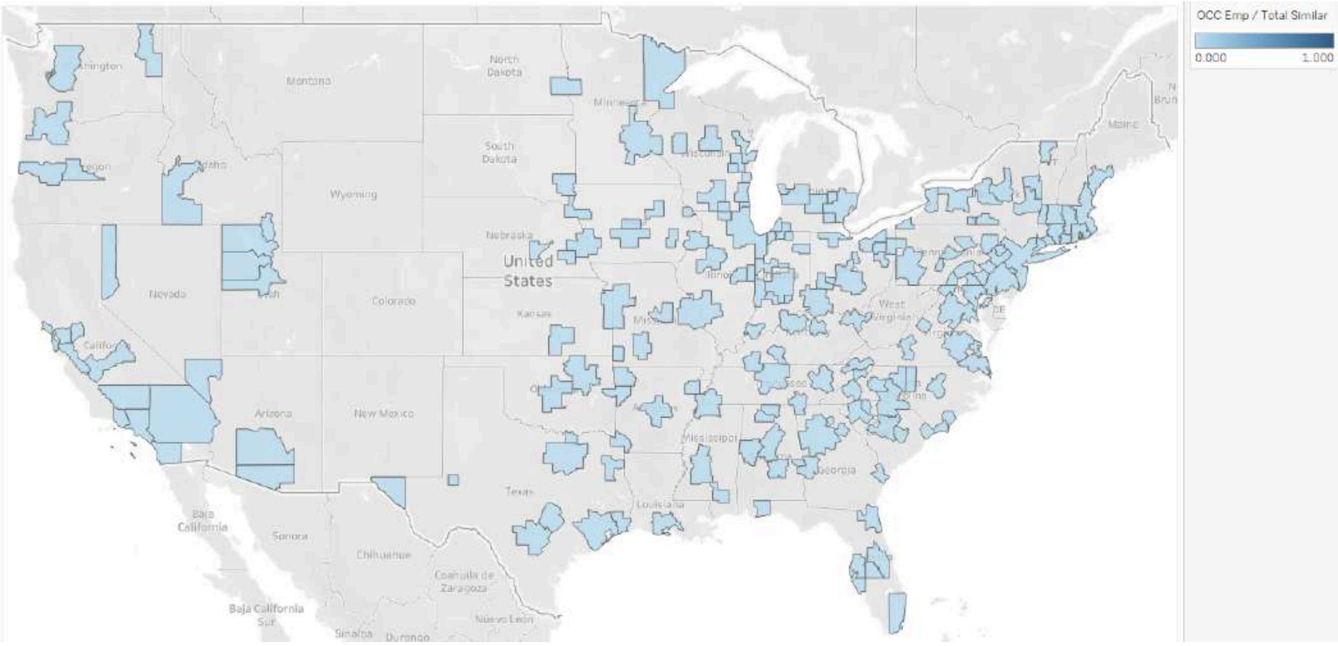


Figure B.16: Quantity of 51-4081 "Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic" workers over quantity of workers in similar occupations, with a similarity rate of 0.7 or greater.

Number of "Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic" (51-4081) divided by Number of Jobs with Skill Similarity>=0.8 by MSA

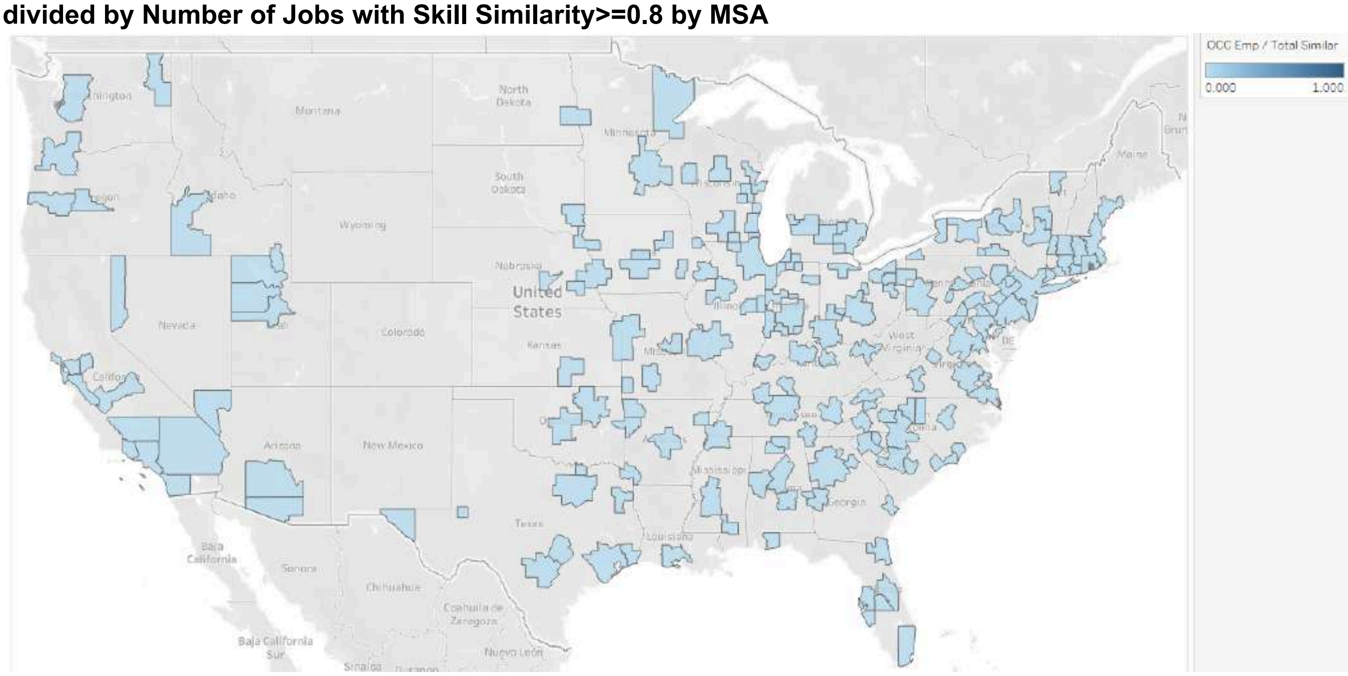


Figure B.17: Quantity of 51-4081 "Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic" workers over quantity of workers in similar occupations, with a similarity rate of 0.8 or greater.

Number of “Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic” (51-4081) divided by Number of Jobs with Skill Similarity>=0.9 by MSA

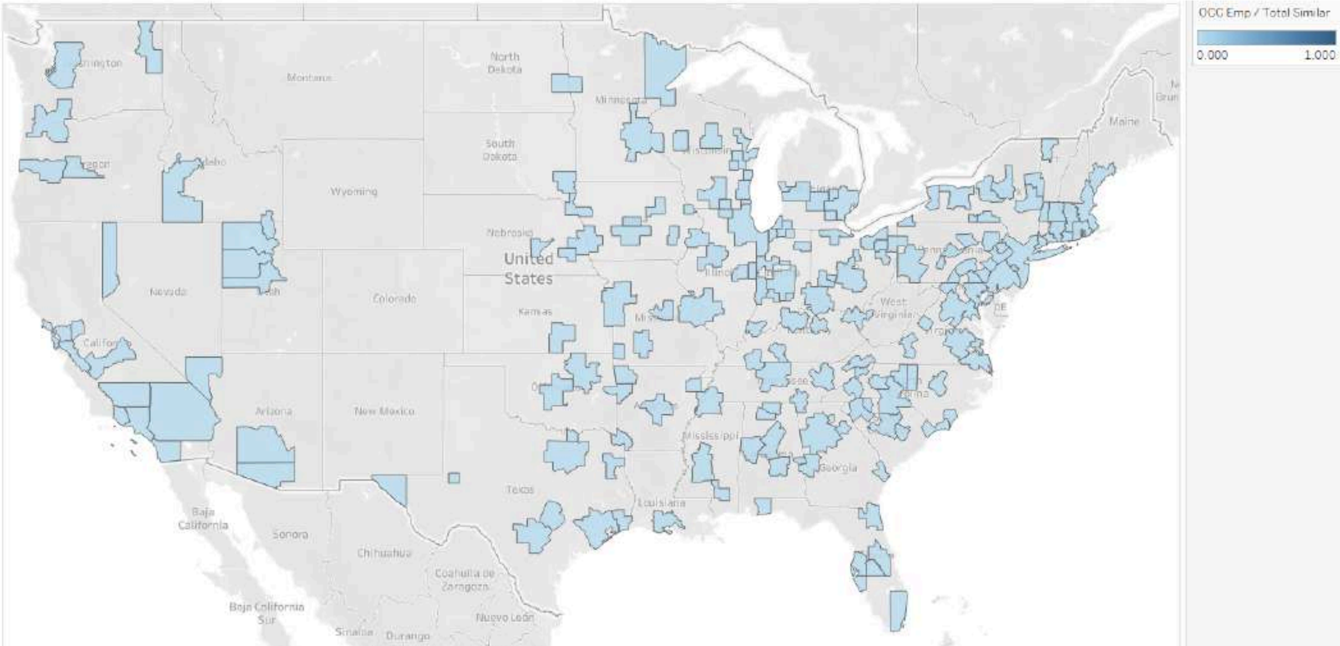


Figure B.18: Quantity of 51-4081 “Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic” workers over quantity of workers in similar occupations, with a similarity rate of 0.9 or greater.

Number of “Welders, Cutters, Solderers, and Brazers” (51-4121) divided by Number of Jobs with Skill Similarity>=0.7 by MSA

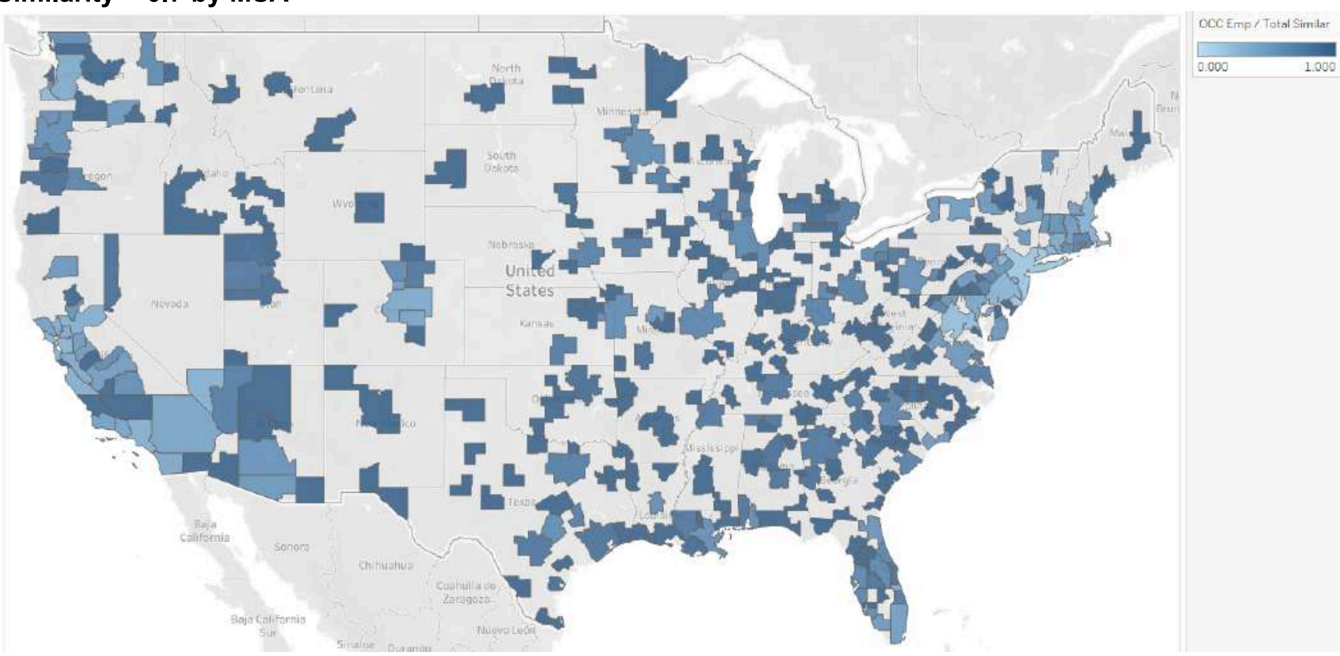


Figure B.19: Quantity of 51-4121 “Welders, Cutters, Solderers, and Brazers” workers over quantity of workers in similar occupations, with a similarity rate of 0.7 or greater.

Number of "Welders, Cutters, Solderers, and Brazers" (51-4121) divided by Number of Jobs with Skill Similarity>=0.8 by MSA

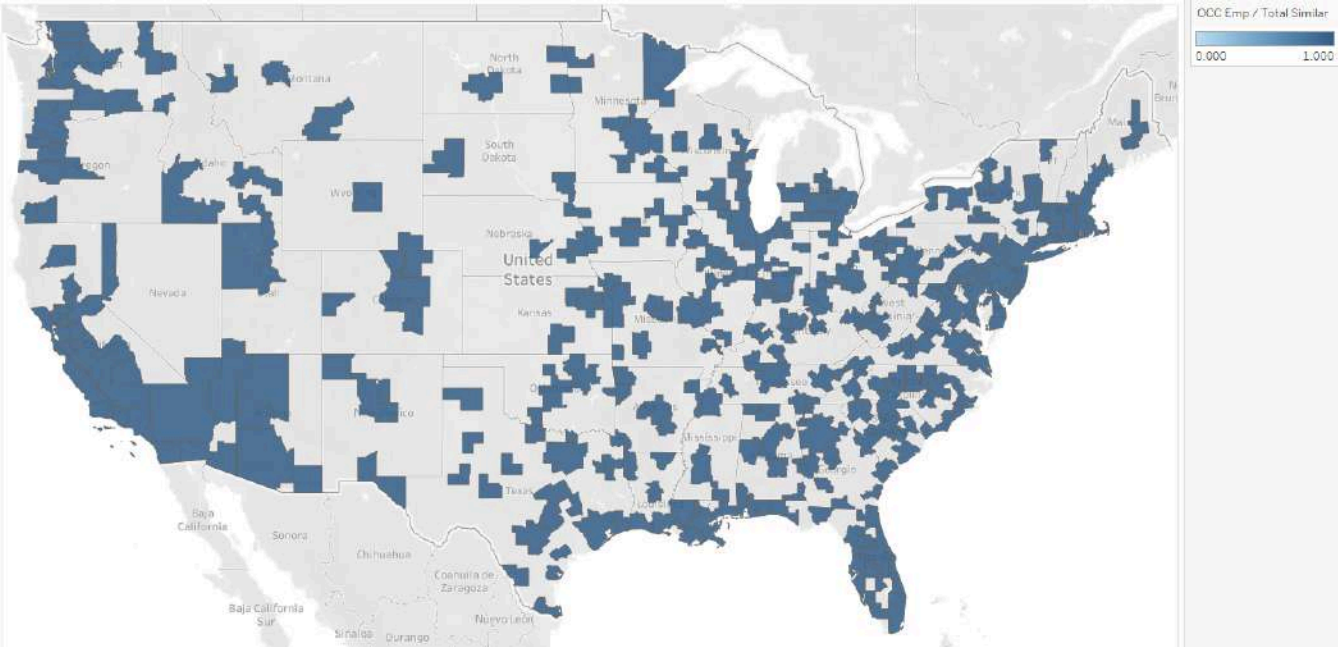


Figure B.20: Quantity of 51-4121 "Welders, Cutters, Solderers, and Brazers" workers over quantity of workers in similar occupations, with a similarity rate of 0.8 or greater.

Number of "Welders, Cutters, Solderers, and Brazers" (51-4121) divided by Number of Jobs with Skill Similarity>=0.9 by MSA

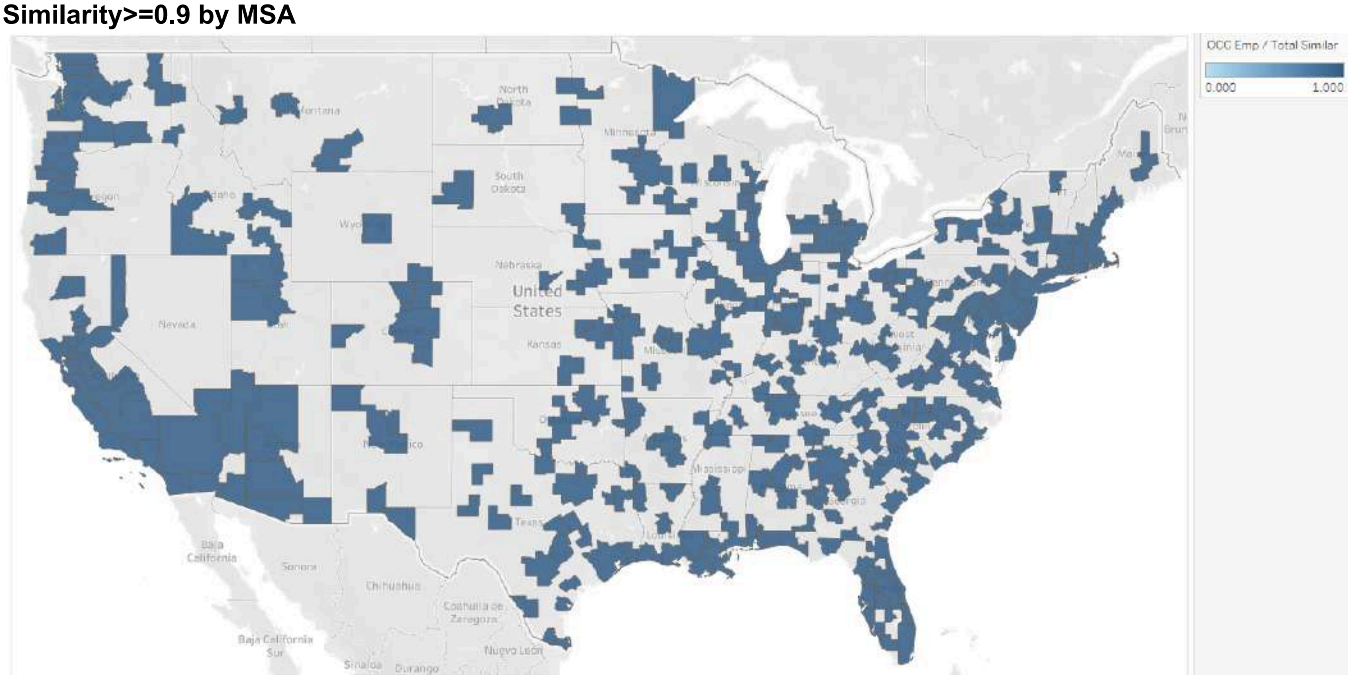


Figure B.21: Quantity of 51-4121 "Welders, Cutters, Solderers, and Brazers" workers over quantity of workers in similar occupations, with a similarity rate of 0.9 or greater.

Number of "Tool and Die Makers" (51-4111) divided by Number of Jobs with Skill Similarity>=0.7 by MSA

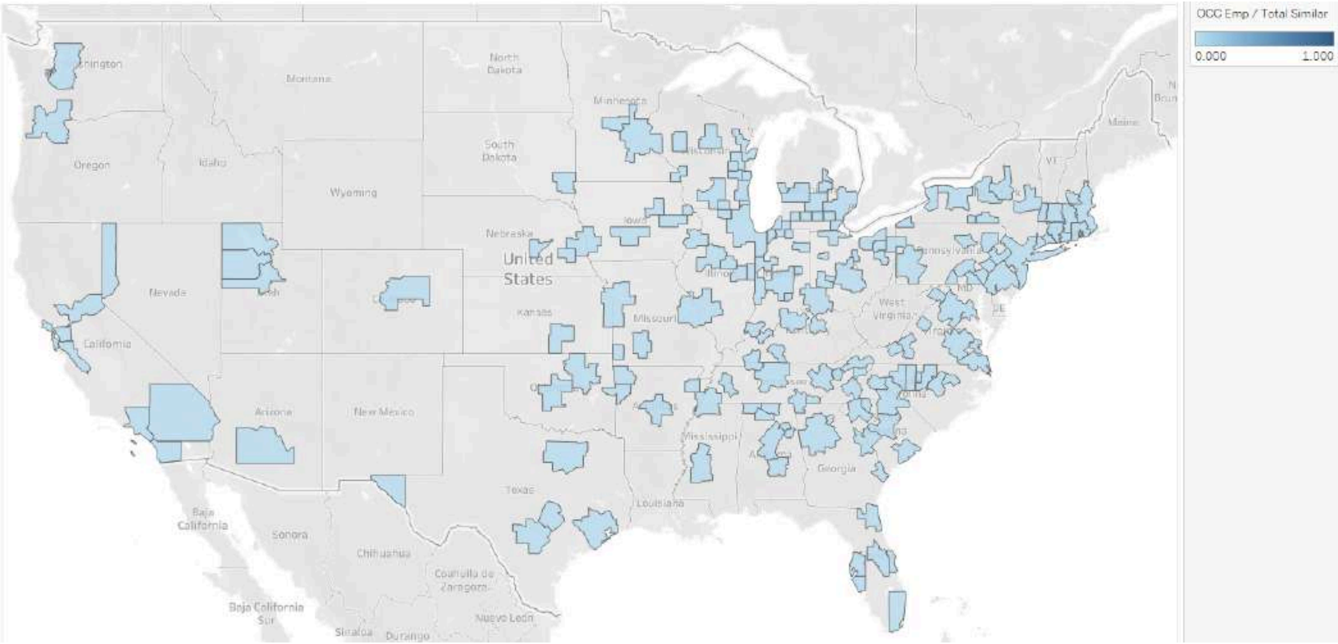


Figure B.22: Quantity of 51-4111 "Tool and Die Makers" workers over quantity of workers in similar occupations, with a similarity rate of 0.7 or greater.

Number of "Tool and Die Makers" (51-4111) divided by Number of Jobs with Skill Similarity>=0.8 by MSA

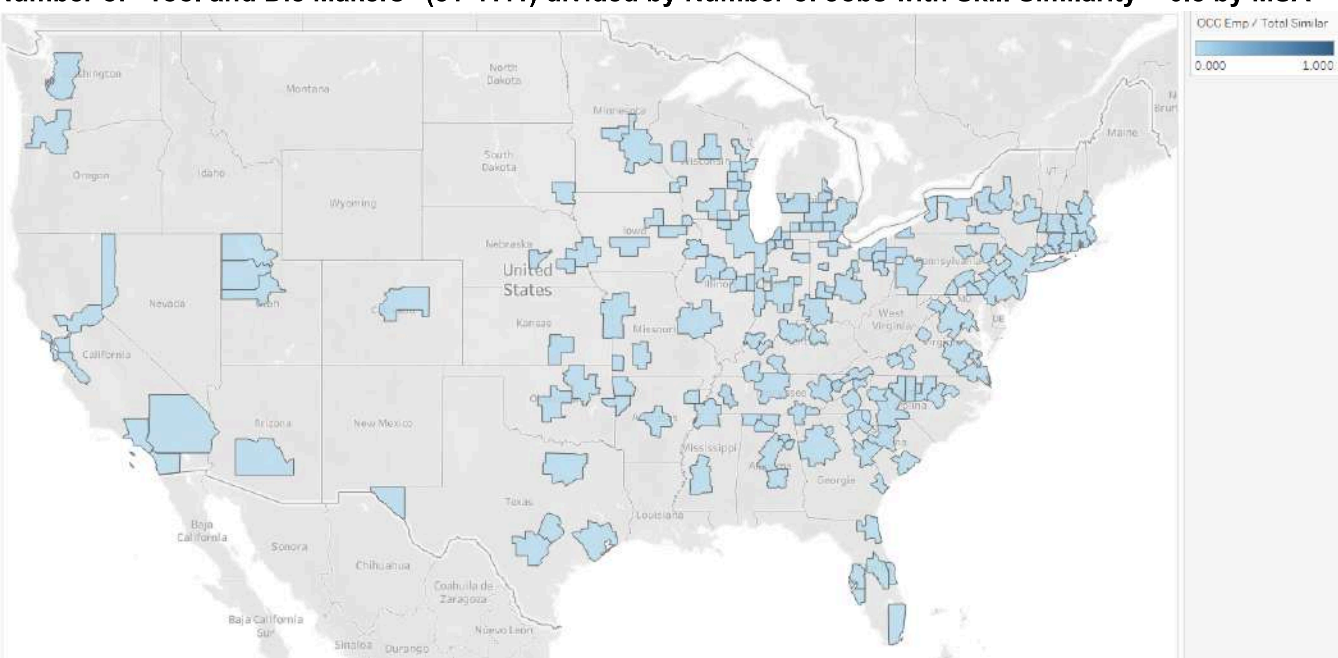


Figure B.23: Quantity of 51-4111 "Tool and Die Makers" workers over quantity of workers in similar occupations, with a similarity rate of 0.8 or greater.

Number of "Tool and Die Makers" (51-4111) divided by Number of Jobs with Skill Similarity>=0.9 by MSA

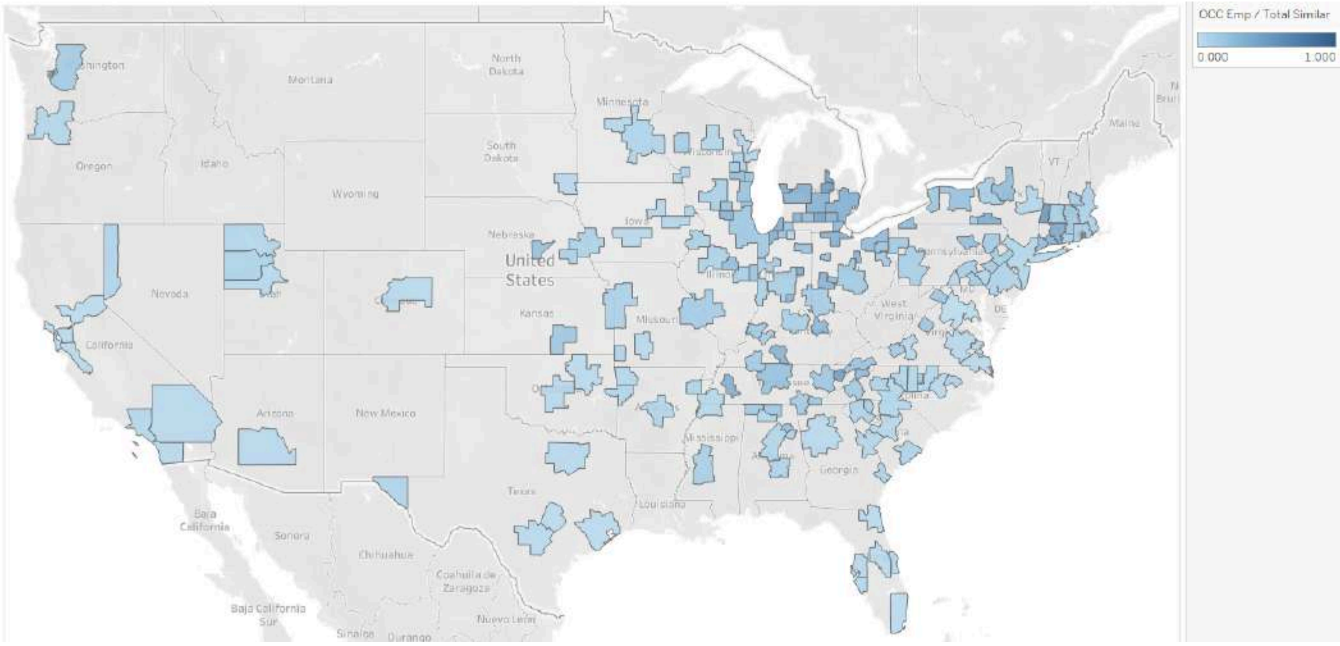


Figure B.24: Quantity of 51-4111 "Tool and Die Makers" workers over quantity of workers in similar occupations, with a similarity rate of 0.9 or greater.

Ratio of EV, Battery, and HST Workers to Workers in Candidate Occupations

This section includes figures for an occupation of interest divided by the number of similar jobs. Similarity is directional, and for these figures that direction moves from the similar occupations to our occupation of interest.

Number of "Industrial Production Managers" (11-3051) divided by Number of Jobs with Skill Similarity>=0.7 by MSA

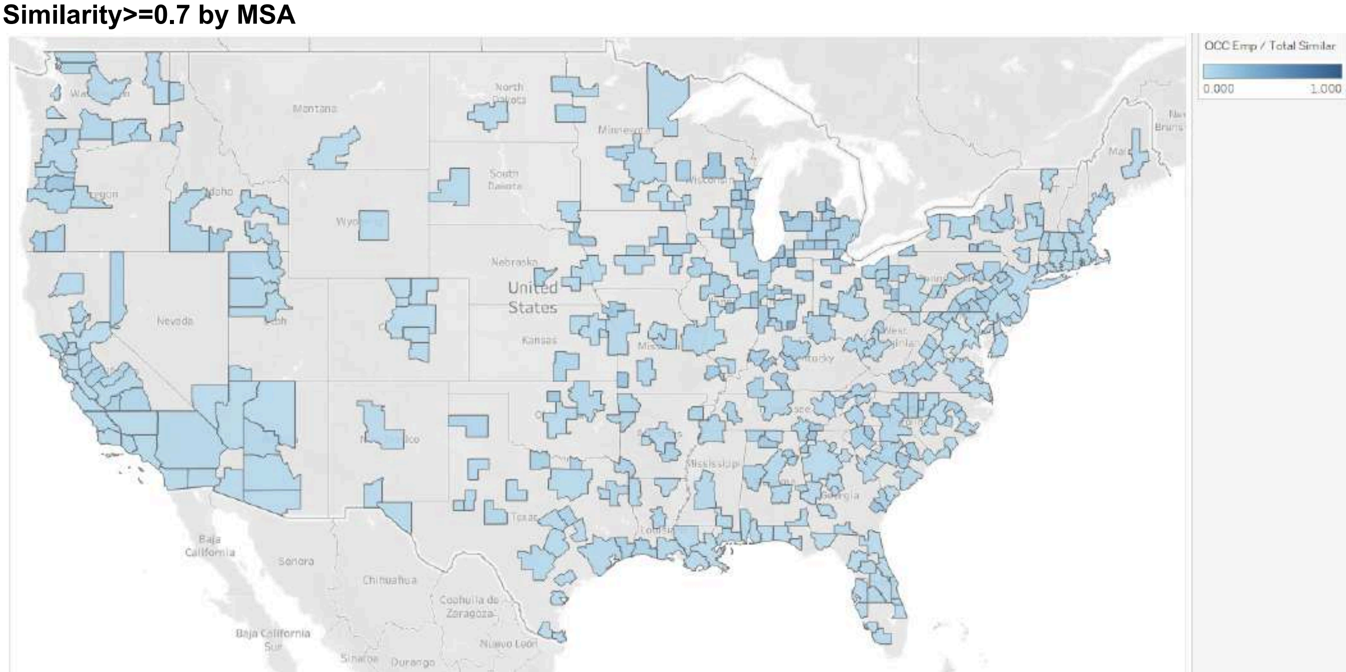


Figure B.25: Quantity of 11-3051 "Industrial Production Managers" workers over quantity of workers in similar occupations, with a similarity rate of 0.7 or greater.

Number of "Industrial Production Managers" (11-3051) divided by Number of Jobs with Skill Similarity>=0.8 by MSA

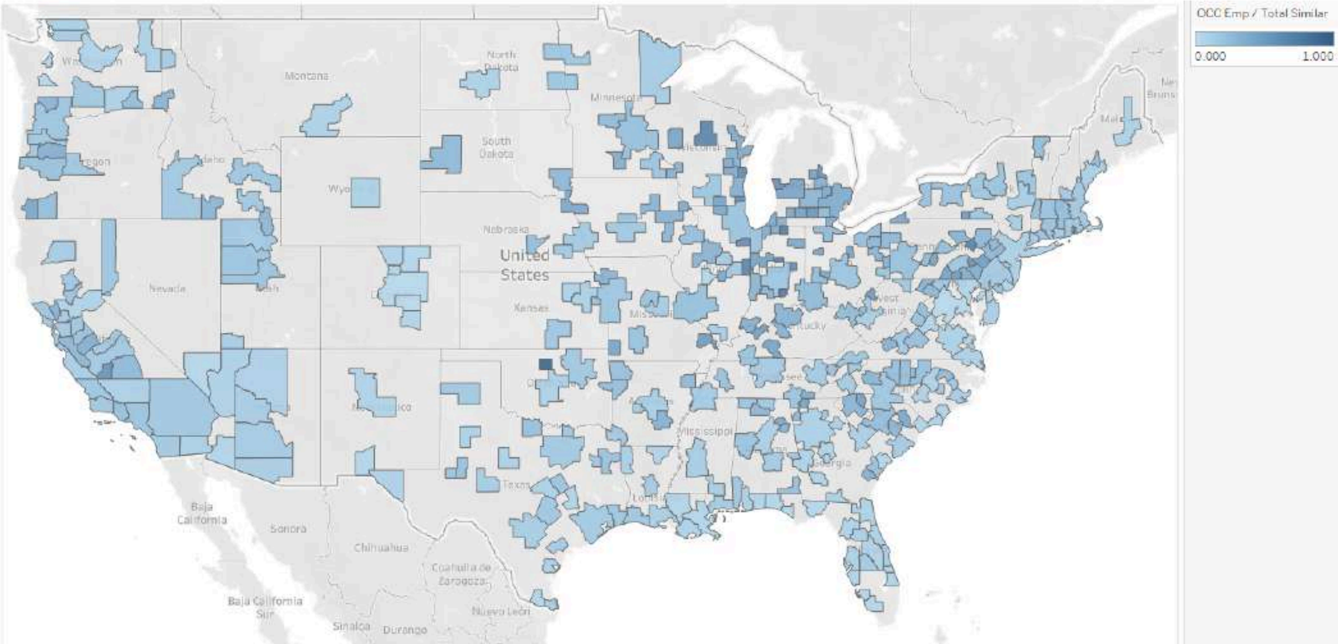


Figure B.26: Quantity of 11-3051 "Industrial Production Managers" workers over quantity of workers in similar occupations, with a similarity rate of 0.8 or greater.

Number of "Industrial Production Managers" (11-3051) divided by Number of Jobs with Skill Similarity>=0.9 by MSA

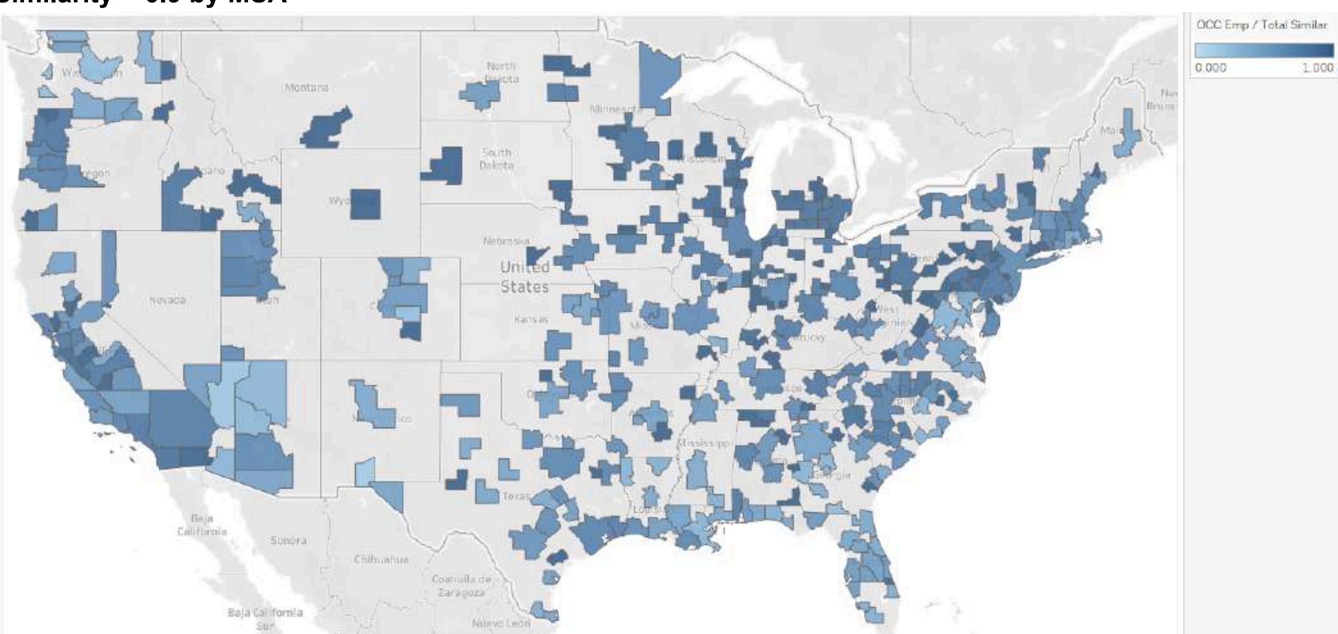


Figure B.27: Quantity of 11-3051 "Industrial Production Managers" workers over quantity of workers in similar occupations, with a similarity rate of 0.9 or greater.

Number of "Electro-Mechanical and Mechatronics Technologists and Technicians" (17-3024) divided by Number of Jobs with Skill Similarity>=0.7 by MSA

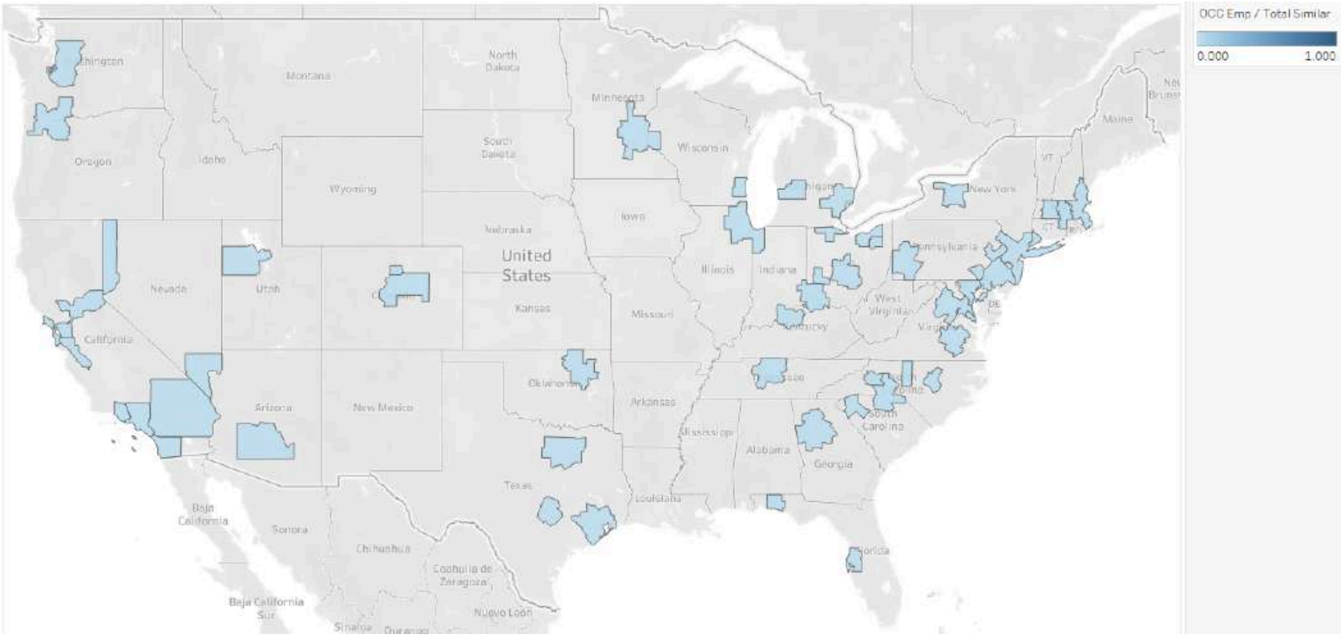


Figure B.28: Quantity of 17-3024 "Electro-Mechanical and Mechatronics Technologists and Technicians" workers over quantity of workers in similar occupations, with a similarity rate of 0.7 or greater.

Number of "Electro-Mechanical and Mechatronics Technologists and Technicians" (17-3024) divided by Number of Jobs with Skill Similarity>=0.8 by MSA

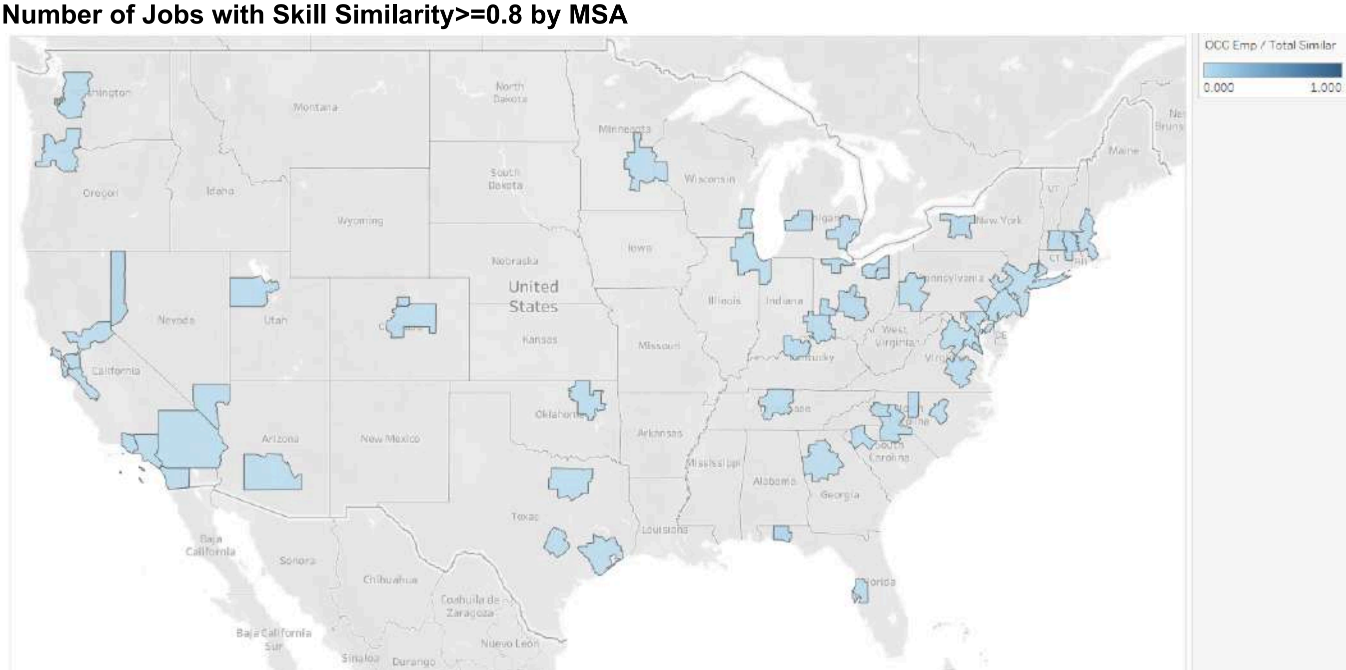


Figure B.29: Quantity of 17-3024 "Electro-Mechanical and Mechatronics Technologists and Technicians" workers over quantity of workers in similar occupations, with a similarity rate of 0.8 or greater.

Number of "Electro-Mechanical and Mechatronics Technologists and Technicians" (17-3024) divided by Number of Jobs with Skill Similarity>=0.9 by MSA

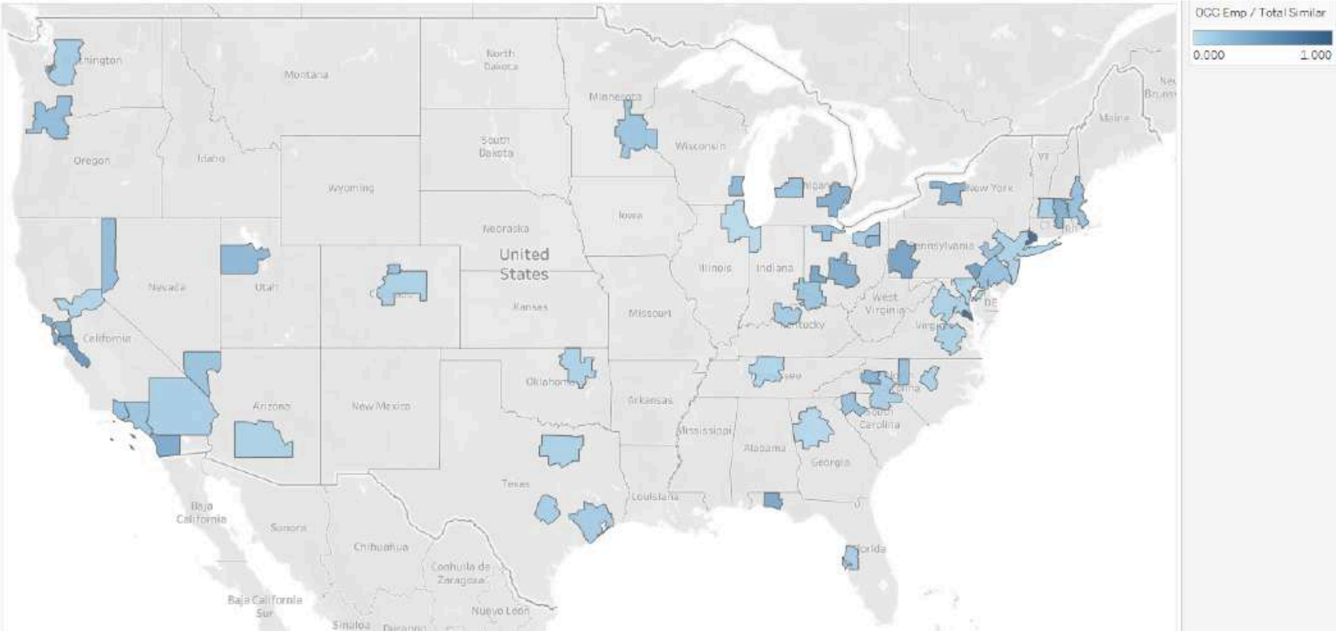


Figure B.30: Quantity of 17-3024 "Electro-Mechanical and Mechatronics Technologists and Technicians" workers over quantity of workers in similar occupations, with a similarity rate of 0.9 or greater.

Number of "Industrial Machinery Mechanics" (49-9041) divided by Number of Jobs with Skill Similarity>=0.7 by MSA

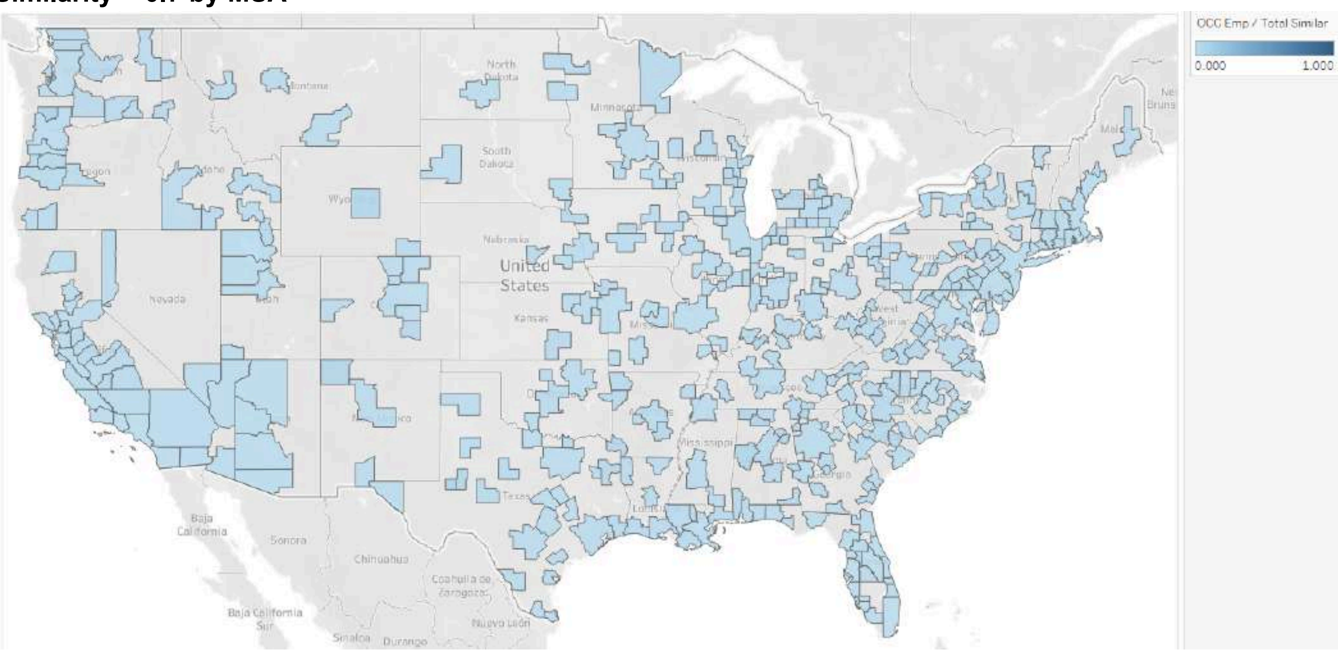


Figure B.31: Quantity of 49-9041 "Industrial Machinery Mechanics" workers over quantity of workers in similar occupations, with a similarity rate of 0.7 or greater.

Number of "Industrial Machinery Mechanics" (49-9041) divided by Number of Jobs with Skill Similarity>=0.8 by MSA

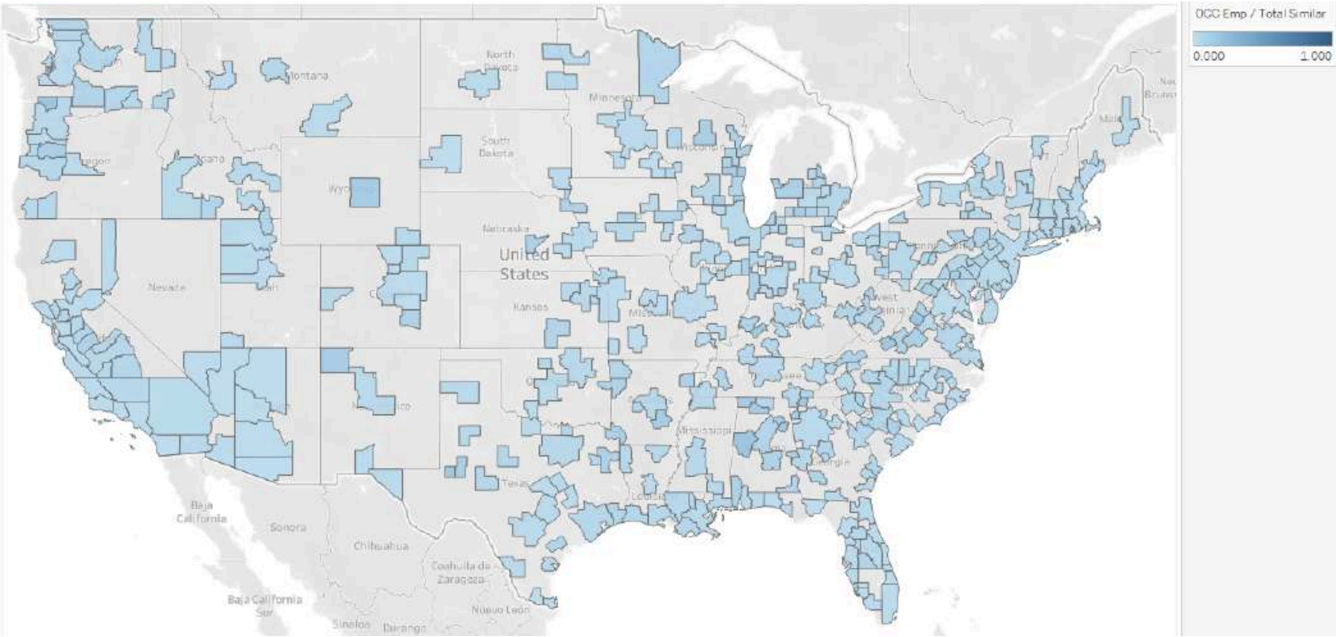


Figure B.32: Quantity of 49-9041 "Industrial Machinery Mechanics" workers over quantity of workers in similar occupations, with a similarity rate of 0.8 or greater.

Number of "Industrial Machinery Mechanics" (49-9041) divided by Number of Jobs with Skill Similarity>=0.9 by MSA

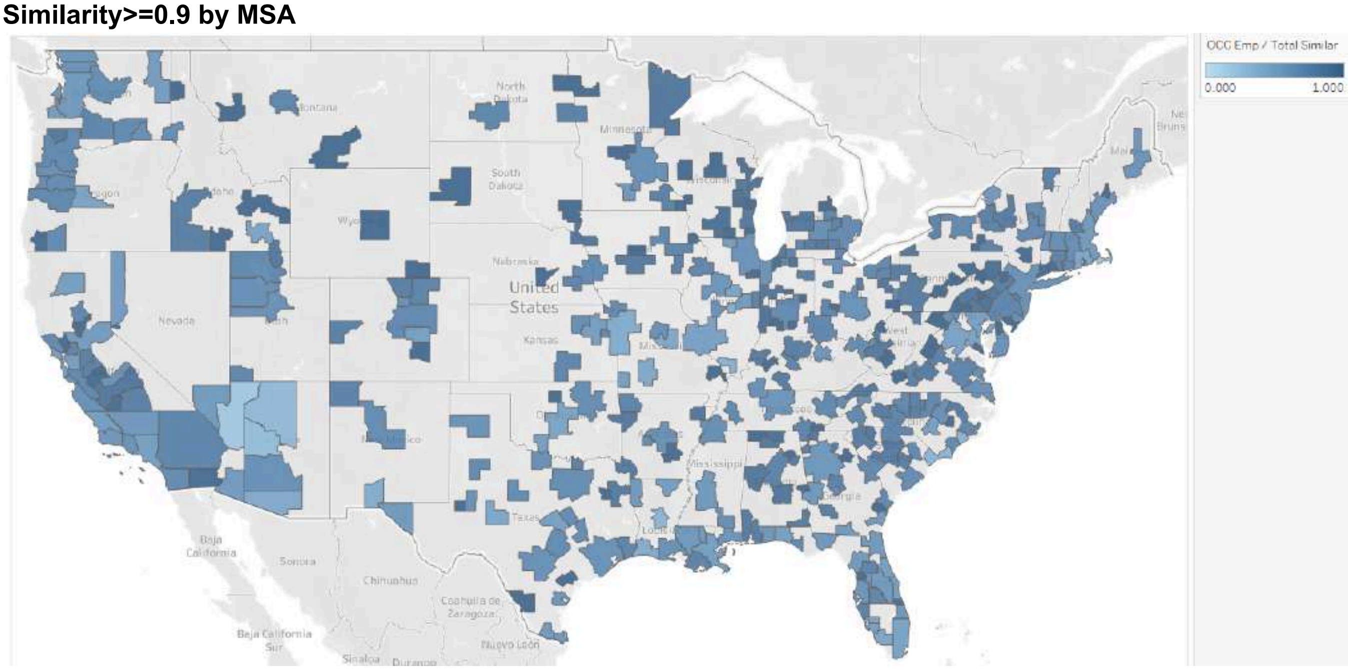


Figure B.33: Quantity of 49-9041 "Industrial Machinery Mechanics" workers over quantity of workers in similar occupations, with a similarity rate of 0.9 or greater.

Number of "Engine and Other Machine Assemblers" (51-2031) divided by Number of Jobs with Skill Similarity>=0.7 by MSA

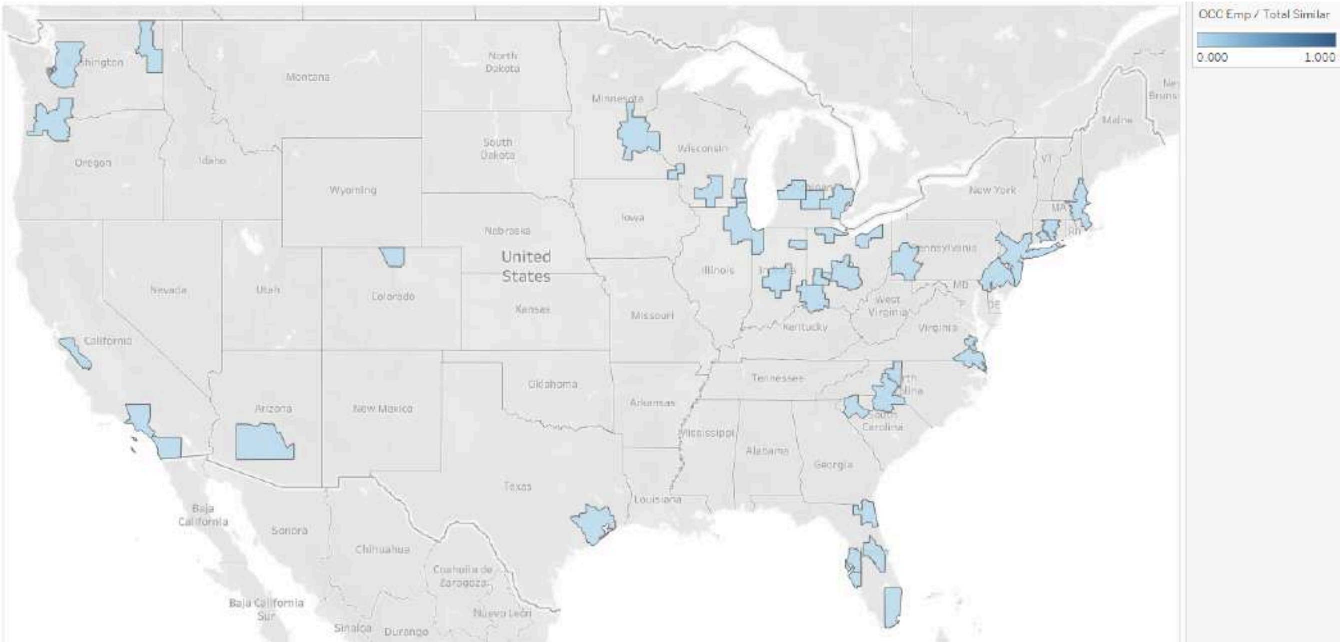


Figure B.34: Quantity of 51-2031 "Engine and Other Machine Assemblers" workers over quantity of workers in similar occupations, with a similarity rate of 0.7 or greater.

Number of "Engine and Other Machine Assemblers" (51-2031) divided by Number of Jobs with Skill Similarity>=0.8 by MSA

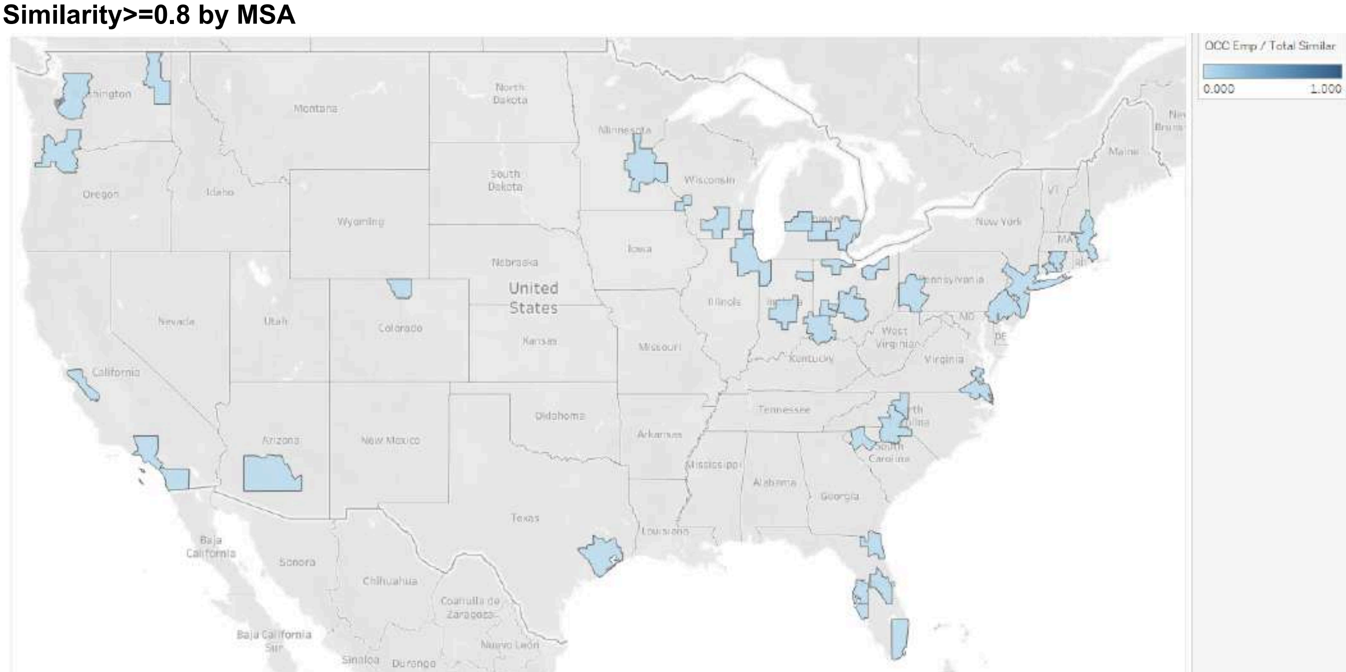


Figure B.35: Quantity of 51-2031 "Engine and Other Machine Assemblers" workers over quantity of workers in similar occupations, with a similarity rate of 0.8 or greater.

Number of "Engine and Other Machine Assemblers" (51-2031) divided by Number of Jobs with Skill Similarity>=0.9 by MSA

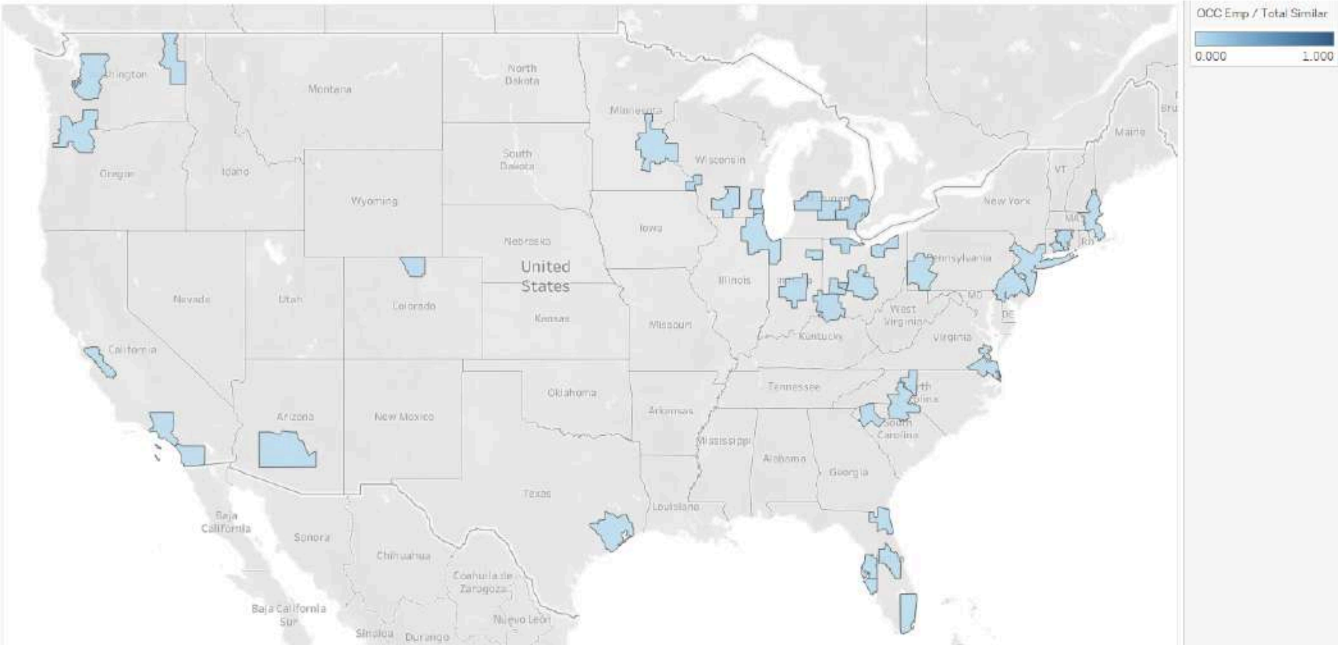


Figure B.36: Quantity of 51-2031 "Engine and Other Machine Assemblers" workers over quantity of workers in similar occupations, with a similarity rate of 0.9 or greater.

Number of "Machinists" (51-4041) divided by Number of Jobs with Skill Similarity>=0.7 by MSA

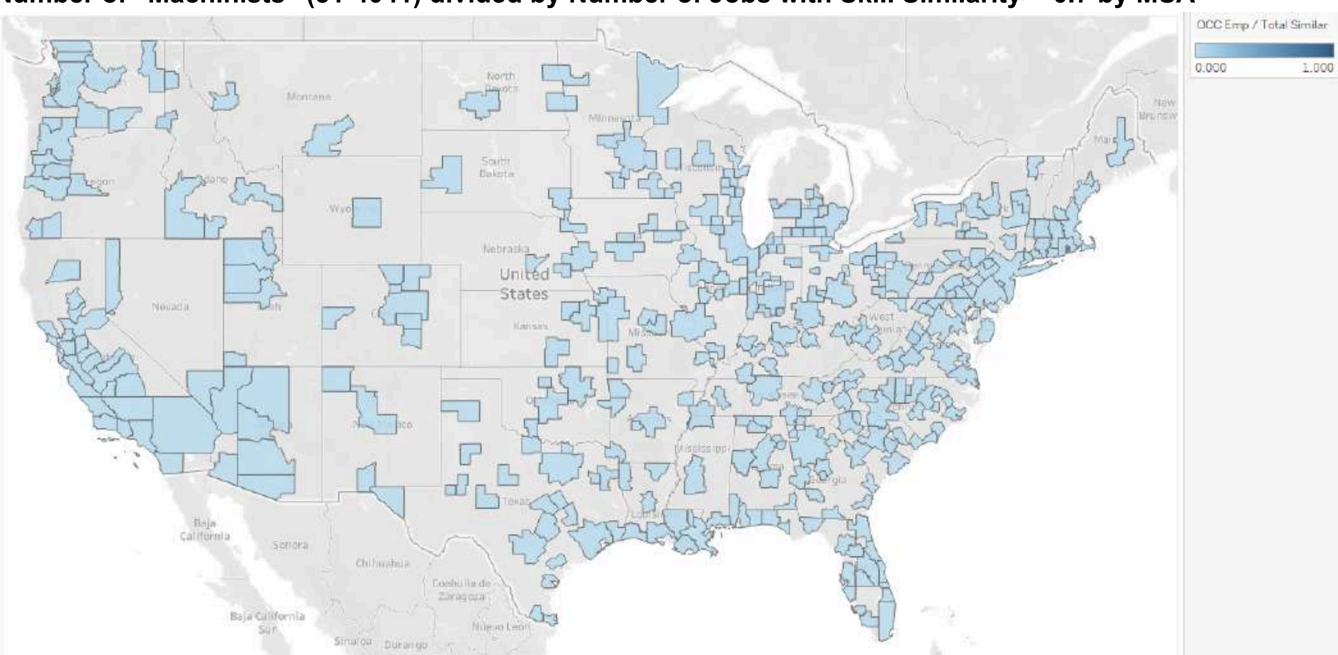


Figure B.37: Quantity of 51-4041 "Machinists" workers over quantity of workers in similar occupations, with a similarity rate of 0.7 or greater.

Number of "Machinists" (51-4041) divided by Number of Jobs with Skill Similarity>=0.8 by MSA

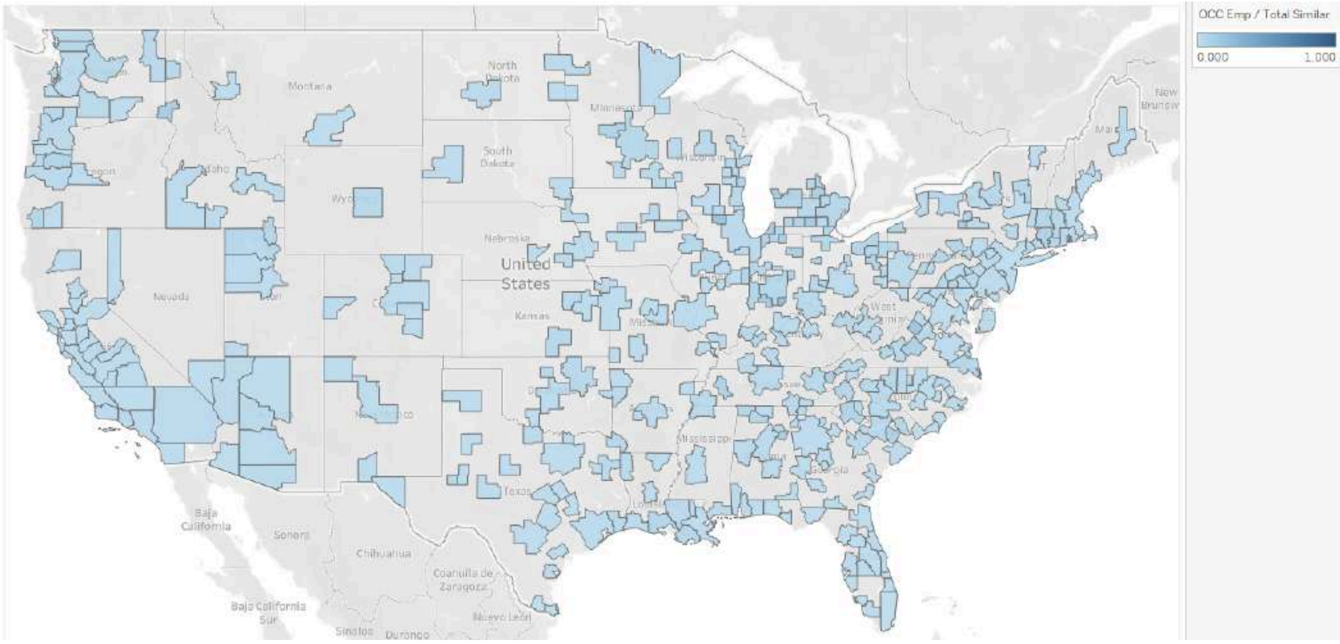


Figure B.38: Quantity of 51-4041 "Machinists" workers over quantity of workers in similar occupations, with a similarity rate of 0.8 or greater.

Number of "Machinists" (51-4041) divided by Number of Jobs with Skill Similarity>=0.9 by MSA

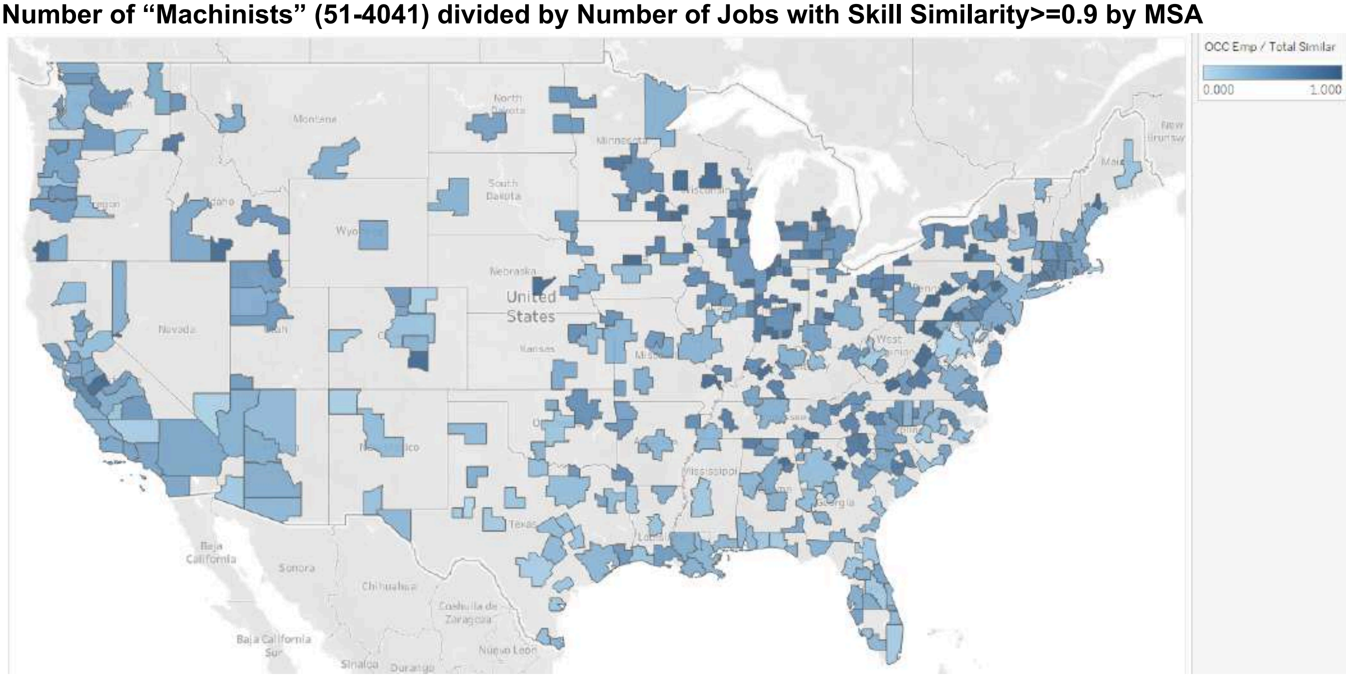


Figure B.39: Quantity of 51-4041 "Machinists" workers over quantity of workers in similar occupations, with a similarity rate of 0.9 or greater.

Number of “Welders, Cutters, Solderers, and Brazers” (51-4121) divided by Number of Jobs with Skill Similarity>=0.7 by MSA

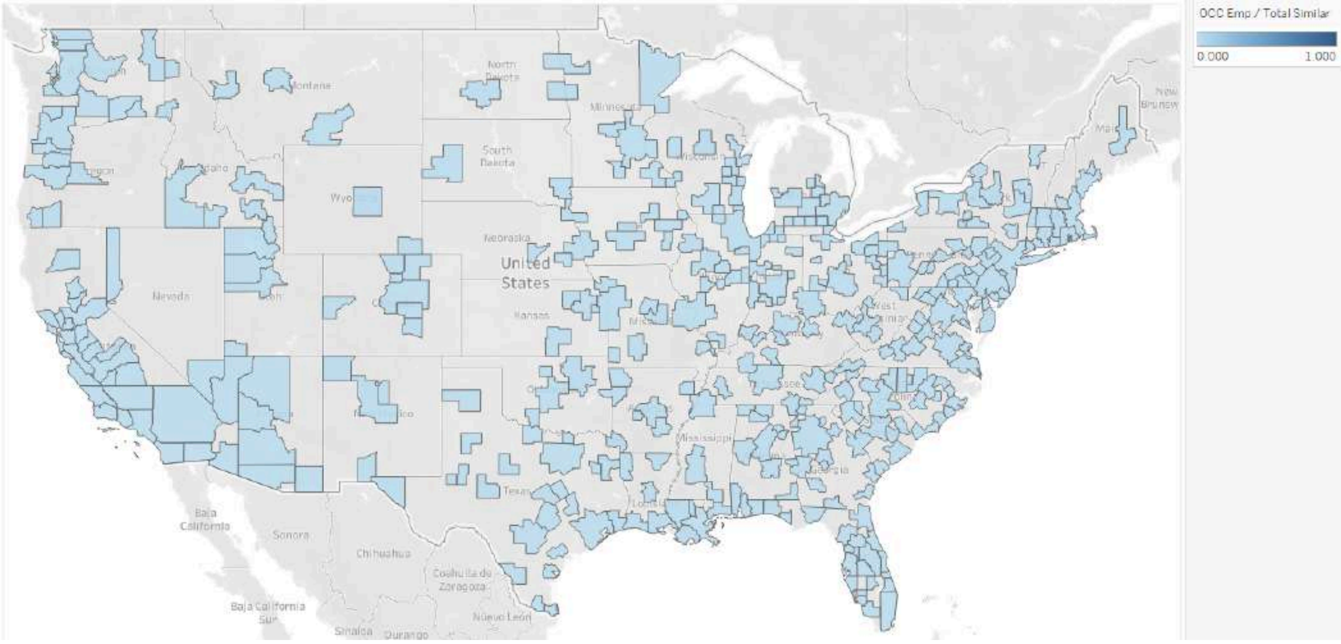


Figure B.40: Quantity of 51-4121 “Welders, Cutters, Solderers, and Brazers” workers over quantity of workers in similar occupations, with a similarity rate of 0.7 or greater.

Number of “Welders, Cutters, Solderers, and Brazers” (51-4121) divided by Number of Jobs with Skill Similarity>=0.8 by MSA

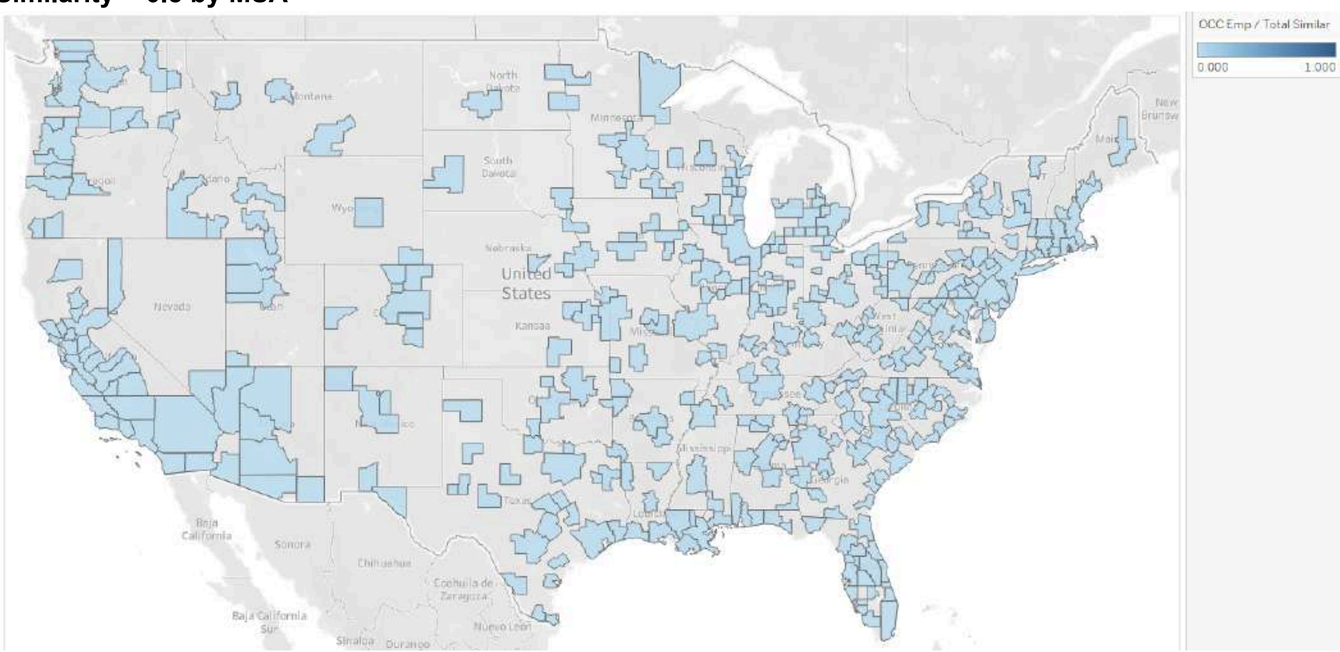


Figure B.41: Quantity of 51-4121 “Welders, Cutters, Solderers, and Brazers” workers over quantity of workers in similar occupations, with a similarity rate of 0.8 or greater.

Number of “Welders, Cutters, Solderers, and Brazers” (51-4121) divided by Number of Jobs with Skill Similarity>=0.9 by MSA

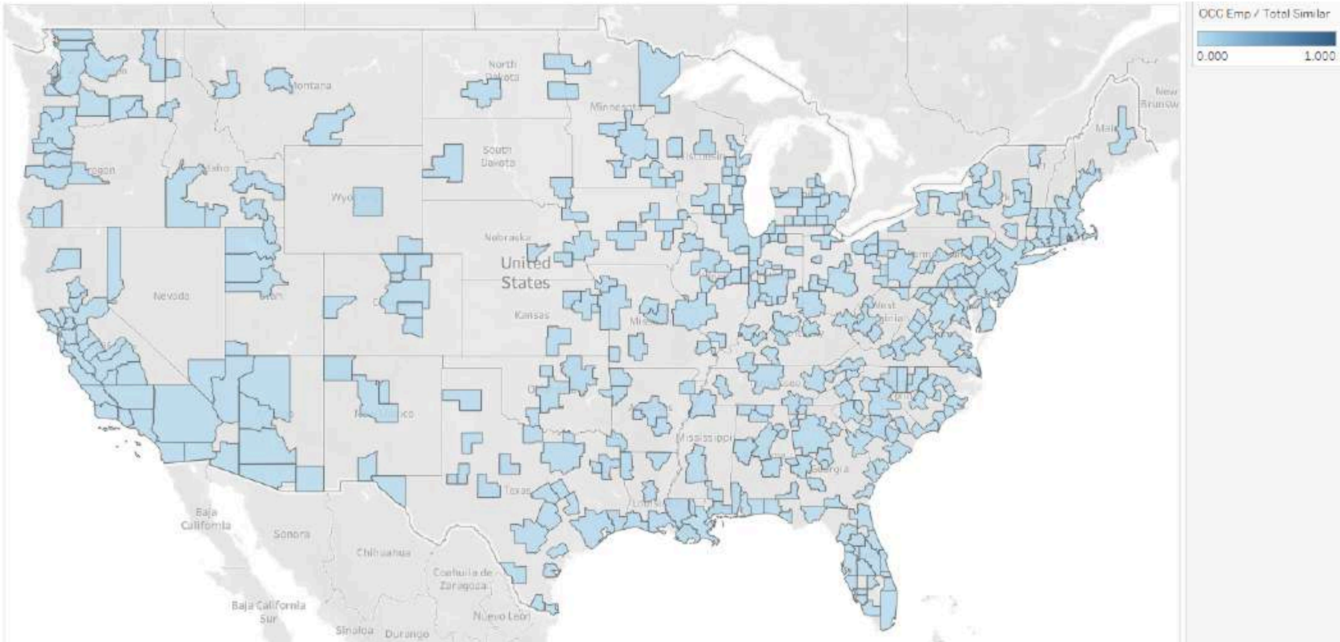


Figure B.42: Quantity of 51-4121 “Welders, Cutters, Solderers, and Brazers” workers over quantity of workers in similar occupations, with a similarity rate of 0.9 or greater.

Number of “Computer Numerically Controlled Tool Operators” (51-9161) divided by Number of Jobs with Skill Similarity>=0.7 by MSA”

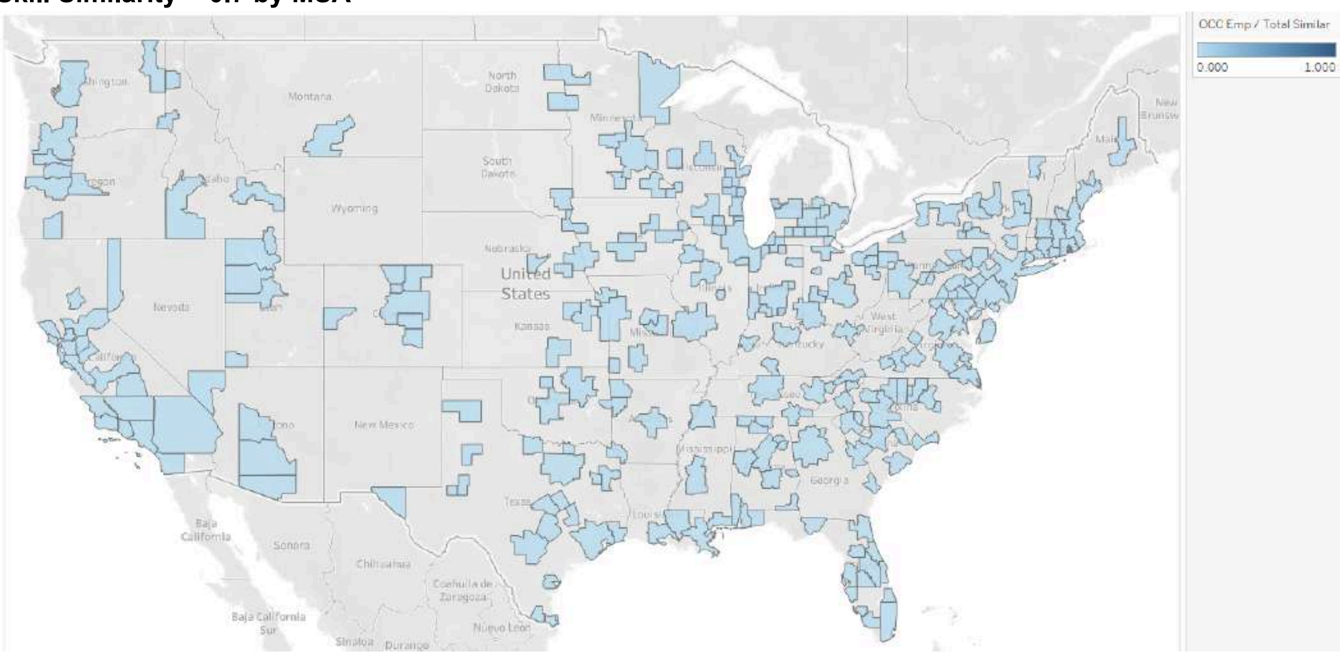


Figure B.43: Quantity of 51-9161 “Computer Numerically Controlled Tool Operators” workers over quantity of workers in similar occupations, with a similarity rate of 0.7 or greater.

Number of “Computer Numerically Controlled Tool Operators” (51-9161) divided by Number of Jobs with Skill Similarity>=0.8 by MSA

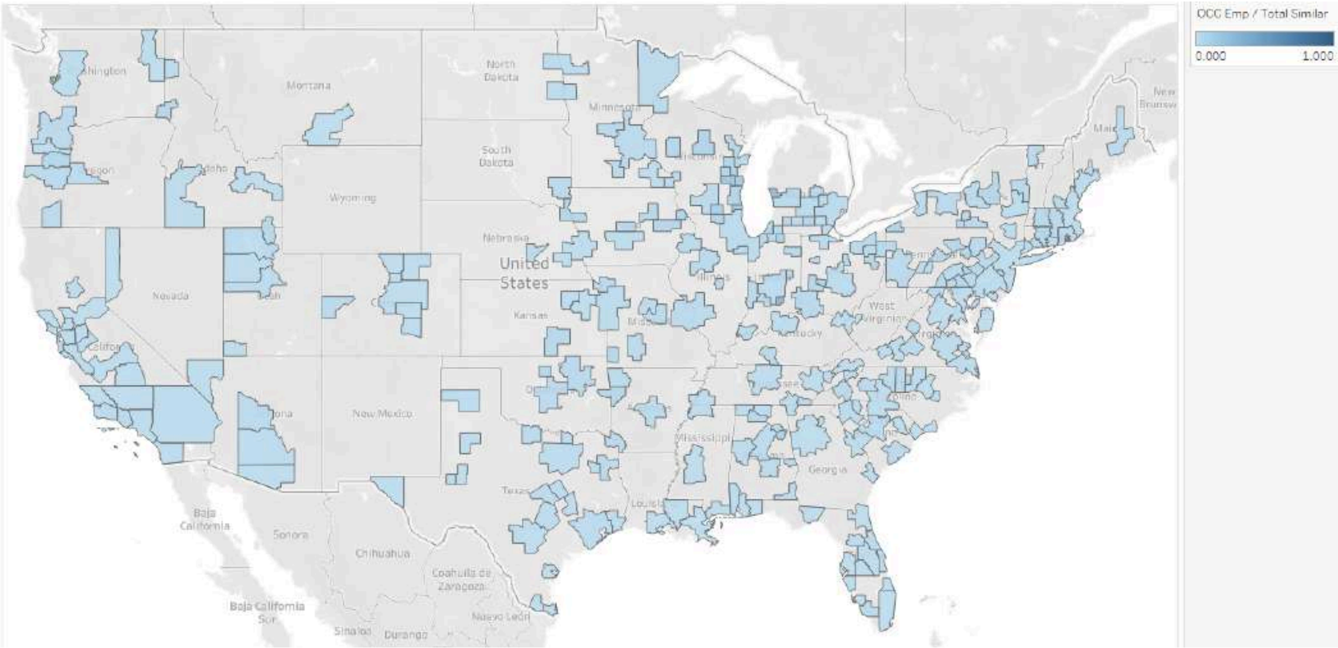


Figure B.44: Quantity of 51-9161 “Computer Numerically Controlled Tool Operators” workers over quantity of workers in similar occupations, with a similarity rate of 0.8 or greater.

Number of “Computer Numerically Controlled Tool Operators” (51-9161) divided by Number of Jobs with Skill Similarity>=0.9 by MSA

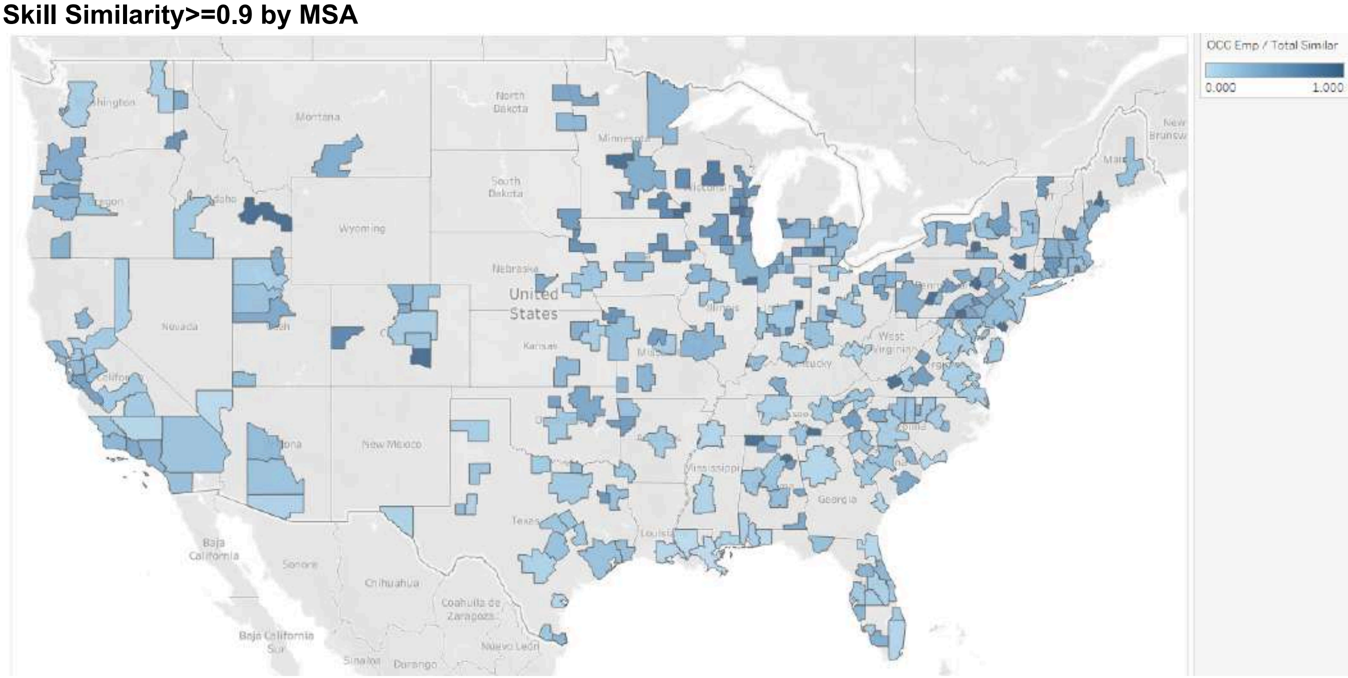


Figure B.45: Quantity of 51-9161 “Computer Numerically Controlled Tool Operators” workers over quantity of workers in similar occupations, with a similarity rate of 0.9 or greater.

Appendix C: Supporting Figures & Logic, Relative Wages of Similar Occupations to those of the ICEV Labor Supply as Well as Emerging EV, Battery, and HST Industries

This appendix comprises the following sections:

1. Wage-Weighted Labor Supply Figures
2. Relative Wage Position Figures (ICEV)
3. Relative Wage Position Figures (EV, Battery, and HST)
4. Wage Premium Figures (ICEV)
5. Wage Premium Figures (EV, Battery, and HST)
6. Wage-Weighted Labor Supply Logic

1. Wage-Weighted Labor Supply Figures

In the following figures, the general interpretation of the color scale is as follows - In red MSAs, the occupation of interest earns relatively more than the similar occupations in the comparison. In green MSAs, the occupation of interest earns less than the similar occupations in the comparison.

Relative Wage Position of "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) When Comparing Jobs with Skill Similarity>=0.7 to 50th Percentile by MSA

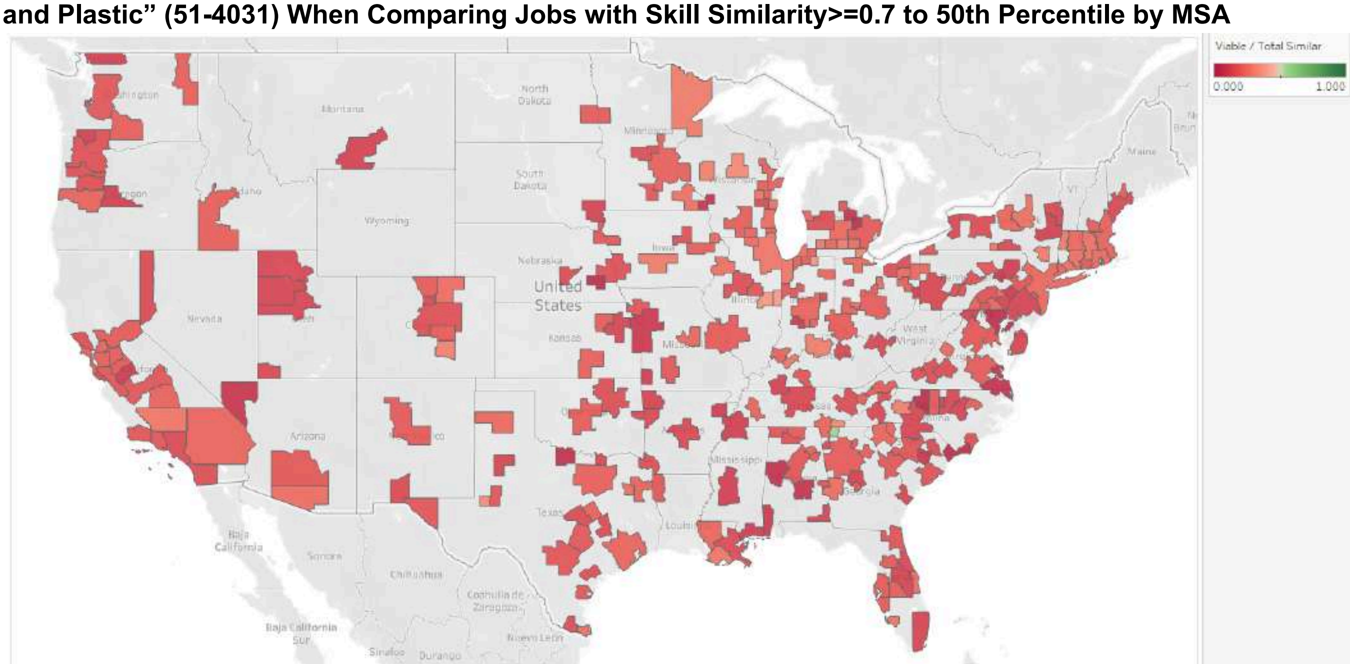


Figure C.1: Quantity of workers earning equal or more than the average worker in occupation 51-4031 "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" over the total number of workers in similar occupations, with 0.7 similarity threshold. Broadly, 51-4031 employees earn more than similar occupations nationally.

Relative Wage Position of "Engine and Other Machine Assemblers" (51-2031) When Comparing Jobs with Skill Similarity>=0.7 to 50th Percentile by MSA

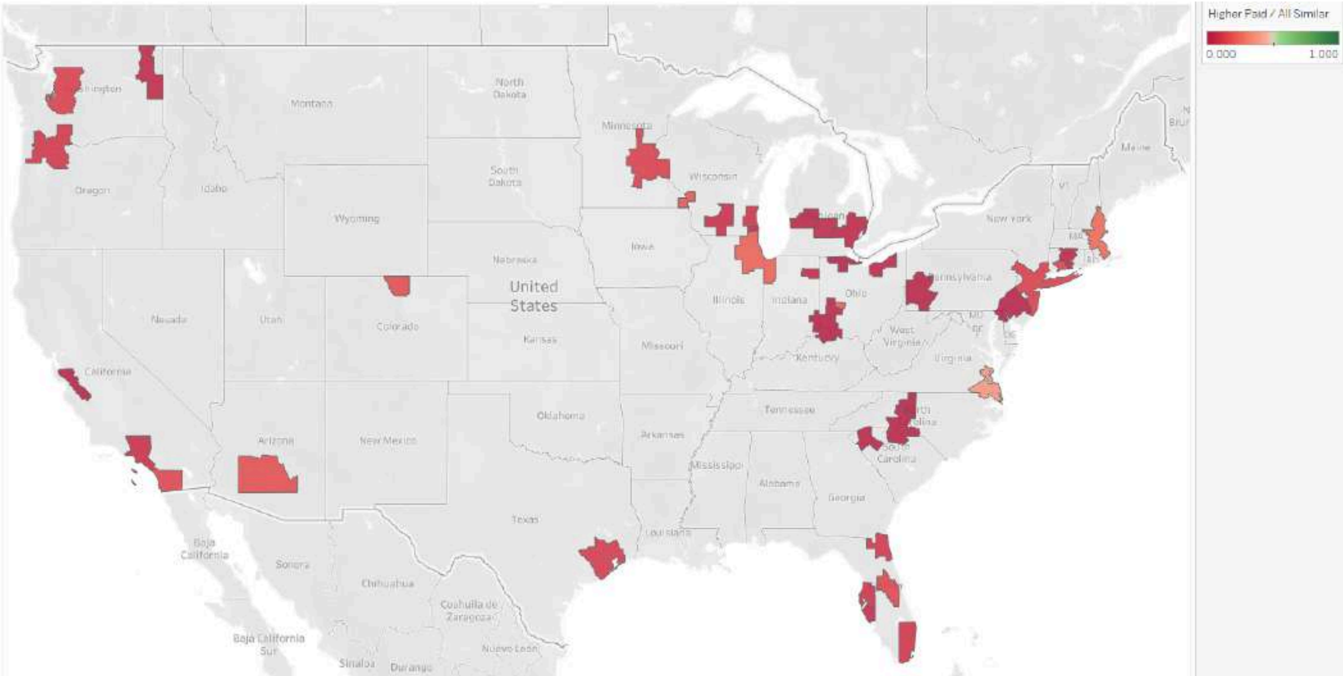


Figure C.2: Quantity of workers earning equal or more than the average worker in occupation 51-2031 "Engine and Other Machine Assemblers" over the total number of workers in similar occupations, with 0.7 similarity threshold. Broadly, 51-2031 employees earn more than similar occupations nationally.

Relative Wage Position of "Machinists" (51-4041) When Comparing Jobs with Skill Similarity>=0.7 to 50th Percentile by MSA

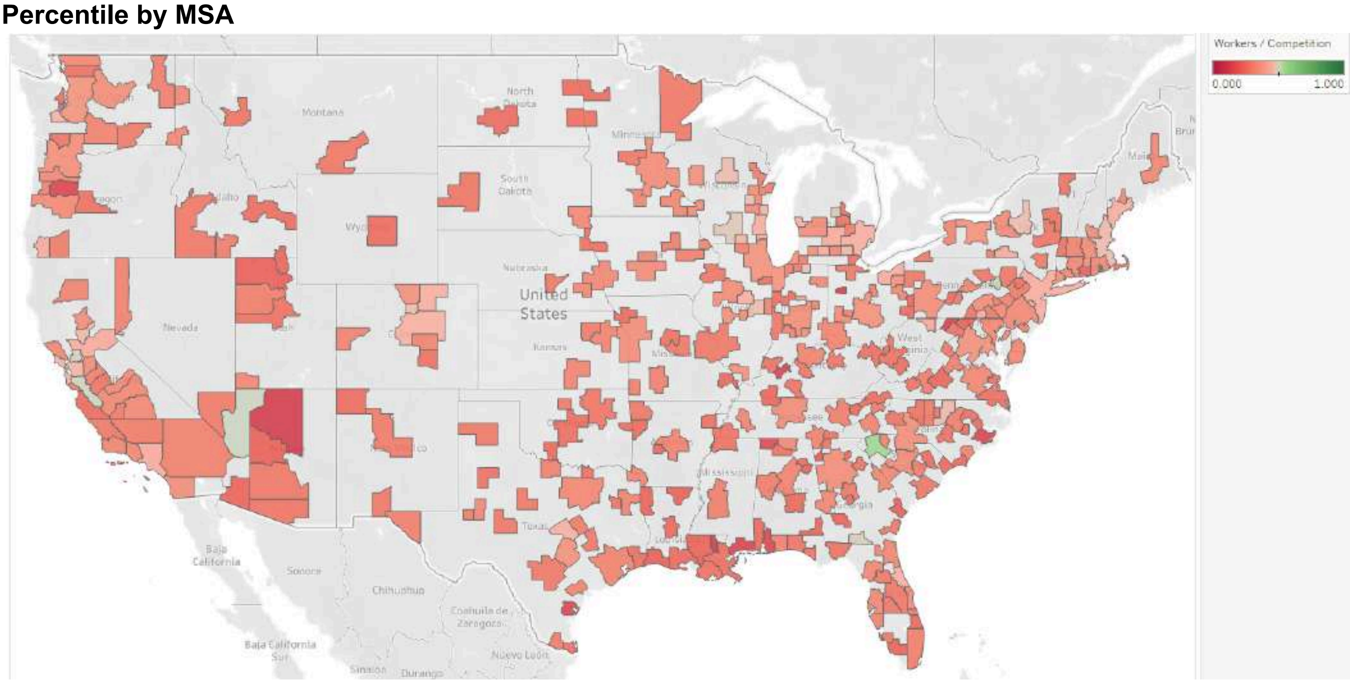


Figure C.3: Quantity of workers earning equal or more than the average worker in occupation 51-4041 "Machinists" over the total number of workers in similar occupations, with 0.7 similarity threshold. Broadly, 51-4041 employees earn more than similar occupations nationally.

Relative Wage Position of "First-Line Supervisors of Production and Operating Workers" (51-1011) When Comparing Jobs with Skill Similarity>=0.7 to 50th Percentile by MSA

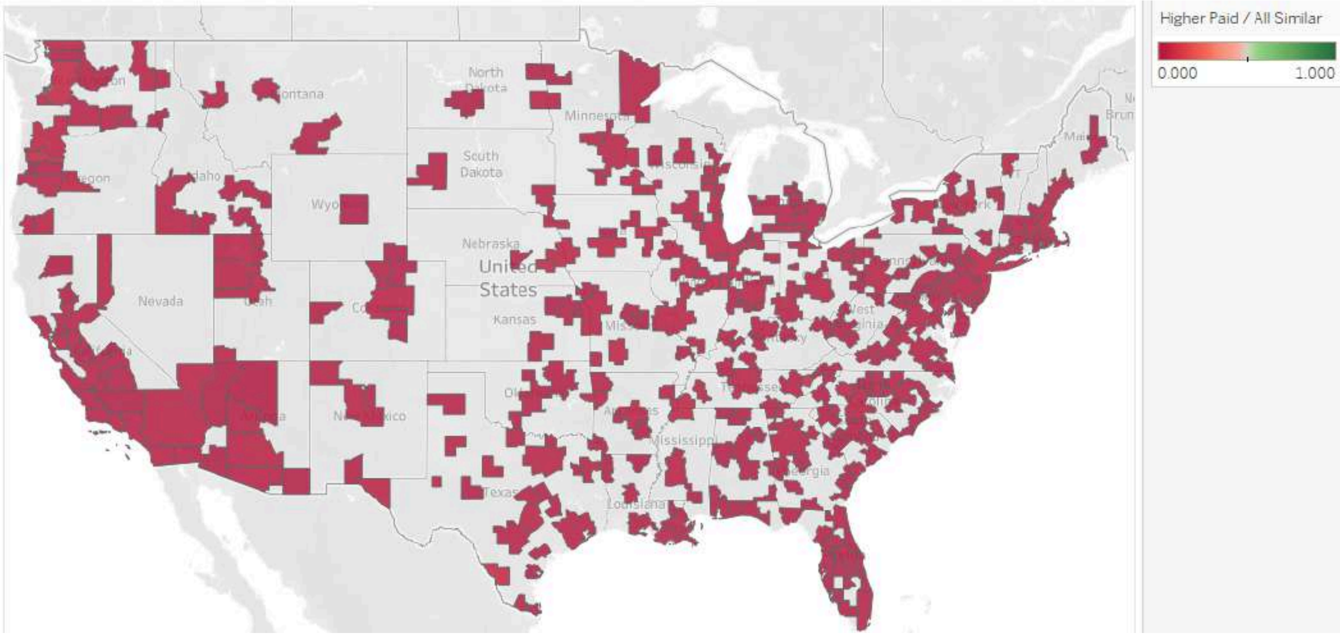


Figure C.4: Quantity of workers earning equal or more than the average worker in occupation 51-1011 "First-Line Supervisors of Production and Operating Workers" over the total number of workers in similar occupations, with 0.7 similarity threshold. Broadly, 51-1011 employees earn more than similar occupations nationally.

Relative Wage Position of "Inspectors, Testers, Sorters, Samplers, and Weighers" (51-9061) When Comparing Jobs with Skill Similarity>=0.7 to 50th Percentile by MSA

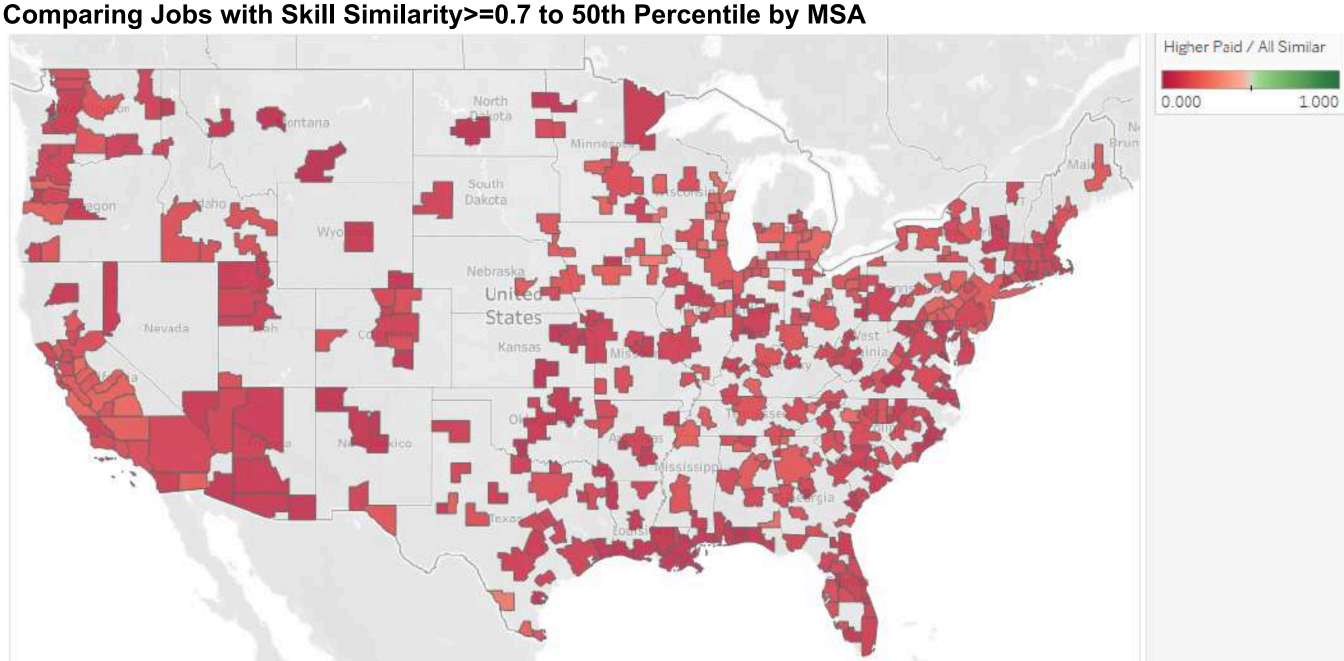


Figure C.5: Quantity of workers earning equal or more than the average worker in occupation 51-9061 "Inspectors, Testers, Sorters, Samplers, and Weighers" over the total number of workers in similar occupations, with 0.7 similarity threshold. Broadly, 51-9061 employees earn more than similar occupations nationally.

Relative Wage Position of “Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic” (51-4081) When Comparing Jobs with Skill Similarity>=0.7 to 50th Percentile by MSA

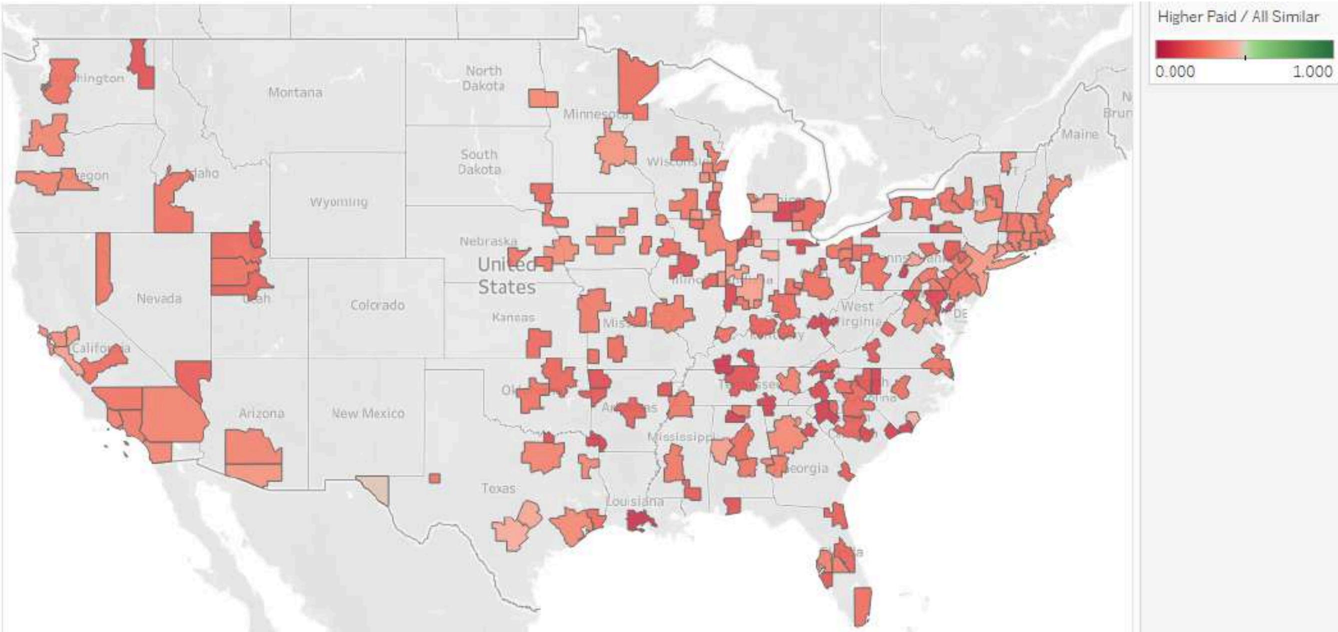


Figure C.6: Quantity of workers earning equal or more than the average worker in occupation 51-4081 “Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic” over the total number of workers in similar occupations, with 0.7 similarity threshold. Broadly, 51-4081 employees earn more than similar occupations nationally.

Relative Wage Position of “Welders, Cutters, Solderers, and Brazers” (51-4121) When Comparing Jobs with Skill Similarity>=0.7 to 50th Percentile by MSA

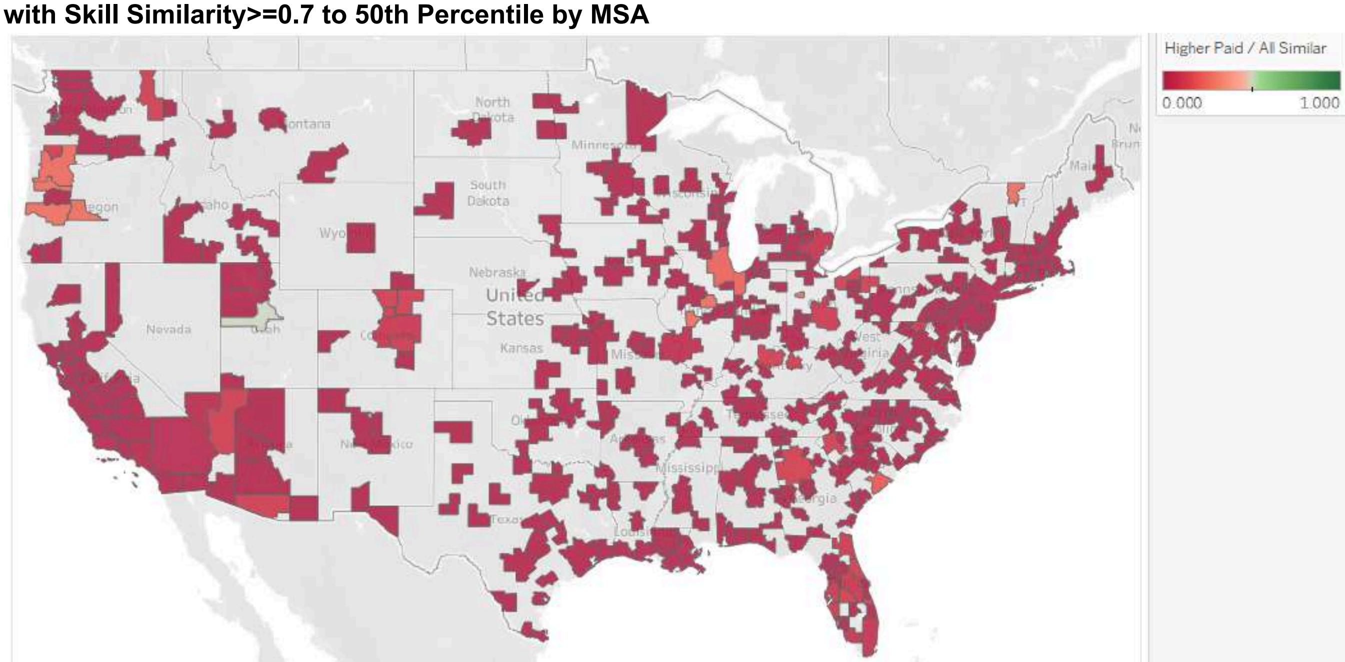


Figure C.7: Quantity of workers earning equal or more than the average worker in occupation 51-4121 “Welders, Cutters, Solderers, and Brazers” over the total number of workers in similar occupations, with 0.7 similarity threshold. Broadly, 51-4121 employees earn more than similar occupations nationally.

Relative Wage Position of "Tool and Die Makers" (51-4111) When Comparing Jobs with Skill Similarity>=0.7 to 50th Percentile by MSA

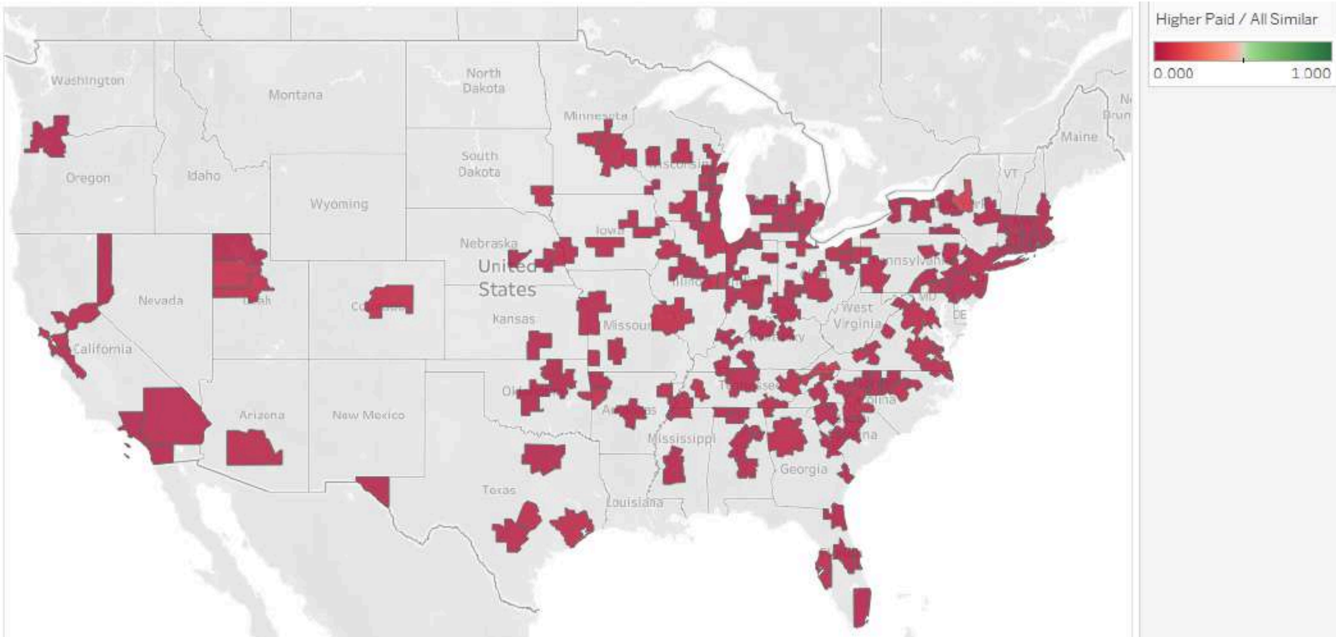


Figure C.8: Quantity of workers earning equal or more than the average worker in occupation 51-4111 "Tool and Die Makers" over the total number of workers in similar occupations, with 0.7 similarity threshold. Broadly, 51-4111 employees earn more than similar occupations nationally.

2. Relative Wage Position Figures (ICEV)

The following figures depict the relative wage positions of ICEV workers when compared to those in similar occupations. Similarity is directional, and for these figures that direction is *from* our occupation of interest *to* the similar occupations. In lay terms, we are asking in this section "what jobs can ICEV employees transition to (with their current skills), and what is their wage position in that transition?".

In the following figures, the general interpretation of the color scale is as follows - In red MSAs, the occupation of interest earns relatively more than the similar occupations in the comparison. This means from a wage perspective, the occupation of interest may be forced to take a pay cut in an occupational transition, because they are currently paid relatively well. In green MSAs, the occupation of interest earns less than the similar occupations in the comparison (and may be able to make a wage-increasing occupation transition).

Relative Wage Position of "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA

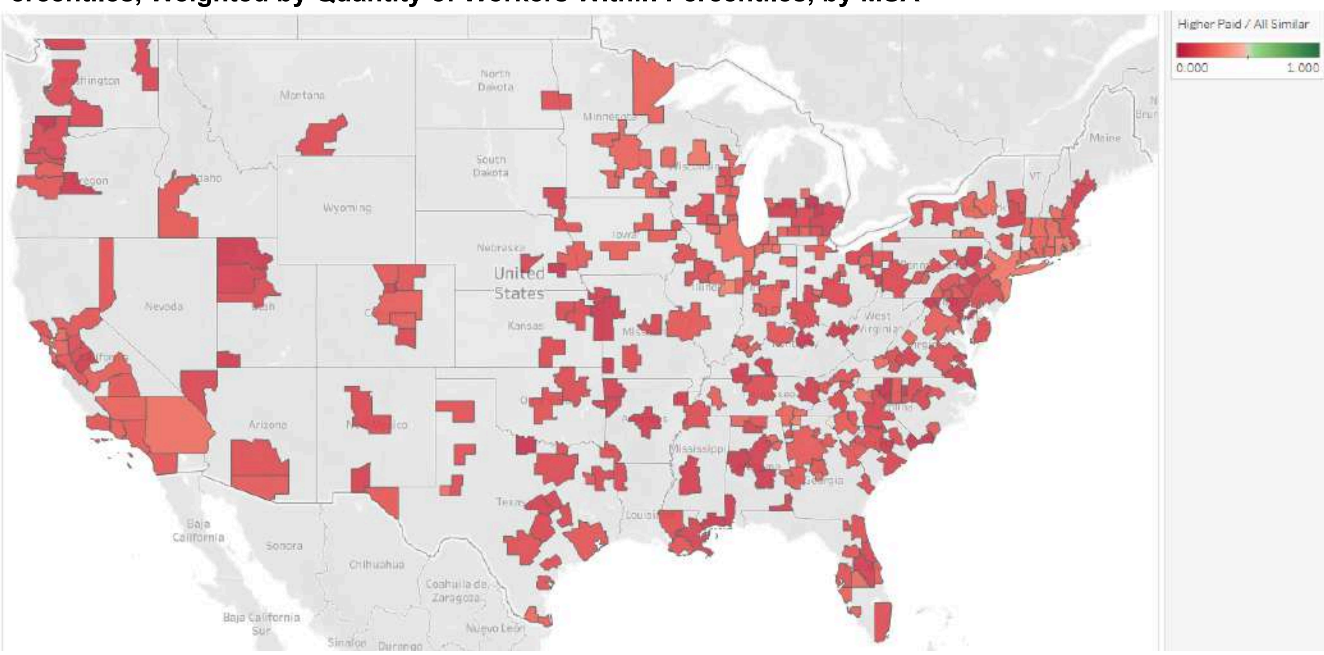


Figure C.9: Weighted average of the quantity of workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile worker in occupation 51-4031 "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" over the total proportional number of workers in similar occupations. Broadly, 51-4031 employees earn more than similar occupations nationally.

Relative Wage Position of "Engine and Other Machine Assemblers" (51-2031) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA

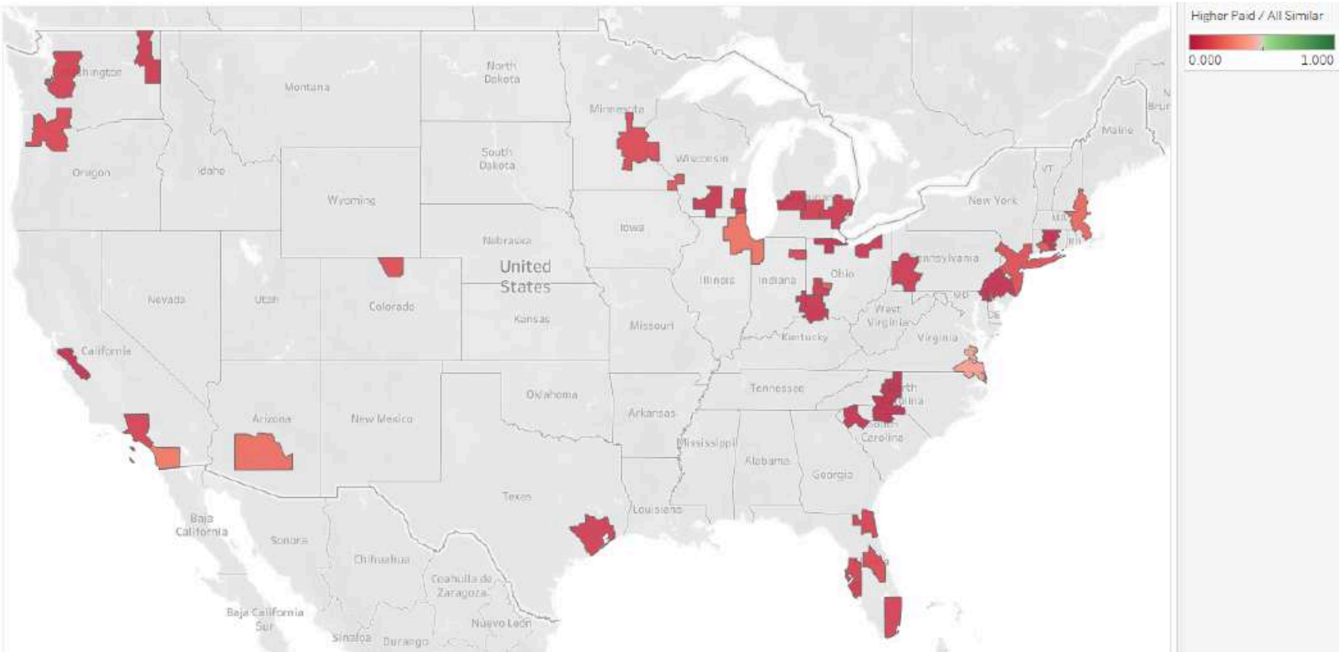


Figure C.10: Weighted average of the quantity of workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile in occupation 51-2031 "Engine and Other Machine Assemblers" over the total proportional number of workers in similar occupations. 51-2031 employees earn more than similar occupations nationally.

Relative Wage Position of "First-Line Supervisors of Production and Operating Workers" (51-1011) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA

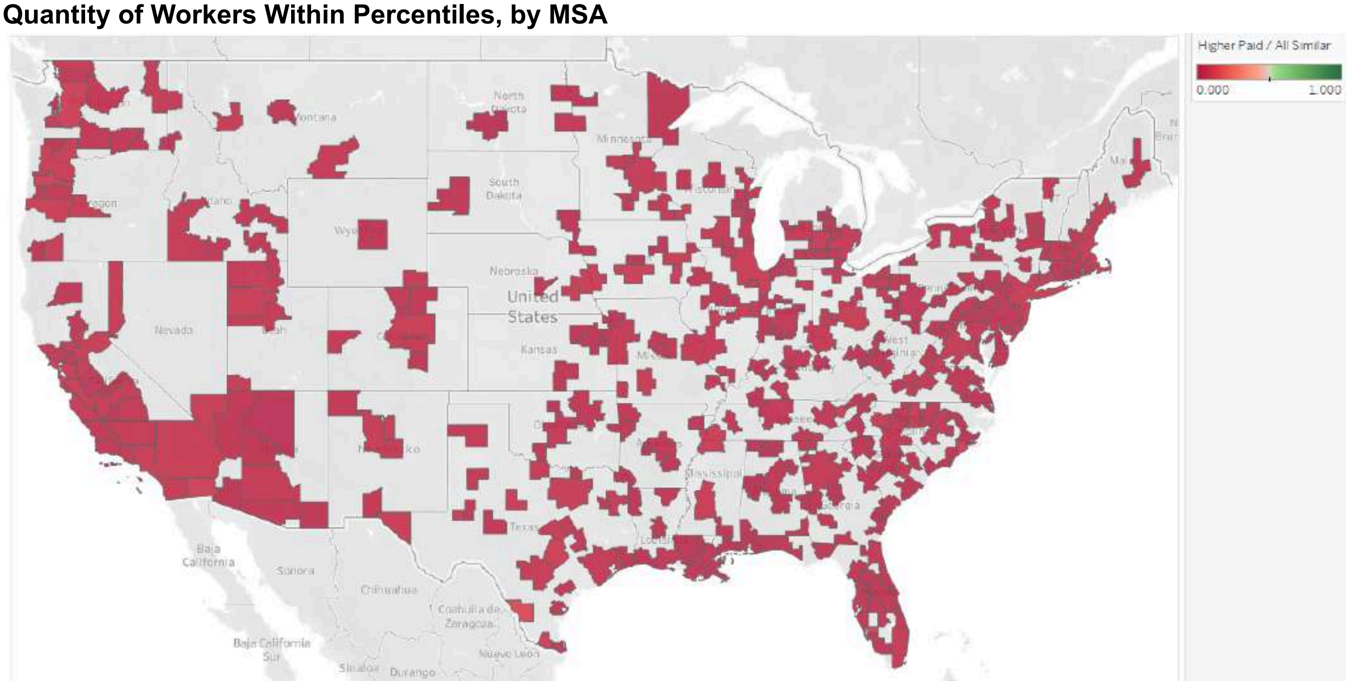


Figure C.11: Weighted average of the quantity of workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile worker in occupation 51-1011 "First-Line Supervisors of Production and Operating Workers" over the total proportional number of workers in similar occupations. Broadly, 51-1011 employees earn more than similar occupations nationally.

Relative Wage Position of "Inspectors, Testers, Sorters, Samplers, and Weighers" (51-9061) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA

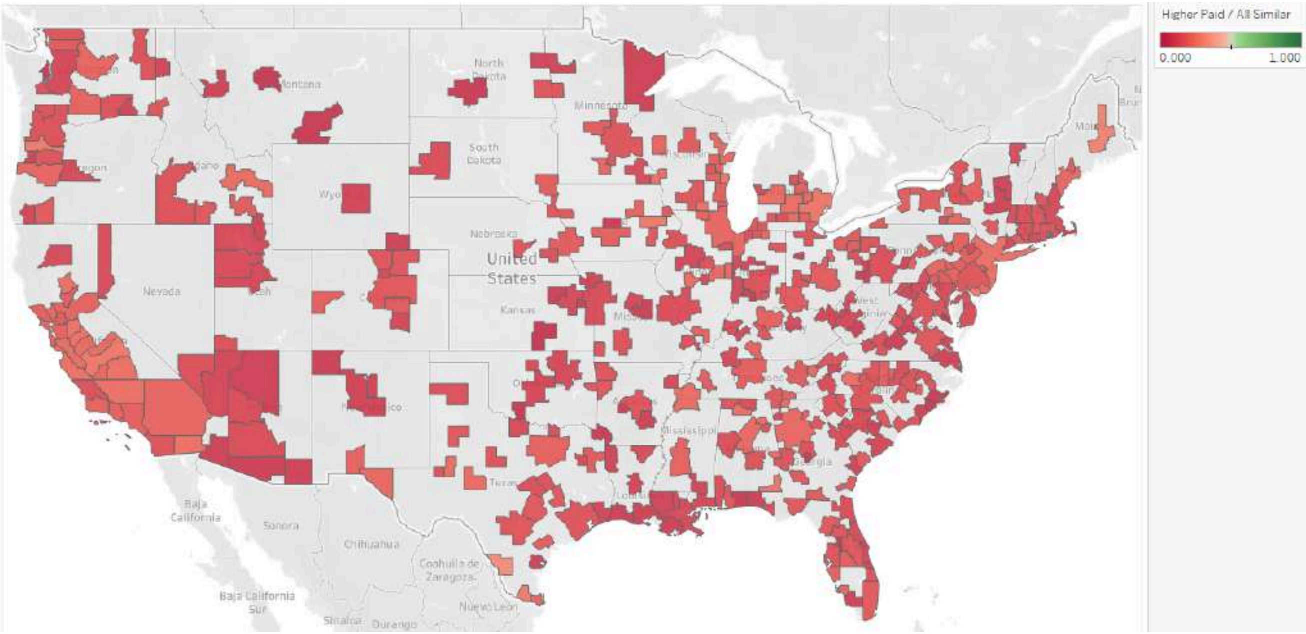


Figure C.12: Weighted average of the quantity of workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile in occupation 51-9061 "Inspectors, Testers, Sorters, Samplers, and Weighers" over the total proportional number of workers in similar occupations. Broadly, 51-9061 employees earn more than similar occupations nationally.

Relative Wage Position of "Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic" (51-4081) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA

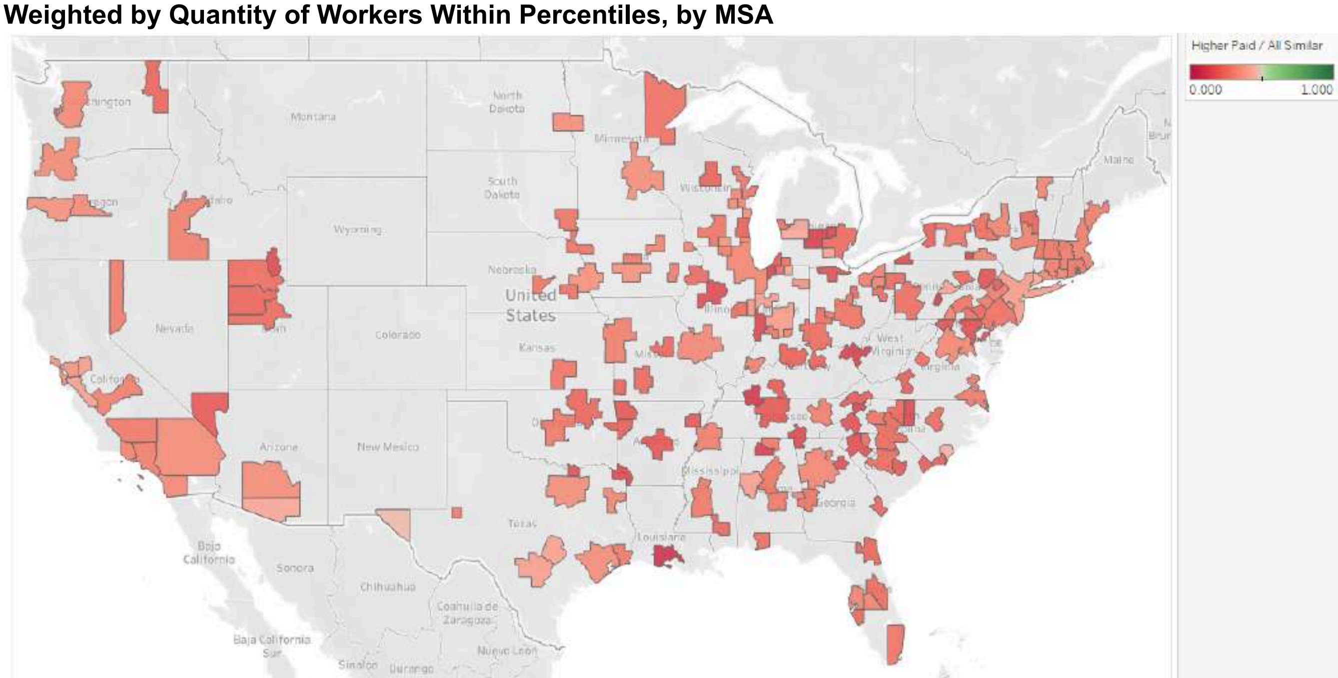


Figure C.13: Weighted average of the quantity of workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile worker in occupation 51-4081 "Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic" over the total proportional number of workers in similar occupations. Broadly, 51-4081 employees earn more than similar occupations nationally.

Relative Wage Position of "Machinists" (51-4041) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA

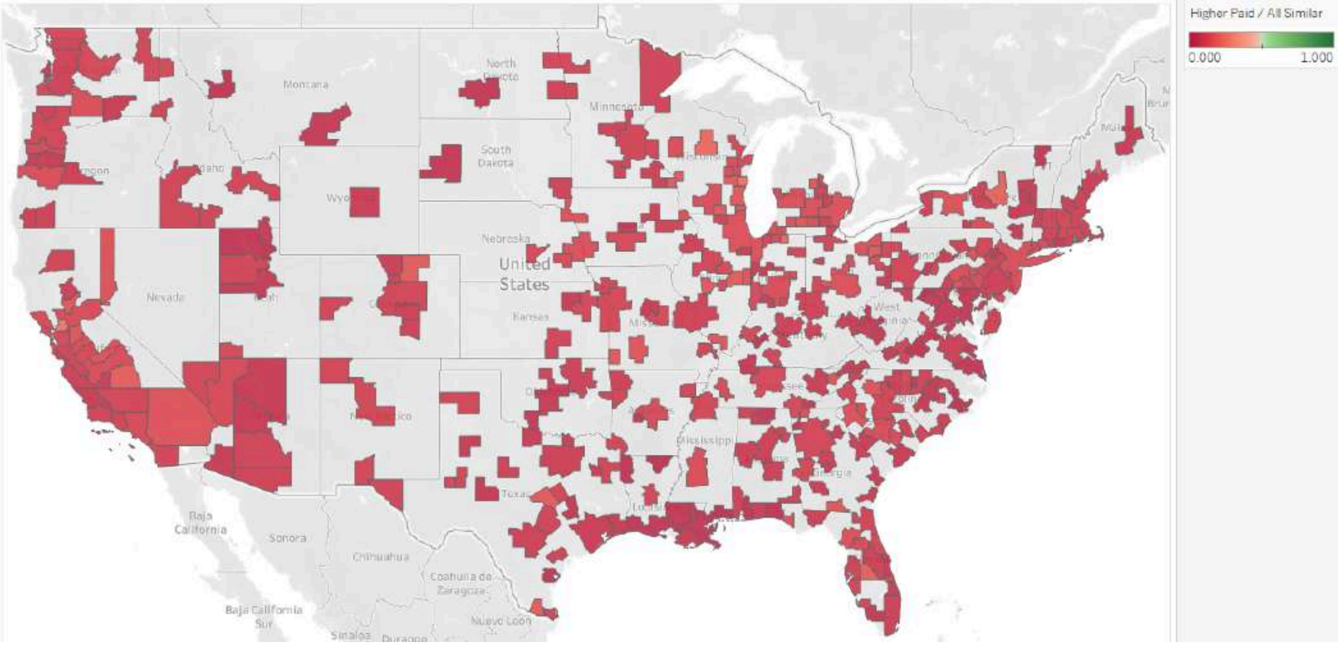


Figure C.14: Weighted average of the quantity of workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile worker in occupation 51-4041 "Machinists" over the total proportional number of workers in similar occupations. Broadly, 51-4041 employees earn more than similar occupations nationally.

Relative Wage Position of "Welders, Cutters, Solderers, and Brazers" (51-4121) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA

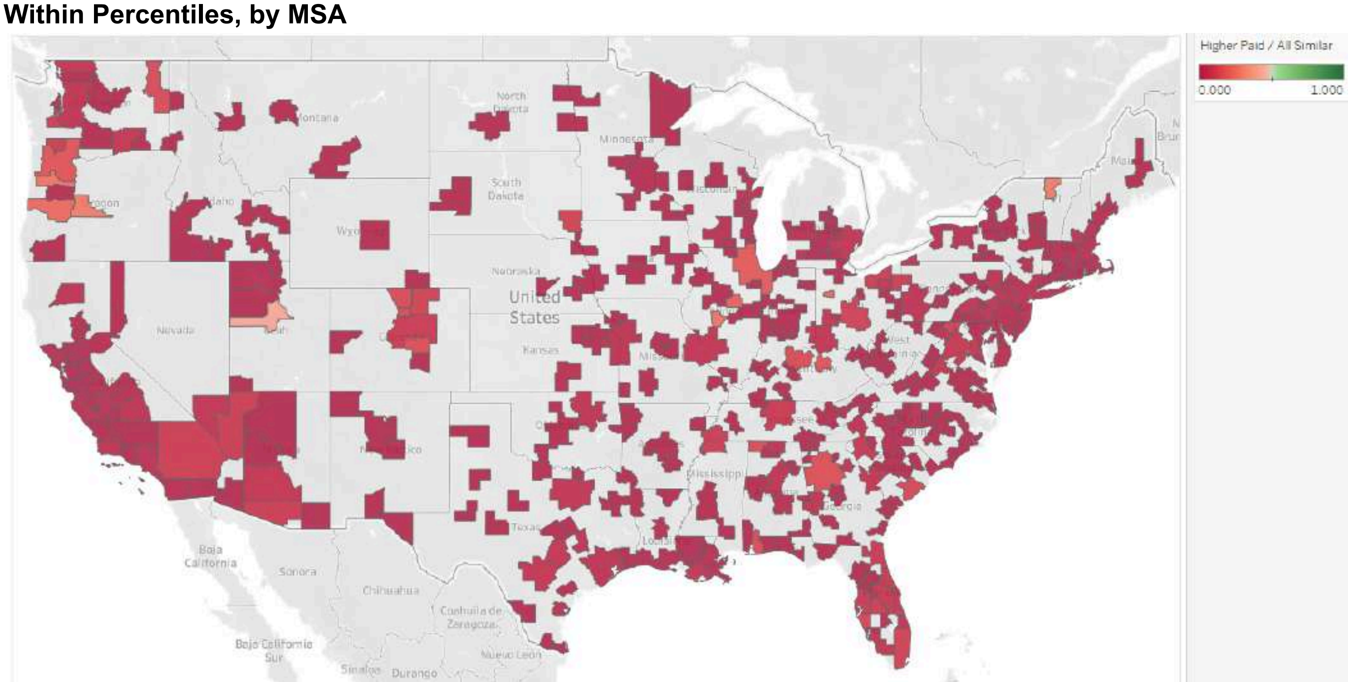


Figure C.15: Weighted average of the quantity of workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile worker in occupation 51-4121 "Welders, Cutters, Solderers, and Brazers" over the total proportional number of workers in similar occupations. Broadly, 51-4121 employees earn more than similar occupations nationally.

Relative Wage Position of "Tool and Die Makers" (51-4111) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA

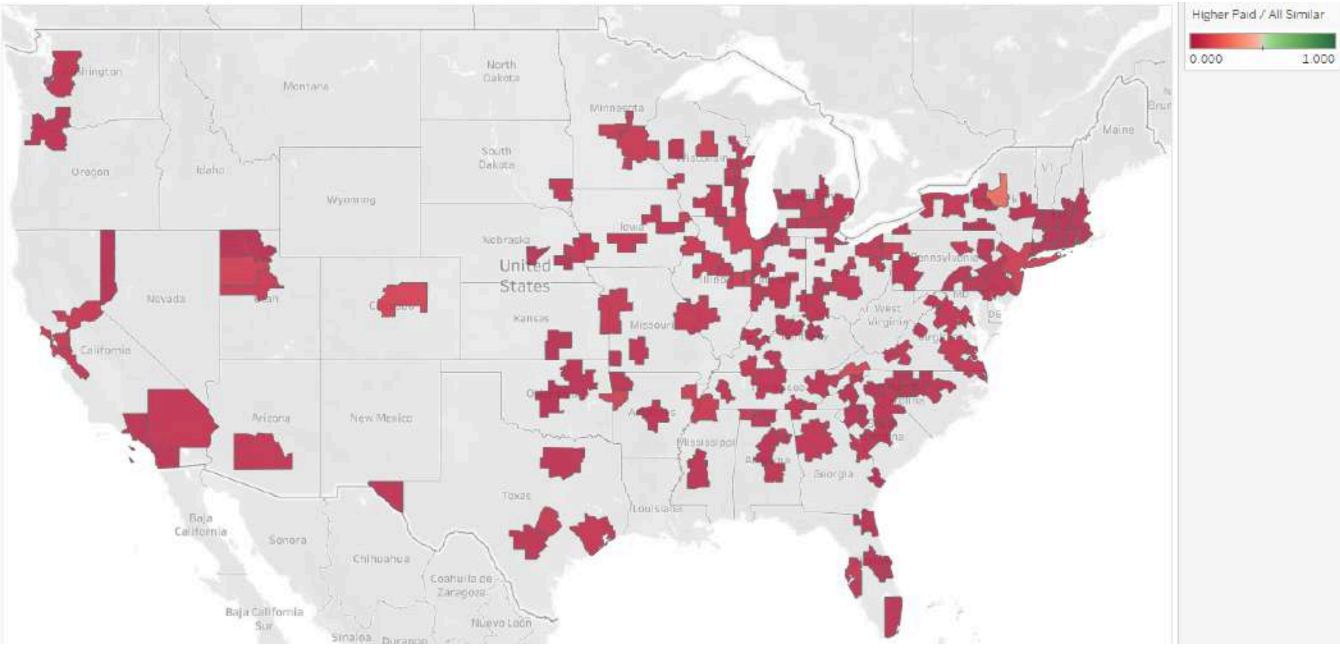


Figure C.16: Weighted average of the quantity of workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile worker in occupation 51-4111 "Tool and Die Makers" over the total proportional number of workers in similar occupations. Broadly, 51-4111 employees earn more than similar occupations nationally.

3. Relative Wage Position Figures (EV, Battery, and HST)

The following figures depict the relative wage positions of EV, Battery, and HST workers when compared to those in similar occupations. Similarity is directional, and for these figures that direction is *to* our occupation of interest *from* the similar occupations. This means the comparison is reversed in a sense from the previous section for ICEV employees. We are asking here "what occupations can fill future EV, Battery, and HST positions (with their current skills), and what is their wage position in that transition?".

While the color coding remains the same here, the implication is quite different. In a red MSA (where the occupation of interest earns more than its similar occupations), potential EV, Battery, and HST jobs may pay more than similar occupations, representing a wage-increasing opportunity. In green MSAs, there may be fewer opportunities to increase one's wages when moving into the EV, Battery, and HST occupations of interest.

Relative Wage Position of "Industrial Production Managers" (11-3051) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA

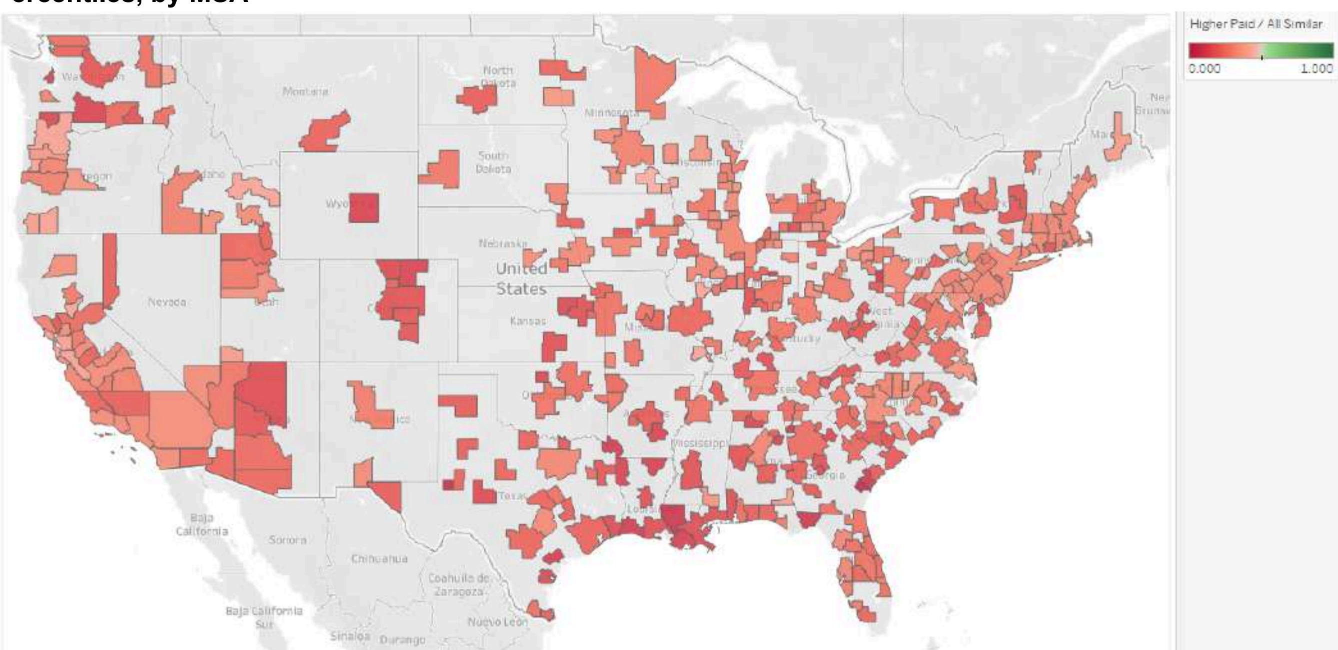


Figure C.17: Weighted average of the quantity of workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile worker in occupation 11-3051 "Industrial Production Managers" over the total proportional number of workers in similar occupations. Broadly, 11-3051 employees earn more than similar occupations nationally.

Relative Wage Position of "Electro-Mechanical and Mechatronics Technologists and Technicians" (17-3024) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA

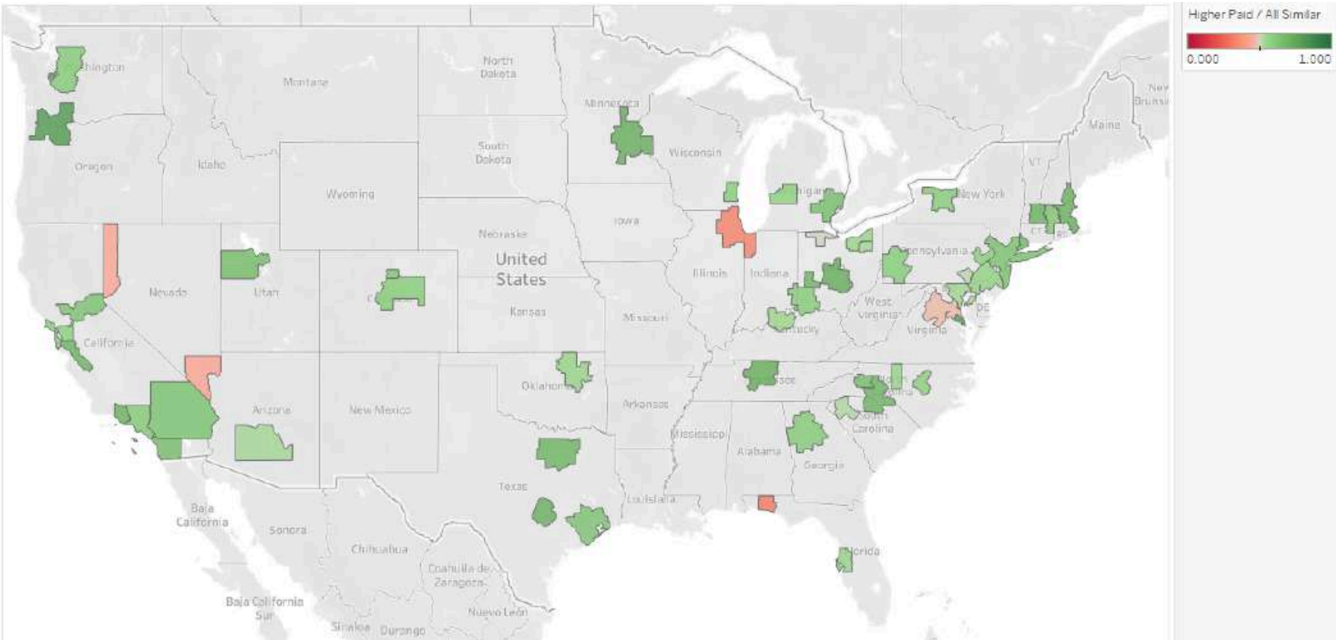


Figure C.18: Weighted average of the quantity of workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile worker in occupation 17-3024 "Electro-Mechanical and Mechatronics Technologists and Technicians" over the total proportional number of workers in similar occupations. Broadly,17-3024 employees earn less than similar occupations nationally, with scattered exceptions in Nevada, Chicago area, Virginia, and the Florida panhandle.

Relative Wage Position of "Industrial Machinery Mechanics" (49-9041) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA

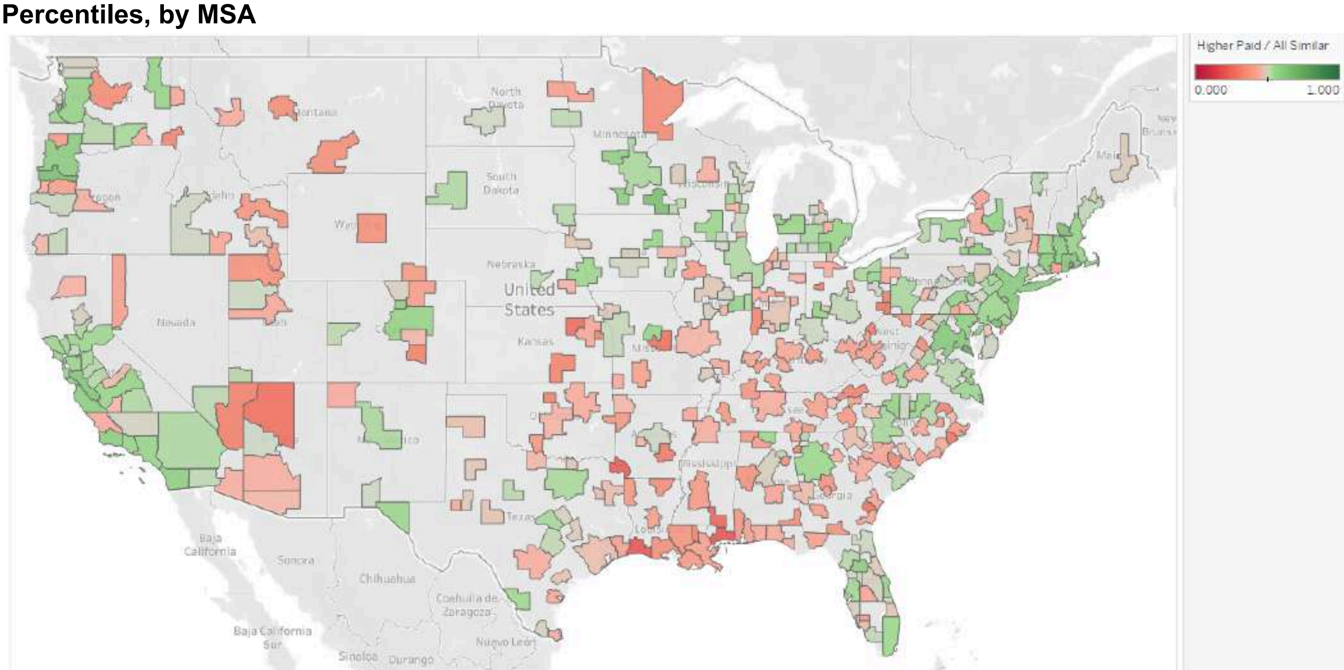


Figure C.19: Weighted average of the quantity of workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile worker in occupation 49-9041 "Industrial Machinery Mechanics" over the total proportional number of workers in similar occupations. 49-9041 employees comparative earnings are heterogenous nationally.

Relative Wage Position of "Engine and Other Machine Assemblers" (51-2031) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA

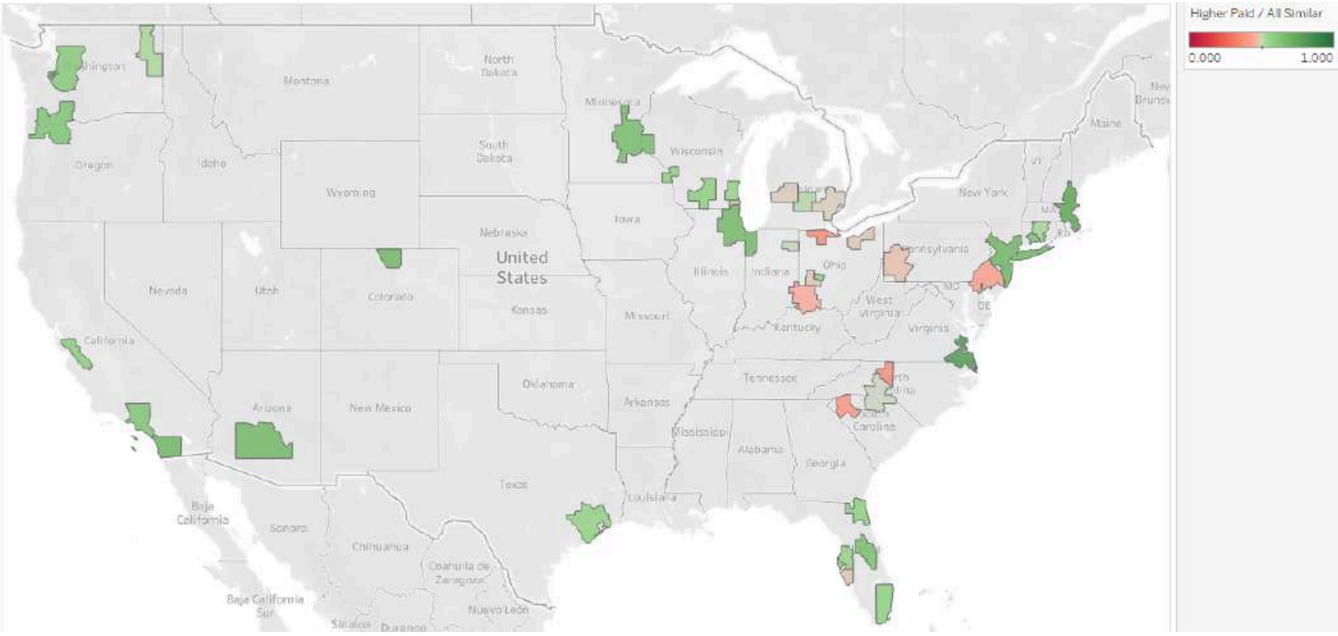


Figure C.20: Weighted average of the quantity of workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile worker in occupation 51-2031 "Engine and Other Machine Assemblers" over the total proportional number of workers in similar occupations. Broadly, 51-2031 employees earn less than similar occupations nationally, with specific exceptions in and around the Rust Belt.

Relative Wage Position of "Machinists" (51-4041) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA

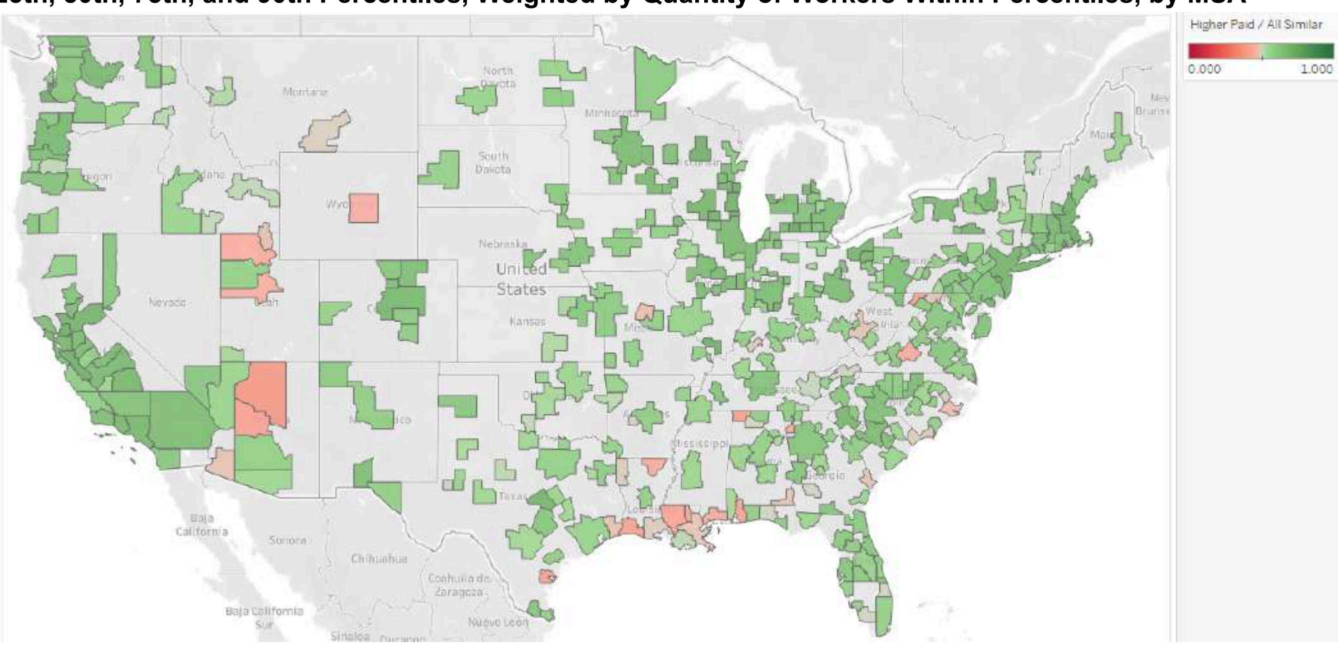


Figure C.21: Weighted average of the quantity of workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile worker in occupation 51-4041 "Machinists" over the total proportional number of workers in similar occupations. Broadly, 51-4041 employees earn less than similar occupations nationally.

Relative Wage Position of “Welders, Cutters, Solderers, and Brazers” (51-4121) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA

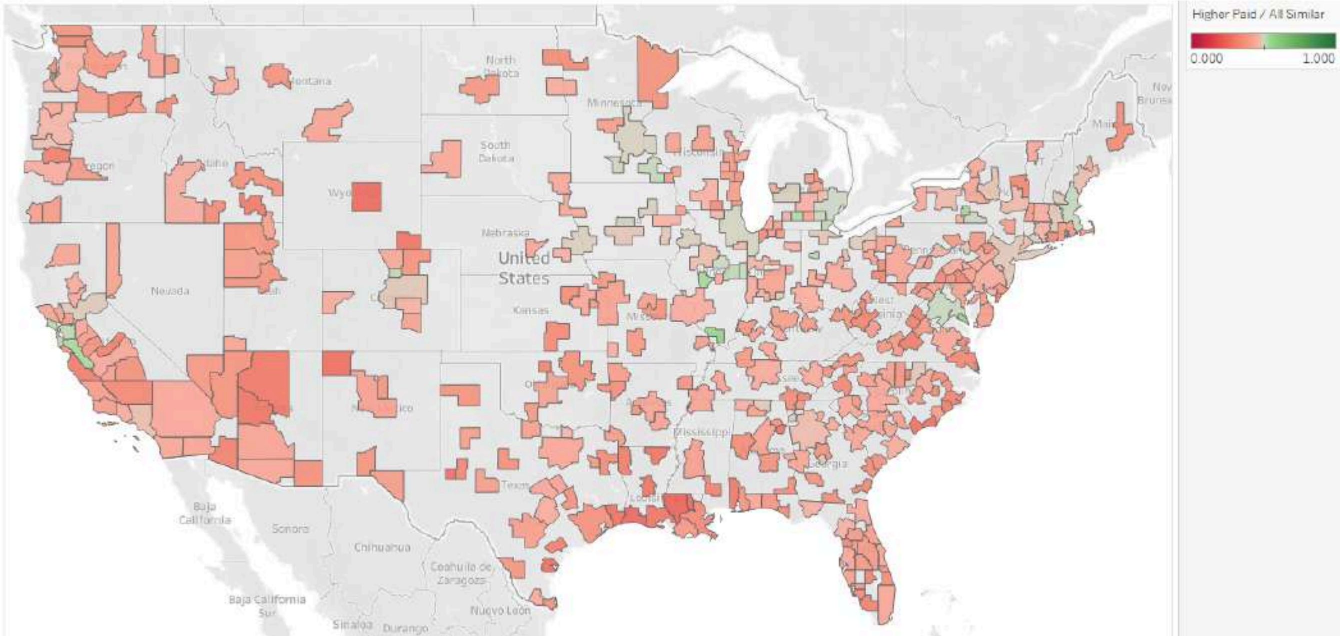


Figure C.22: Weighted average of the quantity of workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile worker in occupation 51-4121 “Welders, Cutters, Solderers, and Brazers” over the total proportional number of workers in similar occupations. Broadly, 51-4121 employees earn more than similar occupations nationally.

Relative Wage Position of “Computer Numerically Controlled Tool Operators” (51-9161) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA

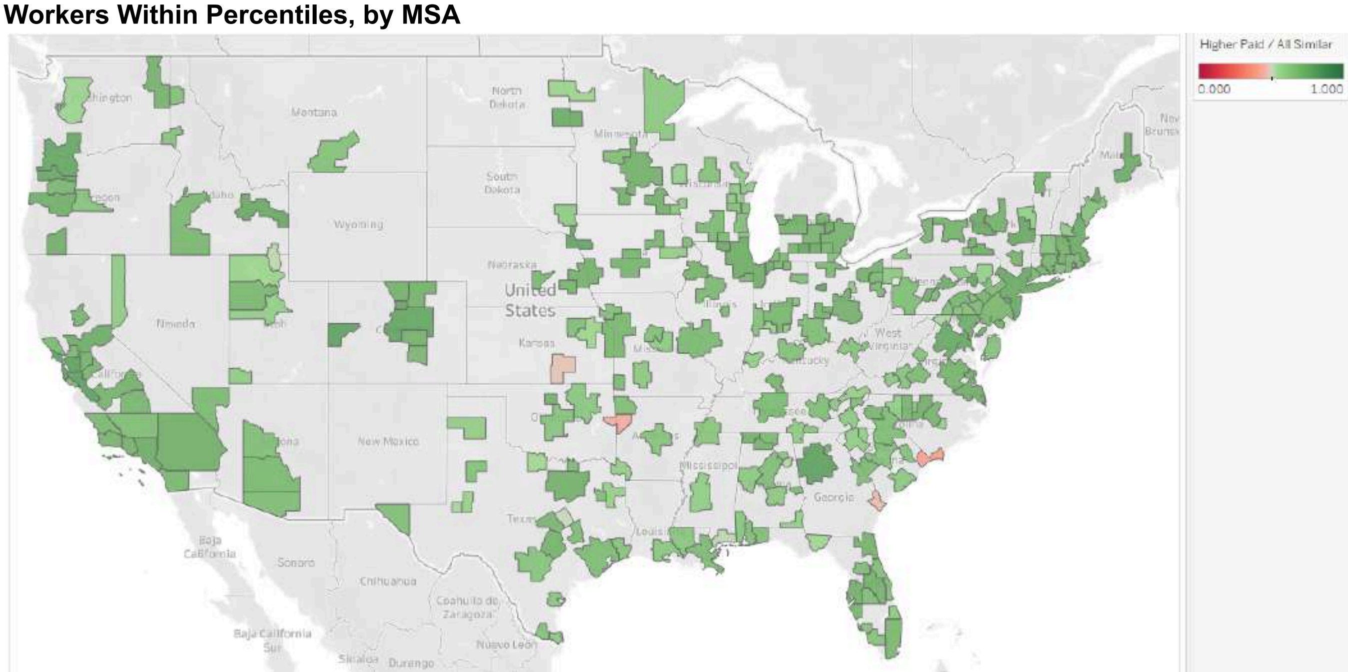


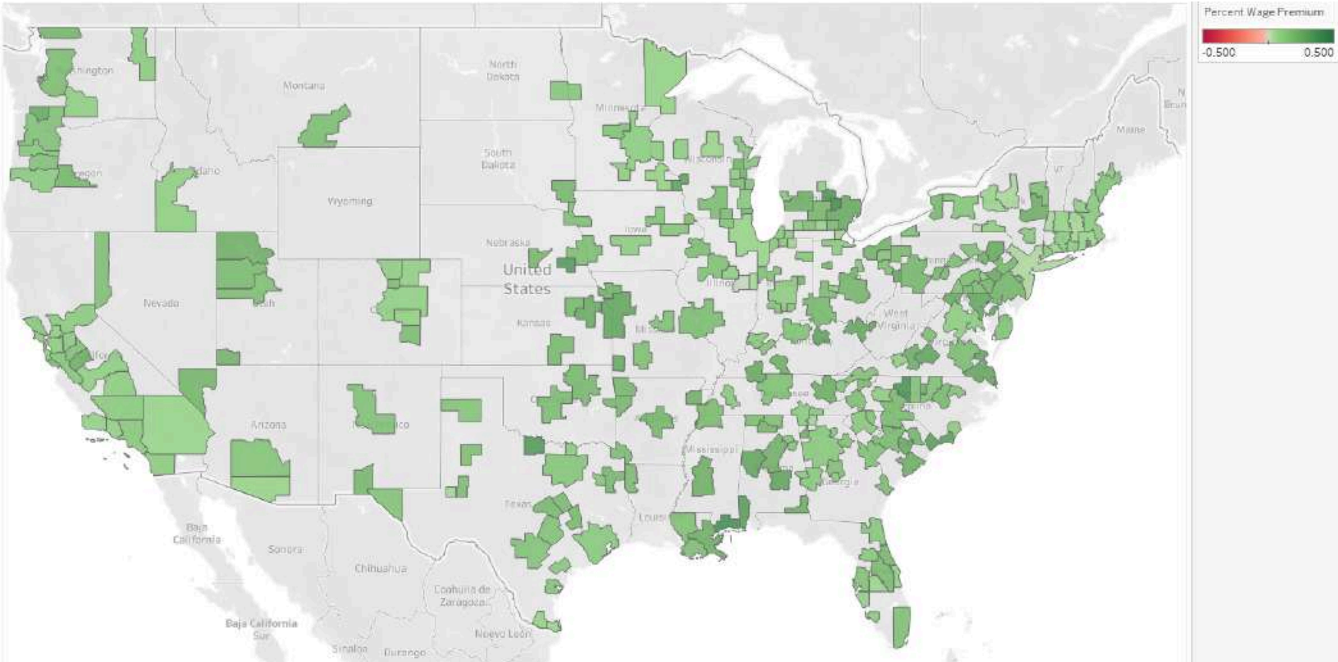
Figure C.23: Weighted average of the quantity of workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile worker in occupation 51-9161 “Computer Numerically Controlled Tool Operators” over the total proportional number of workers in similar occupations. Broadly, 51-9161 employees earn less than similar occupations nationally.

4. Wage Premium Figures (ICEV)

The following figures depict the wage premium demanded by ICEV workers when compared to those in similar occupations. Similarity is directional, and for these figures that direction is *from* our occupation of interest *to* the similar occupations. In lay terms, we are asking in this section "what jobs can ICEV employees transition to (with their current skills), and what is their wage premium in their current ICEV role?".

In the following figures, **Figures C.24 - C.31**, the general interpretation of the color scale is as follows - In green MSAs, the occupation of interest earns relatively more than the similar occupations in the comparison. This means from a wage perspective, the occupation of interest may be forced to take a pay cut in an occupational transition, because they are currently paid relatively well. In red MSAs, the occupation of interest earns less than the similar occupations in the comparison (and may be able to make a wage-increasing occupation transition).

Percentage Wage Premium Demanded by “Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic” (51-4031) When Compared to Jobs with Skill Similarity>=0.7 and >=0.9



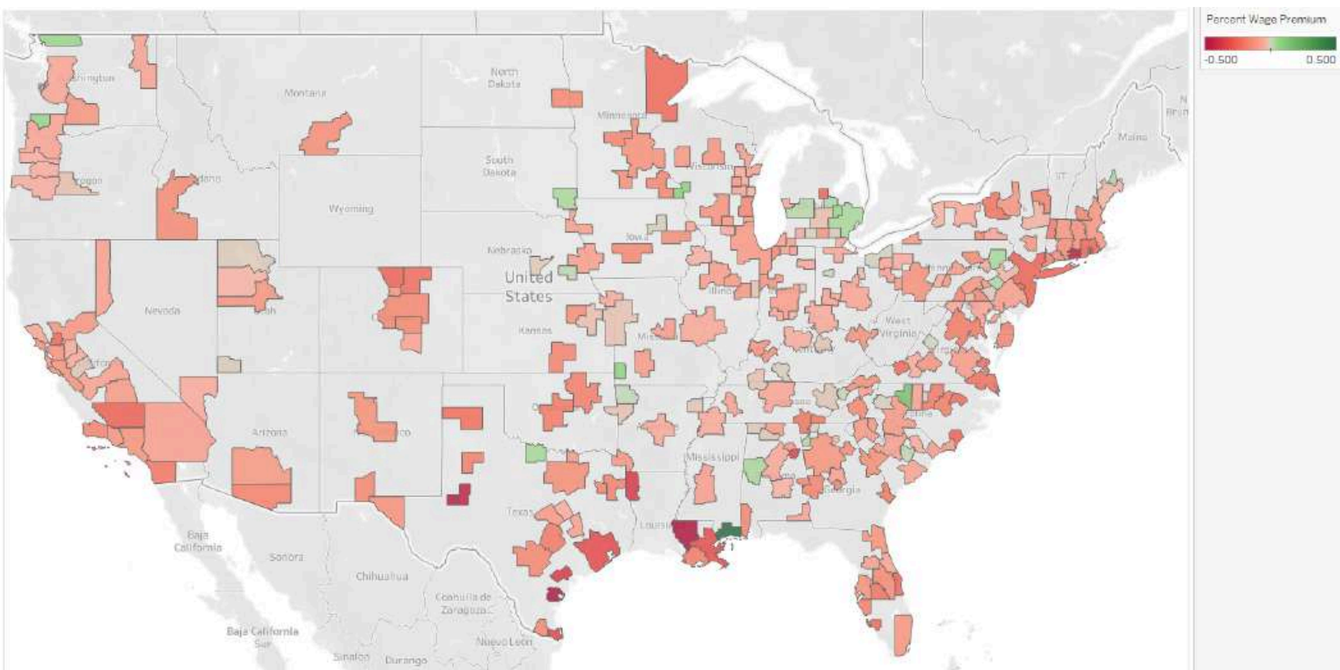
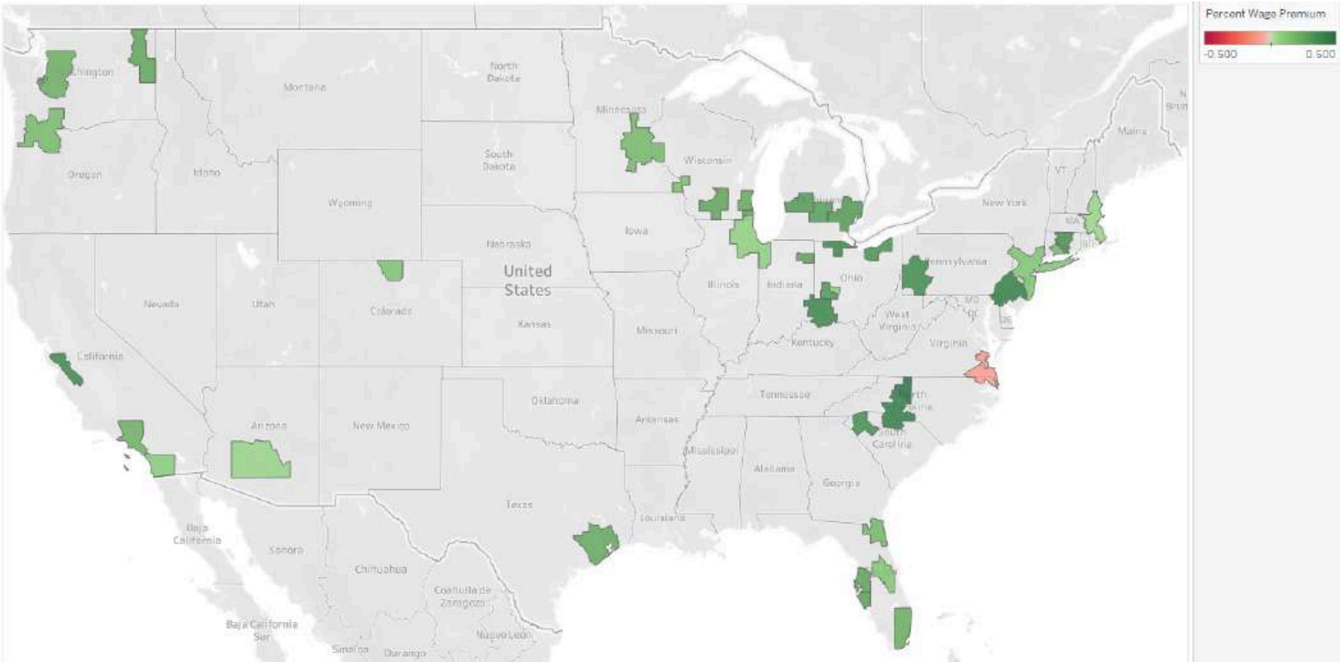


Figure C.24: Local wage premium demanded by workers in occupation 51-4031 “Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic” when compared to workers in alternative occupations. The first map shows comparisons against jobs with skill similarity >= 0.7. The second map shows comparisons against jobs with skill similarity >= 0.9. Broadly, 51-4031 employees earn more than most occupations nationally with 0.7 similarity. They earn less than most occupations with a 0.9 similarity.

Percentage Wage Premium Demanded by “Engine and Other Machine Assemblers” (51-2031) When Compared to Jobs with Skill Similarity>=0.7 and >=0.9



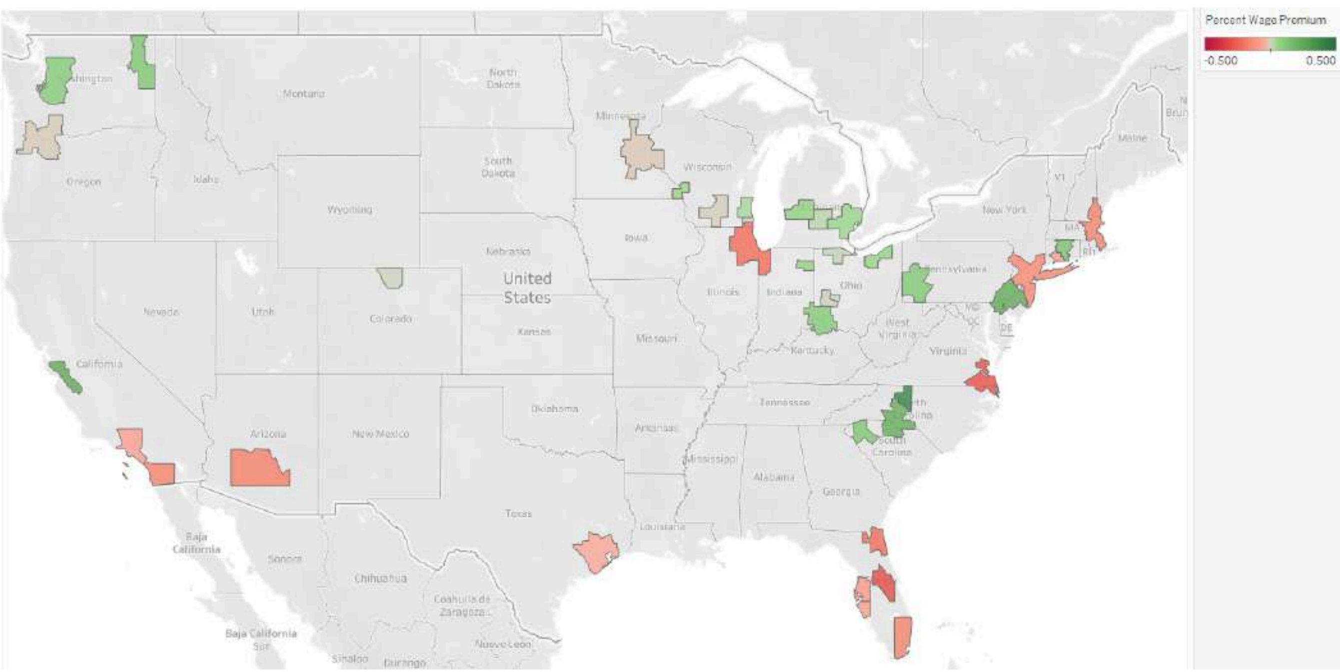
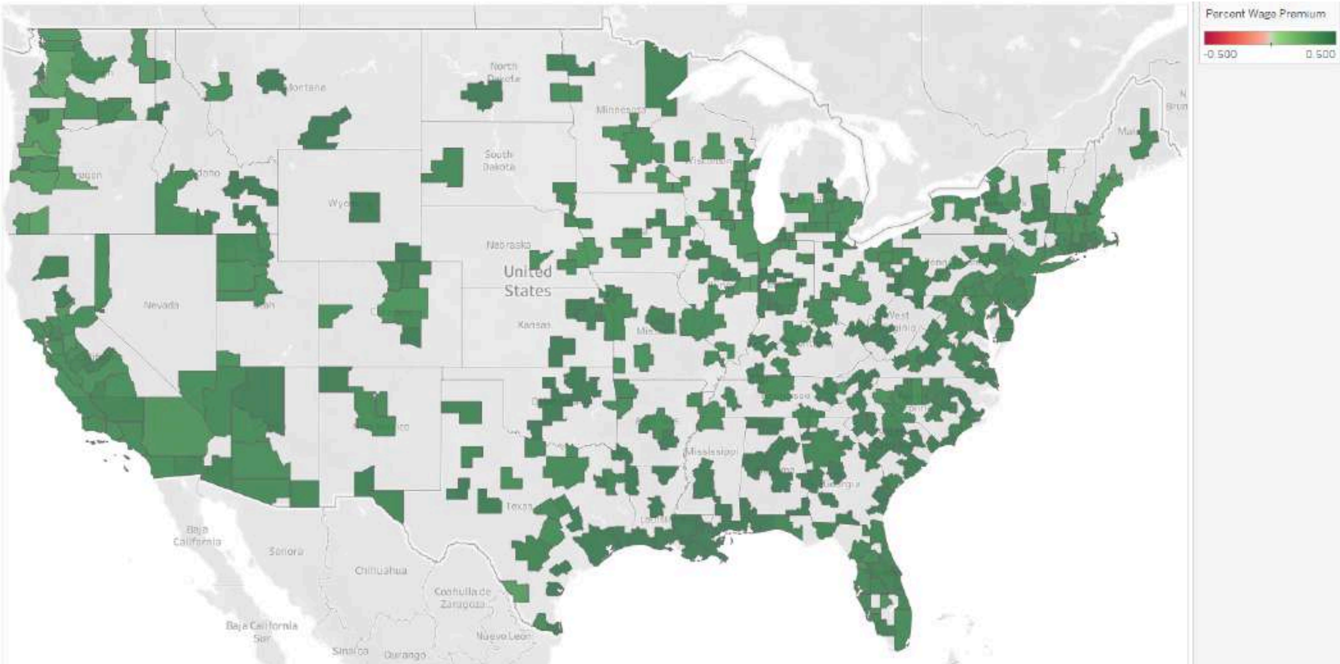


Figure C.25: Local wage premium demanded by workers in occupation 51-2031 “Engine and Other Machine Assemblers” when compared to workers in alternative occupations. The first map shows comparisons against jobs with skill similarity >= 0.7. The second map shows comparisons against jobs with skill similarity >= 0.9. Broadly, 51-2031 employees earn more than most occupations nationally with 0.7 similarity. The comparison is more even when looking at occupations with a 0.9 similarity score.

Percentage Wage Premium Demanded by “First-Line Supervisors of Production and Operating Workers” (51-1011) When Compared to Jobs with Skill Similarity>=0.7 and >=0.9



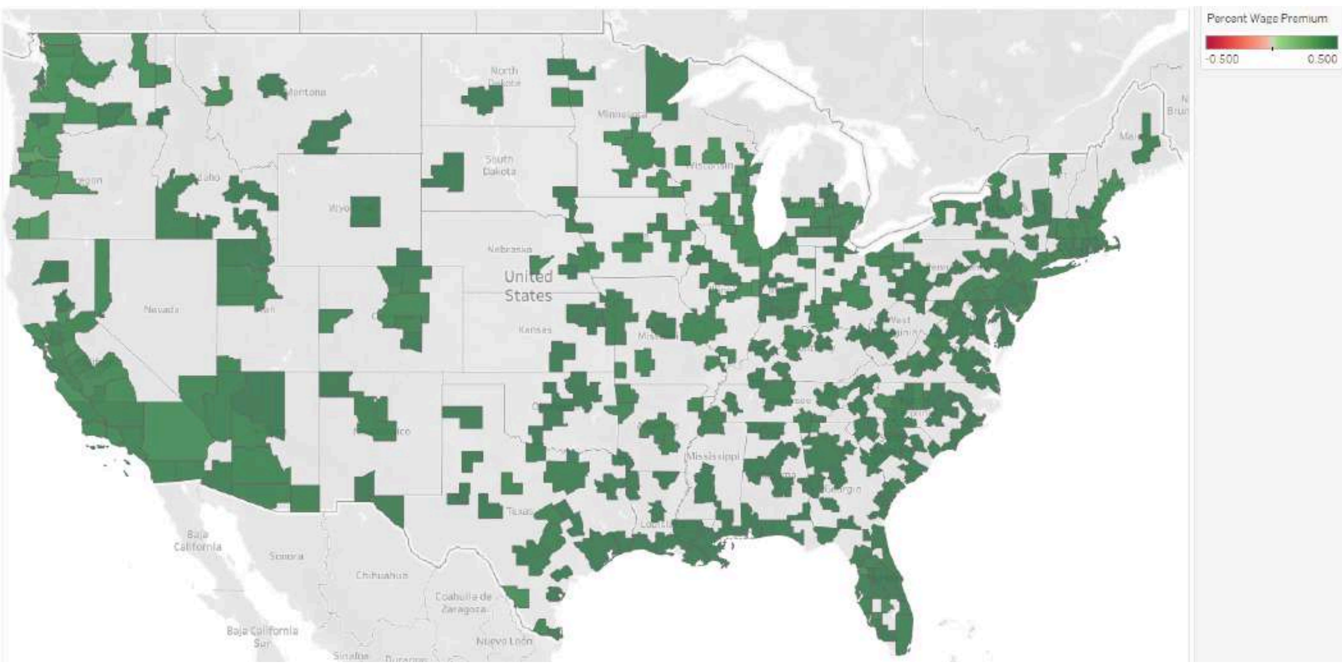


Figure C.26: Local wage premium demanded by workers in occupation 51-1011 “First-Line Supervisors of Production and Operating Workers” when compared to workers in alternative occupations. The first map shows comparisons against jobs with skill similarity >= 0.7. The second map shows comparisons against jobs with skill similarity >= 0.9. 51-1011 workers earn more than their comparison occupations at both similarity scores.

Percentage Wage Premium Demanded by “Inspectors, Testers, Sorters, Samplers, and Weighers” (51-9061) When Compared to Jobs with Skill Similarity>=0.7 and >=0.9

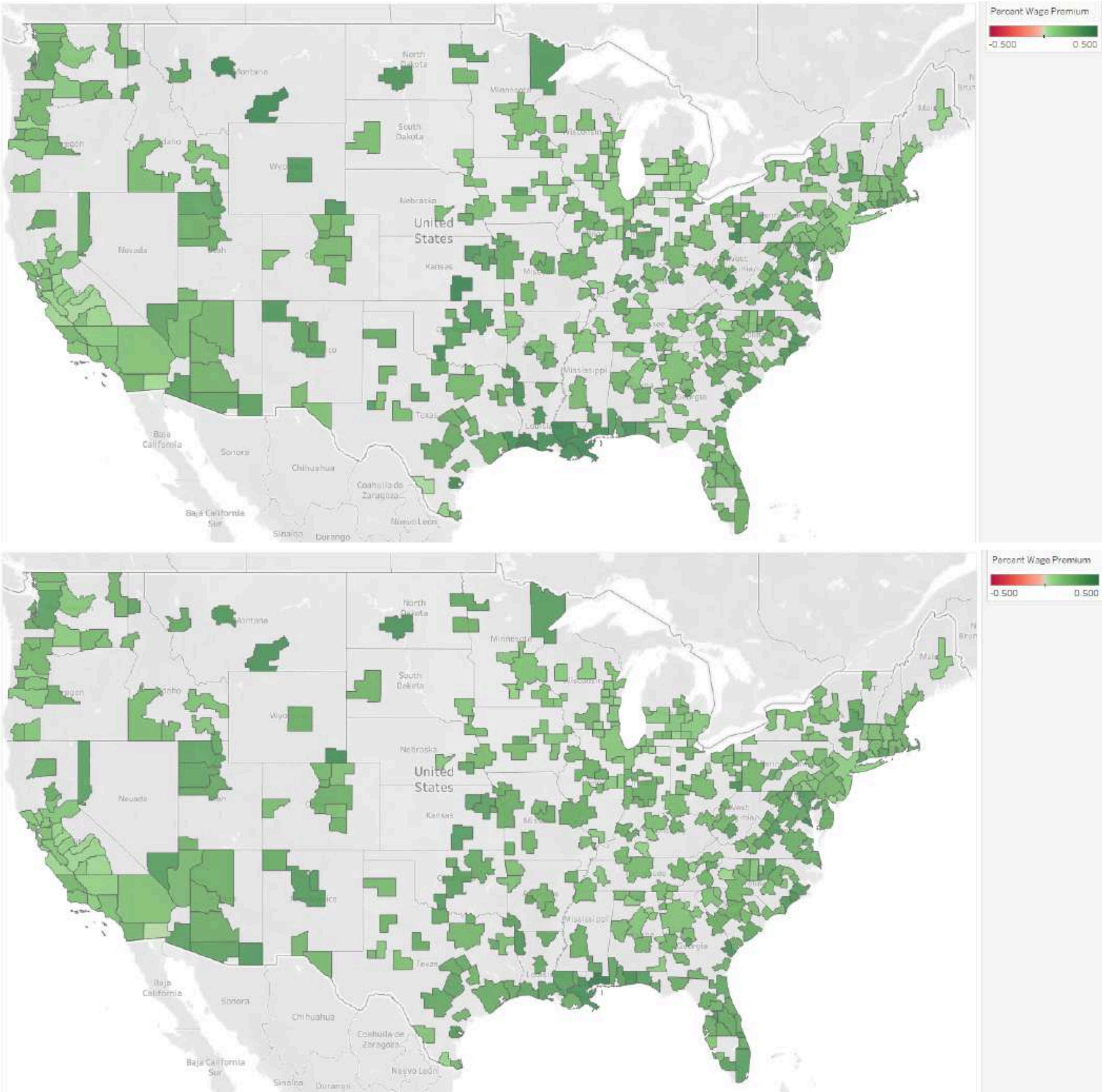


Figure C.27: Local wage premium demanded by workers in occupation 51-9061 “Inspectors, Testers, Sorters, Samplers, and Weighers” when compared to workers in alternative occupations. The first map shows comparisons against jobs with skill similarity >= 0.7. The second map shows comparisons against jobs with skill similarity >= 0.9. 51-9061 workers earn more than their comparison occupations at both similarity scores.

Percentage Wage Premium Demanded by "Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic" (51-4081) When Compared to Jobs with Skill Similarity>=0.7 and >=0.9

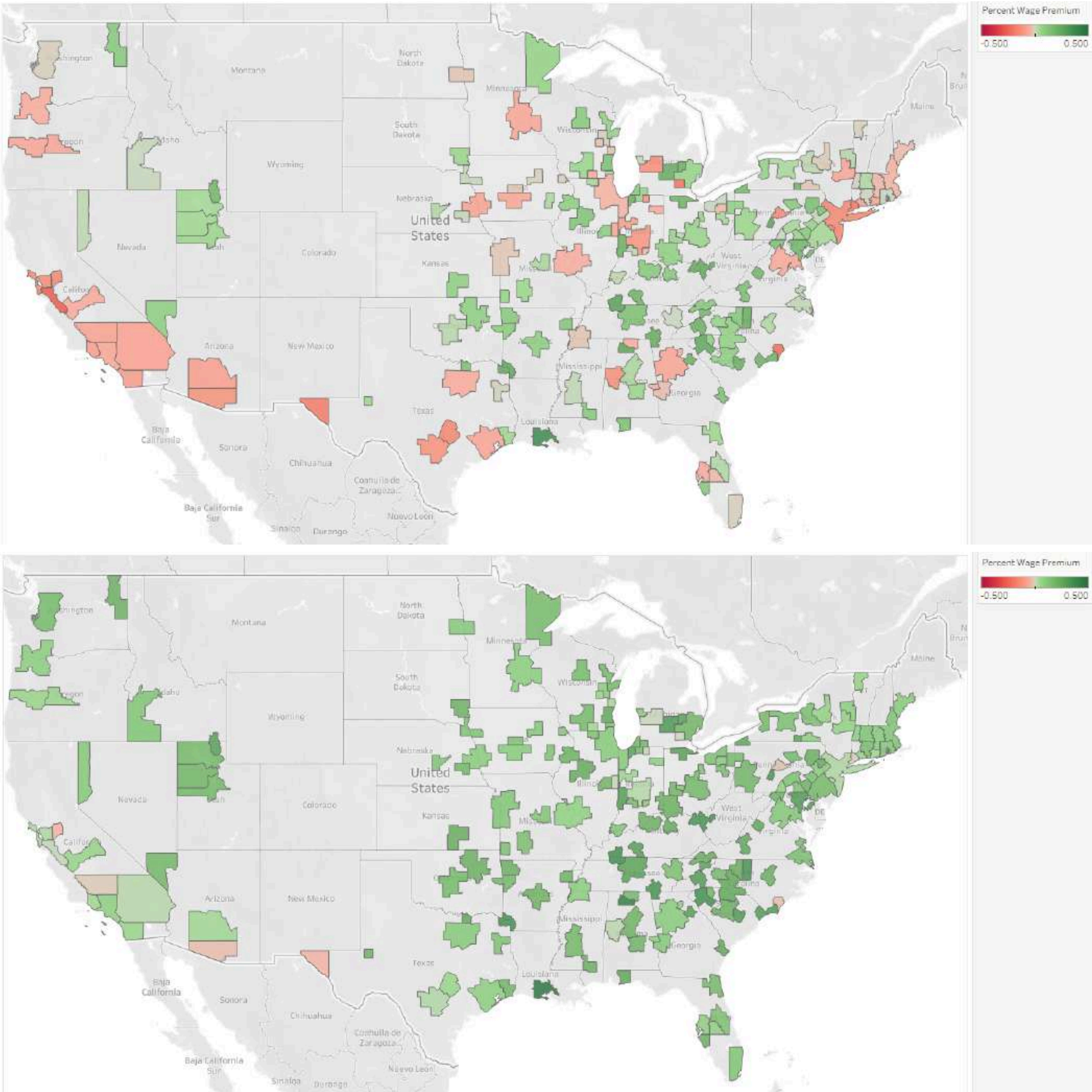
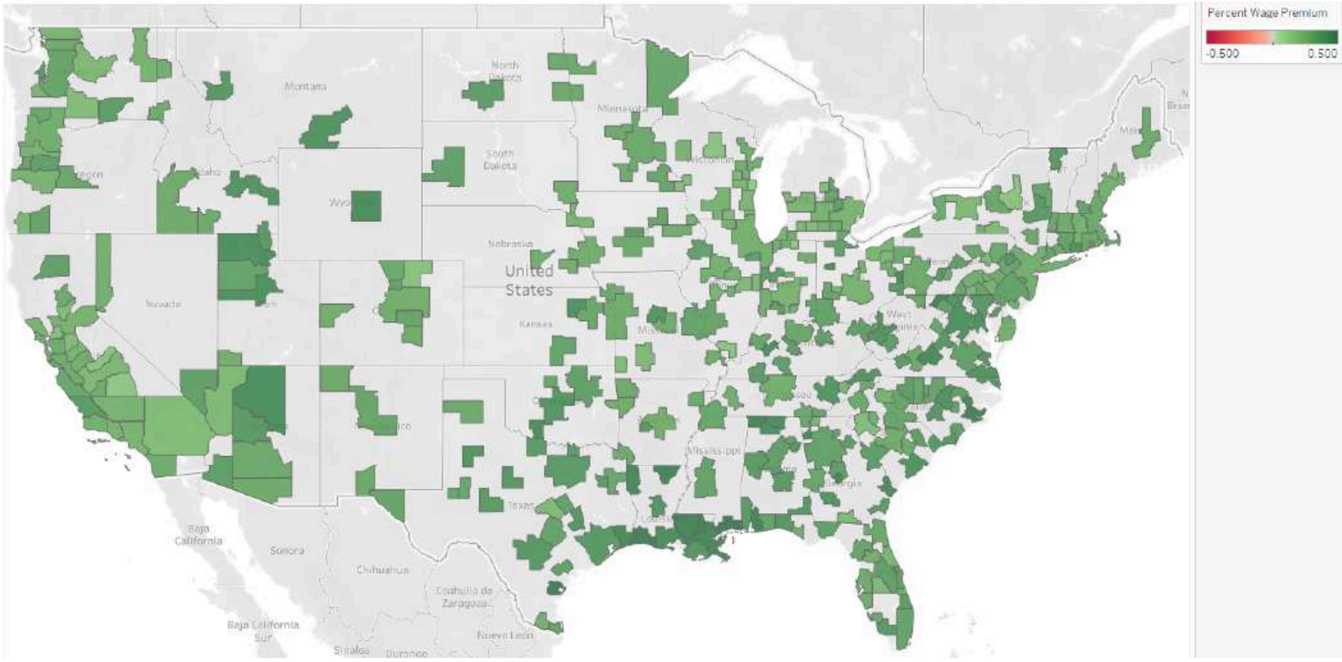


Figure C.28: Local wage premium demanded by workers in occupation 51-4081 "Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic" when compared to workers in alternative occupations. The first map shows comparisons against jobs with skill similarity >= 0.7. The second map shows comparisons against jobs with skill similarity >= 0.9. 51-4081 workers have a heterogenous national earnings comparison at the 0.7 similarity score. They earn more than their comparison occupations at the 0.9 similarity cut point.

Percentage Wage Premium Demanded by "Machinists" (51-4041) When Compared to Jobs with Skill Similarity>=0.7 and >=0.9



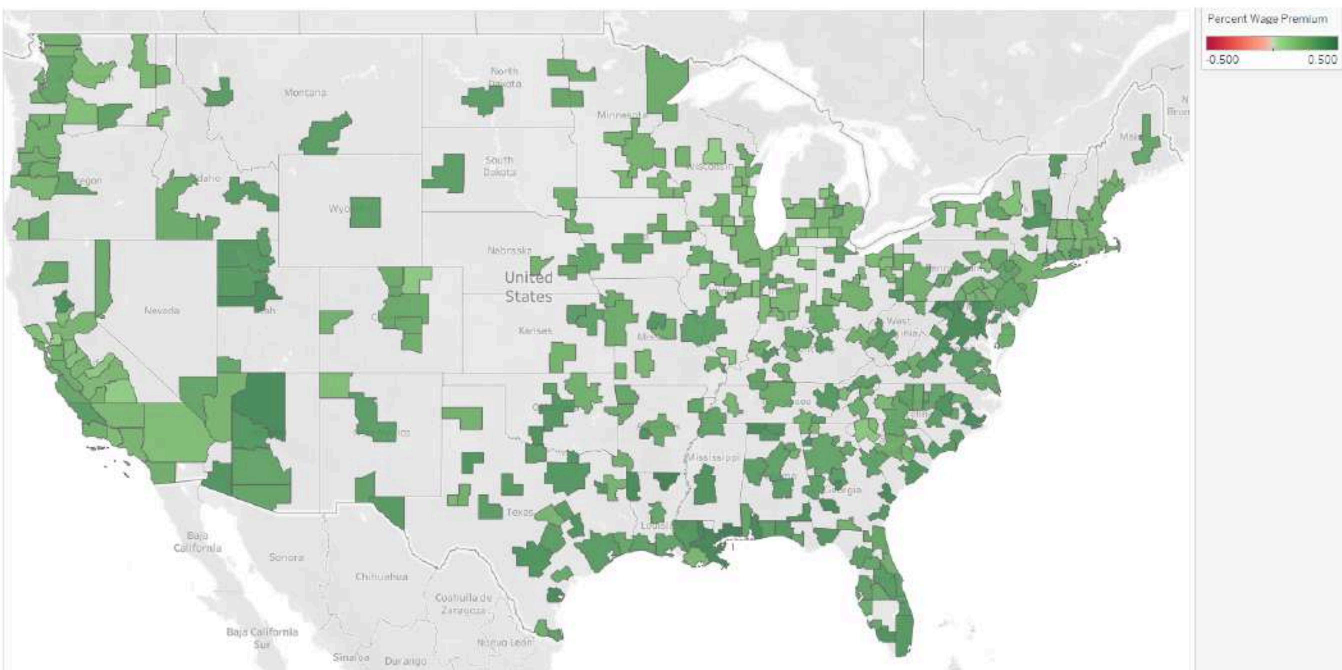


Figure C.29: Local wage premium demanded by workers in occupation 51-4041 "Machinists" when compared to workers in alternative occupations. The first map shows comparisons against jobs with skill similarity >= 0.7. The second map shows comparisons against jobs with skill similarity >= 0.9. 51-4041 workers earn more than their comparison occupations at both similarity scores.

Percentage Wage Premium Demanded by “Welders, Cutters, Solderers, and Brazers” (51-4121) When Compared to Jobs with Skill Similarity>=0.7 and >=0.9

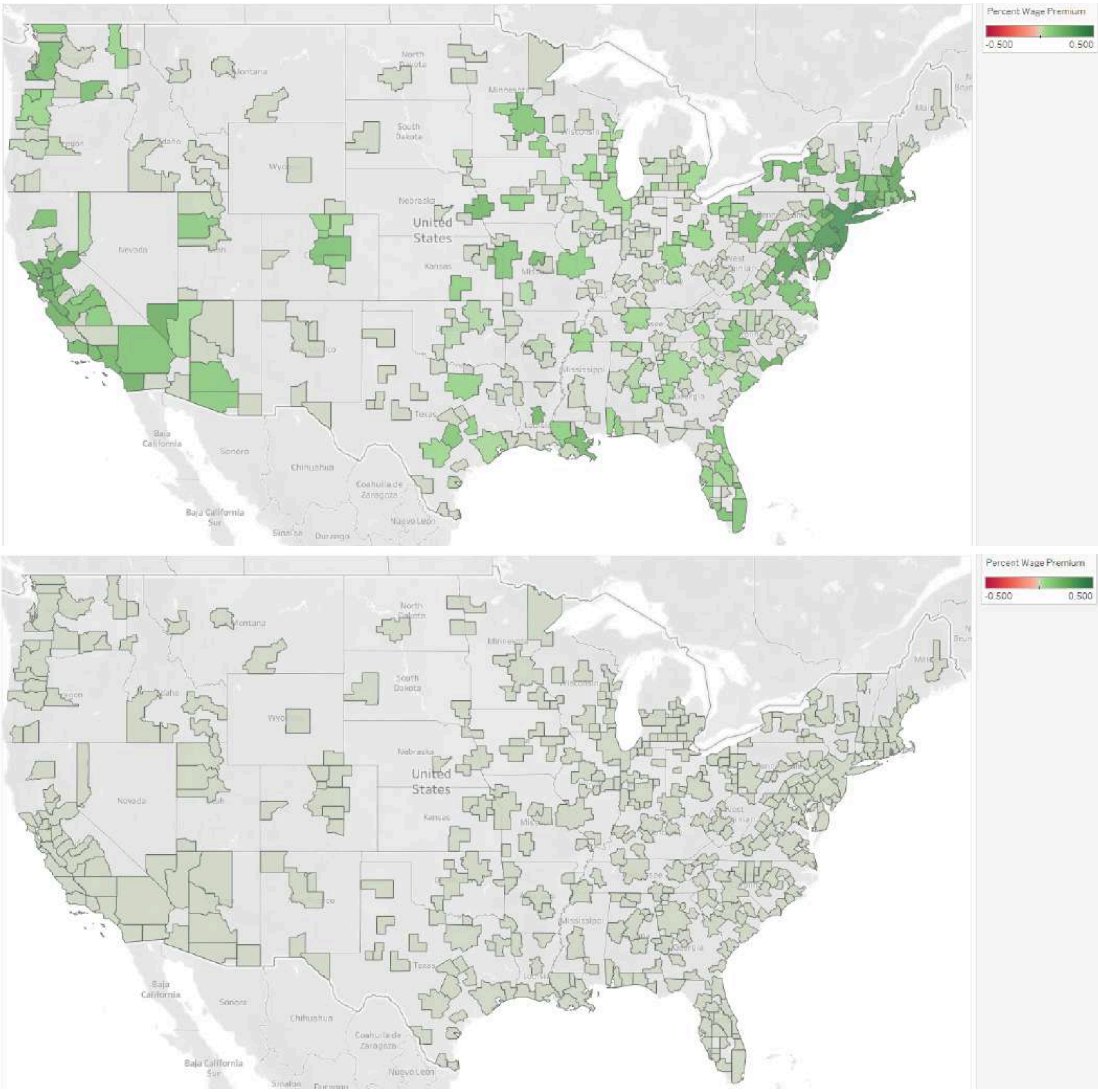
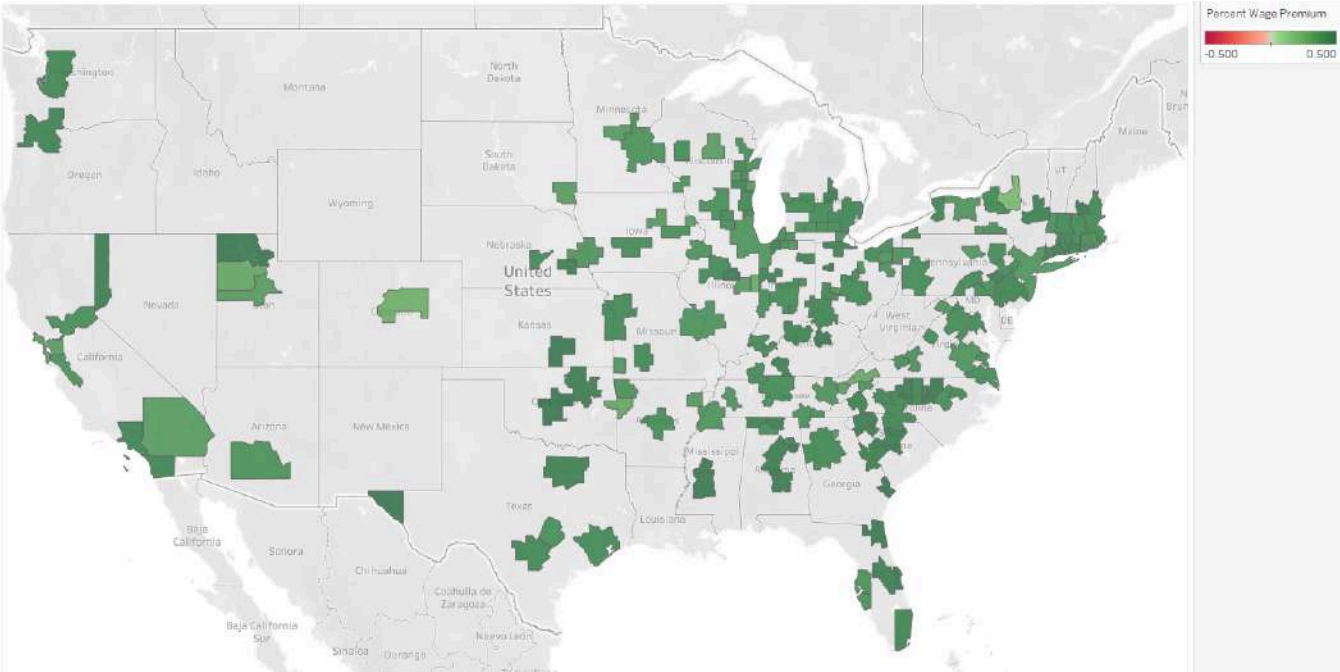


Figure C.30: Local wage premium demanded by workers in occupation 51-4121 “Welders, Cutters, Solderers, and Brazers” when compared to workers in alternative occupations. The first map shows comparisons against jobs with skill similarity >= 0.7. The second map shows comparisons against jobs with skill similarity >= 0.9. The second figure is uniform because there are no occupations with similarity >=0.9 when compared to 51-4121 (Welders, Cutters, Solderers, and Brazers). 51-4121 workers earn more than their comparison occupations at the lower similarity score.

Percentage Wage Premium Demanded by "Tool and Die Makers" (51-4111) When Compared to Jobs with Skill Similarity>=0.7 and >=0.9



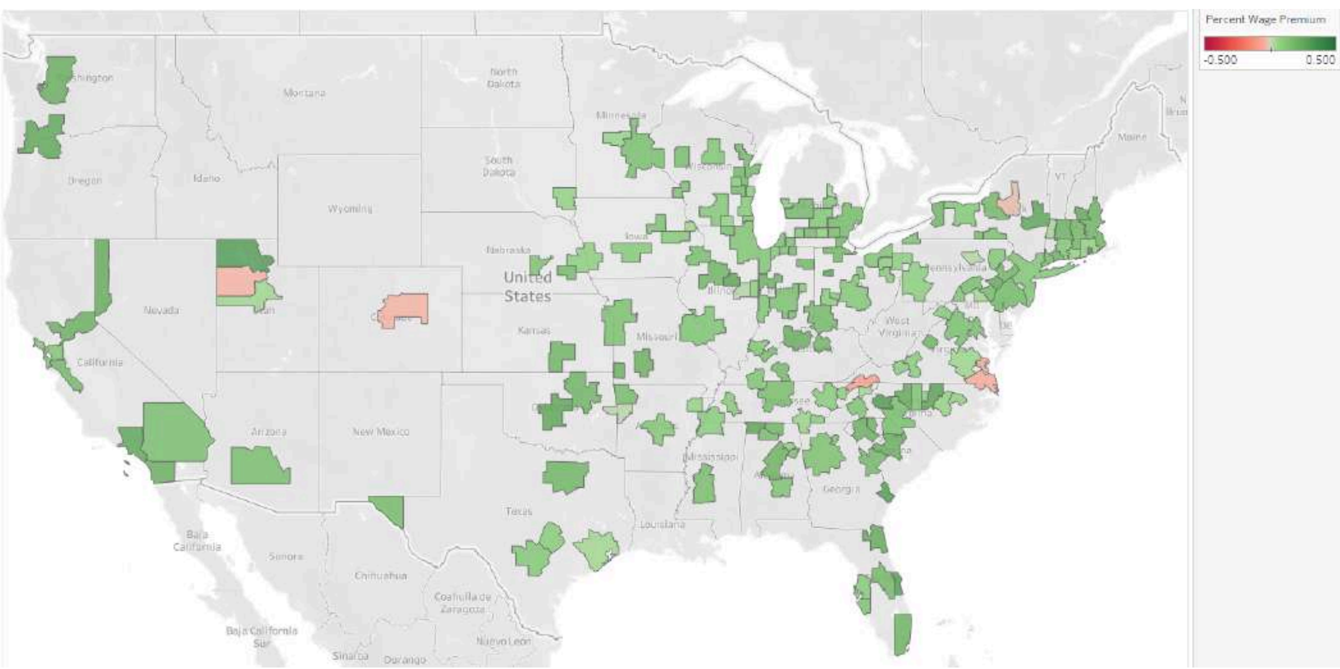


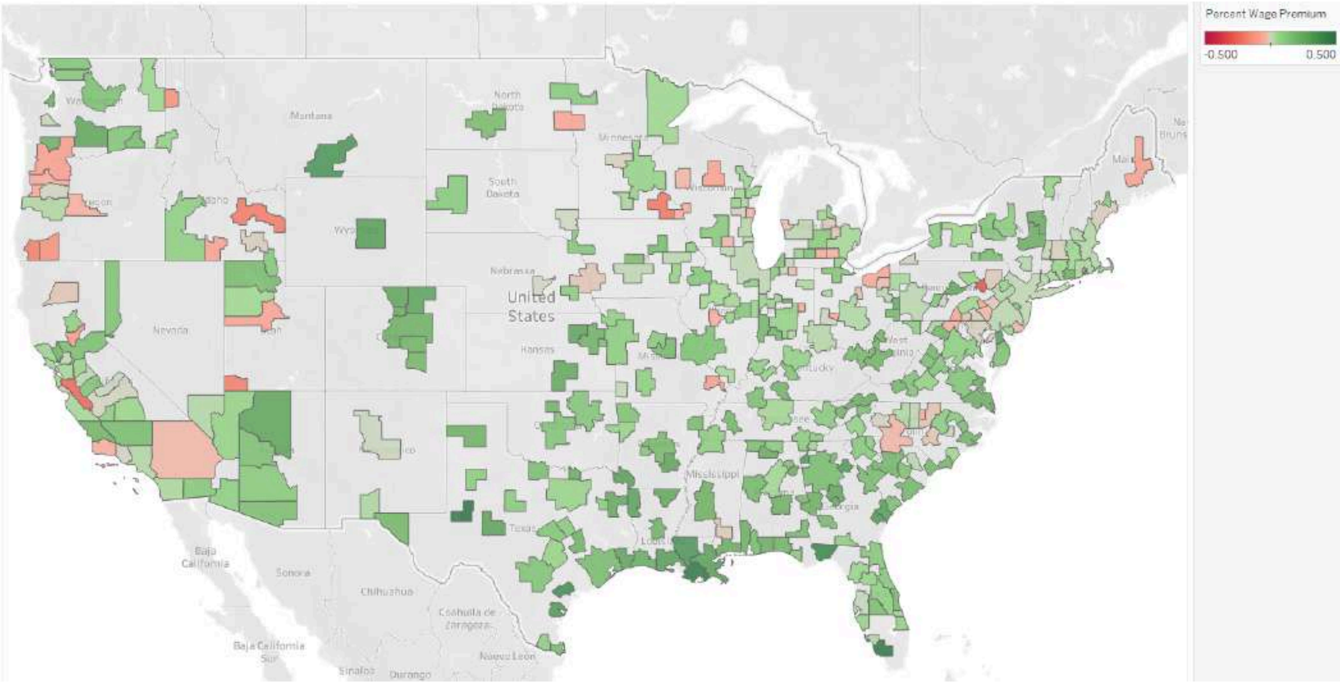
Figure C.31: Local wage premium demanded by workers in occupation 51-4111 "Tool and Die Makers" when compared to workers in alternative occupations. The first map shows comparisons against jobs with skill similarity >= 0.7. The second map shows comparisons against jobs with skill similarity >= 0.9. 51-4111 workers earn more than their comparison occupations at both similarity scores.

5. Wage Premium Figures (EV, Battery, and HST)

The figures following this page, **Figure C.32 - C.38**, depict the wage premium demanded by EV, Battery, and HST workers when compared to those in similar occupations. Similarity is directional, and for these figures that direction is *to* our occupation of interest *from* the similar occupations. The first map shows comparisons against jobs with skill similarity >= 0.7. The second map shows comparisons against jobs with skill similarity >= 0.9. As with the previous relative wage comparisons, the comparison here is reversed from the previous section for ICEV employees. We are asking here “what occupations can fill future EV, Battery, and HST positions (with their current skills), and what is the wage premium they can expect in that transition?”.

While the color coding remains the same as previous wage premium figures, the implication is reversed (as in the relative wage position figures). In a green MSA (where the occupation of interest earns a premium over its similar occupations), potential EV, Battery, and HST jobs may pay more than similar occupations, representing a wage-increasing opportunity. In red MSAs, there may be fewer opportunities to increase one’s wages when moving into the EV, Battery, and HST occupations of interest. We might expect these results to be roughly symmetric to the previous section.

Percentage Wage Premium Demanded by "Industrial Production Managers" (11-3051) When Compared to Jobs with Skill Similarity>=0.7 and >=0.9



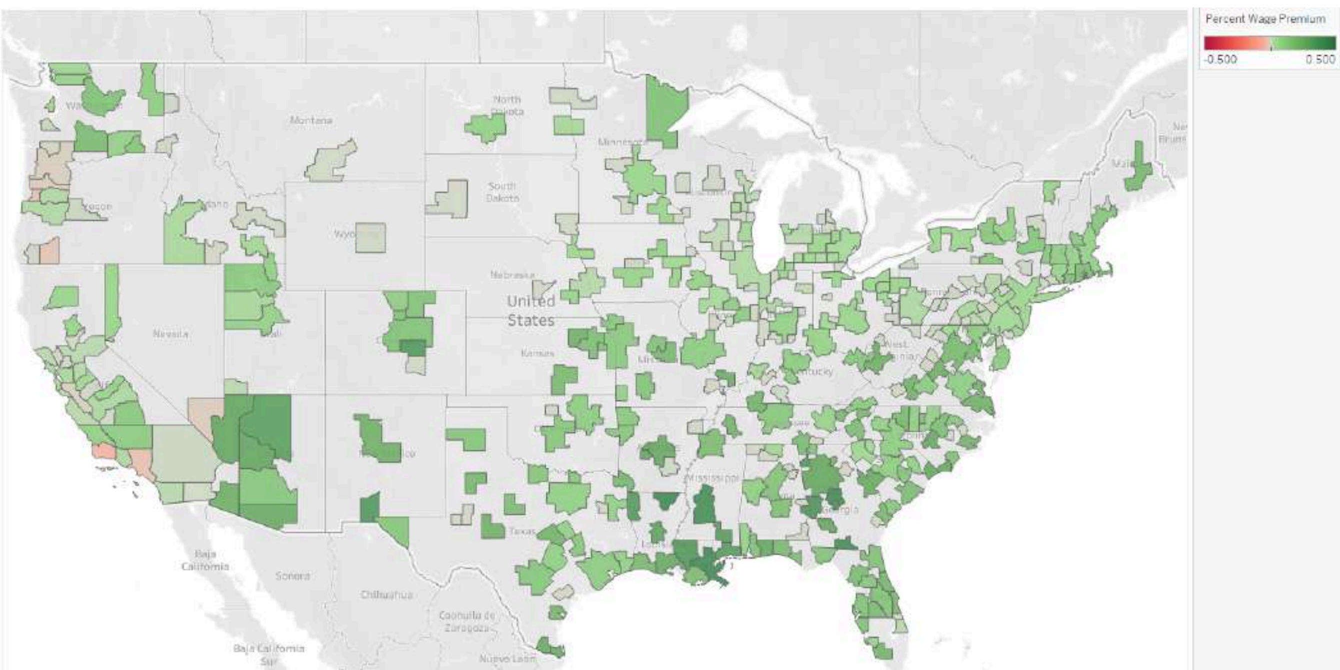
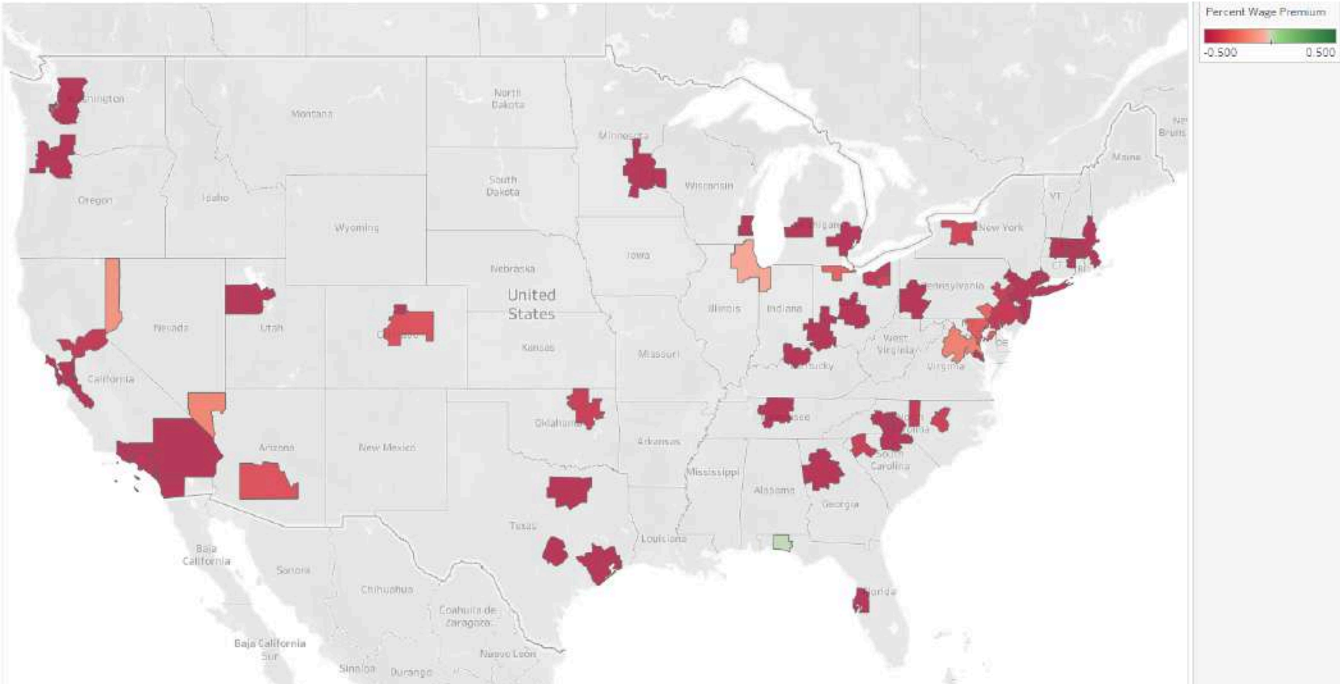


Figure C.32: Local wage premium demanded by workers in occupation 11-3051 "Industrial Production Managers" when compared to workers in alternative occupations. The first map shows comparisons against jobs with skill similarity >= 0.7. The second map shows comparisons against jobs with skill similarity >= 0.9. 11-3051 workers earn more than their comparison occupations at both similarity scores.

Percentage Wage Premium Demanded by "Electro-Mechanical and Mechatronics Technologists and Technicians" (17-3024) When Compared to Jobs with Skill Similarity>=0.7 and >=0.9



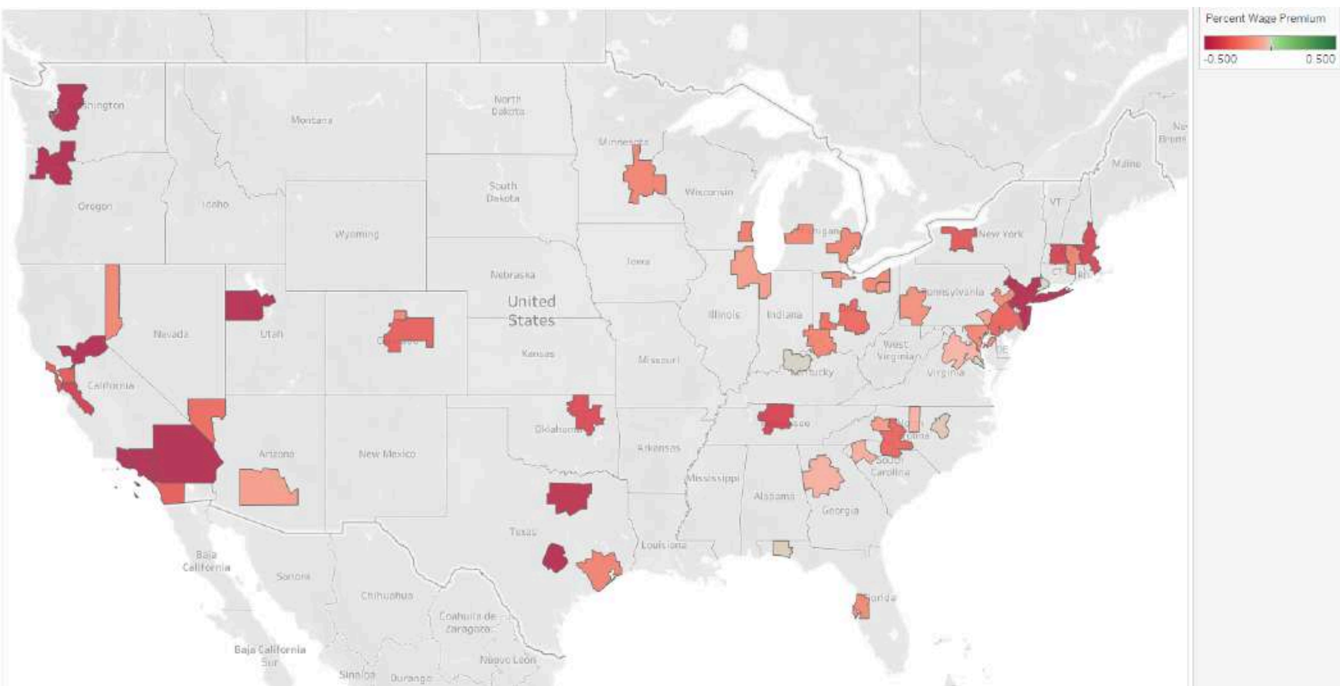
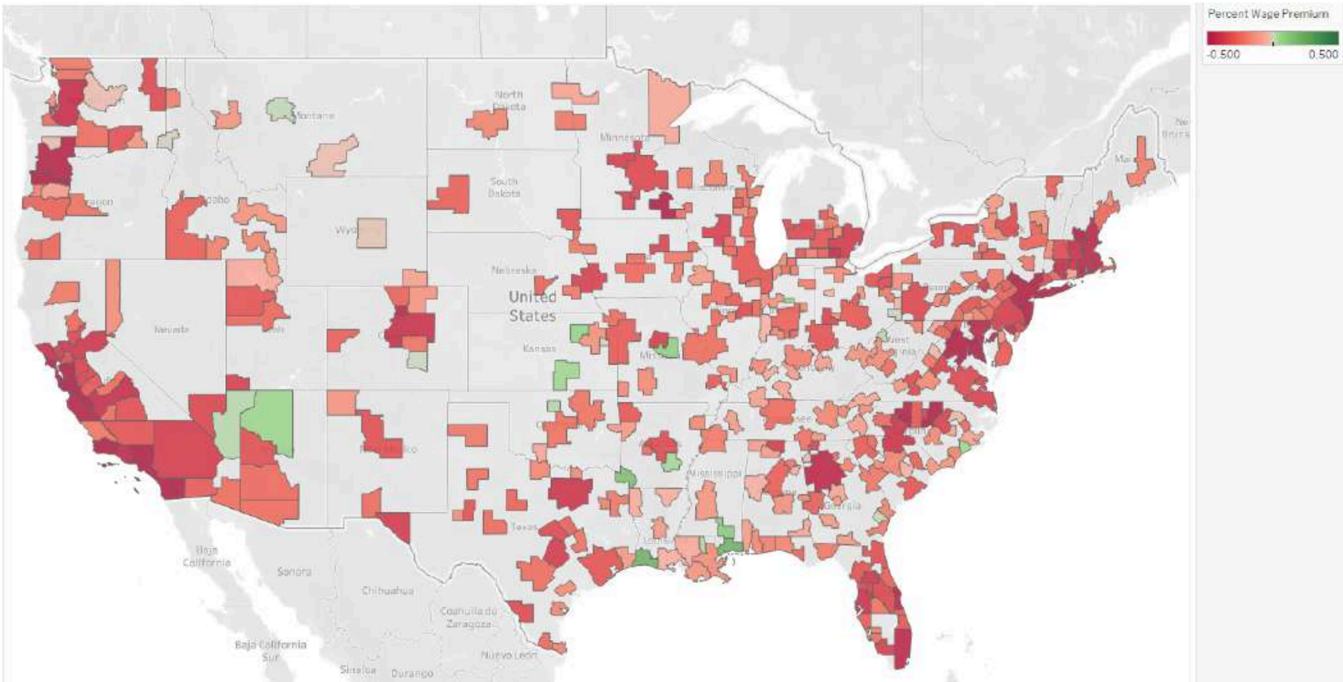


Figure C.33: Local wage premium demanded by workers in occupation 17-3024 "Electro-Mechanical and Mechatronics Technologists and Technicians" when compared to workers in alternative occupations. The first map shows comparisons against jobs with skill similarity >= 0.7. The second map shows comparisons against jobs with skill similarity >= 0.9. 17-3024 workers earn less than their comparison occupations at both similarity scores.

Percentage Wage Premium Demanded by "Industrial Machinery Mechanics" (49-9041) When Compared to Jobs with Skill Similarity>=0.7 and >=0.9



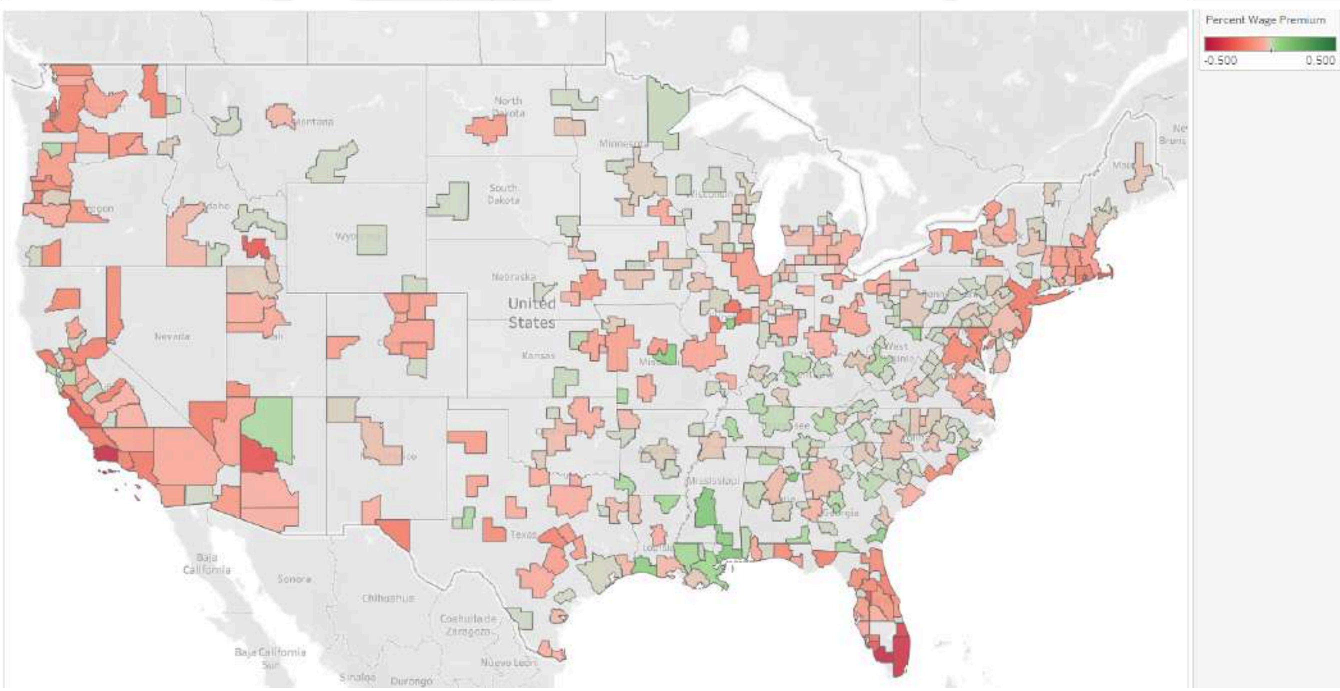


Figure C.34: Local wage premium demanded by workers in occupation 49-9041 "Industrial Machinery Mechanics" when compared to workers in alternative occupations. The first map shows comparisons against jobs with skill similarity >= 0.7. The second map shows comparisons against jobs with skill similarity >= 0.9. 49-9041 workers earn less than their comparison occupations at the lower similarity score. They are more regionally variable at the 0.9 similarity score.

Percentage Wage Premium Demanded by "Engine and Other Machine Assemblers" (51-2031) When Compared to Jobs with Skill Similarity>=0.7 and >=0.9

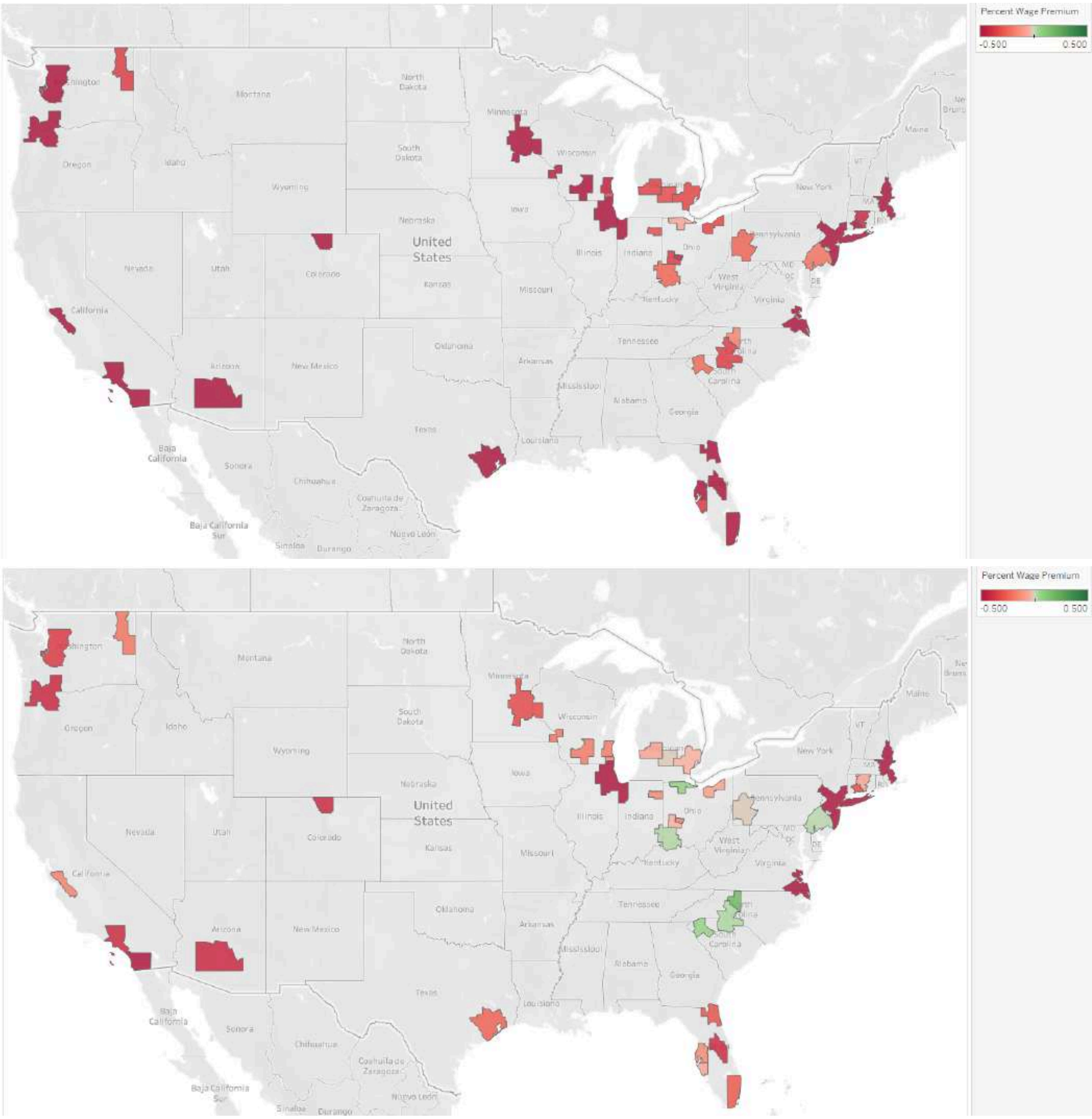


Figure C.35: Local wage premium demanded by workers in occupation 51-2031 "Engine and Other Machine Assemblers" when compared to workers in alternative occupations. The first map shows comparisons against jobs with skill similarity >= 0.7. The second map shows comparisons against jobs with skill similarity >= 0.9. 51-2031 workers earn less than their comparison occupations at both similarity scores, with a few exceptions in the Rust Belt and Mid Atlantic regions.

Percentage Wage Premium Demanded by “Machinists” (51-4041) When Compared to Jobs with Skill Similarity>=0.7 and >=0.9

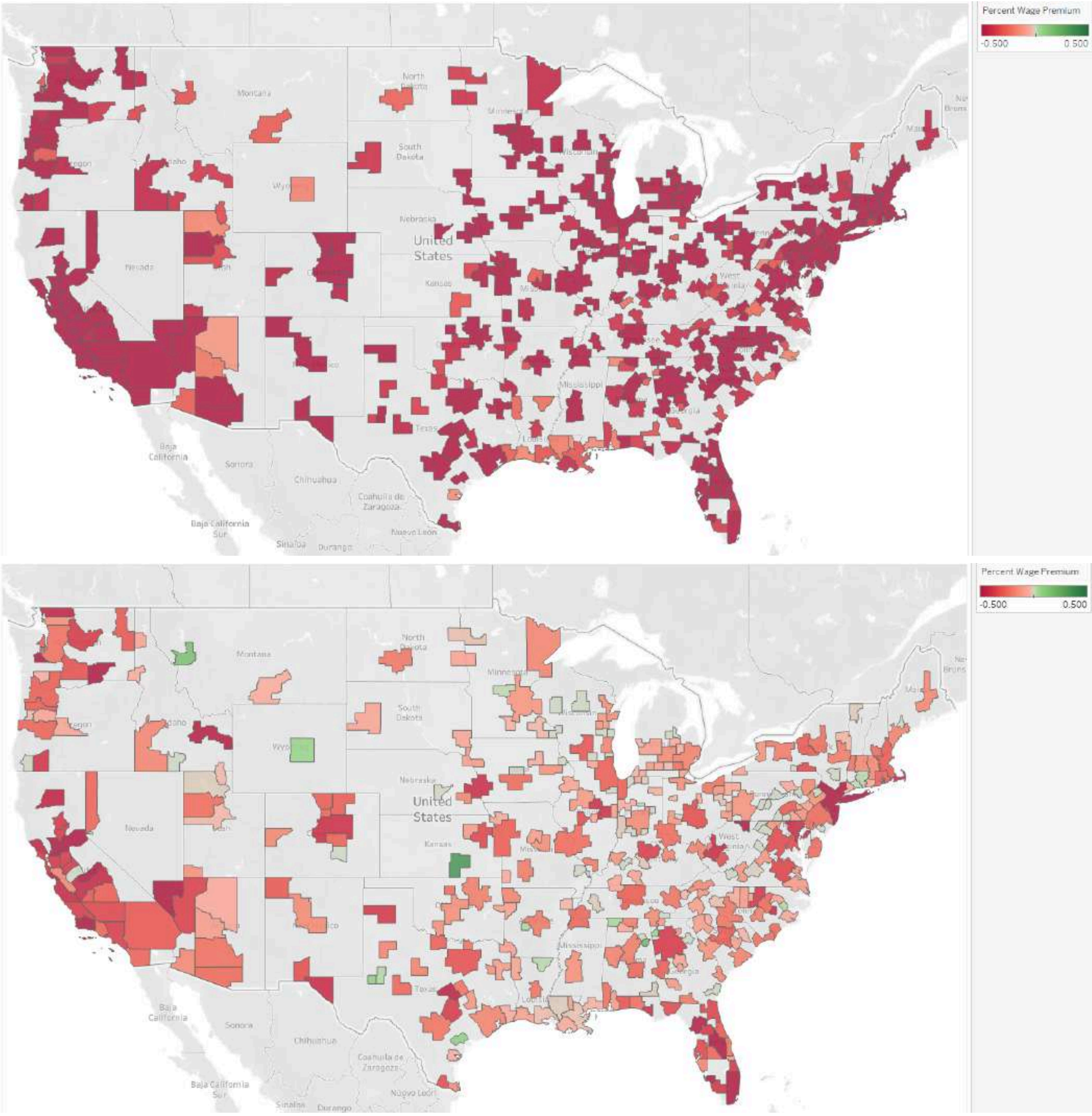


Figure C.36: Local wage premium demanded by workers in occupation 51-4041 “Machinists” when compared to workers in alternative occupations. The first map shows comparisons against jobs with skill similarity >= 0.7. The second map shows comparisons against jobs with skill similarity >= 0.9. 51-4041 workers earn less than their comparison occupations at both similarity scores.

Percentage Wage Premium Demanded by "Welders, Cutters, Solderers, and Brazers" (51-4121) When Compared to Jobs with Skill Similarity>=0.7 and >=0.9

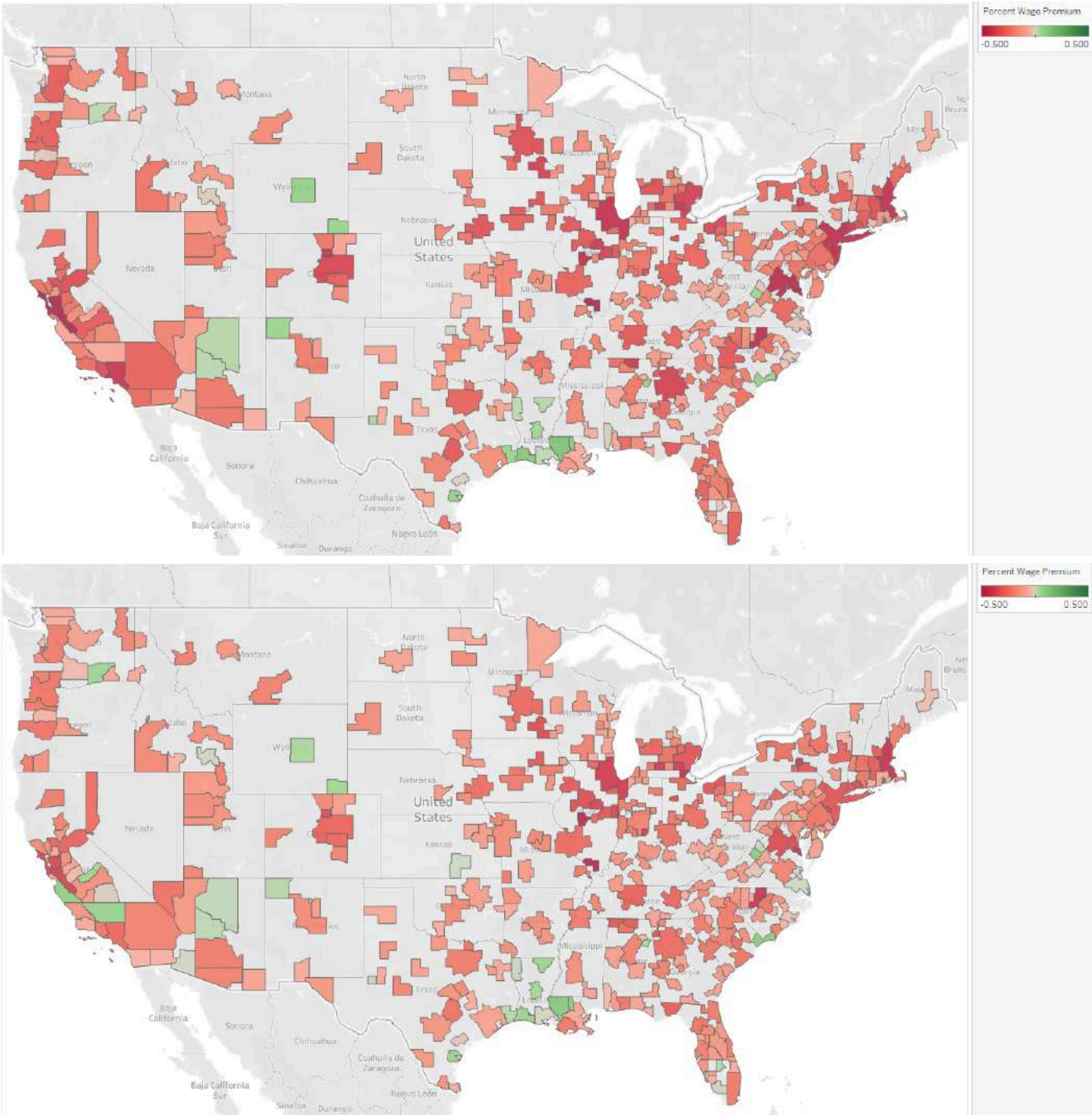


Figure C.37: Local wage premium demanded by workers in occupation 51-4121 "Welders, Cutters, Solderers, and Brazers" when compared to workers in alternative occupations. The first map shows comparisons against jobs with skill similarity >= 0.7. The second map shows comparisons against jobs with skill similarity >= 0.9. 51-4121 workers earn less than their comparison occupations at both similarity scores, with a few regional exceptions.

Percentage Wage Premium Demanded by "Computer Numerically Controlled Tool Operators" (51-9161) When Compared to Jobs with Skill Similarity>=0.7 and >=0.9

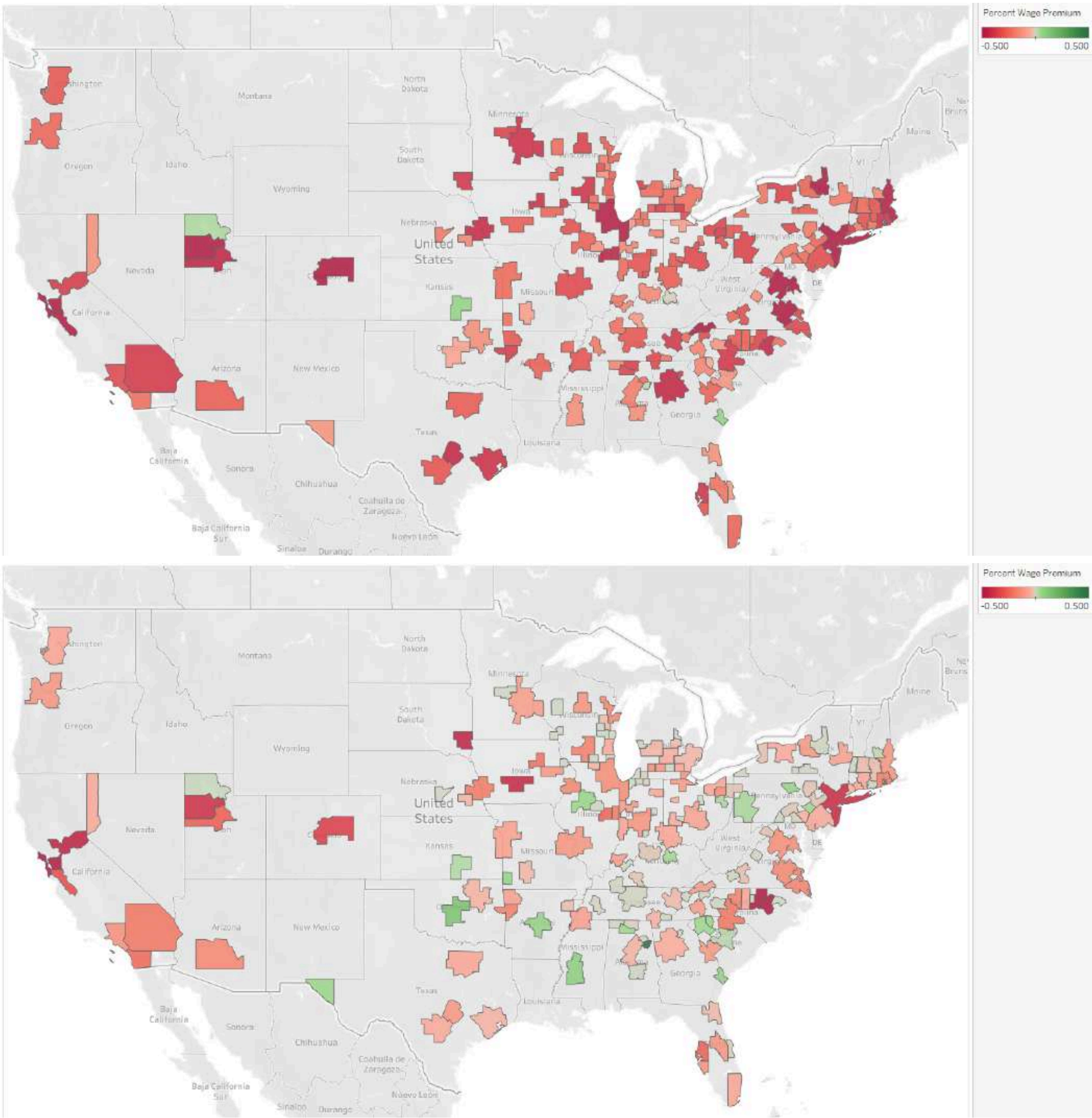


Figure C.38: Local wage premium demanded by workers in occupation 51-9161 "Computer Numerically Controlled Tool Operators" when compared to workers in alternative occupations. The first map shows comparisons against jobs with skill similarity >= 0.7. The second map shows comparisons against jobs with skill similarity >= 0.9. 51-9161 workers earn less than their comparison occupations at the 0.7 similarity score. The picture is more mixed at the higher similarity score cut point.

6. Wage-Weighted Labor Supply Logic

Logic: Wage-Weighted Labor Supply

IF 10th Percentile Related Wage >= Occupation of Interest’s Average Wage THEN [Tot Emp]*0.90
ELSEIF 25th Percentile Related Wage >= Occupation of Interest’s Average Wage THEN [Tot Emp]*0.75
ELSEIF 50th Percentile Related Wage >= Occupation of Interest’s Average Wage THEN [Tot Emp]*0.50
ELSEIF 75th Percentile Related Wage >= Occupation of Interest’s Average Wage THEN [Tot Emp]*0.25
ELSEIF 90th Percentile Related Wage >= Occupation of Interest’s Average Wage THEN [Tot Emp]*0.10
ELSE 0 END

Logic: Relative Wage Position

Plotted values are:

```
(SUM([Occ_of_Interest (>=10th)])*.1+
SUM([Occ_of_Interest (>=25th)])*.15+
SUM([Occ_of_Interest (>=A Median)])*.25+
SUM([Occ_of_Interest (>=75th)])*.25+
SUM([Occ_of_Interest (>=90th)])*.15)
/((sum([Tot Emp])-SUM([Occ_of_Interest (Tot Emp)]))*.9)
```

Where [Occ_of_Interest (>=10th)] is defined as:
IF [Occupation of Interest] = [Occ Code] THEN 0
ELSEIF [A Pct10] >= { FIXED [Area Title]:MAX([Occ_of_Interest (10th)])} THEN [Tot Emp]*.9
ELSEIF [A Pct25] >= { FIXED [Area Title]:MAX([Occ_of_Interest (10th)])} THEN [Tot Emp]*.75
ELSEIF [A Median]>= { FIXED [Area Title]:MAX([Occ_of_Interest (10th)])} THEN [Tot Emp]*.50
ELSEIF [A Pct75] >= { FIXED [Area Title]:MAX([Occ_of_Interest (10th)])} THEN [Tot Emp]*.25
ELSEIF [A Pct90] >= { FIXED [Area Title]:MAX([Occ_of_Interest (10th)])} THEN [Tot Emp]*.10
ELSE 0 END

[Occ_of_Interest (>=25th)] is defined as:
IF [Occupation of Interest] = [Occ Code] THEN 0
ELSEIF [A Pct10] >= { FIXED [Area Title]:MAX([Occ_of_Interest (25th)])} THEN [Tot Emp]*.9
ELSEIF [A Pct25] >= { FIXED [Area Title]:MAX([Occ_of_Interest (25th)])} THEN [Tot Emp]*.75
ELSEIF [A Median]>= { FIXED [Area Title]:MAX([Occ_of_Interest (25th)])} THEN [Tot Emp]*.50
ELSEIF [A Pct75] >= { FIXED [Area Title]:MAX([Occ_of_Interest (25th)])} THEN [Tot Emp]*.25
ELSEIF [A Pct90] >= { FIXED [Area Title]:MAX([Occ_of_Interest (25th)])} THEN [Tot Emp]*.10
ELSE 0 END

[Occ_of_Interest (>=A Median)] is defined as:
IF [Occupation of Interest] = [Occ Code] THEN 0*.9
ELSEIF [A Pct10] >= { FIXED [Area Title]:MAX([Occ_of_Interest (A Mean)])} THEN [Tot Emp]*.9
ELSEIF [A Pct25] >= { FIXED [Area Title]:MAX([Occ_of_Interest (A Mean)])} THEN [Tot Emp]*.75
ELSEIF [A Median]>= { FIXED [Area Title]:MAX([Occ_of_Interest (A Mean)])} THEN [Tot Emp]*.50
ELSEIF [A Pct75] >= { FIXED [Area Title]:MAX([Occ_of_Interest (A Mean)])} THEN [Tot Emp]*.25
ELSEIF [A Pct90] >= { FIXED [Area Title]:MAX([Occ_of_Interest (A Mean)])} THEN [Tot Emp]*.10

ELSE 0 END

[Occ_of_Interest (>=75th)] is defined as:
IF [Occupation of Interest] = [Occ Code] THEN 0
ELSEIF [A Pct10] >= { FIXED [Area Title]:MAX([Occ_of_Interest (75th)])} THEN [Tot Emp]*.9
ELSEIF [A Pct25] >= { FIXED [Area Title]:MAX([Occ_of_Interest (75th)])} THEN [Tot Emp]*.75
ELSEIF [A Median]>= { FIXED [Area Title]:MAX([Occ_of_Interest (75th)])} THEN [Tot Emp]*.50
ELSEIF [A Pct75] >= { FIXED [Area Title]:MAX([Occ_of_Interest (75th)])} THEN [Tot Emp]*.25
ELSEIF [A Pct90] >= { FIXED [Area Title]:MAX([Occ_of_Interest (75th)])} THEN [Tot Emp]*.10
ELSE 0 END

And [Occ_of_Interest (>=90th)] is defined as:
IF [Occupation of Interest] = [Occ Code] THEN 0
ELSEIF [A Pct10] >= { FIXED [Area Title]:MAX([Occ_of_Interest (90th)])} THEN [Tot Emp]*.9
ELSEIF [A Pct25] >= { FIXED [Area Title]:MAX([Occ_of_Interest (90th)])} THEN [Tot Emp]*.75
ELSEIF [A Median]>= { FIXED [Area Title]:MAX([Occ_of_Interest (90th)])} THEN [Tot Emp]*.50
ELSEIF [A Pct75] >= { FIXED [Area Title]:MAX([Occ_of_Interest (90th)])} THEN [Tot Emp]*.25
ELSEIF [A Pct90] >= { FIXED [Area Title]:MAX([Occ_of_Interest (90th)])} THEN [Tot Emp]*.10
ELSE 0 END

All values are calculated on a per-MSA basis.

Logic: Wage Premium

To calculate the wage premium demanded by an occupation, we subtract the population weighted average annual wage from the average annual wage of our occupation of interest, and then divide that value by the average annual wage of our occupation of interest.

(sum([Occ_of_Interest (A Mean)])-
SUM([A_Mean*Tot_Emp])/SUM([Tot Emp]))
/sum([Occ_of_Interest (A Mean)])

Appendix D: Supporting Figures & Logic, MSA-Wage Distributions Alternative Occupations

Distribution of Annual Wages of "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) and Jobs with Similarity>=0.7, >=0.8, and >=0.9 in the Detroit MSA

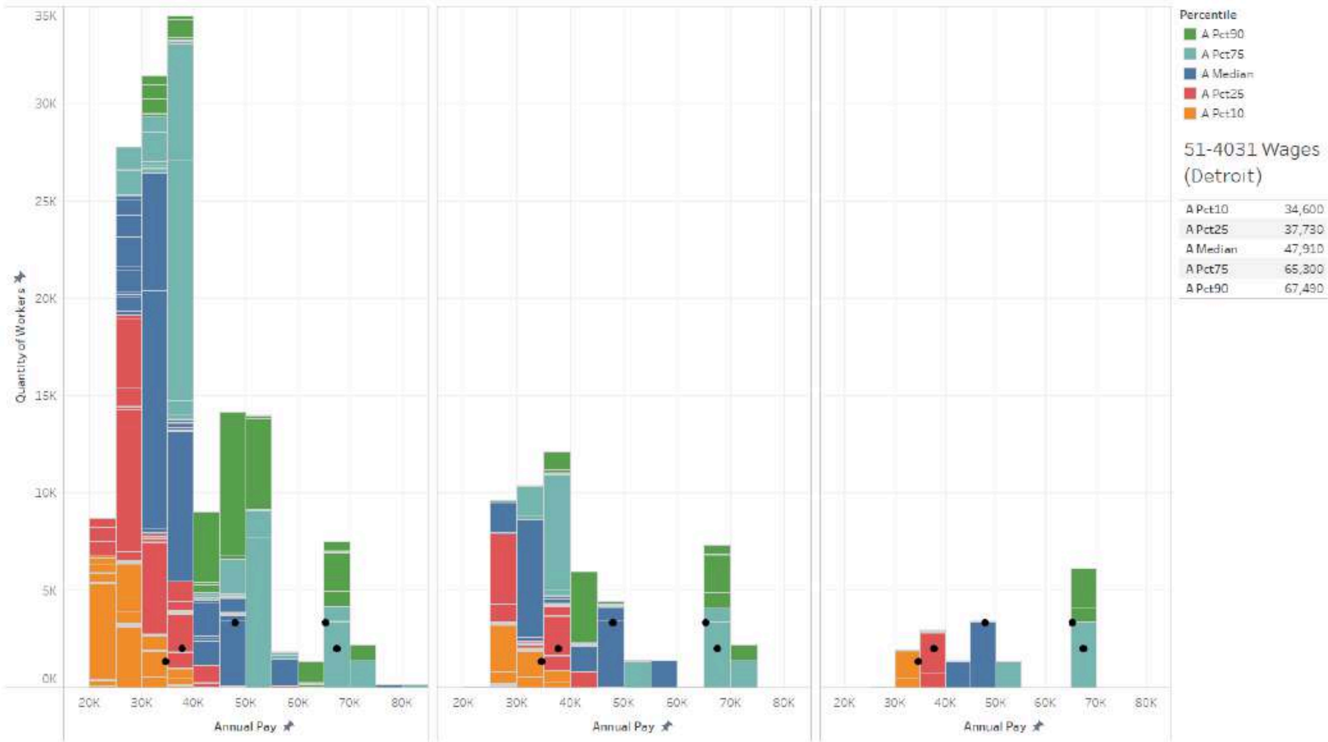


Figure D.1: Histogram of distribution of wages in alternative occupations to 51-4031 "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" by occupation percentile wages, color coded by percentile, in the Detroit MSA.

Distribution of Annual Wages of "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) and Jobs with Similarity>=0.7, >=0.8, and >=0.9 in the Augusta MSA

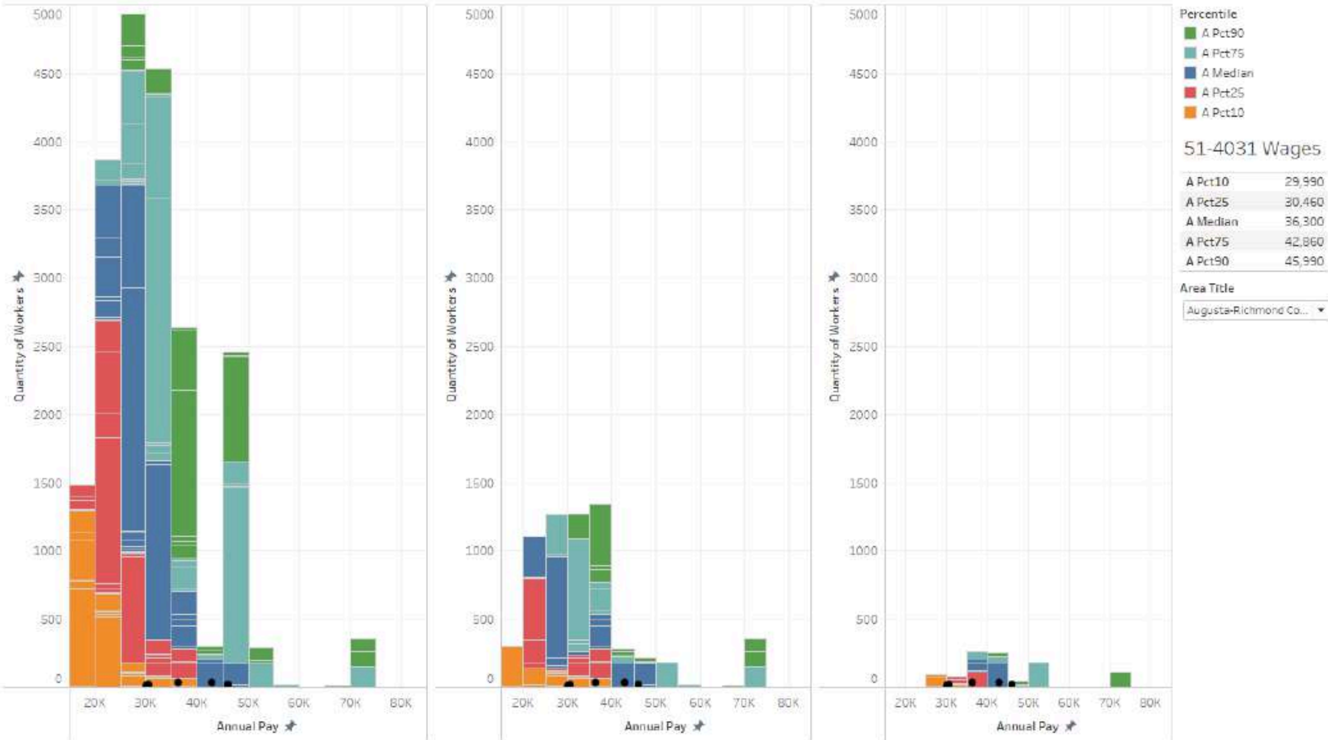


Figure D.2: Histogram of distribution of wages in alternative occupations to 51-4031 "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" by occupation percentile wages, color coded by percentile, in the Augusta MSA.

Distribution of Annual Wages of "Engine and Other Machine Assemblers" (51-2031) and Jobs with Similarity>=0.7, >=0.8, and >=0.9 in the Detroit MSA

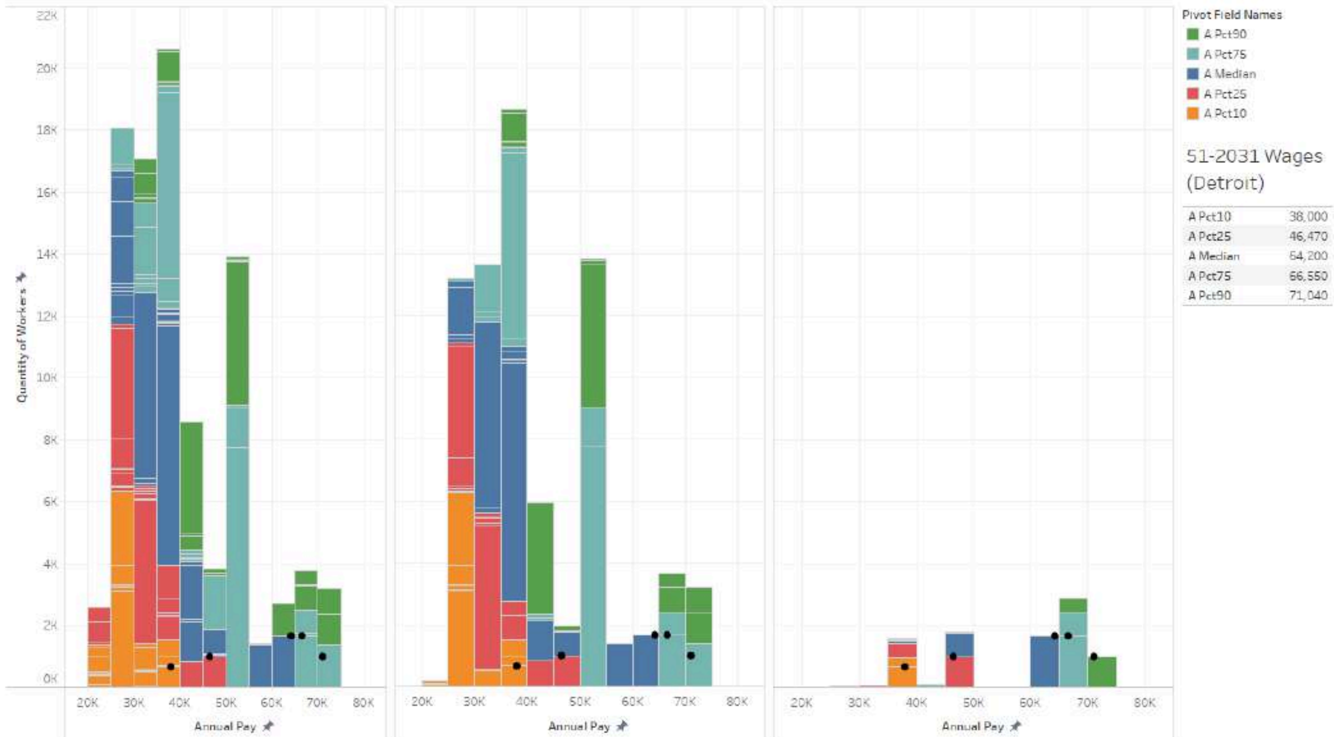


Figure D.3: Histogram of distribution of wages in alternative occupations to 51-2031 "Engine and Other Machine Assemblers" by occupation percentile wages, color coded by percentile, in the Detroit MSA

Distribution of Annual Wages of “Machinists” (51-4041) and Jobs with Similarity>=0.7, >=0.8, and >=0.9 in the Augusta MSA

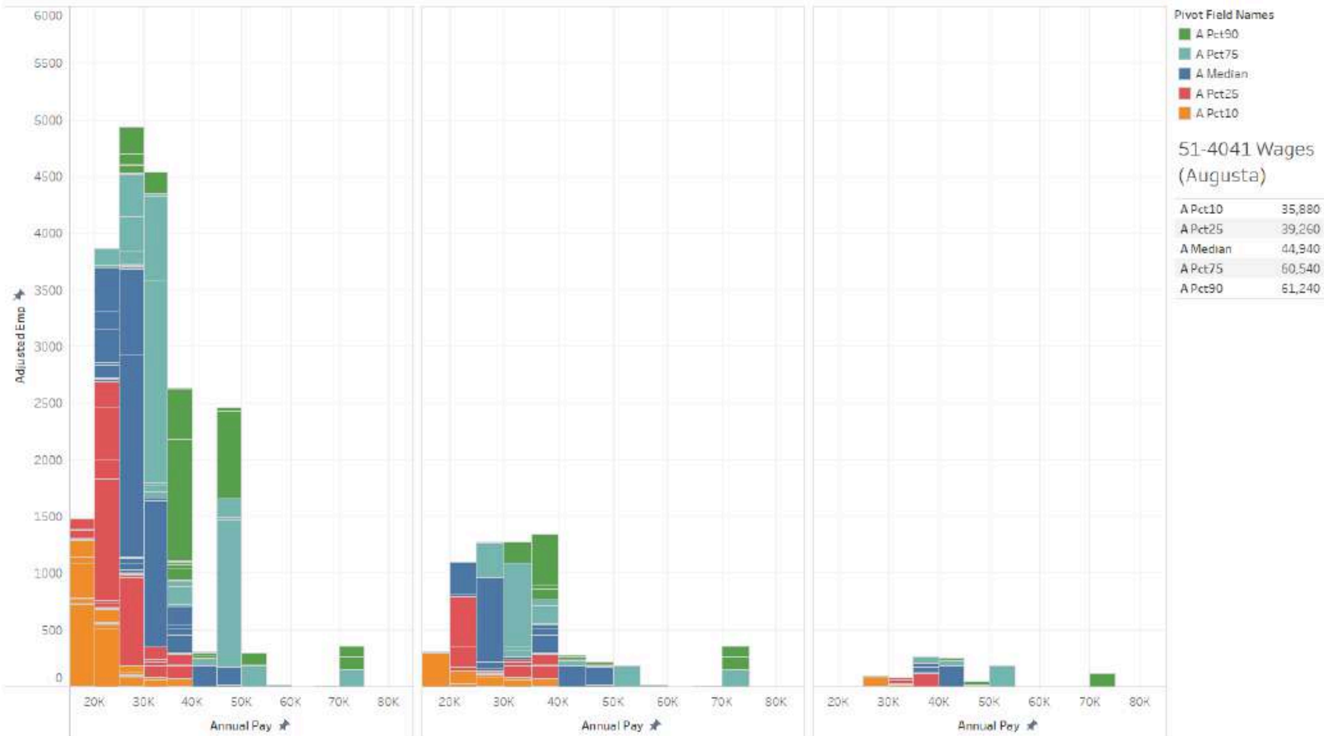


Figure D.4: Histogram of distribution of wages in alternative occupations to 51-4041 “Machinists” by occupation percentile wages, color coded by percentile, in the Augusta MSA

Logic: Percentile Representation

IF [Original Column Header]= "A Pct10" Then [Tot Emp]*0.1
ELSEIF [Original Column Header]= "A Pct25" Then [Tot Emp]*0.15
ELSEIF [Original Column Header]= "A Median" Then [Tot Emp]*0.25
ELSEIF [Original Column Header]= "A Pct75" Then [Tot Emp]*0.25
ELSEIF [Original Column Header]= "A Pct90" Then [Tot Emp]*0.15
ELSE 0 END

APPENDIX E: LINEAR REGRESSION MODEL DETAILS

We observed a relatively strong correlation between reported jobs and reported investment, and the jobs data appeared spatially missing at random (**Figure E.1**). We conducted linear regression models at the technology scale, and at the sub-technology product scale when possible. We used the best model fit available among these estimated models to impute missing reported jobs data.

Figure E.1: *Factory announcements data with reported jobs (gray) versus missing reported jobs (blue)*. Missing data appears spatially missing at random across the continental US. This bolsters confidence in imputing missing data with regressions trained on the reported jobs, because the training set appears spatially representative of the missing data.

Regressions by Technology (Battery & Electric Vehicle)

First we conducted linear regression analysis by technology: one for batteries and one for electric vehicles. For each regression, the model predicting reported jobs y_T for technology T (where $T \in Batteries,\ Electric\ Vehicles$) is:

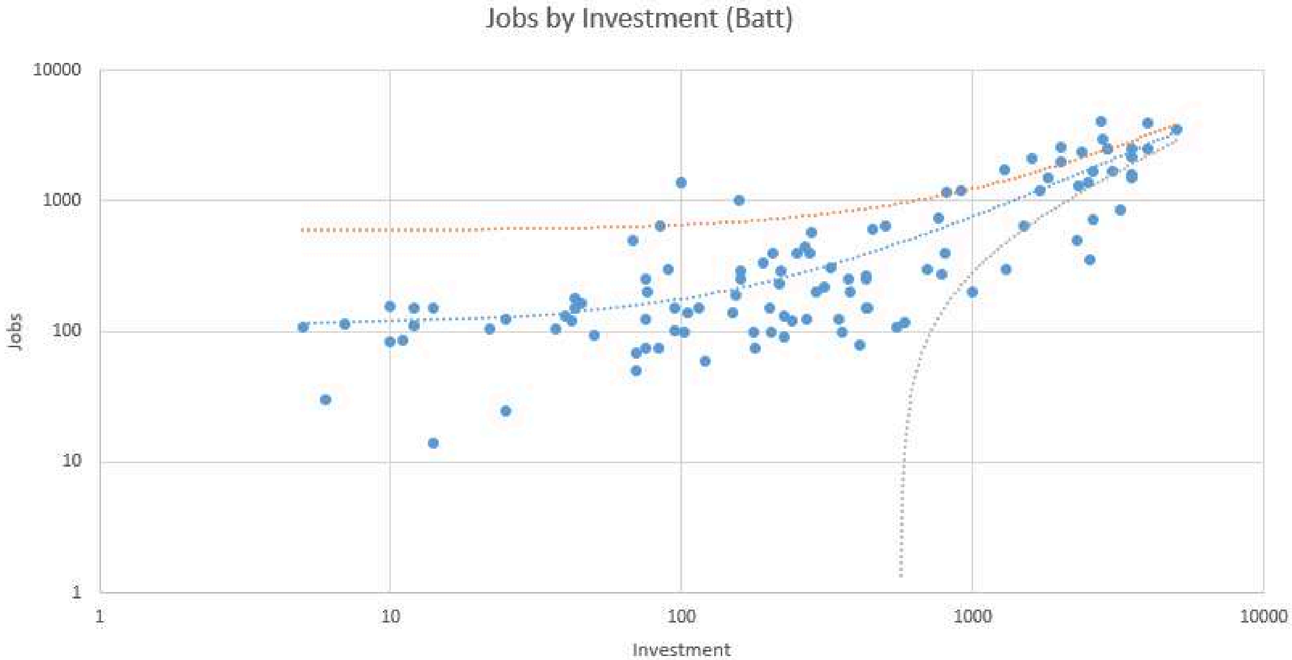
$y_T = \beta_0 + \beta_1 x$	*(E.1)*

where the independent variable is reported investment x.

For batteries, the estimated model is:

$y_{Batteries} = 113.35 + 0.6514x$	*(E.2)*

With an R^2 of 0.7176 and Standard Error of 479.7652. **Figure E.2** plots the best fit regression with its underlying training data.



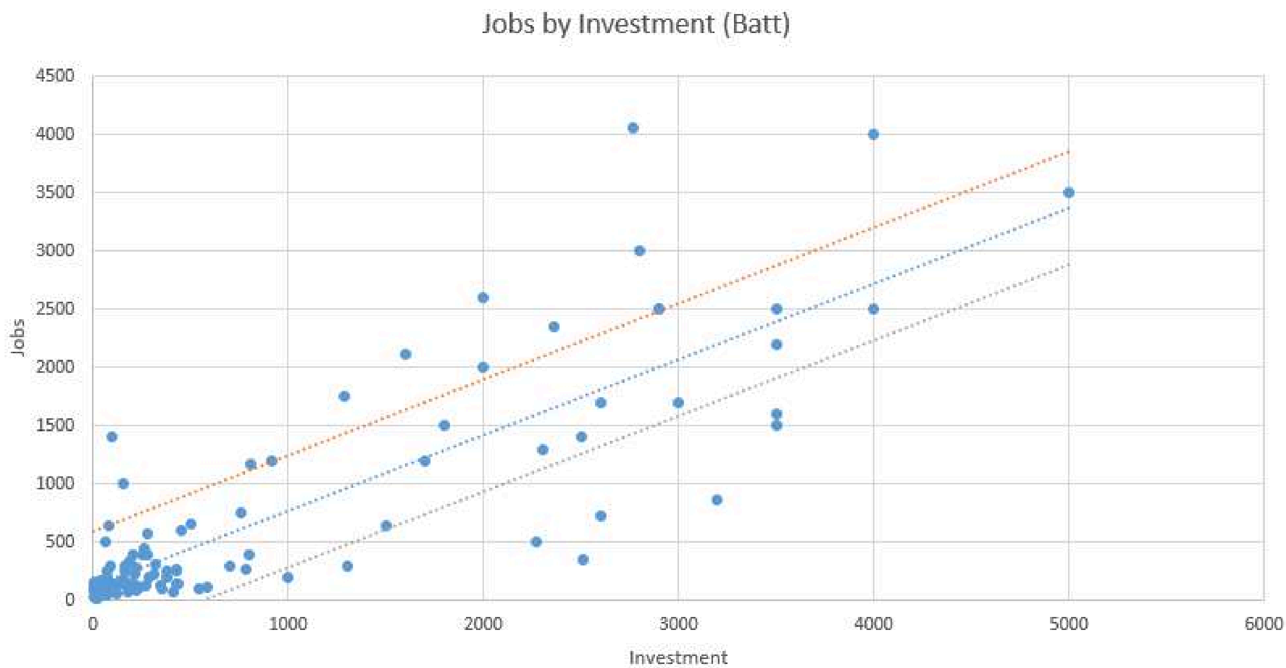
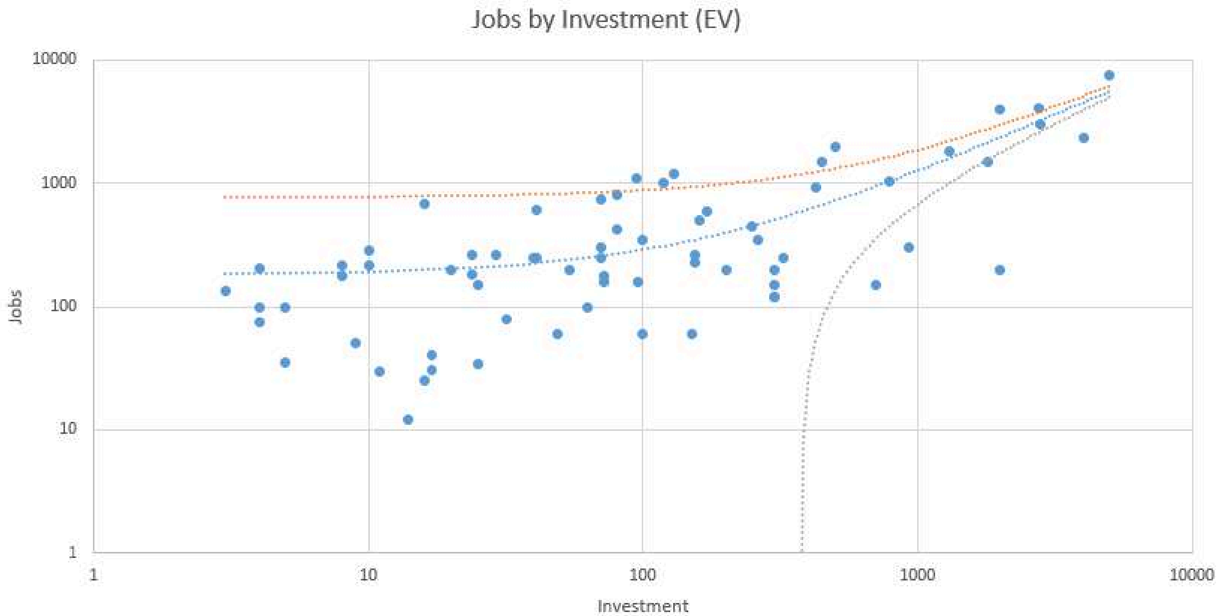


Figure E.2: *Reported jobs plotted by reported investment for the Battery technology subset of data on* ***(a)*** *log base 10 and* ***(b)*** *linear axes.* The blue dotted line corresponds to the best fit linear regression, and the orange and gray dotted lines represent the regression's positive and negative standard error, respectively.

For electric vehicles, the estimated model is:

$y_{Electric\,Vehicles} = 181.39 + 10868x$	*(E.3)*

With an R^2 of 0.7439 and Standard Error of 590.99. **Figure E.3** plots the best fit regression with its underlying training data.



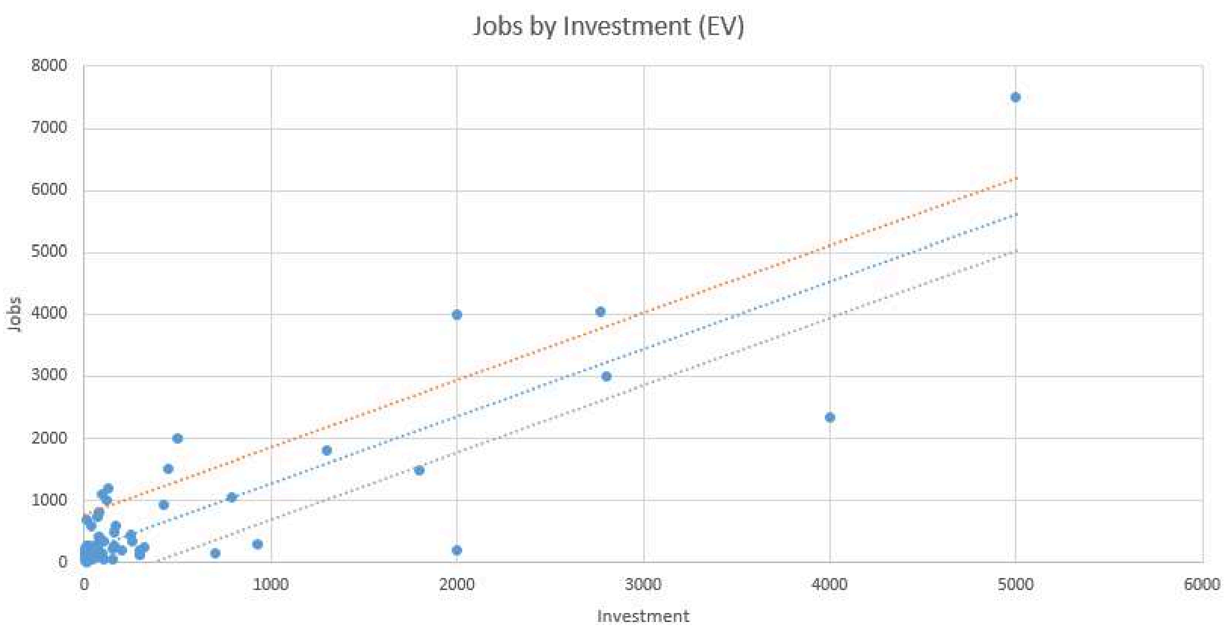


Figure E.3: *Reported jobs plotted by reported investment for the Electric Vehicle technology subset of data on* ***(a)*** *log base 10 and* ***(b)*** *linear axes*. The blue dotted line corresponds to the best fit linear regression, and the orange and gray dotted lines represent the regression's positive and negative standard error, respectively.

Regressions by Product Type (Two Battery Product Sets)

Both Battery and Electric Vehicle technologies have product subtypes. Electric Vehicle product types are (a) components, (b) chargers, and (c) assembly. We did not perform additional regression on individual Electric Vehicle product types due to the number of data points in each product type for Electric Vehicle (33 for the largest grouping). Battery product types are (a) battery components, (b) constituent materials, (c) Cells, (d) Packs, and (e) Cells & Packs. We grouped Battery product subtypes into two sets of similar subtypes for which estimating a linear model was feasible. Set 1 contained (a) Cells, (b), Packs, and (c) Cell & Packs product subtypes. Set 2 contained (a) Battery Components and (b) Constituent Materials.

For each regression, the model predicting reported jobs y_S for Battery product type set S (where $S \in Set\ 1,\ Set\ 2)$ is:

$y_S = \beta_0 + \beta_1 x$	*(E.4)*

where the independent variable is reported investment x.

For Set 1 (Cells, Packs, and Cells & Packs), the estimated model is:

$y_{Set\ 1} = 219.4 + 0.6983x$	*(E.5)*

with an R^2 of 0.7584 and Standard Error of 536.0863. This is a better fit than the combined battery technology regression (0.7584 as opposed to 0.7176), with a steeper slope (0.6983 as opposed to 0.6514), a much greater y intercept (219.4 as opposed to 113.35), and a larger standard error (536.0863 as opposed to 479.7652). Some of this difference (like the larger standard error) can be explained by the generally larger values under consideration when looking at Cells and Packs rather than the battery technology as a whole.

For Set 2 (Battery Components and Constituent Materials), the estimated model is:

$y_{Set\ 2} = 108.23 + 0.3355x$	*(E.6)*

with an R^2 of 0.5768 and Standard Error of 230.9518. This regression yielded a worse fit, smaller magnitude slope, similar intercept, and a much lower standard error. Given the higher granularity available when applying regressions for Battery subtype sets, we still use this regression despite its worse fit compared to the less granular Battery technology regression shown in *Equation E.2*.

Other Findings at the Product Type Level

When we break up our data points by product type, we find some interesting trends. When looking at the average number of jobs expected to be in a factory (**Figure E.4**), we can compare the announced values to calculated values (calculated using the previously described regressions). There are visible differences in the types of factories that do or do not announce their number of anticipated jobs. With the exception of the “Electric Vehicles: Components” category, all product types showed a higher average reported investment when including reported jobs than when determining jobs via regression analysis.

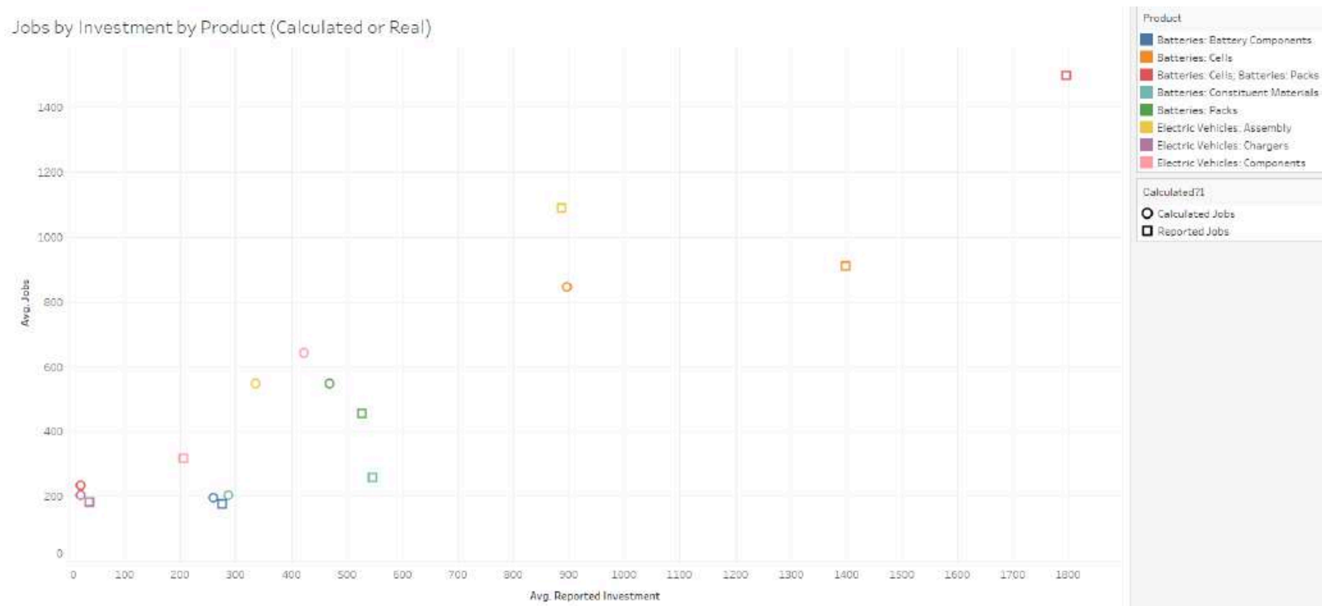


Figure E.4: *Plot of average reported investment vs average job for each factory announcements.* Colors indicate product type, and shapes indicate if the factories have announced jobs or calculated jobs. In almost all cases, the average investment for factories that announced their jobs were higher than the average investment for those who’s jobs were imputed via regression. The same trend is true when comparing average jobs, though that pattern is less consistent observed.

Looking at products as a whole (**Figure E.5**), we can see that this difference is large enough that there is no overlap in standard error between reported investments for factories with reported jobs, and those without reported jobs. The same cannot be said for the anticipated jobs.

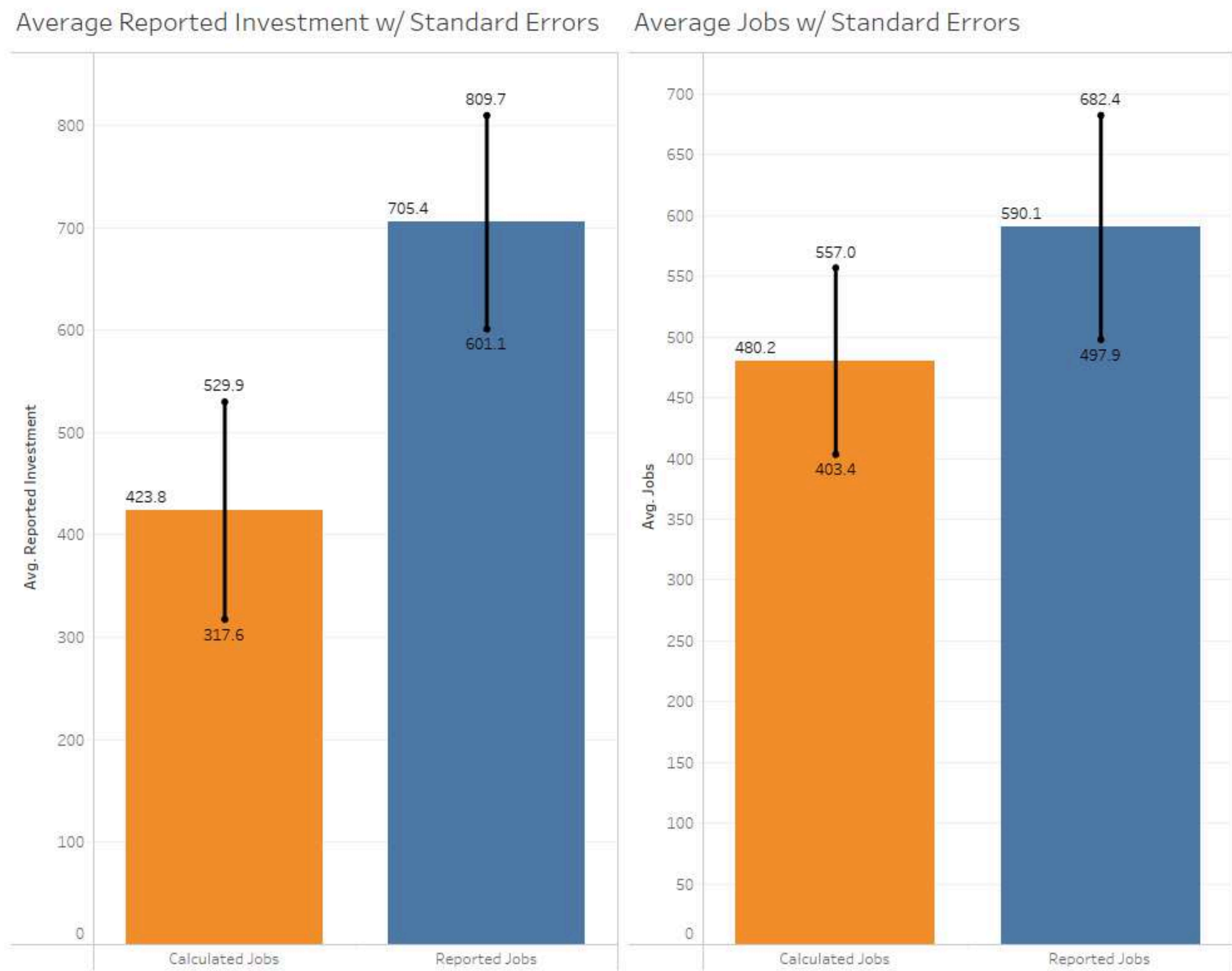


Figure E.5: *Plots of average reported investment and average jobs for both reported and imputed factory job quantities.* The black lines indicate plus or minus one standard error. In the case of jobs, we find that standard errors overlap between calculated and reported jobs, so it is possible that there is no meaningful relationship between quantity of jobs, and whether or not the quantity of jobs is reported. Conversely, the analysis indicates that factories reporting a higher investment are more likely to report an anticipated quantity of jobs created by the factory.

Appendix F: Aggregating Argonne Data Into MSAs

The data set described in Emerging Labor Demand Regression includes a latitude and longitude for each planned factory. In order to map these coordinates to specific MSAs, we used a python program that checks what (if any) MSA contains that point (code below). **Figure F.1** maps total announced jobs aggregated into each MSA. However, not all MSAs with aggregated Argonne data have corresponding data available in the BLS dataset. **Figure F.2** shows the MSAs that have factory announcements, but no associated BLS data.

```
import geopandas as gpd
from shapely.geometry import Point
import pandas as pd

# Load the Excel file and read the data into a DataFrame
file_path = 'argonne_jobs.xlsx'
df = pd.read_excel(file_path)

# Load the MSA boundary data
msa_data = gpd.read_file('cb_2018_us_cbsa_500k.shp')

# Function to perform for each location
def perform_function(latitude, longitude):
    # Create a Point geometry
    point = Point(longitude, latitude)

    # Check if the point is within any MSA boundary
    msa_containing_point = msa_data[msa_data.geometry.contains(point)]

    # Display the MSA containing the point
    print(msa_containing_point['NAME'].values[0] if not msa_containing_point.empty
else "None")

# Iterate over each row and perform the function for each location
for index, row in df.iterrows():
    latitude = row['latitude']
    longitude = row['longitude']
    perform_function(latitude, longitude)
```

This code relies on map data available at census.gov (https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.html). The specific resource that was used is cb_2018_us_cbsa_500k. All files from this source must be in the python code's file directory for this code to execute correctly. Results were spot checked against known MSA coordinates before labor demand heatmaps were generated.

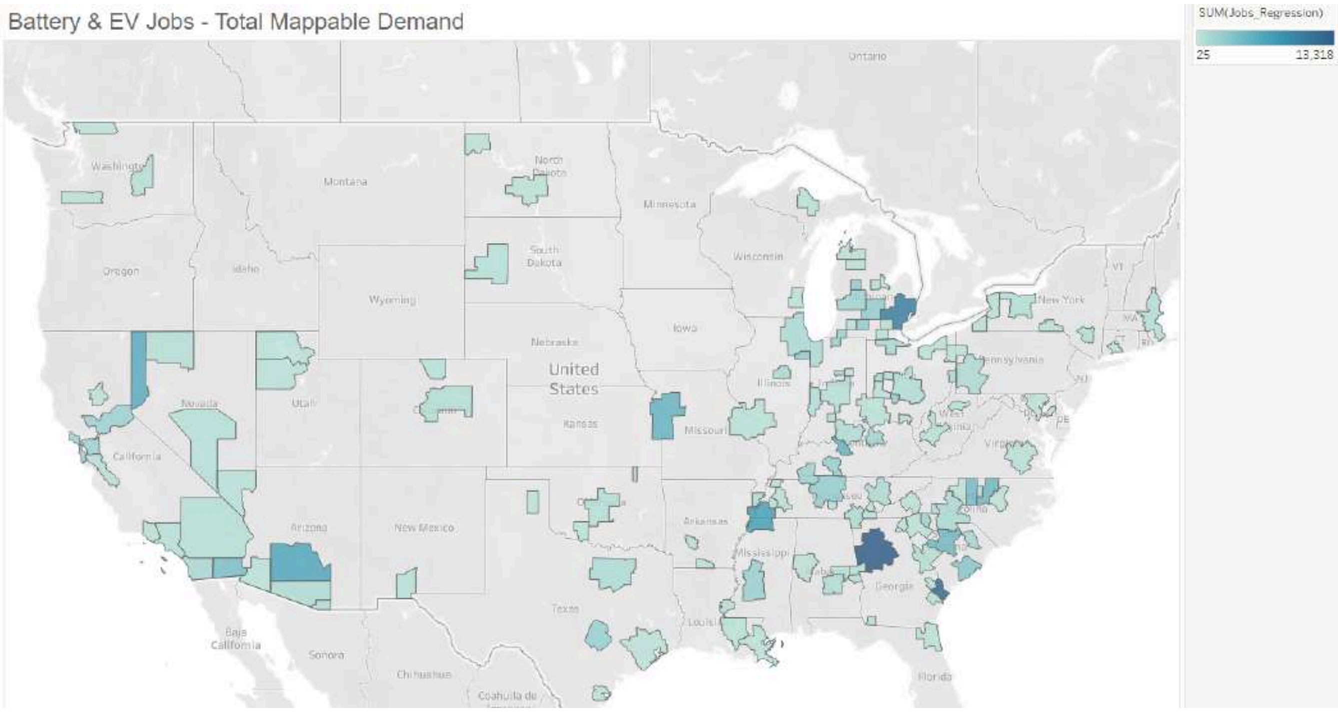


Figure F.1: *Heatmap of job demand for all (mappable) Battery and EV factory announcements*. Darker blue indicates more jobs.

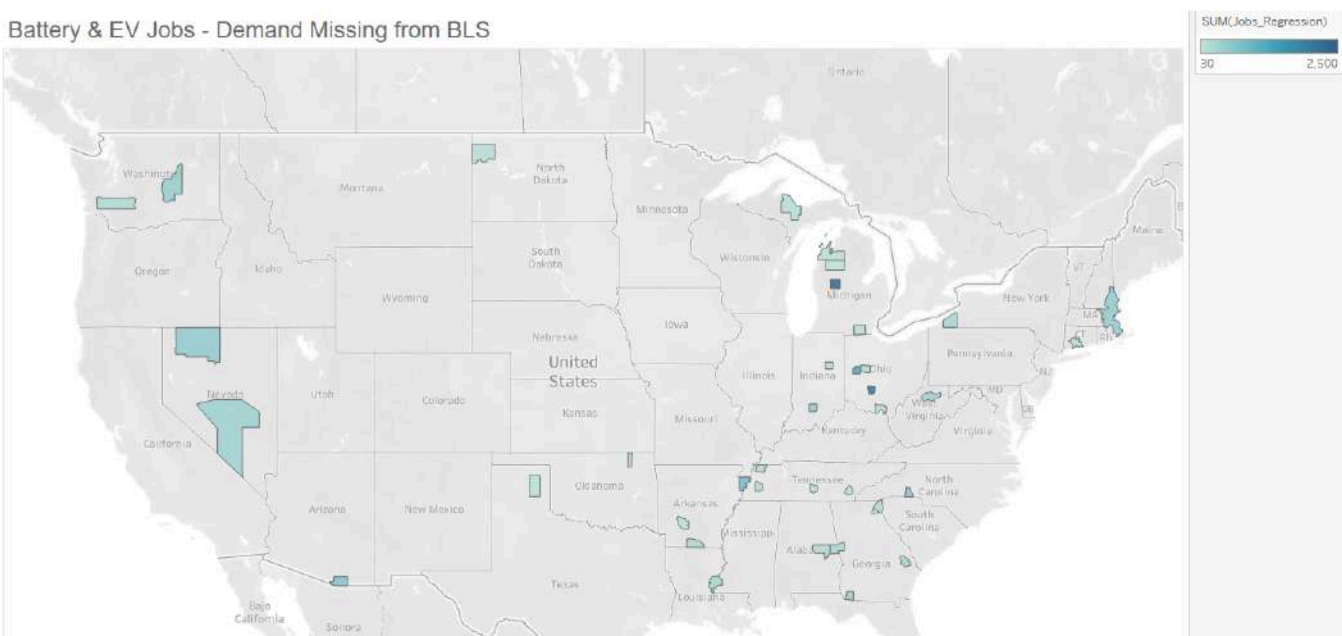


Figure F.2: *Heatmap of job demand for (mappable) Battery and EV factory announcements that are in MSAs with no corresponding BLS labor data*. These locations are excluded from supply and demand analysis, as there is no available data on labor supply.

Appendix G: Interview Protocol

Below is a sample of the sets of questions used in interviews for the project. Not all questions are relevant for every interview. These questions were used as a baseline to guide the interviews, but each interview may contain additional questions not listed here.

Key Differences between EV and ICEV Production

- What major differences do you see between EV and ICEV vehicle production?
- What's the mix of ICEV versus BEV versus hybrid/other electric vehicles?
- Do you anticipate this changing in the future?
- How long have you worked in [relevant sector]?

If switched from ICEV to EV:

- What new skills have you had to learn?
- What skills do you no longer use?
- What did you wish you had known starting out?
- Do you have recommendations for anyone switching into EVs?
- Did you have to reorganize your workforce after switching from ICEV to EV?
- What new skills were required?
- What old skills are no longer necessary?
- Did you hire more or fewer people?
- What did you have to change in your factory to accommodate this shift?
- Did anyone else's jobs change outside of the people directly interacting with the new product line?

Current Workforce

- What percentage of your workforce has an associate's degree? bachelors degree? More advanced? High-school educated? Less than high school?
- What is the age range of your workers?
- How might this change in the future? (If you get more into the EV market?)
- What types of software or user interfaces are used by your workers?
- What kinds of manufacturing technologies do you use? Anticipate using?
- Where do you look for hiring your workers? Are you seeking to hire workers from the ICE automotive sector?
- Do you do internal training? Do you partner with training providers (community colleges, private training programs, other?)
- How many employees work on the shop floor now, and how many do you estimate that you'll need for manufacturing at scale in the future? How might this change over time?
- How do you estimate the number of jobs in future plants or major transitions in the production process?
- We've heard from other firms that there is a slowdown in EV production demand. Does this match your recent experience?
- How do wage costs compare to capital costs?

Battery Production Processes

- Who are your major customers?
- What percentage of your production goes towards EVs versus other verticals? How do you anticipate this changing in the future?
- Can you walk us through the production of an average part/cell, and what types of workers are involved and count at the major steps?
- How is this different from wet dry cell manufacturing?
- Does form factor change production?
- What are your plans for scaling up, if any? What do you need for this to succeed?
- What's the rationale behind moving into full cylindrical cell production?
- What's your average batch size? What do you anticipate this will be at scale?
- What is your current annual production capacity (in Wh)?

Appendix H: Potential Uncertainty Drivers for Steady State Capacity Demand Conditions

Potential Uncertainty Drivers for Steady State Capacity Demand Conditions

Type of uncertainty	Potential Implications for Low Value of Dimension	Potential Implications for High Value of Dimension
Quantity of viable technologies	Decrease heterogeneity at scale, leading to greater scale economic effects (more production, less jobs)	Increased potential for heterogeneity at scale, increasing diversity of skills demanded, and decreasing job loss due to improvements.
Worker Skill Transferability	Heterogeneity of battery technology at scale has a high impact; Increase in demand for retrainings; Lower scalability of process innovations	Battery types can be combined for labor analysis; Decrease in retrainings; Increase in automation over time
Cost/Benefit of new EV/Battery technology	Minimal barrier to adopting new technologies, increasing the diffusion of new and emergent technologies, slowing pace of process innovation	Adopting new technologies with different capital demands becomes cost prohibitive. Factories will focus on process innovations to drive down costs, remaining competitive, but decreasing jobs
Cost/Benefit of new EV/Battery process	Minimal value to process improvements. Worker's jobs remain secure in this branch of technology.	Many workers are displaced as a result of process improvements. The opportunity cost of changing technology in the future increases.
Redeployability of capital	The viability of adopting new technologies and processes will heavily depend on retooling costs.	Minimal barrier to adopting new technologies and processes, increasing the diffusion of new technologies while allowing for process innovations

Table H.1. description as above

Appendix I: Skill Gaps Sensitivity Analysis

SKAW Gaps Between ICEV Workers and Workers in Candidate Occupations

This section includes sensitivity analysis figures depicting gaps between skill requirements for the occupations of ICEV workers and workers in occupations with high overall skill similarity. Similarity is directional, and for these figures that direction is *from* our occupation of interest *to* the similar occupations.

Deficits Between "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) and Workers in Similar Occupations

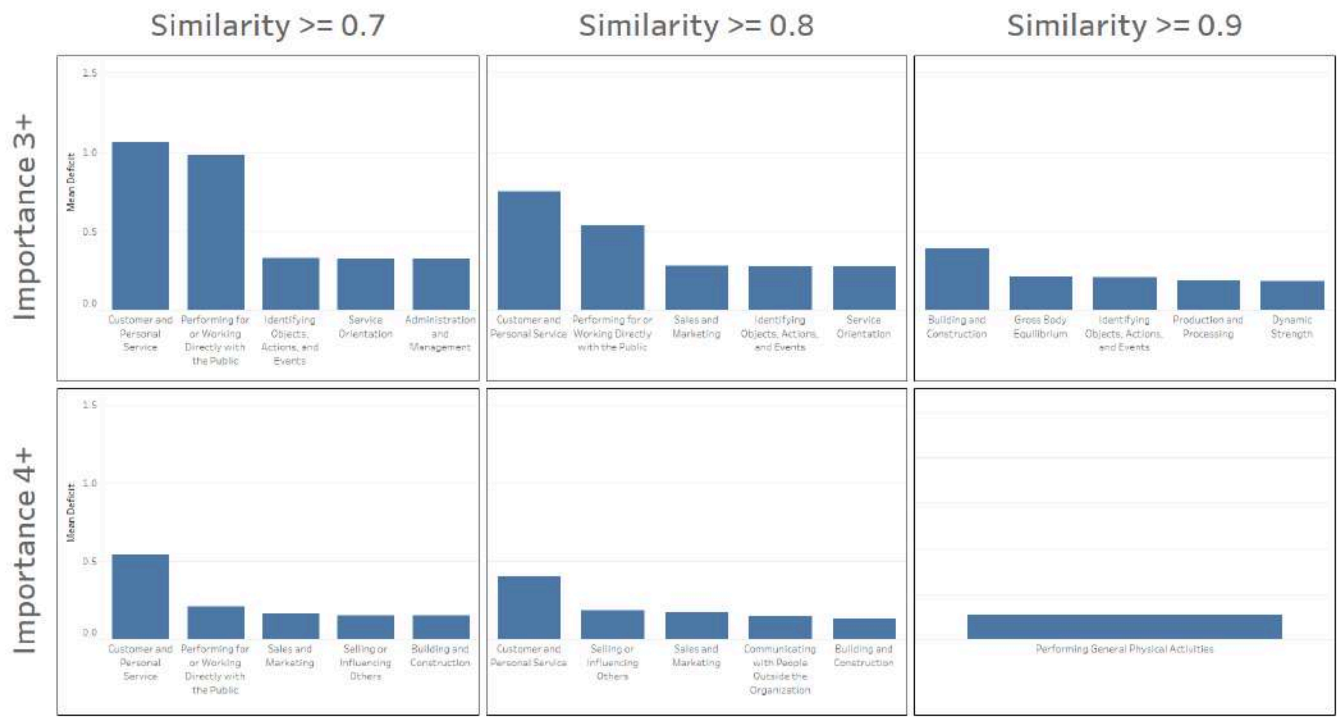


Figure I.1: Average disparity between "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) and Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Relevance is determined by the importance score of that deficit in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Most Frequently Occurring Deficits Between "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) and Workers in Similar Occupations

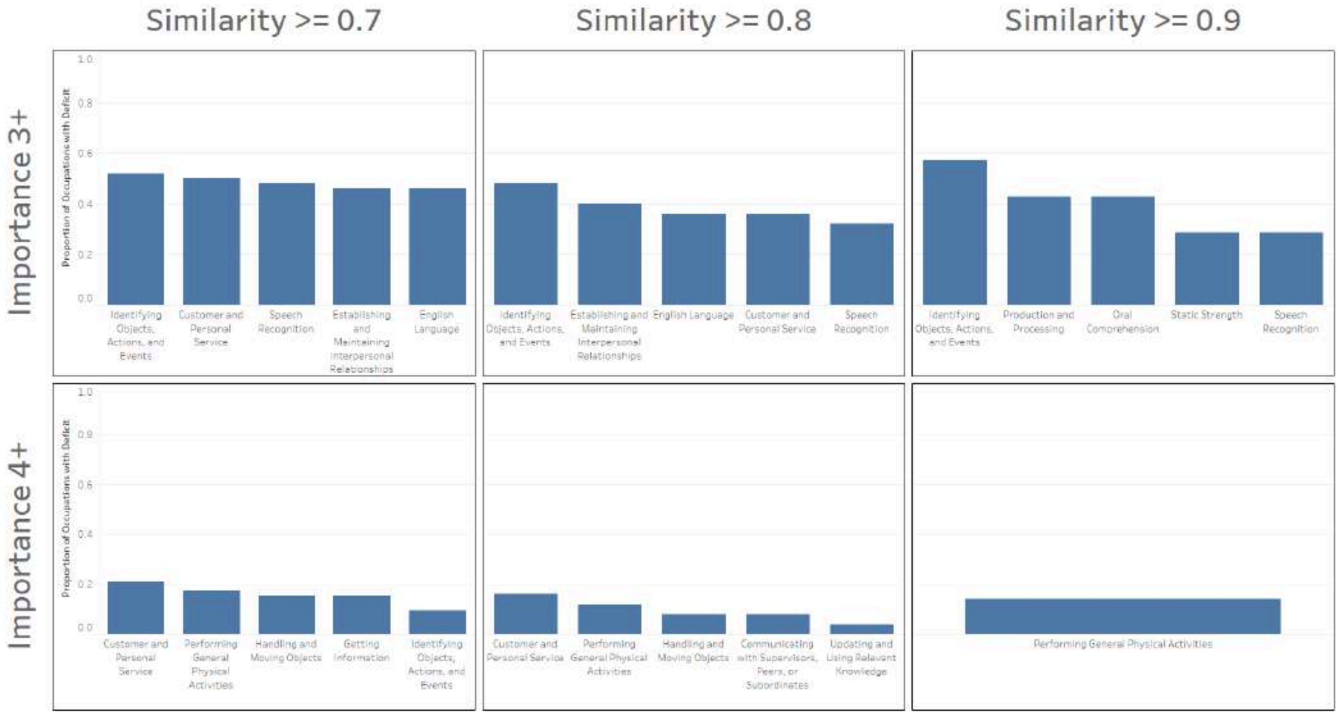


Figure I.2: Most frequently appearing relevant deficits when comparing "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) to Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the importance score of that metric in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Deficits Between "Engine and Other Machine Assemblers" (51-2031) and Workers in Similar Occupations

Figure I.3: Average disparity between "Engine and Other Machine Assemblers" (51-2031) and Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Relevance is determined by the importance score of that deficit in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Most Frequently Occurring Deficits Between "Engine and Other Machine Assemblers" (51-2031) and Workers in Similar Occupations

Figure I.4: Most frequently appearing relevant deficits when comparing "Engine and Other Machine Assemblers" (51-2031) to Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the importance score of that metric in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Deficits Between "First-Line Supervisors of Production and Operating Workers" (51-1011) and Workers in Similar Occupations

Figure I.5: Average disparity between "First-Line Supervisors of Production and Operating Workers" (51-1011) and Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Relevance is determined by the importance score of that deficit in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Most Frequently Occurring Deficits Between "First-Line Supervisors of Production and Operating Workers" (51-1011) and Workers in Similar Occupations

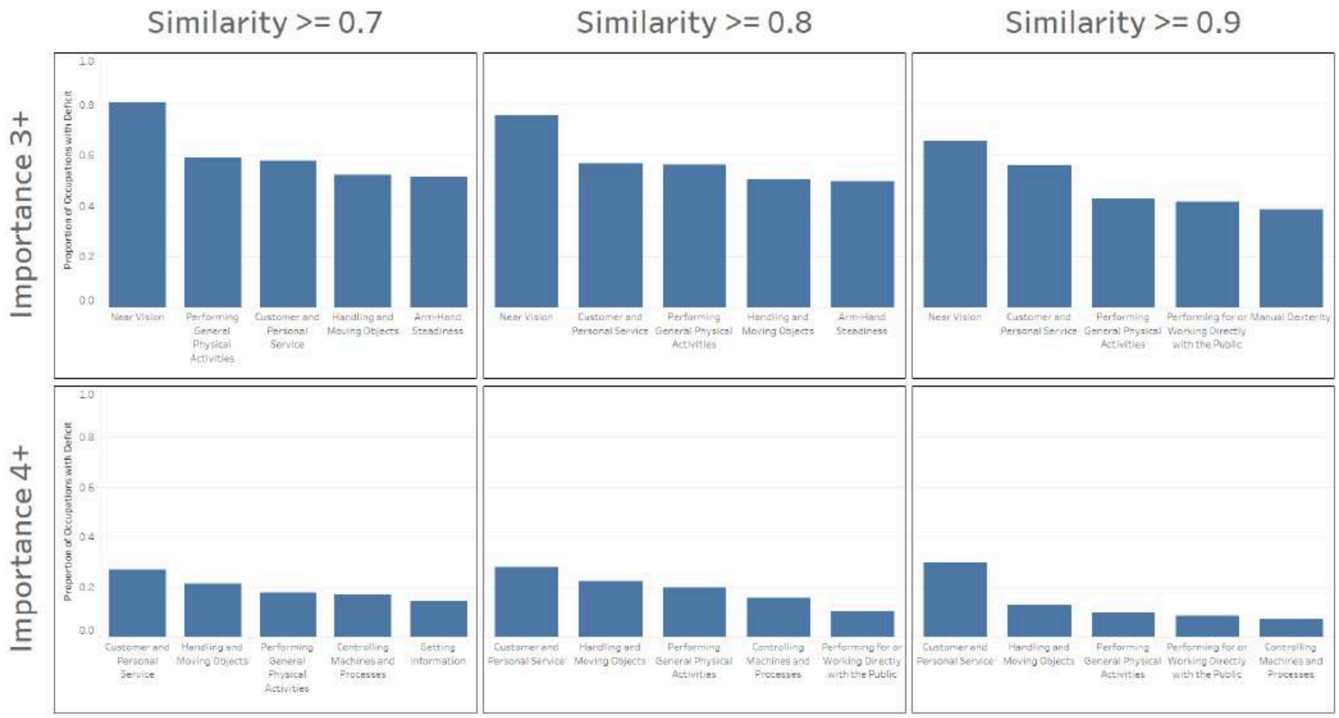


Figure I.6: Most frequently appearing relevant deficits when comparing "First-Line Supervisors of Production and Operating Workers" (51-1011) to Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the importance score of that metric in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Deficits Between “Inspectors, Testers, Sorters, Samplers, and Weighers” (51-9061) and Workers in Similar Occupations

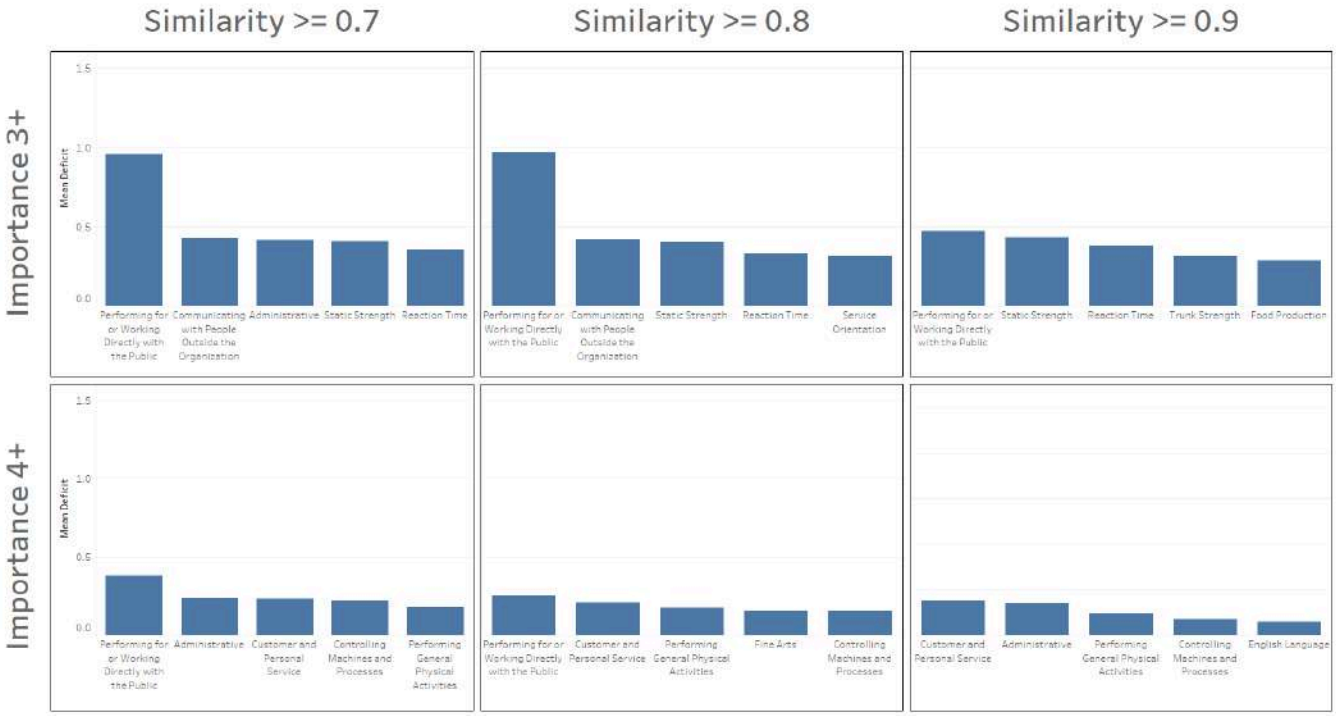


Figure I.7: Average disparity between “Inspectors, Testers, Sorters, Samplers, and Weighers” (51-9061) and Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Relevance is determined by the importance score of that deficit in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Most Frequently Occurring Deficits Between "Inspectors, Testers, Sorters, Samplers, and Weighers" (51-9061) and Workers in Similar Occupations

Figure I.8: Most frequently appearing relevant deficits when comparing "Inspectors, Testers, Sorters, Samplers, and Weighers" (51-9061) to Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the importance score of that metric in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Deficits Between "Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic" (51-4081) and Workers in Similar Occupations

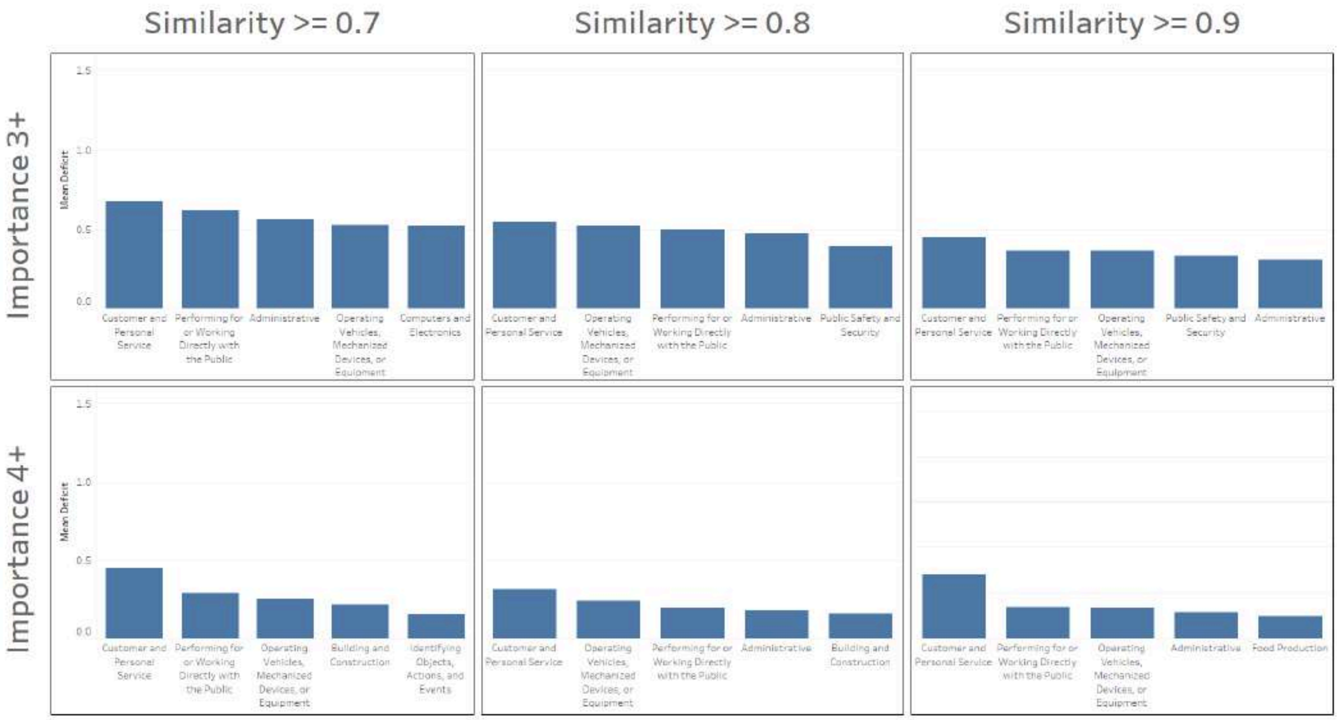


Figure I.9: Average disparity between "Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic" (51-4081) and Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Relevance is determined by the importance score of that deficit in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Most Frequently Occurring Deficits Between “Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic” (51-4081) and Workers in Similar Occupations

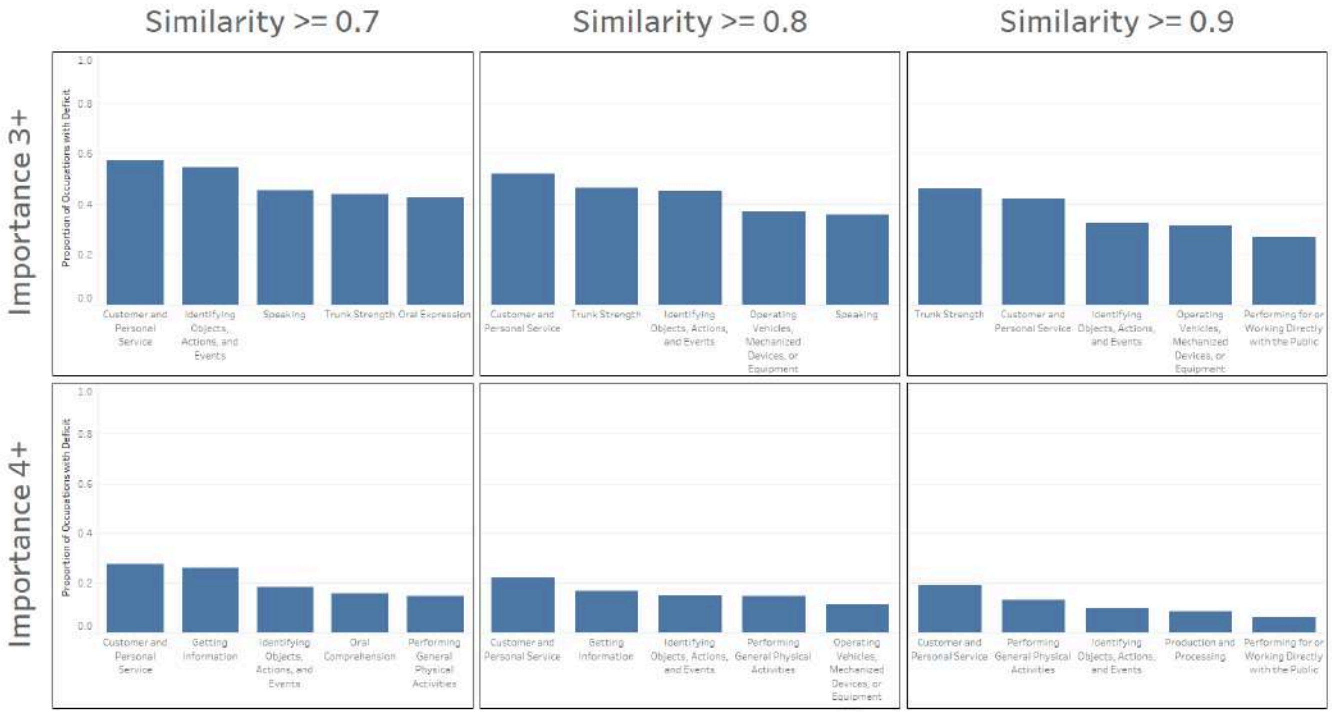


Figure I.10: Most frequently appearing relevant deficits when comparing “Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic” (51-4081) to Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the importance score of that metric in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Deficits Between "Machinists" (51-4041) and Workers in Similar Occupations

Figure I.11: Average disparity between "Machinists" (51-4041) and Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Relevance is determined by the importance score of that deficit in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Most Frequently Occurring Deficits Between "Machinists" (51-4041) and Workers in Similar Occupations

Figure I.12: Most frequently appearing relevant deficits when comparing "Machinists" (51-4041) to Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the importance score of that metric in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Deficits Between "Welders, Cutters, Solderers, and Brazers" (51-4121) and Workers in Similar Occupations

Figure I.13: Average disparity between "Welders, Cutters, Solderers, and Brazers" (51-4121) and Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Relevance is determined by the importance score of that deficit in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar. Note that there were insufficient matches at the 0.8 and 0.9 similarity levels to identify SKAW deficits with sufficiently high levels of importance.

Most Frequently Occurring Deficits Between “Welders, Cutters, Solderers, and Brazers” (51-4121) and Workers in Similar Occupations

Figure I.14: Most frequently appearing relevant deficits when comparing “Welders, Cutters, Solderers, and Brazers” (51-4121) to Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the importance score of that metric in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar. Note that there were insufficient matches at the 0.8 and 0.9 similarity levels to identify SKAW deficits with sufficiently high levels of importance.

Deficits Between “Tool and Die Makers” (51-4111) and Workers in Similar Occupations

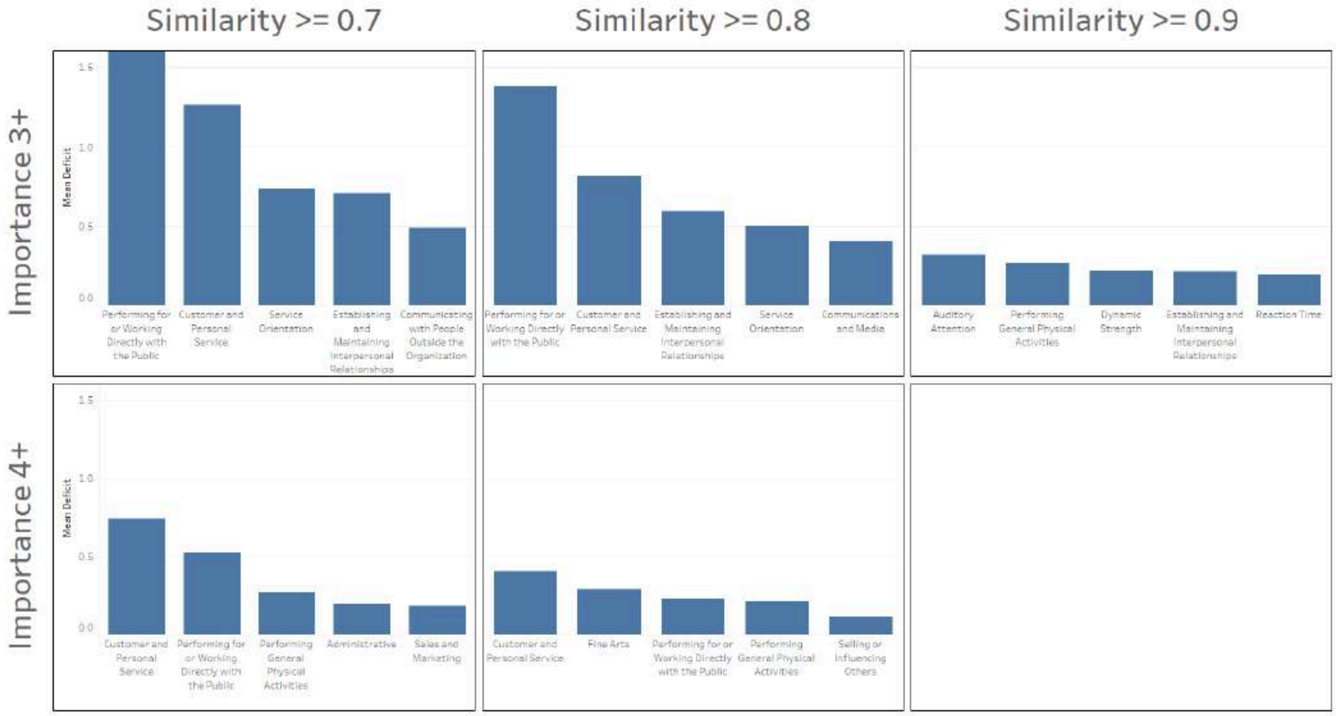


Figure I.15: Average disparity between “Tool and Die Makers” (51-4111) and Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Relevance is determined by the importance score of that deficit in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar. Note that there were insufficient matches at the 0.9 similarity levels to identify SKAW deficits at Importance level 4+.

Most Frequently Occurring Deficits Between "Tool and Die Makers" (51-4111) and Workers in Similar Occupations

Figure I.16: Most frequently appearing relevant deficits when comparing "Tool and Die Makers" (51-4111) to Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the importance score of that metric in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar. Note that there were insufficient matches at the 0.9 similarity levels to identify SKAW deficits at Importance level 4+.

SKAW Gaps of EV, Battery, and HST Occupations vs. Candidate Occupations

This section includes sensitivity analysis figures depicting Skill Gaps Between EV, Battery, and HST Workers and Workers in Occupations that can fill those positions. Similarity is directional, and for these figures that direction is *to* our occupation of interest *from* the similar occupations.

Deficits Between "Industrial Production Managers" (11-3051) and Workers in Similar Occupations

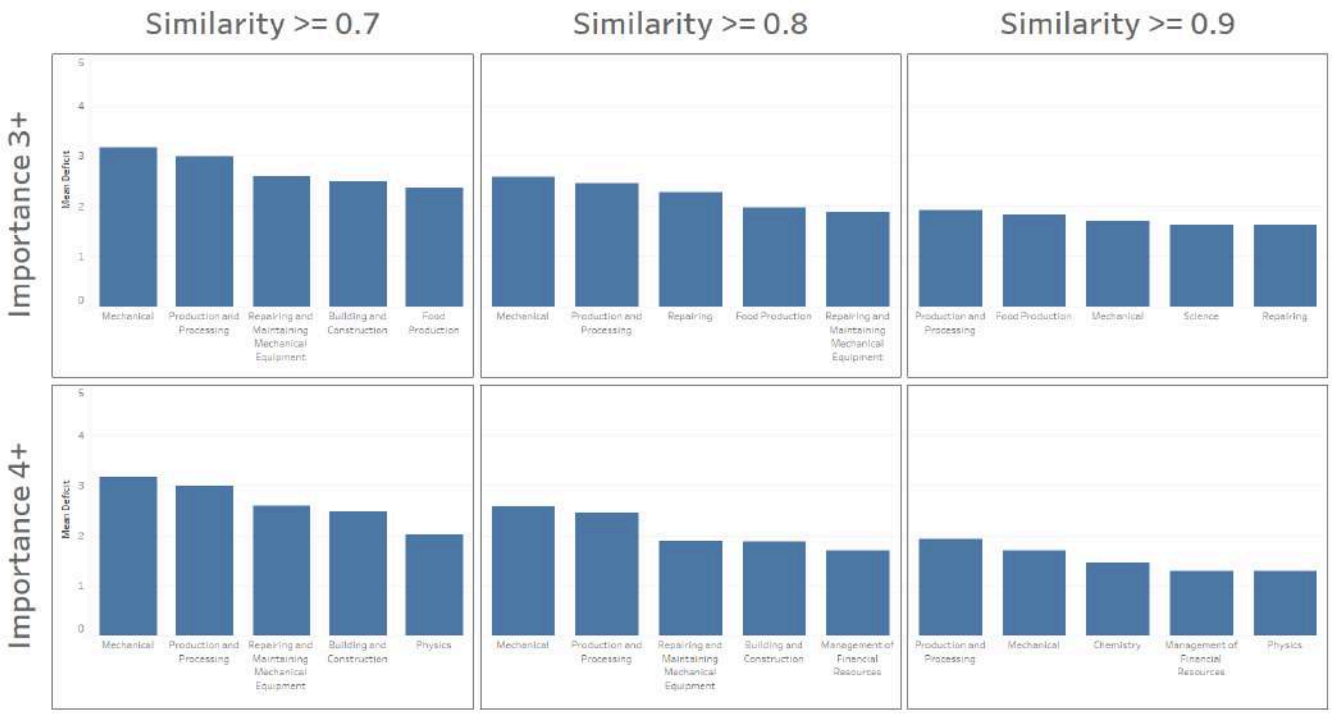


Figure I.17: Average disparity between "Industrial Production Managers" (11-3051) and Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Relevance is determined by the importance score of that deficit in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Most Frequently Occurring Deficits Between "Industrial Production Managers" (11-3051) and Workers in Similar Occupations

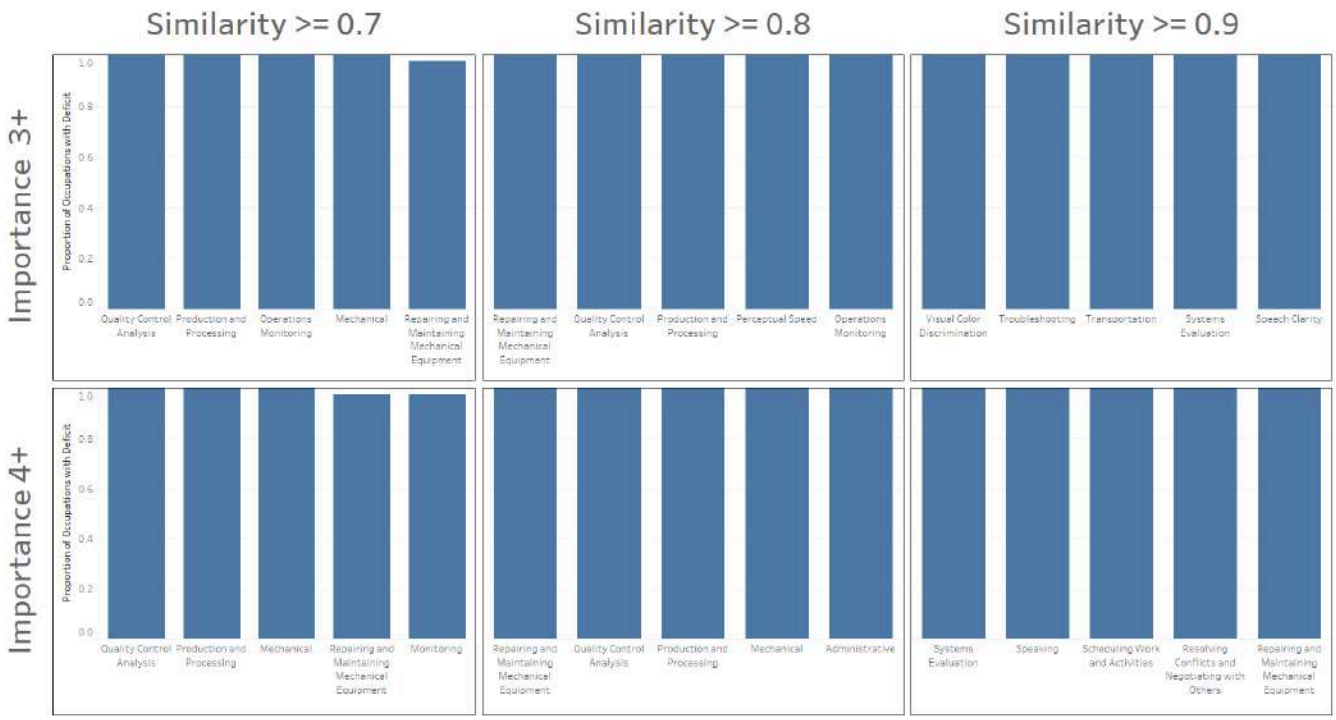


Figure I.18: Most frequently appearing relevant deficits when comparing "Industrial Production Managers" (11-3051) to Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the importance score of that metric in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Deficits Between "Electro-Mechanical and Mechatronics Technologists and Technicians" (17-3024) and Workers in Similar Occupations

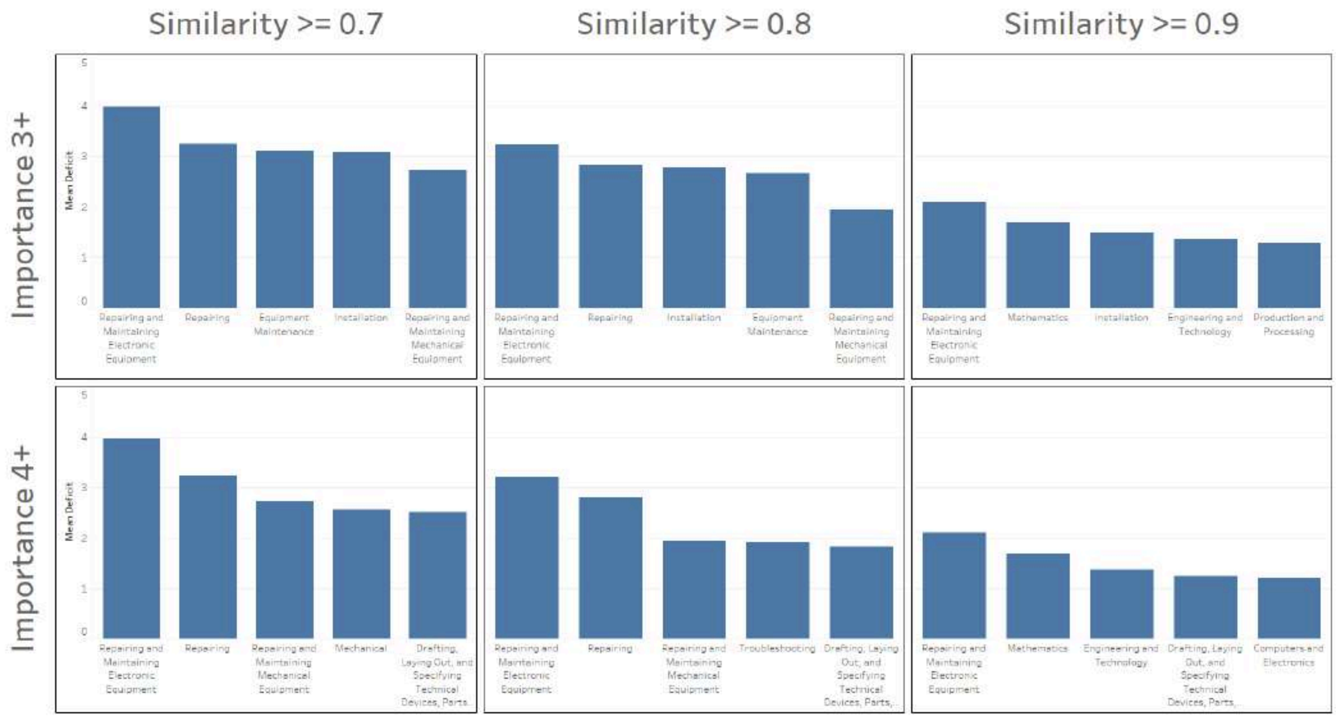


Figure I.19: Average disparity between "Electro-Mechanical and Mechatronics Technologists and Technicians" (17-3024) and Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Relevance is determined by the importance score of that deficit in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Most Frequently Occurring Deficits Between "Electro-Mechanical and Mechatronics Technologists and Technicians" (17-3024) and Workers in Similar Occupations

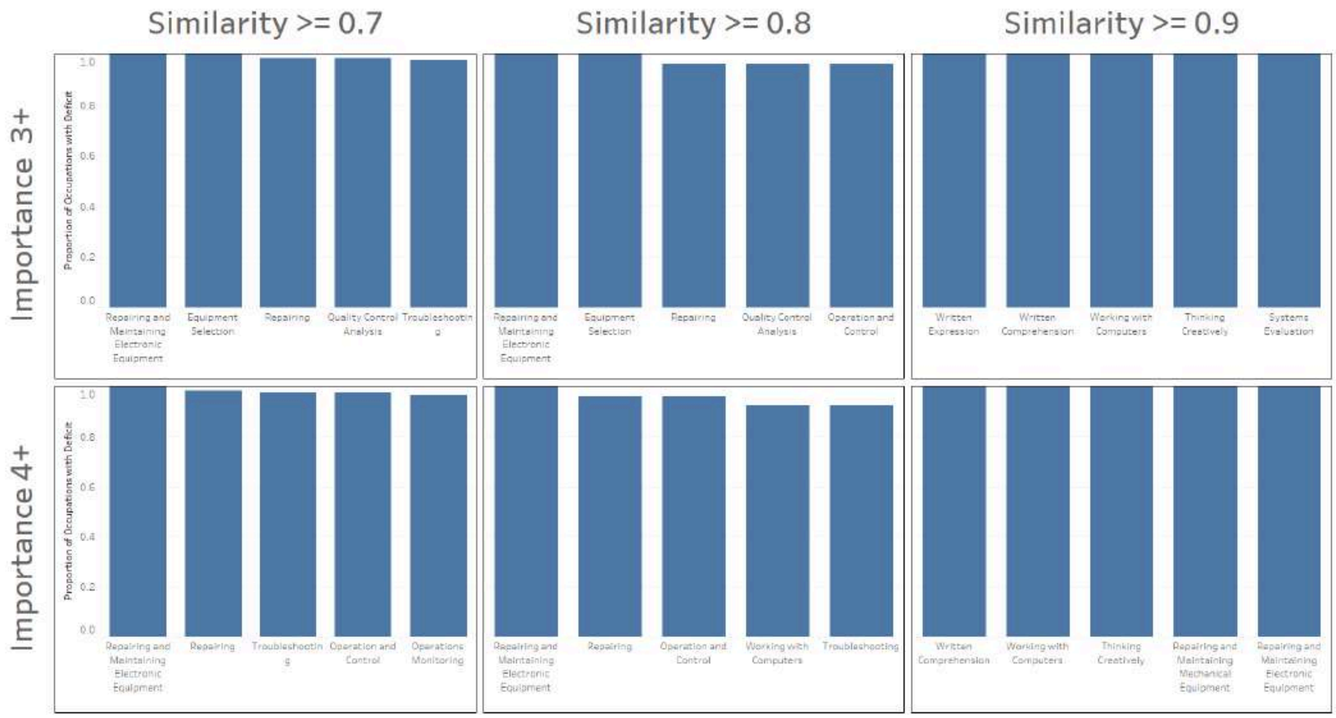


Figure I.20: Most frequently appearing relevant deficits when comparing "Electro-Mechanical and Mechatronics Technologists and Technicians" (17-3024) to Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the importance score of that metric in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Deficits Between 'Industrial Machinery Mechanics" (49-9041) and Workers in Similar Occupations

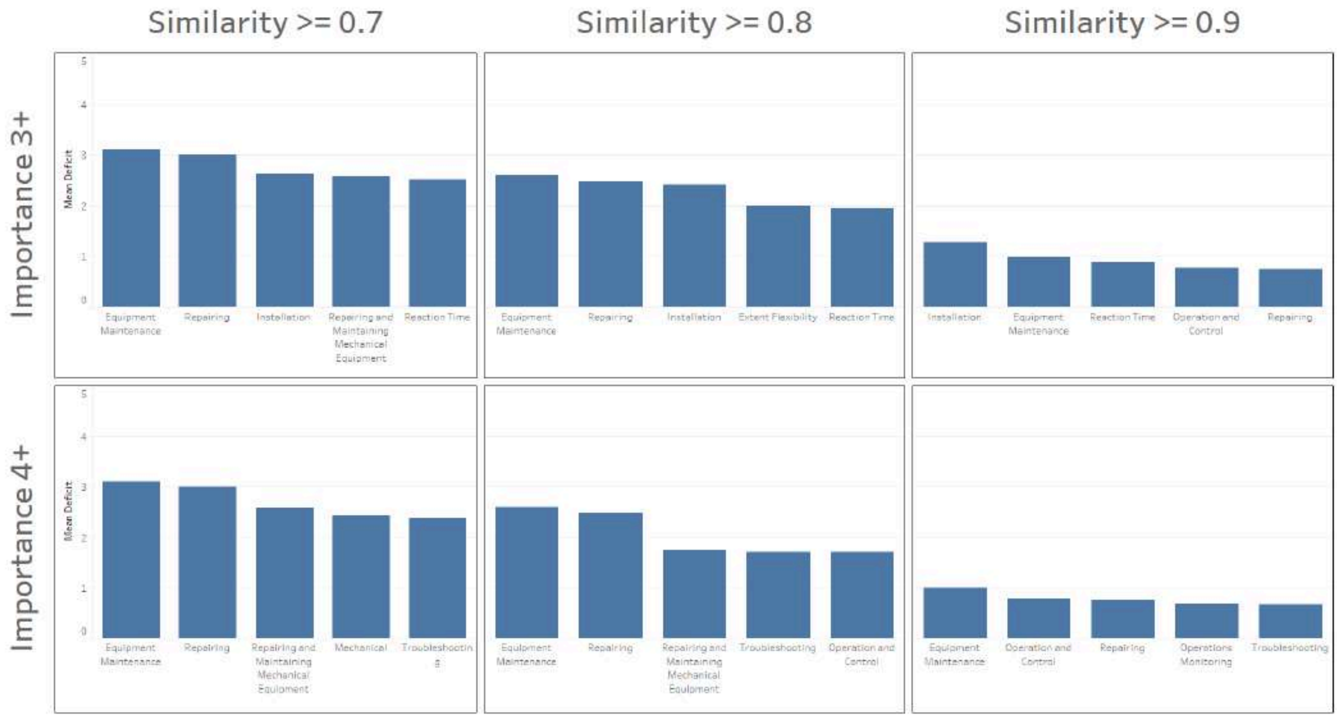


Figure I.21: Average disparity between "Industrial Machinery Mechanics" (49-9041) and Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Relevance is determined by the importance score of that deficit in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Most Frequently Occurring Deficits Between "Industrial Machinery Mechanics' (49-9041) and Workers in Similar Occupations

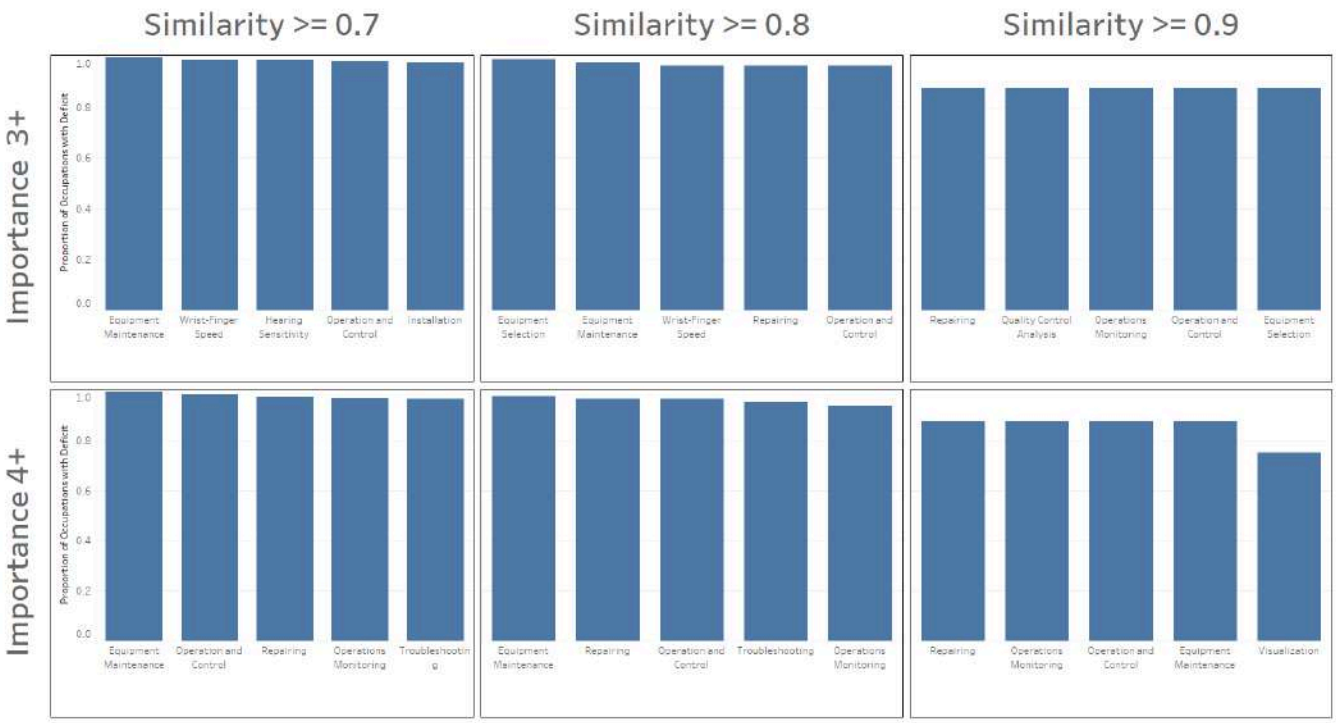


Figure I.22: Most frequently appearing relevant deficits when comparing "Industrial Machinery Mechanics" (49-9041) to Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the importance score of that metric in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Deficits Between "Engine and Other Machine Assemblers" (51-2031) and Workers in Similar Occupations

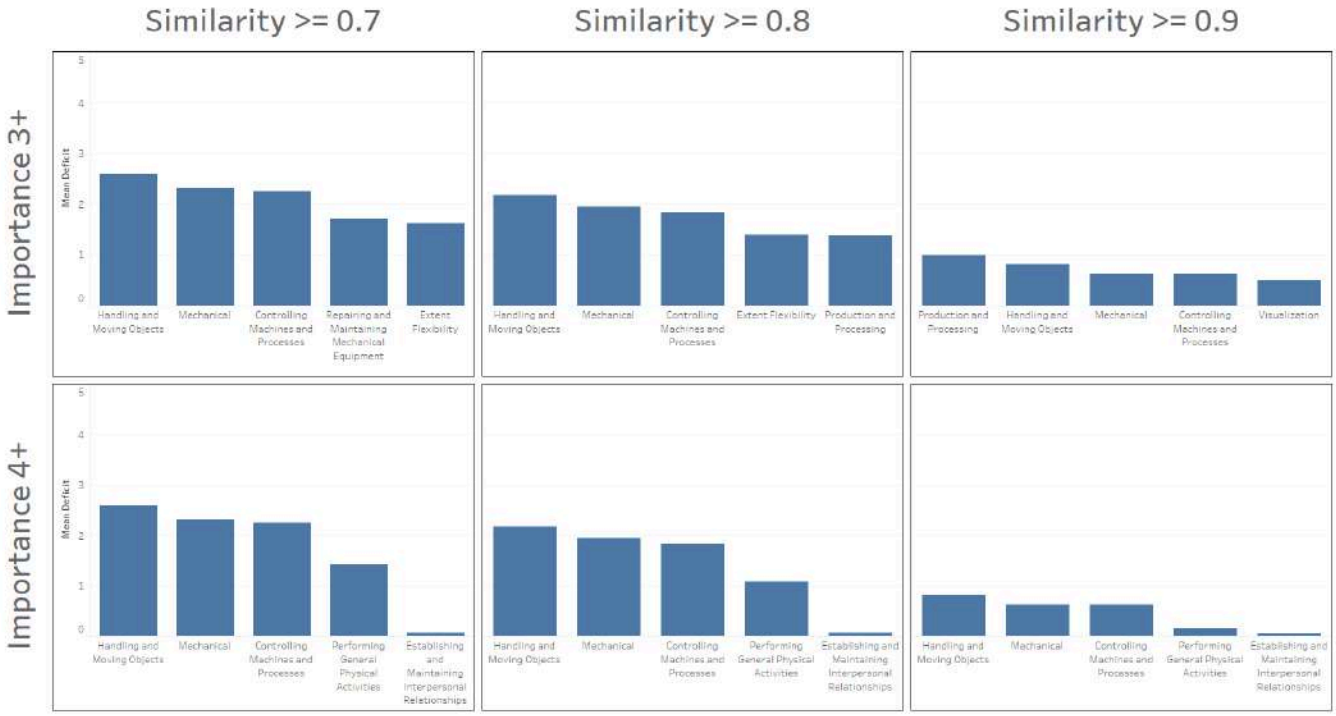


Figure I.23: Average disparity between "Engine and Other Machine Assemblers" (51-2031) and Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Relevance is determined by the importance score of that deficit in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Most Frequently Occurring Deficits Between "Engine and Other Machine Assemblers" (51-2031) and Workers in Similar Occupations

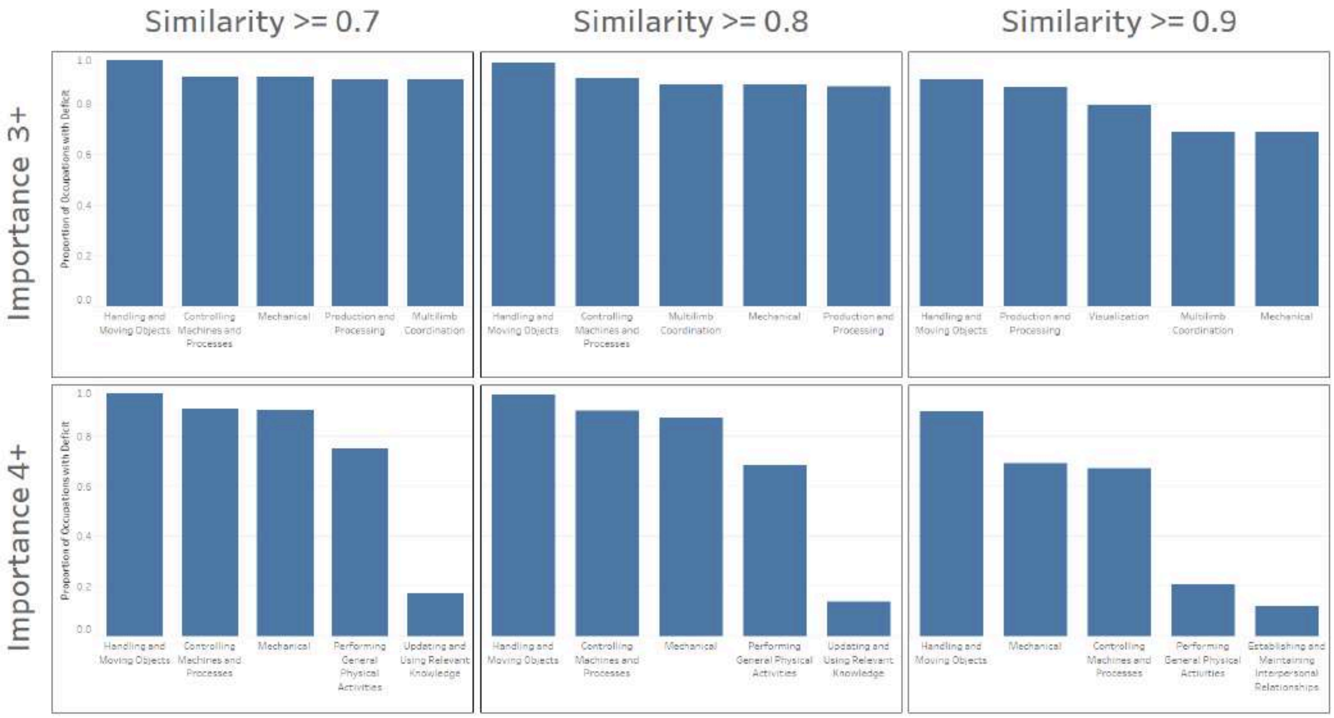


Figure I.24: Most frequently appearing relevant deficits when comparing "Engine and Other Machine Assemblers" (51-2031) to Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the importance score of that metric in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Deficits Between "Machinists" (51-4041) and Workers in Similar Occupations

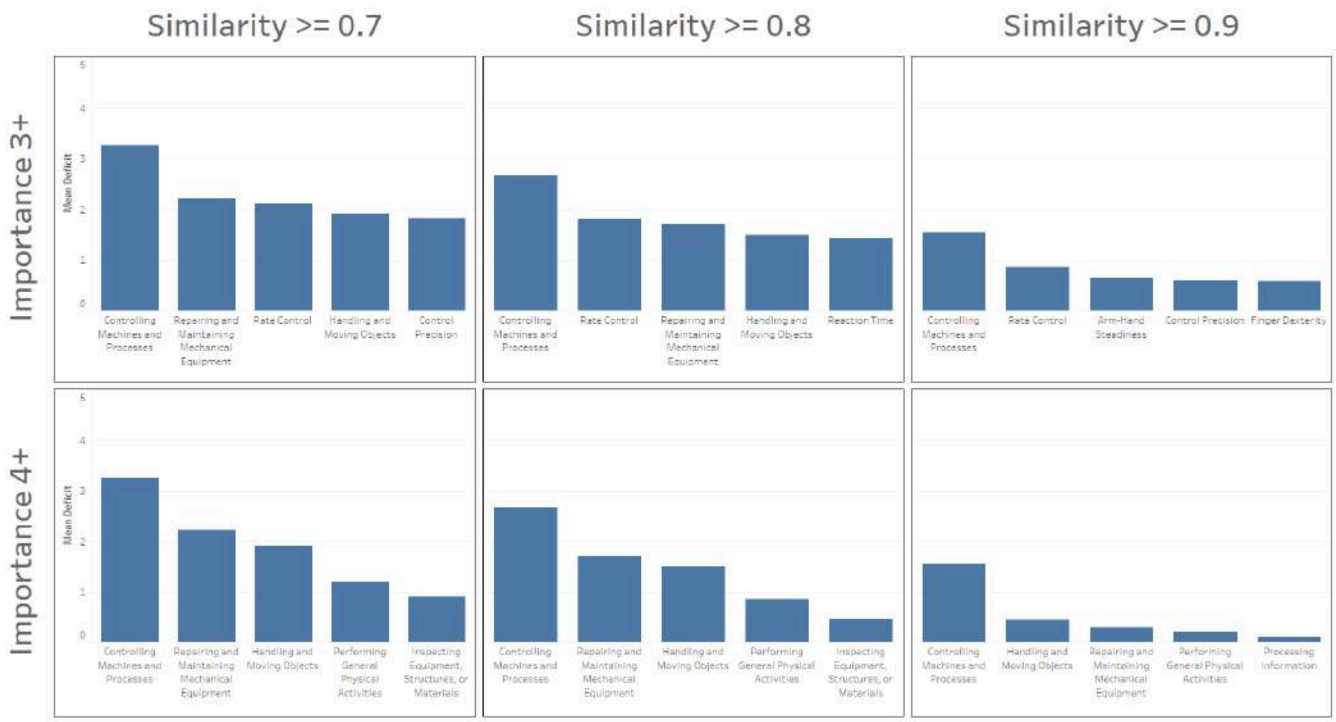


Figure I.25: Average disparity between "Machinists" (51-4041) and Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Relevance is determined by the importance score of that deficit in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Most Frequently Occurring Deficits Between “Machinists” (51-4041) and Workers in Similar Occupations

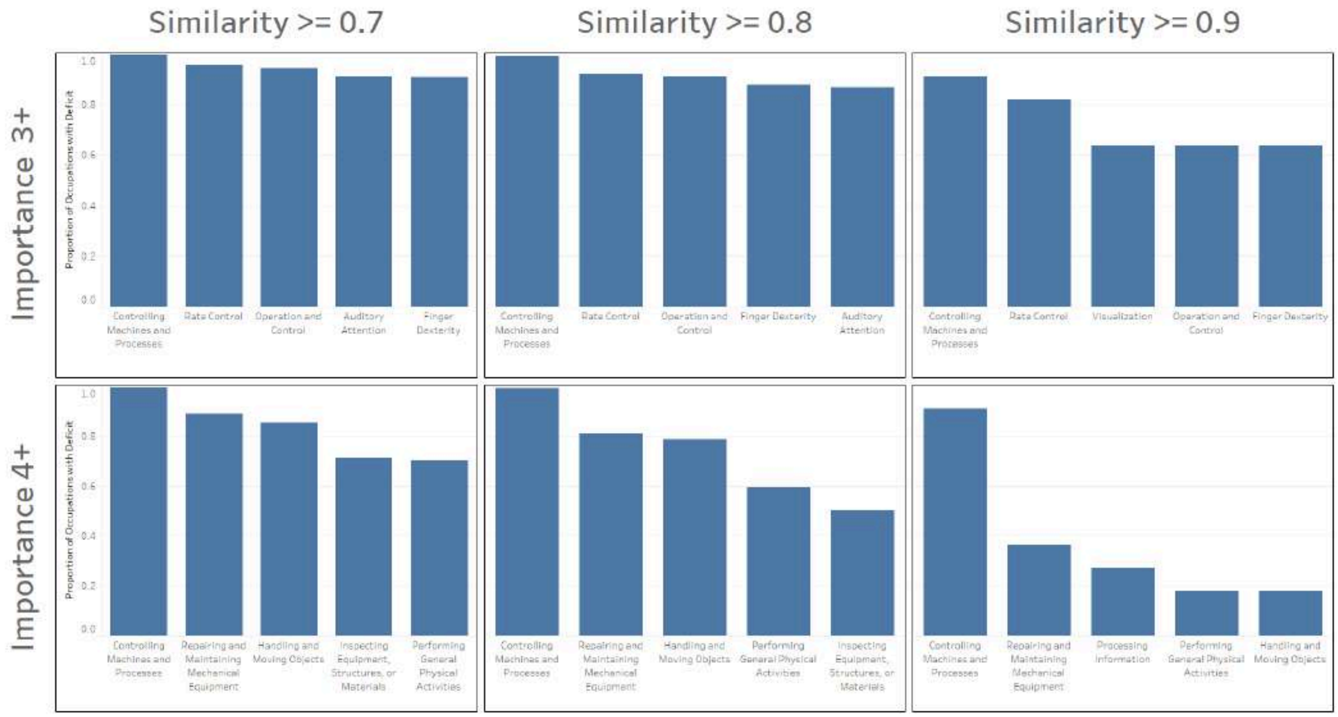


Figure I.26: Most frequently appearing relevant deficits when comparing “Machinists” (51-4041) to Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the importance score of that metric in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Deficits Between “Welders, Cutters, Solderers, and Brazers” (51-4121) and Workers in Similar Occupations

Figure I.27: Average disparity between “Welders, Cutters, Solderers, and Brazers” (51-4121) and Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Relevance is determined by the importance score of that deficit in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Most Frequently Occurring Deficits Between "Welders, Cutters, Solderers, and Brazers" (51-4121) and Workers in Similar Occupations

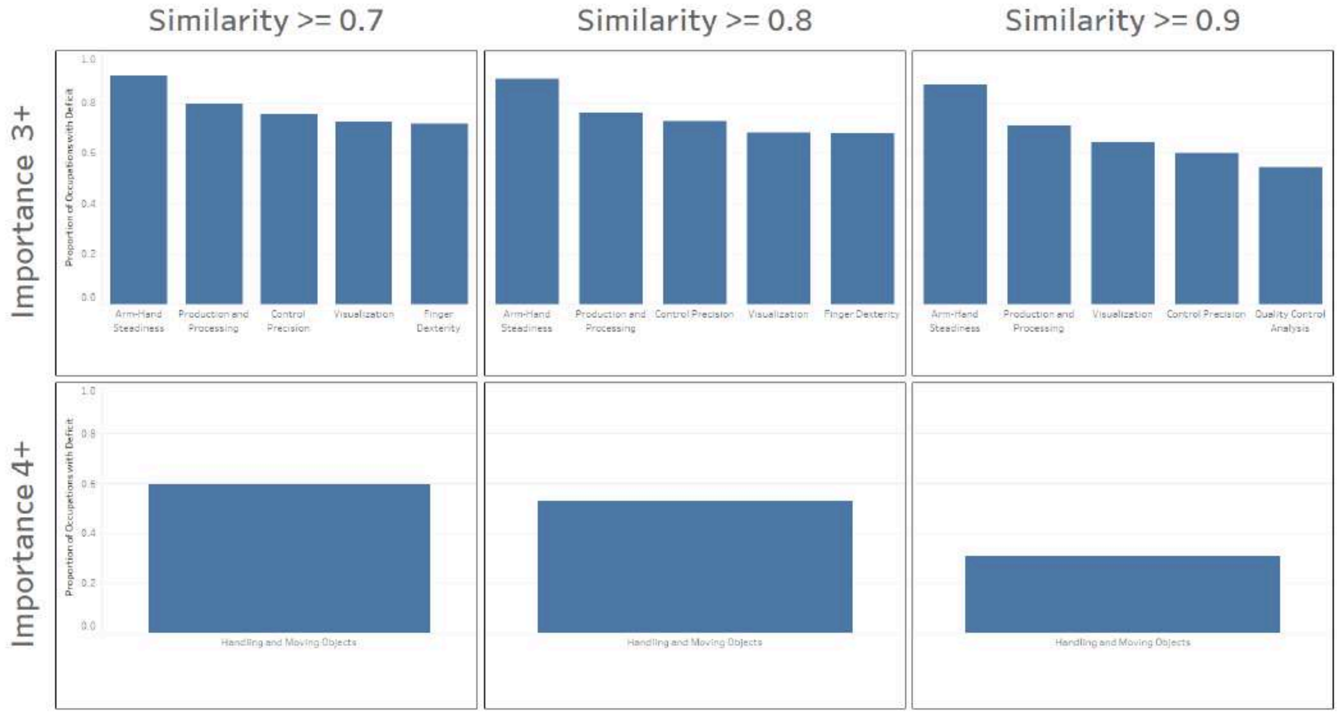


Figure I.28: Most frequently appearing relevant deficits when comparing "Welders, Cutters, Solderers, and Brazers" (51-4121) to Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the importance score of that metric in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Deficits Between 'Computer Numerically Controlled Tool Operators" (51-9161) and Workers in Similar Occupations

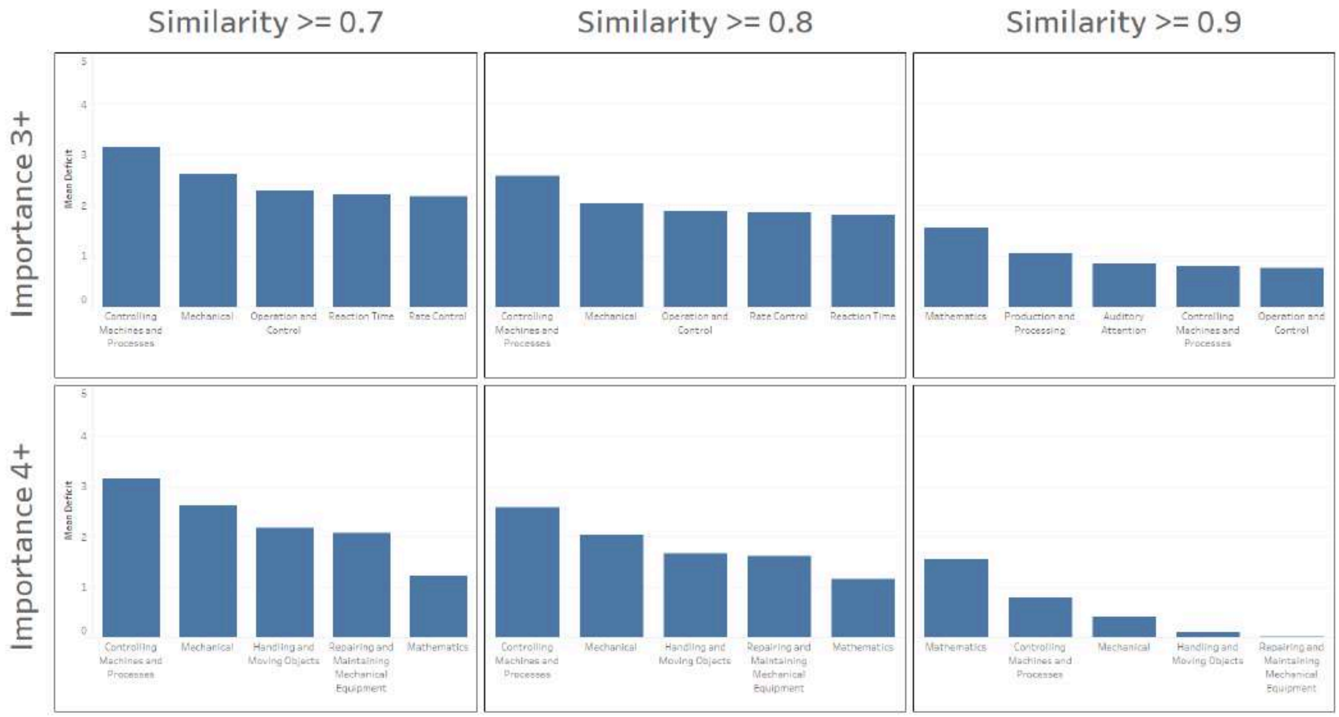


Figure I.29: Average disparity between "Computer Numerically Controlled Tool Operators" (51-9161) and Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Relevance is determined by the importance score of that deficit in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Most Frequently Occurring Deficits Between "Computer Numerically Controlled Tool Operators" (51-9161) and Workers in Similar Occupations

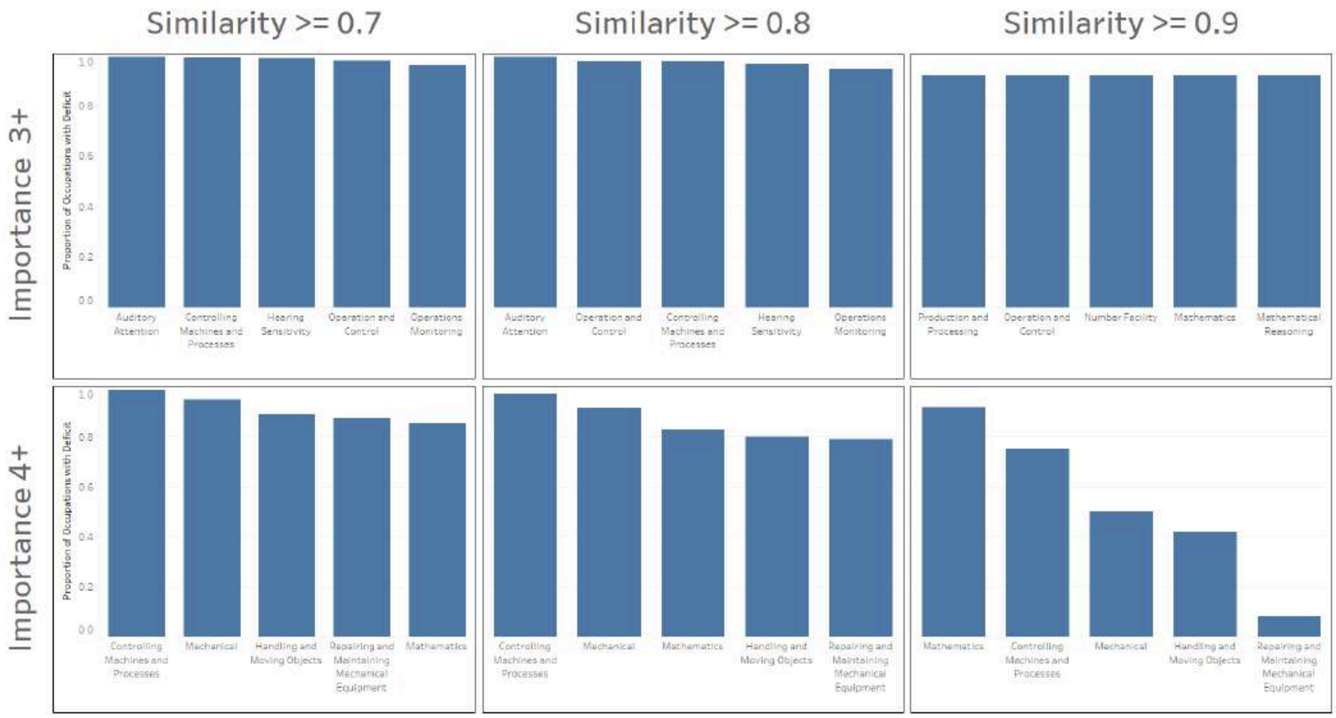


Figure I.30: Most frequently appearing relevant deficits when comparing "Computer Numerically Controlled Tool Operators' (51-9161) to Workers in Similar Occupations where deficits are relevant (capped at top 5 metrics if more exist). Frequency is presented as a portion of similar jobs that the deficit appears in. Relevance is determined by the importance score of that metric in the similar occupation. Cutoffs of 3 and 4 were used for importance. Similarities of 0.7, 0.8, and 0.9 were used as cutoffs for occupations considered similar.

Appendix J: Labor Flow Analysis

This section includes figures similar to those provided in previous appendices, with the difference being that these figures use change in the available labor supply over time instead of the static labor supply in 2022.

Subsections include:
- Change in Labor Supply by MSA Over Time
- Relative Wage Position Weighted by Change in Labor Supply

Change in Labor Supply by MSA Over Time

This section maps the change in labor supply for single occupations by MSA from 2012 to 2022, from 2017 to 2022, and from 2021 to 2022. Increases in the labor supply are green. Decreases in the labor supply are red.

BLS data is unavailable for a Change in Number of Miscellaneous Assemblers and Fabricators (51-2090) Over 10 Years by MSA figure.

BLS data is unavailable for a Change in Number of Miscellaneous Assemblers and Fabricators (51-2090) Over 5 Years by MSA figure.

Change in Number of “Miscellaneous Assemblers and Fabricators” (51-2090) Over 1 Year by MSA

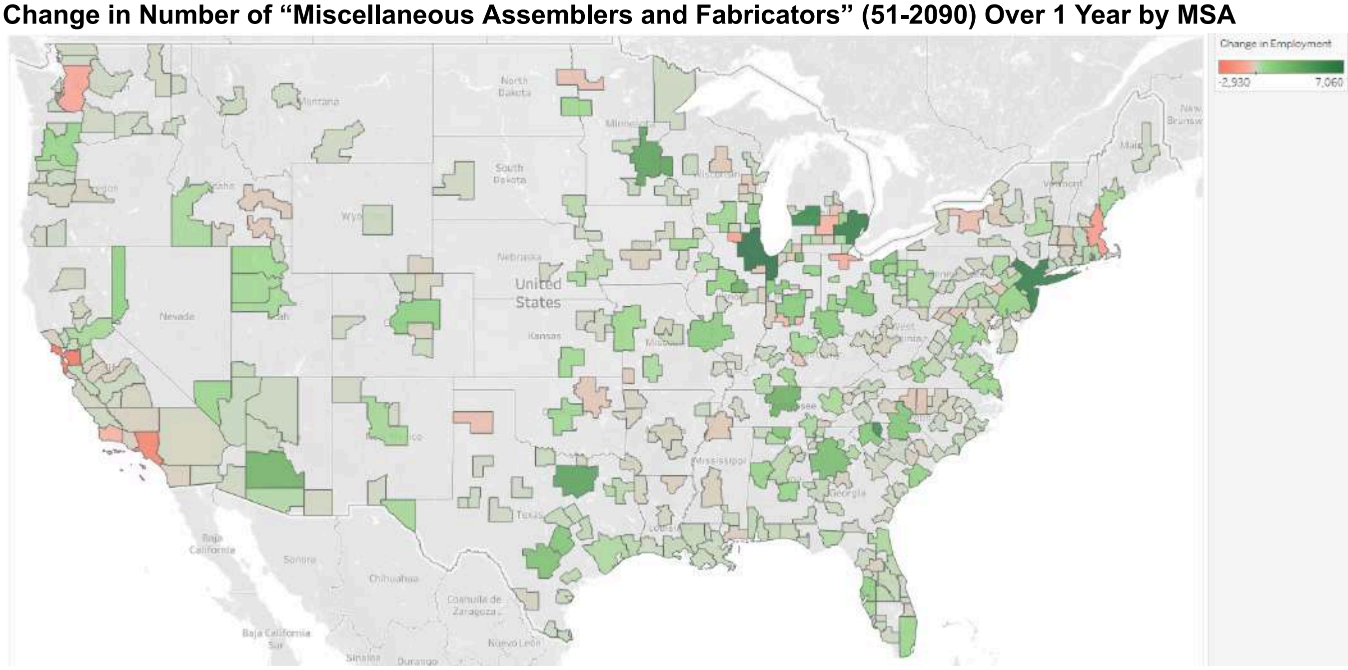


Figure J.1: Map of labor change over 1 year for “Miscellaneous Assemblers and Fabricators” by MSA.

Change in Number of "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) Over 10 Years by MSA

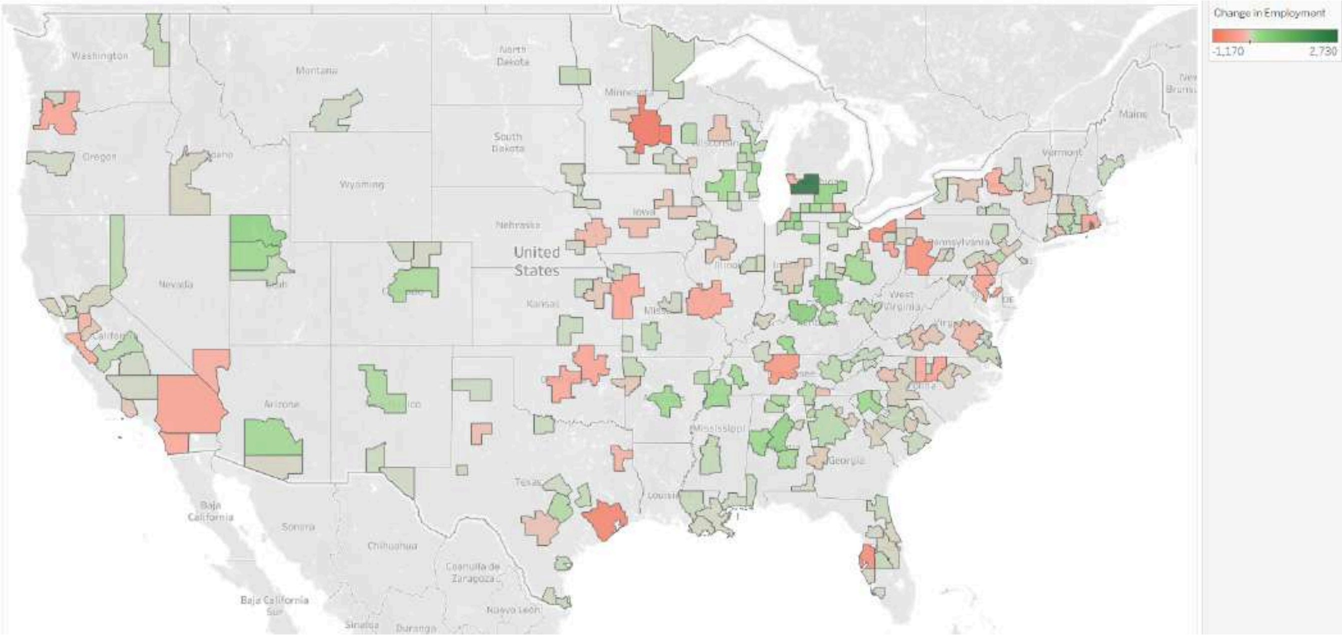


Figure J.2: Map of labor change over 10 years for "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" by MSA.

Change in Number of "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) Over 5 Years by MSA

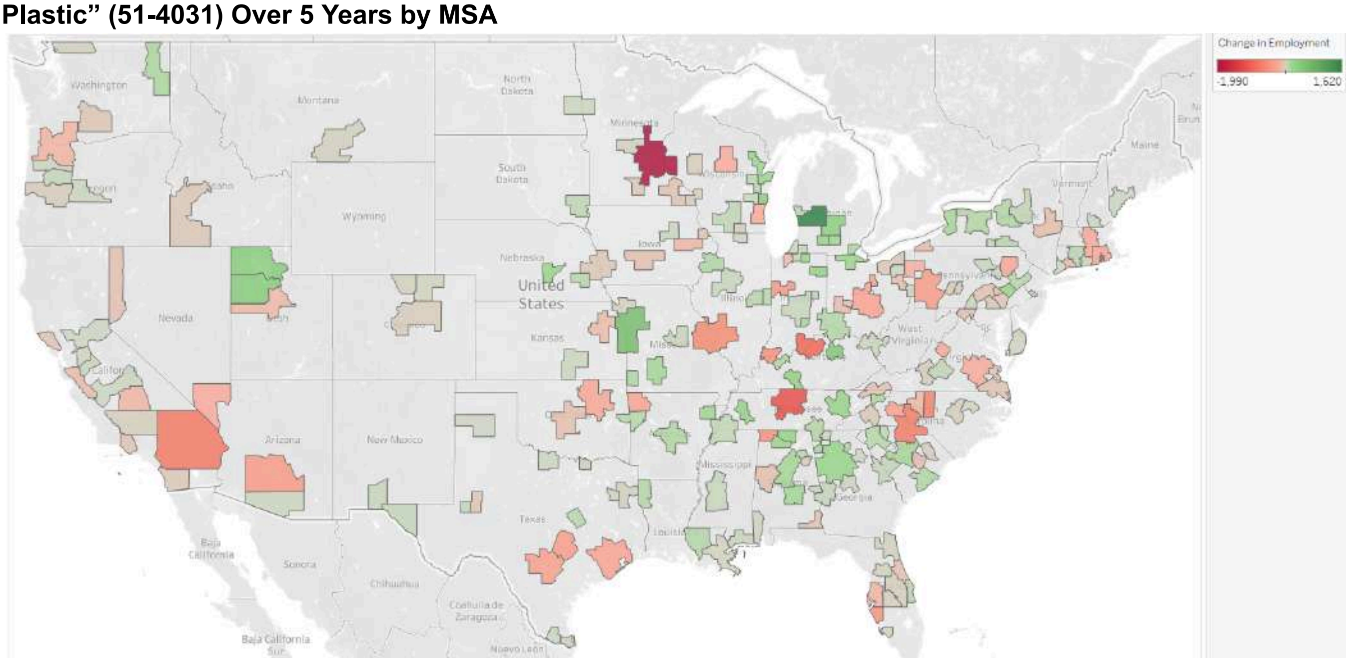


Figure J.3: Map of labor change over 5 years for "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" by MSA.

Change in Number of "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) Over 1 Year by MSA

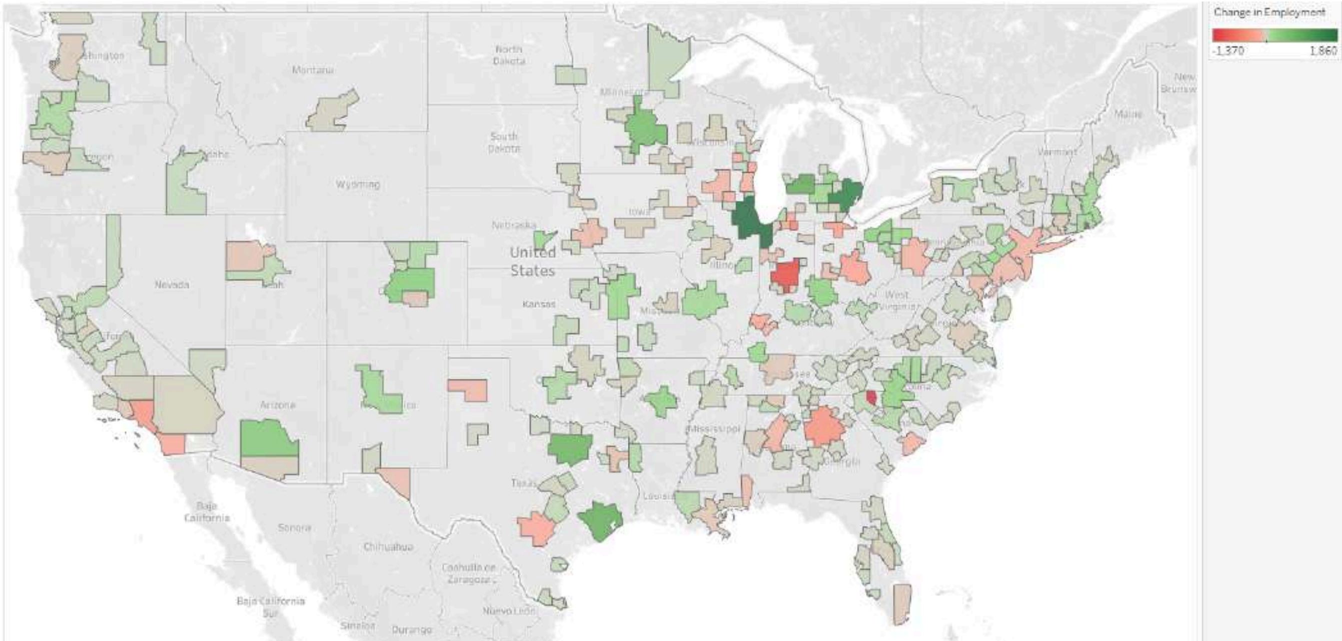


Figure J.4: Map of labor change over 1 year for "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" by MSA.

Change in Number of "Engine and Other Machine Assemblers" (51-2031) Over 10 Years by MSA

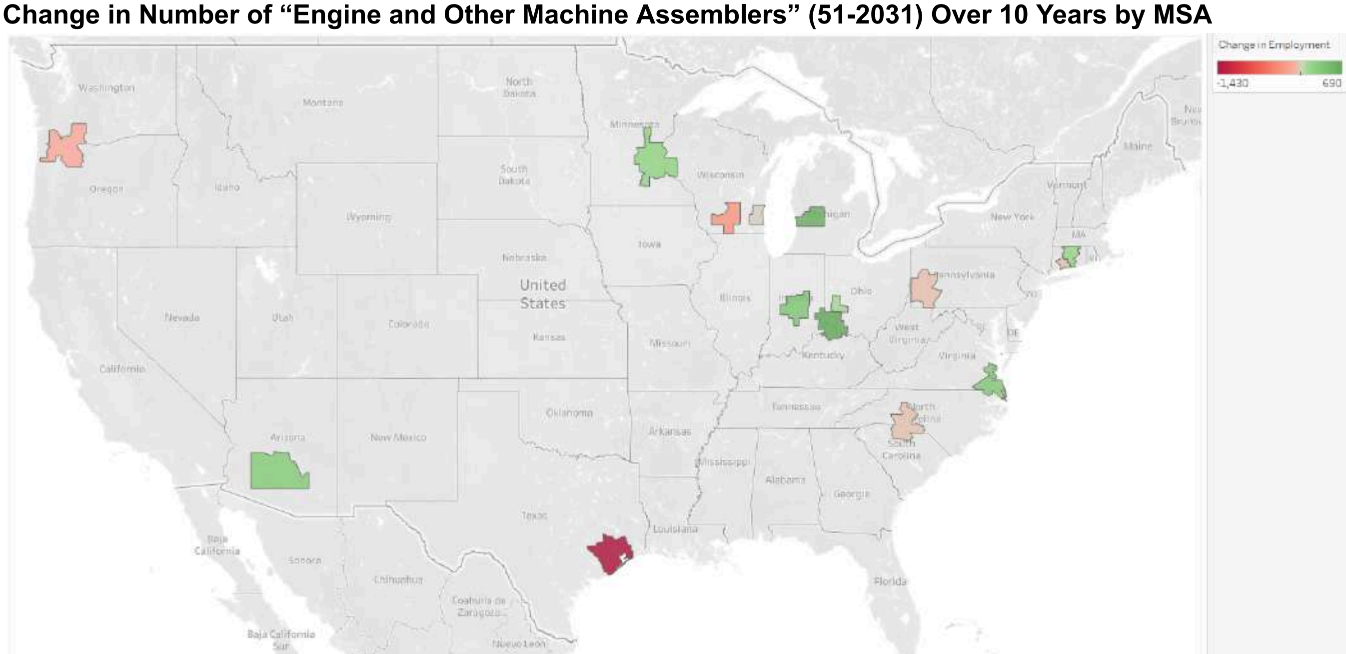


Figure J.5: Map of labor change over 10 years for "Engine and Other Machine Assemblers" by MSA.

Change in Number of "Engine and Other Machine Assemblers" (51-2031) Over 5 Years by MSA

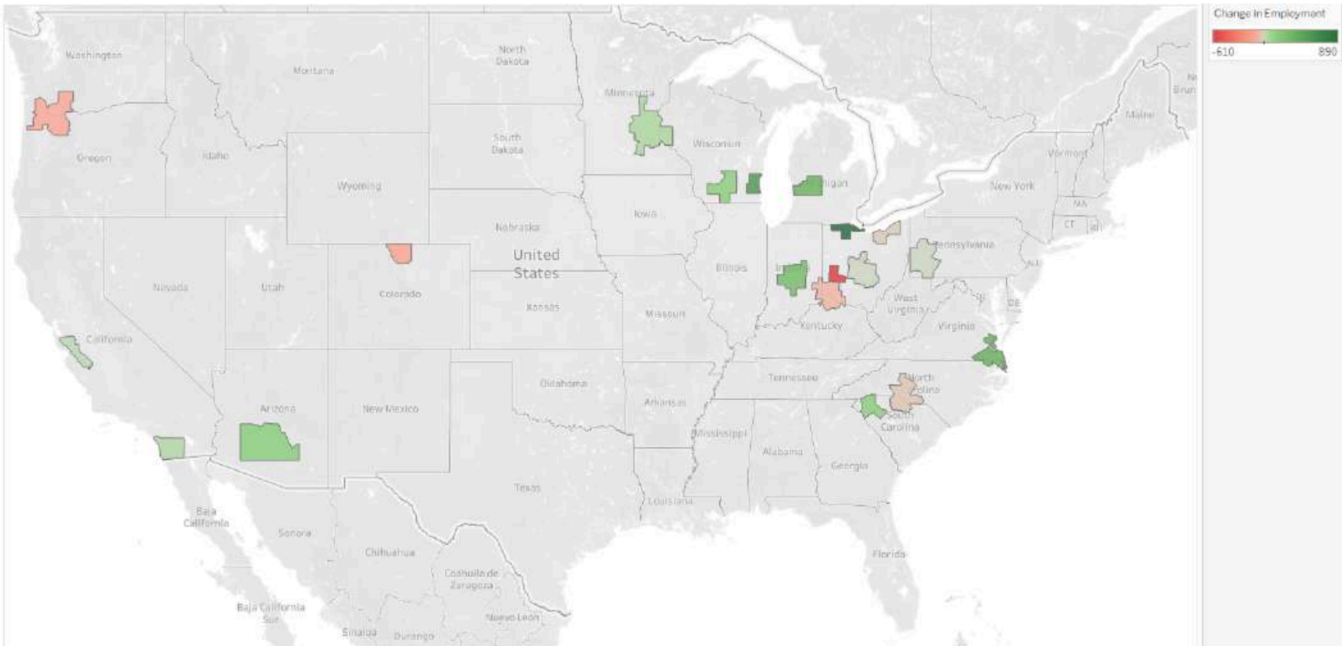


Figure J.6: Map of labor change over 5 years for "Engine and Other Machine Assemblers" by MSA.

Change in Number of "Engine and Other Machine Assemblers" (51-2031) Over 1 Year by MSA

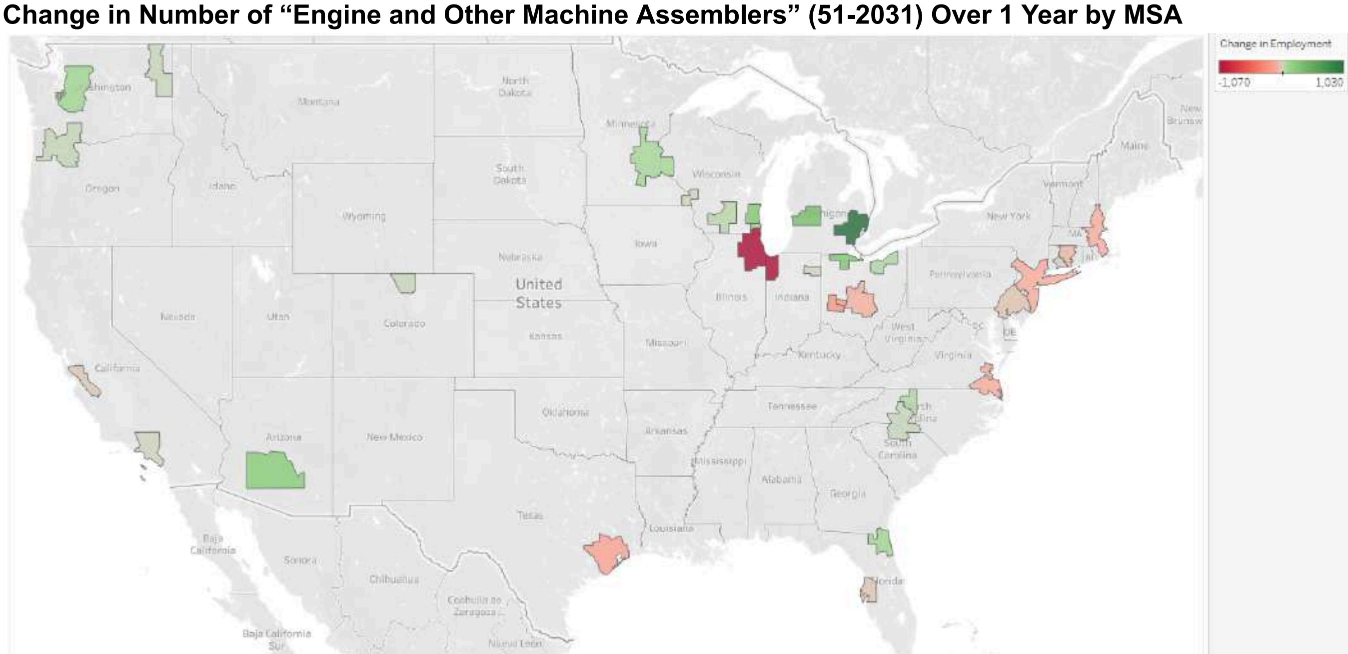


Figure J.7: Map of labor change over 1 year for "Engine and Other Machine Assemblers" by MSA.

Change in Number of "First-Line Supervisors of Production and Operating Workers" (51-1011) Over 10 Years by MSA

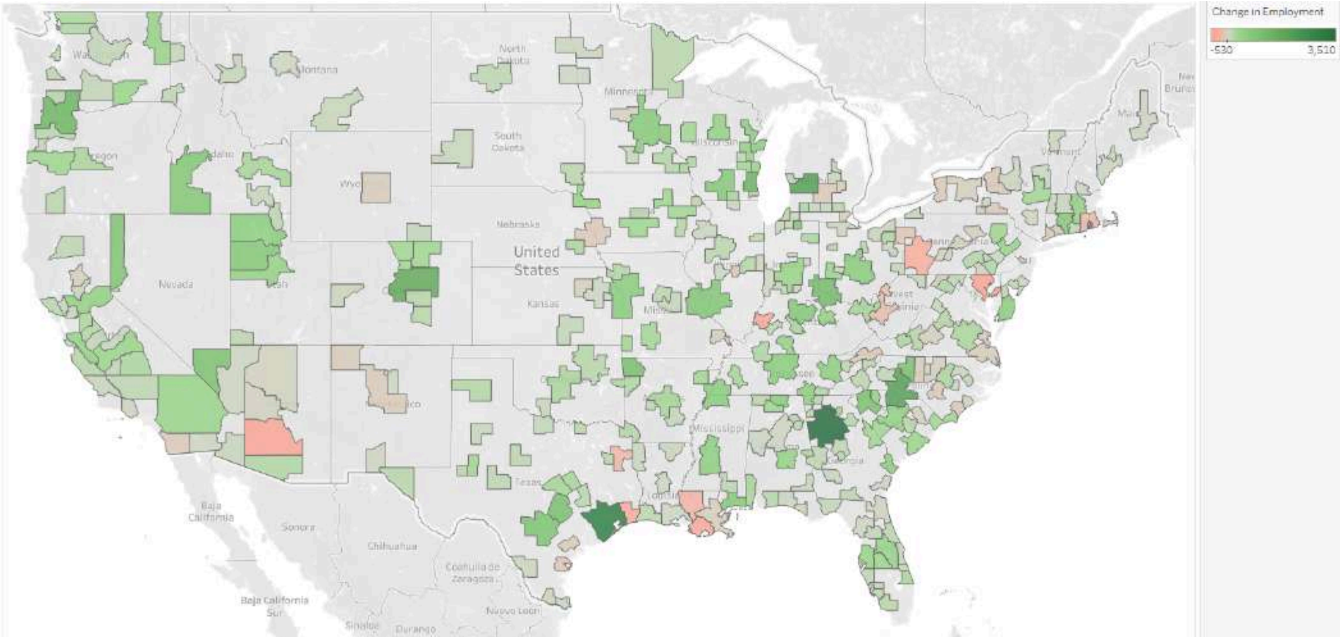


Figure J.8: Map of labor change over 10 years for "First-Line Supervisors of Production and Operating Workers" by MSA.

Change in Number of "First-Line Supervisors of Production and Operating Workers" (51-1011) Over 5 Years by MSA

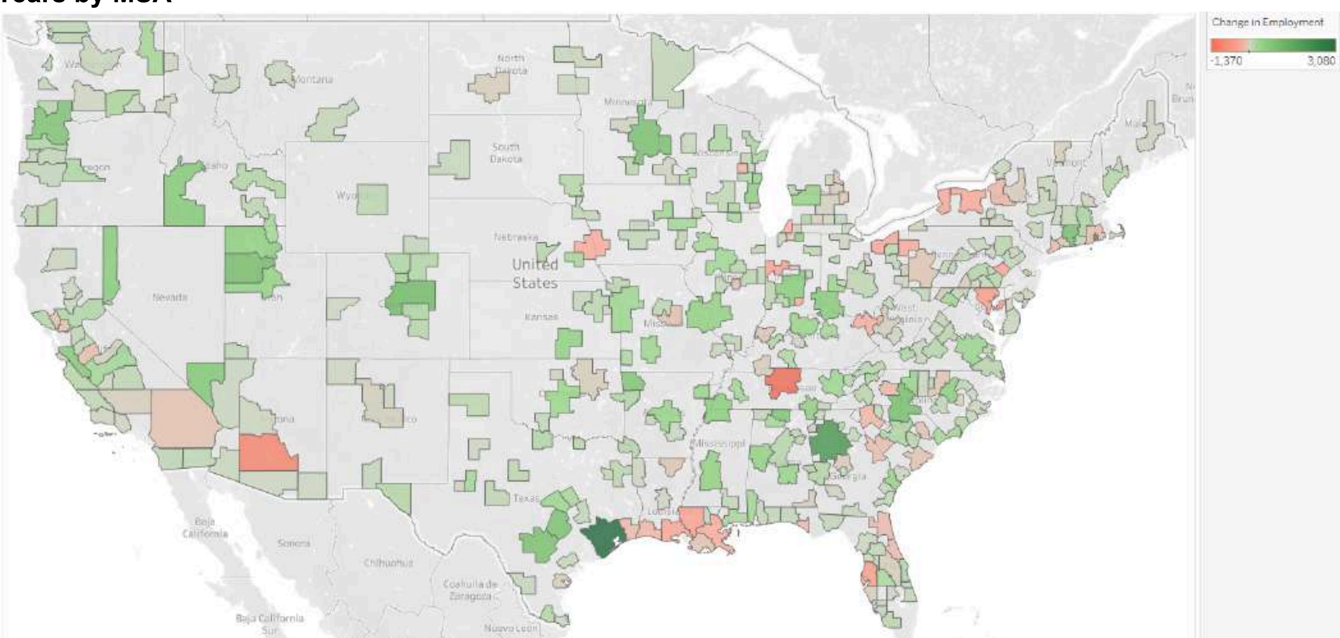


Figure J.9: Map of labor change over 5 years for "First-Line Supervisors of Production and Operating Workers" by MSA.

Change in Number of "First-Line Supervisors of Production and Operating Workers" (51-1011) Over 1 Year by MSA

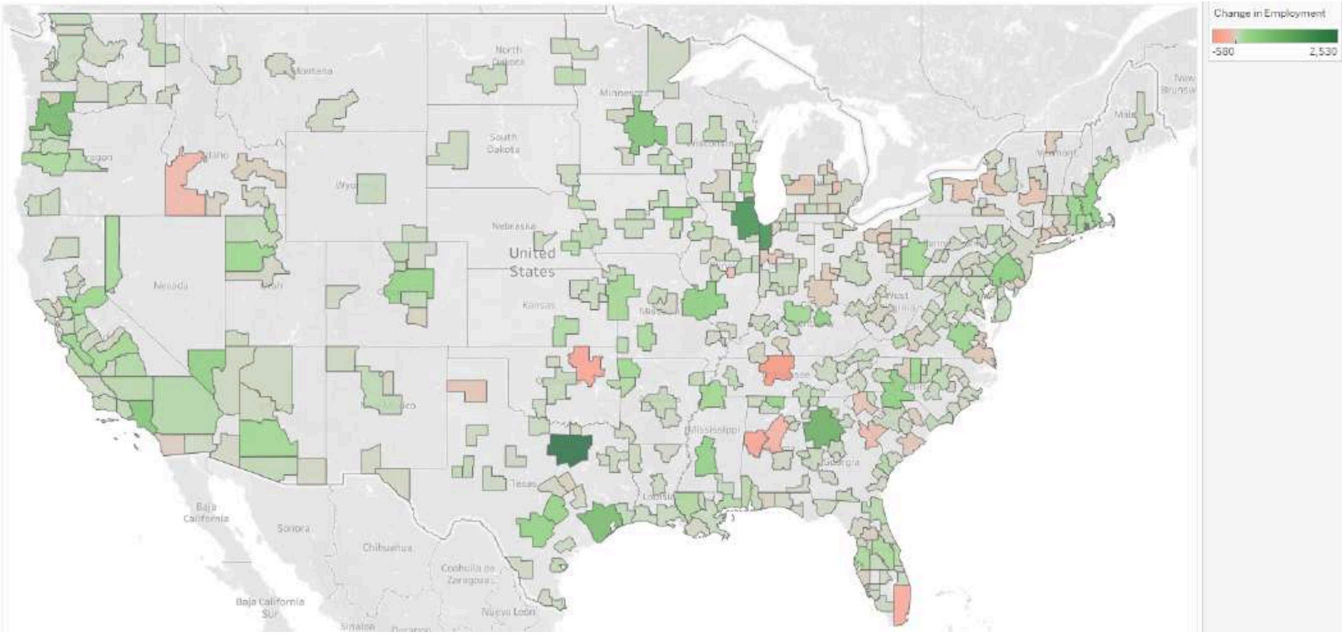


Figure J.10: Map of labor change over 1 year for "First-Line Supervisors of Production and Operating Workers" by MSA.

Change in Number of "Inspectors, Testers, Sorters, Samplers, and Weighers" (51-9061) Over 10 Years by MSA

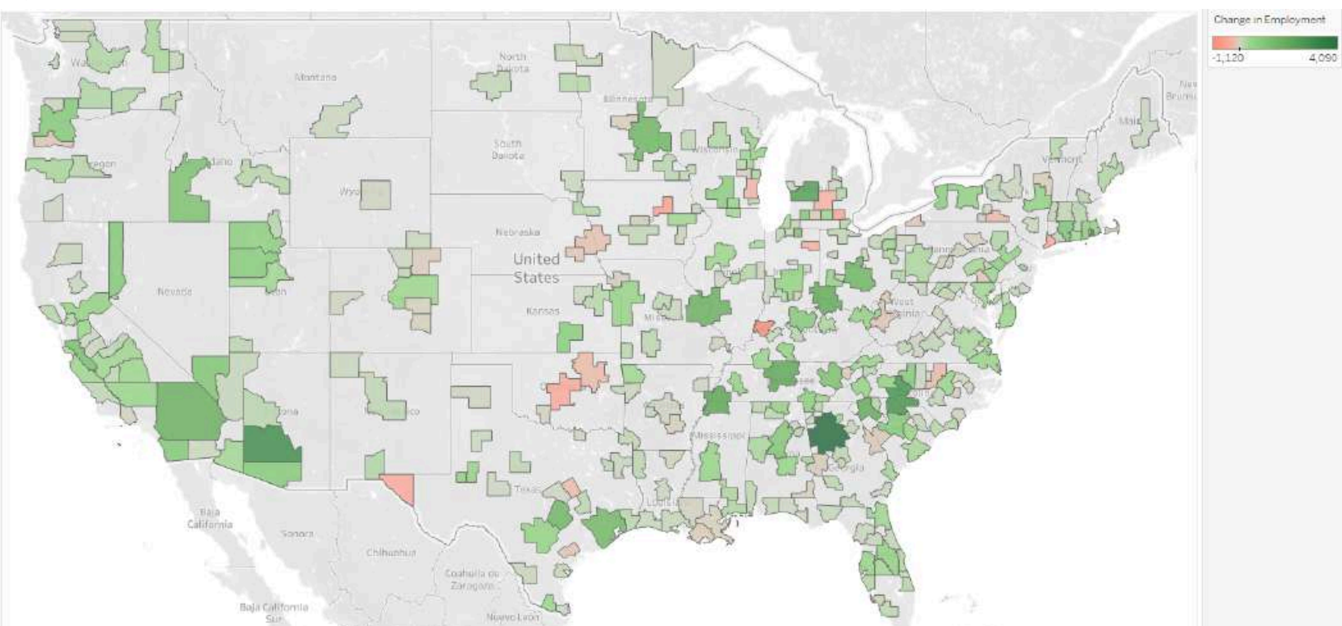


Figure J.11: Map of labor change over 10 years for "Inspectors, Testers, Sorters, Samplers, and Weighers" by MSA.

Change in Number of "Inspectors, Testers, Sorters, Samplers, and Weighers" (51-9061) Over 5 Years by MSA

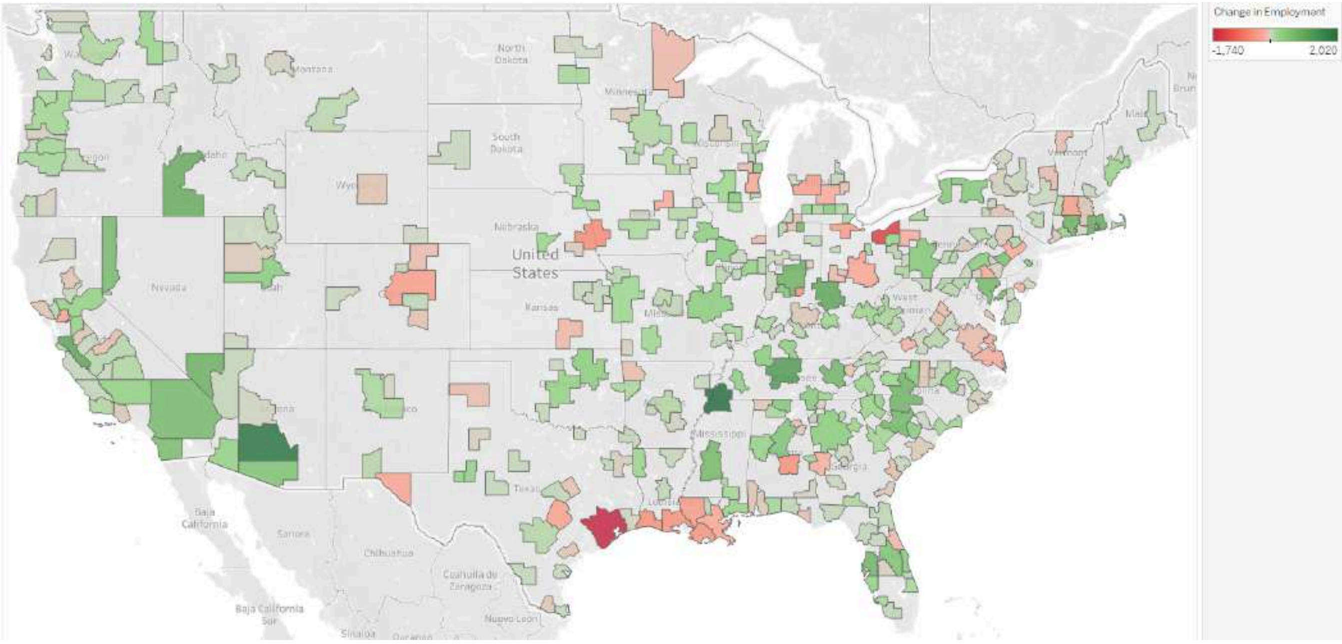


Figure J.12: Map of labor change over 5 years for "Inspectors, Testers, Sorters, Samplers, and Weighers" by MSA.

Change in Number of "Inspectors, Testers, Sorters, Samplers, and Weighers" (51-9061) Over 1 Year by MSA

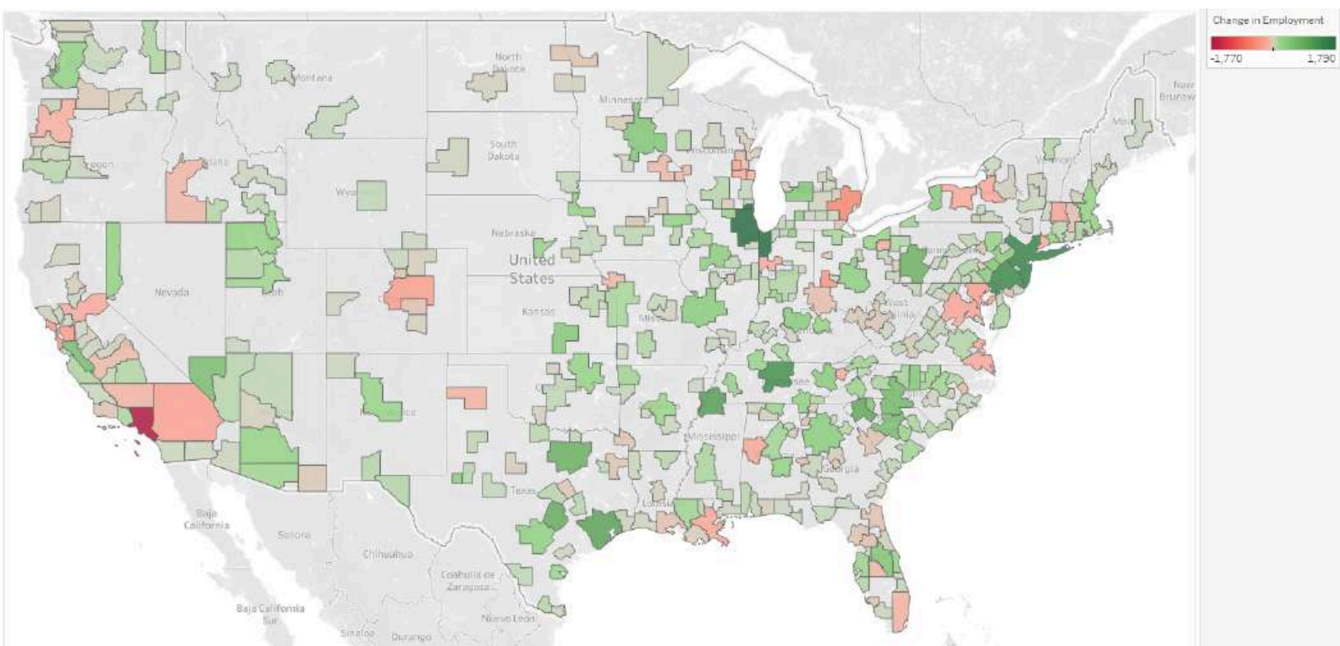


Figure J.13: Map of labor change over 1 year for "Inspectors, Testers, Sorters, Samplers, and Weighers" by MSA.

Change in Number of “Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic” (51-4081) Over 10 Years by MSA

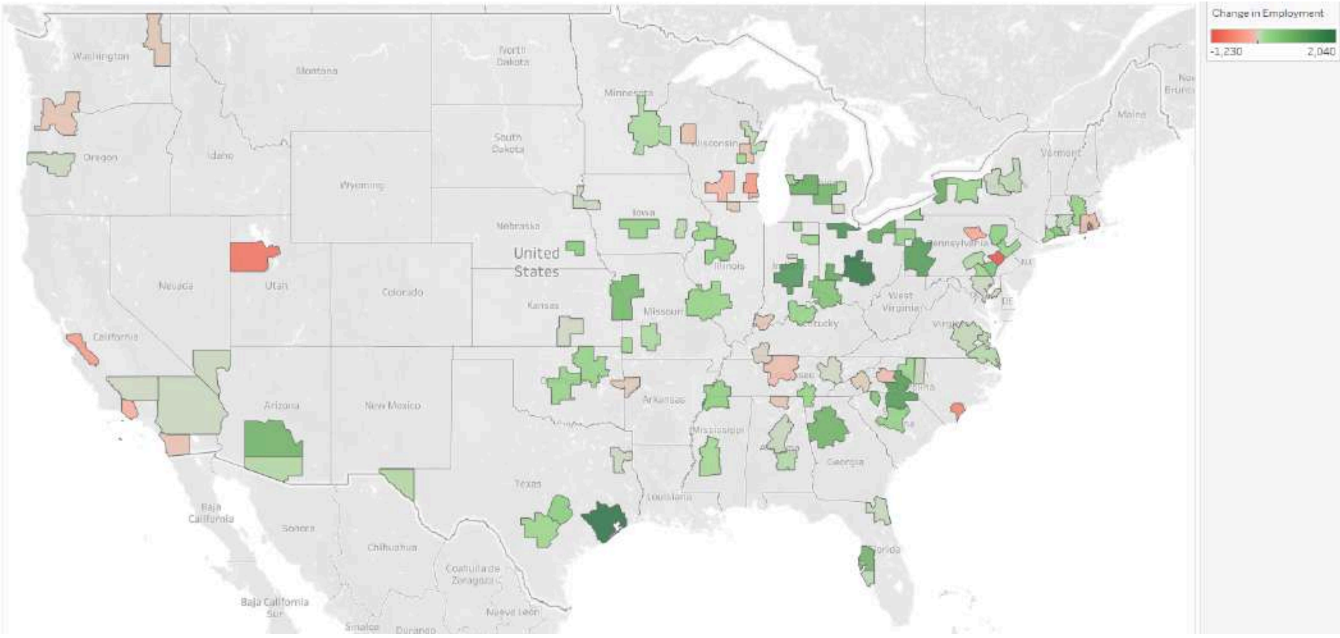


Figure J.14: Map of labor change over 10 years for “Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic” by MSA.

Change in Number of “Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic” (51-4081) Over 5 Years by MSA

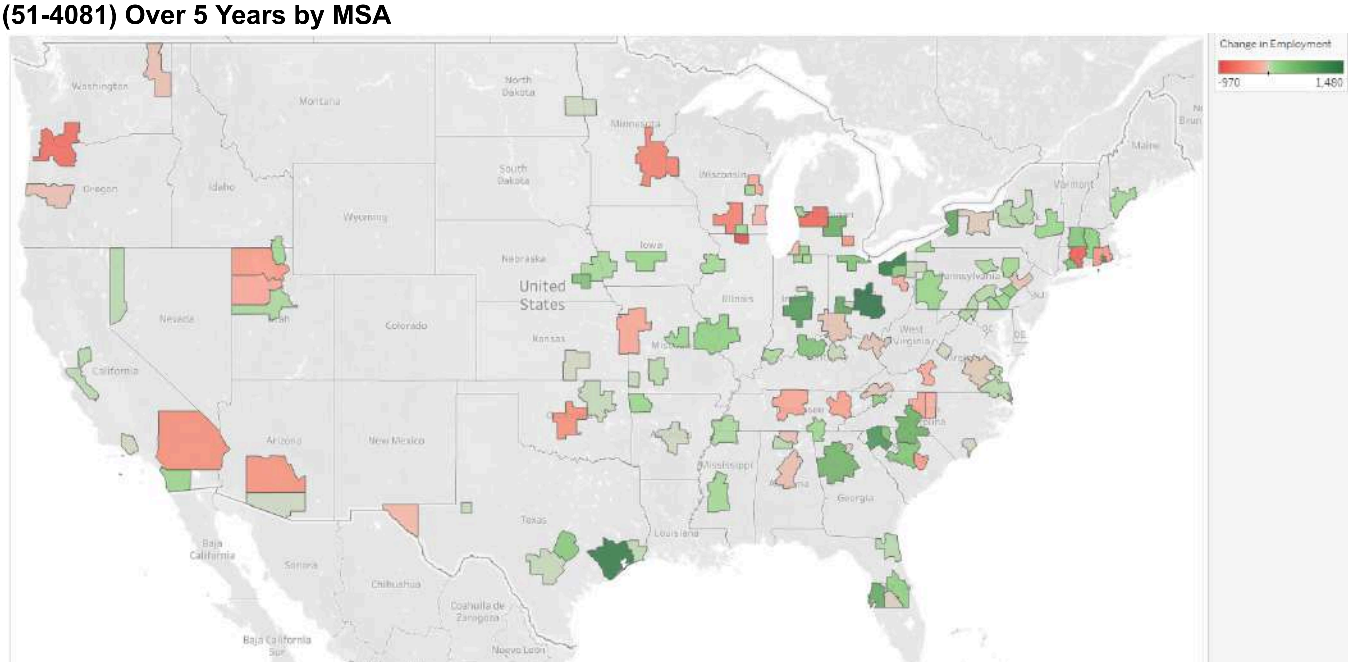


Figure J.15: Map of labor change over 5 years for “Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic” by MSA.

Change in Number of "Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic" (51-4081) Over 1 Year by MSA

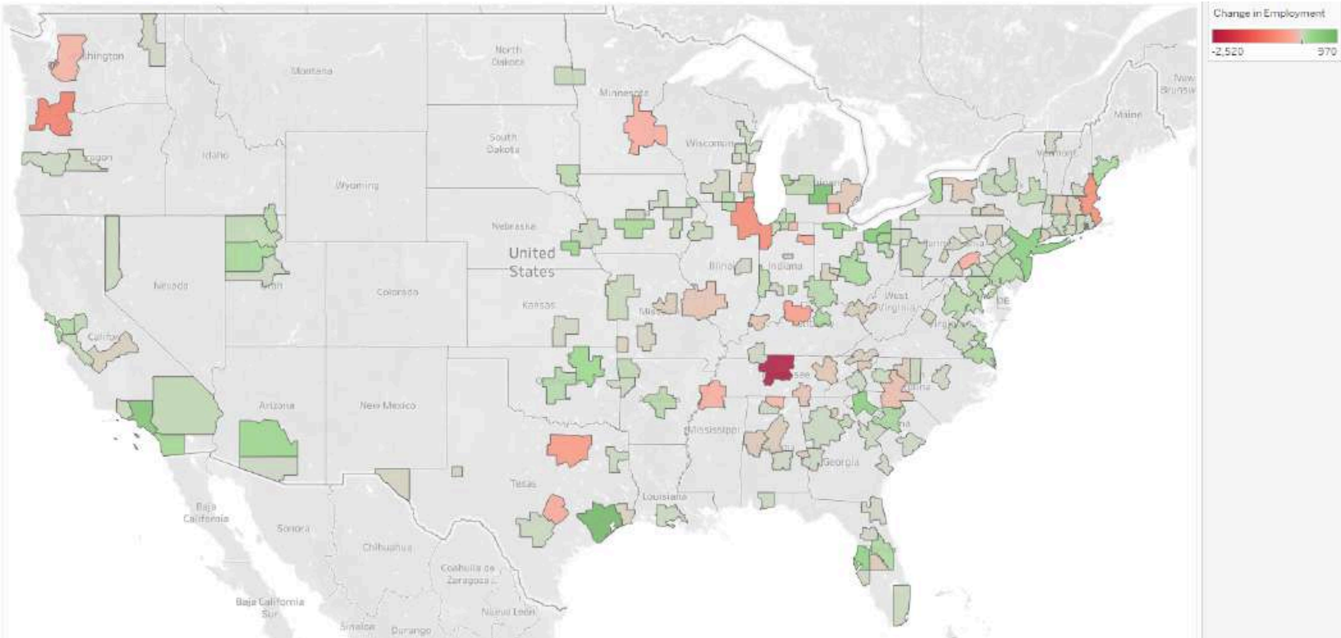


Figure J.16: Map of labor change over 1 year for "Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic" by MSA.

Change in Number of "Machinists" (51-4041) Over 10 Years by MSA

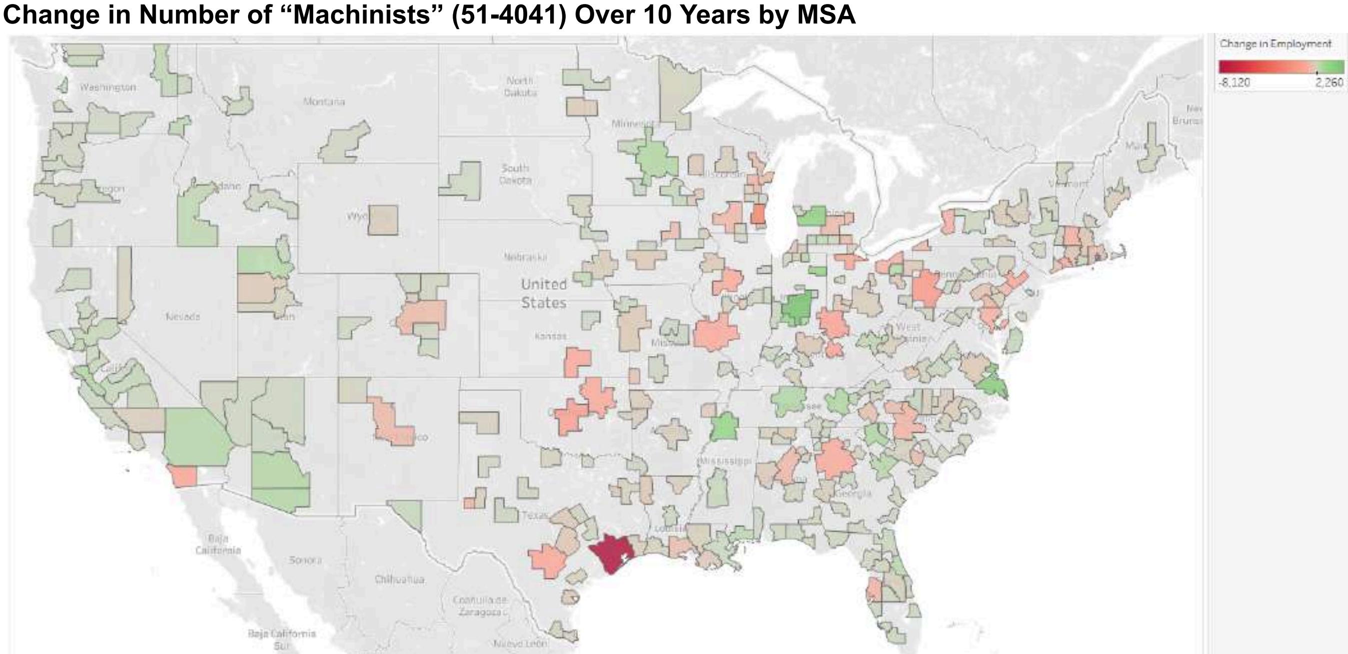


Figure J.17: Map of labor change over 10 years for "Machinists" by MSA.

Change in Number of “Machinists” (51-4041) Over 5 Years by MSA

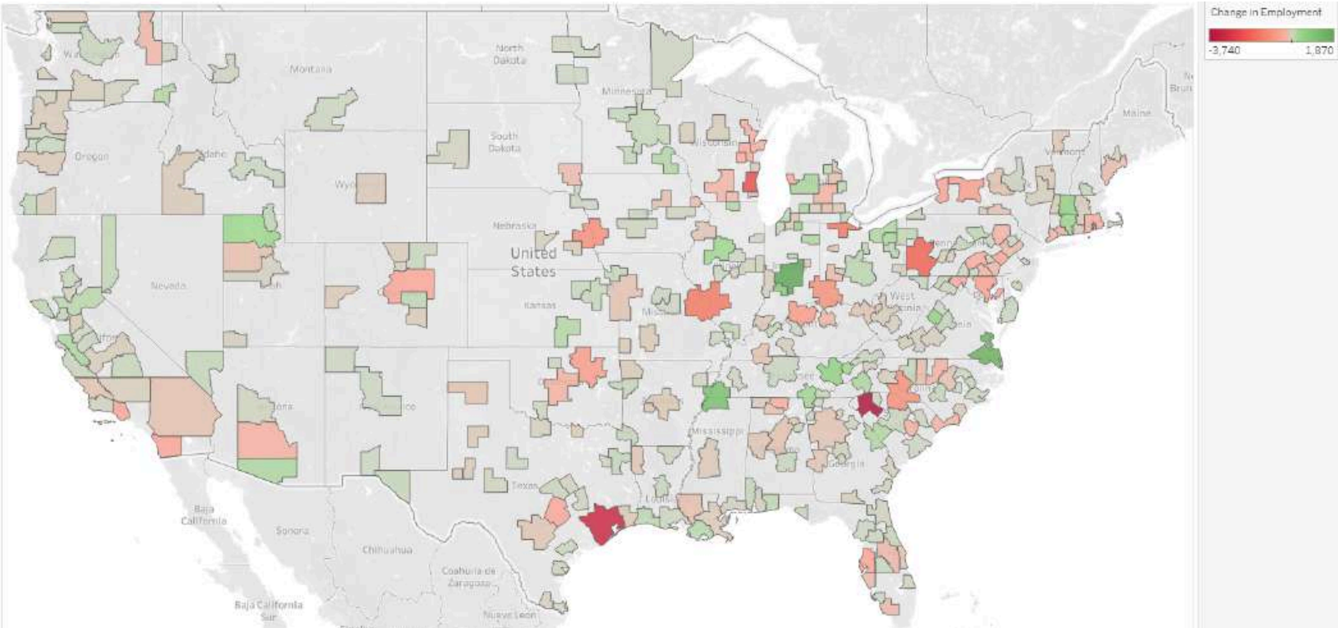


Figure J.18: Map of labor change over 5 years for “Machinists” by MSA.

Change in Number of “Machinists” (51-4041) Over 1 Year by MSA

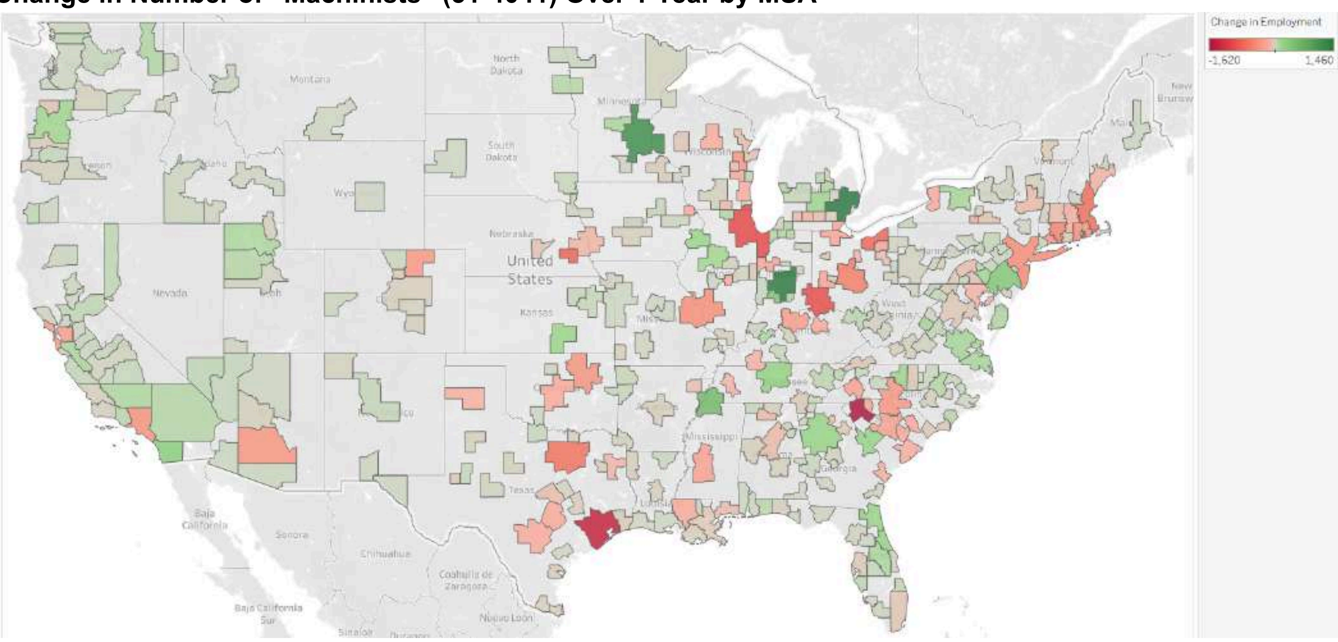


Figure J.19: Map of labor change over 1 year for “Machinists” by MSA.

BLS data is unavailable for a Change in Number of “Electrical, Electronic, and Electromechanical Assemblers, Except Coil Winders, Tapers, and Finishers” (51-2028) Over 10 Years by MSA figure.

Change in Number of "Electrical, Electronic, and Electromechanical Assemblers, Except Coil Winders, Tapers, and Finishers" (51-2028) Over 5 Years by MSA

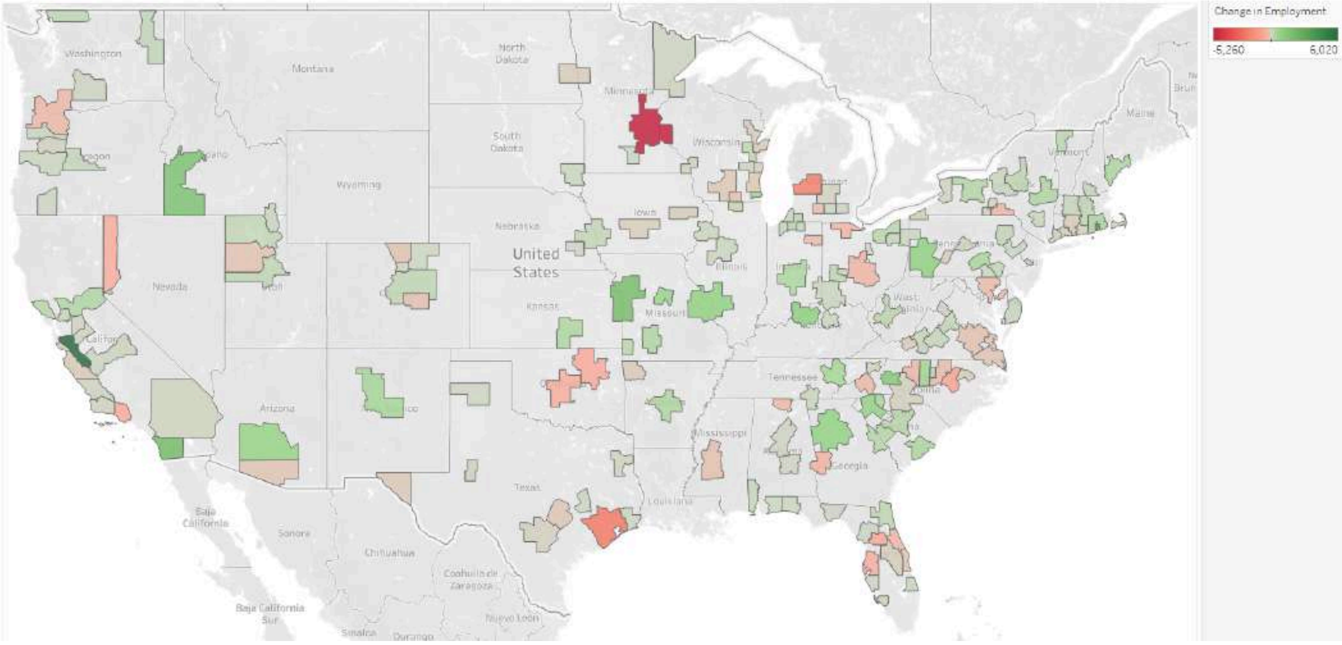


Figure J.20: Map of labor change over 5 years for "Electrical, Electronic, and Electromechanical Assemblers, Except Coil Winders, Tapers, and Finishers" by MSA.

Change in Number of "Electrical, Electronic, and Electromechanical Assemblers, Except Coil Winders, Tapers, and Finishers" (51-2028) Over 1 Year by MSA

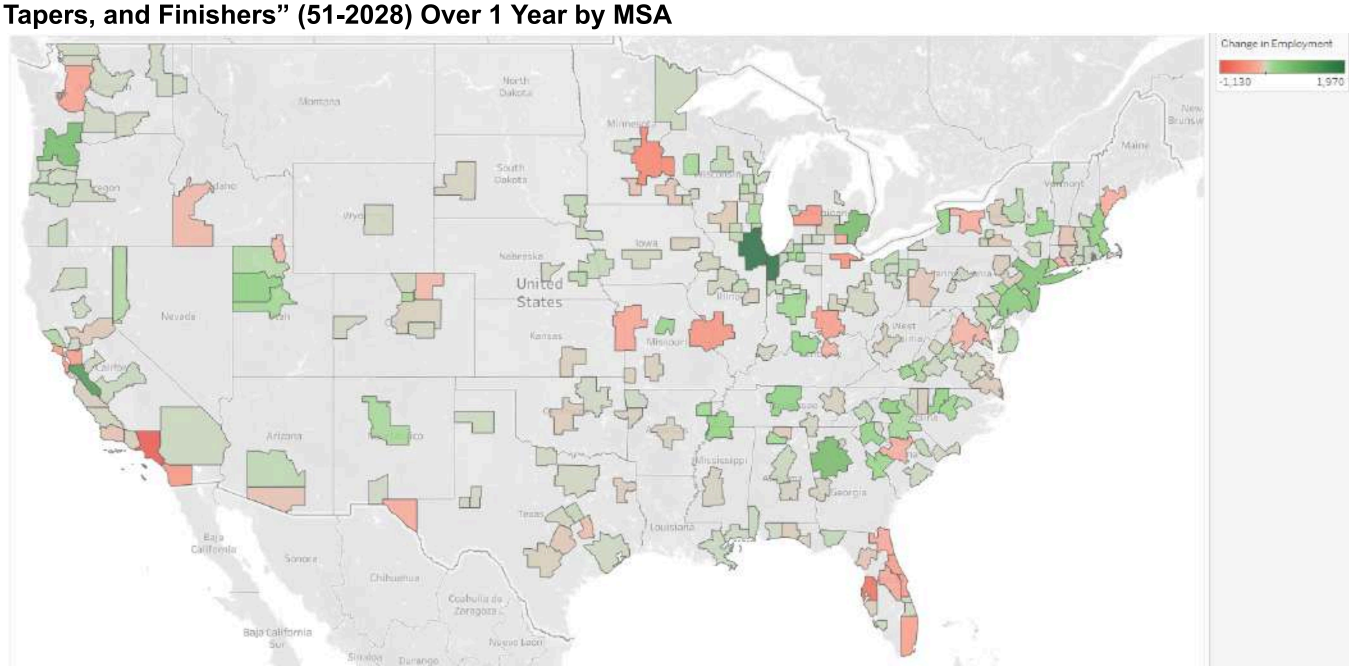


Figure J.21: Map of labor change over 1 year for "Electrical, Electronic, and Electromechanical Assemblers, Except Coil Winders, Tapers, and Finishers" by MSA.

Change in Number of "Welders, Cutters, Solderers, and Brazers" (51-4121) Over 10 Years by MSA

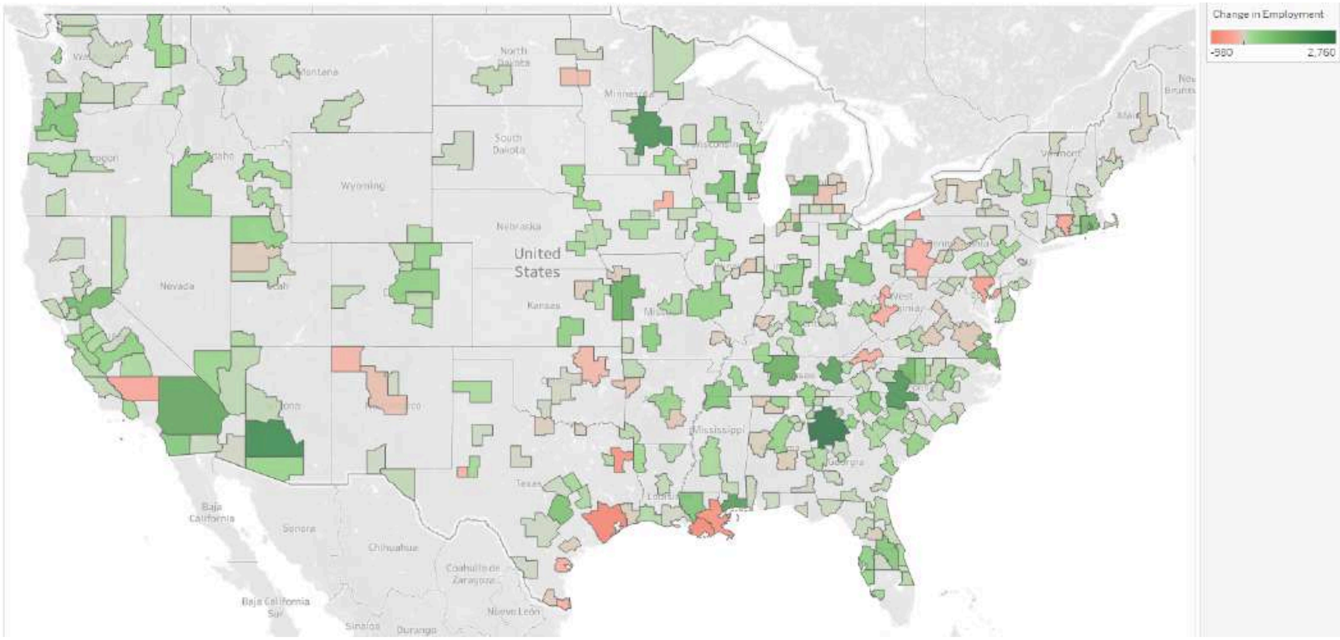


Figure J.22: Map of labor change over 10 years for "Welders, Cutters, Solderers, and Brazers" by MSA.

Change in Number of "Welders, Cutters, Solderers, and Brazers" (51-4121) Over 5 Years by MSA

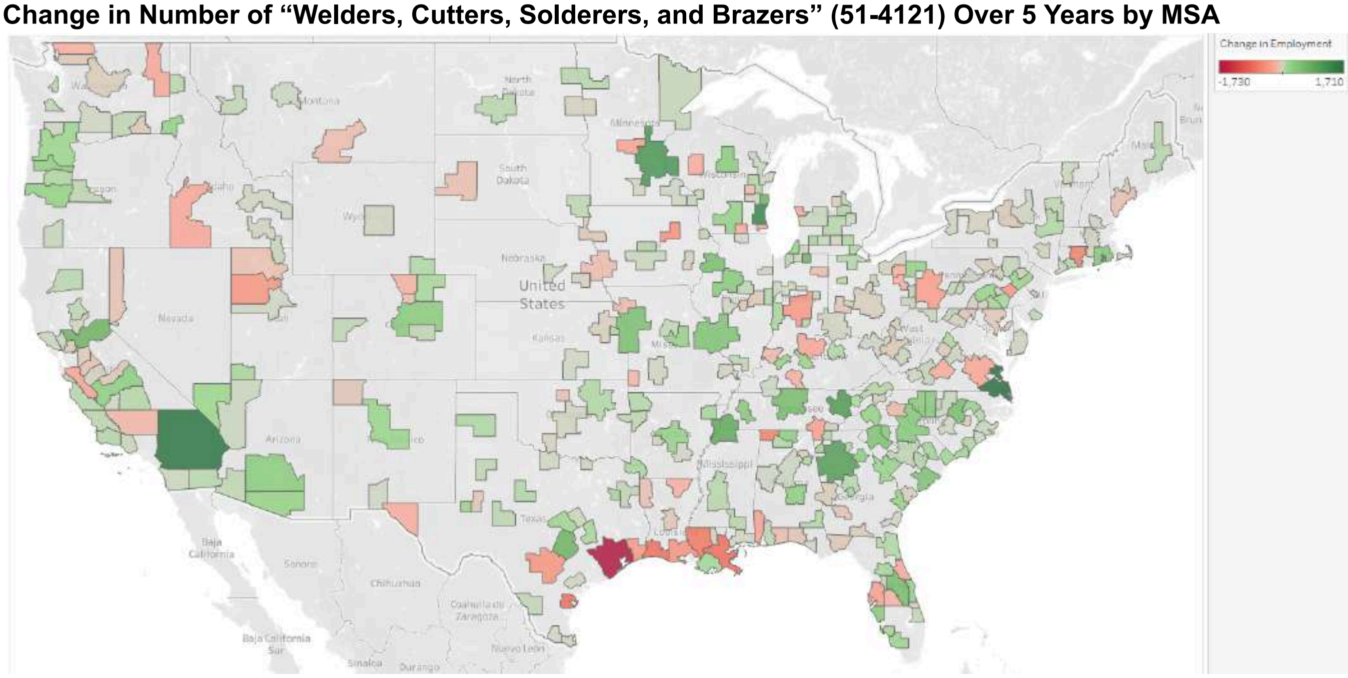


Figure J.23: Map of labor change over 5 years for "Welders, Cutters, Solderers, and Brazers" by MSA.

Change in Number of "Welders, Cutters, Solderers, and Brazers" (51-4121) Over 1 Year by MSA

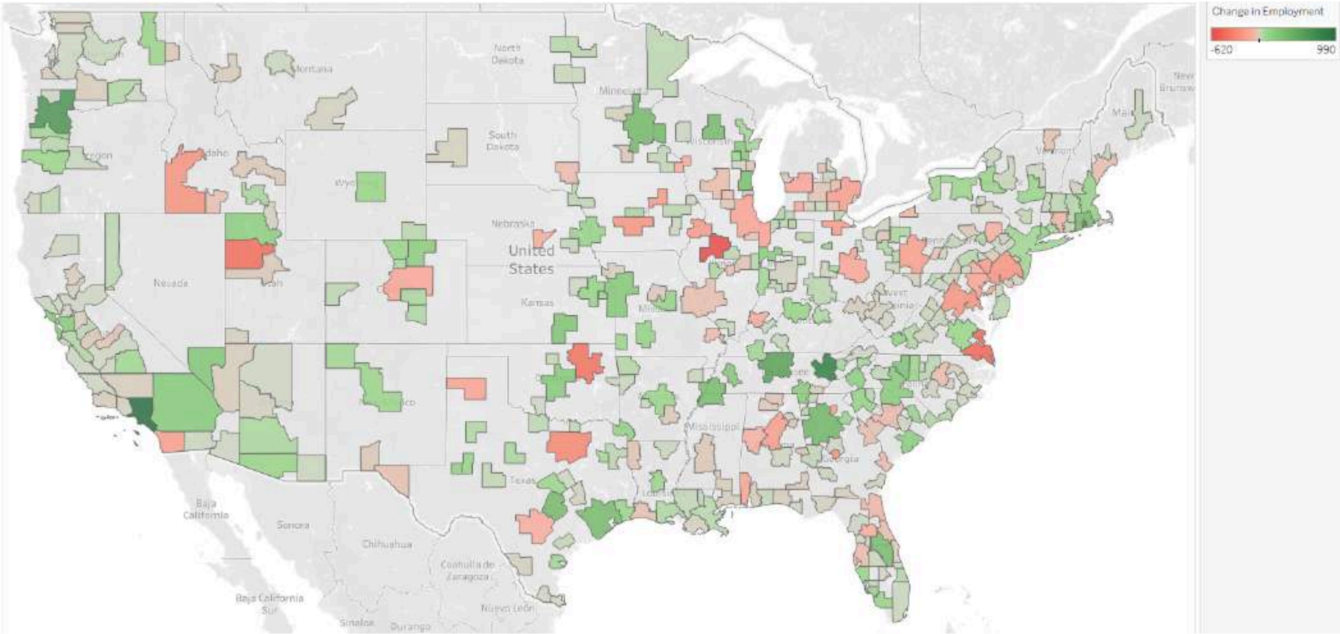


Figure J.24: Map of labor change over 1 year for "Welders, Cutters, Solderers, and Brazers" by MSA.

Change in Number of "Tool and Die Makers" (51-4111) Over 10 Years by MSA

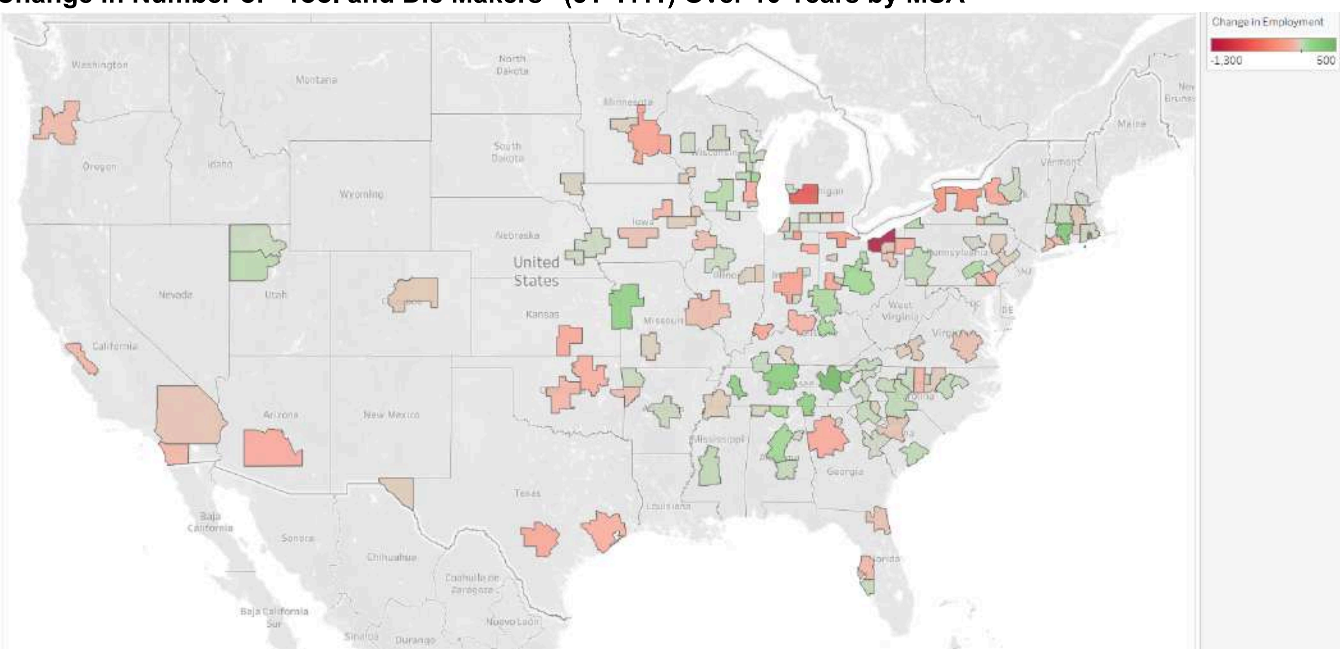


Figure J.25: Map of labor change over 10 years for "Tool and Die Makers" by MSA.

Change in Number of "Tool and Die Makers" (51-4111) Over 5 Years by MSA

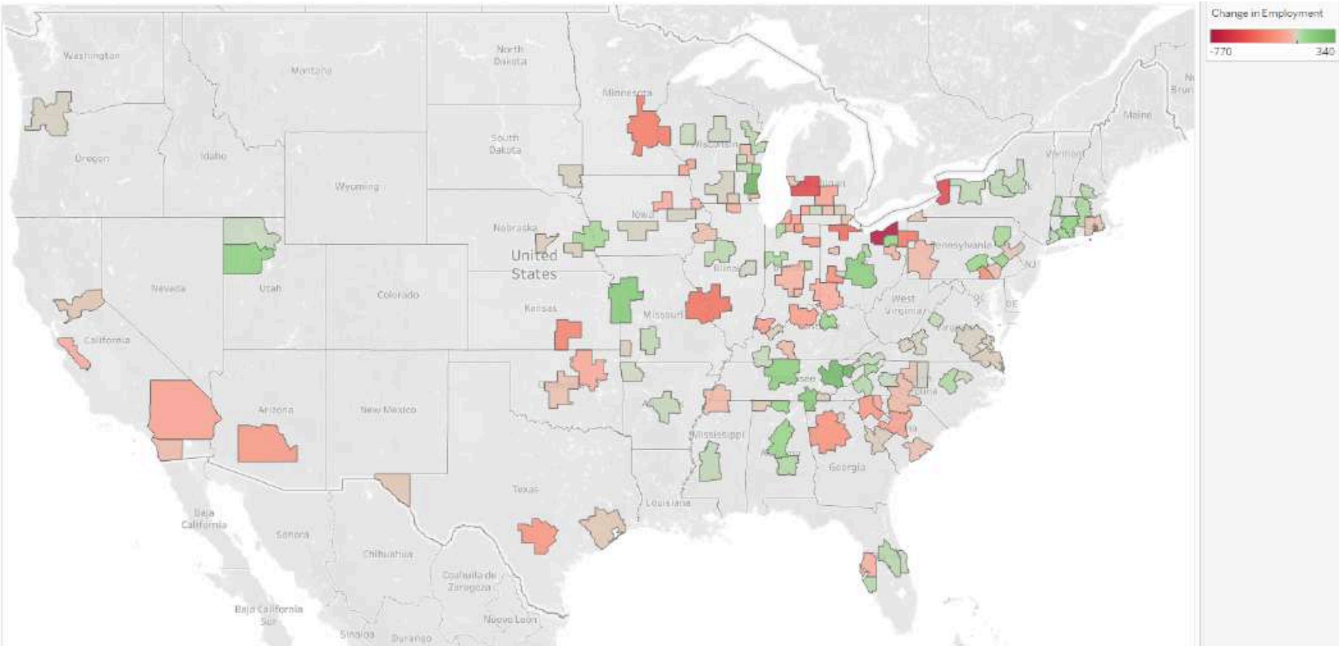


Figure J.26: Map of labor change over 5 years for "Tool and Die Makers" by MSA.

Change in Number of "Tool and Die Makers" (51-4111) Over 1 Year by MSA

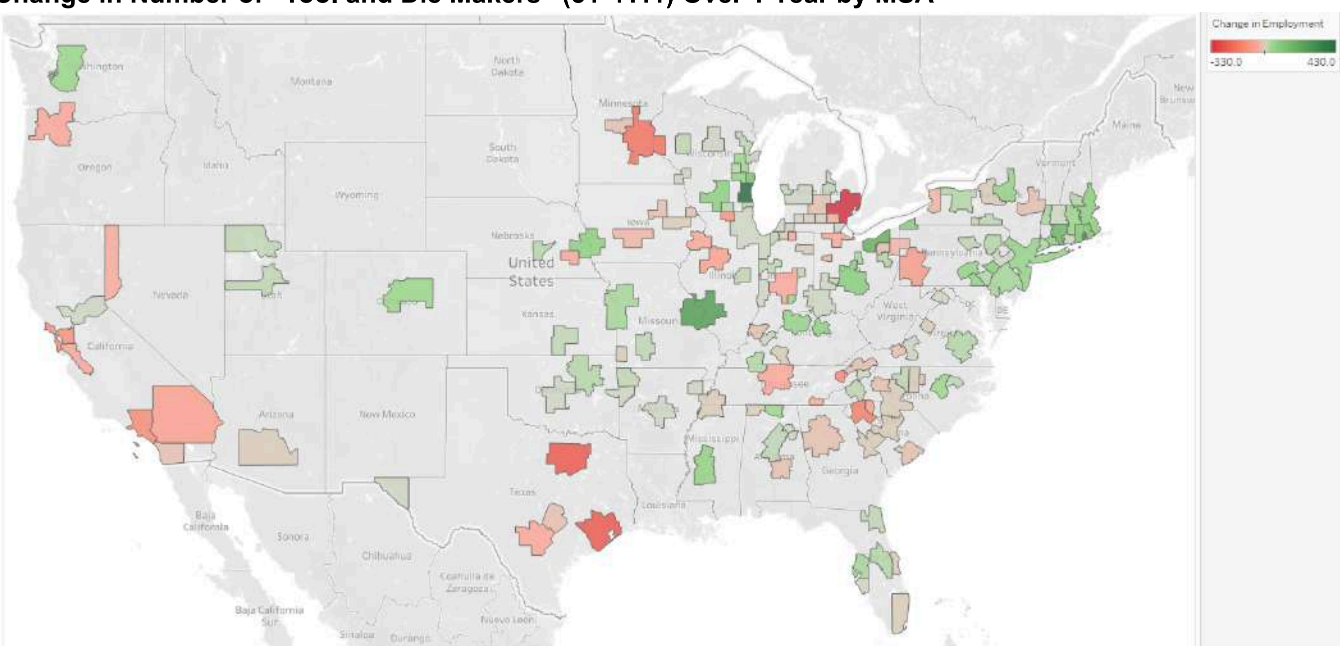


Figure J.27: Map of labor change over 1 year for 'Tool and Die Makers" by MSA.

Change in Number of “Industrial Production Managers” (11-3051) Over 10 Years by MSA

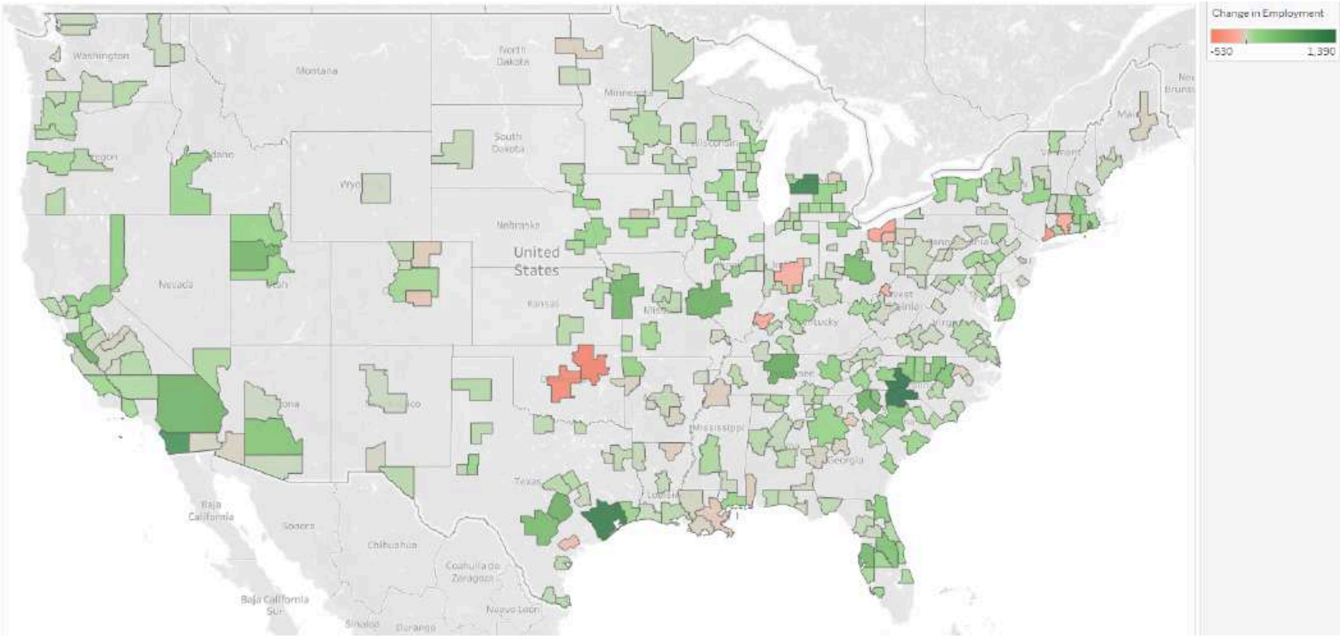


Figure J.28: Map of labor change over 10 years for “Industrial Production Managers” by MSA.

Change in Number of “Industrial Production Managers” (11-3051) Over 5 Years by MSA

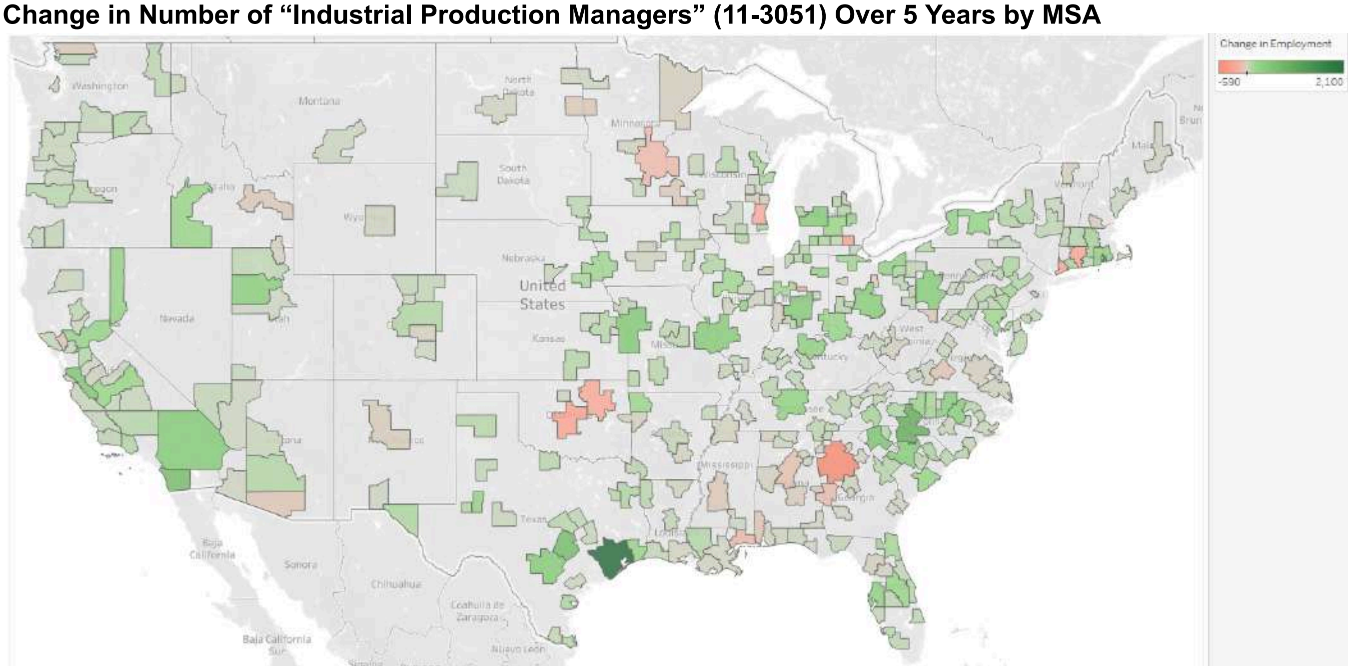


Figure J.29: Map of labor change over 5 years for “Industrial Production Managers” by MSA.

Change in Number of "Industrial Production Managers" (11-3051) Over 1 Year by MSA

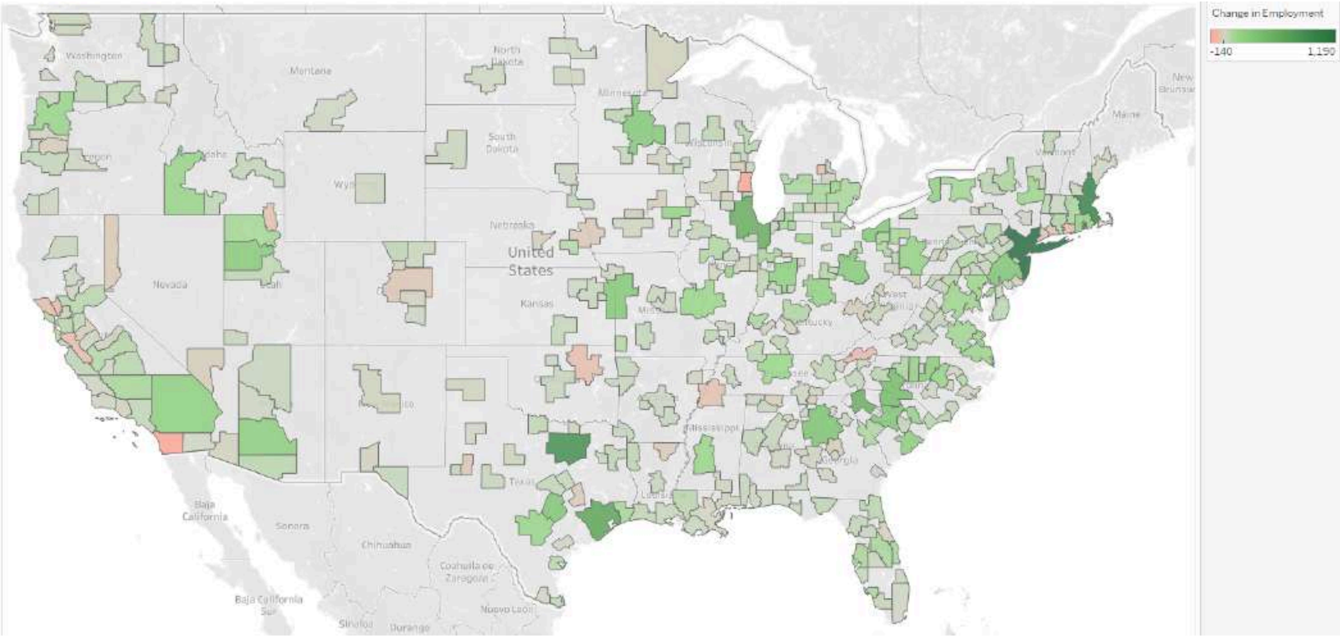


Figure J.30: Map of labor change over 1 year for "Industrial Production Managers" by MSA.

Change in Number of "Electro-Mechanical and Mechatronics Technologists and Technicians" (17-3024) Over 10 Years by MSA

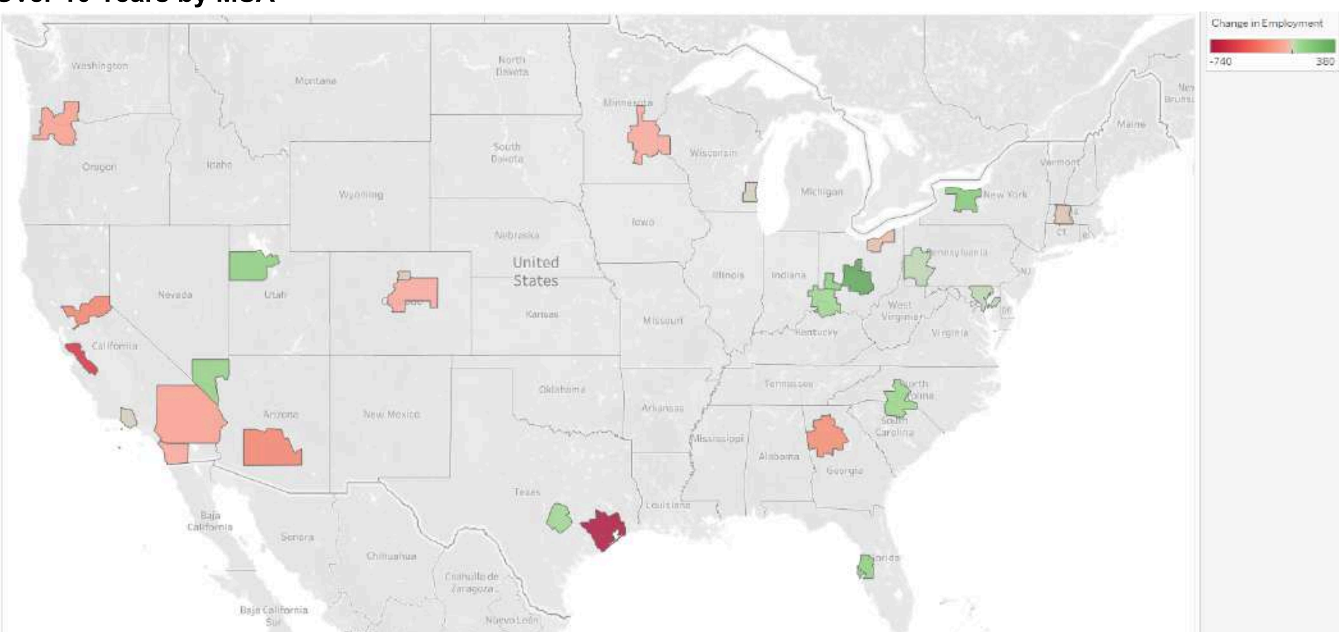


Figure J.31: Map of labor change over 10 years for "Electro-Mechanical and Mechatronics Technologists and Technicians" by MSA.

Change in Number of "Electro-Mechanical and Mechatronics Technologists and Technicians" (17-3024) Over 5 Years by MSA

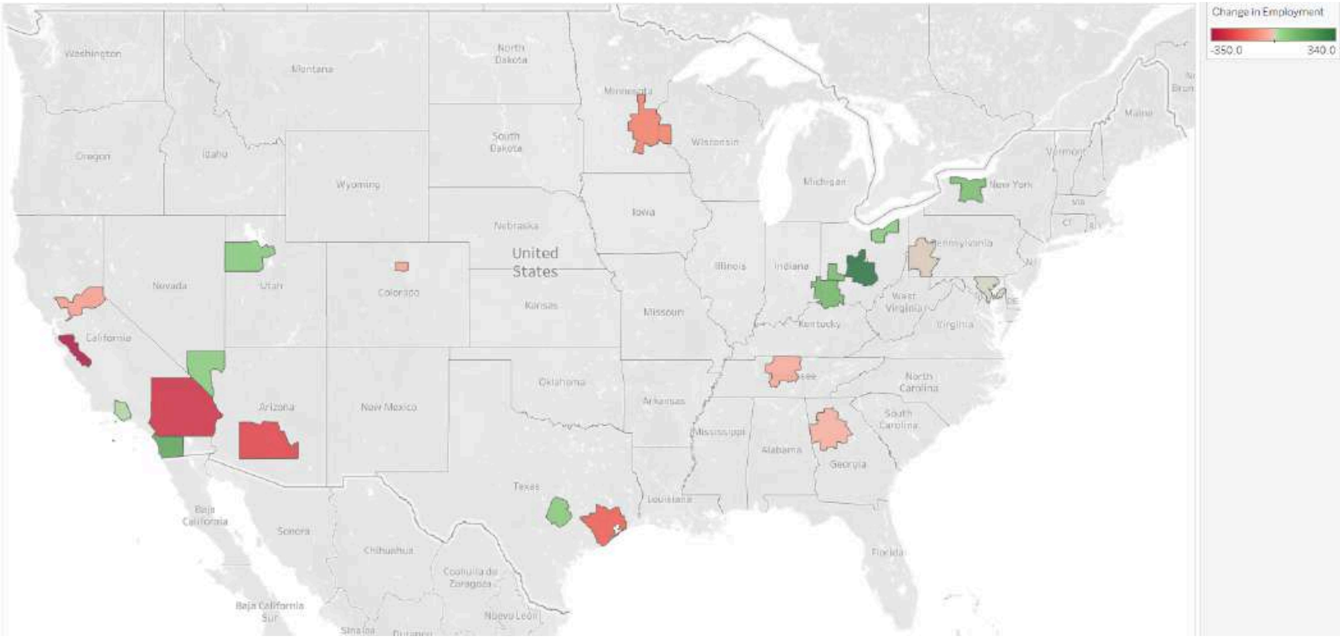


Figure J.32: Map of labor change over 5 years for "Electro-Mechanical and Mechatronics Technologists and Technicians" by MSA.

Change in Number of "Electro-Mechanical and Mechatronics Technologists and Technicians" (17-3024) Over 1 Year by MSA

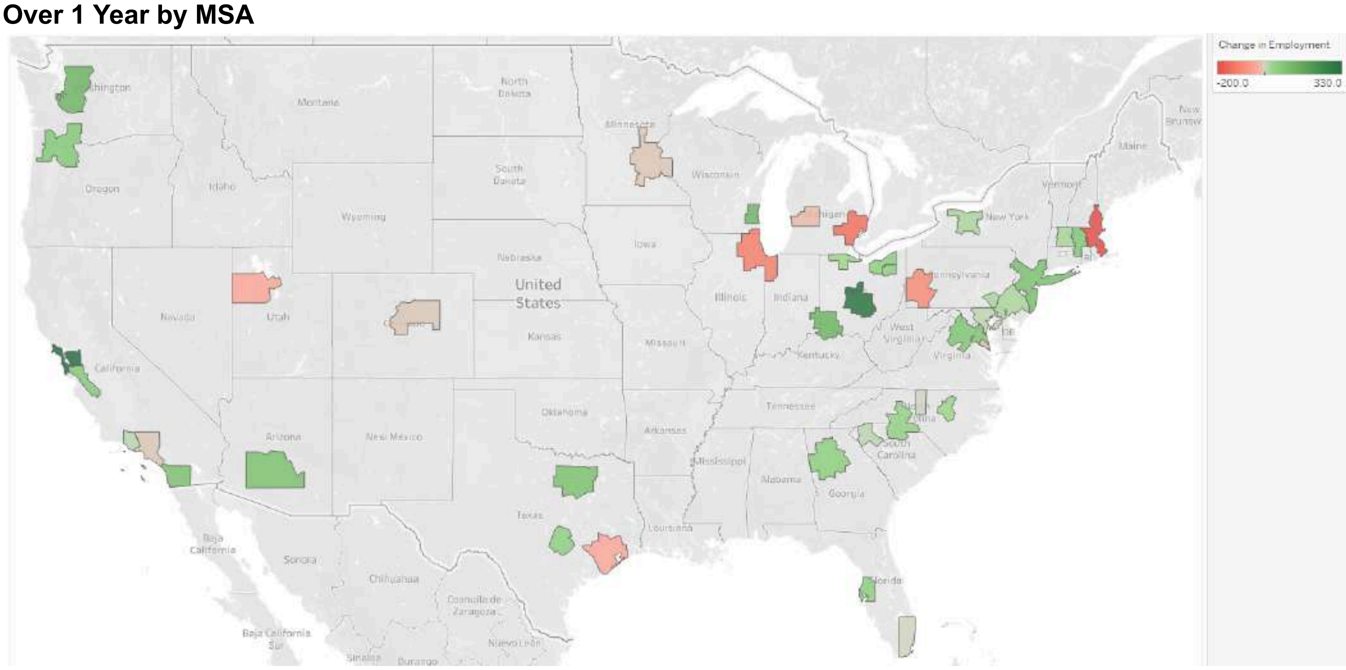


Figure J.33: Map of labor change over 1 year for "Electro-Mechanical and Mechatronics Technologists and Technicians" by MSA.

Change in Number of “Industrial Machinery Mechanics” (49-9041) Over 10 Years by MSA

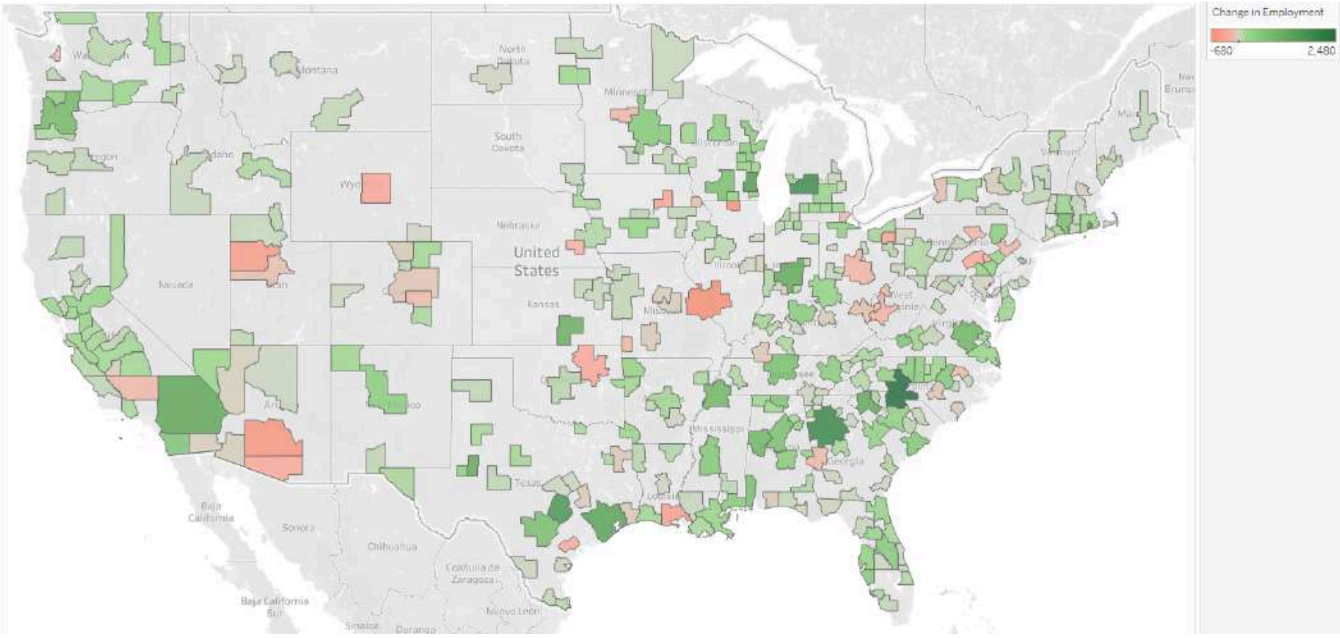


Figure J.34: Map of labor change over 10 years for “Industrial Machinery Mechanics” by MSA.

Change in Number of “Industrial Machinery Mechanics” (49-9041) Over 5 Years by MSA

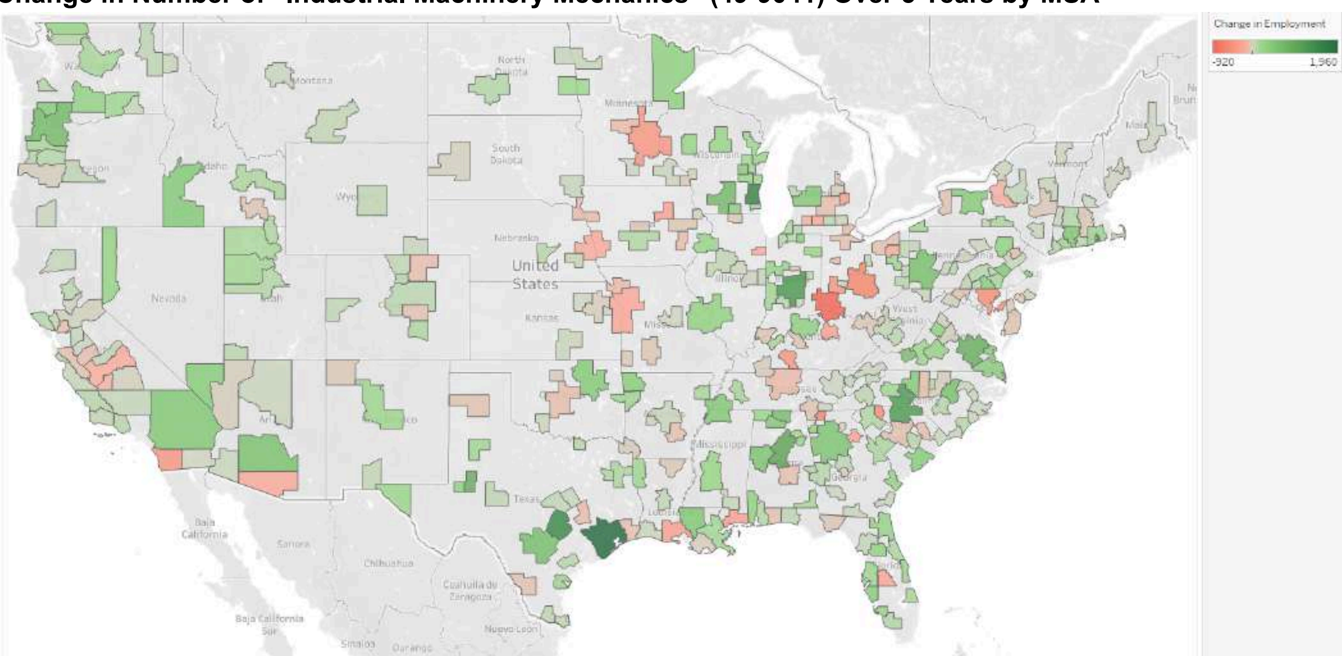


Figure J.35: Map of labor change over 5 years for “Industrial Machinery Mechanics” by MSA.

Change in Number of "Industrial Machinery Mechanics" (49-9041) Over 1 Year by MSA

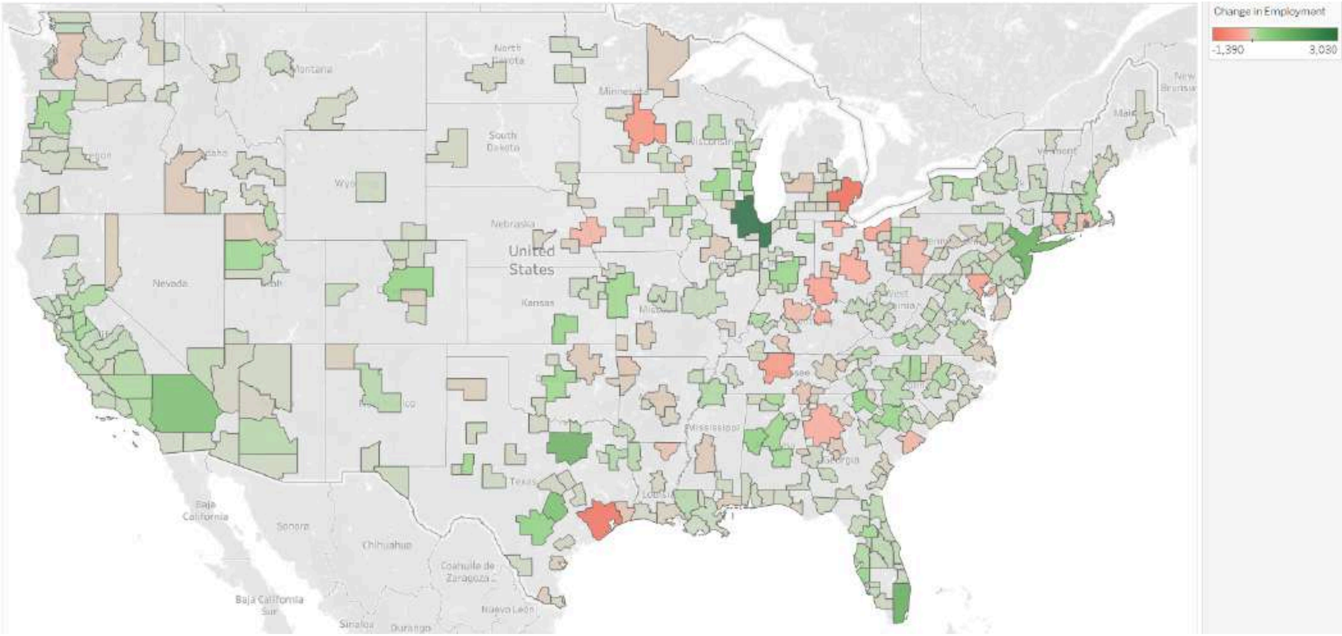


Figure J.36: Map of labor change over 1 year for "Industrial Machinery Mechanics" by MSA.

BLS data is unavailable for a Change in Number of "Computer Numerically Controlled Tool Operators" (51-9161) Over 10 Years by MSA figure

BLS data is unavailable for a Change in Number of "Computer Numerically Controlled Tool Operators" (51-9161) Over 5 Years by MSA figure.

Change in Number of "Computer Numerically Controlled Tool Operators" (51-9161) Over 1 Year by MSA

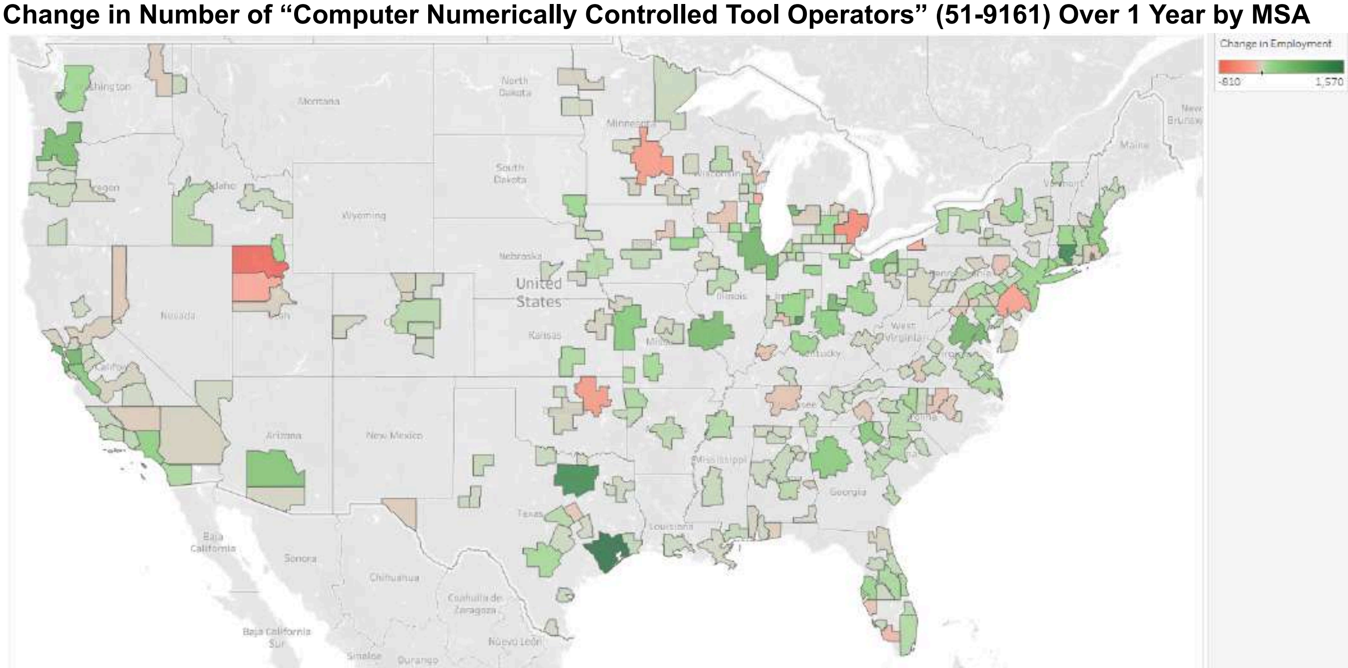


Figure J.37: Map of labor change over 1 year for "Computer Numerically Controlled Tool Operators" by MSA.

Relative Wage Position Weighted by Change in Labor Supply

These figures use the same logic used to produce **Figure 13**, replacing all references to *total employment* with the corresponding *change in employment* from 2021 to 2022. They show the percentage of new similar workers projected to be paid a greater salary than the occupation of interest. For the purpose of these figures, we assume that the distribution of wages remains approximately the same as new workers enter a given occupation. These figures exclude occupations that had a decrease in total employees in their MSA. This section uses similarity scores of 0.7 and above to determine which occupations incumbent ICEV workers can transition to. Similarity is directional, and for these figures that direction is *from* our occupation of interest *to* the similar occupations.

Relative Wage Position of "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA, Weighted by Change in Labor Supply

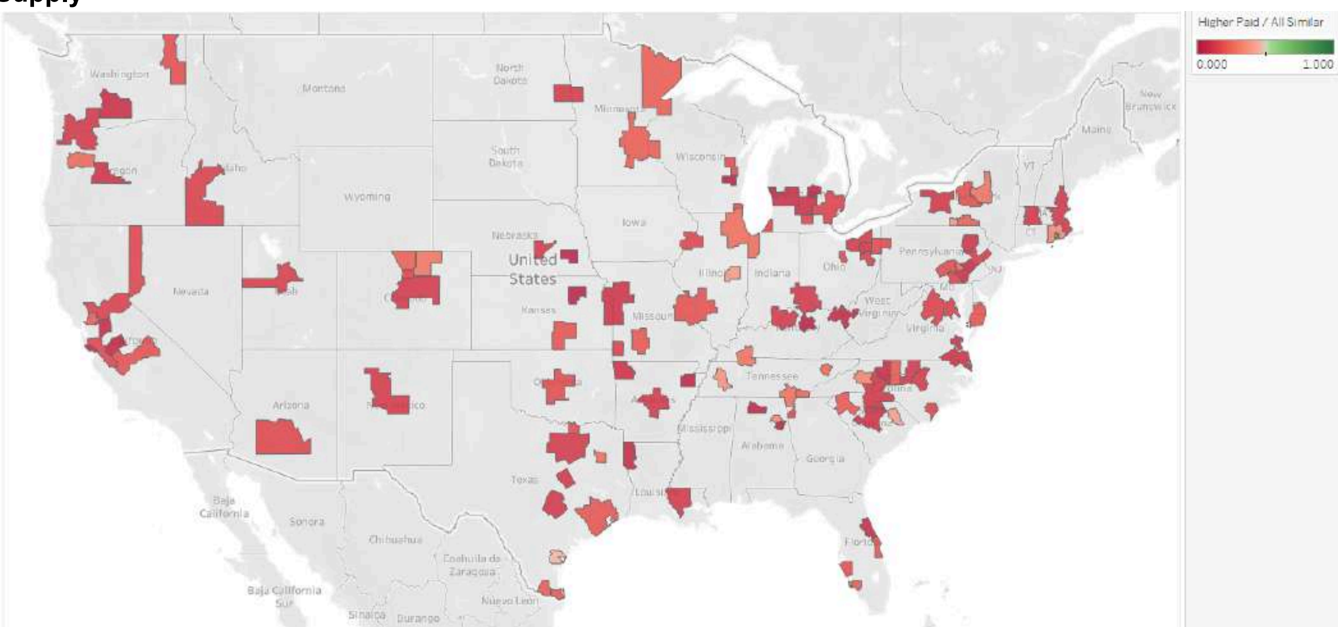


Figure J.38: Weighted average of the change in workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile workers in occupation 51-4031 "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" over the total number of change in workers in similar occupations.

Relative Wage Position of "Engine and Other Machine Assemblers" (51-2031) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA, Weighted by Change in Labor Supply

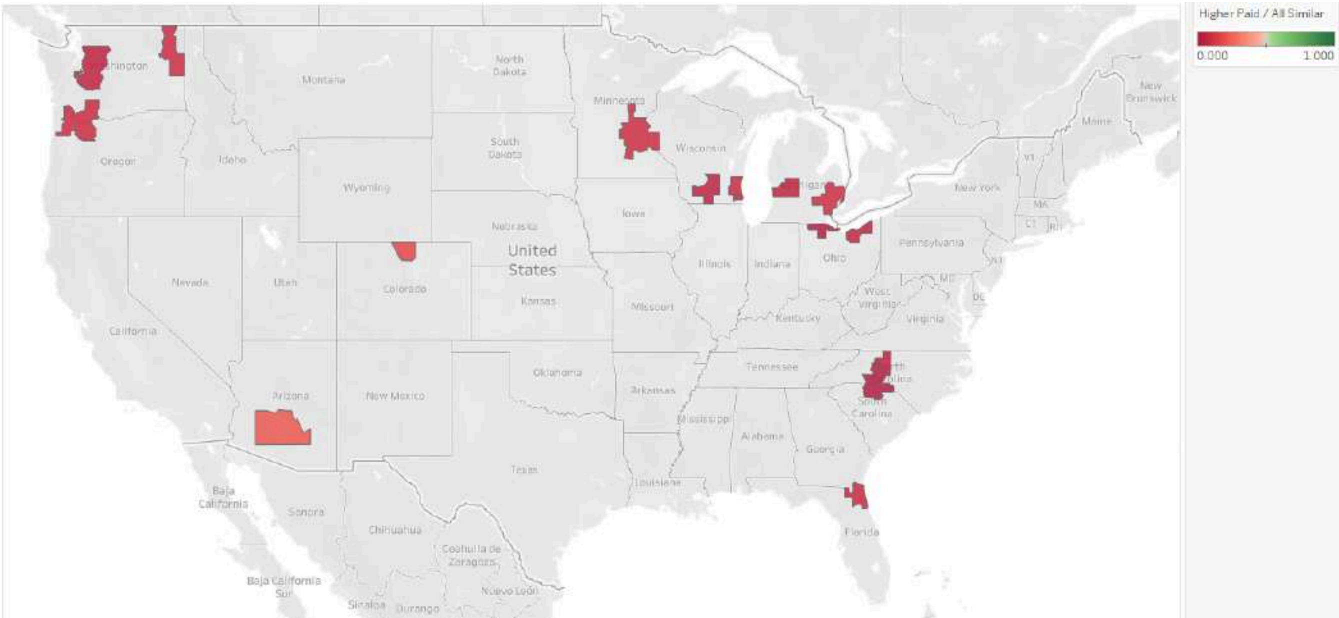


Figure J.39: Weighted average of the change in workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile workers in occupation 51-2031 "Engine and Other Machine Assemblers" over the total number of change in workers in similar occupations.

Relative Wage Position of "First-Line Supervisors of Production and Operating Workers" (51-1011) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA, Weighted by Change in Labor Supply

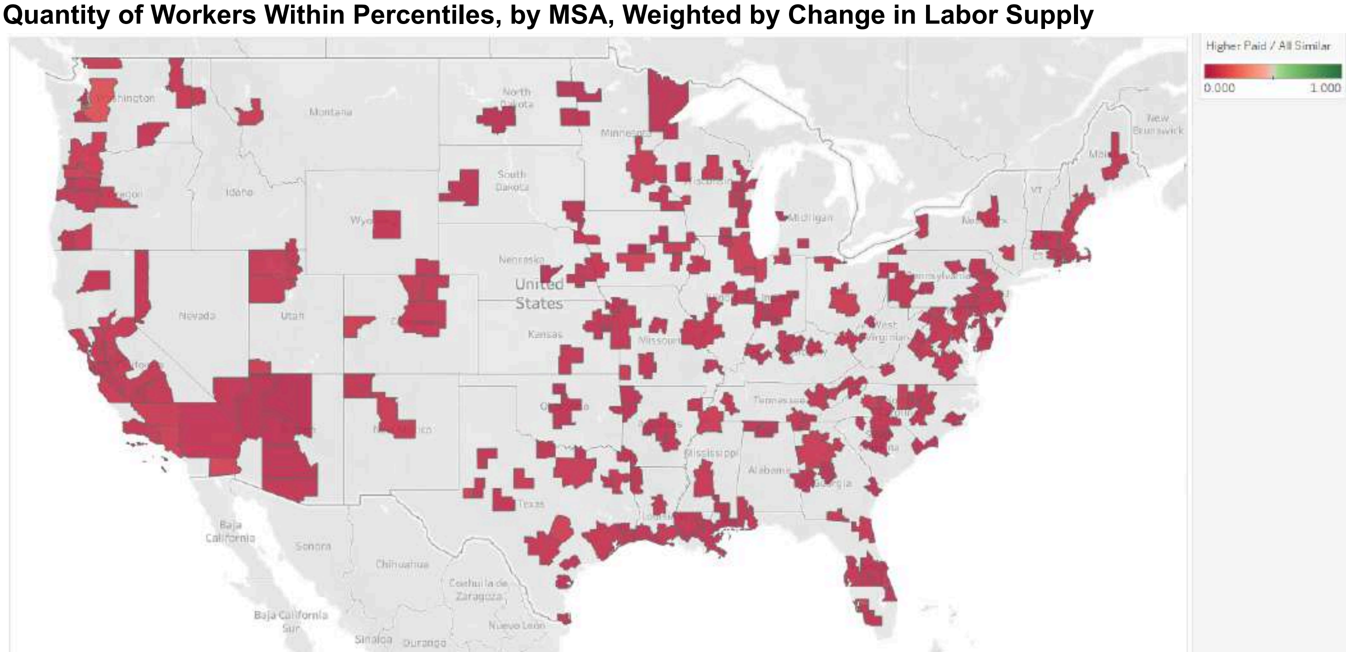


Figure J.40: Weighted average of the change in workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile workers in occupation 51-1011 "First-Line Supervisors of Production and Operating Workers" over the total number of change in workers in similar occupations.

Relative Wage Position of "Inspectors, Testers, Sorters, Samplers, and Weighers" (51-9061) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA, Weighted by Change in Labor Supply

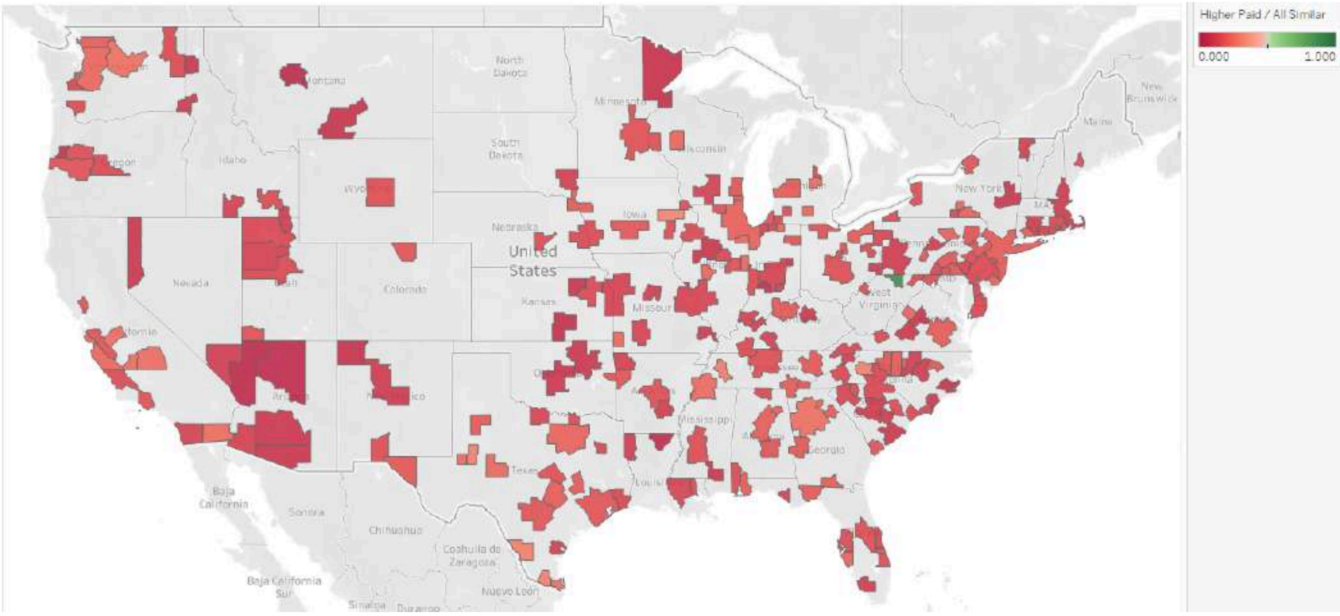


Figure J.41: Weighted average of the change in workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile workers in occupation 51-9061 "Inspectors, Testers, Sorters, Samplers, and Weighers" over the total number of change in workers in similar occupations.

Relative Wage Position of "Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic" (51-4081) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA, Weighted by Change in Labor Supply

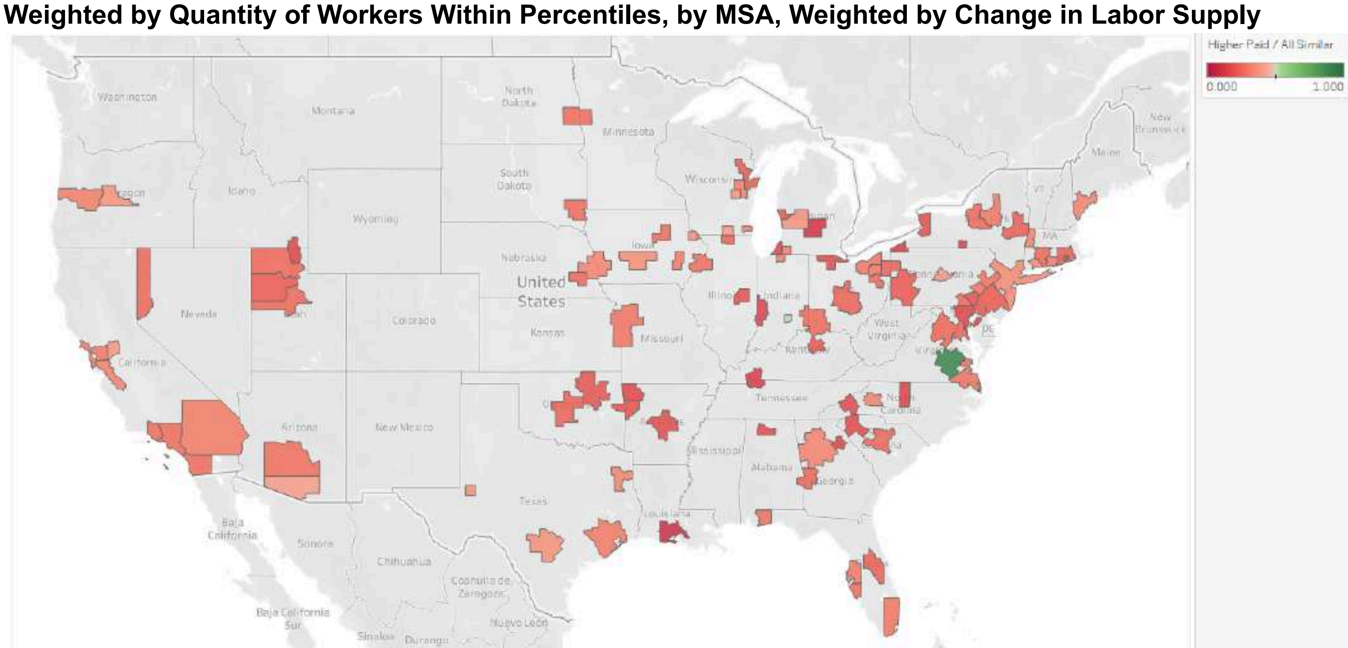


Figure J.42: Weighted average of the change in workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile workers in occupation 51-4081 "Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic" over the total number of change in workers in similar occupations.

Relative Wage Position of "Machinists" (51-4041) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA, Weighted by Change in Labor Supply

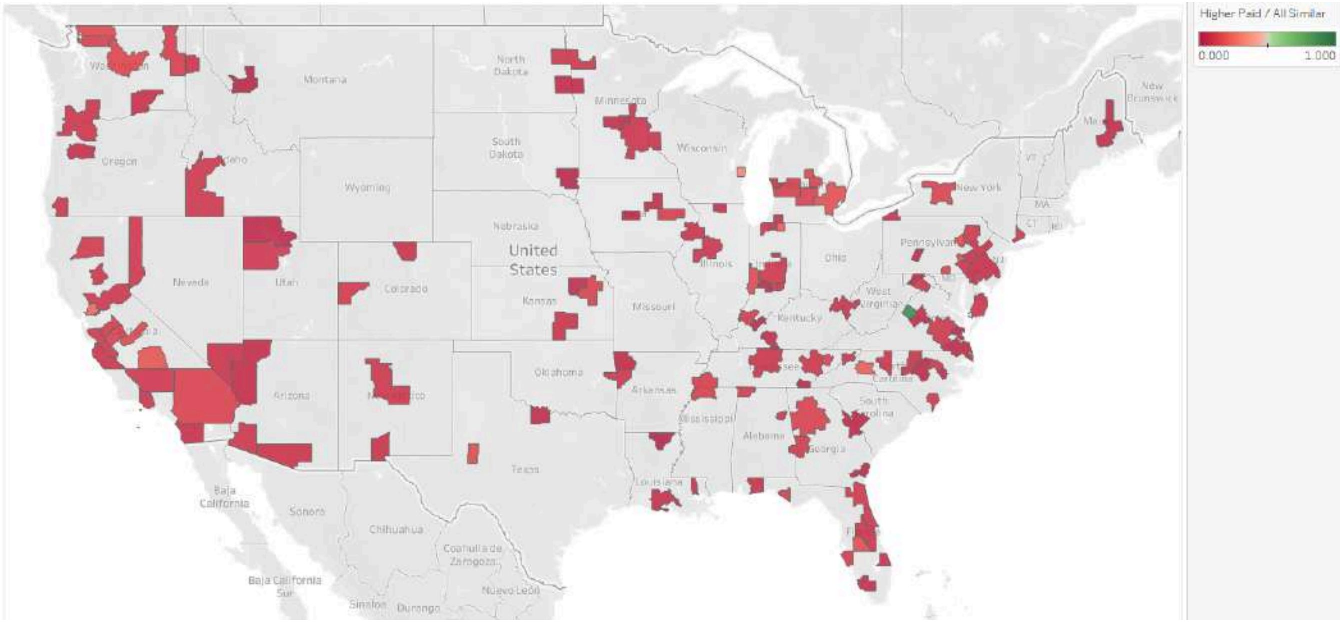


Figure J.43: Weighted average of the change in workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile workers in occupation 51-4041 "Machinists" over the total number of change in workers in similar occupations.

Relative Wage Position of "Welders, Cutters, Solderers, and Brazers" (51-4121) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA, Weighted by Change in Labor Supply

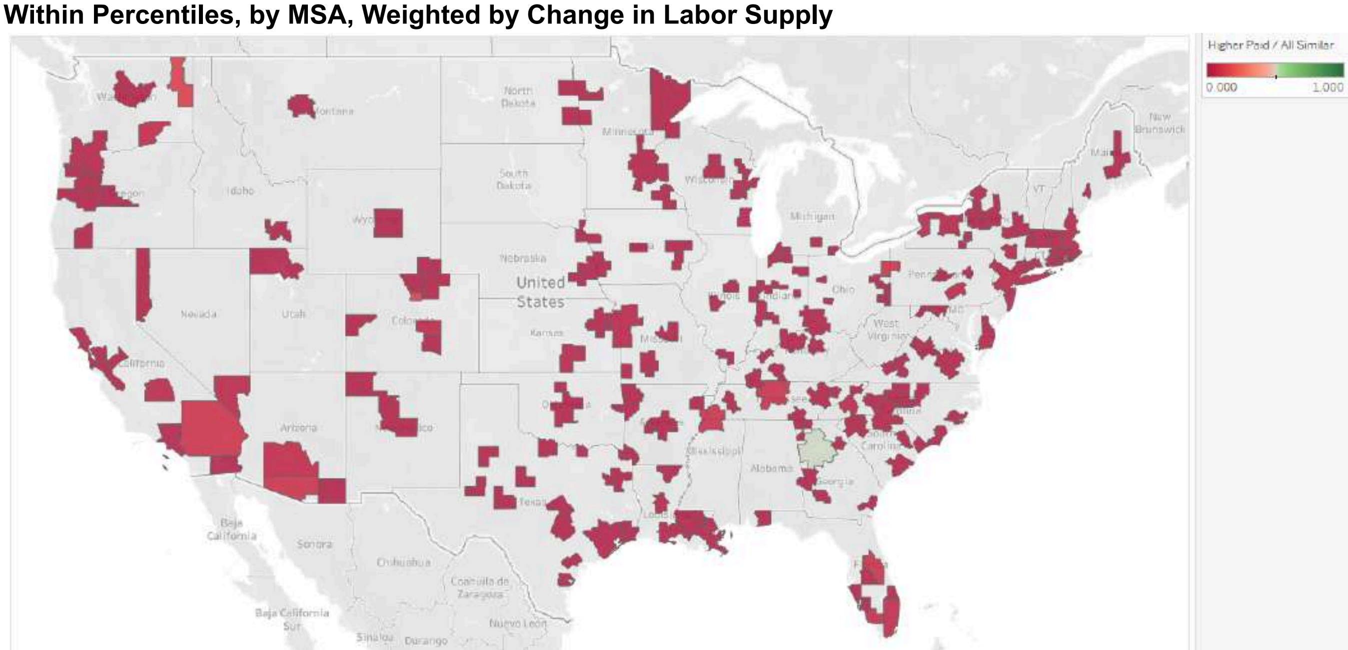


Figure J.44: Weighted average of the change in workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile workers in occupation 51-4121 "Welders, Cutters, Solderers, and Brazers" over the total number of change in workers in similar occupations.

Relative Wage Position of "Tool and Die Makers" (51-4111) When Comparing Jobs with Skill Similarity>=0.7 to 10th, 25th, 50th, 75th, and 90th Percentiles, Weighted by Quantity of Workers Within Percentiles, by MSA, Weighted by Change in Labor Supply

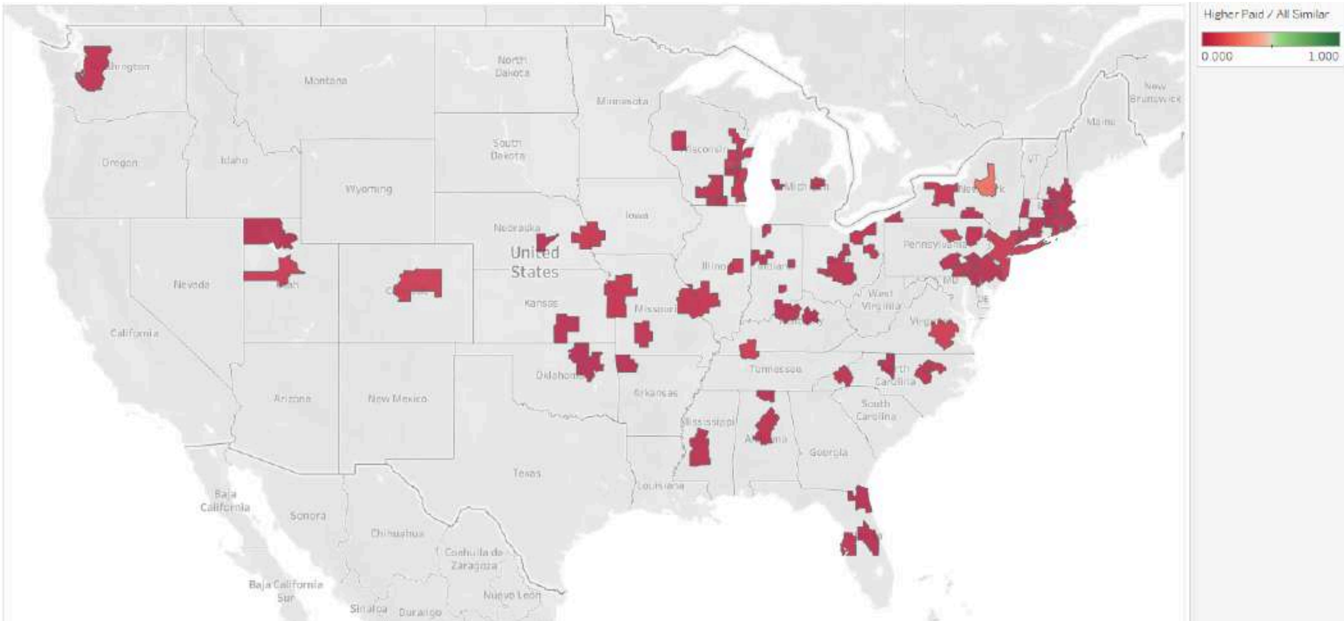


Figure J.45: Weighted average of the change in workers earning equal or more than the 10th, 25th, 50th, 75th, and 90th percentile workers in occupation 51-4111 "Tool and Die Makers" over the total number of change in workers in similar occupations.

Wage Premium Weighted by Change in Labor Supply (From ICEV)

For these figures (**Figure J.46 - J.53**) we weigh each similar occupation's average annual wages by the change in the quantity of workers in that occupation in the same MSA. This section uses similarity scores of 0.7 and above to determine which occupations incumbent ICEV workers can transition to. Similarity is directional, and for these figures that direction is *from* our occupation of interest *to* the similar occupations. These figures only include occupations that had an increase in workforce in their MSA. This is because a continued upward trend will lead to labor shortages that can be filled by incumbent ICEV workers.

Percentage Wage Premium Demanded by "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" (51-4031) When Compared to Jobs with Skill Similarity>=0.7 Weighted by Change in Labor Supply

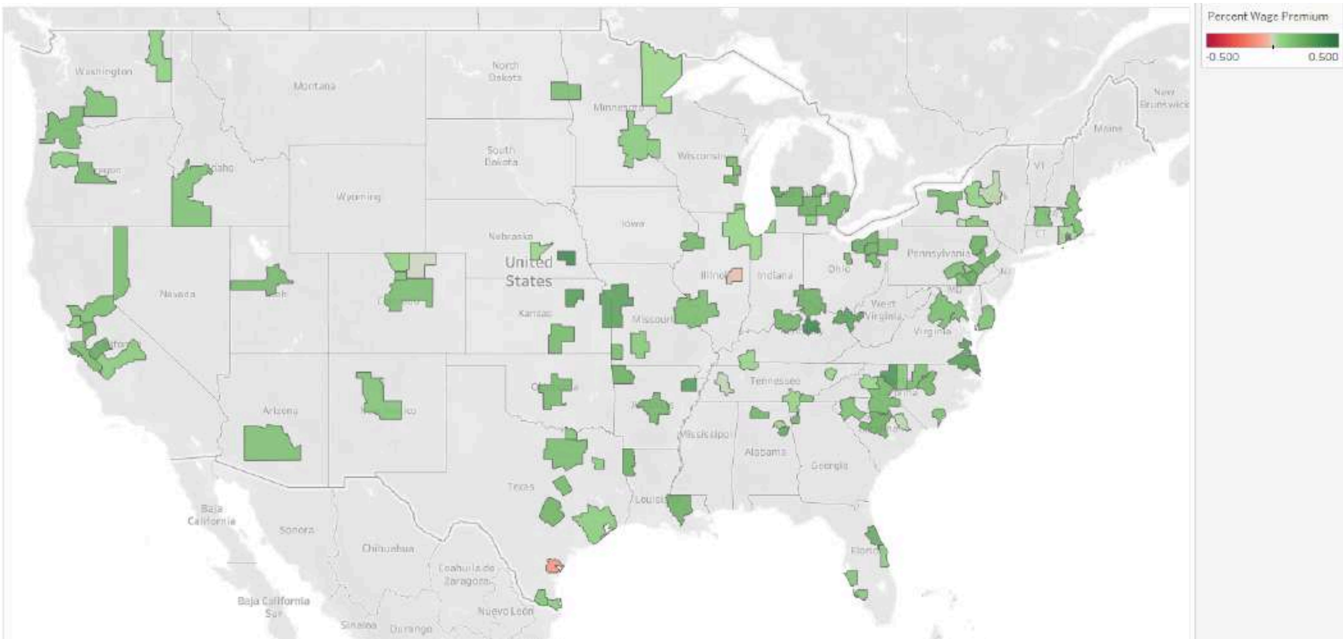


Figure J.46: Local wage premium demanded by workers in occupation 51-4031 "Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic" when compared to workers in alternative occupations, weighted by change in labor supply from 2021 to 2022.

Percentage Wage Premium Demanded by "Engine and Other Machine Assemblers" (51-2031) When Compared to Jobs with Skill Similarity>=0.7 Weighted by Change in Labor Supply

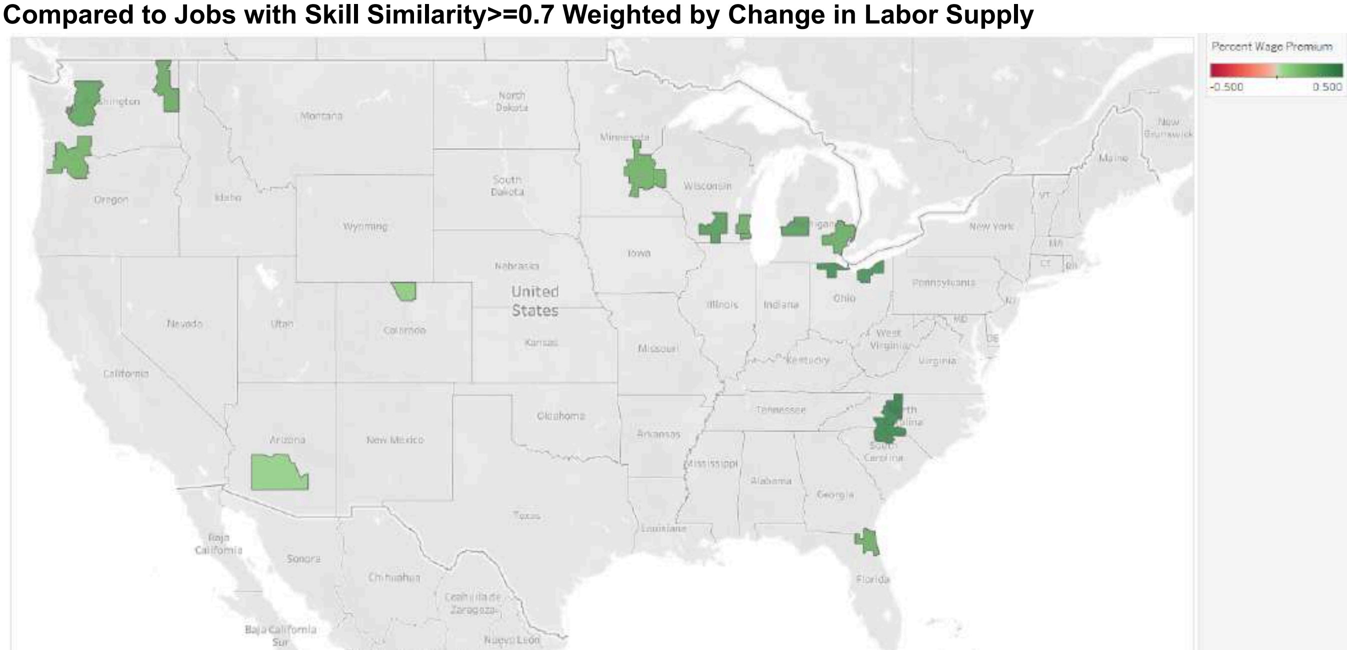


Figure J.47: Local wage premium demanded by workers in occupation 51-2031 "Engine and Other Machine Assemblers" when compared to workers in alternative occupations, weighted by change in labor supply from 2021 to 2022.

Percentage Wage Premium Demanded by “First-Line Supervisors of Production and Operating Workers” (51-1011) When Compared to Jobs with Skill Similarity>=0.7 Weighted by Change in Labor Supply

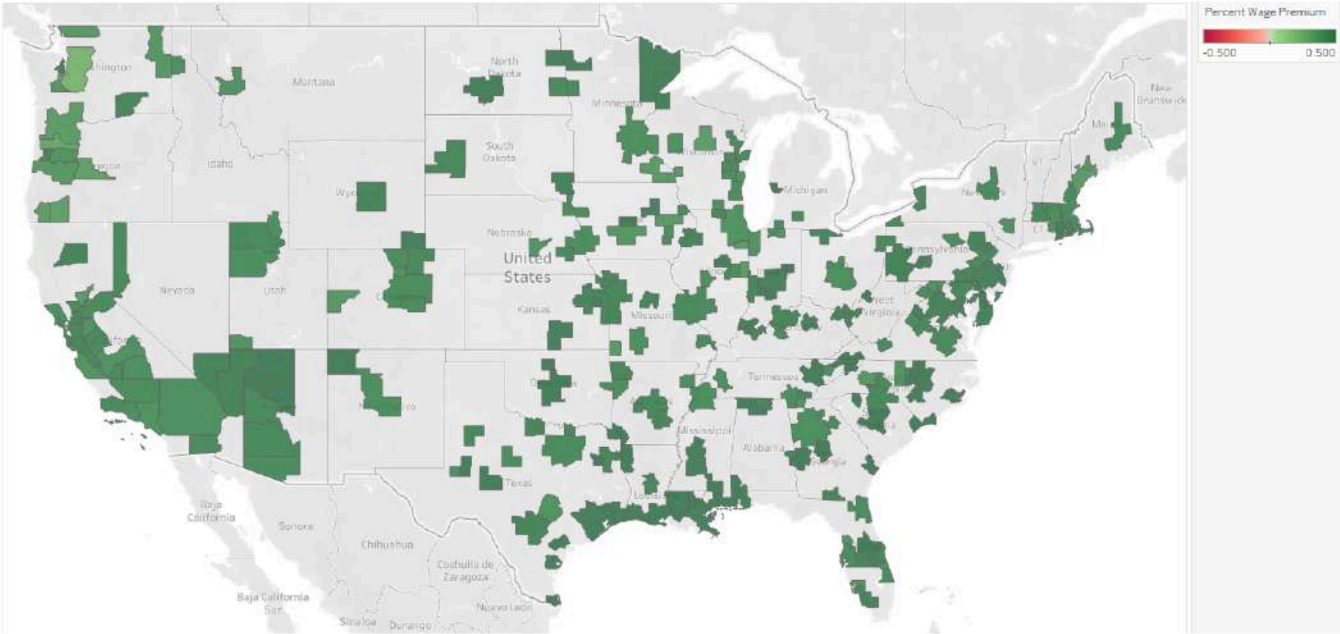


Figure J.48: Local wage premium demanded by workers in occupation 51-1011 “First-Line Supervisors of Production and Operating Workers” when compared to workers in alternative occupations, weighted by change in labor supply from 2021 to 2022.

Percentage Wage Premium Demanded by “Inspectors, Testers, Sorters, Samplers, and Weighers” (51-9061) When Compared to Jobs with Skill Similarity>=0.7 Weighted by Change in Labor Supply

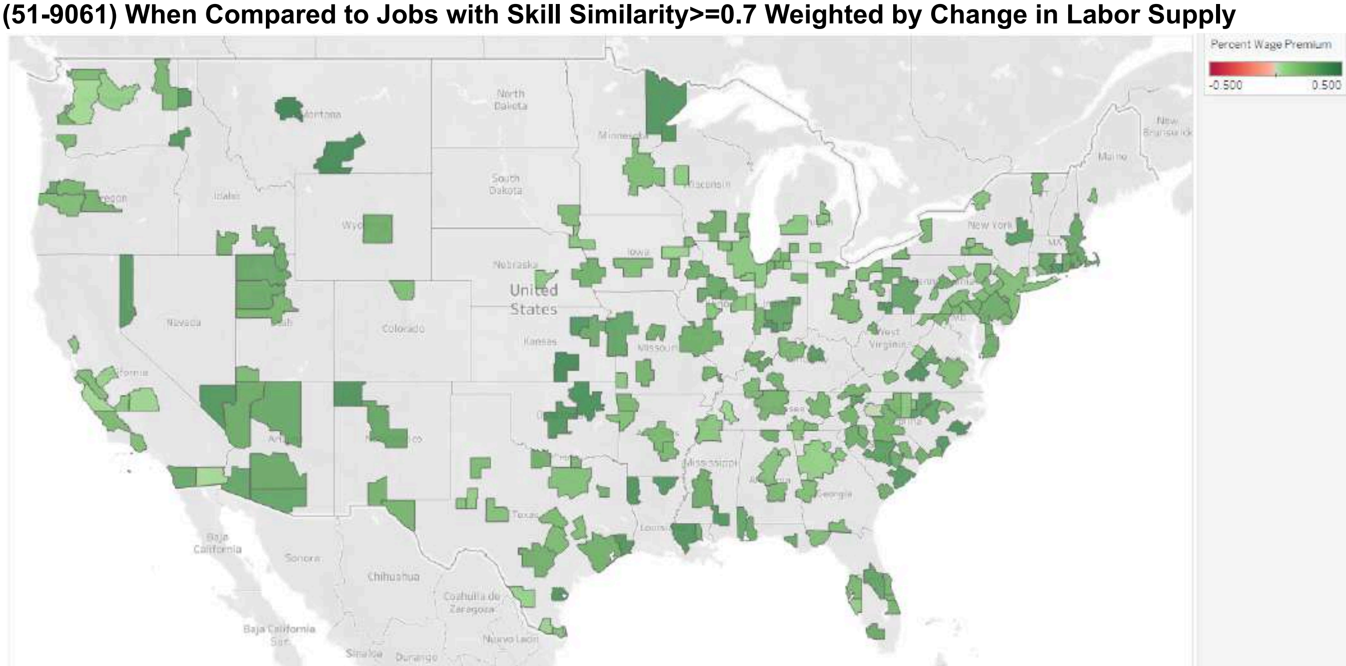


Figure J.49: Local wage premium demanded by workers in occupation 51-9061 “Inspectors, Testers, Sorters, Samplers, and Weighers” when compared to workers in alternative occupations, weighted by change in labor supply from 2021 to 2022.

Percentage Wage Premium Demanded by "Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic" (51-4081) When Compared to Jobs with Skill Similarity>=0.7 Weighted by Change in Labor Supply

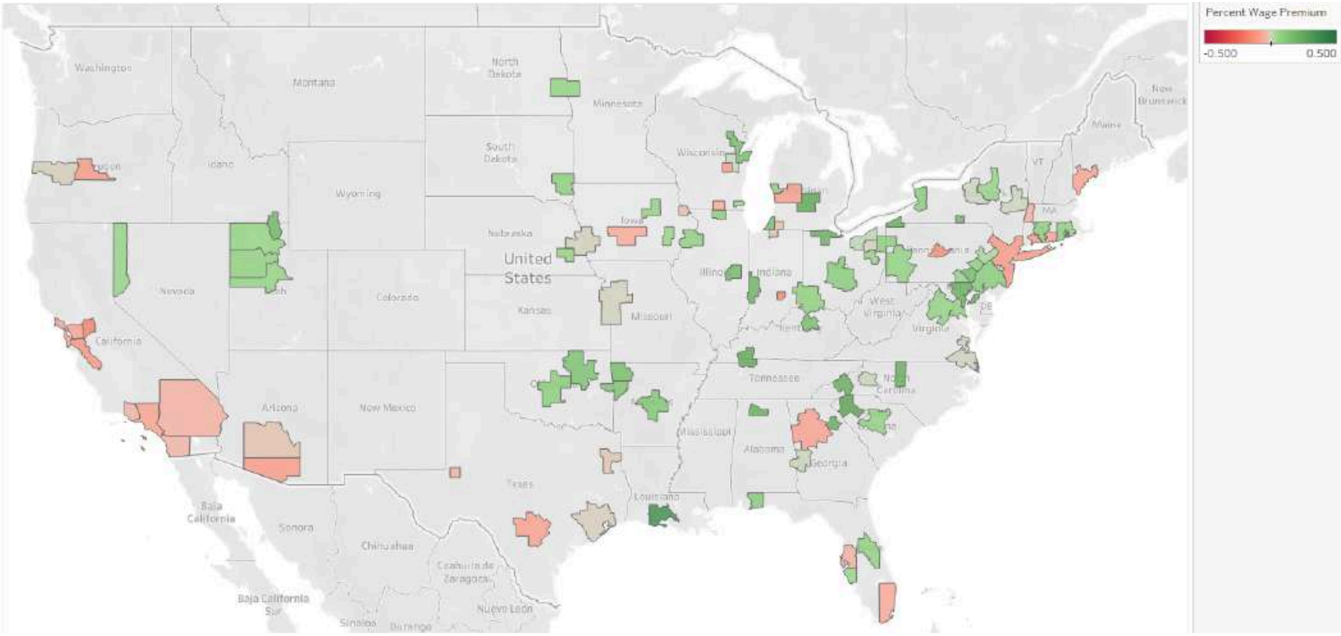


Figure J.50: Local wage premium demanded by workers in occupation 51-4081 "Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic" when compared to workers in alternative occupations, weighted by change in labor supply from 2021 to 2022.

Percentage Wage Premium Demanded by "Machinists" (51-4041) When Compared to Jobs with Skill Similarity>=0.7 Weighted by Change in Labor Supply

Figure J.51: Local wage premium demanded by workers in occupation 51-4041 "Machinists" when compared to workers in alternative occupations, weighted by change in labor supply from 2021 to 2022.

Percentage Wage Premium Demanded by "Welders, Cutters, Solderers, and Brazers' (51-4121) When Compared to Jobs with Skill Similarity>=0.7 Weighted by Change in Labor Supply

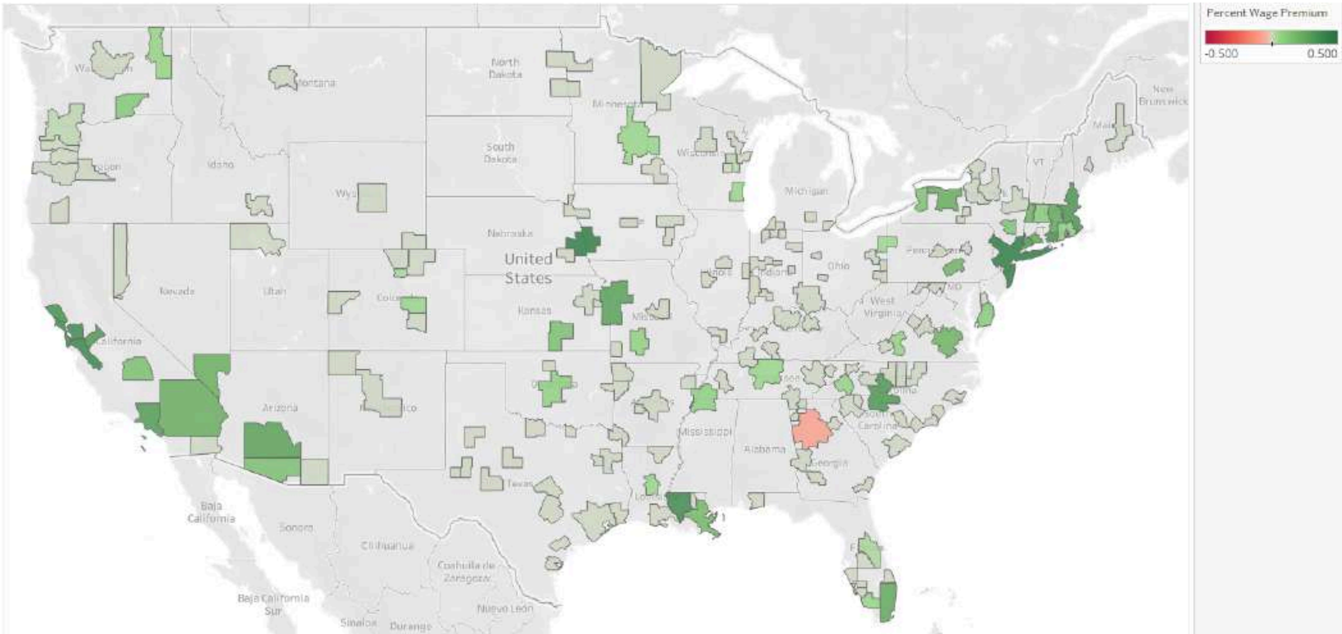


Figure J.52: Local wage premium demanded by workers in occupation 51-4121 "Welders, Cutters, Solderers, and Brazers" when compared to workers in alternative occupations, weighted by change in labor supply from 2021 to 2022.

Percentage Wage Premium Demanded by "Tool and Die Makers" (51-4111) When Compared to Jobs with Skill Similarity>=0.7 Weighted by Change in Labor Supply

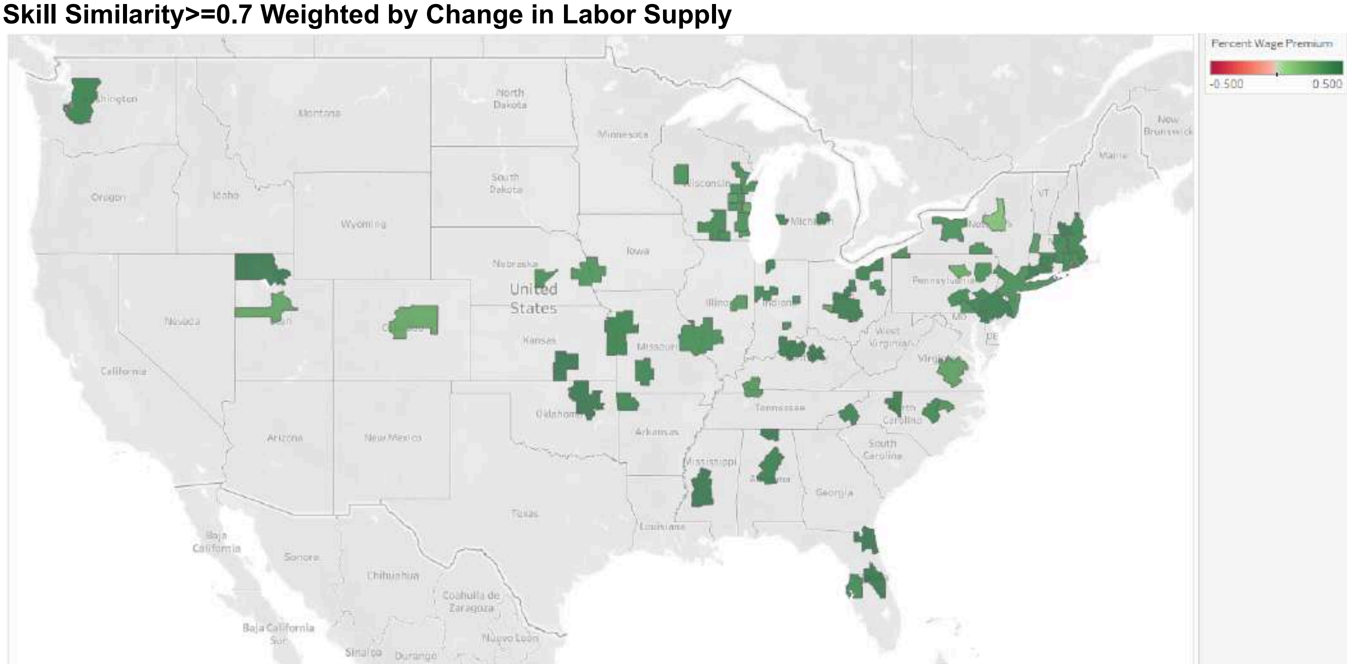


Figure J.53: Local wage premium demanded by workers in occupation 51-4111 "Tool and Die Makers" when compared to workers in alternative occupations, weighted by change in labor supply from 2021 to 2022.

Wage Premium Weighted by Change in Labor Supply (to EV, Battery, and HST Production)

For these figures (**Figure J.54 - J.60**) we weigh each similar occupation's average annual wages by the change in the quantity of workers in that occupation in the same MSA. This section uses similarity scores of 0.7 and above to determine which occupations incumbent ICEV workers can transition to. Similarity is directional, and for these figures that direction is *to* our occupation of interest *from* the similar occupations. These figures only include occupations that had a decrease in workforce in their MSA. This is because a continued downward trend will lead to a labor surplus that EV, Battery, and HST production jobs can be filled by.

Percentage Wage Premium Demanded by "Industrial Production Managers" (11-3051) When Compared to Jobs with Skill Similarity>=0.7 Weighted by Change in Labor Supply

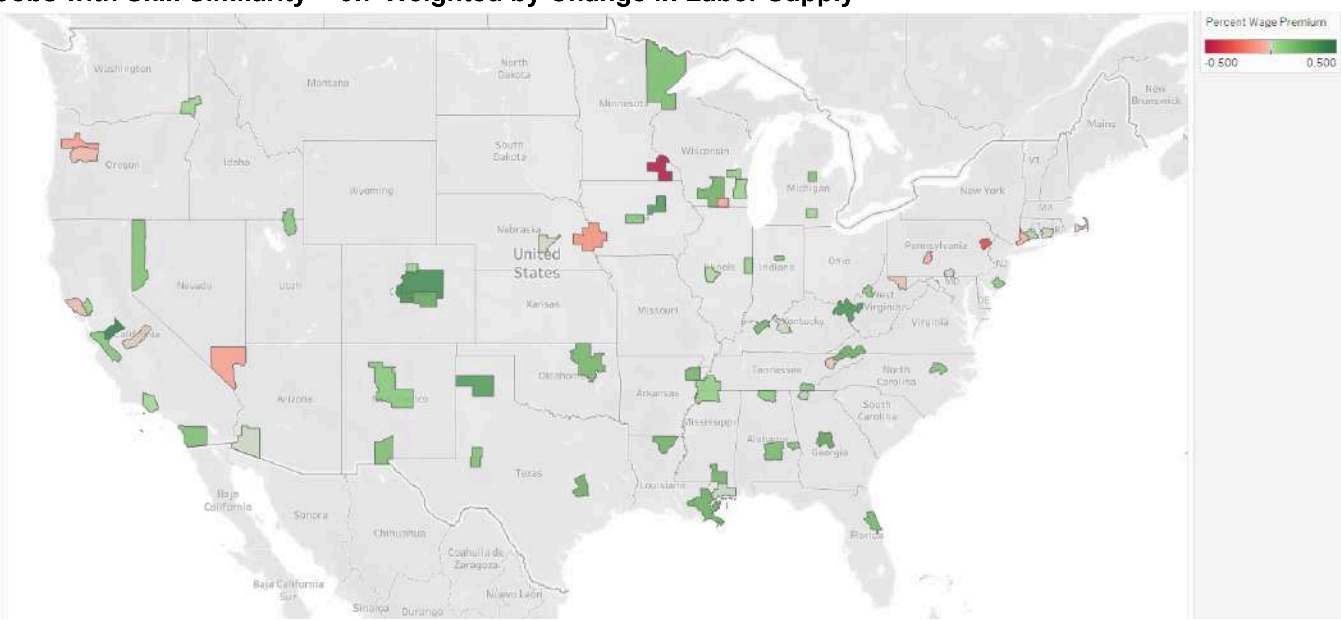


Figure J.54: Local wage premium demanded by workers in occupation 11-3051 "Industrial Production Managers" when compared to workers in alternative occupations, weighted by change in labor supply from 2021 to 2022.

Percentage Wage Premium Demanded by “Electro-Mechanical and Mechatronics Technologists and Technicians” (17-3024) When Compared to Jobs with Skill Similarity>=0.7 Weighted by Change in Labor Supply

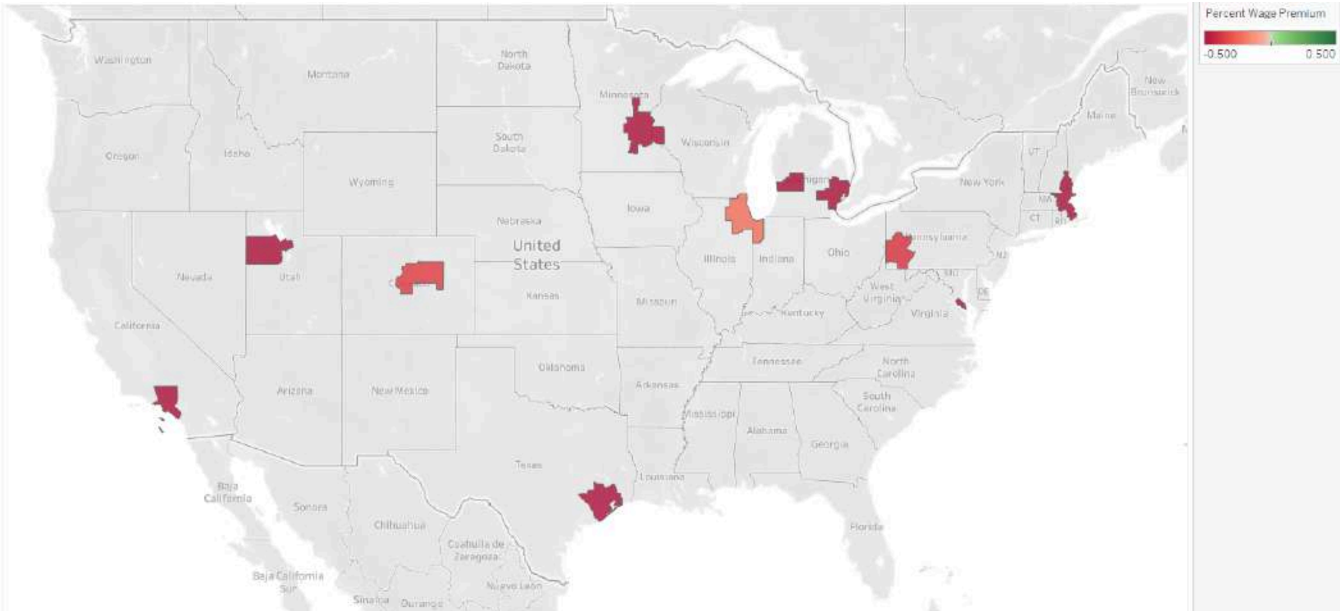


Figure J.55: Local wage premium demanded by workers in occupation 17-3024 “Electro-Mechanical and Mechatronics Technologists and Technicians” when compared to workers in alternative occupations, weighted by change in labor supply from 2021 to 2022.

Percentage Wage Premium Demanded by “Industrial Machinery Mechanics” (49-9041) When Compared to Jobs with Skill Similarity>=0.7 Weighted by Change in Labor Supply

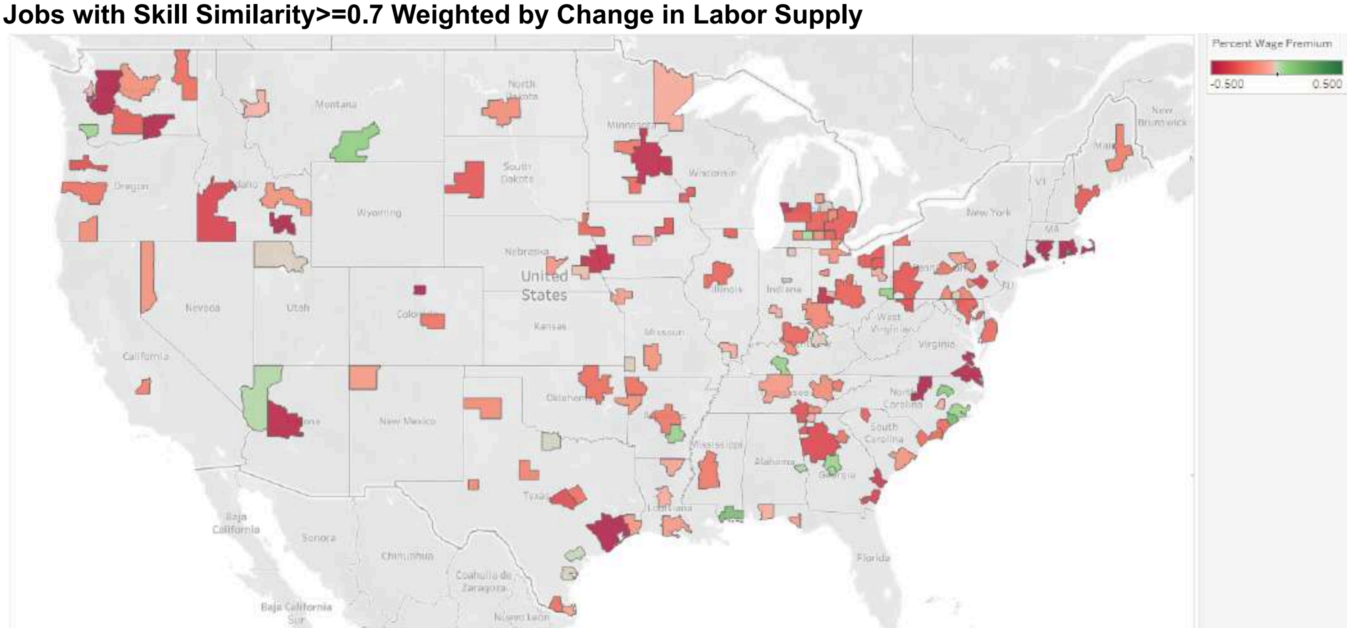


Figure J.56: Local wage premium demanded by workers in occupation 49-9041 “Industrial Machinery Mechanics” when compared to workers in alternative occupations, weighted by change in labor supply from 2021 to 2022.

Percentage Wage Premium Demanded by "Engine and Other Machine Assemblers" (51-2031) When Compared to Jobs with Skill Similarity>=0.7 Weighted by Change in Labor Supply

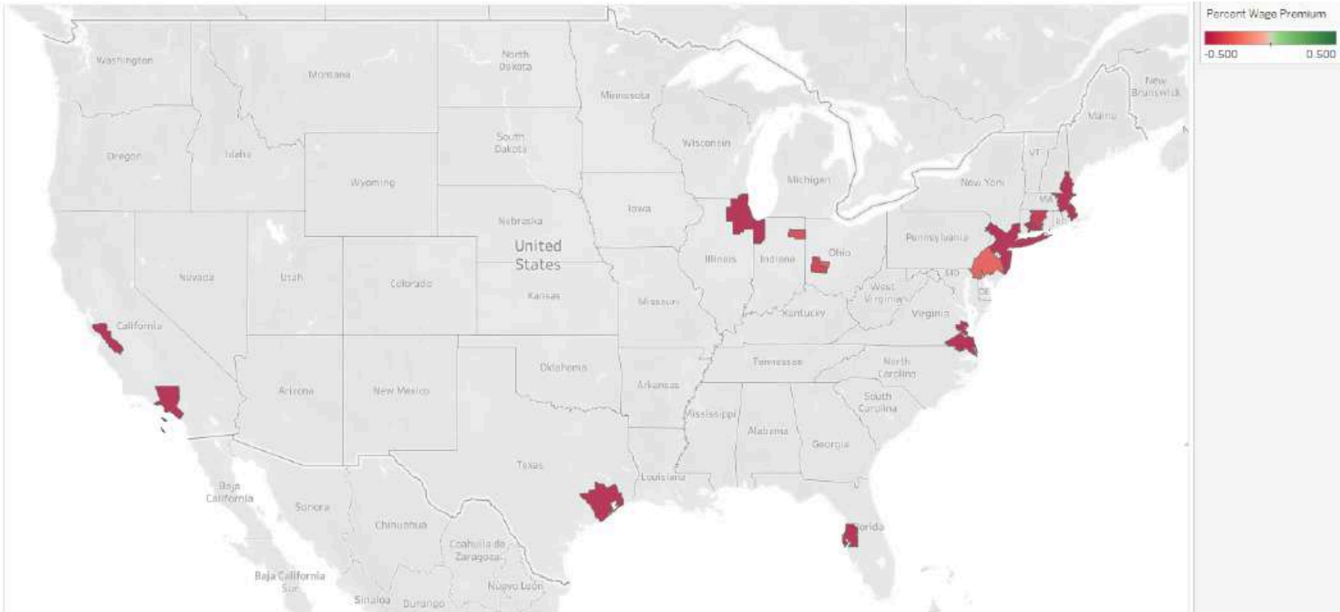


Figure J.57: Local wage premium demanded by workers in occupation 51-2031 "Engine and Other Machine Assemblers" when compared to workers in alternative occupations, weighted by change in labor supply from 2021 to 2022.

Percentage Wage Premium Demanded by "Machinists" (51-4041) When Compared to Jobs with Skill Similarity>=0.7 Weighted by Change in Labor Supply

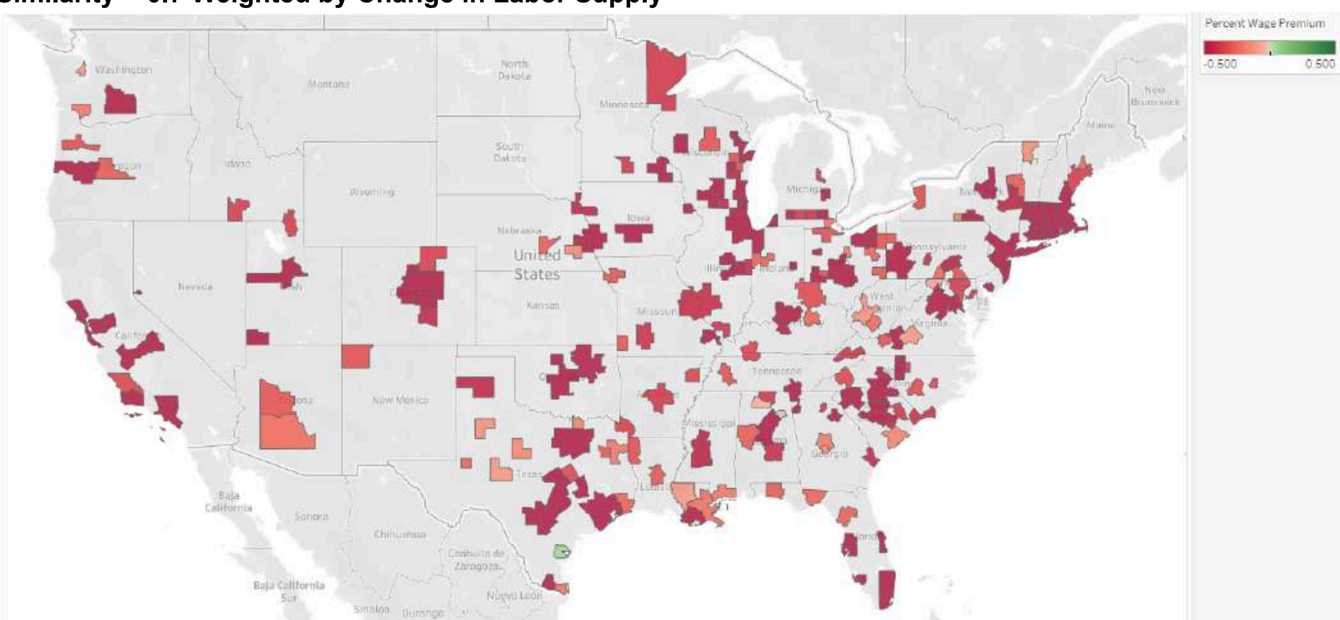


Figure J.58: Local wage premium demanded by workers in occupation 51-4041 "Machinists" when compared to workers in alternative occupations, weighted by change in labor supply from 2021 to 2022.

Percentage Wage Premium Demanded by "Welders, Cutters, Solderers, and Brazers" (51-4121) When Compared to Jobs with Skill Similarity>=0.7 Weighted by Change in Labor Supply

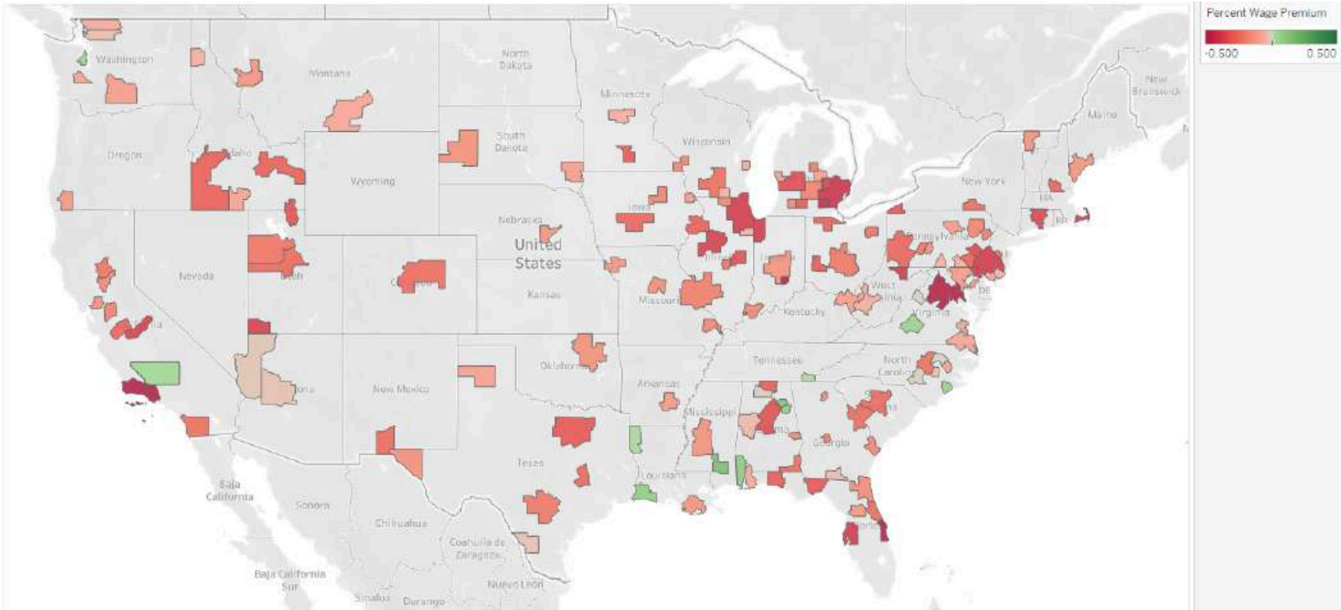


Figure J.59: Local wage premium demanded by workers in occupation 51-4121 "Welders, Cutters, Solderers, and Brazers" when compared to workers in alternative occupations, weighted by change in labor supply from 2021 to 2022.

Percentage Wage Premium Demanded by "Computer Numerically Controlled Tool Operators" (51-9161) When Compared to Jobs with Skill Similarity>=0.7 Weighted by Change in Labor Supply

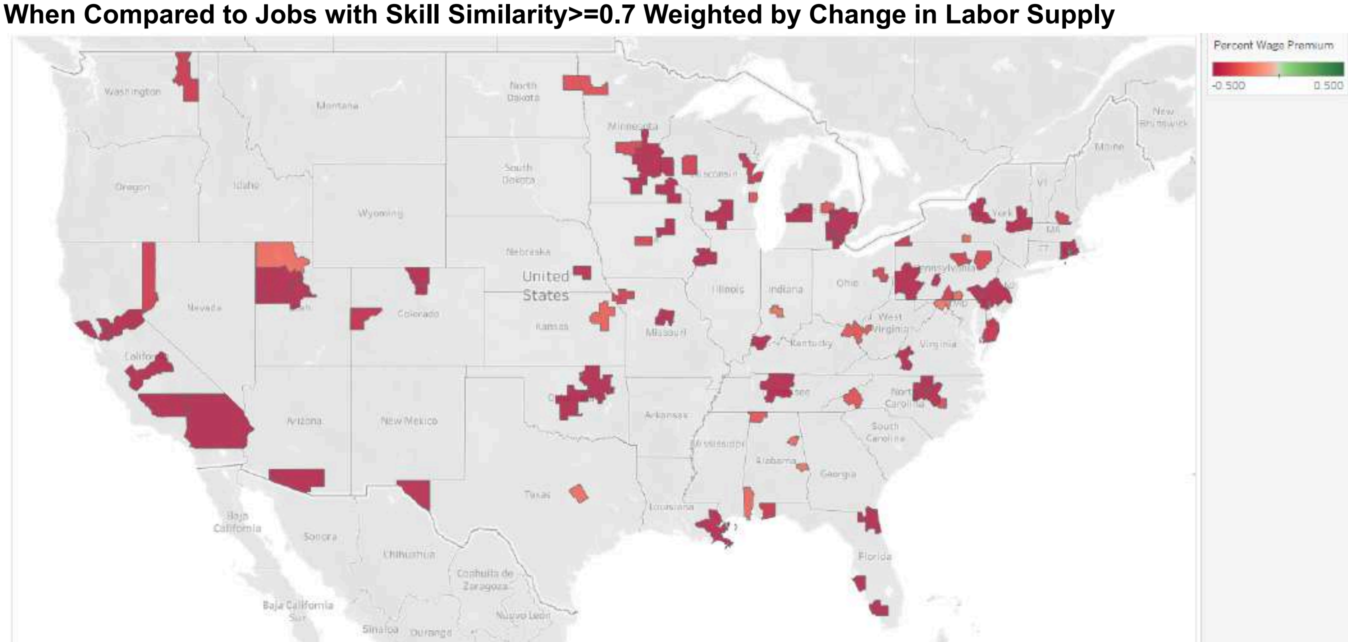


Figure J.60: Local wage premium demanded by workers in occupation 51-9161 "Computer Numerically Controlled Tool Operators" when compared to workers in alternative occupations, weighted by change in labor supply from 2021 to 2022.

Appendix K: Detail on SKAW Similarity Score

In order to determine labor competition for the selected occupation codes, we employed the Workforce Insights Tool (Combemale *et al.* 2023).

For each occupation in the O*NET database, BLS collects data on Skills, Abilities, Knowledge, and Work Activities (SKAWs) requirements. Each of these 4 SKAW categories has multiple subcategories so that each individual occupation has 161 attributes that describe the occupation. For each of these attributes there are two elements: Level and Importance. Level is a measure of the degree of expertise required in that attribute to complete the requirements of the occupation and Importance is the emphasis placed on that attribute relative to other attributes within the occupation. The following quotation from the full methods paper by Gonchar and Combemale describes the computation for Skills, while the same process is applied to Skills, Abilities, Knowledge, and Work Activities to measure overall similarity:

Let X be a set of skills, and let Y be either a subset of X such that each occupation in Y has a corresponding occupation in X or Y is a test occupation. For each occupation x ∈ X, let AVG_x be the average value of a particular skill across all workers in occupation x. For each occupation y ∈ Y, let AVG_y be the average value of the same skill across all workers in occupation y.

$$\mathbb{1}(x) = \begin{cases} 1, & \text{if } \mathrm{AVG_x} \geq \mathrm{AVG_y} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Then, the percentage of occupations in X that meet the above condition can be computed as:

$$\text{Percentage of skills meeting bounds} = \frac{1}{|\mathrm{X}|} \sum_{\mathrm{x} \in \mathrm{X}} \mathbb{1}(\mathrm{x}) \times 100\% \tag{2}$$

This percentage match between Levels of all occupations and a test occupation is then modified by the vector of Importance values. Specifically a cosine similarity is calculated between all occupations and the test occupation using the method from Blair *et al*. 2021. This cosine similarity measures the angle between the Importance vectors of each occupation in the comparison (see Equation 3 below). This method accounts for differences in how each occupation scales Level and Importance. Here *m* represents the calculation for Level or Importance. The cosine similarity can be calculated for either Level or Importance or both where the product of the two is included in the final similarity score.

$$\mathrm{Cosine}^m(x, y) = \frac{\sum_{i=1}^{N} (x_i^m \cdot y_i^m)}{\sqrt{\sum_{i=1}^{N} (x_i^m)^2 \cdot \sum_{i=1}^{N} (y_i^m)^2}} \tag{3}$$

Take the two simplified example occupations (A and B) listed below with their respective average Levels and Importances on three SKAWs (X, Y and Z).

Occupation A

	Skill X	Skill Y	Skill Z
Level	5	5	4
Importance	5	3	5

Occupation B

	Skill X	Skill Y	Skill Z
Level	5	5	5
Importance	5	5	3

What is the similarity score when assessing if an employee in Occupation A can transition to Occupation B?

$$Similarity\ Score\ =\ Percentage\ of\ SKAWs\ meeting\ bounds\ *\ Cosine\ Similarity_{Level}\ *\ Cosine\ Similarity_{Importance}$$

$$=\ \frac{2}{3}\ *\ \frac{5*5\ +\ 5*5\ +\ 5*4}{\sqrt{(5^2*+5^2+4^2)*(5^2+5^2+5^2)}} * \frac{5*5\ +\ 5*3\ +\ 3*1}{\sqrt{(5^2*+3^2+5^2)*(5^2+5^2+3^2)}}$$

$$Similarity\ Score =\ 0.62$$

If the question is reversed to ask “what is the similarity score when an employee from Occupation B is attempting to transition into Occupation A”, the similarity score is 0.92. This example highlights why the skill similarity score is not equivalent when going from A to B vs B to A. As the number of SKAWs included in the real comparison is significantly larger (161 total instead of the three in this example), no single SKAW will completely disqualify a candidate occupation from a potential transition. And while we use 0.7, 0.8, and 0.9 as similarity score cut points for transition occupations, we see from this toy problem that a specific similarity score must be validated before determining what level of similarity is required for a successful transition. A one point difference in Level score for a single SKAW is not likely to disqualify someone in Occupation A from moving to Occupation B in the real world.

This tool is an evolving methodology that we are continuing to develop and validate. Our analysis in this report shows broad comparison trends in the occupations and industries of interest, but further refinement of cut points (and how they may vary by industry) is required. Future work will also include sensitivity analysis to exclusion of low Importance SKAWs.

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