DISSERTATION

MAPPING THE IMPACT OF ROBOTIC INVESTMENT ON THE U.S. MANUFACTURING INDUSTRY: A MULTI-LEVEL LONGITUDINAL ANALYSIS OF EMPLOYMENT, INDUSTRY FIRM COMPOSITION, AND OCCUPATIONAL CHANGE.

Submitted by

William S. Freshwater

School of Education

In partial fulfillment of the requirements

For the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Fall 2025

Doctoral Committee:

Advisor: Gene Gloeckner

Tobin Lopes
Travis Maynard
Troy Mumford

ABSTRACT

MAPPING THE IMPACT OF ROBOTIC INVESTMENT ON THE U.S. MANUFACTURING INDUSTRY: A MULTI-LEVEL LONGITUDINAL ANALYSIS OF EMPLOYMENT, INDUSTRY FIRM COMPOSITION, AND OCCUPATIONAL CHANGE.

The purpose of this study was to investigate how capital expenditures (CAPEX) on robotic automation are reshaping employment patterns, occupational structures, and firm composition within the U.S. manufacturing sector. The study focuses on industry sectors categorized under the North American Industry Classification System (NAICS) codes 31–33 from 2018 to 2021. The study delves into the growing discussion about the long-term labor market effects of automation, specifically extending beyond traditional manual labor roles. The existing literature primarily focuses on the displacement of blue-collar jobs. This study centers on white-collar supervisory occupations, including industrial production managers, engineers, technicians, and front-line supervisors.

This research is designed as a descriptive study, utilizing publicly accessible national and state-level statistics from the U.S. Census Bureau and the Bureau of Labor Statistics. Using simple statistical methods, correlation analysis, and industry quartile groupings to find patterns in CAPEX spending and how it relates to the number of firms, total manufacturing jobs, and job types at different levels of analysis. Lagged relationships are also explored to capture delayed labor responses to investment activity.

The key findings indicate a steady rise in investment in robotic automation during the research period, including the years affected by the COVID-19 pandemic. Conversely, there has

been a notable decline in manufacturing employment accompanied by a trend toward firm consolidation. At the occupational level, white-collar employment outcomes varied: managerial roles showed consistent positive alignment with both year-matched and lagged CAPEX levels, while engineering and technical occupations displayed more volatility. At the state level, high-CAPEX states tended to have higher concentrations of white-collar employment but did not consistently gain firms, revealing regional disparities in the diffusion and benefits of automation.

By focusing on white-collar supervisory labor and employing a descriptive-analytic approach, this study provides new empirical evidence on how automation is shaping workforce structures and organizational dynamics within the U.S. manufacturing sector. The results are relevant for workforce development initiatives, organizational planning, and state and federal policy efforts. They indicate that responses to industrial automation should be flexible, occupation-specific, and regionally tailored to reflect the uneven impacts of robotic investment in the industry. A key finding is that while capital expenditures in automation have grown, their effect on white-collar employment varies significantly across regions and industries, suggesting a non-linear, context-dependent relationship between automation and organizational change.

ACKNOWLEDGEMENTS

I wish to express my sincere gratitude to the members of my dissertation committee for their time, expertise, and thoughtful feedback. Your guidance, constructive critique, and encouragement throughout this process have been invaluable in shaping the quality and direction of my research.

To my committee chair, Dr. Gene Gloekner, thank you for your continued support, insightful counsel, and patience in guiding me through each stage of this journey.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF KEYWORDS

The key terms used in this research study are described and defined in the following paragraphs.

Skill, is a worker's endowment of capabilities for performing various tasks (Acemoglu & Autor, 2010). Workers apply their skill endowments to tasks in exchange for wages, and skills applied to tasks produce output (p. 2).

Task, is a specific work activity that individuals in a particular occupation are expected to perform as part of their job responsibilities. These tasks are typically observable and measurable actions that contribute to the completion of job duties (*National Center for O*NET Development. O*NET OnLine*, n.d.).

Artificial intelligence, is a form of automation referring to algorithms that learn to complete high-skilled tasks by identifying statistical patterns in data, rather than following instructions provided by humans (Webb, 2019) Artificial intelligence does not require physical manipulation, but rather computer-based (machine) learning (Raj & Seamans, 2019)

Machine learning, implies the machine can improve at its programmed, routine, automated task with more application of these data (Raj & Seamans, 2019). For this study, these two terms artificial intelligence and machine learning will be used interchangeably in relation to how it is used in the sourced literature.

Industrial Robots (Robots), is defined by The International Federation of Robots (IFR) (*World robotics Industrial Robots 2019.*, 2019) defines an industrial robot as an automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications.

Information technology, refers to the application of technologies used in an organization to solve business or organizational problems on a broad scale (Nissen, 2018; Nissen & Seifert, 2016).

White-collar occupations, are typically representative of occupations that require higher skill, educational backgrounds, and task requirements that are less replicable (Autor, 2015). The tasks associated with these occupations require leadership decision-making and problem-solving.

Blue-collar occupations, are typically representative of manual tasks occupations that have tasks that are repeatable or replicable and can be relatively easily or prone to be displaced by automation technologies (Acemoglu & Restrepo, 2018). These occupations normally require minimal skills, minimal problem-solving abilities, and require minimal decision-making (Autor, 2015).

Future of work, refers to the expected labor markets and skills gaps shaped by the proliferation of artificial intelligence in the workplace, and the expansion of the workforce to include both on- and off-balance-sheet talent. (Economics, 2019).

Industry 4.0., is a term that refers to the fourth industrial revolution which is representative of our current global environment. This is a new level of organization and management of the entire value chain across the product and organizational lifecycle (Oeij et al., 2017; Zezulka et al., 2016).

The Standard Occupational Classification (SOC), categorizes occupations based on their similarities in job duties, skill level, and educational requirements. Each occupation is assigned a unique six-digit code. The SOC system is revised periodically to reflect changes in the labor market and emerging occupations (*National Center for O*NET Development. O*NET OnLine*, n.d.).

North American Industry Classification System (NAICS), codes that are used in the United States, Canada, and Mexico to classify business establishments to collect, analyze, and publish statistical data related to the economy. NAICS codes are typically categorized into two to six-digit codes Each industry is assigned a unique 6-digit code, with the first three digits representing the sector, subsector, or industry group, and the subsequent digits providing further detail (*National Center for O*NET Development. O*NET OnLine*, n.d.).

Capital Expenditures (CAPEX), refer to the overall dollar amount spent on acquiring new and used industrial robotic equipment, including software, installation, and other one-time expenses, within specific industries or geographic regions (U.S. Census Bureau, n.d.).

.

CHAPTER ONE - INTRODUCTION AND BACKGROUND

The unprecedented expansion and impact of technology are creating a massive restructuring of global economies that will generate definitive winners and losers in the future of work. The winners are those who can proficiently and innovatively collaborate with intelligent technologies, whereas those who lose to technology are rendered inefficient, and their tasks redundant (Acemoglu & Restrepo, 2020; Arntz et al., 2017; Frey et al., 2016). Estlund (2017) argued that technology has played a significant role in driving economic advancement and wealth since the mid-twentieth century. Achieving both the elimination and creation of jobs, as well as reducing suffering and monotonous tasks, both within and outside of employment. Nevertheless, the rapid pace at which technology is progressing introduces substantial degrees of uncertainty and complexity throughout the entire organization.

According to Estlund (2017), the implementation of automation in businesses offers a comprehensive solution to the expenses, uncertainties, and psychological requirements associated with human labor. It lessens the financial strain of hiring human workers compared to machines. The forthcoming wave of automation, encompassing technologies such as artificial intelligence, 'big data' advancements, the internet of things, and machine learning, can execute numerous tasks previously believed to necessitate human judgment, logic, and intervention (Acemoglu & Restrepo, 2018). In the future of work, technological advancements like artificial intelligence are expected to have the greatest impact on direct job displacement of white-collar professions (Webb, 2019).

According to Frey et al. (2016), nearly half of U.S. employment was projected to be at high risk of automation over a 20-year period. Recent evidence suggests that while automation has significantly reshaped many work processes, the large-scale displacement of jobs has been more limited than originally forecast (Bessen, 2022; Dillon et al., 2025; McKinsey, 2025). Instead, the trend points toward task-level transformation, particularly within white-collar and supervisory roles. Acemoglu and Restrepo (2019) predicted that by 2022, one in five workers engaged in mostly "non-routine" knowledge-based tasks will rely on some form of automation to do parts of their job, and occupations will be impacted by automation at every level of the organization. McKinsey (2025), this projection has largely materialized as over 75% of organizations now use AI in at least one function, and a growing share of knowledge workers report using AI tools for upwards of 30% of their daily tasks. Studies further show that generative AI adoption among professionals has reduced time spent on communication tasks and increased overall efficiency (Dillon et al., 2025). Collectively, these findings suggest that automation's influence has shifted from potential job elimination toward widespread task augmentation, reshaping organizational workflows without uniformly displacing workers.

Furthermore, on a global scale, existing technologies can automate approximately 49% of global labor tasks (Filippi et al., 2023; Manyika et al., 2017). Four distinct economies: China, India, Japan, and the United States, carry out 66% of these automated tasks (Manyika et al., 2017).

Blue-collar workers primarily perform cognitive and manual tasks in manufacturing environments. "Repetitive nature and adherence to well-defined procedures" characterize these tasks, making them easily documented and automated (Acemoglu & Autor, 2010, pp. 23–24; Acemoglu & Restrepo, 2018). White-collar jobs, like cognitive interpersonal and management tasks and non-routine cognitive analytical tasks, don't always follow prescribed methods and are difficult to automate (Autor, 2015; Sampson, 2020).

Given the current capabilities and advancements in robotics, it seems certain that these technologies will eventually, directly and indirectly, permeate the realm of management and supervisory labor. Resulting in a reduction in the overall demand for managers in manufacturing organizations (Dixon et al., 2019; Leavitt, 1958). Acemoglu and Autor (2010) argued that it is possible to construct models that demonstrate how the introduction of "new machinery" can directly replace jobs carried out by different skill groupings. Moreover, ongoing academic research and the evolution of economic and organizational frameworks enable the understanding and modeling of how automation technologies will substitute both directly and indirectly for tasks performed by individuals with varying levels of skills and competencies.

More than half a century ago, we witnessed the warning signs of automation technology causing disruptions inside businesses and leading to significant job losses in white-collar sectors. Models can now effectively simulate the way emerging digital and physical technologies can directly replace occupations executed by various skill groups. However, further research is needed to develop frameworks that help organizations understand and conceptualize how automation technologies will not only "directly" replace jobs performed by low-skilled workers, but also "indirectly" replace employment at the knowledge-based levels of the organization (Acemoglu & Autor, 2010; Autor, 2015; Filippi et al., 2023; Webb, 2019).

The Problem

Automation is not a new phenomenon. Moreover, it has assumed the role of overseeing worldwide economic progress ever since the inception of the initial Industrial Revolution. According to Dixon et al. (2019), the impact of automation on labor is more complex than previously anticipated. To gain a comprehensive understanding of this phenomenon, it is necessary to delve deeper into the specific occupations within organizations rather than solely concentrating on the economy in its entirety (Acemoglu & Restrepo, 2020; Bessen & Righi, 2019; Bonfiglioli et al., 2020; McGuinness et al., 2021). Dixon et al. (2019) underscore the need for more comprehensive research on how firms utilize automation to complement and substitute human labor" (p. 2).

Manufacturing organizations recognize the role of automation technologies in enhancing operational efficiency and generating a favorable return on investment. Jobs traditionally performed by blue-collar workers largely achieve this. Current research does not sufficiently examine the indirect effects of manufacturing automation on the managerial and supervisory roles that support it. This includes examining changes in work structures, required skills and competencies, and the changing demand in the industry for white-collar professionals (DeWitt, 2019; Waldman-Brown, 2020; Waschull et al., 2022). While direct job losses as a result of technological advancement are relatively straightforward to quantify. The indirect effects are more nuanced and multifaceted, and resulting changes to firms and their occupational job designs are largely undefined.

Problem Statement

The problem statement that frames the basis of this research is:

Over the past decade, rapid advancements in robotic automation technologies have transformed various industries, particularly manufacturing. While significant attention during this time has been given to the direct displacement of blue-collar occupations due to robotic automation, the indirect displacement of white-collar workers remains largely unexplored.

Significance of the Problem

Technology has been continually automating various aspects of work for more than two and a half centuries. We are now approaching a critical juncture where workers, whether in blue-collar or white-collar roles, must possess the knowledge and skills to harness technology's potential, or risk being controlled by it (Acemoglu & Restrepo, 2020; Arntz et al., 2017; Frey et al., 2016). Although jobs and titles have changed over time, work has not disappeared; rather, it has generally improved. The workforce has become more educated and has increased general productivity by adopting new technologies, making the "average job less arduous, safer, and better compensated" (Finneran, 2018, p. 18).

In previous decades, it was common for executives to adopt an approach where they initially focused on resolving complicated organizational issues inside before considering the option of outsourcing to augment their capacity. Contrastingly, the current wave of automation is distinct, shifting work dynamics significantly over the past two decades, favoring “robots/capital and against labor” (Estlund, 2017; Freeman, 2015, pp. 4–5). This change reflects a fundamental shift in organizational strategies in response to advancements in automation and changing economic landscapes. The evolving capabilities of automation are giving rise to its role as a financially viable substitute for human work, hence impacting the cost dynamics between human and machine labor (Freeman, 2015). In response, manufacturing organizations increasingly choose automation as a result of its reduced expenses, diminished safety hazards, and absence of emotional requirements associated with human labor (Estlund, 2017).

North et al. (2018) argued that automation not only has an impact on the future skillset and qualification requirements of production workers [blue-collar] but is also associated with technological trends that offer new opportunities for directly and indirectly displacing knowledge workers. However, empirical research does not appear to have sufficiently recognized this potential. And it will not be long before automation not only takes on the ability to perform the majority of specialized skills but also those that require logic and cognition (Grace et al., 2018).

According to Dixon et al. (2019), organization researchers are “late to the game” and have only just started to focus on the “organizational implications of automation technologies as they now present a unique opportunity for organizational scholars” (p. 1). Waschull et al. (2022) and Moulds (2018, as cited in Dixon et al., 2019, pp. 13-14) argued that while both could contribute to the decline in “managerial employment that the indirect effect is likely to dominate the direct effect.” Given that technological advancements in AI automating managerial work are still relatively uncertain, Acemoglu and Restrepo (2019) observed that organizational practices are changing with automation through the reallocation of decision authority for certain tasks to different layers of the hierarchy, away from managers. This would indicate that manufacturing automation could further reduce managerial employment, and the nature of managerial work would continue to evolve as automation in the manufacturing industry evolves.

Purpose of the Research

The purpose of this study is to examine the longitudinal relationship between capital expenditures on robotic equipment, firm counts, and employment in total and white-collar supervisory occupations. Using national and state-level data from 2018 to 2021, the study explores how changes in CAPEX influence employment and firm structure across NAICS 31–33 industries, highlighting how automation-related investments are reshaping workforce and organizational trends across U.S. manufacturing.

Research Question

Considering the problem statement and significance of the problem, the research questions that form the foundation of this research are:

Q1: What are the observable trends in capital expenditures (CAPEX) on robotic equipment across U.S. manufacturing industries (NAICS 31–33) between 2018 and 2021?

Q1a: How has CAPEX changed year-over-year across 3-digit NAICS manufacturing industries?

Q1b: How Has CAPEX Intensity Varied Across Industries, and Which Have Consistently Received the Highest or Lowest Investment?

Q1c: How has year-over-year CAPEX change varied across industries grouped by average CAPEX quartiles?

Q2: How does CAPEX influence total firm employment outcomes in the U.S. manufacturing sector from 2018 to 2021?

Q2a: How have year-over-year changes in CAPEX been associated with corresponding changes in total firm employment?

Q2b: How Does CAPEX in One Year Correspond With Total Employment in the Subsequent Year?

Q2c: How does CAPEX quartile level correspond to differences in total employment across industries?

Q3: How does CAPEX affect employment in white-collar supervisory occupations across manufacturing sub-sectors from 2018 to 2021?

Q3a: How has CAPEX influenced SoC-coded white-collar occupations over time?

Q3b: How has lagged CAPEX been associated with changes in white-collar employment levels?

Q3c: How has CAPEX variation affected year-over-year trends in white-collar employment across occupations and sectors?

Q4: How does CAPEX relate to firm composition trends in U.S. manufacturing from 2018 to 2021?

Q4a: How has CAPEX coincided with changes in firm composition across industries?

Q4b: How has CAPEX quartile grouping influenced differences in firm composition?

Q4c: How has CAPEX level been associated with trends in firm expansion, consolidation, or restructuring?

Q5: How does CAPEX vary across U.S. states, and how is it associated with differences in employment and firm composition from 2018 to 2021?

Q5a: How Have Year-Over-Year Changes in State-Level CAPEX Varied Across U.S. States and Investment Quartiles?

Q5b: How Have Year-Over-Year Changes in Total Manufacturing Employment Varied Across State-Level CAPEX Quartiles?

Q5c: How Does White-Collar Employment Vary Across State-Level CAPEX Quartiles in U.S. Manufacturing From?

Q5d: How Have Year-Over-Year Changes in State-Level CAPEX Been Associated With Changes in White-Collar Employment Across U.S. States?

Q5e: How Do Lagged Relationships Between State-Level CAPEX and White-Collar Employment Vary by Investment Quartile and Sub-Industry?

Q5f: How Has Manufacturing Firm Count and Growth Varied Across State-Level CAPEX Quartiles?

Q6: How does CAPEX investment at the state level compare with national trends, and how is it associated with differences in employment and firm composition from 2018 to 2021?

Q6a: How has state-level CAPEX aligned with or diverged from national trends?

Q6b: How has CAPEX concentration at the state level been associated with total and white-collar employment outcomes compared to national employment trends?

Q6c: How has CAPEX quartile level at the state level been associated with differences in firm growth relative to national averages?

Summary

The rapid expansion of automation technologies is reshaping global economies, with success increasingly tied to how effectively individuals and organizations can adapt to working alongside intelligent automated systems. While automation offers opportunities to eliminate repetitive tasks and drive economic growth, its swift advancement also brings uncertainty and complexity. In the US, approximately half of all jobs are vulnerable to automation, impacting both blue-collar and white-collar occupations. Although much attention has focused on the direct impact of robotics on blue-collar roles in manufacturing, there is limited research on its indirect effects on managerial and supervisory positions. This gap highlights the need to examine how robotic automation is influencing the structure and employment of white-collar jobs in manufacturing firms.

CHAPTER TWO: REVIEW OF THE LITERATURE

This chapter synthesizes and summarizes the existing body of knowledge on robotic automation in manufacturing, with a focus on how robotic automation that targets blue-collar occupations may indirectly affect white-collar managerial and supervisory roles. While the displacement of routine, blue-collar labor has been widely studied, the effects of robotic investment on the structure of white-collar occupations remain underexplored. This chapter reviews the theoretical and empirical literature that shapes the scope of this research, particularly how capital expenditures (CAPEX) in robotic equipment influence total employment, white-collar occupations, and firm count. The review comprises four interconnected sections: (1) the historical evolution and theoretical underpinnings of automation, (2) the transformative effects of automation on industries, organizational frameworks, and workforce demographics, (3) the labor market implications of automation, including job displacement and enhancement, and (4) emerging trends in U.S. manufacturing concerning employment and firm numbers. This chapter builds the rationale for an industry-level empirical investigation of how robotic investments affect total employment, white-collar supervisory occupations, and firm count within NAICS 31–33 manufacturing industries.

Method

With the guidance of Randolph (2009) and Machi (2016), the following outlines the strategy for selecting the articles, texts, and documents used in this review. Literature was located from October 2019 to June 2025 utilizing databases EBSCO Academic Search Premier, Business Source Complete, and JSTO, and Google Scholar. The databases were queried using the keywords: “white-collar automation,” “direct effects of automation on manufacturing firms,”” in-direct automation displacement” “robots in manufacturing” “knowledge worker automation," "the effects of tactile automation on knowledge worker tasks," "manufacturing automation," "task automation," "blue-collar automation," "future of work," and "industry 4.0.". Approximately 100 articles were reviewed, and the publication dates ranged from 1911 to 2025.

Section One: The History and Theoretical Foundations of Automation

In 1769, wigmaker, inventor, and entrepreneur Richard Arkwright designed a water-powered cotton spinning machine called the "Waterframe." Arkwright's hydraulic spinning machine pioneered mass production by eliminating the tedious work of hand-spinning cotton to produce yarn. The textile sector was "the first to take on new forms of industrial organization," and the Waterframe served as a harbinger of the first industrial revolution and a transformative shift in societal paradigms (Tann, 1973).

According to Tvedt (2010), the cotton mill became the "definitive symbol of the Industrial Revolution" as there were "109,626 power looms in use in the cotton industry in the United Kingdom" alone by 1835 (p. 42). The definition of the first industrial revolution may vary amongst the literature; however, they all highlight the importance of the emergence of modern factories, which began in England during the latter part of the 18th century.

The public at that time only moderately embraced the advancements in Great Britain, maintaining the belief that traditional methods remained superior (Tvedt, 2010). Moreover, established interest groups resistant to institutional changes and social innovations further impeded progress, satisfied with maintaining the status quo. The 19th-century "Luddite" movement was an example of this dissent (Acemoglu & Autor, 2010). The Luddite movement involved a group of English textile artisans who violently protested the automation of textile production by seeking to destroy some of the machines and factories. The concerns and fears for the "contra-labor" effects of automation have been constant since (Tvedt, 2010).

Manufacturing in the United States expanded rapidly through the mid-20th century as product demand grew domestically and abroad (Hanley, 2013). Manufacturing employment and incomes were growing; however, new production technologies designed to automate specific tasks and monitor continuous production processes had "by 1955, raised the public alarm about job displacement and the future of work" (p. 406).

The first Industrial Revolution and the subsequent revolutions to date have resulted in radical changes in manufacturing, from water- and steam-powered machines to electrical and digital automated production (Qin et al., 2016). Manufacturing processes have undergone significant advancements, incorporating automated and sustainable processes that enable machines to function autonomously, efficiently, and continuously. These advancements have had and will continue to have a significant impact on the occupational frameworks in manufacturing settings.

Automation is more than just a 'catch-all' term for every improvement occurring in a factory. It is important to distinguish automation as "only one phase in the process of technological progress and the natural evolutionary step in man's continuing effort to use the discoveries of science to get the world's work done" (Oldfield, 1995, pp. 406–407). Automation technologies are essential methods to use knowledge and machinery to allow an organization to be "able to make new physical goods more efficiently" (Fish, 2012, p. 6). Acemoglu and Restrepo (2019) asserted that automation technologies fundamentally transform labor-intensive tasks into capital-intensive ones. This change in the task content of production adversely affects labor due to a displacement effect, where capital (robots) takes over tasks previously performed by labor (Acemoglu & Restrepo, 2018, 2019; Autor, 2019; Webb, 2019).

Classical Theoretical Frameworks of Automation Research

The development of today's automation efficiency frameworks has its roots in three classical thinkers: Frederick Taylor, Max Weber, and Henri Fayol (Chermack & Nimon, 2013; Chowdhury, 2019; Swanson & Holton, 1999). Chowdhury (2019) argued that the classical thinkers approached organizational efficiency as “dependent upon the management-centric pathway” of understanding the work situation, which is “independent of the world outside” (pp. 9–10). Organizational performance and efficiency perspectives have also received criticism that they lack the human psychological and social elements in their analysis (Chowdhury, 2019; Cummings & Worley, 2015; Swanson & Holton, 1999; Visser & Chermack, 2009).

Taylor’s Scientific Management. Taylor (1911) developed his theory of management around the idea of the “one right way” of handling responsibility that can be diagnosed by rigorous scientific observation and calculations. Taylor was the forefather of utilizing a scientific theory in his approach to management and how managers lead organizations (Chowdhury, 2019; Swanson & Holton, 2005). Taylor (1911) new theory of management, also known at the time as “scientific management,” is comprised of two components: “1) break complex tasks down into simple rote tasks that can be performed with machine-like efficiency, and 2) control the large number of workers needed for production with a hierarchical management structure” (Swanson & Holton, 2005, p. 44; Taylor, 1911). Taylor (1911) believed it is the need of both the management and the workers to transform their perspective towards work and embrace scientific modernism, which can be diagnosed with time-and-motion studies. Chowdhury (2019) argued that Taylor exhibited remarkable optimism regarding the favorable outcomes that his scientific management methods could yield.

Weber’s Rational-Legal Authority. In 1947, Max Weber used the term “rational-legal authority” to describe organizations as a “manifestation of a well-structured set of hierarchies with normative behaviors and interactions” or systemized entities (Chowdhury, 2019, p. 8). Weber believed that efficiency is managed through a clear structure based on the division of duties and responsibilities, governed by a strict hierarchy and formal rules and regulations. Directed deliverables guide roles and responsibilities, ensuring success through adherence and rejecting any deviation from innovation. Most large organizations at the time adopted Weber's formal and rigid view of organizational management and performance.

However, Cotgrove (1975) argued that Weber not only didn’t embrace technological innovation, but he also considered it to be arbitrary and irrational and a threat to human values by eliminating human agency, judgment, and decision-making within organizations. This "technical rationality" fostered a disregard for the value of technical process innovations in structured environments and was deemed "unscientific" due to its inability to be measured. The assertion was made that "technology cannot put up with institutions and literature,” and further, “we must exclude everything in life that does not lend itself to mathematical treatment” (pp. 59–61).

Fayol’s Administrative Management Theory. Henri Fayol's "Administrative Management Theory" departed from Taylor and Weber by incorporating a human-centered approach to managing efficiency (Chowdhury, 2019). Fayol argued that administrative functions are expressed through individuals and that this is the sole means of expression (Hatch & Cunliffe, 2013). Fayol argued for the importance of flexibility and adaptability, as well as the manager's ability to administer subordinates by achieving a unique integration of his theory's fourteen principles. Chowdhury (2019) acknowledges that the academic and organizational climate at the time of Fayol’s writing was “biased towards the notions of focalised centralisation and managerial superiority” (p. 9). During the 1960s and 1970s, corporations began incorporating elements of Fayol's ideas into worker welfare programs, to improve collaboration and motivate workers. These practices have greatly influenced modern human resource development (HRD) practices.

Fayol's theory has endured more than a century of critique, reinforcement, and refutation (Hatch & Cunliffe, 2013). Fayol owned a large steel factory in France and recognized the importance of technological advancement in large manufacturing environments. However, he held the belief that all technical functions were subordinate to managerial functions, given that specialists manage the technologies and that the managerial level must support these activities to achieve organizational goals. Similar to other scientific disciplines, Mintzberg (1998) emphasized the significance of observation and asserted that we can derive management rules and principles from observation and experience. Workers may claim that they engage in planning, organizing, coordinating, and controlling; however; "the actual data observed is unlikely to support these four principles" (Hanley, 2013, pp. 421–422).

Robots and Manufacturing

Karel Capek, the Czech science fiction playwright, coined the word "robot" in 1920 as a reference in his play about a factory of "androids that each do the work of two-and-a-half humans at a fraction of the cost" (Manyika et al., 2017, p. 3). At the time, Capek's work was just that of vacuous storytelling that unknowingly tells of a plausible and soon-to-be reality.

Industrial robots (robots) are technological tools that organizations use. To comprehend their impact, it is crucial to determine if they act as substitutes or complements to human workers in firms that undergo automation (Bonfiglioli et al., 2020). It is also critical to understand whether these effects are heterogeneous across nations, firms, and occupations. According to Bonfiglioli et al. (2020), from a theoretical perspective, the answer to all these questions is ambiguous. From an empirical perspective, the available evidence is limited due to the lack of data on the use of robotics.

In 1930, British macroeconomist Keynes (Harcourt Brace, 1932/1930) predicted that rapid technological progress over the next 90 years would change the course of society and also conjectured it would bring disruption and unemployment that would affect every industry and occupation in every country (Acemoglu & Restrepo, 2020; Keynes, Harcourt Brace, 1932/1930). Keynes (Harcourt Brace, 1932/1930) believed that “We are being afflicted with a new disease — namely, technological unemployment” (Harcourt Brace, 1932/, pp. 3–4). Keynes implied the term “technological unemployment” to describe a situation in which “innovation that economized the use of labor outstripped the pace at which new jobs could be created” (Acemoglu & Restrepo, 2020; Agrawal et al., 2019; Kanagachidambaresan, 2020; Manyika et al., 2017, p. 30). However, he warned this “new disease” would result in a “temporary phase of maladjustment,” as the markets would eventually correct and redeploy the labor (Manyika et al., 2017, pp. 30–31). Nobel Laureate economist Leontief disagreed with Keynes’s assessment of the redeployment of labor (Acemoglu & Restrepo, 2020). Leontief contended that human labor would become “less and less important” and “more and more workers will be replaced by machines; I do not see that new industries can employ everybody who wants a job” (Leontief, 1952; as cited in Acemoglu & Restrepo, 2020, p. 1).

The first programmable robot was the ‘Unimate, ’which was an electronically controlled hydraulic heavy-lifting arm capable of repeating arbitrary sequences of operations (Bonfiglioli et al., 2020). GM's Inland Fisher Guide Plant in Ewing Township, New Jersey, deployed the first Unimate robot in 1961. Its purpose was to handle the task of lifting hot metal components from a die-casting machine and stacking them, as well as perform basic welding tasks. Chrysler, Ford, and Fiat quickly recognized the need, following GM, and acquired a significant number of Unimate robots.

Since the Unimate, industrial robot usage globally has been increasing exponentially. According to Acemoglu and Restrepo (2020), the increase in industrial robot usage has amounted to one for every thousand workers in the United States and 1.6 for every thousand workers in Western Europe. In 2018, approximately 2.44 million industrial robots operated globally, performing tasks previously performed by humans. The International Federation of Robotics (IFR) estimates the number of industrial robots will increase to 4 to 6 million by 2025. (IFR, Acemoglu & Restrepo, 2020).

Robophobia and Rationalization. 'Robophobia' is a phenomenon that occurs when individuals exhibit abnormal behavior towards unfamiliar things or acts related to robots (Dzedzickis et al., 2024). Generally, humans tend to be cautious when it comes to unfamiliar processes or objects. Humans' responses to robots vary depending on various contexts, including geographical location. For example, the acceptance of robots in Greek society is significantly lower (57%) compared to Denmark (95%) (Hofstede Insights ,2023, as cited in Dzedzickis et al., 2024). The mentioned fears directly relate to the robots themselves, stemming from concerns about their skills and abilities, as well as the potential outcomes of their integration into society.

A 2019 Pew Research report showed 82% of American workers hold the belief that robots will likely or certainly assume many of the tasks currently performed by humans within the next three decades (Anderson & Rainie, 2023; Parker et al., 2019). However, 37% of these workers think the phenomenon will not affect their work (Anderson & Rainie, 2023). Regardless, half of the respondents believe that automation has primarily had negative consequences and has only affected American workers. Individuals aged 50 and over who are employed are more like to believe that automation has predominantly harmed workers compared to individuals aged 18-49 (55% vs. 43%, respectively). Furthermore, 53% of individuals with a high school diploma or lower level of education believe that it negatively impacts American workers, compared to only 42% of those who have obtained a college degree.

According to Filippi et al. (2023), robots have a negative overall impact on employment, especially in traditional manufacturing sectors and for low- or medium-skilled workers. Robotic technologies have made significant advancements since the Unimate. They are now able to challenge manual tasks and provide a comparative advantage to human labor. However, "the flexible movement in three dimensions remains firmly in human hands, despite the current waves of advanced robotics" (Graetz & Michaels, 2018, p. 753). Adoption of robots can lead to positive productivity effects, especially in successful firms. Understanding the capabilities and limitations of complex technology can help mitigate fears of a "robocalypse" and highlight the activities where workers still have a comparative advantage. Non-machine-based digital technologies, such as AI and machine learning, have a more labor-friendly impact.

The Future of Automation: The Future of Work

The nebulous term ‘Future of Work’ has been a buzzword in organizational literature over the last decade to describe and project how work, workers, and the workplace will evolve in the years ahead (Tidd, 2020). The technological advancements in industries over the past ten years have surpassed those witnessed during the 3rd Industrial Revolution of general computers and automation, which began more than 30 years ago (Altenried, 2022; Deloitte, 2017; Rana & Sharma, 2019; Zezulka et al., 2016).

How can leaders adapt to the rapid changes and prepare for the unknowns of the future of work and the impact these volatile technological changes have on organizations? In support of these concerns, the Academy of Management (AOM) conference proceedings have emphasized the topic of understanding and codifying the complex issues encapsulated in the future of work (AOM, 2022). Innovation and automation create new industries, wealth, and jobs, but they also destroy some established organizations that can't adapt. According to Darwin's Origin of Species, it is not the most intellectual or strongest of the species that survives; rather, "the species that survives is the one that is best able to adapt and adjust to the changing environment in which it finds itself" (Megginson, 1963, p. 4).

Raj and Seamans (2019) suggested that while we need to draw from lessons learned in prior episodes of automation, the forthcoming effects of artificial intelligence, robotics, and other types of automation could have unique and profound consequences on the organizational landscape. They defined the differences from prior episodes of automation as follows: "(1) the nature of business activity has shifted dramatically, and many businesses now rely on new forms of business models; and (2) artificial intelligence is likely to affect white-collar workers more so than blue-collar workers, while robotics may affect blue-collar workers more so than white-collar workers" (pp. 3-5). Remarkably, the academic literature scarcely discusses the financial benefits of replacing white-collar workers with blue-collar workers or the formal connection to the indirect shift in supervision and decision-making process (Autor et al., 2022; Dixon et al., 2019; Qi, 2022; Raj & Seamans, 2019; Scully-Russ & Torraco, 2020).

Section Two: Organizational Transformation Through Automation

Automation advancement in organizations can be Janus-faced; one face appears negative, while the opposite face looks towards a positive future. The "neutral language" of technological progress is often used to minimize fears that new automation technologies will dramatically change workplace structure and power dynamics (Hanley, 2013). "Progress toward greater technology use is nothing new; only the expression 'automation' is new" (p. 408).

Change is constant, but its accelerating speed in the age of robotics and AI has created novel challenges for organizations, particularly in manufacturing (Cummings & Worley, 2015; Poole & Van de Ven, 2021; Young, 2022). The velocity of change and the fast-moving and unpredictable nature of events cause the most concern for organizations now and in the age of advanced technology. The technological forces and changes that organizations are facing are not only impactful but also globalized and interrelated (Brettel, 2014; Chowdhury, 2019; Cummings & Worley, 2015). Cummings and Worley (2015) argued that these interrelations and interactions create highly uncertain and complex operating environments for all types of organizations, but specifically manufacturing. Chowdhury (2019) emphasized that a resilient organization must continuously adapt by building internal capacity to respond to change. Organizations that succeed in doing so develop the ability to recognize and manage change as an ongoing process, enabling them to remain flexible in the face of a dynamic environment. In contrast, those that fail to adapt often fall behind or exit the market altogether (Cummings & Worley, 2015; Senge, 2010).

Church and Burke (2017) proposed that organizations are experiencing a velocity of change analogous to “Moore’s Law” from the world of semiconductor development. Moore’s law states that advancements in technology double every 18–24 months. North et al. (2018) described volatility as the rapid and accelerated pace of change in an organization’s environment; the real and perceived lack of predictability of this external environment creates uncertainty. Uncertainty compounds this leadership challenge, intensifying the difficulty of defining industries today, let alone developing growth strategies and managing people.

Grant (2013) argued that accelerating technological change and other environmental factors, such as volatile geopolitical and financial markets, make it very difficult for an organization's leadership to plan beyond the foreseeable future. Volatility and uncertainty in business environments, according to Chowdhury (2019), have allowed “complexity theory to come into the business and management discourse as a way of understanding patterns and trends” (p. 13). Complexity is an unknown combination of size and volume, awareness, variety, and disorder that makes a “system” complex. Chowdhury (2019) and Senge (1994) both highlighted the distinction that it is just not a system with size and variety that makes it complex. Rather, organizations encounter a complex system when their "actors" struggle to understand the system, its behavior, its hidden relationships, and the observed disorder. Organizational actors (employees) generally do not support change unless compelling reasons convince them to do so. However, the degree to which an organization’s environment and technology are rapidly changing has forced organizations and their workforce to adapt very quickly to survive.

Cummings and Worley (2015) stated that many organizations today are changing to become more agile by creating efficient and simple structures and processes that can quickly respond to outside demands. The organizational consequences of this transformation are wide-reaching. From the shift to flatter hierarchies to the redefinition of decision-making roles, automation prompts a re-examination of the structure and coordination of work (Cummings & Worley, 2015). When automation technologies reduce the value of routine management tasks, firms often restructure supervisory roles, redistribute decision-making, and change performance metrics. The move from command-and-control structures to commitment-based or learning organizations reflects the broader shift induced by robotic technologies (Cummings & Worley, 2015; Senge, 2010).

When technology and people are incompatible, according to Cummings and Worley (2015), two primary changes can be made to design work that satisfies both employee needs and organizational objectives: change the technology or change the people to bring them more in line with each other and the technology. When "capital costs are high relative to labor costs, such as in highly automated plants, work design is likely to favor the technology" (p. 158). In contrast, in knowledge work, "where labor is expensive relative to capital, organizations may design work for employee motivation and satisfaction at the risk of shortchanging the technology" (p. 428).

Technostructural Change Intervention

Technostructural change interventions involve redesigning an organization's core work processes to enhance coordination and strengthen the connections between tasks and the decisions needed to complete them (Church & Burke, 2017; Cummings & Worley, 2015). Cummings and Worley (2015) noted that when organizations create and broadly share key information, it reduces the concentration of power at the top. By providing employees with access to the same critical information once reserved for senior managers, decision-making becomes more distributed across the organization. These interventions include structural and technological changes that occur during organizational transformation, especially the implementation of automation and new technology.

In manufacturing, these trends are particularly pronounced. High capital costs associated with robotic automation often favor redesigns that optimize machinery use rather than employee discretion(Cummings & Worley, 2015). The trade-off becomes pronounced for blue-collar roles, where automation may displace workers, versus white-collar roles, where technology tends to augment decision-making (Acemoglu & Restrepo, 2018; Qi, 2022). Understanding how firms restructure in response to automation, who makes decisions, who gets displaced, and hierarchical changes is critical to evaluating organizational transformation in the age of robotics (Dixon et al., 2019; Bonfiglioli et al., 2020).

Increasing productivity and effectiveness drives organizational sustainability (Cummings & Worley, 2015). Technostructural change interventions are effective because they are “based on engineering, sociology, psychology, sociotechnical systems, and organization design" (p. 158). These disciplines combine to form a comprehensive approach that effectively addresses employee engagement, and the organizational design needed to support technology.

Automation Technologies in Manufacturing

Automation technologies are defined as the use of largely automatic, controlled systems and equipment in manufacturing and production processes that replace some or all of the tasks previously done by human labor (Acemoglu & Restrepo, 2017a). For the purposes of this study, the focus will be on industrial robotics. The concept of automation is not new, as innovations such as the steam engine or the cotton gin can be viewed as the automating of previously manual tasks brought on centuries ago during the development of the first Industrial Revolution (Manyika et al., 2017; Tvedt, 2010). The history of automation is the history of economic development (Keynes, Harcourt Brace, 1932/1930). Technological innovations from the first industrial revolution to today have brought vast improvements in most people’s lives and standards of living However, it is critical to understand that no single tool, technology, or machine can replace humans; the current scope of automation involves a combination of tools and technologies (Estlund, 2017; Manyika et al., 2017).

Digital and physical technologies such as robotic process automation (RPA), robotics, data mining, machine learning, computational statistics, and the forms of artificial intelligence (AI) can turn a wide range of knowledge into well-defined and solvable problems (Frey et al., 2016). Robotics and physical automation technologies will have the most direct impact on blue-collar occupations, particularly in the manufacturing sector (Acemoglu et al., 2023; Chiarini et al., 2023).

Distinguishing Between Augmentation and Automation

Building upon the work of Acemoglu and Restrepo (2018), Acemoglu and Restrepo (2020), Autor (2019), and Autor et al. (2022), draw the linkage between new task creation, task automation, innovation incentives, and new work skill demands. In "occupations where innovations complement their outputs [augmentation] or market size expands, new tasks emerge or replace existing ones, and conversely, employment contracts contract in occupations where innovations replace labor inputs [automation] or market size decreases" (Autor et al., 2022, pp. 1–2).

Qi (2022) argues that the distinction between augmentation and automation will be very beneficial to future research. Differentiating between the two types of technological change helps to separate jobs that machines will augment from those that machines will replace. The distinction is also important in predicting the breadth and depth of change at the firm [organizational] level, as well as how different jobs may change as working automation technologies, especially in manufacturing, become more prevalent and sophisticated.

Mechanization and Computerization. Mechanization, defined in 1934 as “the use of tools or equipment of any kind to aid the human brain and muscle,” dates to the Industrial Revolution” (Qi, 2022, p. 5). Smart computerization represents a recent change and refers to the “increased reliance on artificial intelligence and computing systems to make decisions” (p. 5). Classic industrialized concerns about workplace automation often focused on manufacturing blue-collar workers losing their jobs to mechanization (Qin et al., 2016). However, workers in numerous occupations and traditional white-collar professions, including managers and physicians, saw their jobs change due to computerization. Both mechanization and computerization can lead to drastic changes in the workplace, as they replace or supplement tasks with machines, computers, and advanced technologies such as artificial intelligence.

From an organizational perspective, automation may resemble augmentation for white-collar professions but may resemble automation for blue-collar jobs. Automation may be associated with “reduced responsibility, less teamwork, lower-impact decisions from the managerial level, and less freedom over decision-making” (Qi, 2022, p. 8). Some studies do not find any reallocation effect between different types of workers and occupational categories (Aghion et al., 2021). A reallocation effect within jobs could explain this, as automation technologies typically replace only a specific number of tasks, not entire jobs (Acemoglu & Autor, 2010). Perhaps paradoxically, some human skills may become more valuable than ever in the presence of machines (Brynjolfsson & McAfee, 2011; Brynjolfsson et al., 2018). Automation may thus lead to a restructuring of the task content of different jobs within workers, enhancing labor productivity and, potentially, employment, but without any change in the skill structure of employment (Aghion et al., 2021).

The quantity of knowledge and data required to make a decision primarily determines the investment required for automating any task, decision, or job (Fish, 2012). he implications for the cost and return on investment at the different levels of decision-making are higher for strategic decisions and lower for operational decisions. Fish (2012) defined strategic decisions as those made infrequently by management, as well as high-value decisions involving a large amount of data. While operational decisions are frequent, lower-value decisions are the responsibility of frontline staff. Operational decisions involve a relatively small amount of data and business knowledge, and they are straightforward and inexpensive to automate. Furthermore, the "return on automating operational decisions can be as high as that for strategic decisions, as the value of operational decisions may be small," and their "aggregated value may be comparable to that of strategic decisions"(p. 11).

Pressured by the threat of technological unemployment, the extant literature has focused on the quantity of jobs potentially displaced by robots, mainly by taking advantage of International Federation of Robotics (IFR) datasets (e.g. Acemoglu and Restrepo, 2019a, 2019b; Graetz and Michaels, 2018), and on the specific functions and tasks that automation might directly substitute, primarily relying on the U.S. Occupational Information Network (O*NET) (Frey et al., 2016). Both areas of research agree that the jobs and tasks most at risk are those done by low- and medium-skilled workers who mainly perform routine activities, but they do not differentiate between various types of technology, like robotic automation and digitization, which are often seen as having the same effect on jobs (Dosi et al., 2021)

Skill-biased technological change

Skill-biased technological change (SBTC) is a leading theory explaining the increasing disparity in wage distribution in the field of economics. According to the SBTC, advancements in workplace technologies have led to an increase in the productivity and compensation of highly skilled and educated workers, primarily in the service industry. The SBTC suggests that the introduction of new technology in the workplace has had a greater impact on the productivity of workers with advanced expertise since the 1980s (Acemoglu & Restrepo, 2020; Hanley, 2013). The changing skill content of jobs associated with new workplace technologies, which has led to a surge in demand for their services and enhanced returns on investment in higher education, provides supporting evidence for the theory (Autor et al., 2003).

Card and DiNardo (2002) argued that there are problems with the timeline linking the implementation of automation technologies and earnings and skills restructuring. The example of personal computers and inventory management networks does not align with the observed pattern in earnings, as wage inequality experienced a significant increase from 1979 to 1984, coinciding with the integration of computerized systems. However, this trend stabilized by the 1990s, even as the computerization of specific tasks and inventory management continued. Furthermore, the SBTC analyses primarily focus on the service industry, which often has a higher ratio of skilled and educated workers to low-skilled workers compared to the manufacturing sector (Avent-Holt & Tomaskovic-Devey, 2010; Hanley, 2013). The automobile industry demonstrated this in the 1960s and 1970s. Robotics automation first fragmented production across a greater number of workers and plant locations, then shifted the focus to operational efficiency by eliminating worker-led slowdowns, repetitive error-prone tasks, and sabotage on the line, while reducing the number of factories (Freeman, 2019; Hanley, 2013). However, the white-collar service sector is characterized by the absence of labor unions and working-class identities (Freeman, 2019).

The academic perspective has shifted, emphasizing the replacement of labor with automation in tasks that are repetitive and predictable (Autor et al., 2003; Card & DiNardo, 2002). Historical and cross-national trends challenge the SBTC, while industry and institutional frameworks influence the effects of new technology (Card & DiNardo, 2002; Hanley, 2013). To comprehend the impact of automation technologies on white-collar workers, it is necessary to examine how ability, merit, and productivity are socially formed within specific organizational settings (Card & DiNardo, 2002). The SBTC framework rests on assumptions about the definition and measurement of skill, productivity, and abilities that are challenged by a relational model of workplace inequality (Avent-Holt & Tomaskovic-Devey, 2010). The SBTC also fails to adequately account for the decline in employment in middle-skilled occupations and the simultaneous rise in high-skill and low-skill jobs, commonly known as job polarization, observed in the United States during the 1990s, as well as in Western European economies (Filippi et al., 2023).

The relational theory of wage inequality challenges the assumptions of the SBTC theoretical framework by arguing “that earnings are determined in workplaces and firms, not the labor market, via a process of workplace relational claims-making” (Avent-Holt & Tomaskovic-Devey, 2010; Hanley, 2013, p. 404). The initial design and implementation of the relational theories constructed the distinctions between skill and operational efficiency around new workplace technologies. White-collar automation technologies' distributional effects necessitate examining the processes that socially construct skills and efficiency within organizational contexts, rather than relying on environmental stimuli. The relational perspective looks at how new technologies in the workplace create differences in skill, productivity, and merit during their initial design and implementation, as well as how the meanings, routines, and norms that come from them become more common (Avent-Holt & Tomaskovic-Devey, 2010; Hanley, 2013).

Need for Firm and Industry-Level Research

Firm-level automation research typically refers to studies that investigate how automation technologies, such as robotics, artificial intelligence, and machine learning, impact specific industries, specific-sized firms, and individual firms (Acemoglu et al., 2022; Bonfiglioli et al., 2020). It is more centered on strategies, while macro- or national multi-industry-level research that is more focused on policy implications and contextual determinants (Dillender & Forsythe, 2019; Dixon et al., 2019; Waldman-Brown, 2020). Firm-level research focuses on understanding how firms adopt, implement, and utilize automation technologies within their operations, as well as the implications of automation for firm performance, productivity, competitiveness, organizational dynamics, and the market and industry consequences.

Industry-level research is required to examine the overall benefit, the substitution effects, and the firm capabilities required to maximize ROI in a specific industry resulting from robotic investment (Acemoglu & Restrepo, 2017a; Brynjolfsson et al., 2018). This guidance led Dixon et al. (2019) to perform the and first industry-level study of the effect of robot adoption on employment. By examining the changes in labor composition, it was discovered that manager headcount had decreased but non-managerial employee headcount had increased, indicating that robots are replacing managerial work that previous waves of technology adoption considered more challenging to replace. Dixon et al. (2019) made a significant contribution to the field by using an industry-level measure of robot investments to show how robots can affect work, which is something that is difficult to show in broad multi-industry or multi-geographic region analyses.

Dixon et al. (2019) argued that some manufacturing organizations that innovate through robotic automation fail to understand the consequences of job displacement correlation on managerial or white-collar-level jobs. Therefore, Dixon et al. (2019) emphasized the importance of examining the effect of robot investment at the industry level and contributing to the important debate about the consequences of robot investments on labor (pp. 2-3). Previous studies investigating the "impact of modern automation technologies on firms and workers have been constrained by insufficient data" (pp. 2–3). These studies have either used "indirect proxies of technology or relied on datasets that provide limited and course coverage" and are "focused on industry-level robot adoption measures from the International Federation of Robotics" (pp. 3-4).

Employment and Firm-Level Effects of Robotic Capital Investment

While much of the automation literature focuses on job displacement at the task level, a growing body of research has explored the broader relationship between robotic capital investment and aggregate employment trends. Graetz and Michaels (2018) found that industrial robot adoption in 17 developed countries was associated with increases in labor productivity and value-added output, with only modest declines in total employment. Conversely, Acemoglu and Restrepo (2020) demonstrated a negative correlation between employment and exposure to industrial robots in the U.S. These differing results indicate that how spending on robots affects overall jobs is complicated and can vary based on things like new businesses, how flexible the job market is, and additional investments in worker skills. Understanding this relationship at the national and state industry levels, particularly in manufacturing, is essential for gauging the long-term labor market implications of automation technologies.

In addition to employment outcomes, robotic capital investment has notable implications for firm composition, particularly in the manufacturing sector. Evidence suggests that automation may accelerate firm consolidation by reallocating market share toward more capital-intensive and productive firms. Bonfiglioli et al. (2020) and Domini et al. (2021) found that robot-adopting firms were typically larger, more efficient, and employed fewer supervisory workers, often leading to a decline in the number of smaller, non-adopting firms over time. Bessen and Righi (2019) further argued that technologies like robotics tend to produce 'winner-take-most' dynamics, increasing industry concentration and decreasing firm counts, especially in markets where smaller firms cannot absorb high capital costs. These shifts underscore the need to examine how automation-related investments influence not only labor demand but also structural changes in the firm landscape, including entry, exit, and growth patterns. Industry-level analysis is therefore critical to understanding the full organizational impact of automation adoption.

Section Three: Displacement Effects of Automation

The displacement of labor resulting from automation is a well-documented phenomenon that continues to evolve as technologies grow more sophisticated. Chin et al. (2006) highlighted a historical precedent in the transition from sail to steam power, which exemplified the shift in labor-capital dynamics. Steam-powered vessels required significantly fewer skilled seamen, as one engineer could now control a large amount of capital. On the other hand, sail vessels demanded substantial skilled labor relative to capital. This change marked one of the earliest examples of large-scale factor-augmenting technological displacement, where productivity gains were achieved through a reduction in skilled labor demand (Chin et al., 2006).

Building on this foundation, Acemoglu and Restrepo (2019) emphasized that the defining feature of automation is its capacity to reassign tasks previously performed by human labor to capital, resulting in a "displacement effect." This phenomenon arises when automation technologies substitute workers in specific tasks, especially routine or manual ones, reducing the demand for labor in those areas and redefining jobs (Acemoglu & Autor, 2010; Acemoglu & Restrepo, 2018, 2019; Webb, 2019). Such changes shift the task content of occupations and reorganize how labor and capital interact in the production process.

Bonfiglioli et al. (2020) in an analysis of French manufacturing firms between 1994 and 2013, found that firms adopting robots experienced a significant shift in skill distribution. The share of high-skilled occupations in these firms was twice as high compared to non-adopters. While robots reduced the demand for routine production staff, they increased the need for non-production personnel such as engineers, technicians, and managers, indicating that automation may lead not only to displacement but also to occupational upgrading. Bonfiglioli et al. (2020) argued that when the cost of capital decreases, companies facing rising demand are more inclined to invest in automation and are more willing to downsize their staff.

Bonfiglioli et al. (2020) also indicated that organizations that elect to adopt robots into their operations differ significantly from most other entities. Specifically, these organizations tend to be larger in size, have higher levels of productivity, employ a larger number of highly qualified experts, and require less overall supervision. Typically, the adoption of robots coincides with periods of business growth, leading to improvements in company efficiency and an increase in the need for workers with lower skill levels. More precisely, it is anticipated that the implementation of robots will reallocate market shares away from non-adopters, thereby decreasing firm counts as less efficient operations cease (Bessen & Righi, 2019; Bonfiglioli et al., 2020; Domini et al., 2021).

At the firm level, Waldman-Brown (2020) challenged the assumption that automation necessarily leads to immediate job loss. Drawing on interviews with small and medium-sized manufacturers, the study explored whether firms pursued complementary, substitutive, or lights-out automation strategies. The findings showed that none of the firms planned imminent workforce reductions due to automation. Rather, the technology was primarily introduced to enhance quality and expand service or product offerings. Moreover, a tight labor market and shortages of skilled workers made significant short-term layoffs unlikely, even as future investments could eventually lead to modest employment reductions. This aligns with Barley (1998) argument that automation is not typically implemented through abrupt, organization-wide transformations but unfolds slowly over time. Innovations often take root across multiple business cycles, especially in industries with entrenched workflows and legacy systems. As a result, technological change may be gradual, layered, and cumulative rather than revolutionary

Consequently, the displacement effects of automation are not uniformly negative or immediate. Rather, they are highly context-dependent, varying by firm size, technological maturity, labor market conditions, and region or territory (Barley, 1998; Chin et al., 2006; Waldman-Brown, 2020). Understanding these patterns is critical for assessing how capital expenditures in robotic technologies influence not only total employment but also the composition and distribution of occupations and firms within industries.

Cross-nation, Cross-industry Differentiation

Although automation technologies are spreading globally, their effects vary significantly across national, regional, and sectoral boundaries. Much of the early research on automation adopted a broad, macroeconomic lens, examining how technologies like robotics impact labor displacement, wage polarization, and employment structures. However, these studies often treated industries and occupations homogeneously, overlooking important differences in how automation unfolds within specific sectors such as manufacturing. For example, four countries: China, India, Japan, and the United States, account for nearly two-thirds of global automation activity, illustrating the highly concentrated and uneven diffusion of robotic technologies (Filippi et al., 2023).

In advanced economies, manufacturing firms face dual pressures: competition from low-wage countries and the rising cost of labor-intensive production. These dynamics have driven many firms to adopt robotic automation to remain competitive (Kromann et al., 2020). Between 1995 and 2011, the share of global manufacturing output produced in developing countries nearly doubled, prompting firms in high-income nations to either close, outsource, or reconfigure operations in response to international cost pressures. Kromann et al. (2020)found that within high-wage countries, manufacturing firms facing intense international competition were more likely to invest in robotic technologies, often accompanied by higher productivity and wage levels.

Cross-national variation in automation exposure is also evident in job-level risk estimates. In Organisation for Economic Co-operation and Development (OECD) countries, approximately 9% of jobs are considered fully automatable, with an additional 46% at medium-to-high risk depending on task structure (Arntz et al., 2017). In contrast, countries in the ASEAN-5 region (Cambodia, Indonesia, the Philippines, Thailand, and Vietnam) face much higher risks of automation, with up to 56% of jobs classified as highly substitutable. In the European Union, 47.4% of jobs are projected to be affected by automation within the next decade, with over one-third being fully automatable (Arntz et al., 2017; Filippi et al., 2023).

The disparities are indicative of various structural and institutional factors, such as differences in national education systems, labor market flexibility, industrial specialization, firm distribution, and prior investment in automation infrastructure. (Arntz et al., 2017; Filippi et al., 2023; Kromann et al., 2020). The composition of national and regional industries, as well as the organization of tasks within occupations, significantly influence the risk of automation. As Manyika et al. (2017) emphasized, automation exposure depends not only on technological feasibility but also on the economic, regulatory, and organizational context in which work is performed. Chiarini et al. (2023) also noted that the same occupational title may include very different job requirements across countries or industries, leading to varied automation probabilities. While estimates such as those by (Frey et al., 2016) suggest that up to 49% of labor activities globally could be automated using currently available technologies, such figures vary significantly based on whether a task-based or occupation-based approach is used. These findings highlight the importance of doing research focused on specific sectors and industries to understand all the impacts of robotic automation on jobs and organizations.

Task-Based or Occupational-Based Approaches

A critical methodological distinction in automation research lies in how automation risk is measured, whether through occupation-based or task-based approaches. Occupation-based models, such as those used in early projections by (Frey et al., 2016), assume that all tasks within a given occupation are equally susceptible to automation. This approach often assumes that all tasks in a job are equally likely to be automated, which can lead to an exaggerated view of how many jobs are at risk, ignoring the fact that many tasks need skills like critical thinking, social interaction, or physical ability that current technology can't handle (Arntz et al., 2017; Filippi et al., 2023). Automation might get rid of simple production jobs, but it can also change or improve supervisory and managerial positions, especially in companies where new technology changes how they manage, coordinate, or make decisions (Autor et al., 2022; Dixon et al., 2019; Qi, 2022).

This distinction has important implications for understanding how capital expenditures in robotics translate into organizational and employment change. In many cases, automation does not entirely eliminate jobs but modifies the internal structure of labor, necessitating new skills, redefining task boundaries, and rearranging hierarchical relationships. As a result, dependence exclusively on occupational categories may conceal the nuanced, task-specific changes that are pivotal to this study's examination of white-collar restructuring and industry-level variations in employment outcomes (Arntz et al., 2017; Bonfiglioli et al., 2020; Acemoglu & Restrepo, 2020).

While task-based approaches offer a more granular view by assessing the automatability of specific job functions rather than entire occupations, they are not the primary focus of this study. These approaches help illustrate the importance of accounting for task variation within job categories, especially in industries like manufacturing, where the same occupational title may encompass different responsibilities across firms (Chiarini et al., 2023). For example, Arntz et al. (2017) estimated that only 9% of U.S. jobs are at high risk of full automation when task-level heterogeneity is considered, significantly lower than earlier projections based on occupational averages. Although this task-level nuance supports a more refined understanding of automation risk, the current study takes an industry-level perspective, focusing on broader patterns in capital expenditures and their relationship to employment trends and industry firm composition.

Section Four: The Role of Robotic Automation in Shifting U.S. Manufacturing Occupations

Predictions that automation technologies would transform organizational structures and significantly affect white-collar employment have existed for over half a century. While it is now possible to model how digital and physical technologies directly replace routine tasks across various skill levels, the broader organizational implications remain less understood. Emerging research suggests that the most profound disruptions may not result from direct substitution alone, but from the indirect reconfiguration of knowledge-based roles, decision-making structures, and managerial functions (Acemoglu & Autor, 2010; Autor, 2015; Webb, 2019). This section explores how robotic automation is reshaping the occupational landscape of U.S. manufacturing, with attention to both the direct and indirect effects on employment, particularly among supervisory and managerial roles.

The U.S. Manufacturing Industry Composition

Firm-level employment across the U.S. manufacturing sector (NAICS 31–33) remained relatively stable from 2018 to 2021, averaging approximately 11.93 million workers during this period (U.S. Census Bureau, n.d.). However, employment was not evenly distributed across subsectors. Four key industries: Food Manufacturing (NAICS 311), Fabricated Metal Product Manufacturing (NAICS 332), Machinery Manufacturing (NAICS 333), and Transportation Equipment Manufacturing (NAICS 336) collectively accounted for nearly 47.6% of total manufacturing employment, representing the core of the U.S. manufacturing workforce. Specifically, Transportation Equipment Manufacturing (NAICS 336) had the highest average employment, with 1,609,572 workers, representing 13.49% of total manufacturing employment. Food Manufacturing (NAICS 311) closely followed, employing an average of 1,595,739 workers (13.37%). The Fabricated Metal Product Manufacturing industry (NAICS 332) averaged 1,423,868 workers (11.93%), while Machinery Manufacturing (NAICS 333) employed 1,050,044 workers on average (8.80%) (U.S. Census Bureau, n.d.)(U.S. Census Bureau, n.d.).

These subsectors are central to understanding the structural transformation of manufacturing employment. Their scale and concentration suggest that capital expenditures in automation, particularly in robotics, are likely to influence firm count, overall employment, and the distribution of white-collar occupations such as supervisors and managers (Acemoglu & Restrepo, 2020; Dixon et al., 2019; Bonfiglioli et al., 2020). Accordingly, these industries serve as focal points for analyzing the evolving organizational dynamics within the U.S. manufacturing sector.

Occupational Displacement and the Changing Role of White-Collar Work

Acemoglu and Restrepo (2020) argued that industrial robots negatively affect employment across nearly all occupational categories, except at the managerial level, which showed no significant change. Robots primarily displace routine manual workers such as machinists, operators, and assembly workers, roles traditionally associated with blue-collar labor. However, Dixon et al. (2019) believed that managers may also be vulnerable, noting that robotics and related technologies are increasingly influencing white-collar tasks and decision-making processes.

Research in industrial psychology and economics suggests that automation affects white- and blue-collar workers differently (Gruchmann et al., 2021; Keltner et al., 2003; Qi, 2022). Dixon et al. (2019) stressed that organizational researchers have been slow to examine the indirect impacts of automation, presenting a valuable opportunity to study how these technologies affect internal decision-making, structure, and leadership. Scully-Russ and Torraco (2020) supported this perspective, noting the lack of research on how automation transforms the nature of work.

While direct task substitution is well studied, indirect displacement, or the erosion of supervisory roles due to declining need for oversight and decision-making, remains underexplored. For example, as automation streamlines production tasks, the ratio of managers to front-line workers declines (Garicano & Rossi-Hansberg, 2006). Acemoglu and Restrepo (2018) and Raj and Seamans (2019) also suggested that displaced blue-collar workers often reduce the need for direct supervisors. Dixon et al. (2019) found a polarization effect: mid-skilled managerial employment shrinks as robotic investments rise, while both high- and low-skilled jobs increase.

Impacts of Robots on White-collar Occupations in the Manufacturing Industry

"If you find yourself working with, or under the direction of, a smart software system, it's probably a pretty good bet that... you are also training the software to ultimately replace you." (Ford, 2015, p. 122). While automation continues to displace manual labor, its next frontier lies in reducing the demand for managerial roles (Dixon et al., 2019; Leavitt, 1958). Bonanomi (2019) added that while robot adoption often correlates with increased overall employment, firms with automatable functions, like those in manufacturing, will experience sharper employment declines.

Bonanomi (2019) suggested that there exists a correlation between the adoption of robots and a general increase in employment. However, firms with easily replaceable functions and operating in industries more conducive to automation, such as manufacturing, will experience a more pronounced decline in employment compared to other industries. More precisely, a rise in robot utilization frequently leads to a decline in jobs. Robots reduce the need for production personnel, but they frequently increase the demand for non-production workers such as engineers and managers. A decrease in the cost of capital often leads companies to increase their investment in automation, which has uncertain consequences for employment. While machines have the effect of replacing workers, they also contribute to an increase in productivity, which in turn leads to a higher demand for all factors. Importantly, the impact of automation differs depending on the specific characteristics of organizations, industries, and nations. When it comes to cost savings, firms with higher demand tend to invest more extensively in automation and are more inclined to reduce their workforce.

As robotic capability expands Dixon et al. (2019) predicted complementary tasks, once requiring management oversight, will be absorbed into automated systems. Several researchers have also argued that the incorporation of industrial robots in companies consistently leads to reduced levels of overall employment (Acemoglu & Autor, 2010; Bonfiglioli et al., 2020; Dzedzickis et al., 2024; Economics, 2019; Graetz & Michaels, 2018; Trenerry et al., 2021).

With automation rapidly increasing in prevalence and capability, Dixon et al. (2019) expected that, in addition to the reallocation of management decision authority, other complementary work practices and tasks were likely to continue to shift. Understanding this implication is critical for organizations, especially in advanced manufacturing. Prioritize efficient automation investments that are tied to and are likely to have profound effects on both managerial "white-collar" employment and organizational structure. Predictions suggest that automation will lead to a decrease in the number of managers within the firm and an increase in non-management employees, however, there is a lack of industry-level research that would empirically support this (Acemoglu & Restrepo, 2017a, 2017b; Agrawal et al., 2019; Brynjolfsson et al., 2018; Canada, 2017; Dixon et al., 2019).

Autor et al. (2024) observed that increased adoption of industrial robots in U.S. manufacturing is associated with measurable reductions in employment, with indirect effects observed in non-production roles, including supervisors and support staff. These findings provide industry-specific validation that organizational flattening and white-collar displacement may be significant outcomes of continued robot integration. These findings offer industry-specific support that organizational flattening and white-collar displacement may be substantial outcomes of further robot integration.

Furthermore, an (Robotics, 2025) report revealed that automation has transformed factory operations, resulting in workforce reductions. Noting that he impact of industrial robots is not evenly distributed across different demographic groups, indicating a complex effect on employment patterns. Additionally, a significant shift in the skill profile of the manufacturing workforce due to rising automation, emphasizing the growing demand for positions such as industrial engineers and first-line supervisors, suggesting a change in the requirements for white-collar jobs within the manufacturing sector.

Robot Scalability. Most current industrial automation systems lack flexibility and scalability (Arockiarajan, 2019; Autor, 2015; Kasowaki & Jack, 2023). Autor (2015) illustrated this using modern automobile manufacturing plants that employ industrial robots to install windshields on new vehicles as they move through the assembly line. However, aftermarket windshield replacement companies employ technicians, not robots, to install replacement windshields. However, Manyika et al. (2017) argued that automation can make the unlikely combination of scale and agility possible by allowing changes to be made across an entire organization when "the activities of the organization are controlled by automatic systems, and changing the behavior of the enterprise can be achieved by software download rather than an extensive change management program" (p. 110). They provide industry examples as Uber takes advantage of automation for operation coordination and, through this, only utilizes one human manager per 1,000 drivers, compared with a typical taxi company that has about one manager per 20 to 30 drivers.

Occupational Automation: From Tasks to Organizational Models

Automation technologies are technologies designed to replace "human labour input by machine input for some types of tasks within economic processes" (Filippi et al., 2023, p. 1). Acemoglu and Autor (2010) defined a task as a predetermined or specific unit of work activity that produces output (goods or services). It is a worker's endowment of capabilities for performing various tasks. Workers apply their "skill endowments to tasks in exchange for wages, and skills applied to tasks produce output" (p. 2). Acemoglu and Restrepo (2018) broadly described the range of tasks that the current battery of automation technologies can perform. Low-skill automation broadens the range of tasks within the low-end complexity distribution of job functions. In contrast, high-skill automation assumes that new developments in advanced technologies compete against high-skill labor in complex tasks. Acemoglu and Restrepo (2018) and Frey et al. (2016) proposed that we can already automate almost "any" task technologically, as long as we gather sufficient data for pattern recognition.

Autor (2015) argued that there are some inhibiting challenges to digitalizing and automating tasks. Polanyi's Paradox (Polanyi, 1966, as cited in Autor, 2015) presents a challenge for codifying the task processes and suggests that "we know more than we can tell" and people understand how to perform a task only tacitly and have difficulty "describing" the components that make it up (p. 12). Waschull et al. (2022) and Waldman-Brown (2020) highlighted that neither the employees nor the owners of the firms fully understand what automation entails or how to describe the stack of tasks to gain a clear picture of their jobs' vulnerability to automation.

Automation is a complex concept that necessitates clear definitions in research, particularly when distinguishing between jobs that can be fully automated, typically affecting blue-collar workers, and jobs that are enhanced by automation, which often impact white-collar supervisors and managers, in addition to the specific technologies that drive these changes (Acemoglu & Restrepo, 2018; Autor et al., 2022; Dixon et al., 2019; Sampson, 2020; Waschull et al., 2022). Robotic automation in manufacturing environments not only "enable the off-loading of physical work, but also take on many analytical tasks; therefore, they hold great potential to change the nature of work for workers across all skills and occupations" (Scully-Russ & Torraco, 2020, p. 77).

Automation may not replace entire jobs outright, but it can readily displace individual tasks within them, often with significant implications for supervisory and managerial occupations. These occupations, which historically required extensive training and were once considered resistant to technological disruption, are increasingly exposed as automation technologies gain the capacity to perform complex, high-order cognitive tasks (Acemoglu & Restrepo, 2020; Frey et al., 2016; Sampson, 2020). Qi (2022) argued that a key limitation in past research has been the tendency to treat automation as a singular construct, overlooking its differentiated effects across the occupational landscape. Automation interacts differently with blue-collar and white-collar job functions, and its full impact, especially on managerial and supervisory positions, cannot be understood without acknowledging this multidimensionality.

Automation's effects extend beyond direct task substitution. Indirect effects, such as shifts in workflow, authority, and organizational design, may exert even greater pressure on white-collar roles (Dixon et al., 2019; Garicano & Rossi-Hansberg, 2006; Qi, 2022; McGuinness et al., 2021). As McGuinness et al. (2021) stated, the outcome for any given job depends on whether task augmentation and role reengineering counterbalance or reinforce displacement. Organizational technical change introduces transformative opportunities, particularly in reshaping business models to exploit both automation and human capital in new ways. North et al. (2018) argued that this shift will redefine the skill and qualification requirements for both blue- and white-collar roles. However, empirical research has not kept up with these developments, particularly when it comes to the indirect pathways that automation may use to undermine white-collar employment. As automation continues to expand its reach into logic-driven and cognitively demanding tasks, roles once viewed as secure are becoming increasingly vulnerable (Grace et al., 2018).

White-Collar Task Automation and Knowledge Hierarchies

The automation of white-collar work is being shaped by two distinct but interconnected technological forces: digital automation technologies such as artificial intelligence (AI) and robotic process automation (RPA), which directly replace specific cognitive and decision-based tasks, and robotic automation, which indirectly reshapes white-collar roles through organizational restructuring and changing supervisory demands (Dixon et al., 2019; Frey et al., 2016; Sampson, 2020). However, the common thread for these occupations requires the ability to supervise, make decisions, and solve problems (Frey et al., 2016).

Digital automation technologies target routine and semi-routine cognitive functions traditionally performed by knowledge workers. These tools, ranging from machine learning systems to AI-enabled decision support, are capable of performing tasks once thought immune to automation, including information processing, problem-solving, and even some judgment-based decisions (Frey et al., 2016; Sampson, 2020). Although such technologies often require long implementation and training periods, they are increasingly capable of replicating sophisticated, high-stakes activities that were once considered uniquely human (Finneran, 2018; Violante, 2008).

In contrast to earlier waves of information technology that displaced primarily low- and middle-skill labor, robotic automation affects white-collar occupations by indirectly altering the structure and scope of managerial work. These forms of automation are not necessarily designed to replace managers outright, but rather to optimize production and operational efficiency in ways that reduce the need for traditional supervisory oversight (Dixon et al., 2019).

Consequently, flatter, technology-driven hierarchies may redistribute, redefine, or absorb managerial tasks. Siegman (1962) anticipated this transformation, suggesting that technical change would eventually affect the size and configuration of white-collar workgroups and decision-making structures.

Garicano and Rossi-Hansberg (2006) explained these dynamics using the idea of "knowledge hierarchies," wherein task-level employees solve routine problems and escalate complex issues to supervisors with higher cognitive capabilities. This hierarchical structure, common in manufacturing, relies on skill stratification and layered decision-making authority. As robots take on more routine and somewhat complex tasks, these management layers might shrink, leading to fewer middle management jobs and greater responsibilities for both regular workers and managers.

Autor (2019) expanded the theoretical arguments of Acemoglu and Restrepo (2018), which suggest the "countervailing forces" of task automation (p. 22). Autor (2019) described this phenomenon as a balance between task displacement and task reinstatement. While automation eliminates low-value tasks, it can also generate new roles that capitalize on uniquely human skills such as creativity, judgment, and interdisciplinary coordination. This "task polarization" does not necessarily result in widespread job loss but instead leads to the evolution of new specializations and responsibilities (Autor, 2019; Trenerry et al., 2021).

Autor et al. (2024) Autor, Dorn, Hanson, and Majlesi (2024) noted that the adoption of industrial robots was associated with significant workforce reductions, not only among production workers but also in supervisory and administrative roles. The Robotics (2025) similarly reported increased demand for technically skilled white-collar employees, such as automation supervisors and industrial engineers, accompanied by a decline in traditional middle-management positions. Deloitte (2024) further supported these findings, arguing that companies are now more likely to have fewer management levels, different ways of making decisions, and changes in job responsibilities due to the use of robots in production.

Despite the growing integration of automation, many employees and organizational leaders lack clarity about its full implications (Waschull et al., 2022; Waldman-Brown, 2020). Research shows that both groups often struggle to articulate how automation affects task structures and jobs. Successfully implementing automation, especially in high-automation industries like manufacturing, requires not only technical upgrades but also systemic thinking, organizational redesign, and a focus on efficiency (Madsen & Mikkelsen, 2017; Tan et al., 2013). As a result, there is a growing gap in skills needed for jobs, especially in management and supervision, because blue-collar workers are quickly learning new technical skills from robotic technologies, which means less need for traditional oversight (Dixon et al., 2019; Waschull et al., 2022; Waldman-Brown, 2020; Garicano & Rossi-Hansberg, 2006). As jobs at the front lines become more independent and skilled with technology, some office jobs may become unnecessary because management skills and training programs are not keeping up (Dixon et al., 2019; Qi, 2022).

Summary

This chapter has reviewed the historical, theoretical, and empirical literature on robotic automation, tracing its evolution from early mechanization to today's advanced industrial robotics. While much of the existing research emphasizes the displacement of routine, blue-collar labor, this review identifies a critical gap: the indirect and often underrecognized ways that automation reshapes white-collar supervisory and managerial roles. In manufacturing, automation does not always eliminate jobs outright, it frequently restructures task compositions, redistributes decision-making, and reconfigures organizational hierarchies. These indirect effects may prove more disruptive to white-collar roles than previously acknowledged.

The literature highlights how the effects of automation impact vary widely among nations, sectors, and types of firms. Differences in labor market structures, industrial specialization, and job task design affect the implementation of automation. This study examines industry-level trends and structural changes in the manufacturing sector to examine how capital expenditures in robotic technologies align with patterns in employment and industry firm composition.

Given the increasing sophistication of automation technologies and the growing presence of robots in manufacturing, a need exists for research that documents and describes how CAPEX trends relate to workforce and firm structure change. The transformation of supervisory roles, reduction of mid-tier managers, and flattening of knowledge hierarchies are emerging phenomena that have yet to be comprehensively explored at the industry, sub-industry, and regional levels.

CHAPTER THREE: METHODOLOGY

This chapter outlines the methodology used to describe the relationship between capital expenditures (CAPEX) on robotic equipment and trends in employment and firm dynamics within the U.S. manufacturing sector. It outlines research questions, design, population, sampling methods, data sources, measurement instruments, and data analysis strategies.

Research Context

This study examined trends in CAPEX for the U.S. manufacturing industry from 2018 to 2021 and their association with workforce and organizational dynamics at both national and state levels. It aimed to describe how CAPEX investments related to changes in employment, white-collar supervisory roles, and firm counts without making causal inferences. Publicly available datasets were used to explore the relationship between robotic automation and changes in employment and firm composition within the manufacturing sector.

Review of the Research Questions

This study focused on answering the following research questions [1].

Q1: What are the observable trends in capital expenditures (CAPEX) on robotic equipment across U.S. manufacturing industries (NAICS 31–33) between 2018 and 2021?

Q1a: How has CAPEX changed year-over-year across 3-digit NAICS manufacturing industries?

[1] A comprehensive classification of the research questions, categorized by focus, comparison type, temporal aspect, and level of analysis, is provided in Appendix A.

Q1b: How Has CAPEX Intensity Varied Across Industries, and Which Have Consistently Received the Highest or Lowest Investment?

Q1c: How has year-over-year CAPEX change varied across industries grouped by average CAPEX quartiles?

Q2: How does CAPEX influence total firm employment outcomes in the U.S. manufacturing sector from 2018 to 2021?

Q2a: How have year-over-year changes in CAPEX been associated with corresponding changes in total firm employment?

Q2b: How Does CAPEX in One Year Correspond with Total Employment in the Subsequent Year?

Q2c: How does CAPEX quartile level correspond to differences in total employment across industries?

Q3: How does CAPEX affect employment in white-collar supervisory occupations across manufacturing sub-sectors from 2018 to 2021?

Q3a: How has CAPEX influenced SoC-coded white-collar occupations over time?

Q3b: How has lagged CAPEX been associated with changes in white-collar employment levels?

Q3c: How has CAPEX variation affected year-over-year trends in white-collar employment across occupations and sectors?

Q4: How does CAPEX relate to firm composition trends in U.S. manufacturing from 2018 to 2021?

Q4a: How has CAPEX coincided with changes in firm composition across industries?

Q4b: How has CAPEX quartile grouping influenced differences in firm composition?

Q4c: How has CAPEX level been associated with trends in firm expansion, consolidation, or restructuring?

Q5: How does CAPEX vary across U.S. states, and how is it associated with differences in employment and firm composition from 2018 to 2021?

Q5a: How Have Year-Over-Year Changes in State-Level CAPEX Varied Across U.S. States and Investment Quartiles?

Q5b: How Have Year-Over-Year Changes in Total Manufacturing Employment Varied Across State-Level CAPEX Quartiles?

Q5c: How Does White-Collar Employment Vary Across State-Level CAPEX Quartiles in U.S. Manufacturing From?

Q5d: How Have Year-Over-Year Changes in State-Level CAPEX Been Associated with Changes in White-Collar Employment Across U.S. States?

Q5e: How Do Lagged Relationships Between State-Level CAPEX and White-Collar Employment Vary by Investment Quartile and Sub-Industry?

Q5f: How Has Manufacturing Firm Count and Growth Varied Across State-Level CAPEX Quartiles?

Q6: How does CAPEX investment at the state level compare with national trends, and how is it associated with differences in employment and firm composition from 2018 to 2021?

Q6a: How has state-level CAPEX aligned with or diverged from national trends?

Q6b: How has CAPEX concentration at the state level been associated with total and white-collar employment outcomes compared to national employment trends?

Q6c: How has CAPEX quartile level at the state level been associated with differences in firm growth relative to national averages?

Research Design

This research design explores the relationship between CAPEX on robotic equipment and changes in employment and firm composition within the U.S. manufacturing sector. Specifically, it investigates how investments in robotic automation technologies influence employment in white-collar supervisory roles, overall industry employment, and firm structure over time. Robotic automation extends beyond technological innovation, driving significant shifts in workforce dynamics, organizational structures, and operational processes across the manufacturing industry (Acemoglu & Restrepo, 2019; Autor, 2015).

Understanding these implications is vital for fostering informed organizational growth, efficient management practices, and effective leadership in an evolving technological landscape (Agrawal et al., 2019; Jamwal et al., 2021). To achieve these objectives, the study utilized publicly available data from the U.S. Census Bureau and the Bureau of Labor Statistics (BLS). The U.S. Census Bureau provides firm-level and regional economic data, including CAPEX and employment figures, while the BLS contributes national and state-level employment statistics, with an emphasis on white-collar supervisory occupations.

Rather than focusing on specific tasks within these roles, the study examined the broader employment trends and organizational impacts. Figure 1 illustrates a conceptual framework connecting capital expenditure patterns for robotic equipment in manufacturing to changes in industry firm composition and employment at both national and state levels, specifically for the four white-collar supervisory roles in major sub-sectors, accompanied by supporting lag effects and comparative analyses.

By leveraging comprehensive datasets from the Census and BLS, this study aligns with prior research in labor economics, occupational psychology, and workforce development (Acemoglu et al., 2023; Brynjolfsson et al., 2018; DeWitt, 2019; Kogan et al., 2023; Lim et al., 2023). Offering valuable insights into how automation influences employment patterns and organizational dynamics across U.S. manufacturing industries.

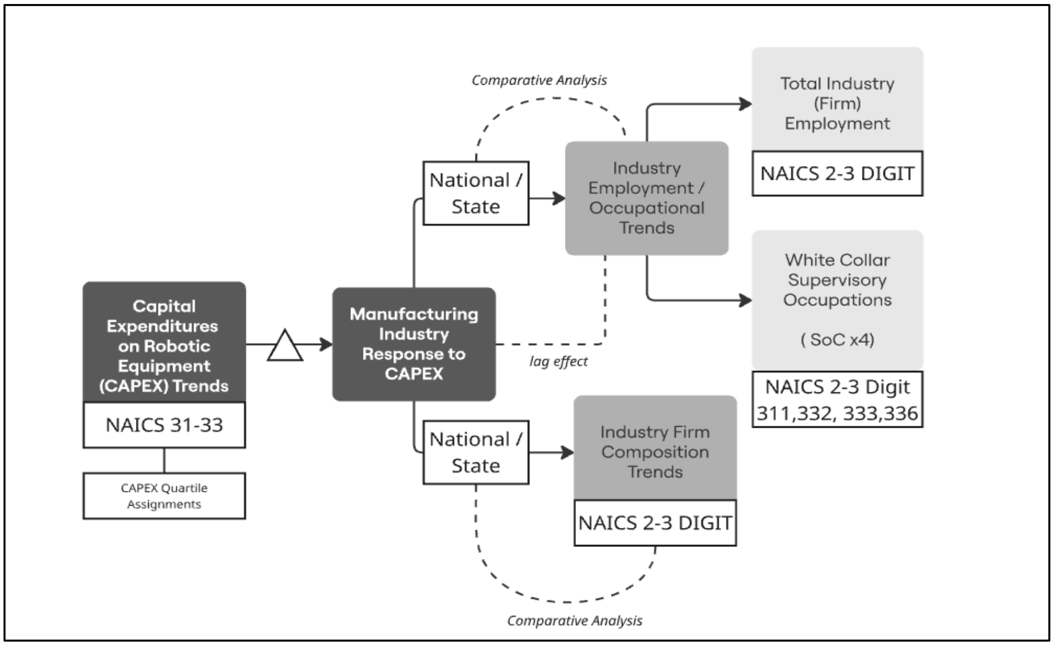

Figure 1

Conceptual framework for analyzing the impact of robotic equipment CAPEX on manufacturing employment and firm composition.

Population, Data Sources and Sampling Methods, and Measurement

This section outlines the population, data sources, sampling methods, and measurement of key variables used in this research. Limitations related to these elements are acknowledged and will be discussed in a later section.

Population

The population includes U.S. manufacturing firms classified under the two-digit North American Industry Classification System (NAICS) codes 31–33, further divided into 21 three-digit subsectors, as shown in Figure 2.

To examine occupational impacts, the study used the Standard Occupational Classification (SOC) system, which categorizes workers into detailed occupations based on job duties and required skills. This study focuses on white-collar managerial and supervisory occupations categorized under four selected Standard Occupational Classification (SOC) codes, see Appendix B for the occupational task descriptions. (*National Center for O*NET Development. O*NET OnLine*, n.d.). These were selected to explore workforce dynamics in leadership and oversight positions within manufacturing firms

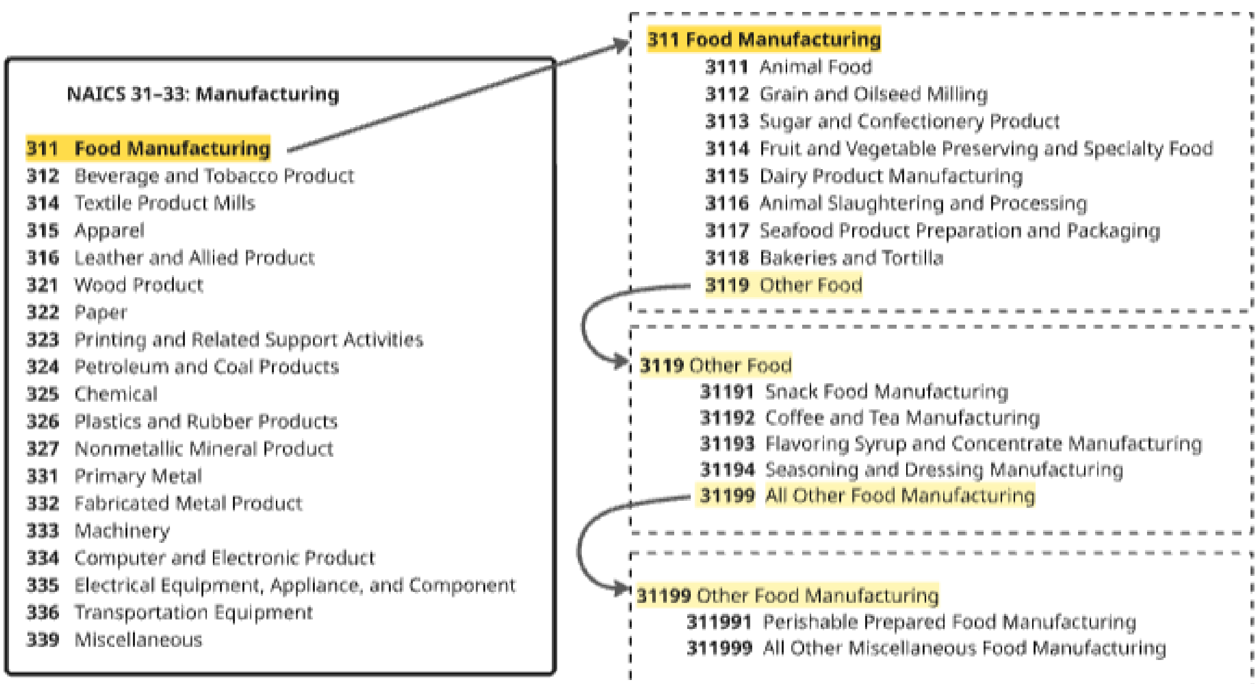

Figure 2

Subset example of the industry code classification breakdown of the North American Industry Classification System (NAICS) code 31-33 for the manufacturing sector in the United States.

Data Sources and Sampling Methods

Two primary, publicly available data sources are utilized: the U.S. Census Bureau and the Bureau of Labor Statistics (BLS). Together, these sources provide comprehensive coverage of capital investments, employment trends, and firm characteristics within the U.S. manufacturing sector.

U.S. Census Bureau Data. Annual Survey of Manufacturers (ASM). The ASM employs a stratified random sampling method to represent manufacturing establishments in the U.S., focusing on firms under NAICS codes 31–33. Covering the years 2017 to 2021, the survey collects data on capital expenditures (CAPEX), employment, and firm counts. Approximately 50,000 firms are sampled annually, with data derived from (Bureau, n.d.–a) (1) Internal Revenue Service (IRS) records for single-establishment firms, and (2) Company Organization Survey (COS) for a multi-establishment firm. The ASM Industrial Robotic Equipment Module (2018–2021) provided longitudinal data specifically on CAPEX related to robotics, disaggregated by NAICS codes and geographic regions.

Statistics of U.S. Businesses (SUSB). The SUSB provided annual data on firm counts, and employment at national and regional levels. It focuses exclusively on employer-based businesses, excluding self-employed individuals, to ensure accurate representation of employer establishments (Bureau, n.d.–b).

Bureau of Labor Statistics (BLS) Data

Occupational Employment Statistics (OES). The OES offered annual employment data categorized by SOC codes, industry, and geographic location. It provides subnational economic information on establishments with paid employees, enabling detailed analysis of occupational trends across national and state levels within the manufacturing sector (Bureau of Labor, n.d.).

Measurement

This study focuses on key variables related to capital expenditures on robotic equipment (CAPEX), firm composition, and employment trends in the U.S. manufacturing sector, with a emphasis on white-collar supervisory occupations.

Capital Expenditures (CAPEX) on Robotic Equipment

Data on CAPEX are derived from the ASM Industrial Robotic Equipment Module (2018–2021). The dataset provides industry-level estimates of capital expenditures on robotic equipment, categorized by (1) 21 three-digit NAICS industries, and (2) national and state-level data. These CAPEX estimates enable an analysis of the relationship between automation investments and firm and workforce changes.

Firm Count and Employment (SUSB Data).

Time series data from the Census SUSB (2018–2021) are used to assess total firm counts and employment levels. Employment figures were categorized by SOC codes (see Table 1) and aligned with the 21 three-digit NAICS industries, reported at both national and state levels to ensure consistency with the CAPEX data and SOC Employment (BLS OES Data).

The BLS OES dataset (2018–2022) provides employment estimates for the four targeted SOC occupations listed in Table 1, focusing on white-collar managerial and supervisory roles within the manufacturing sector. Employment data extends to 2022 to capture potential lagged effects of CAPEX investments, reflecting the time needed for capital expenditures to influence employment trends. The dataset includes industry-level estimates aligned with the 21 three-digit NAICS industries, along with analysis of four key subsector NAICS codes, 311 (Food Manufacturing), 332 (Fabricated Metal Product Manufacturing), 333 (Machinery Manufacturing), and 336 (Transportation Equipment Manufacturing) at the state level to support a detailed understanding of employment variations within these prominent manufacturing subsectors. National and state-level employment data are also included to support broader trend analysis. See Appendix C for the selection rationale of the NAICS subsectors and the condensed summary of CAPEX and employment data. This focus on prominent supervisory occupations ensured alignment with the study's objectives. Details of the four selected SOC occupations, including sample sizes and sector concentrations, are shown in Table 1. The inclusion of state-level data for the four subsectors enhanced the study's capacity to explore geographic variations in employment impacts related to robotic automation.

Table 1

Highlights the populations for the four selected SOC occupations concentrations in the NAICS manufacturing sector.

Occupation #	SOC Code	O*NET-SOC 2019 Title	N	Percent in 31-33
1	11-3051.00	Industrial Production Managers	116	100
2	17-2112.00	Industrial Engineers	84	88.1
3	17-3027.00	Mechanical Engineering Technologists and Technicians	95	92.6
4	51-1011.00	First-line Supervisors of Production and Operating Workers	98	99

By integrating data from the ASM and SUSB, and the OES, this study ensured comprehensive coverage of capital investments, employment trends, and firm counts in the U.S. manufacturing sector. Consistent alignment of anchor and outcome variables across these datasets strengthens the study's capacity to explore how investments in robotic automation influence employment and firm composition.

Collection

Utilizing standardized data from the Census Bureau and BLS ensures high levels of validity and reliability. These sources employed rigorous data collection and quality assurance methods, minimizing measurement error and enhancing external validity. The data collection process was well aligned with the study's objectives, allowing for accurate measurement of key variables and effective analysis to address the research questions.

Validity and Reliability

Validity

The validity of this study is supported by the use of high-quality data sources from the U.S. Census Bureau and the Bureau of Labor Statistics (BLS), both of which are widely recognized for their reliability and alignment with research objectives (Acemoglu et al., 2022; Autor et al., 2022; DeWitt, 2019; Lim et al., 2023). the datasets drawn from the U.S. Census enabled a more accurate and representative sample of the American people, thus increasing the external validity of the research. At the same time, the datasets from the BLS supplemented an enhancement of criterion validity by providing critical economic outlook and labor market figures. The blending of these two datasets through triangulation helps reduce possible confounding variables and biases, hence increasing the internal validity of the research(Lim et al., 2023).

External validity refers to "the extent to which the findings will generalize to other populations, settings, measures, and treatments"(Gliner et al., 2017, p. 120). Creswell (2013) highlighted potential threats to external validity, such as making inaccurate generalizations from sample data to broader populations, settings, or timeframes. Similarly, (Cohen, 1988) emphasized the importance of population validity, ecological validity, and temporal validity to strengthen the generalizability of research findings. This study addresses these aspects by utilizing robust and representative data sources from the U.S. Census Bureau and the Bureau of Labor Statistics (BLS).

Population validity is achieved through the Census Bureau's comprehensive data, which captures a wide range of manufacturing firms across various sizes, industries, and geographic regions, ensuring generalizability to the broader U.S. manufacturing sector. Ecological validity is supported by the Census data's ability to reflect real-world economic and demographic conditions, providing insights applicable to actual business environments and workforce structures. Temporal validity is enhanced by the BLS data, which includes historical employment trends and longitudinal information, allowing for the analysis of workforce changes over time and ensuring that findings remain relevant to evolving industry conditions.

By integrating data from both the Census and BLS, this study provides a robust framework for generalizing findings across diverse populations, organizational contexts, and timeframes. This comprehensive approach ensures that the results accurately reflect real-world dynamics and maintain their relevance over time, thereby enhancing the study's overall external validity.

Reliability

Reliability refers to the consistency and stability of measurement instruments and data collection methods over time (Creswell, 2013). In this study, reliability is ensured using authoritative and systematically collected datasets from the U.S. Census Bureau and the Bureau of Labor Statistics (BLS), both of which employ well-established methodologies to gather, validate, and update their data.

The Annual Survey of Manufactures (ASM) and the Statistics of U.S. Businesses (SUSB), conducted by the Census Bureau, follow standardized protocols and stratified sampling techniques, ensuring consistent and comprehensive coverage of the U.S. manufacturing sector. Similarly, the BLS reinforces reliability through its County Business Patterns (CBP) data, which is collected using rigorous procedures designed to provide accurate and consistent labor market statistics across industries and geographic locations.

By incorporating these validated datasets, the study minimizes potential measurement errors and ensures consistency in analyzing trends and correlations over multiple years. The reliability of these data sources strengthens the robustness of the study's findings and enhances their applicability in understanding the impacts of automation on the U.S. manufacturing workforce. Several data points were not reported in the Census and BLS datasets due to disclosure protection policies, which suppress estimates in cases where employer confidentiality may be compromised (Bureau of Labor Statistics, n.d; US Census, n.d). Additional omissions resulted from insufficient sample sizes, particularly at the state and sub-industry level, or when occupational detail was unavailable below major SOC group classifications. These limitations are consistent with federal statistical standards and reflect common constraints in publishing granular labor and firm-level data for small or low-response geographies.

Data Merging and Cleaning

A systematic process was followed to combine the two big datasets, aimed at generating a standardized and consolidated dataset for purposes of analyses. The datasets first passed through focused preprocessing and cleansing processes to ensure consistency of variable names, variable types, and class codes. The significant common identifiers, such as NAICS codes for industry classification, SOC codes for occupation definition, and temporal variables, were then leveraged for harmonizing datasets. Once standardized, a merge process was conducted, using these common variables to accurately link records across the sources. The process ensured that CAPEX, employment levels, and firm counts were properly matched to their corresponding industry, occupation, and geographic information.

The resulting dataset provided a comprehensive view of the U.S. manufacturing sector, integrating both firm-level data and employment statistics across national and state levels. This process enabled effective analysis of trends and relationships between automation investments, employment changes, and firm composition while managing the complexity and scope of the original data sources.

Data Analysis

This study employed descriptive analysis to examine trends and associations between capital expenditures on CAPEX, the anchor variable, and employment outcomes, including overall employment, white-collar supervisory occupations, and firm composition, across national and state levels from 2018 to 2021.

Statistical Tests

Descriptive statistics (mean, median, standard deviation) were used to summarize CAPEX, employment, and firm counts, while pivot tables in Excel facilitated exploration by year, state, and industry (NAICS codes 31–33). Trend comparisons using line and bar charts highlighted changes over time and geographic differences.

To assess the associations, correlation analysis examined the relationships between CAPEX and employment variables, and lagged effect analysis explored how prior-year CAPEX related to subsequent changes in employment. State CAPEX quartile comparisons described how varying investment levels corresponded with shifts in workforce and firm composition. Quartile definitions and CAPEX range thresholds, based on state-level mean CAPEX from 2018 to 2021, are summarized in Table 2, and the full list of state assignments by quartile is provided in Appendix D.

Table 2

S*tate-Level CAPEX quartile definitions, range thresholds and counts.*

Quartile	Definition	Mean Capex Range	State Count
Q1	Lowest investment	≤ $5,513,791	13
Q2	Low-mid investment	$5,513,791 – $25,471,683	12
Q3	Mid-high investment	$25,471,683 – $69,558,417	12
Q4	Highest investment	> $69,558,417 to $393,737,253	13

Analyses were conducted using Excel for data cleaning, organization, and visualization, enabling rapid investigation of patterns and the generation of initial descriptive statistics. This included computing fundamental metrics such as means, percentages, and year-over-year variations, along with generating charts to depict employment and CAPEX trends. Excel was also employed for more complex statistical procedures, including correlation analyses and lagged effect analyses to investigate how capital investments in prior years affected employment trends in subsequent years.

Effect Size

Gliner et al. (2017) defined size as the “strength of the relationship between the independent variable and the dependent variable, and/or the magnitude of the difference between levels of the independent variable with respect to the dependent variable" (p. 177). Cohen (1988) offered guidelines for effect sizes by standardizing a method to interpret the magnitude of statistical effects. The interpretation of effect sizes should take into account the research field's context. In certain disciplines, the nature of the studied phenomena or the implications of the findings may still make a small effect size practical. Conversely, in other fields, only larger effect sizes may be considered meaningful. This study set the small effect size at 0.1, the medium effect size at 0.3, and the large effect size at 0.5 for the correlational analyses. coefficient *r*.

Limitations

The study faced several potential limitations that may have impacted its findings. These included the static nature of the secondary data, potential discrepancies in data collection methods across different datasets, and the inherent inability to establish causality due to the non-experimental research design (Rovai et al., 2013; Stevens, 1992). The temporal and spatial resolution of publicly available data restricted detailed trend analysis at finer, more granular levels, making it difficult to analyze trends over time or within specific contexts (Lloyd et al., 2019). Additionally, external variables may have influenced the observed correlations, but these could not be identified within the scope of the study.

Ethical Considerations

This study obtained exempt status from the Colorado State University IRB, as it used existing data exclusively. Confirmation of this exemption is provided in Appendix E. Given that the data utilized in this study were secondary and publicly available, ethical concerns were minimal. Nonetheless, the researcher ensured that all analysis and dissemination of results were conducted with integrity and transparency, with no manipulation or misrepresentation of the findings.

Conclusion

This chapter outlined the methodology that was used to describe the relationship between CAPEX investments and trends in employment and firm dynamics within the U.S.

manufacturing sector. The research design, data sources, measurement instruments, and analysis strategies were selected to ensure a comprehensive descriptive examination of automation's influence on industry structures. Chapter 4 presented the results and their interpretation in line with the study's descriptive objectives.

CHAPTER FOUR: FINDINGS

The purpose of this study is to explore the relationship between capital investments in robotics technologies and the effects on the number of firms and jobs, including managerial white-collar positions, in NAICS 31–33 U.S. manufacturing industries. Using national and state-level data from 2018 to 2021, this chapter presents descriptive findings that explore how trends in automation-related investment correspond with structural changes in employment and firm composition within the manufacturing sector.

This section outlines substantial trends in the general manufacturing industry of the United States (NAICS 31-33), focusing primarily on four sub-industries representing a considerable proportion of investment capital and employment: Food Manufacturing (NAICS 311), Fabricated Metal Product Manufacturing (NAICS 332), Machinery Manufacturing (NAICS 333), and Transportation Equipment Manufacturing (NAICS 336). These sub-industries have consistently shown above-average capital expenditures (CAPEX) and employment rates between the years 2018 and 2021. Additionally, employment trends were examined over four white-collar occupations involved with automation-related tasks: Occupation 1 (SOC 11-3051.00 [Industrial Production Managers]), Occupation 2 (SOC 17-2112.00 [industrial engineers]), Occupation 3 (SOC 17-3027.00 [engineering technicians]), and Occupation 4 (SOC 51-1011.00 [first line supervisors]). The following sections examine temporal patterns, CAPEX quartiles, and employment dynamics across these occupational groups and industry categories to assess how automation investments may be shaping workforce and firm structure outcomes.

The findings are structured around the six main research questions guiding the study, supported by multi-year data visualizations, year-to-year change calculations, and quartile-based comparisons. The chapter is concluded with a summary of major findings and as a lead-in to Chapter Five's interpretative discussion.

Q1: What are the observable trends in capital expenditures (CAPEX) on robotic equipment across U.S. manufacturing industries (NAICS 31–33) between 2018 and 2021?

The following section explores how CAPEX on robotic manufacturing equipment evolved across the U.S. manufacturing sector (NAICS 31–33) between 2018 and 2021. This section evaluates year-over-year investment patterns, variation in CAPEX intensity across industries, and group-level differences based on mean CAPEX quartiles. The goal is to identify which industries led or lagged in automation investment and how CAPEX growth patterns may reflect broader structural transformations in U.S. manufacturing.

As shown in Figure 3, total CAPEX exhibited a consistent year-over-year increase across the four years. In 2018, mean CAPEX was approximately \$2.62 billion, increasing to \$3.19 billion in 2019, \$3.41 billion in 2020, and reached \$3.76 billion in 2021. Across the four years, the mean CAPEX investment was approximately \$3.44 billion. A linear trendline applied to the CAPEX data reveal a positive slope and a high degree of fit with a very highly unusual R^2 value ($R^2 = 0.9665$), indicating a strong and stable upward trend over the observed period. According to Morgan et al. (2013), R^2 represents the proportion of variance in the dependent (anchor) variable that is explained by the independent (comparison) variable with higher values indicating a stronger predictive relationship. Field (2017) also noted that an R^2 value close to 1.0 indicates a model that explains a substantial proportion of the observed variance, reinforcing the interpretation that CAPEX growth followed a systematic and predictable trajectory during this period. While based on a limited four-year sample, this descriptive trendline does not imply causality but highlights a consistent and strong investment pattern during the observed timeframe.

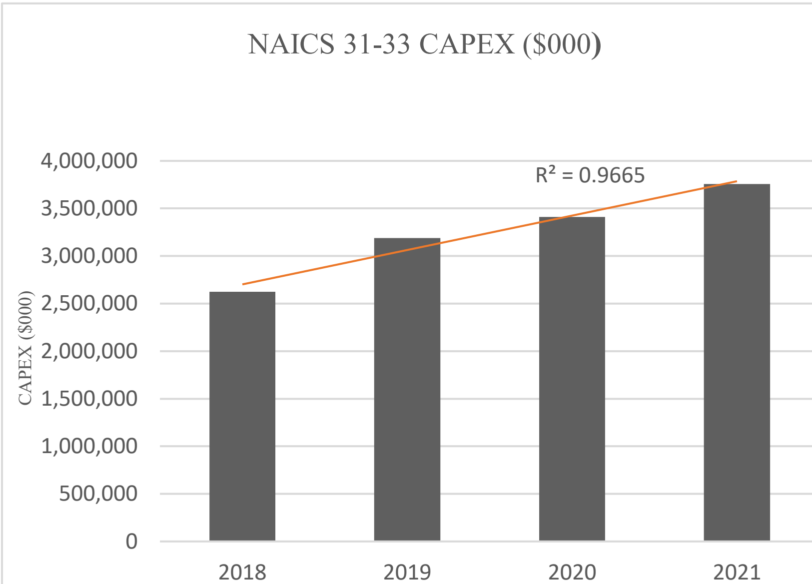

Figure ***3***

National CAPEX in ($000) and Linear Trend for NAICS 31–33 Manufacturing Industries, 2018–2021.

Q1a: How Has CAPEX Changed Year-Over-Year Across 3-Digit NAICS Manufacturing Industries?

Several industries posted notable year-over-year (YoY) CAPEX growth during 2019, with NAICS 321 (Wood Product Manufacturing) rising approximately 269.8% and NAICS 339 (Miscellaneous Manufacturing) increasing by about 203.1%, as shown in Figure 4. In contrast, NAICS 312 (Beverage and Tobacco Product Manufacturing) recorded a sharp decline of 53.0%. CAPEX volatility continued into 2020, led by NAICS 334 (Computer and Electronic Product Manufacturing), which saw a YoY increase of 226.2%, while NAICS 327 (Non-metallic Mineral Product Manufacturing) declined by 58.6%. By 2021, overall investment trends had begun to stabilize, though variation remained: NAICS 336 (Transportation Equipment Manufacturing) grew by 36.6%, whereas NAICS 335 (Electrical Equipment, Appliance, and Component Manufacturing) fell by 47.1%.

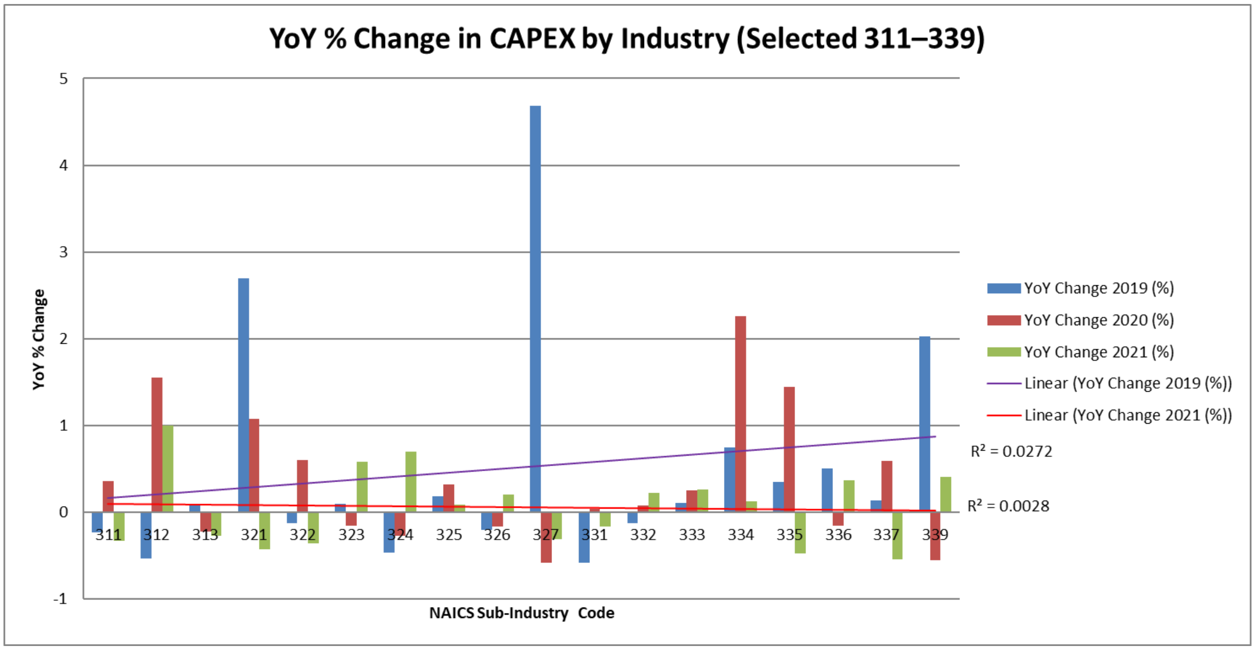

Figure 4

Year-over-Year (YoY) Percentage Changes in CAPEX for Selected 3-Digit NAICS Industries (311–339; 314-316 removed), 2019–2021.

Note. NAICS codes 314, 315, and 316 were removed due to multiple years of missing CAPEX data.

Standard deviations calculated for each year's YoY changes further highlight the extent of industry variation. The calculated standard deviation of YoY CAPEX percentage change was approximately 1.34 in 2019, 0.78 in 2020, and 0.45 in 2021, indicating that variability was highest at the beginning of the period and narrowed by 2021. Trendline analysis for annual CAPEX changes indicated very low coefficients of determination (R^2 values of approximately 0.0028 for 2019 and 0.0272 for 2021), suggesting that linear patterns did not meaningfully explain the observed industry variations (Gliner et al., 2017).

Q1b: How Has CAPEX Intensity Varied Across Industries, and Which Have Consistently Received the Highest or Lowest Investment?

To address Research Question 1b, year-over-year capital expenditures (CAPEX) were analyzed across U.S. manufacturing sub-industries using 3-digit NAICS codes (311–339) from 2018 to 2021. Industries 314 (Textile Product Mills), 315 (Apparel Manufacturing), and 316 (Leather and Allied Product Manufacturing) due to incomplete data across the four years. The results provide insight into both the magnitude and consistency of investment in robotic automation technology.

Figure 5 presents annual CAPEX by industry. NAICS 336 (Transportation Equipment Manufacturing) dominated every year, ranging from $865.5 million in 2018 to nearly $1.5 billion in 2021. Other high-investment sectors included NAICS 333 (Machinery Manufacturing) and NAICS 332 (Fabricated Metal Product Manufacturing), which showed consistent growth over time. In contrast, industries like NAICS 313 (Textile Mills) and NAICS 323 (Printing and Related Support Activities) received minimal investments year-over-year, with values consistently below $10 million. These patterns emphasize the scale and consistency of disparity in capital allocation.

NAICS 336 (Transportation Equipment Manufacturing) consistently recorded the highest mean CAPEX, at approximately $1.19 million, followed by NAICS 333 (Machinery Manufacturing) and NAICS 332 (Fabricated Metal Product Manufacturing). In contrast, industries such as NAICS 313 (Textile Mills) and NAICS 323 (Printing and Related Support

Activities) reported the lowest mean CAPEX levels, at approximately $3,478 and $7,993, respectively.

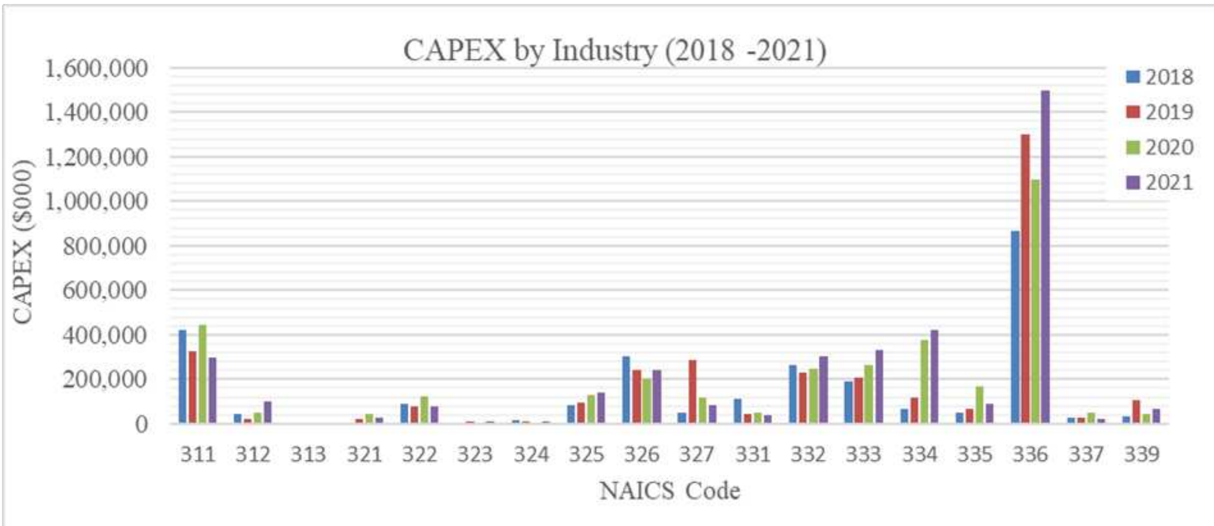

Figure 5

Annual CAPEX Investment by Selected 3-Digit NAICS Industries (311–339; 314, 315, and 316 removed), 2018–2021.

Mean capital expenditures (CAPEX) varied widely across manufacturing sub-industries from 2018 to 2021, as shown in Figure 6. NAICS 336 (Transportation Equipment Manufacturing) led all sectors with average annual investments exceeding $1.19 billion, followed by NAICS 333 (Machinery Manufacturing) and NAICS 332 (Fabricated Metal Product Manufacturing). In contrast, industries such as NAICS 313 (Textile Mills) and NAICS 323 (Printing and Related Support Activities) averaged less than $10 million per year in CAPEX. These pronounced differences reveal a highly uneven distribution of investment, with a small group of capital-intensive sectors consistently absorbing the largest share of robotic automation-related expenditures.

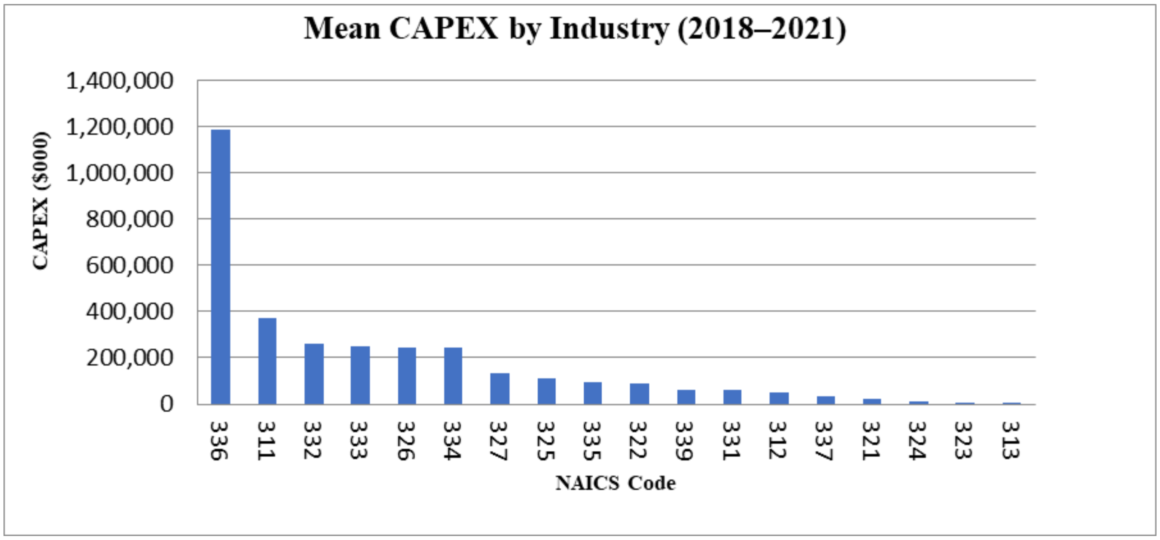

Figure 6

Average CAPEX Investment by Selected 3-Digit NAICS Industries (311–339; 314,315, and 316 removed), 2018–2021.

The standard deviation of mean CAPEX across industries was approximately $266,269,000, with a mean CAPEX of $180,148,000, resulting in a coefficient of variation (CV) of 1.48 as shown in Table 3. Morgan et al. (2013) argued that a higher CV indicates greater dispersion relative to the mean, suggesting significant variability in CAPEX investments across industries. These results highlight the uneven distribution of capital expenditures within the manufacturing sector during the period analyzed.

Table 3

Standard Deviation, Mean, and Coefficient of Variation for Mean CAPEX Investments Across NAICS Sub-industries (311–339), 2018–2021.

Metric	Value
Standard Deviation (000)	$266,269
Mean (000)	$180,148
Coefficient of Variation	1.48

Q1c: How Has Year-Over-Year CAPEX Change Varied Across Industries Grouped by Average CAPEX Quartiles?

To address Research Question 1c, industries were grouped into quartiles based on their average CAPEX from 2018 to 2021. Industries with the highest average investments were assigned to Quartile 4, while the lowest were placed in Quartile 1. The complete quartile industry list is shown in Appendix F, Table A.1.

Rather than limiting the analysis to absolute CAPEX values, this study focuses on year-over-year (YoY) changes in capital expenditures to assess how investment behavior varied across quartile groups. Industries classified under NAICS 314 (Textile Product Mills), NAICS 315 (Apparel Manufacturing), and NAICS 316 (Leather and Allied Product Manufacturing) were excluded due to incomplete or missing CAPEX data across the reference period. Figure 7 presents the average YoY CAPEX change for each quartile from 2018 to 2021.

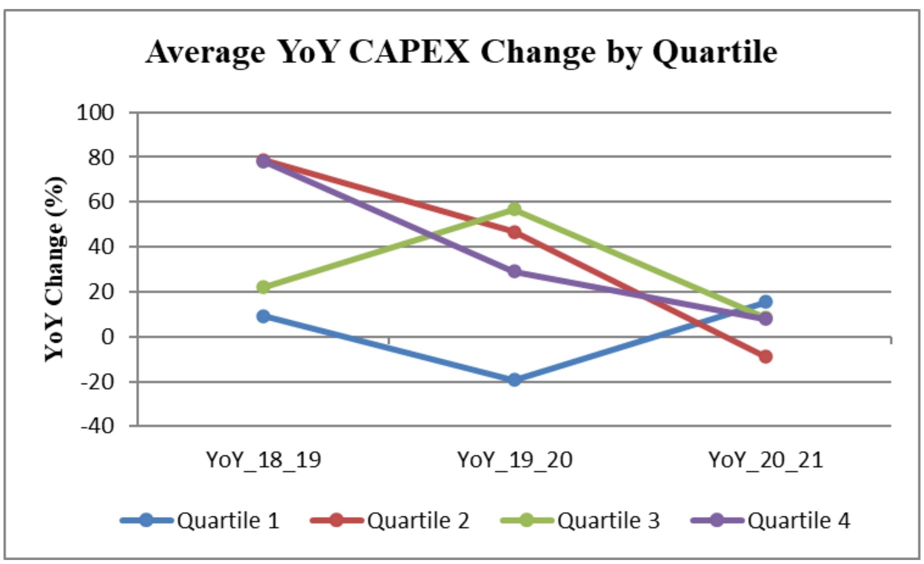

Figure 7

Average Year-over-Year CAPEX Change by Quartile (Excluding NAICS 314, 315, 316), 2018–2021.

The findings indicate distinct investment patterns across the CAPEX quartiles. Quartile 4 industries, such as NAICS 336 (Transportation Equipment Manufacturing), NAICS 333 (Machinery Manufacturing), and NAICS 332 (Fabricated Metal Product Manufacturing), exhibited the greatest volatility. These quartile sectors experienced a sharp 78.2% increase in CAPEX from 2018 to 2019, followed by a 29.1% increase in 2020 and a modest 7.8% gain in 2021. While this trend demonstrates a sustained upward trajectory, the deceleration in growth rates over time suggests that high-CAPEX industries may respond aggressively to initial macroeconomic incentives but eventually plateau as capital-intensive investments are fulfilled and operationalized. These findings align with prior research indicating that high-CAPEX industries often exhibit early surges in investment driven by macroeconomic incentives or automation policies, followed by stabilization as major capital upgrades are completed (Acemoglu & Restrepo, 2019; Domini et al., 2021). Conversely, lower-capital industries may display limited variation due to resource constraints or lower automation readiness (Chiarini et al., 2023; Manyika et al., 2017; Bessen & Righi, 2019).

In contrast, Quartile 3 industries displayed relatively steady investment behavior, with CAPEX growth peaking in 2020 and a gradual decline in 2021, indicating a more balanced and consistent investment strategy. Quartile 2 industries exhibited a sharp increase in capital investment between 2019 and 2020, followed by a decline in 2021, a pattern that may reflect reactive rather than strategic decision-making, such as short-term responses to supply chain disruptions or pandemic-driven automation needs, rather than planned modernization efforts (Bonfiglioli et al., 2020; Waldman-Brown, 2020).

Finally, Quartile 1 industries, which include low-CAPEX sectors such as NAICS 313 (Textile Mills) and NAICS 323 (Printing and Related Support Activities), demonstrated minimal year-over-year variation. These industries recorded a small dip in CAPEX in 2020 with slight recovery in 2021, suggesting either constrained capital resources or limited readiness for automation-related investments (Chiarini et al., 2023; Bonfiglioli et al., 2020; Bessen & Righi, 2019).

Q2: How Does CAPEX Influence Total Firm Employment Outcomes in the U.S. Manufacturing Sector From 2018 To 2021?

Building on the CAPEX investment trends described in Research Question 1, Research Question 2 investigates how CAPEX relates to total firm employment within the U.S. manufacturing sector (NAICS 31–33) from 2018 to 2021. While the previous analysis confirmed steady year-over-year growth in CAPEX, this section explores whether those investments in robotic automation corresponded with changes in workforce size or structure. Sub-questions examine year-over-year (YoY) changes in CAPEX and employment, potential lagged effects of CAPEX on employment in the subsequent year, and differences in mean employment levels across CAPEX quartiles. This multi-part analysis provides a foundation for understanding how capital intensity may be reshaping labor dynamics across the sector.

Q2a: How Have Year-Over-Year Changes in CAPEX Been Associated with Corresponding Changes in Total Firm Employment?

This section analyzes trends in capital expenditures (CAPEX) and total firm employment within the U.S. manufacturing sector (NAICS 31–33) from 2018 to 2021. As shown in Table 4, aggregate CAPEX increased steadily over the period, rising from approximately $2.62 billion in 2018 to $3.76 billion in 2021. Year-over-year (YoY) growth rates were +21.5% (2018–2019), +6.9% (2019–2020), and +10.2% (2020–2021). In contrast, total employment declined from 12.35 million to 11.60 million over the same period, with YoY decreases of –2.0%, –2.5%, and –

1.7%, respectively. This inverse relationship is especially evident in 2019, where a 21.5% increase in CAPEX coincided with a 2.0% drop in employment, a pattern that persisted throughout the study period.

Table 4

Year-over-Year Percentage Changes in Capital Expenditures and Total Firm Employment in the U.S. Manufacturing Sector (NAICS 31–33), 2018–2021.

Year	Total CAPEX (000)	Total Employment	CAPEX YoY %	Employment YoY %	Pearson Correlation (r)
2018	$2,624,449	12,345,000			
2019	$3,187,568	12,100,000	21.5	-2.0	
2020	$3,408,999	11,800,000	6.9	-2.5	
2021	$3,755,334	11,600,000	10.2	-1.7	-0.98

Table 5 presents this analysis in terms of mean value changes across industries. Mean CAPEX increased drastically by 31.26% in 2018–2019, followed by slower growth of 2.27% (2019–2020) and 11.92% (2020–2021). In contrast, mean employment was highly volatile, rising by 74.43% in 2019, falling by 44.66% in 2020, and then bouncing back by 136.82% in 2021. The volatility in employment size growth is not mirrored in the more stable increase in CAPEX and highlights the lack of connection between employment outcomes and investment levels.

Table 5

Mean CAPEX and Employment, and Year-over-Year Percentage Changes for NAICS 31–33 Manufacturing Industries, 2018–2021

Year	Mean CAPEX ($000)	Mean Employment	CAPEX YoY % Change	Employment YoY % Change
2018	149,378	517,999		
2019	196,068	903,539	31.26	74.43
2020	200,524	499,978	2.27	-44.66
2021	224,422	1,184,055	11.92	136.82

A Pearson correlation analysis confirms this pattern, revealing a strong negative relationship between YoY changes in CAPEX and employment, with r ≈ –0.98. According to Morgan et al. (2013), coefficients between –0.80 and –1.00 suggest a highly stable inverse association. Field (2017) similarly noted that values near –1 reflect meaningful and consistent trends. Figure 8 illustrates these opposing trends as capital investment steadily increased, and employment declined. These results strongly support the hypothesis that increasing capital intensity, through investment in automation, robotics, and advanced manufacturing technologies,

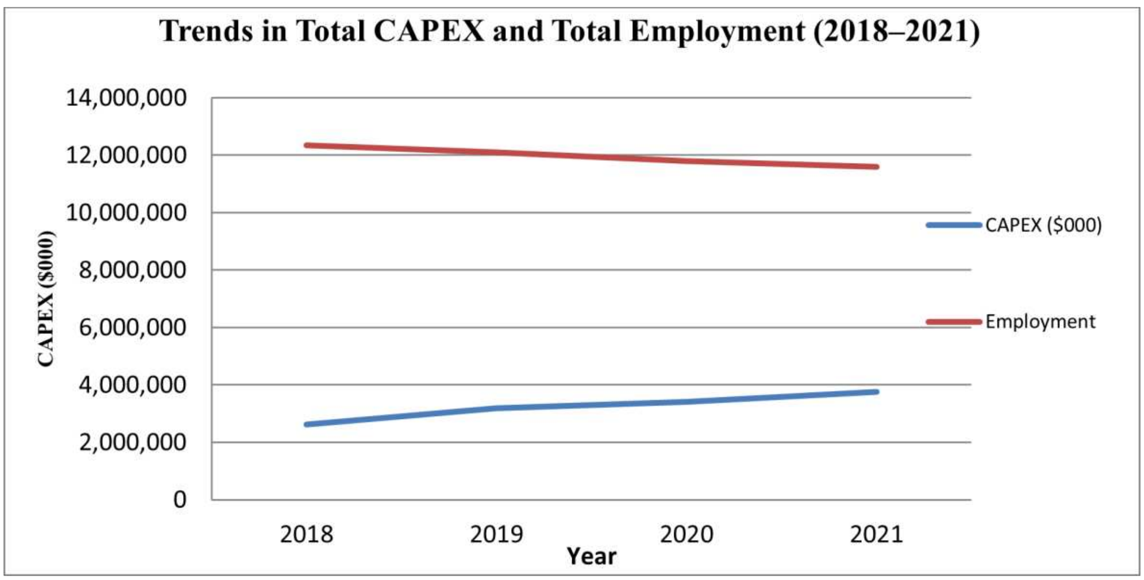

Figure 8

Trends in Total Capital Expenditures and Total Firm Employment in the U.S. Manufacturing Sector (NAICS 31–33), 2018–2021.

may contribute to structural workforce reductions. Rather than driving employment growth, higher CAPEX may enable firms to boost productivity while reducing reliance on labor (Acemoglu & Restrepo, 2020; Autor et al., 2003).

Core Sub-Industry Analysis.

Mean CAPEX and employment levels were summarized for four key NAICS sub-industries: Food Manufacturing (311), Fabricated Metal Product Manufacturing (332), Machinery Manufacturing (333), and Transportation Equipment Manufacturing (336, covering the period from 2018 to 2021. For NAICS 311, the mean CAPEX was $372.4 million, with a mean employment level of 1,595,739; however, CAPEX declined by 30.0% over the four years, while employment increased modestly by 2.2%. NAICS 332 reported a mean CAPEX of $261.2 million and a mean employment level of 1,423,868, with CAPEX rising 16.3% but employment declining by 5.4%. NAICS 333 recorded a mean CAPEX of $247.4 million and a mean employment level of 1,050,044; notably, it experienced a substantial 74.7% increase in CAPEX, while employment declined by 4.3%. Finally, NAICS 336 exhibited the highest CAPEX and employment figures, with a mean CAPEX of $1.19 billion and a mean employment level of 1,609,572. It also demonstrated a 72.8% increase in CAPEX and a relatively stable employment trend, with a 0.6% gain from 2018 to 2021. These descriptive results are summarized in Table 6.

Table 6

Mean and 4-Year % Change of CAPEX and Employment for Selected NAICS Sub-Industries (311, 332, 333, 336), 2018–2021.

Sub-Industry NAICS Code	CAPEX 2018 (000)	CAPEX 2019 (000)	CAPEX 2020 (000)	CAPEX 2021 (000)	Mean CAPEX (2018-2021) (000)	4-Year % Change
311	$423,600	$326,700	$442,600	$296,600	$372,375	-30.0
332	$261,900	$230,100	$248,300	$304,500	$261,200	16.3
333	$189,100	$208,900	$261,100	$330,300	$247,350	74.7
336	$865,500	$1,298,000	$1,095,000	$1,496,000	$1,188,625	72.8
	Employment 2018	Employment 2019	Employment 2020	Employment 2021	Mean Employment (2018-2021)	
311	1,570,295	1,593,960	1,614,185	1,604,515	1,595,739	2.2
332	1,437,086	1,466,779	1,431,651	1,359,954	1,423,868	-5.4
333	1,057,407	1,079,338	1,051,305	1,012,124	1,050,044	-4.3
336	1,585,194	1,640,937	1,617,836	1,594,321	1,609,572	0.6

Compared to the total manufacturing sector, which experienced a steady 43.1% increase in total CAPEX and a 6.1% decline in employment from 2018 to 2021, the four core sub-industries exhibited more varied trajectories. While NAICS 333 and 336 both saw substantial CAPEX growth (+74.7% and +72.8%, respectively), only NAICS 336 maintained relatively stable employment levels. Conversely, NAICS 311 saw a sharp decline of 30.0% in CAPEX even while there was a marginal increase in employment, and NAICS 332 experienced modest growth in CAPEX with a considerable reduction in employment. These variances emphasise the uneven distribution of capital investment across manufacturing sub-sectors, emphasizing that an increase in CAPEX does not necessarily lead to a rise in employment.

Q2b: How Does CAPEX in One Year Correspond with Total Employment in the Subsequent Year?

This analysis examined whether changes in CAPEX in one year were associated with changes in total firm employment in the following year. A lagged first-differences model was used, aligning year-over-year percentage changes in CAPEX (Δ $CAPEX_t$) with the year-over-year percentage change in total employment in the subsequent year (Δ $Employment_{t+1}$). This method facilitates the identification of delayed effects between capital investment and workforce change, a foundational approach in time-lagged correlation analysis (Cohen, 1988; Gliner et al., 2017). Three valid lagged pairs were available for analysis. A +21.5% increase in CAPEX in 2018 was followed by a –2.5% decline in employment from 2019 to 2020. Similarly, a +6.9% CAPEX increase in 2019 was followed by a –1.7% employment decrease from 2020 to 2021. In contrast, a +10.2% rise in CAPEX in 2020 was followed by a +10.1% employment increase from 2021 to 2022, suggesting a potential shift in the relationship during the pandemic recovery period.

The lagged relationship is illustrated in Figure 9, which presents a clustered bar chart comparing year-over-year changes in CAPEX in Year t with corresponding changes in total employment in Year t+1. The observed pattern reveals inconsistent directional effects: the first two intervals coincide with lagged employment declines, while the third reflects a notable rebound. Although the sample is too limited to support statistical inference, the descriptive trend suggests that sharp increases in capital investment may be followed by short-term employment contractions or restructuring. However, under certain macroeconomic or firm-specific conditions, such investments may also precede employment growth. These mixed results reinforce the importance of considering external mediating variables and broader economic context in longitudinal assessments of investment-employment dynamics (Brynjolfsson & McAfee, 2011; Field, 2017).

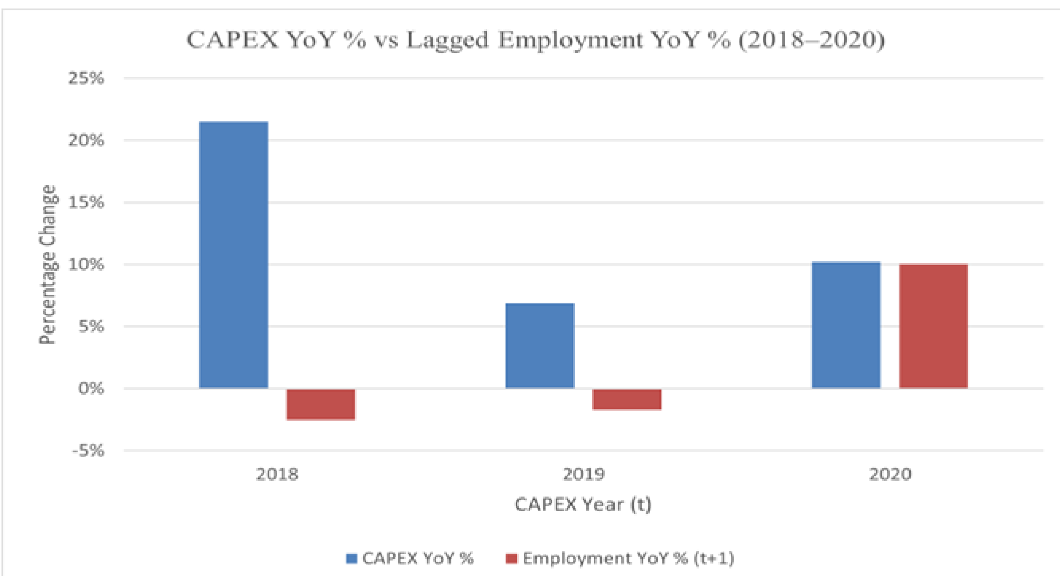

Figure 9

Lagged Relationship Between CAPEX YoY % Change (Year t) and Employment YoY % Change (Year t+1), 2018–2020.

Note. Table summarizes mean employment across NAICS 311–339 industries, categorized by mean CAPEX quartile. Employment values reflect national industry means from 2018 to 2021. The quartile breakdown is summarized in Appendix F, Table E.1.

Q2c: How Does CAPEX Quartile Level Correspond to Differences in Mean Employment Across Industries?

To further examine how automation investment relates to industry-level workforce structures, mean employment was compared across CAPEX quartiles at the 3-digit NAICS level. Industries were categorized into four quartiles based on their mean CAPEX between 2018 and 2021. The results, displayed in Figure 10 show a positive association between CAPEX intensity and total employment. Industries in Quartile 4 reported the highest mean employment levels (e.g., NAICS 311 and 336), while Quartile 1 industries, typically less automated and more labor-intensive, reported substantially lower mean employment.

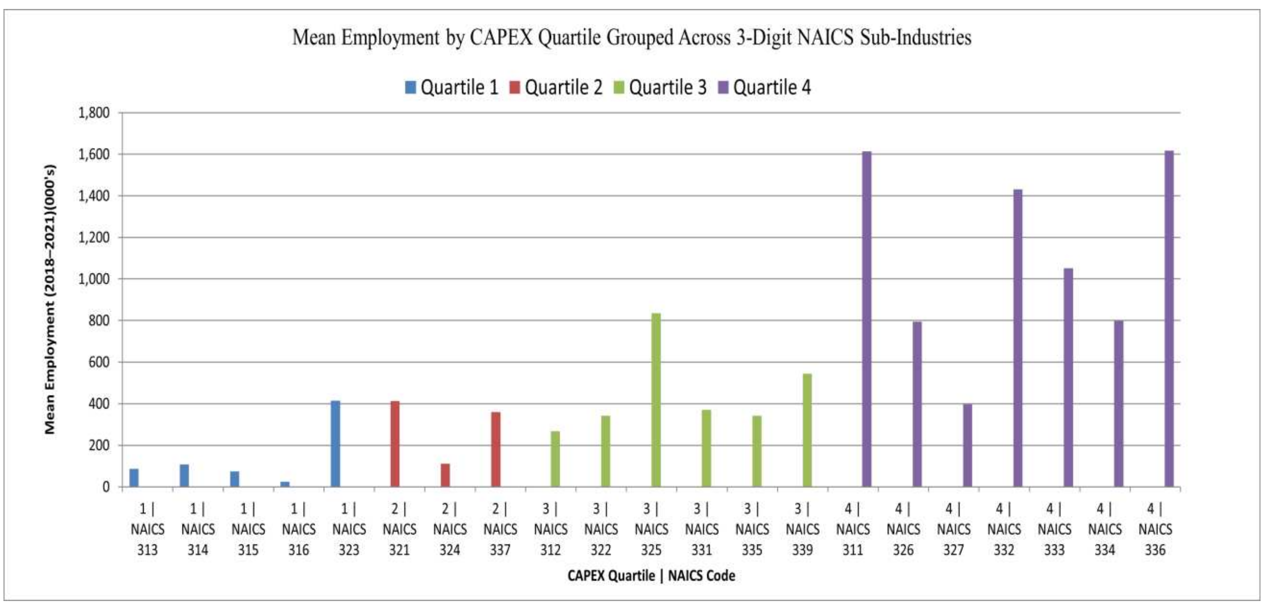

Figure 10

Mean employment by CAPEX quartile and 3-digit NAICS sub-industry (2018–2021).

A one-way ANOVA confirmed that the differences in mean employment across quartile groups were statistically significant, $F(3, 17) = 10.72$, $p = .0003$, $\eta^2 = .65$. This large effect size indicates that approximately 65% of the variance in employment can be attributed to CAPEX quartile groupings. As described by (Morgan et al., 2013), ANOVA is appropriate to assess whether the means of multiple independent groups differ significantly. Post hoc inspection of the group means revealed that Quartile 4 industries, such as NAICS 311 (Food Manufacturing) and NAICS 336 (Transportation Equipment Manufacturing), consistently maintained both high automation investment and workforce levels.

To further explore the relationship between automation investment and workforce size, both Spearman's correlation (ρ) and Pearson's correlation (r) were computed. Given that CAPEX quartiles represent ordinal groupings and employment levels across industries exhibit a non-normal and potentially skewed distribution, Spearman's ρ was selected as the primary measure of association. This decision is supported by Morgan et al. (2013), who recommend Spearman's method when assumptions of Pearson's correlation, such as "normality and linearity, are violated" or when "one or more variables are ordinal in nature" (pp. 131–133). Pearson's r was also reported to assess the strength of the linear relationship and to confirm the robustness of the association under parametric assumptions. The results revealed a strong, statistically significant positive relationship between CAPEX investment and total employment: Spearman's $\rho = .79$, $p < .001$; Pearson's $r = .75$, $p < .001$. These findings indicate that industries with higher levels of capital expenditures on automation tend to exhibit larger workforces. While this association does not imply causality, it may reflect the structural demands of highly capitalized sectors, where large-scale automation often complements, rather than replaces, human labor

(Acemoglu & Restrepo, 2020; Autor et al., 2003). Supporting summary statistics and correlation outputs are provided in Appendix F, Table E.2 and Table E.3.

Q3: How Does CAPEX Affect Employment in White-Collar Supervisory Occupations Across Manufacturing Sub-Sectors From 2018 To 2021?

This section investigates how capital investment activity (CAPEX) is associated with year-over-year changes in white-collar supervisory employment. The analysis focuses on four occupational groups selected for their technical and managerial relevance to automation deployment and production oversight: industrial production managers, industrial engineers, mechanical engineering technologists and technicians, and first-line supervisors of production and operating workers. Occupational coding follows the U.S. Bureau of Labor Statistics Standard Occupational Classification (SOC) system and aligns with recent literature examining automation exposure among high-skill roles (Bessen & Righi, 2019; Frey et al., 2016). This analysis establishes a descriptive foundation for subsequent CAPEX-related testing by capturing baseline employment trends and occupational variability (Bessen & Righi, 2019; Frey et al., 2016; Mindell & Reynolds, 2023).

Q3a: How Has CAPEX Influenced Soc-Coded White-Collar Occupations Over Time?

Descriptive employment trends for the four occupations from 2018 to 2021 are summarized in Table 7 and graphically represented in Figure 10, which depicts the mean employment levels over the four years. Appendix F, Table E.2 also reports the standard deviation and coefficient of variation (CV%) for each role to assess consistency over time. Standard deviation reflects the absolute spread in employment, while CV standardizes this variation as a percentage of the occupation's mean, enabling meaningful cross-occupation comparison (Field, 2017).

Table 7

Mean, standard deviation and coefficient of variation (CV%) for white-collar supervisory employment in NAICS 31-33 employment (2018–2021).

Occupation	Mean Employment 2018	Mean Employment 2019	Mean Employment 2020	Mean Employment 2021	4-Year Mean	Std Dev	CV (%)
Occ 1: Prod Mgrs.	6,434	6,500	6,143	7,410	6,622	474.59	7.17
Occ 2: Ind. Engr.	7,482	9,357	9,533	10,123	9,124	989.39	10.84
Occ 3: Engr. Tech.	800	696	644	710	713	56.26	7.89
Occ 4: F-L Supr.	21,699	21,880	20,690	22,729	21,750	724.87	3.33

Occupation 4 (first line supervisors), the largest by employment volume, remained the most stable with the lowest CV (3.33%). In contrast, Occupation 2 (industrial engineers) had the highest mean employment variation (CV = 10.84%), suggesting greater fluctuation, possibly due to changing demand for engineering talent. Occupation 1 (industrial production managers) remained moderately stable (CV = 7.17%), while Occupation 3 (engineering technicians) showed low total volume with modest variability. These patterns provide baseline insight into occupational responsiveness before testing associations with CAPEX levels.

Q3b: How Has CAPEX Been Associated with Lagged Changes in White-Collar Employment Levels?

Mean employment levels were calculated for four supervisory white-collar occupational categories within NAICS 31–33 manufacturing industries from 2018 to 2021 and visualized in Figure 11. To examine potential delayed effects of automation investment, lagged employment variables were also derived by aligning each year's employment with CAPEX from the previous year. Specifically, employment figures from 2019, 2020, and 2021 were matched to CAPEX investments made in 2018, 2019, and 2020, respectively. These lagged indicators offer a foundation for analyzing whether capital expenditures influence white-collar employment structures over time.

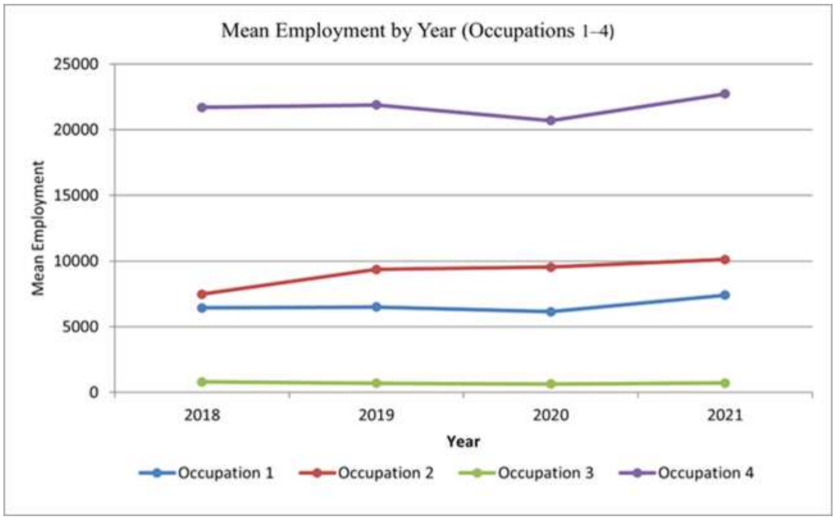

Figure 11

Mean employment by year for the four white-collar supervisory occupations.

To assess the delayed impact of capital investment on employment, CAPEX data from 2018 to 2021 were paired with employment data from 2019 to 2022 across four supervisory and technical white-collar occupations. This lagged relationship aligns with prior automation research, indicating that investments in technology often affect workforce structure over time rather than immediately (Acemoglu & Restrepo, 2020; Brynjolfsson & McAfee, 2011; Brynjolfsson et al., 2018).

Table 8 presents the annual CAPEX values (aggregated across all manufacturing quartiles in NAICS 31–33) and the corresponding employment levels in the subsequent year. The percent change in CAPEX each year is visualized alongside percent changes in employment (t+1) in Figure 12 to highlight potential directional relationships.

Table 8

Lagged Association Between CAPEX (t) and White-Collar Employment (t+1), 2018–2022

CAPEX Year	Employ. Year	%Δ CAPEX	Δ Occ 1	Δ Occ 2	Δ Occ 3	Δ Occ 4	%Δ Occ 1	%Δ Occ 2	%Δ Occ 3	%Δ Occ 4
2018	2019									
2019	2020	0.22	-60	360	40	-1090	0.00	0.07	NA	-0.02
2020	2021	0.07	1390	-460	-40	2170	0.11	-0.08	-1.00	0.04
2021	2022	0.10	1580	-310	40	5470	0.11	-0.06	NA	0.09

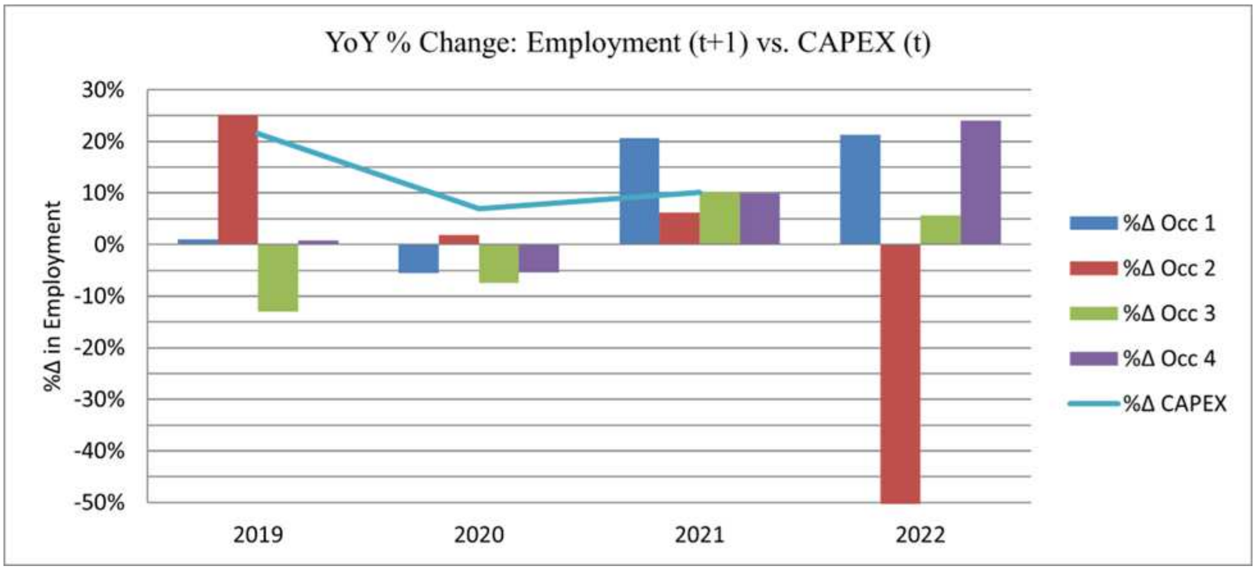

Figure 12

Year-over-Year Percentage Change in Employment by Occupation (t+1) and Capital Expenditures (CAPEX) in Year t for U.S. Manufacturing (2018–2022).

Note. This figure compares the annual percentage change in employment across four white-collar manufacturing occupations with the corresponding percentage change in capital expenditures on robotic equipment from the previous year (lagged CAPEX). CAPEX changes are visualized as a line, while employment changes are shown as clustered bars for each occupation. The employment data represent year-over-year changes in total employment for each occupation, measured in year t+1; one year after the capital investment was made. CAPEX values reflect capital investments made in year t and are used here as a potential leading indicator of employment change, consistent with prior research on automation's delayed labor effects (Acemoglu & Restrepo, 2020; Brynjolfsson & McAfee, 2011).

Overall, CAPEX increased steadily across the four-year period, with the largest jump occurring between 2018 and 2019 (+22.29%). Employment responses in the subsequent years, however, varied by occupation. Occupation 1 (industrial production managers) and Occupation 4 (first-line supervisors) showed strong, consistent growth, rising by 22.5% and 11.2%, respectively, suggesting that automation investments may reinforce supervisory roles. However, Occupation 2 (industrial engineers) increased initially but declined thereafter, while Occupation 3 (engineering technicians) remained limited in scale and fluctuated irregularly. These patterns suggest that automation tends to support sustained growth in leadership and oversight functions, while technical roles may be more susceptible to short-term demand cycles, task restructuring, or displacement depending on how automation is implemented (Acemoglu & Restrepo, 2020; Autor et al., 2022).

To assess the strength of the relationship between capital investment and occupational employment outcomes, Pearson correlation coefficients were computed between CAPEX values in year t and employment in year t+1 for each occupation. The use of lagged (t+1) employment reflects the expectation that automation-related capital expenditures do not yield immediate workforce changes but instead influence employment structures in subsequent years. This approach aligns with prior research indicating that technology investments typically require lead time for implementation, integration, and organizational adjustment (Acemoglu & Restrepo, 2020; Brynjolfsson & McAfee, 2011).

The analysis revealed a strong positive correlation for Occupation 1 (industrial production managers) ($r \approx +0.80$) and a moderate positive correlation for Occupation 4 (first-line supervisors) (r ≈ +0.73), suggesting a consistent alignment between capital investment and growth in supervisory employment. These results imply that automation may enhance or expand managerial oversight functions in manufacturing environments. Occupation 3 (engineering technicians) showed a moderate positive relationship (r ≈ +0.53), indicating that technician roles may benefit from automation investments, possibly during periods of system deployment or technical configuration. In contrast, Occupation 2 (industrial engineers) exhibited a moderately negative correlation (r ≈ –0.63), suggesting that automation may reduce demand for engineering roles or shift them toward shorter, project-based assignments. These patterns reflect the differential impact of automation based on job function and integration timing, with supervisory roles more likely to be augmented and technical roles potentially displaced or restructured.

Field (2017) noted that correlation coefficients above 0.30 generally indicate meaningful associations, even if causality cannot be established. Gliner et al. (2017) also emphasized the need to examine subgroup variation in applied research, as aggregated analysis can obscure important occupational differences. These findings reinforce earlier literature suggesting that automation tends to support leadership roles while displacing or reshaping technical positions, particularly when tasks are highly routinized or subject to reorganization (Acemoglu & Restrepo, 2018; Autor et al., 2022).

Q3c: How Has CAPEX Variation Affected Year-Over-Year Trends in White-Collar Employment Across Occupations and Sectors?

To uncover patterns in how automation and employment evolved across 3-digit NAICS manufacturing industries, a K-means clustering analysis was applied. This method grouped industries into three distinct clusters (k = 3) based on their standardized year-over-year (YoY) percentage changes in capital expenditures (CAPEX) and lagged white-collar employment between 2018 and 2021. Standardization was used to place both variables on a common scale (mean of 0, standard deviation of 1), ensuring that industries were compared fairly despite differences in absolute size or growth magnitude. K-means was selected for its ability to classify continuous data into meaningful and interpretable groups, a technique commonly used in labor and automation research (Domini et al., 2021; Qi, 2022).

The results, visualized in Figure 13, reveal three distinct clusters:

Cluster 0: Automation-Heavy Sectors.

These industries showed high CAPEX growth but flat or declining employment, reflecting potential labor-substituting automation. Representative examples of industries within the resulting clusters include NAICS 312 (Beverage and Tobacco Product Manufacturing), NAICS 314 (Textile Product Mills), and NAICS 334 (Computer and Electronic Product Manufacturing).

Cluster 1: Growth-Aligned Sectors.

Characterized by moderate to strong increases in both CAPEX and employment, these sectors suggest expansionary automation where investment coincides with rising labor demand. Representative examples include NAICS 321 (Wood Product Manufacturing), NAICS 326 (Plastics and Rubber Products Manufacturing), and NAICS 325 (Chemical Manufacturing).

Cluster 2: Declining or Static Sectors.

These industries exhibited minimal or negative change in both CAPEX and employment, possibly indicating contraction, stagnation, or cost containment. Representative examples of industries within the resulting clusters include NAICS 311 (Food Manufacturing), NAICS 313 (Textile Mills), and NAICS 322 (Paper Manufacturing).

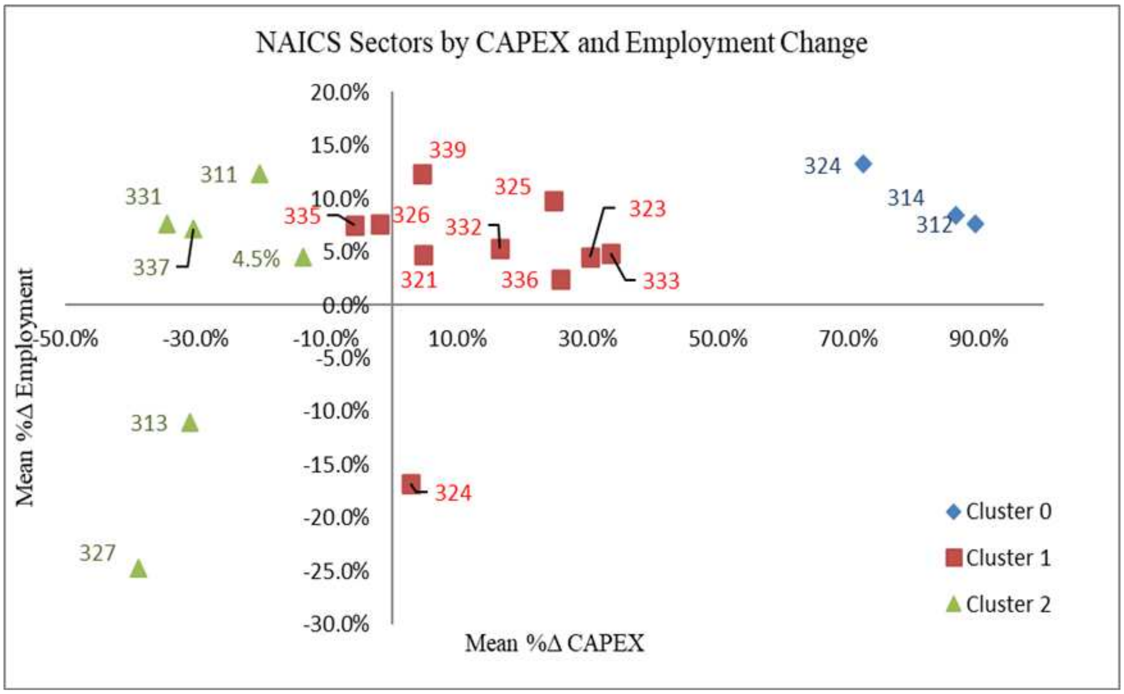

Figure 13

Clustered NAICS Subsectors by CAPEX and Employment Change (2018–2022).

This segmentation provides a high-level typology of automation behavior across U.S. manufacturing, highlighting the variation in how capital investment aligns with employment outcomes. It supports the broader research consensus that automation's labor market effects are not uniform but instead shaped by sector-specific investment trajectories, implementation timelines, and workforce structures (Bessen & Righi, 2019; Frey et al., 2016).

Q4: How Does CAPEX Relate to Firm Composition Trends in U.S. Manufacturing From 2018 to 2021?

This section examines whether increases in CAPEX coincided with observable changes in firm composition, how CAPEX quartile groupings influenced industry-level patterns, and whether CAPEX surges were associated with broader trends of firm expansion, consolidation, or restructuring within the manufacturing sector.

Between 2018 and 2021, total CAPEX on robotic equipment in U.S. manufacturing industries rose from approximately $2.62 billion to $3.76 billion. During this same period, the total number of manufacturing firms declined slightly, from 250,869 to 243,580. These shifts occurred alongside changes in firm composition across industries, with some sectors experiencing firm expansion amid rising investment, while others underwent consolidation or contraction.

Q4a: How Has CAPEX Coincided with Changes in Firm Composition Across Industries?

This analysis examines whether changes in CAPEX from 2018 to 2021 coincided with shifts in the number of manufacturing firms across 3-digit NAICS industries. By comparing CAPEX trends to changes in firm count over the same period, the analysis identifies patterns of industry expansion, contraction, and potential consolidation. Figure 14 shows a scatterplot of CAPEX change (in millions of dollars) against firm count change, with each point labeled by NAICS code. The corresponding data for each industry is provided in Appendix F, Table E.3.

Several sector-specific patterns emerge. NAICS 312 (Beverage and Tobacco) and 325 (Chemicals) showed increases in both CAPEX and firm count, suggesting capital investment in these sectors may have supported firm growth or entry. In contrast, NAICS 334 (Computer and Electronic Products) and 333 (Machinery) experienced significant CAPEX growth despite declining firm counts, pointing to consolidation potentially driven by automation and economies of scale. Meanwhile, industries such as 313 (Textile Mills) and 315 (Apparel Manufacturing) showed simultaneous declines in both investment and firm count, indicating sectoral contraction.

To assess the overall relationship between investment and firm composition, a Pearson correlation was calculated between changes in CAPEX and changes in firm count across all

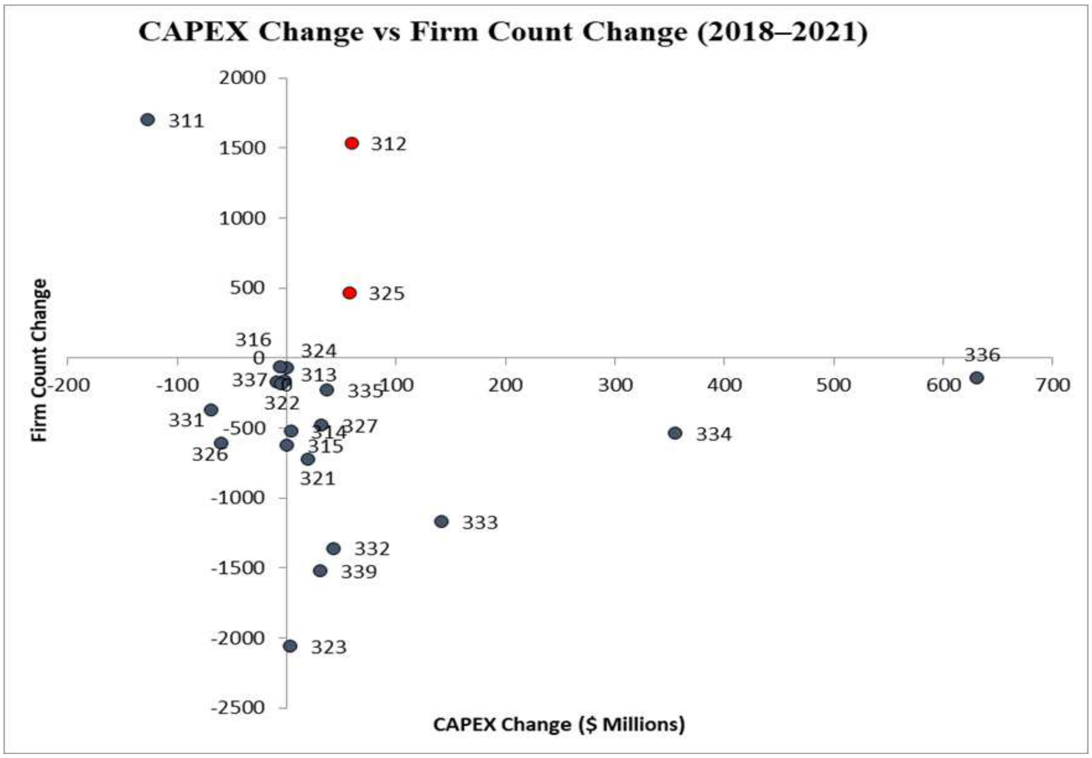

Figure 14

The relationship between changes in capital expenditures (in millions of dollars) and changes in firm count across 21 U.S. manufacturing industries. Each data point is labeled by its 3-digit NAICS code.

industries. Results indicate a weak and non-significant association ($r \approx -0.09$, $p \approx .73$) as shown in Appendix A, Table A.3. These results suggest that while sector-specific patterns exist, there is no consistent statistical relationship between investment levels and firm count change across the but reflect consolidation or strategic restructuring in others.

Q4b: How Has CAPEX Quartile Grouping Influenced Differences in Firm Composition?

To assess whether capital investment levels are associated with differences in firm composition, industries were grouped into four quartiles based on mean CAPEX from 2018 to 2021. Quartile 1 includes the lowest-investment industries, such as NAICS 313 (Textile Mills) and NAICS 323 (Printing and Related Support Activities), while Quartile 4 includes the highest-investment industries, such as NAICS 336 (Transportation Equipment Manufacturing) and NAICS 333 (Machinery Manufacturing). Table 9 presents the mean firm counts, firm count changes, and CAPEX change per quartile, enabling comparison of structural differences across investment levels.

The results as shown in Figure 15, reveal a modest pattern: industries in Quartile 1 experienced the largest mean decline in firm count (–3,440 firms, or –9.2%) despite minimal mean CAPEX growth (+$1.85 million). In contrast, Quartile 3 industries, those with moderate CAPEX growth (+$17.56 million), showed the smallest mean decline in firm count (–291 firms, or –0.5%). Interestingly, Quartile 4, which had the highest mean CAPEX increase (+$144.91 million), still experienced a mean decline in firm count of 2,588 (–2.0%). This suggests that elevated investment levels may coincide with restructuring or consolidation, rather than expansion in firm numbers.

Table 9

The mean number of firms in 2018 and 2021 by CAPEX quartile, along with calculated changes in firm count and percentage change over the period.

CAPEX Quartile	Mean Firm Count (2018)	Mean Firm Count (2021)	Mean Firm Count Δ	% Δ in Firm Count
1	37251	33811	-3440	-9.23
2	27371	26401	-970	-3.54
3	53720	53429	-291	-0.54
4	132527	129939	-2588	-1.95

Overall, the trend indicates that lower-CAPEX industries experienced steeper declines in firm count, while firm losses were more moderate among middle- and high-investment sectors. However, even among top-quartile industries, CAPEX surges were not associated with firm growth. These findings suggest that capital investment alone may not drive firm expansion but may instead reflect strategic realignment within high-tech or automation-intensive industries.

Q4c: How Has CAPEX Level Been Associated with Trends in Firm Expansion, Consolidation, or Restructuring?

To assess whether CAPEX correlates with structural changes in the manufacturing sector, changes in mean capital expenditures and mean firm counts were analyzed across 3-digit NAICS industries from 2018 to 2021. Industries were then categorized into three structural trend groups based on firm count trajectories: (1) Expansion, defined as a firm count increase greater than +3%; (2) Consolidation, defined as a firm count decrease greater than –3%; and (3) Restructuring, defined as a relatively stable firm count change between –3% and +3%.

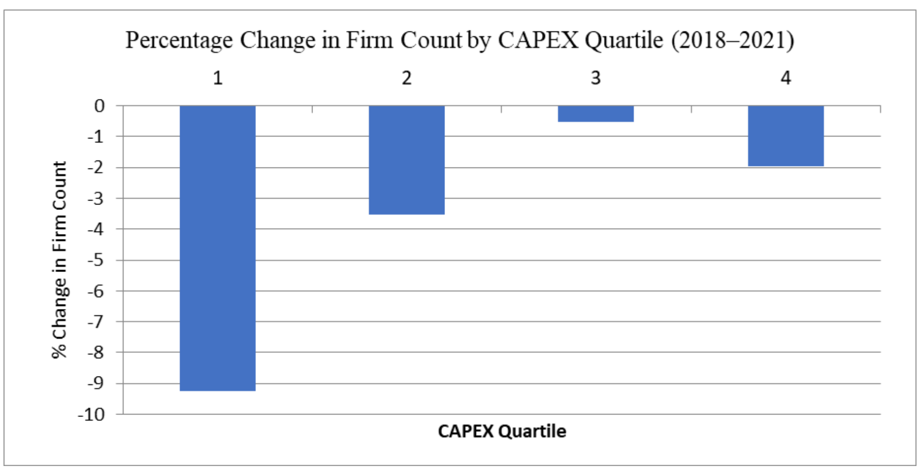

Figure 15

The mean percentage change in firm count across four CAPEX quartiles for U.S. manufacturing industries. Quartiles were based on total capital expenditures from 2018 to 2021.

To interpret structural change across industries, a ±3% threshold was applied to year-over-year changes in firm count. This threshold balances sensitivity to meaningful shifts with the need to exclude minor fluctuations. It also aligns with organizational research that distinguishes between expansion, consolidation, and restructuring dynamics in response to market or technological change (Bonfiglioli et al., 2020; Caroli & Van Reenen, 2001).

Industries classified as expanding experienced firm growth, suggesting favorable conditions for market entry and diversification. In contrast, consolidation reflects declining firm numbers, often driven by rising capital intensity, automation adoption, or scale economies favoring larger firms (Acemoglu & Restrepo, 2020; Bessen & Righi, 2019). Restructuring captures industries with stable firm counts but internal changes, such as modernization or realignment, potentially signaling technological absorption rather than disruptive exits.

Figure 16 presents a clustered bar chart comparing mean percentage changes in CAPEX and firm count across the three structural categories. The chart illustrates a clear divergence: consolidation is associated with the highest mean increase in CAPEX but the steepest firm losses, while

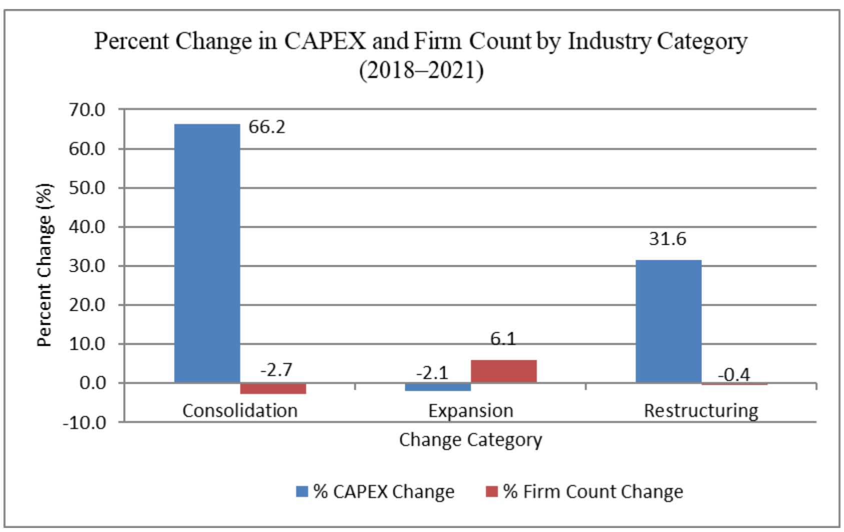

Figure 16

Comparison of average percentage changes in capital expenditures and firm counts across manufacturing industries categorized as Expansion, Consolidation, or Restructuring.

Note. The chart illustrates how consolidation is associated with high CAPEX growth but declining firm numbers, while expansion reflects firm growth despite lower investment. expansion involves firm growth despite limited investment. This pattern suggests that capital investment in some industries may reflect automation or concentration rather than broad-based industry growth.

Figure 17 displays a scatterplot of individual industries, showing how changes in CAPEX and firm count vary across the sector. Each industry is labeled by its 3-digit NAICS code and categorized by structural trajectory. The scatterplot reveals that while a few industries—such as NAICS 312 (Beverage and Tobacco Product Manufacturing) and NAICS 325 (Chemical Manufacturing), exhibited both investment growth and firm expansion, several others with sharp CAPEX increases, such as NAICS 334 (Computer and Electronic Product Manufacturing), NAICS 333 (Machinery Manufacturing), and NAICS 327 (Nonmetallic Mineral Product Manufacturing), also experienced firm contraction, consistent with consolidation or automation-driven scaling. A complete listing of NAICS industries, associated percentage changes, and category assignments appears in Appendix A, Table A4.

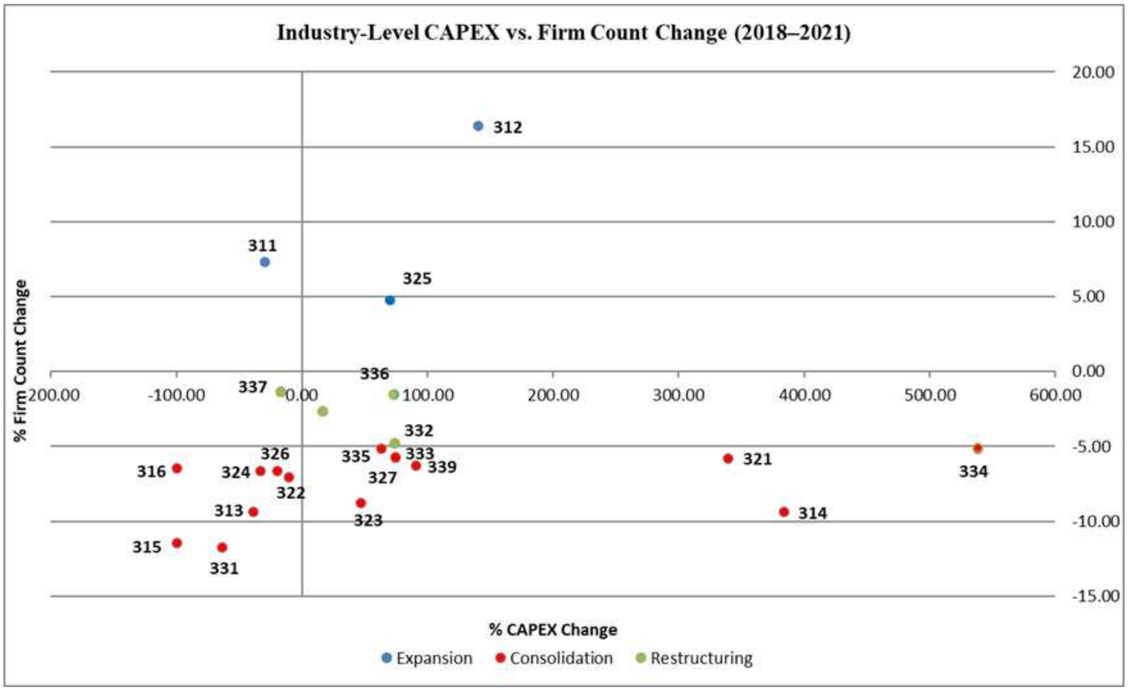

Figure 17

Industry-level CAPEX vs. Firm Count Change (2018-2012).

Note. This scatterplot shows the relationship between percentage changes in capital expenditures and firm counts across 3-digit NAICS manufacturing industries. Each point represents one industry, labeled by NAICS code and color-coded by structural category. The visual highlights variation in how investment trends align with firm composition shifts.

Q5: How Does CAPEX Vary Across U.S. States, and How Is It Associated With Differences in Employment and Firm Composition From 2018 to 2021?

This section examines how CAPEX in the manufacturing sector (NAICS 31–33) varied across U.S. states from 2018 to 2021. Nationally, CAPEX increased each year, rising from approximately $2.58 billion in 2018 to $3.76 billion in 2021. However, investment levels varied significantly by state. States such as Ohio, Michigan, and Illinois reported consistently high CAPEX. In contrast, states such as Hawaii, Montana, and Wyoming reported little to no investment activity, with some missing data entirely.

To highlight the range of investment intensity, Figure 18 presents only the top and bottom 10 states based on their four-year mean CAPEX, drawn from states with complete data for all four years. This approach sharpens the comparison by focusing on the most and least capital-intensive manufacturing states, avoiding distortion from mid-range states with less pronounced trends. The top 10 states indicate strong, sustained investment in manufacturing modernization, while the bottom 10 show minimal engagement with capital-intensive automation, likely due to smaller industrial bases, limited reinvestment activity, or gaps in reporting. Together, these contrasts reveal persistent regional disparities in automation adoption and robotic automation investment across the United States.

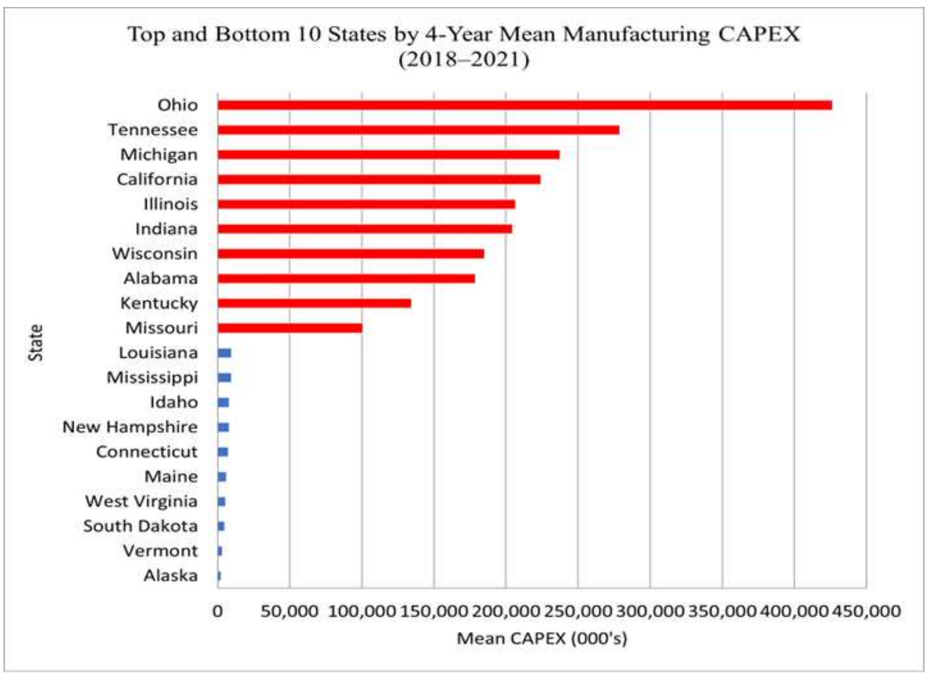

Figure 18

Top and Bottom 10 States by 4-year Mean Manufacturing CAPEX (2018-2021).

Note. States are ranked by mean annual capital expenditures reported in the NAICS 31–33 manufacturing sector from 2018 to 2021. Missing values were treated as non-reported data. The bottom 10 states are represented by the lowest with data input for all four years.

Q5a: How Have Year-Over-Year Changes in State-Level CAPEX Varied Across U.S. States and Investment Quartiles?

To examine year-over-year (YoY) shifts in manufacturing investment, percent change in CAPEX was calculated across three annual intervals (2018–2019, 2019–2020, and 2020–2021) for all U.S. states in NAICS 31–33. Pearson correlation coefficients were then used to assess the consistency of these trends across states and investment quartiles.

As shown in Table 10, overall correlations between year-pair intervals were weak and negative, with coefficients ranging from –0.36 to –0.05. These results indicate that year-over-year investment behavior was generally unstable and declining. States experiencing high growth in one year were not likely to sustain or reverse those trends predictably in subsequent years.

Table 10

Pearson's r values for year-over-year CAPEX changes across all U.S. states in the manufacturing sector (NAICS 31–33).

Interval Comparison	Pearson's r
2018–2019 vs. 2019–2020	-0.36
2019–2020 vs. 2020–2021	-0.24
2018–2019 vs. 2020–2021	-0.05

Note. Correlations were computed between three sequential year-pair intervals to assess trend consistency.

To further investigate whether investment volatility varied by level of CAPEX, states were grouped into four quartiles based on total manufacturing investment from 2018 to 2021. As illustrated in Table 11, Quartiles 1 and 2 (lowest CAPEX states) exhibited inconsistent behavior, with multiple negative correlations suggesting sharp reversals or inconsistent trajectories. Quartile 3 showed the strongest directional relationship, with a moderate positive correlation (*r* = +0.49) between 2018–2019 and 2020–2021, indicating partial recovery or stability in mid-tier investment states. In contrast, states in Quartile 4 (highest total CAPEX) demonstrated relatively milder fluctuations but still lacked directional continuity across the period.

Table 11

Correlation coefficients by quartile, (2018-2021)

Quartile	2018–2019 vs 2019–2020	2019–2020 vs 2020–2021	2018–2019 vs 2020–2021
Q1 (Lowest CAPEX)	-0.26	-0.42	-0.05
Q2	-0.46	-0.45	-0.1
Q3	-0.59	-0.39	0.49
Q4 (Highest CAPEX)	-0.32	-0.11	-0.25

Note. States were grouped into quartiles based on total CAPEX from 2018 to 2021 (see Appendix D: State Assignments by Capex Quartile). This table summarizes the correlation of year-over-year CAPEX changes within each quartile, highlighting variation in investment consistency across state groups.

These trends are visualized in Figure 19, which presents a comparative bar chart of correlation coefficients by quartile. While no quartile displayed fully consistent year-over-year trends, the relative stability in Quartile 3 suggests that states with moderate CAPEX may have been more resilient or structured in their investment recovery post-2020.

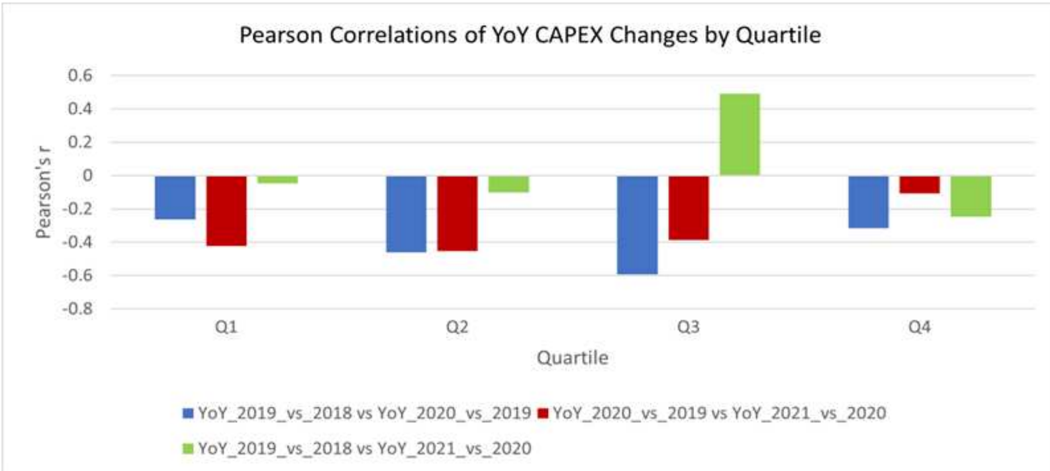

Figure 19

Pearson correlation coefficients comparing year-over-year (YoY) changes in capital expenditures (CAPEX) across state-level quartiles of investment intensity from 2018 to 2021.

Note. Pearson's r values reflect the strength and direction of linear correlations between year-over-year (YoY). CAPEX quartiles were calculated based on average investment levels, with Q1 representing the lowest and Q4 the highest investment groups

Q5b: How Has State-Level CAPEX by Quartile Level Been Associated with Changes in Total Manufacturing Employment at the State Level?

This section analyzes the relationship between state-level capital expenditures (CAPEX) and changes in total manufacturing employment from 2018 to 2021. State-level employment data were converted into year-over-year (YoY) percentage changes, and descriptive trends were compared across CAPEX quartiles.

Table 12 summarizes the mean YoY employment percentage change by CAPEX quartile. In 2019, all quartiles experienced employment declines, with Quartile 1 (lowest CAPEX states) declining the most (–3.23%). A recovery occurred in 2020 across all quartiles, led again by Quartile 1 (+7.54%), though employment dropped again in 2021—most sharply in Quartile 1 (–

8.38%). A dramatic outlier in Quartile 2 (originally +347%) was capped in visualizations at +15% for interpretability.

Table 12

Mean Year-over-Year Employment Percentage Change by State-Level CAPEX Quartile, 2019–2021.

CAPEX Quartile	Avg YoY % Change 2019	Avg YoY % Change 2020	Avg YoY % Change 2021
Q1	-3.23	7.54	-8.38
Q2	-1.93	4.67	347.37
Q3	-2.11	3.73	-6.75
Q4	-2.35	2.82	-6.03

Figure 20 displays a clustered bar chart comparing the mean YoY employment change for each CAPEX quartile from 2019 to 2021. Each bar represents the mean of all states assigned

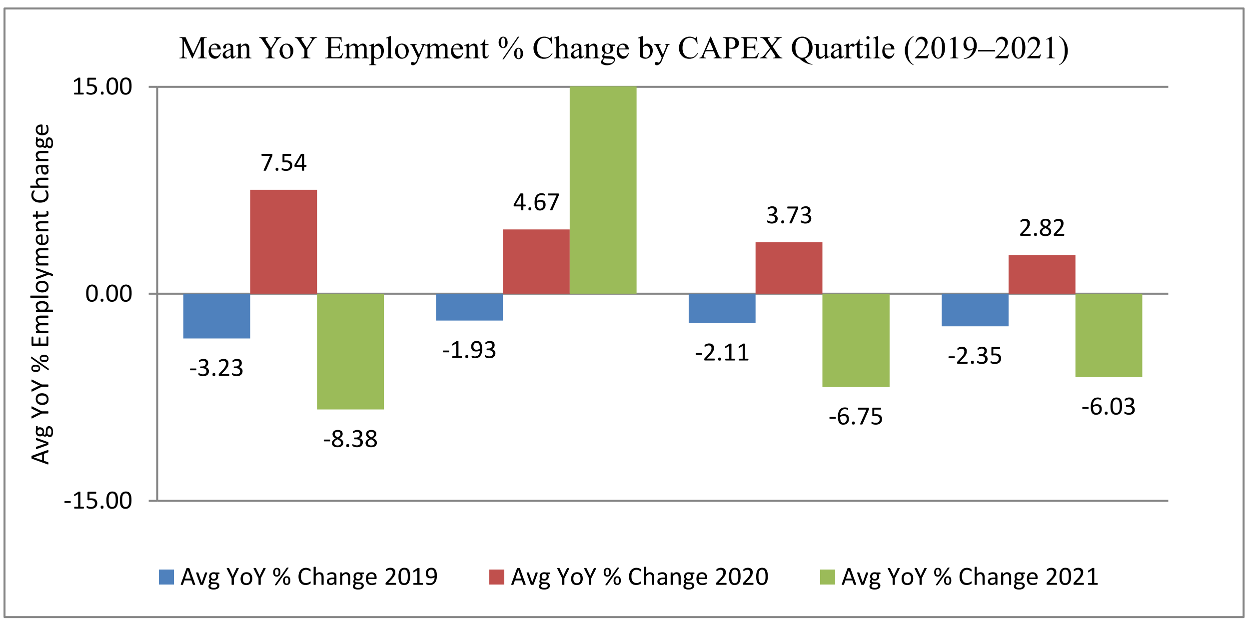

Figure 20

Mean YoY employment % change (2019–2021) by CAPEX quartile.

to that quartile. While some higher CAPEX quartiles showed moderate employment growth in 2020, lower quartiles experienced stronger rebounds but also more volatility in 2021.

Note. This analysis evaluates state-level employment changes in manufacturing (NAICS 31–33) in relation to annual capital expenditures. Each bar reflects the mean of all states within each quartile. Quartiles reflect total CAPEX investment levels from 2018 to 2021. Chart reflects a capped outlier in Quartile 2 (2021) to improve visual interpretability.

These findings suggest that CAPEX level alone does not determine short-term employment trends. While some higher CAPEX states exhibited temporary employment gains, lower-CAPEX states experienced both sharper rebounds and steeper losses. This inconsistency implies that employment responsiveness to CAPEX may depend on industry structure, automation maturity, and regional labor dynamics (Acemoglu & Restrepo, 2020; Domini et al., 2021). Overall, the results underscore that capital investment is not always associated with simultaneous employment growth. In several cases, employment declined despite rising CAPEX, reinforcing the need to explore lagged effects and contextual mediators in future analyses.

Q5c: How Does White-Collar Employment Vary Across State-Level CAPEX Quartiles in U.S. Manufacturing?

This section analyzes whether capital investment at the state level is associated with the scale of white-collar employment in U.S. manufacturing industries (NAICS 31–33). While Question 3 assessed the year-over-year or lagged effect of CAPEX on occupational change at the national level, this section provides a structural, cross-sectional view of how mean white-collar employment aligns with cumulative state-level CAPEX. This analysis focused on four SoC-coded white-collar occupations and evaluated how their mean employment levels varied across CAPEX quartiles from 2018 to 2021.

Table 13 presents the 4-year mean employment levels for each occupation, grouped by state-level CAPEX quartiles. A consistent pattern emerges, mean employment increases with higher investment levels across all four occupations. States in the highest investment tier (Quartile 4) report employment levels approximately 2.5 to 6.5 times higher than those in the lowest quartile, depending on the occupation.

Table 13

4-year state-level mean white-collar employment by CAPEX quartile (2018–2021).

	Occupation 1 Production Managers	Occupation 2 Industrial Engineers	Occupation 3 Engineering Technicians	Occupation 4 First Line Supervisors
Quartile 1	1,328	1,419	1,354	1,426
Quartile 2	3,292	3,350	3,356	3,529
Quartile 3	5,879	5,916	5,873	6,353
Quartile 4	8,636	8,472	8,413	8,764

Figure 21 visualizes these findings with a clustered bar chart. The pattern indicates that highly automated states tend to support a larger volume of white-collar managerial and technical roles, potentially due to increased production complexity, expanded oversight, or integration of advanced technologies.

To assess whether these trends reflect statistically meaningful associations, Pearson correlation coefficients were calculated at both the aggregate and occupation-specific levels. Table 14 presents the correlation between total state-level CAPEX and the 4-year mean of total white-collar employment, yielding $r = 0.7274$, $p < .0000001$, indicating a strong, significant relationship. These results align with prior automation research (e.g., Autor et al., 2022), which suggests that automation often drives growth in technical oversight and managerial roles, even as employment in frontline positions declines or remains stagnant.

Figure 21

Clustered bar chart of average state-level white-collar employment (2018–2021) by CAPEX quartile

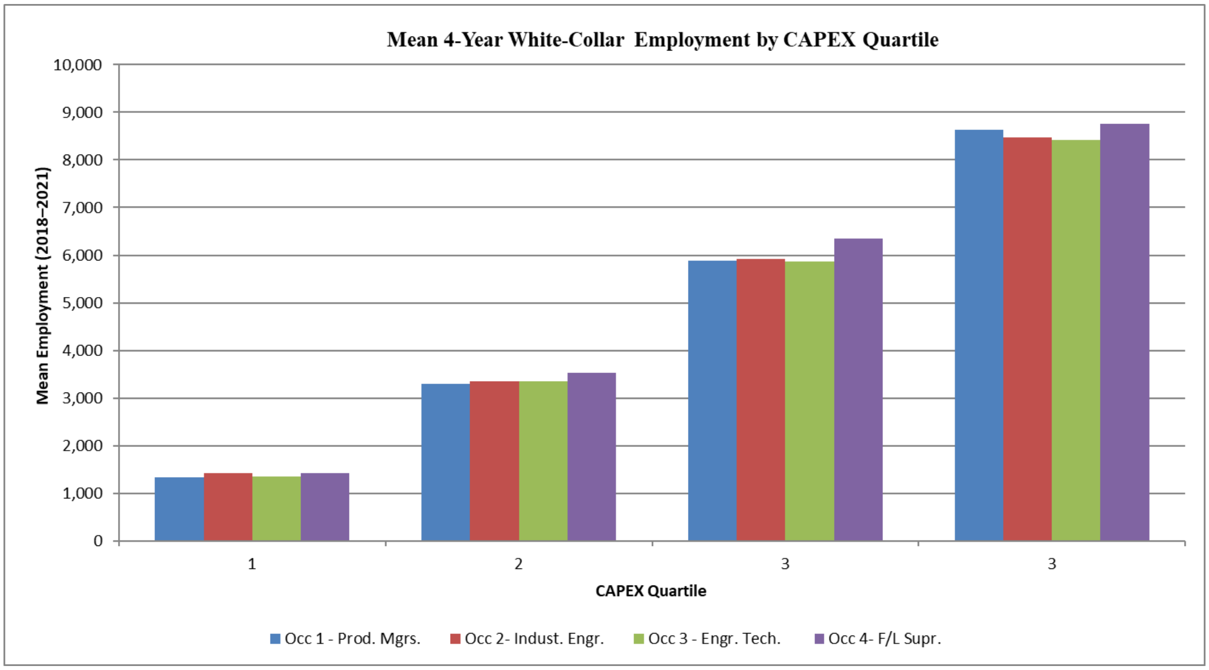

Table 14

Pearson Correlation Between State-level Total CAPEX (2018–2021) and 4-Year Mean White-Collar Employment (Aggregate).

Variable	Mean	Standard Deviation	r	p-value
Total CAPEX	$183.7M	$226.5M	—	—
Mean Employment	24,156	29,317	—	—
Correlation	—	—	0.7274	< .0000001

Q5d: How Have Year-Over-Year Changes in State-Level CAPEX Been Associated With Changes in White-Collar Employment Across U.S. States?

To assess the relationship between capital investment and white-collar employment change at the state level, Pearson correlations were computed using year-over-year (YoY) percentage changes in state CAPEX and employment for each year from 2019 to 2021, as well as in aggregate. As shown in Table 15, no statistically significant correlations were observed in any year. In 2019, the correlation was weak and negative ($r = –.09$, $p = .54$, $n = 46$). In 2020, a stronger negative relationship emerged ($r = –.23$, $p = .13$, $n = 44$), though still not significant at the $p < .05$ level. By 2021, the relationship shifted to a weak positive correlation ($r = .21$, $p = .16$, $n = 45$). When data from all three years were aggregated ($n = 135$), the overall correlation remained weak and nonsignificant ($r = –.08$, $p = .33$).

Table 15

Pearson Correlations Between State-Level CAPEX Change and White-Collar Employment Change by Year (2019–2021).

Year	Pearson r	n	p value
2019	-0.09	46	0.54
2020	-0.23	44	0.13
2021	0.21	45	0.16
Aggregate	-0.08	135	0.33

Note. CAPEX = capital expenditures; YoY = year-over-year change. Correlations based on white-collar SoC-coded occupations (n= is for states showing capex or employment data only)

These results suggest that short-term fluctuations in capital investment are not systematically associated with concurrent changes in white-collar employment across states. This pattern is visually represented in Figure 22, which displays a combined-state scatterplot with a single linear regression line across all observations from 2019 to 2021. The trendline confirms the statistical findings, illustrating a broadly dispersed relationship with no consistent positive or negative slope

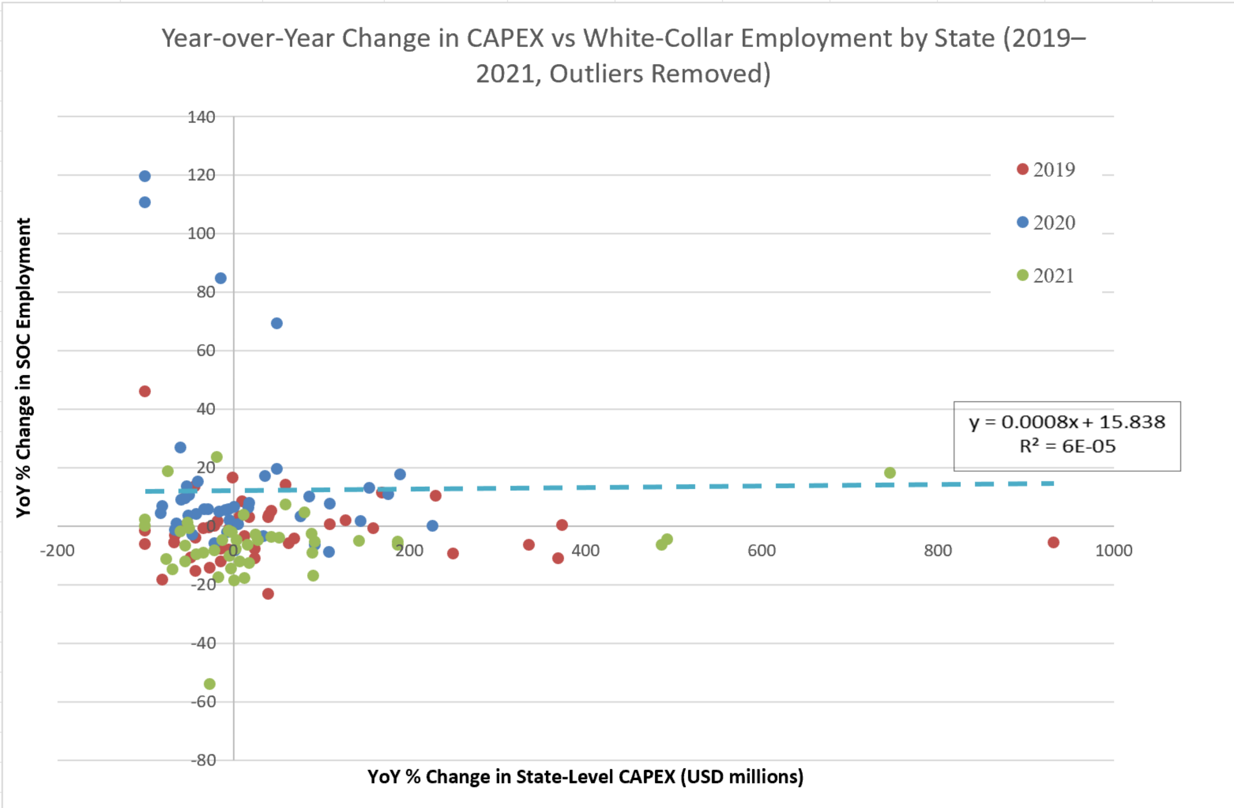

Figure 22

Year-over-Year Change in State-Level CAPEX vs. White-Collar Employment , 2019–2021.

Note. This scatterplot displays the annual percentage change in state-level capital CAPEX compared to the percentage change in white-collar supervisory employment (SOC-coded occupations). Each point represents a state-year observation, color-coded by year. The fitted regression line indicates a near-zero relationship ($R^2 = 0.00006$), suggesting minimal predictive association between CAPEX growth and changes in white-collar employment at the state level. Outliers were removed to enhance interpretability.

Q5e: How Do Lagged Relationships Between State-Level CAPEX and White-Collar Employment Vary by Investment Quartile and Sub-Industry?

To assess how the relationship between capital investment and white-collar employment varies by investment intensity, Pearson correlation coefficients were calculated between state-level CAPEX in year t and state-level employment in Occupations 1–4 in year t+1 across the full NAICS 31–33 manufacturing sector. States were stratified into quartiles based on their cumulative CAPEX from 2018 to 2021, as shown in Appendix D, allowing for comparisons of lagged investment-employment relationships across varying levels of capital intensity. This approach was structured to evaluate whether states with higher levels of manufacturing investment demonstrated stronger or more consistent associations between automation-related spending and changes in white-collar employment over time.

The results are presented in Figure 23. Overall, states in Quartiles 3 and 4, those with moderate to high levels of capital investment, demonstrated moderately to strongly positive lagged correlations between CAPEX and white-collar employment. This pattern was especially pronounced in Occupation 3 (engineering technicians) and Occupation 4 (first-line supervisors). In these higher-investment quartiles, correlation coefficients often ranged from $r = .40$ to .70, suggesting a relatively stable and predictive relationship between capital investment and employment one year later.

In contrast, Quartile 1 states, which had the lowest levels of CAPEX, consistently showed weak or negative correlations, with r values near zero or below. These states also displayed more variability across both years and occupational groups. This divergence suggests that the magnitude of investment may shape the strength and consistency of the employment response to automation-related expenditures. Specifically, more robust and reliable employment effects appear in environments where capital investment is more substantial.

Each data point in Figure 23 represents the mean correlation between CAPEX in year t and white-collar employment in year t+1 for a given occupation. The x-axis labels reflect the lagged employment year and occupational group (e.g., “2020_O3” represents employment in Occupation 3 in 2020 lagged from CAPEX in 2019). States in higher CAPEX quartiles (Q3 and Q4) consistently exhibit stronger and more stable correlations than those in Q1.

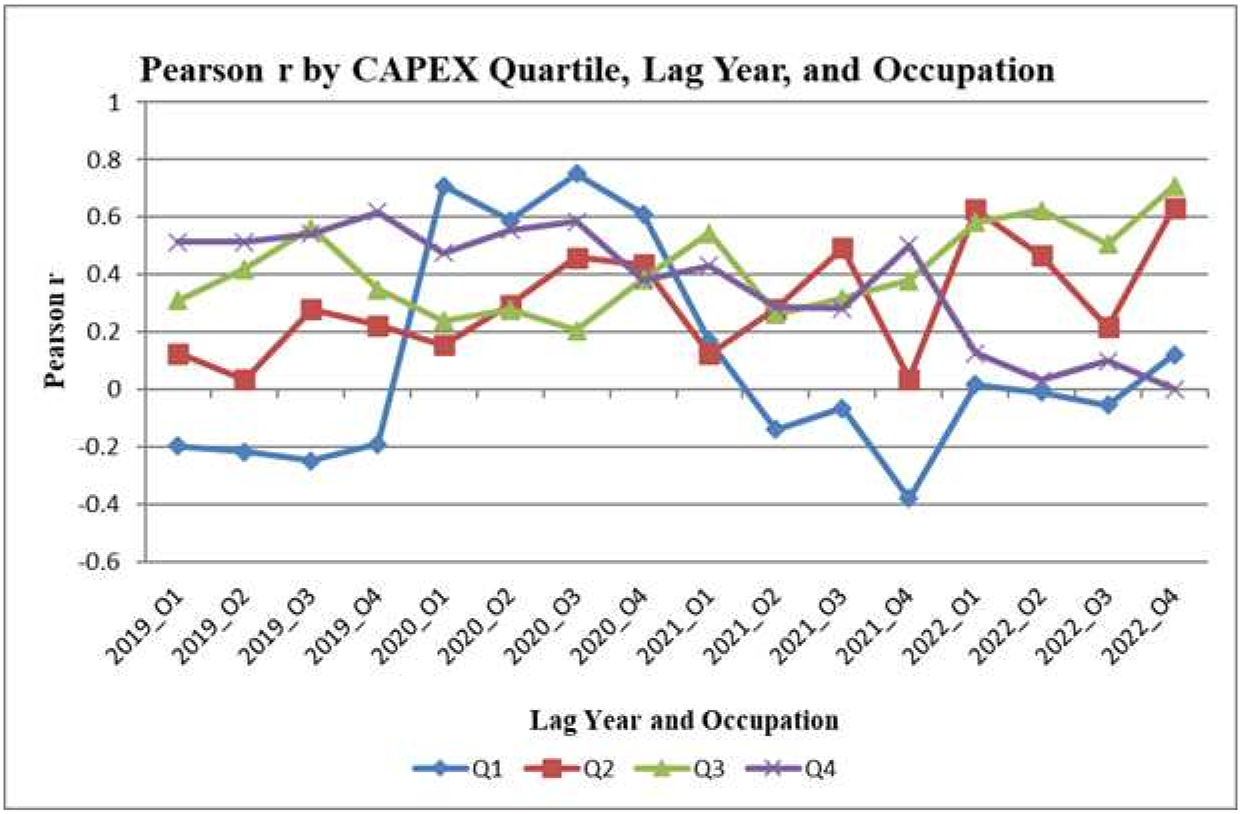

Figure 23

Pearson correlation coefficients (r) between state-level capital expenditures (CAPEX) and lagged white-collar employment, stratified by CAPEX quartile (Q1–Q4).

The strength of these lagged relationships varied by occupation. Occupation 3 (engineering technicians) and Occupation 4 (first-line supervisors) displayed the strongest and most consistent correlations with prior-year CAPEX. In contrast, Occupation 1 (industrial production managers) and Occupation 2 (industrial engineers) showed weaker and less consistent patterns. These differences suggest that mid-level technical and supervisory roles may be more responsive to capital investment trends than executive or design-oriented roles.

The findings support a differentiated lagged impact of CAPEX on white-collar employment, moderated by both investment intensity and occupation type. States with higher cumulative capital expenditures were more likely to experience positive and stable year-over-year growth in white-collar employment, particularly in occupations that play a key role in overseeing and supporting automation initiatives.

Q5f: How Has Manufacturing Firm Count and Growth Varied Across State-Level CAPEX Quartiles?

To assess how capital investment intensity shaped manufacturing firm composition across U.S. states, two supportive analyses were conducted: a quartile-based comparison and a targeted review of the top and bottom five states by firm count change. First, a clear gradient was observed in firm scale across CAPEX quartiles. As shown in Table 16, states in Quartile 4 (highest CAPEX) averaged more than 9,000 manufacturing firms, while Quartile 1 states averaged just over 1,000. This pattern, also visualized in Figure 24, indicates a strong structural association between higher capital investment and larger industrial ecosystems. These findings align with prior research suggesting that capital-intensive regions often host more firms due to established infrastructure, technological readiness, and economies of scale (Bonfiglioli et al., 2020; Domini et al., 2021).

Table 16

Average firm count by CAPEX quartile across U.S. states (2018–2021).

Capex Quartile	Firm Count 2018	Firm Count 2019	Firm Count 2020	Firm Count 2021
1	1,047	1,048	1,036	1,039
2	2,875	2,854	2,828	2,827
3	7,650	7,584	7,470	7,458
4	9,613	9,511	9,343	9,294

However, when firm growth was examined, a more complex picture emerged. As shown in Figure 25, the top five states for firm count growth from 2018 to 2021 were Idaho (+6.5%), Utah (+4.0%), Texas (+1.5%), Georgia (+1.4%), and Florida (+0.67%). Notably, these states were not all in the highest CAPEX quartile. Conversely, New York (–7.8%), Massachusetts (–

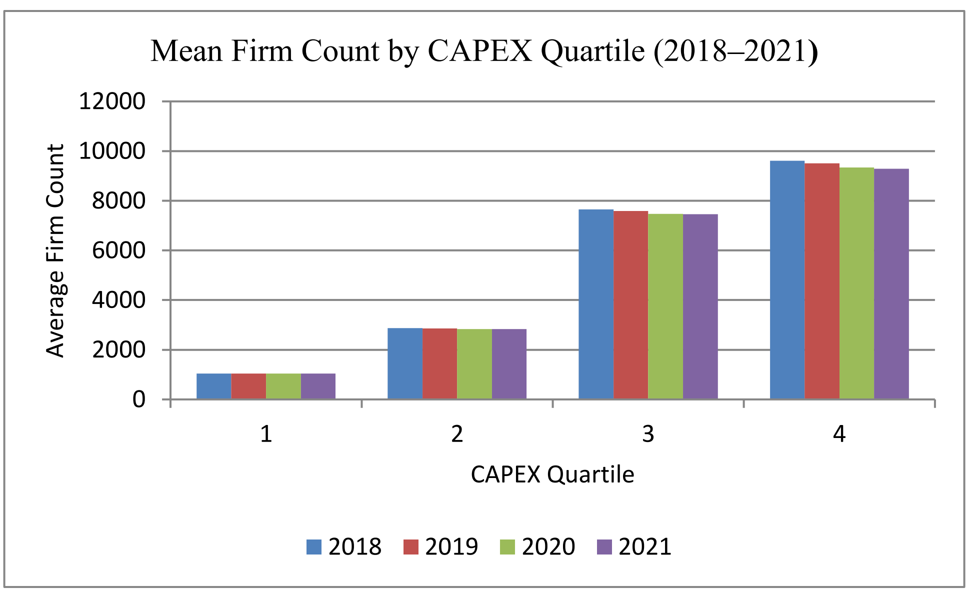

Figure 24

Mean manufacturing firm counts per CAPEX quartile (2018–2021). Quartile 4 states averaged 9,000+ firms; Quartile 1 states averaged ~1,000.

5.7%), Illinois (–5.1%), California (–4.4%), and Ohio (–3.8%) experienced the steepest declines in firm count, despite several being among the top CAPEX investors.

The correlation between CAPEX quartile and firm growth was weakly negative (r ≈ –0.21), suggesting that states investing more heavily in automation did not experience higher rates of firm creation. This pattern suggests that spending on automation might help larger, established companies grow, making it harder for smaller new companies to compete, which could lead to fewer companies in a specific area (Bessen & Righi, 2019).

These findings illustrate an important distinction. Higher CAPEX quartiles are associated with a higher number of firms; they are not associated with firm expansion. In fact, automation investment may lead to fewer, larger firms, consistent with broader national trends toward consolidation in capital-intensive sectors(Bessen & Righi, 2019; Bonfiglioli et al., 2020).

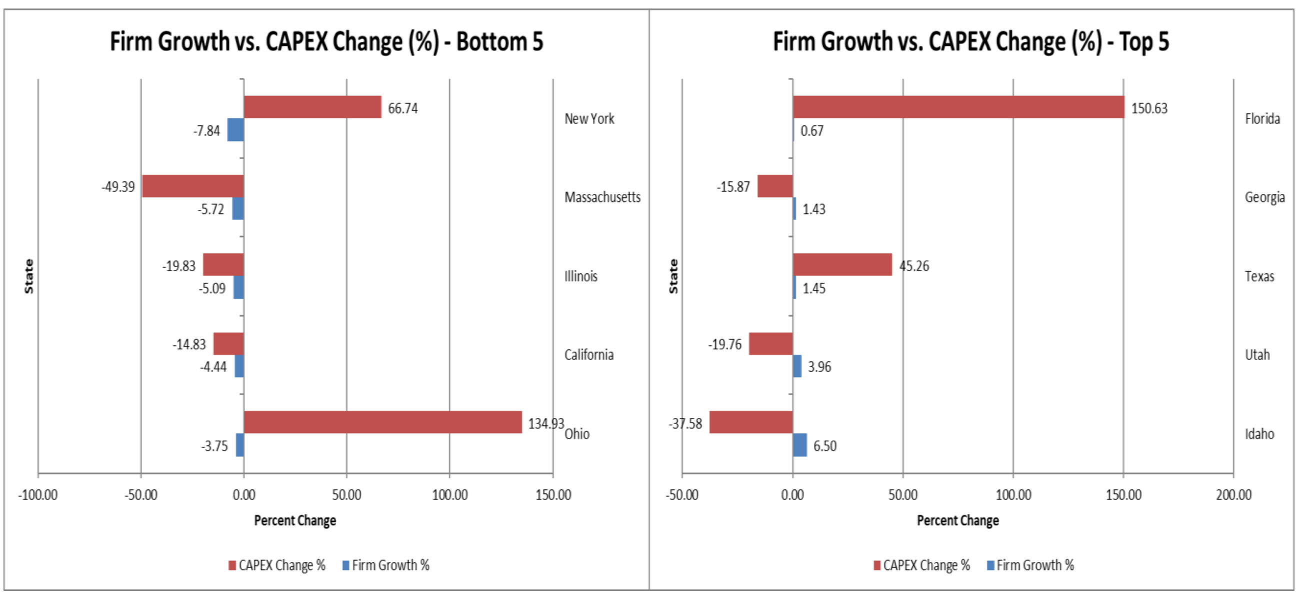

Figure 25

Firm growth% and CAPEX change% for the top and bottom 5 U.S. states.

Note. States are ordered by firm count change from 2018 to 2021, illustrating that high CAPEX did not consistently yield firm growth.

Q6: How Does CAPEX Investment at the State Level Compare with National Trends, and How is it Associated with Differences in Employment and Firm Composition From 2018 To 2021?

This section presents a detailed analysis of how CAPEX investment patterns at the state level compare to national manufacturing trends and how these patterns relate to employment and firm composition between 2018 and 2021. The analysis addresses Research Question 6 and its sub-questions, focusing on (a) CAPEX alignment between state and national levels, (b) CAPEX concentration and employment outcomes, particularly in supervisory white-collar occupations, and (c) the association between state-level CAPEX quartiles and firm growth. The occupational analysis emphasizes four high-skill supervisory roles central to U.S. manufacturing: General and Operations Managers (SOC 11-1021), Industrial and Mechanical Engineers (SOC 17-2112, 17-2141), Engineering and Maintenance Technicians (SOC 49-9041, 49-2094), and Front-Line Supervisors of Production Workers (SOC 51-1011). By examining these roles, alongside firm counts and CAPEX levels (based on NAICS 31–33), this section provides insights into how investment in automation may reshape organizational structures and employment dynamics at the regional level.

Q6a: How Has State-Level CAPEX Aligned with or Diverged from National Trends?

CAPEX varies widely across U.S. states, revealing significant disparities in automation intensity and industrial modernization. From 2018 to 2021, average state-level capital expenditures (CAPEX) were assessed and compared to a national benchmark, calculated by dividing total U.S. investment by 50 reporting states. This yielded a standardized benchmark of approximately $62.4 million per state, offering a normalized frame of reference. Figure 26 visualizes these data, presenting average CAPEX by state with the national benchmark indicated by a red reference bar.

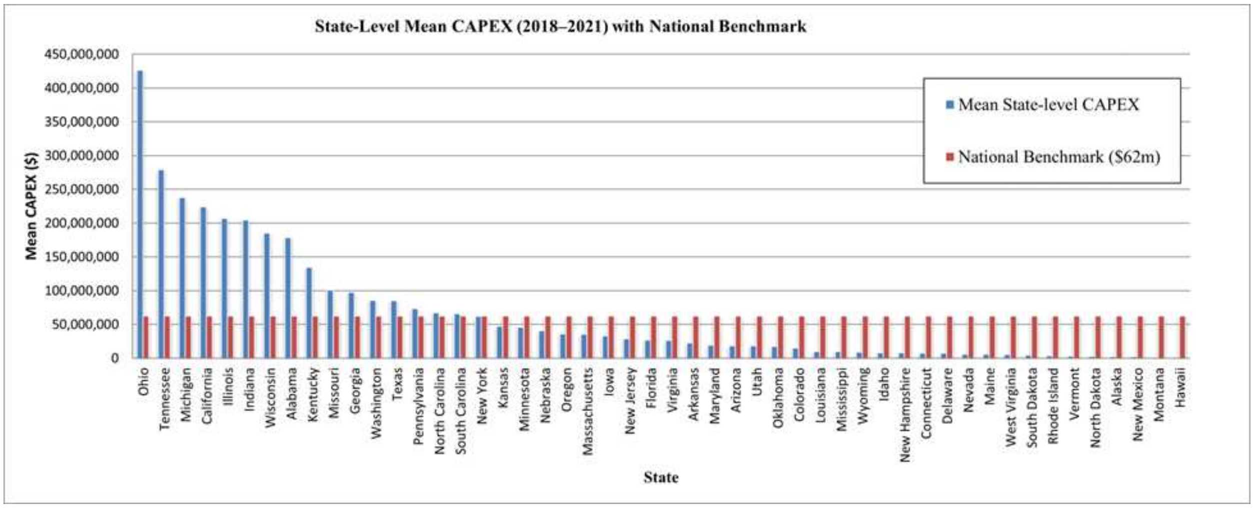

Figure 26

Average state-level capital expenditures (CAPEX) on robotic equipment, 2018–2021, compared to national per-state benchmark (avg).

The results show a highly skewed distribution of investment. Only 16 states (31%) exceeded the national per-state average, while 34 states (69%) fell below the benchmark. This pattern reflects a geographic concentration of automation-related spending, where a small group of high-investment states, such as Ohio, Tennessee, Michigan, and California, account for a disproportionate share of total national CAPEX.

While national figures suggest a steady rise in automation investment, the state-level distribution reveals a more nuanced reality. The fact that more than two-thirds of states are investing below the national average points to persistent regional disparities in automation readiness, access to capital, and industrial reinvestment. These imbalances may shape the pace and inclusivity of technological adoption across the broader U.S. manufacturing landscape.

.

Q6b: How Has CAPEX Concentration at The State Level Been Associated With Total and White-Collar Employment Outcomes Compared to National Employment Trends?

To examine how capital investment concentration relates to employment outcomes in manufacturing, this analysis compared state-level mean employment across four white-collar occupations (occupations 1 to 4) within NAICS 31–33 from 2018 to 2021. States were grouped into four quartiles based on their total capital expenditures (CAPEX), with Quartile 4 representing the highest-investment states. Figure 27 presents two employment indicators for each state: the bar height reflects the four-year average white-collar employment, while the green triangle markers show the average year-over-year (YoY) employment change. Together, these

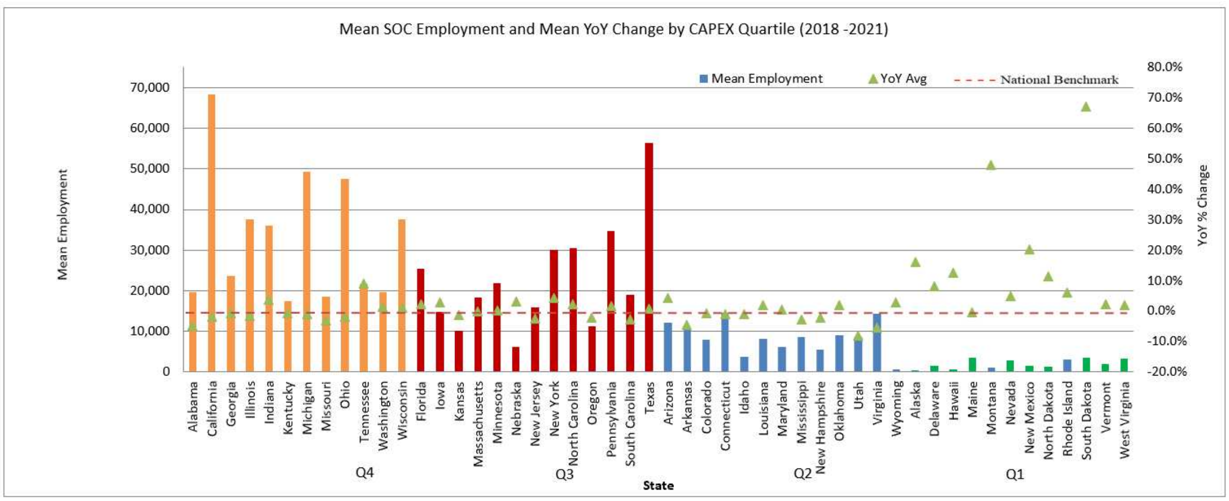

Figure 27

Total mean manufacturing employment by state (2018–2021), sorted by CAPEX quartile.

indicators highlight both the scale and trajectory of white-collar manufacturing employment across varying levels of investment intensity.

The occupational focus includes four supervisory and technical roles, as defined by Standard Occupational Classification (SOC) codes: Occupation 1 (Industrial Production Managers), Occupation 2 (Industrial Engineers), Occupation 3 (Engineering Technicians), and

Occupation 4 (First-Line Supervisors of Production and Operating Workers). Employment data for these roles were averaged at the state level and analyzed by CAPEX quartile. The findings reveal a clear and consistent relationship between investment intensity and white-collar employment outcomes. States in Quartiles 3 and 4, those with moderate to high levels of CAPEX, reported both higher average employment and more favorable YoY growth. For instance, Ohio (Quartile 4) averaged employment of over 46,000, well above the national per-state benchmark of 16,370 (4, with a positive employment trajectory. Similarly, Illinois, Texas, and Indiana also maintained employment levels two to three times above the national average, reflecting the demand for skilled managerial and technical labor in capital-intensive environments.

In contrast, Quartile 1 states, such as Montana, Alaska, and North Dakota, reported significantly lower average white-collar employment and more volatile growth patterns. Montana, for example, averaged fewer than 1,000 employees across the four occupations and exhibited extreme swings in YoY change, including a 368% increase in 2020 following a 75% drop the year prior. These states consistently underperformed relative to the national benchmark and showed particularly unstable employment patterns in engineering (Occupation 2) and technical (Occupation 3) roles. By comparison, average white-collar employment in Quartile 4 states was three to five times higher, highlighting a clear structural divide shaped by investment intensity.

Overall, these findings suggest that capital investment is a strong predictor of both the size and stability of white-collar employment in U.S. manufacturing. High-CAPEX states are more likely to sustain larger and more resilient supervisory and technical occupations, particularly in roles that support automation, operational oversight, and production system coordination. These results are consistent with prior research showing that modernization tends to augment rather than displace skilled labor, increasing demand for occupations that enable, manage, and complement technological transformation (Acemoglu & Restrepo, 2019; Bonfiglioli et al., 2020; Bessen & Righi, 2019; Domini et al., 2021).

Q6c: How Has CAPEX Quartile Level at the State Level Been Associated with Differences in Firm Growth Relative to National Averages?

This analysis explored whether states with higher levels of capital expenditure (CAPEX) also experienced greater firm growth in the manufacturing sector. Using data from 2018 to 2021, average firm counts were calculated for each U.S. state and grouped by CAPEX quartile, with Quartile 4 representing states with the highest capital investment. The analysis compared both the mean number of manufacturing firms and year-over-year (YoY) percentage changes across quartiles, with national trends used as a benchmark for contextual comparison.

States in Quartile 4 (highest CAPEX investment) displayed the highest average firm counts, suggesting that regions with greater capital investment generally support larger industrial environment. However, this association was not consistently linear across all measures. Several Quartile 1 and 2 states, despite lower overall CAPEX, showed notable firm growth in certain years. For example, states like Utah and Idaho recorded strong YoY increases in firm counts despite being outside the top investment quartile. This variation suggests that firm growth can occur independently of total investment levels and may be influenced by other regional or sectoral factors.

Figure 28 illustrates these trends, showing the mean firm count for each state grouped by CAPEX quartile, along with percentage labels indicating year-over-year change in firm totals. States above the national benchmark line typically represent more established manufacturing bases, while changes in firm count signal differing levels of market entry, retention, or exit. These visual patterns provide insight into both the density and dynamics of manufacturing firms across investment tiers.

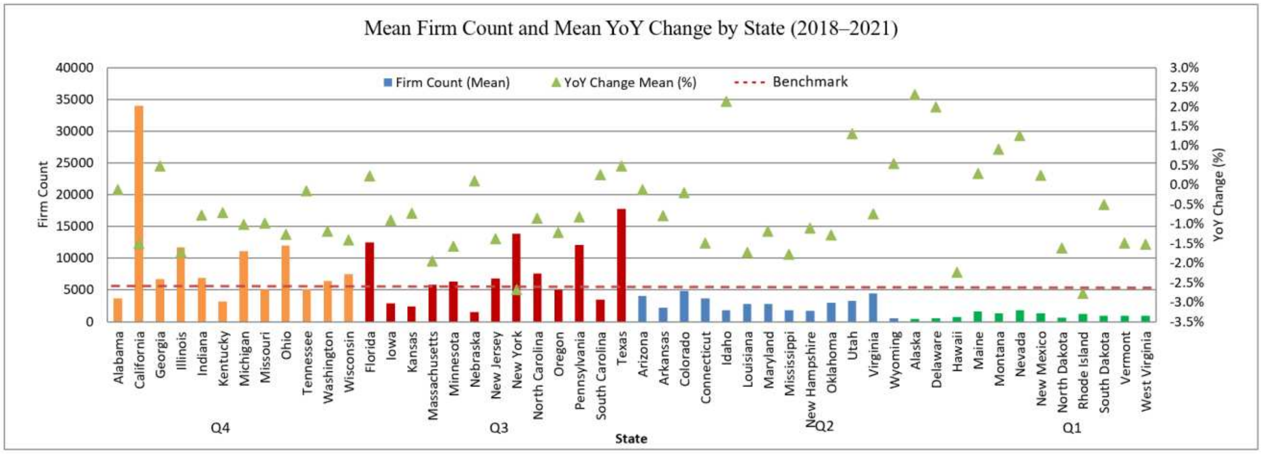

Figure 28

Mean manufacturing firm count and year-over-year change by state, grouped by CAPEX quartile (2018–2021).

Note: Bars represent each state's 4-year mean number of firms in the NAICS 31–33 manufacturing sector. Line markers indicate year-over-year percent change in firm count from 2018 to 2021. States are grouped by CAPEX quartile (Q4 = highest capital investment). The red dashed line denotes the national benchmark firm count, calculated as the national mean divided by the number of states (n=50).

A Pearson correlation between CAPEX quartile and year-over-year change in firm count yielded a weak and non-significant negative relationship (r = –0.21, p = .149), suggesting that CAPEX intensity is not reliably predictive of firm growth. These findings align with broader research on the organizational impacts of automation, which suggests that high levels of capital investment tend to concentrate in mature manufacturing regions with larger firm bases (Acemoglu & Restrepo, 2020; Bonfiglioli et al., 2020; Bessen & Righi, 2019). However, the lack of significant correlation with firm growth underscores the non-linear dynamics of automation-related restructuring. In many cases, firm consolidation, turnover, or context-specific scaling may obscure growth effects (Dixon et al., 2019; Waldman-Brown, 2020). This reinforces the need to distinguish between firm size and firm dynamism when evaluating the structural consequences of automation.

Summary

Based on national and state-level patterns, this chapter presented the empirical results of the study, which defined how CAPEX on robotic equipment corresponded to employment trends and firm composition in the U.S. manufacturing sector from 2018 to 2021. Although the study revealed that CAPEX investment grew consistently over the period, it remained significantly concentrated in a small number of industry sectors and states. Although sectors and states with highest CAPEX quartiles typically had more businesses and higher workforces, these investments were not consistently predictive of firm growth or consistent employment increases.

Nationally, total employment fell even as investment in automation grew, implying in some cases labor-displacing consequences. Particularly in Occupation 1 (industrial production managers), white-collar supervisory roles at the occupational level showed stronger positive alignment with both current and lagged CAPEX levels. While Occupation 2 (industrial engineers), and Occupation 3 (engineering technicians) showed more volatility over time, Higher CAPEX was linked to greater concentrations of white-collar employment, according to state-level data, but it did not consistently translate to an increase in firm counts, indicating geographical differences in automation diffusion. Previous studies have shown that industry characteristics, occupational structure, and regional capacity define the effects of automation investment, highlighting the unequal and context-dependent character of technological transformation (Acemoglu & Restrepo, 2020; Bessen & Righi, 2019; Domini et al., 2021; Waldman-Brown, 2020).

CHAPTER FIVE: DISCUSSION OF FINDINGS

The purpose of this study was to investigate how capital expenditures (CAPEX) on robotic automation relate to employment trends, white-collar occupational change, and firm composition across the U.S. manufacturing sector (NAICS 31–33). This chapter synthesizes the findings presented in Chapter Four and contextualizes them within broader economic and labor market developments. The following discussion is guided by the six core research questions, identifying structural patterns and interpreting the implications of the results. The chapter concludes with implications, limitations, and directions for future research.

Summary of the Study

This study examined how CAPEX in robotic automation has reshaped employment structures, occupational roles, and firm composition within the U.S. manufacturing sector. Guided by the growing social and economic concerns about the labor market impacts of automation, the research focused on how trends in CAPEX in robotic technologies relate to firm-composition changes and occupational shifts across national, state, and sub-industry levels between 2018 and 2021. While past studies have primarily focused on broad trends in automation-driven displacement, this study contributes novel empirical insights by analyzing variation at the sub-industry and state levels, with a specific emphasis on white-collar supervisory roles due to specific technological change (Autor, 2015; Acemoglu & Restrepo, 2019; Chiarini et al., 2023).

The study employed a descriptive and correlational research design. Using publicly available federal datasets, it integrated annual robotic-specific CAPEX data with firm counts and SOC-aligned occupational employment figures for four supervisory white-collar roles: Industrial Production Managers (SOC 11-3051), Industrial Engineers (SOC 17-2112), Mechanical

Engineering Technologists and Technicians (SOC 17-3027), and First-Line Supervisors of Production and Operating Workers (SOC 51-1011). The overall framework made possible an analysis of the structural impact of automation across time, industry sectors, and geography.

Findings indicated a consistent rise in CAPEX during the study period, and especially in capital-intensive sectors like transportation equipment and machinery manufacturing. Investment growth, though, did not come with the associated increases in employment. Instead, total employment declined, and the CAPEX showed high-negative correlations with the levels of workforce, mostly in the periods after large-scale investment. These results suggest that robotic automation is associated with gradual workforce restructuring rather than immediate displacement.

Occupational outcomes varied. Managerial roles showed consistent growth, a pattern that corresponded with expanded oversight functions observed in more automated environments. Engineering and technician roles displayed volatility, peaking during early implementation phases and declining thereafter. These patterns suggest that automation's effects are not uniformly disruptive or beneficial but are contingent on occupational function, industry context, and timing.

Firm composition analysis revealed that industries in the highest CAPEX quartile experienced the greatest declines in firm count, suggesting a trend toward consolidation. Firm composition analysis revealed that industries in the highest CAPEX quartile experienced the steepest declines in firm count, suggesting a trend toward consolidation. This trend could mean that larger firms have a better position to deal with the expenses of automation and to scale investment (Acemoglu et al., 2023; Bessen & Righi, 2019). At the state level, high CAPEX investment was not always associated with employment gains, reflecting the influence of regional factors such as workforce composition, industry structure, and prevailing policy environments (Bonfiglioli et al., 2020; Chiarini et al., 2023).

This study illustrates that automation investment is neither uniformly disruptive nor broadly beneficial but, instead, generate variable outcomes across occupations, geographic regions, and in industry firm composition. The findings are consistent with broader literature suggesting that automation simultaneously displaces, transforms, and reorganizes labor, depending on organizational and economic conditions (Domini et al., 2021; Dosi et al., 2021). The complex characteristics of robotic automation are profoundly reshaping U.S. manufacturing in multidimensional and uneven ways, with discernible trends manifesting across industries, occupations, and states, thus providing a foundation for workforce planning, policy, and future research. At the same time, limitations in current data, such as reporting lags and the absence of detailed demographic and financial variables, constrain more granular analysis of distributional effects. It is important to understand how automation capital interfaces with employment systems and corporate dynamics to support inclusive, context-dependent approaches in the face of a progressively automated industrial economy (Agrawal et al., 2019; Arntz et al., 2017; Autor, 2019).

Discussion of Findings

This study examined the relationship between CAPEX on robotic equipment and employment patterns, occupational roles, and firm composition within the U.S. manufacturing sector (NAICS 31–33) from 2018 to 2021. Utilizing a descriptive analytical method supported with correlational and trend analysis, these findings bridge knowledge gaps by revealing how automation-related investments align with uneven employment responses across states and industries, particularly when stratified by CAPEX quartiles and white-collar occupational roles.

Q1: What are the observable trends in capital expenditures (CAPEX) on robotic equipment across U.S. manufacturing industries (NAICS 31–33) between 2018 and 2021?

Between 2018 and 2021, total CAPEX increased from $2.62B to $3.76B nationally with top quartile industries like NAICS 336 (Transportation Equipment) averaging over $1.19B, exceeding Quartile 1 industries such as NAICS 313 (Textile Mills) and NAICS 323 (Printing and Related Support Activities). This finding is consistent with existing research that indicates that industries with high capital intensity and exposure to international markets are likely to adopt automation more (Bessen & Righi, 2019; Dosi et al., 2021).

The uneven distribution of CAPEX across the manufacturing sub-industries reflects underlying sector-specific dynamics, including differences in profit margins, exposure to international competition, and technological readiness (Autor et al., 2022; Bonfiglioli et al., 2020). These findings reinforce the view that automation adoption does not follow a uniform path but instead progresses through distinct industrial trajectories shaped by structural and contextual factors.

Q2: How Does CAPEX Influence Total Firm Employment Outcomes in the U.S. Manufacturing Sector From 2018 To 2021?

A strong negative correlation ($r \approx -0.98$) was observed between total capital expenditures (CAPEX) and aggregate manufacturing employment across the NAICS 31–33 sector during the 2018 to 2021 period. This inverse relationship suggests that increased automation investment is broadly associated with reductions in workforce size. However, sub-industry comparisons reveal more complex dynamics. For example, NAICS 333 (Machinery Manufacturing) recorded a 74.7% increase in CAPEX while experiencing a 4.3% decline in employment, whereas NAICS

336 (Transportation Equipment Manufacturing) also demonstrated substantial CAPEX growth and maintained relative employment.

These findings highlight the necessity of incorporating lagged effects into explanatory models, as employment responses often do not occur concurrently with capital investment. This temporal lag is consistent with recent research, which emphasizes that productivity gains from emerging technologies, particularly those linked to generative AI technologies and automation, may not immediately displace labor but instead reconfigure task allocation and job structures over time (Dillon et al., 2025). The relationship between CAPEX and employment should be interpreted within a sector-specific and time-sensitive framework, recognizing the varying capacities of sub-industries to absorb and integrate automation technologies.

Q3: How Does CAPEX Affect Employment in White-Collar Supervisory Occupations Across Manufacturing Sub-Sectors From 2018 To 2021?

Analysis of white-collar supervisory occupations revealed differentiated employment trajectories in response to capital investment in automation technologies. Among the four targeted occupations, lagged correlations between capital expenditures (CAPEX) and subsequent employment levels were strongest for Occupation 1 (industrial production managers) and Occupation 4 (first line supervisors). These findings suggest that managerial and supervisory roles are more positively aligned with the implementation cycles of robotic technologies, reflecting the increased need for oversight, coordination, and system-level integration in automated production environments.

By contrast, employment in engineering and technical roles demonstrated greater volatility and weaker alignment with capital investment. Occupation 2 (industrial engineers) exhibited a moderately strong negative lagged correlation, suggesting that increased automation investment may not reliably support sustained employment in this category. Occupation 3 (engineering technicians) showed a moderate positive association, but with inconsistent year-over-year variation. These results align with recent literature noting that high-skill roles in engineering and technical fields may be increasingly susceptible to disruption from generative AI, advanced robotics, and automation-assisted design tools that alter traditional task structures (Mindell & Reynolds, 2023; Dillon et al., 2025).

Q4: How Does CAPEX Relate to Firm Composition Trends in U.S. Manufacturing From 2018 to 2021?

Industries classified within the highest capital expenditure quartile experienced an average firm count decline of approximately, despite demonstrating the greatest growth in CAPEX investment. This pattern suggests a structural shift toward consolidation, where increased CAPEX supports operational scaling and process optimization, often at the expense of firm proliferation. In contrast, industries in lower CAPEX quartiles, particularly Quartile 3, experienced only modest reductions in firm counts despite more moderate investment levels, indicating a potential threshold effect in which only the most capital-intensive industries undergo substantive structural consolidation.

This trend is further supported by the observed weak and statistically non-significant correlation between changes in CAPEX and firm counts across the sector, suggesting that automation investment is not consistently associated with firm expansion. Rather, it appears to facilitate efficiency-driven realignment, in which fewer, larger firms dominate increasingly automated production ecosystems. These results align with prior research indicating that automation adoption frequently accelerates industry concentration, favoring firms with the financial and technological capacity to scale (Bonfiglioli et al., 2020; Domini et al., 2021).

Furthermore, (Waldman-Brown, 2020) noted that small and mid-sized firms often face heightened challenges in adapting to capital-intensive automation transitions, which may result in reduced competitiveness or exit from the sector altogether. These findings underscore the dual effect of automation on organizational structure: enhancing productivity while contributing to market consolidation and reduced firm diversity.

These patterns are consistent with broader recent research of automation adoption, which suggest that leadership and supervisory functions, particularly those emphasizing coordination, exception handling, and system monitoring, are more likely to expand in highly automated environments (Autor et al., 2024; Robotics, 2025). In contrast, technical roles often experience fluctuating demand, contingent upon the routinization of tasks and the specific ways automation is implemented across industries. (Autor et al., 2024) emphasized that while automation can displace certain categories of labor, it simultaneously increases demand for roles that complement technology, particularly those involving judgment, oversight, and complex problem-solving.

Q5: How Does CAPEX Vary Across U.S. States, and How Is It Associated with Differences in Employment and Firm Composition From 2018 to 2021?

State-level analysis revealed substantial volatility in capital investment patterns across the U.S. manufacturing sector between 2018 and 2021. Year-over-year correlations in CAPEX were inconsistent and frequently negative, with coefficients, indicating a lack of continuity in investment behavior across time. While states in the highest investment tier (Quartile 4) reported the largest mean CAPEX levels and the strongest positive association with white-collar employment, they did not consistently experience greater firm growth. In fact, several high-

CAPEX states showed declining firm counts, suggesting that capital investment alone does not guarantee expansion and may instead contribute to consolidation or restructuring.

These findings emphasize the geographically unequal effects of automation whereby structural benefits, including proximity to capital, initial firm size, and technological infrastructure, compound imbalances in labor and firm dynamics. This explanation is consistent with research showing that automation will disproportionately locate economic activity in already capital-intensive areas and can accelerate firm-level concentration and inequality within labor markets (Acemoglu, 2021; Bonfiglioli et al., 2020; Domini et al., 2021).

Q6: How Does CAPEX Investment at the State Level Compare with National Trends, and How is it Associated with Differences in Employment and Firm Composition From 2018 To 2021

While national CAPEX on automation technologies increased steadily from 2018 to 2021, state-level trends reveal revealed growing unevenness in both investment intensity and labor market outcomes. Only a subset of states exceeded the national per-state CAPEX benchmark, highlighting the geographic concentration of automation-related investments. Employment growth was also not uniformly distributed but disproportionately concentrated in states within the highest CAPEX quartile, particularly among white-collar supervisory occupations. In contrast, lower-CAPEX states often experienced stagnant or declining employment levels, reinforcing spatial disparities in technological adoption and workforce transformation.

Furthermore, a weak negative correlation between CAPEX growth and firm count change at the state level which suggests that increased automation investment is more closely associated with organizational restructuring and consolidation than with entrepreneurial expansion. These findings align with prior studies demonstrating that automation often enhances productivity within existing firms while simultaneously creating barriers to market entry for smaller or less capitalized firms (Acemoglu & Restrepo, 2020; Domini et al., 2021; Graetz & Michaels, 2018). These findings taken together suggest a complex, spatially uneven automation environment formed by local conditions as well as national investment patterns.

Implications

The findings of this study carry important implications for industry leaders, policymakers, and researchers seeking to understand and manage the ongoing effects of automation investment in the U.S. manufacturing sector.

For Industry Leaders

The observed growth in white-collar managerial roles underscores the increasing importance of investing in white-collar capacity, particularly in domains such as systems coordination, data analytics, and technology management. Between 2019 and 2022, Occupation 1 (industrial production managers) experienced a 22.5% increase in employment, making it the most consistent area of growth among the supervisory occupational categories examined in the manufacturing sector. This trend corresponded with a strong positive correlation between CAPEX and employment in this occupational group ($r \approx 0.80$), suggesting that managerial functions are becoming increasingly important to the operationalization of automation technologies. Bessen and Righi (2019), observed that large-scale IT and automation investments often elevate the demand for managerial and coordination roles rather than eliminate them. Similarly, Domini et al. (2021) identified automation investment as a catalyst for workforce restructuring, particularly in white-collar roles associated with overseeing integrated systems and technical processes. Together, these results reinforce the notion that managerial employment is not displaced by automation but is instead reshaped and expanded in support of more complex, technology-driven production environments. These findings support an emerging academic research that managerial roles are not displaced by automation but are instead restructured and expanded to facilitate more technology-oriented production environments (Autor et al., 2024).

For Policymakers

The decline in the size of firms in the high-CAPEX quartiles reflects the increased investment in robotic automation fueling consolidation in the industry. Though this analysis did not directly measure firm size, the emerging trend causes concern about the possible disproportionate impact on smaller manufacturers from increased capital intensity and the pressure of competition. Policies aimed at improving capital access for small and mid-sized firms may help offset these challenges (Bessen & Righi, 2019). Workforce development initiatives can support these at-risk workers through retraining in high-demand technical areas such as robotics maintenance, AI-enhanced diagnostics, and systems integration (Arntz et al., 2017; Dillon et al., 2025; Dosi et al., 2021). Additionally, policymakers should consider promoting regional innovation hubs that explicitly link automation adoption to inclusive workforce development. Cross-sector partnerships among industry, educational institutions, and local governments can help ensure that the benefits of automation are distributed more equitably across geographies and workforce segments (Altenried, 2022; Autor et al., 2022).

For Researchers

The findings emphasize the importance of extending the temporal scope of analysis. While this study covers 2018 to 2021, more recent data will be critical to assessing post-pandemic automation dynamics and distinguishing between short-term disruptions and long-term structural trends. The U.S. Census Bureau has transitioned from the Annual Survey of Manufactures (ASM) to the new Annual Integrated Economic Survey (AIES), with manufacturing data for the 2023 survey year collected in 2024 and scheduled for release in 2025 (U.S. Census Bureau, n.d.). The expanded scope and integrated design of the AIES may allow future research to capture more detailed firm-level indicators related to automation and performance. In addition, linking CAPEX to broader outcomes, such as productivity, profitability, and innovation, could yield a more comprehensive understanding of automation's organizational effects (Bonanomi, 2019; Graetz & Michaels, 2018). Finally, qualitative methods such as case studies or interviews could offer important information about how firms internally adapt to automation, including decision-making processes, strategic planning, and cultural change (Church & Burke, 2017).

Limitations

This study has several limitations that should be considered when interpreting the findings. First, as a descriptive study supported by complementary correlational analysis, the research was designed to identify patterns and associations, not to establish causality. While strong correlations were observed between CAPEX and employment or firm composition, these relationships cannot be interpreted as causal. It is possible that broader macroeconomic or sector-specific forces influenced both automation investment and workforce changes simultaneously.

Second, the analysis is based upon standardized occupational groups developed from the United States Standard Occupational Classification (SOC) system. Although this allows for cross-country comparison, the variation within certain occupations might inadvertently be obscured. As a result, groups like "engineers" or "technicians" might include a broad range of tasks, levels of exposure to automation, or workplaces, differences that could not be examined within the structure of this dataset (Frey et al., 2016).

Third, the data set spans a period heavily impacted by the COVID-19 pandemic, particularly in the years 2020 and 2021. Although year-to-year comparisons were used to reduce the impact of short-run shocks, the distortions introduced to labor markets and capital investment by the pandemic could still have created inaccurate outcomes. As a result, some findings that emerge from the data might be short-run anomalies rather than lasting consequences associated with automation.

Fourth, the study could not incorporate data related to the exits of companies, such as closure, acquisition, or mergers, as a result of the limitations of publicly available data. Such a limitation is problematic in assessing the total concentration rate of the industry, and more so for small and medium-sized companies that are not represented fully in the national statistical data (Bessen & Righi, 2019).

Fifth, aggregating datasets from multiple federal sources, each with its own structure, update frequency, and geographic or industrial scope, introduced challenges related to alignment and comparability. For example, matching CAPEX data from the Annual Survey of Manufactures with occupational employment data from the Occupational Employment and Wage Statistics (OEWS) program required cross-referencing distinct timeframes and classification systems. These types of multi-source aggregations can introduce measurement inconsistencies, data harmonization errors, or temporal mismatches (Groshen, 2021; Molloy et al., 2011).

Finally, a key limitation is the lag in federal data reporting. The most recent manufacturing data available at the time of analysis were from 2021, following the discontinuation of the Annual Survey of Manufactures (ASM)(Bureau, n.d.–a). Future automation investment trends will be reported under the new Annual Integrated Economic Survey (AIES), with the first release of manufacturing-specific data for the 2023 survey year expected in 2025 (U.S. Census Bureau, n.d.). This reporting delay constrains the study's ability to capture post-pandemic automation patterns and more recent investment effects.

Directions for Future Research

In response to the findings and constraints of the study, there are various lines of follow-up inquiry. First, future studies should investigate what effects firm-level characteristics, firm size, unionization, or industry concentration, have upon the impact of automation upon organizational and employment structures. Previous research has shown that unionized firms could pursue differing approaches to automation, including negotiating retraining programs or delaying workforce reduction (Acemoglu & Restrepo, 2020; Freeman, 2019; Freeman, 2015). Additionally, researchers should investigate the dynamic interaction between occupational exposure to automation and demographic indicators. When considering employment outcomes across gender, age, and education, matters of inequality take on greater significance, especially as the structure of engineering and technical occupations is constantly developing (Chiarini et al., 2023; Frey et al., 2016).

A focused analysis using 4-digit NAICS industry codes would allow for a more accurate differentiation among the sub-sectors and potentially uncover industry-specific trends masked at the 3-digit classification level. For example, the trends for the use of automation in the production of aerospace would be expected to differ from the manufacturers of farm machinery, even if both industries fall under NAICS code 336. Further research could also extend beyond the manufacturing sector to examine how automation-related investment is shaping workforce outcomes in other domains of the economy. While robotics deployment is better documented in logistics and intralogistics contexts, particularly within transportation and warehousing (NAICS 48–49)(*World robotics Industrial Robots 2019.*, 2019), another important growth area is agriculture (NAICS 11), where automation technologies such as robotic harvesters, drones, and precision farming systems are increasingly transforming production processes (Andrew et al., 2019; Jamwal et al., 2021). Broadening the scope of analysis to these sectors would provide a more comprehensive understanding of how robotics and automation intersect with different organizational and labor market structures.

Future studies should include a larger set of outcome variables to fully capture the far-reaching effects of automation. Examples of such variables could include measures of firm-level productivity, wage patterns, profit margins, or innovation indicators, and all are important for evaluating the overall macro-economic effects of investment in robotic capita (Graetz & Michaels, 2018; Kogan et al., 2023). Combining these quantitative measures with qualitative methods would provide a more comprehensive picture of how companies adapt to technologic change in realistic situations.

Additionally, future research should expand beyond the U.S. context to examine how robotic automation affects employment levels and firm counts in other regions. Given that the North American Industry Classification System (NAICS) is harmonized across Canada, Mexico, and the U.S., comparative studies could yield valuable insights into whether similar industries experience parallel or divergent outcomes from automation. Beyond North America, extending this line of research to regions such as Europe or China would provide a broader understanding of how automation-related investments reshape workforce composition and firm structures in different economic systems. These cross-national comparisons would not only enhance the external validity of U.S.-based findings but also highlight the global patterns and variations in automation's organizational and labor market impacts.

Conclusion

This study contributes to the understanding of how investments in robot-specific capital affect labor markets, and especially supervisory positions in white-collar sectors and firm dynamics within U.S. manufacturing. While robotic automation has enabled growth in white-collar managerial occupations, it has also introduced greater uncertainty for technical roles and contributed to the consolidation of firms. These patterns coincided with a broader decline in total manufacturing employment during the study period, despite rising capital investment, pointing to the complex and uneven structural changes reshaping the sector. The effects of these changes vary by occupation, region, and sub-industry, pointing to the need for workforce strategies and policy responses that are tailored to specific local environments. As federal statistical infrastructures are brought up to date and automation technologies continue to become ever-more sophisticated, future scholarship can build upon these findings to derive more responsive, adaptive, equitable, and evidence-based responses to industrial automation transformation.

REFERENCES

Acemoglu, D., & Restrepo, P. (2021). Tasks, automation, and the rise in us wage inequality. *NBER Working Paper No. 28920*. https://doi.org/https://doi.org/10.3386/w28920

Acemoglu, D., Anderson, G. W., Beede, D. N., Buffington, C., Childress, E. E., Dinlersoz, E., Foster, L. S., Goldschlag, N., Haltiwanger, J. C., & Kroff, Z. (2022). *Automation and the workforce: A firm-level view from the 2019 Annual Business Survey*.

Acemoglu, D., & Autor, D. (2010). Skills, Tasks and Technologies: Implications for Employment and Earnings. *National Bureau of Economic Research Working Paper Series*, *16082*. https://doi.org/10.3386/w16082

Acemoglu, D., Koster, H. R., & Ozgen, C. (2023). *Robots and workers: Evidence from the Netherlands*. https://www.nber.org/papers/w31009

Acemoglu, D., & Restrepo, P. (2017a). The Race between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment. *SSRN Electronic Journal*, *(Vol. 22252)*. https://doi.org/10.2139/ssrn.2781320

Acemoglu, D., & Restrepo, P. (2017b). Secular Stagnation? The Effect of Aging on Economic Growth in the Age of Automation. *American Economic Review*, *107*(5), 174–179. https://doi.org/10.1257/aer.p20171101

Acemoglu, D., & Restrepo, P. (2018). Low-Skill and High-Skill Automation. *Journal of Human Capital*, *12*(2), 204–232. https://doi.org/10.1086/697242

Acemoglu, D., & Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives*, *33*(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Acemoglu, D., & Restrepo, P. (2020). Unpacking Skill Bias: Automation and New Tasks. *AEA Papers and Proceedings*, *110*, 356–361. https://doi.org/10.1257/pandp.20201063

Aghion, P., Antonin, C., Bunel, S., & Jaravel, X. (2021). The direct and indirect effects of automation on employment: A survey of the recent literature. *Unpublished manuscript*.

Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction [NBER Working Paper No. 25619]. 1–26. https://doi.org/10.1186/s41469-019-0050-0

Altenried, M. (2022). *The digital factory: The human labor of automation*. University of Chicago Press.

Anderson, J., & Rainie, L. (2023). The future of human agency. *Pew Research Center.*

Andrew, J. J., Srinivasan, S. M., Arockiarajan, A., & Dhakal, H. N. (2019). Parameters influencing the impact response of fiber-reinforced polymer matrix composite materials: A critical review. *Composite Structures*, *224*, 111007.

AOM. (2022). *The 82nd annual meeting of the academy of management: A hybrid experience: Program agenda* https://my.aom.org/ProgramDocs/2022/pdf/AOM_2022_Annual_Meeting_Program.pdf

Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters*, *159*, 157–160. https://doi.org/10.1016/j.econlet.2017.07.001

Arockiarajan, A., Duraiselvam, M., Raju, R., & (Eds.). (2019). *Advances in Industrial Automation and Smart Manufacturing: Select Proceedings of ICAIASM 2019*. Springer.

Autor, D. (2019). Work of the Past, Work of the Future. *Social Science Research Network*. https://doi.org/10.3386/w25588 (NBER Working Paper Series)

Autor, D., Chin, C., Salomons, A., & Seegmiller, B. (2022). New frontiers: The origins and content of new work 1940-2018. *MIT Economics Working Paper Series*, 80. https://doi.org/10.3386/w30389

Autor, D., Dorn, D., Hanson, G., & Majlesi, K. (2024). Industrial Robots and Employment Gaps in the U.S. *American Economic Journal: Macroeconomics*.

Autor, D. H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives*, *29*(3), 3–30. https://doi.org/10.1257/jep.29.3.3

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration*. *The Quarterly Journal of Economics*, *118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Avent-Holt, D., & Tomaskovic-Devey, D. (2010). The relational basis of inequality: Generic and contingent wage distribution processes. *Work and Occupations*, *37*(2), 162–193.

Barley, S. R. (1998). What can we learn from the history of technology? *ournal of Engineering and Technology Management*, *15*(4), 237–255.

Bessen, J. (2022). *The New Goliaths*

How Corporations Use Software to Dominate Industries, Kill Innovation, and Undermine Regulation. Yale University Press. https://doi.org/10.2307/j.ctv2jn91q7

Bessen, J., & Righi, C. (2019). Shocking technology: what happens when firms make large IT investments? *Boston University School of Law, Law and Economics Research Paper*.

Bonanomi, M. M. (2019). *Digital Transformation of Multidisciplinary Design Firms*. https://doi.org/10.1007/978-3-030-19701-8

Bonfiglioli, A., Crino, R., Fadinger, H., & Gancia, G. (2020). Robot imports and firm-level outcomes. *CESifo Working Papers*.

Brettel, M., Friederichsen, N., Keller, M., & Rosenberg, M. . (2014). How Virtualization, Decentralization and Network Building Change the Manufacturing Landscape: An Industry 4.0 Perspective. *International Journal of Information and Communication Engineering*, *8*(1), 37–44.

Brynjolfsson, E., & McAfee, A. (2011). *Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy*. Brynjolfsson and McAfee.

Brynjolfsson, E., Mitchell, T., & Rock, D. (2018). What Can Machines Learn and What Does It Mean for Occupations and the Economy? *AEA Papers and Proceedings*, *108*, 43–47. https://doi.org/10.1257/pandp.20181019

Bureau of Labor, S. (n.d.). *County Business Patterns (CBP)*. https://www.census.gov/programs-surveys/cbp.html

Bureau of Labor Statistics. (n.d). *Disclosure avoidance and data protection*

Handbook of Methods: Confidentiality. Retrieved from

https://www.census.gov/about/policies/privacy/statistical_safeguards.htmlER

https://www.bls.gov/opub/hom/methodology.htmER

Bureau, U. S. C. (n.d.–a). *Annual Survey of Manufactures (ASM)*. https://www.census.gov/programs-surveys/asm.html

Bureau, U. S. C. (n.d.–b). *Statistics of U.S. Businesses (SUSB)*. https://www.census.gov/programs-surveys/susb.html

Canada, G. o. (2017). *Learning Nation: Equipping Canada's Workforce with Skills For The Future*.

Card, D., & DiNardo, J. E. (2002). Skill-biased technological change and rising wage inequality: Some problems and puzzles. *Journal of labor economics*, *20*(4), 733–783.

Caroli, E., & Van Reenen, J. (2001). Skill-Biased Organizational Change? Evidence from A Panel of British and French Establishments*. *The Quarterly Journal of Economics*, *116*(4), 1449–1492. https://doi.org/10.1162/003355301753265624

Chermack, T. J., & Nimon, K. (2013). Drivers and outcomes of scenario planning: a canonical correlation analysis. *European Journal of Training and Development*, *37*(9), 811–834. https://doi.org/10.1108/ejtd-03-2013-0030

Chiarini, A., Grando, A., Venturini, S., & Borgonovo, E. (2023). Do automation and AI impact on job reduction? A study on perceived risk of losing job among white-collars in the Italian manufacturing companies. *Production Planning & Control*, 1–14.

Chin, A., Juhn, C., & Thompson, P. (2006). Technical Change and the Demand for Skills during the Second Industrial Revolution: Evidence from the Merchant Marine, 1891–1912. *Review of Economics and Statistics*, *88*(3), 572–578. https://doi.org/10.1162/rest.88.3.572

Chowdhury, R. (2019). *Systems Thinking for Management Consultants*. Springer Publishing. https://doi.org/10.1007/978-981-13-8530-8_1

Church, A., & Burke, W. (2017). Four Trends Shaping the Future of Organizations and Organization Development. *OD Practitioner*, *49*, 14–22.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Routledge. https://doi.org/https://doi.org/10.4324/9780203771587

Cotgrove, S. (1975). Technology, Rationality and Domination. *Social Studies of Science*, *5*(1), 55–78. https://doi.org/10.1177/030631277500500104

Creswell, J. W. (2013). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. SAGE Publications, Inc.

Cummings, T. G., & Worley, C. G. (2015). *Organization Development and Change*. Cengage Learning.

Deloitte. (2017). *Industry 4.0 and manufacturing ecosystems*. D. U. Press.

Deloitte. (2024). *2024 Manufacturing Industry Outlook: Building Smart, Resilient, and Sustainable Operations*. https://www2.deloitte.com/us/en/insights/industry/manufacturing/manufacturing-industry-outlook.html

DeWitt, T. W. (2019). *Mapping the transition of work in labor markets and entrepreneurial organizations* [Dissertation, University of Michigan]. ProQuest Dissertations & Theses, Ann Arbour.

Dillender, M., & Forsythe, E. (2019). Computerization of White Collar Jobs. *Social Science Research Network*, 19–310. https://doi.org/10.17848/wp19-310

Dillon, E., Lee, S., Lin, H., & Zhang, D. (2025). Generative AI's Effect on Productivity in Knowledge Work. *arXiv*.

Dixon, J., Hong, B., & Wu, L. (2019). The Employment Consequences of Robots: Firm-Level Evidence. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3422581

Domini, G., Grazzi, M., Moschella, D., & Treibich, T. (2021). Threats and opportunities in the digital era: automation spikes and employment dynamics. *Research Policy*, *50*(7), 104137.

Dosi, G., Piva, M., Virgillito, M. E., & Vivarelli, M. (2021). Embodied and disembodied technological change: The sectoral patterns of job-creation and job-destruction. *Research Policy*, *50*(4). https://doi.org/10.1016/j.respol.2021.104199

Dzedzickis, A., Vaičiūnas, G., Lapkauskaitė, K., Viržonis, D., & Bučinskas, V. (2024). Recent advances in human–robot interaction: robophobia or synergy. *Journal of Intelligent Manufacturing*. https://doi.org/10.1007/s10845-024-02362-x

Economics, O. (2019). How robots change the world: What automation really means for jobs and productivity. *Oxford Economic Outlook*, *43*(3), 5–8. https://doi.org/10.1111/1468-0319.12431

Estlund, C. L. (2017). What Should We Do After Work? Automation and Employment Law. *Yale Law Journal*. https://doi.org/10.2139/ssrn.3007972

Field, A. (2017). *Discovering Statistics Using IBM SPSS Statistics* (Fourth ed.). SAGE Publications Ltd.

Filippi, E., Bannò, M., & Trento, S. (2023). Automation technologies and their impact on employment: A review, synthesis and future research agenda. *Technological Forecasting and Social Change*, *191*, 122448. https://doi.org/https://doi.org/10.1016/j.techfore.2023.122448

Finneran, K. (2018). Overdetermined. *Issues in Science and Technology*, *35*(1), 1–19.

Fish, A. (2012). *Knowledge Automation: How to Implement Decision Management in Business Processes*. John Wiley & Sons, Inc.

Ford, M. (2015). *Rise of the robots: technology and the threat of a jobless future*. Basic Books.

Freeman, C. (2019). History, Co-Evolution and Economic Growth. *Industrial and Corporate Change*, *28*(1), 1–44. https://doi.org/10.1093/icc/dty075

Freeman, R. (2015). Who owns the robots rules the world. *IZA, World of labor, Harvard University, USA, and IZA, Germany*.

Frey, C. B., Osborne, M. A., & Holmes, C. (2016). *Technology at work v2.0: the future is not what it used to be.* C. Group.

Garicano, L., & Rossi-Hansberg, E. (2006). Organization and Inequality in a Knowledge Economy. *The Quarterly Journal of Economics*, *121*(4), 1383–1435. https://doi.org/10.1093/qje/121.4.1383

Gliner, J. A., Morgan, G. A., & Leech, N. L. (2017). *Research Methods in Applied Settings: An Integrated Approach to Design and Analysis* (Third ed.). Routledge.

Grace, K., Salvatier, J., Dafoe, A., Zhang, B., & Evans, O. (2018). Viewpoint: When Will AI Exceed Human Performance? Evidence from AI Experts. *Journal of Artificial Intelligence Research*, *62*, 729–754. https://doi.org/10.1613/jair.1.11222

Graetz, G., & Michaels, G. (2018). Robots at Work. *The Review of Economics and Statistics*, *100*(5), 753–768. https://doi.org/10.1162/rest_a_00754

Grant, R., Valdani, E., & Arbore, A. (2013). *Competitive Strategies: Managing the Present, Imagining the Future*. Palgrave Macmillan.

Groshen, E. L. (2021). The future of official statistics. *Harvard Data Science Review*, *3*(4).

Gruchmann, T., Mies, A., Neukirchen, T., & Gold, S. (2021). Tensions in sustainable warehousing: including the blue-collar perspective on automation and ergonomic workplace design. *Journal of Business Economics*, *91*(2), 151–178. https://doi.org/10.1007/s11573-020-00991-1

Hanley, C. (2013). Putting the Bias in Skill-Biased Technological Change? A Relational Perspective on White-Collar Automation at General Electric. *American Behavioral Scientist*, *58*(3), 400–415. https://doi.org/10.1177/0002764213503339

Hatch, M. J., & Cunliffe, A. L. (2013). *Organization Theory: Modern, Symbolic, and Postmodern Perspectives* (3rd, Ed.). Oxford Universtity Press.

Jamwal, A., Agrawal, R., Sharma, M., & Giallanza, A. (2021). Industry 4.0 technologies for manufacturing sustainability: A systematic review and future research directions. *Applied Sciences*, *11*(12), 5725.

Kanagachidambaresan, G. R., Anand. R., Mahima. V. (2020). *Internet of Things for Industry 4.0* (Vol. EAI Springer Innovations in Communication and Computing). Springer International Publishing. https://doi.org/https://doi.org/10.1007/978-3-030-32530-5

Kasowaki, L., & Jack, E. (2023). Robots at Work: Robotics Process Automation and the Future of Employment.

Keltner, D., Gruenfeld, D. H., & Anderson, C. (2003). Power, Approach, and Inhibition. *Psychological review*, *110*(2), 265–284. https://doi.org/10.1037/0033-295X.110.2.265

Keynes, J. M. (1930). Economic Possibilities for our Grandchildren. *Essays in Persuasion*, 358–373. https://doi.org/10.7551/mitpress/7757.003.0004 (2008) (Original work published Harcourt Brace, 1932)

Kogan, L., Papanikolaou, D., Schmidt, L. D., & Seegmiller, B. (2023). *Technology and labor displacement: Evidence from linking patents with worker-level data*. http://www.nber.org/papers/w31846

Kromann, L., Malchow-Møller, N., Skaksen, J. R., & Sørensen, A. (2020). Automation and productivity—a cross-country, cross-industry comparison. *Industrial and Corporate Change*, *29*(2), 265–287.

Leavitt, H. J. (1958). Management in the 1980's. *Harvard Business Review*, *36*(6), 41–48.

Lim, J., Aklin, M., & Frank, M. R. (2023). Location is a major barrier for transferring US fossil fuel employment to green jobs. *Nature Communications*, *14*(1), 5711. https://doi.org/10.1038/s41467-023-41133-9

Lloyd, C. T., Chamberlain, H., Kerr, D., Yetman, G., Pistolesi, L., Stevens, F. R., Gaughan, A. E., Nieves, J. J., Hornby, G., MacManus, K., Sinha, P., Bondarenko, M., Sorichetta, A., & Tatem, A. J. (2019). Global spatio-temporally harmonised datasets for producing high-resolution gridded population distribution datasets. *Big Earth Data*, *3*(2), 108–139. https://doi.org/10.1080/20964471.2019.1625151

Machi, L. A., & McEvoy, B. T. (2016). *The literature review: Six steps to success*. Corwin Press.

Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Willmott, P., & Dewhurst, M. (2017). *A future that works: Automation, employment, and productivity* (McKinsey Global Institute, Issue. M. Company.

McGuinness, S., Pouliakas, K., & Redmond, P. (2021). Skills-displacing technological change and its impact on jobs: challenging technological alarmism? *Economics of Innovation and New Technology*, 1–23. https://doi.org/10.1080/10438599.2021.1919517

McKinsey. (2025). *The State of AI in 2025: How Organizations Are Rewiring to Capture Value*. https://www.mckinsey.com/~/media/mckinsey/business%20functions/quantumblack/our%20insights/the%20state%20of%20ai/2025/the-state-of-ai-how-organizations-are-rewiring-to-capture-value_final.pdf

Megginson, L. C. (1963). Lessons from Europe for American Business. *The Southwestern Social Science Quarterly*, *44*(1), 3–13.

Mindell, D. A., & Reynolds, E. (2023). *The work of the future: Building better jobs in an age of intelligent machines*. Mit Press.

Mintzberg, H., Ahlstrand, B., & Lampel, J. (1998). *Strategy safari: A guided tour through the wilds of strategic management* (First ed.). The Free Press.

Molloy, R., Smith, C. L., & Wozniak, A. (2011). Internal Migration in the United States. *Journal of Economic Perspectives*, *25*(3), 173–196. https://doi.org/10.1257/jep.25.3.173

Morgan, G. A., Barrett, K. C., Leech, N. L., & Gloeckner, G. W. (2013). *IBM SPSS for introductory statistics* (5th ed.). Routledge, Taylor et Francis Group.

*National Center for O*NET Development. O*NET OnLine*. (n.d.). https://www.onetonline.org/

Nissen, V. (2018). *Digital Transformation of the Consulting Industry* (1 ed.). Springer International Publishing. https://doi.org/10.1007/978-3-319-70491-3

Nissen, V., & Seifert, H. (2016). *Virtualization of Consulting – Benefits, Risks and a Suggested Decision Process.* Twenty-first Americas Conference on Information Systems, Puerto Rico, 2015.

North, K., Haas, O., & Maier, R. (2018). *Knowledge Management in Digital Change* (1st ed.). Springer International Publishing. https://doi.org/10.1007/978-3-319-73546-7

Oeij, P. R. A., Rus, D., & Pots, F. D. (2017). *Workplace Innovation*. Springer International Publishing. https://doi.org/10.1007/978-3-319-56333-6

Oldfield, H. (1995). General Electric enters the computer business-revisited. *IEEE Annals of the History of Computing*, *17*(4), 46–55.

Parker, K., Morin, R., & Horowitz, J. M. (2019). Looking to the future, public sees an America in decline on many fronts. *Pew Research Center*, *21*.

Poole, M. S., & Van de Ven, A. H. (2021). *The Oxford Handbook of Organizational Change and Innovation*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780198845973.001.0001

Qi, W. (2022). The Organizational Correlates of Automation Depend on Job Status. *PsyArXiv Preprints.*, 23. https://doi.org/https://doi.org/10.31234/osf.io/2r53z

Qin, J., Liu, Y., & Grosvenor, R. (2016). A Categorical Framework of Manufacturing for Industry 4.0 and Beyond. *Procedia CIRP*, *52*, 173–178. https://doi.org/10.1016/j.procir.2016.08.005

Raj, M., & Seamans, R. (2019). Primer on artificial intelligence and robotics. *Journal of Organization Design*, *8*(1). https://doi.org/10.1186/s41469-019-0050-0

Rana, G., & Sharma, R. (2019). Emerging human resource management practices in Industry 4.0. *Strategic HR Review*, *18*(4), 176–181. https://doi.org/10.1108/SHR-01-2019-0003

Randolph, J. (2009). A Guide to Writing the Dissertation Literature Review. *Practical Assessment, Research & Evaluation,*, *14*(13), 13. https://doi.org/https://doi.org/10.7275/b0az-8t74

Robotics, A. (2025). *Labor Market & Skills in the Future of Work: Impacts of Robotics on the Manufacturing Workforce*. https://arminstitute.org/news/labor-skills-fow/

Rovai, A. P., Baker, J. D., & Ponton, M. K. (2013). *Social science research design and statistics: A practitioner's guide to research methods and IBM SPSS*. Watertree Press LLC.

Sampson, S. E. (2020). A Strategic Framework for Task Automation in Professional Services. *Journal of Service Research*, *24*(1), 122–140. https://doi.org/10.1177/1094670520940407

Scully-Russ, E., & Torraco, R. (2020). The Changing Nature and Organization of Work: An Integrative Review of the Literature. *Human Resource Development Review*, *19*(1), 66–93. https://doi.org/10.1177/1534484319886394

Senge, P. M. (1994). *The Fifth Discipline Fieldbook: Strategies for Building a Learning Organization*. DoubledAY.

Senge, P. M. (2010). *The fifth discipline: the art and practice of the learning organization* (Second ed.). Random House.

Siegman, J., & Karsh, B. (1962). Some organizational correlates of white collar automation. *Sociological Inquiry*, *32*(1), 108–116. https://doi.org/https://doi.org/10.1111/j.1475-682X.1962.tb00534.x

Stevens, J. (1992). *Applied Multivariate Statistics for the Socila Sciences* (2nd ed.). Lawrence Erlbaum Associates Inc.

Swanson, R. A., & Holton, E. F. (1999). *Results: How to assess performance, learning, and perceptions in organizations* (Vol. 5). Berrett-Koehler Publishers.

Swanson, R. A., & Holton, E. F. (2005). *Research in organizations: Foundations and methods in inquiry*. Berrett-Koehler Publishers.

Tann, J. (1973). Richard Arkwright and Technology. *History*, *58(192)*, 29–44. https://doi.org/10.1111/j.1468-229X.1973.tb02131.x

Taylor, F. W. (1911). Principles and methods of scientific management. *Journal of Accountancy*, *12*(3), 3.

Tidd, J., & Bessant, J. R. (2020). *Managing innovation: Integrating technological, market and organizational change*. John Wiley & Sons.

Trenerry, B., Chng, S., Wang, Y., Suhaila, Z. S., Lim, S. S., Lu, H. Y., & Oh, P. H. (2021). Preparing Workplaces for Digital Transformation: An Integrative Review and Framework of Multi-Level Factors [Review]. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.620766

Tvedt, T. (2010). Why England and not China and India? Water systems and the history of the Industrial Revolution. *Journal of Global History*, *5*(1), 29–50. https://doi.org/10.1017/s1740022809990325

U.S. Census Bureau. (n.d.). *Explore Census Data*. https://data.census.gov/

US Census. (n.d). *Statistical Safeguards*

Violante, G. L. (2008). Skill-biased technical change. *The New Palgrave dictionary of economics*, *2*.

Visser, M. P., & Chermack, T. J. (2009). Perceptions of the relationship between scenario planning and firm performance: A qualitative study. *Futures*, *41*(9), 581–592. https://doi.org/10.1016/j.futures.2009.04.010

Waldman-Brown, A. (2020). Redeployment or robocalypse? Workers and automation in Ohio manufacturing SMEs. *Cambridge Journal of Regions, Economy and Society*, *13*(1), 99–115. https://doi.org/10.1093/cjres/rsz027

Waschull, S., Bokhorst, J. A. C., Wortmann, J. C., & Molleman, E. (2022). The redesign of blue- and white-collar work triggered by digitalization: collar matters. *Computers & Industrial Engineering*, *165*, 1–14. https://doi.org/https://doi.org/10.1016/j.cie.2021.107910

Webb, M. (2019). The Impact of Artificial Intelligence on the Labor Market. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3482150

World robotics Industrial Robots 2019. (2019).

Young, J. (2022). *Leadership resilience in a digital age*. Routledge. https://doi.org/https://doi.org/10.4324/9780367280970

Zezulka, F., Marcon, P., Vesely, I., & Sajdl, O. (2016). Industry 4.0 – An Introduction in the phenomenon. *IFAC-PapersOnLine*, *49*(25), 8–12. https://doi.org/https://doi.org/10.1016/j.ifacol.2016.12.002

APPENDIX A

Research Questions Classification Framework

This framework is designed to provide clarity on how the research questions align with the study's objectives, ensuring comprehensive coverage of CAPEX-related trends, employment dynamics, and firm growth across national, state, and industry levels. The temporal aspect highlights whether the questions address trend analysis, cross-sectional comparisons, or lagged effect analyses.

Primary Question	Sub-Question	Anchor Variable	Primary Focus	Unit of Analysis	Data Level	CAPEX Dimension	Temporal Analysis
Q1	Q1a	CAPEX	Trend analysis	Industry (3-digit NAICS)	National	Trend	Year-over-year
	Q1b	CAPEX	Investment intensity	Industry (3-digit NAICS)	National	Average trend	Year-over-year + Average
	Q1c	CAPEX	CAPEX trend variation by quartile	Industry (3-digit NAICS)	National	Quartile (Avg. CAPEX) + YoY	Year-over-year by quartile
Q2	Q2a	CAPEX	CAPEX ↔ Employment association	Employment (3-Digit)	National	Trend	Year-over-year
	Q2b	CAPEX	Lag effect	Employment (3-Digit)	National	Lagged CAPEX	Lagged
	Q2c	CAPEX	CAPEX quartile comparison	Employment (3-Digit)	National	Quartile (Avg. CAPEX)	Average (quartile level)
Q3	Q3a	CAPEX	CAPEX effect on white-collar occupations	Occupation (SoC-coded; 3-Digit)	National	Trend	Year-over-year
	Q3b	CAPEX	Lag effect	Occupation (SoC-coded; 3-Digit)	National	Lagged CAPEX	Lagged

	Q3c	CAPEX	Occupational YoY variation by sector	Occupation (SoC-coded; 3-Digit)	National	Trend	Year-over-year
Q4	Q4a	CAPEX	CAPEX ↔ Firm composition	Industry (3-digit NAICS)	National	Overall CAPEX	Overall
	Q4b	CAPEX	CAPEX quartile vs. firm composition	Industry (3-digit NAICS)	National	Quartile	Quartile-based
	Q4c	CAPEX	Firm expansion/consolidation trends	Industry (3-digit NAICS)	National	CAPEX Level	Trend (consolidation/expansion)
Q5	Q5a	CAPEX	State CAPEX trends	Industry (3-digit NAICS)	State	Trend	Year-over-year
	Q5b	CAPEX	CAPEX ↔ Total employment	Employment (3-Digit)	State	Overall CAPEX	Overall
	Q5c	CAPEX	CAPEX ↔ White-collar employment	Occupation (SoC-coded; 3-Digit)	State	Overall CAPEX	Overall
	Q5d	CAPEX	CAPEX quartile comparison	Occupation (SoC-coded; 3-Digit)	State	Quartile	Quartile-based
	Q5e	CAPEX	Sub-industry CAPEX variation	Industry (SoC-coded; 3-digit)	State	Trend	Year-over-year
	Q5f	CAPEX	CAPEX quartile ↔ firm composition	Industry (3-digit NAICS)	State	Quartile	Quartile-based
Q6	Q6a	CAPEX	Alignment with national trends	Industry (3-digit NAICS)	State + National	Trend	Comparison: State vs. National
	Q6b	CAPEX	CAPEX ↔ Employment comparison (state vs. national)	Employment, Occupation (SoC-coded; 3-Digit)	State + National	CAPEX Concentration	Comparison: State vs. National
	Q6c	CAPEX	CAPEX quartile vs. firm growth (state vs. national)	Industry (3-digit NAICS)	State + National	Quartile	Comparison: State vs. National

APPENDIX B

White Collar Occupational Descriptions

Occupation 1- Industrial Production Managers' Task IDs & Descriptions

#	SOC	TASK ID	TASK DESCRIPTION
1	11-3051.00	39	Set and monitor product standards, examining samples of raw products or directing testing during processing, to ensure finished products are of prescribed quality.
2	11-3051.00	32	Direct or coordinate production, processing, distribution, or marketing activities of industrial organizations.
3	11-3051.00	34	Review processing schedules or production orders to make decisions concerning inventory requirements, staffing requirements, work procedures, or duty assignments, considering budgetary limitations and time constraints.
4	11-3051.00	35	Review operations and confer with technical or administrative staff to resolve production or processing problems.
5	11-3051.00	36	Hire, train, evaluate, or discharge staff or resolve personnel grievances.
6	11-3051.00	40	Develop or implement production tracking or quality control systems, analyzing production, quality control, maintenance, or other operational reports to detect production problems.
7	11-3051.00	38	Prepare and maintain production reports or personnel records.
8	11-3051.00	41	Review plans and confer with research or support staff to develop new products or processes.
9	11-3051.00	33	Develop budgets or approve expenditures for supplies, materials, or human resources, ensuring that materials, labor, or equipment are used efficiently to meet production targets.
10	11-3051.00	44	Maintain current knowledge of the quality control field, relying on current literature pertaining to materials use, technological advances, or statistical studies.
11	11-3051.00	43	Coordinate or recommend procedures for facility or equipment maintenance or modification, including the replacement of machines.
12	11-3051.00	37	Initiate or coordinate inventory or cost control programs.
13	11-3051.00	45	Negotiate materials prices with suppliers.

Occupation 2 - Industrial Engineers Task IDs & Descriptions

#	SOC	TASK ID	TASK DESCRIPTION
1	17-2112.00	18607	Estimate production costs, cost saving methods, and the effects of product design changes on expenditures for management review, action, and control.
2	17-2112.00	1394	Plan and establish sequence of operations to fabricate and assemble parts or products and to promote efficient utilization.
3	17-2112.00	1391	Analyze statistical data and product specifications to determine standards and establish quality and reliability objectives of finished product.
4	17-2112.00	18609	Confer with clients, vendors, staff, and management personnel regarding purchases, product and production specifications, manufacturing capabilities, or project status.
5	17-2112.00	1400	Communicate with management and user personnel to develop production and design standards.
6	17-2112.00	1407	Evaluate precision and accuracy of production and testing equipment and engineering drawings to formulate corrective action plan.
7	17-2112.00	1393	Recommend methods for improving utilization of personnel, material, and utilities.
8	17-2112.00	1403	Record or oversee recording of information to ensure currency of engineering drawings and documentation of production problems.
9	17-2112.00	1398	Draft and design layout of equipment, materials, and workspace to illustrate maximum efficiency using drafting tools and computer.
10	17-2112.00	1405	Direct workers engaged in product measurement, inspection, and testing activities to ensure quality control and reliability.
11	17-2112.00	1392	Develop manufacturing methods, labor utilization standards, and cost analysis systems to promote efficient staff and facility utilization.
12	17-2112.00	1399	Review production schedules, engineering specifications, orders, and related information to obtain knowledge of manufacturing methods, procedures, and activities.
13	17-2112.00	1408	Complete production reports, purchase orders, and material, tool, and equipment lists.
14	17-2112.00	18608	Coordinate and implement quality control objectives, activities, or procedures to resolve production problems, maximize product reliability, or minimize costs.
15	17-2112.00	1406	Implement methods and procedures for disposition of discrepant material and defective or damaged parts, and assess cost and responsibility.
16	17-2112.00	1395	Apply statistical methods and perform mathematical calculations to determine manufacturing processes, staff requirements, and production standards.
17	17-2112.00	1404	Study operations sequence, material flow, functional statements, organization charts, and project information to determine worker functions and responsibilities.
18	17-2112.00	1402	Formulate sampling procedures and designs and develop forms and instructions for recording, evaluating, and reporting quality and reliability data.
19	17-2112.00	1410	Regulate and alter workflow schedules according to established manufacturing sequences and lead times to expedite production operations.
20	17-2112.00	1409	Schedule deliveries based on production forecasts, material substitutions, storage and handling facilities, and maintenance requirements.

Occupation 3- Mechanical Engineering Technologists and Technicians Task IDs & Descriptions

#	SOC	TASK ID	TASK DESCRIPTION
1	17-3027.00	22072	Assemble or disassemble complex mechanical systems.
2	17-3027.00	22082	Interpret engineering sketches, specifications, or drawings.
3	17-3027.00	1485	Calculate required capacities for equipment of proposed system to obtain specified performance and submit data to engineering personnel for approval.
4	17-3027.00	1476	Review project instructions and blueprints to ascertain test specifications, procedures, and objectives, and test nature of technical problems such as redesign.
5	17-3027.00	22086	Provide technical support to other employees regarding mechanical design, fabrication, testing, or documentation.
6	17-3027.00	1475	Draft detail drawing or sketch for drafting room completion or to request parts fabrication by machine, sheet or wood shops.
7	17-3027.00	1482	Analyze test results in relation to design or rated specifications and test objectives, and modify or adjust equipment to meet specifications.
8	17-3027.00	1486	Record test procedures and results, numerical and graphical data, and recommendations for changes in product or test methods.
9	17-3027.00	22085	Prepare specifications, designs, or sketches for machines, components, or systems related to the generation, transmission, or use of mechanical or fluid energy.
10	17-3027.00	1487	Read dials and meters to determine amperage, voltage, electrical output and input at specific operating temperature to analyze parts performance.
11	17-3027.00	22077	Design molds, tools, dies, jigs, or fixtures for use in manufacturing processes.
12	17-3027.00	1477	Review project instructions and specifications to identify, modify and plan requirements fabrication, assembly and testing.
13	17-3027.00	22078	Design specialized or customized equipment, machines, or structures.
14	17-3027.00	22075	Conduct failure analyses, document results, and recommend corrective actions.
15	17-3027.00	1480	Assist engineers to design, develop, test, or manufacture industrial machinery, consumer products, or other equipment.
16	17-3027.00	22073	Assist engineers to design, develop, test, or manufacture industrial machinery, consumer products, or other equipment.
17	17-3027.00	22084	Prepare layouts of machinery, tools, plants, or equipment.
18	17-3027.00	22083	Prepare layouts of machinery, tools, plants, or equipment.
19	17-3027.00	1489	Set up prototype and test apparatus and operate test controlling equipment to observe and record prototype test results.
20	17-3027.00	1483	Evaluate tool drawing designs by measuring drawing dimensions and comparing with original specifications for form and function using engineering skills.
21	17-3027.00	22070	Analyze energy requirements and distribution systems to maximize the use of intermittent or inflexible renewable energy sources, such as wind or nuclear.
22	17-3027.00	1474	Prepare parts sketches and write work orders and purchase requests to be furnished by outside contractors.
23	17-3027.00	1488	Estimate cost factors including labor and material for purchased and fabricated parts and costs for assembly, testing, or installing.
24	17-3027.00	22074	Assist mechanical engineers in product testing through activities such as setting up instrumentation for automobile crash tests.
25	17-3027.00	22076	Conduct statistical studies to analyze or compare production costs for sustainable and non-sustainable designs.

Occupation 4 - First-Line Supervisors of Production and Operating Workers Task IDs & Descriptions

#	SOC	TASK ID	TASK DESCRIPTION
1	51-1011.00	8450	Enforce safety and sanitation regulations.
2	51-1011.00	20155	Keep records of employees' attendance and hours worked.
3	51-1011.00	8455	Inspect materials, products, or equipment to detect defects or malfunctions.
4	51-1011.00	8452	Read and analyze charts, work orders, production schedules, and other records and reports to determine production requirements and to evaluate current production estimates and outputs.
5	51-1011.00	8454	Observe work and monitor gauges, dials, and other indicators to ensure that operators conform to production or processing standards.
6	51-1011.00	8453	Direct and coordinate the activities of employees engaged in the production or processing of goods, such as inspectors, machine setters, or fabricators.
7	51-1011.00	8459	Conduct employee training in equipment operations or work and safety procedures or assign employee training to experienced workers.
8	51-1011.00	8457	Evaluate employee performance.
9	51-1011.00	8451	Confer with management or subordinates to resolve worker problems, complaints, or grievances.
10	51-1011.00	20154	Determine standards, budgets, production goals, and rates, based on company policies, equipment and labor availability, and workloads.
11	51-1011.00	21207	Calculate labor and equipment requirements and production specifications, using standard formulas.
12	51-1011.00	8461	Recommend or implement measures to motivate employees and to improve production methods, equipment performance, product quality, or efficiency.
13	51-1011.00	8460	Maintain operations data, such as time, production, and cost records, and prepare management reports of production results.
14	51-1011.00	8463	Requisition materials, supplies, equipment parts, or repair services.
15	51-1011.00	8465	Set up and adjust machines and equipment.
16	51-1011.00	20156	Recommend or execute personnel actions, such as hirings, evaluations, or promotions.
17	51-1011.00	8467	Plan and develop new products and production processes.

APPENDIX C

Justification for Selecting NAICS Subsectors 311, 332, 333, and 336

The selection of NAICS subsectors 311 (Food Manufacturing), 332 (Fabricated Metal Product Manufacturing), 333 (Machinery Manufacturing), and 336 (Transportation Equipment Manufacturing) for state-level analysis is based on their significant representation within the U.S. manufacturing sector and their high employment concentrations relative to the national manufacturing average.

NAICS Code	Subsector	Total CAPEX ($) 2018-2021	% of Manufacturing CAPEX (31–33)	Average Employment	% of Manufacturing Employment (31–33)
311	Food Manufacturing	1,489,500,000	12.58%	1,595,739	13.37%
332	Fabricated Metal Product Manufacturing	1,044,800,000	8.82%	1,423,868	11.93%
333	Machinery Manufacturing	989,400,000	8.35%	1,050,044	8.80%
336	Transportation Equipment Manufacturing	4,754,500,000	40.16%	1,609,572	13.49%

These four subsectors were selected due to their high employment concentrations and substantial CAPEX investments, reflecting their significance in the U.S. manufacturing sector and their prominent role in automation adoption.

APPENDIX D

State Assignments by CAPEX Quartile

State	2018	2019	2020	2021	Min	Max	Mean	Quartile (Means)
Alabama	$ 194,700,000	$ 110,900,000	$ 281,900,000	$ 127,600,000	$ 110,900,000	$ 281,900,000	$ 166,940,155	4
Alaska	$ 2,409,000	$ 2,654,000	$ 3,964,000	$ 960,000	$ 960,000	$ 3,964,000	$ 2,220,934	1
Arizona	$ 17,650,000	$ 15,070,000	$ 20,520,000	$ 21,330,000	$ 15,070,000	$ 21,330,000	$ 18,471,686	2
Arkansas	$ 47,250,000	$ 15,830,000	$ 12,410,000	$ 15,840,000	$ 12,410,000	$ 47,250,000	$ 19,581,791	2
California	$ 265,700,000	$ 209,200,000	$ 195,200,000	$ 226,300,000	$ 195,200,000	$ 265,700,000	$ 222,602,173	4
Colorado	$ 6,211,000	$ 21,710,000	$ 8,620,000	$ 24,730,000	$ 6,211,000	$ 24,730,000	$ 13,020,815	2
Connecticut	$ 1,603,000	$ 16,540,000	$ 5,879,000	$ 6,053,000	$ 1,603,000	$ 16,540,000	$ 5,542,246	2
Delaware		$ 2,224,000		$ 12,570,000	$ 2,224,000	$ 12,570,000	$ 5,287,313	1
Florida	$ 14,320,000	$ 38,540,000	$ 18,930,000	$ 35,890,000	$ 14,320,000	$ 38,540,000	$ 24,745,413	2
Georgia	$ 110,300,000	$ 136,800,000	$ 51,270,000	$ 92,790,000	$ 51,270,000	$ 136,800,000	$ 92,046,340	4
Hawaii					$ -	$ -		1
Idaho	$ 9,326,000	$ 9,240,000	$ 7,959,000	$ 5,821,000	$ 5,821,000	$ 9,326,000	$ 7,948,879	2
Illinois	$ 193,100,000	$ 326,500,000	$ 152,900,000	$ 154,800,000	$ 152,900,000	$ 326,500,000	$ 196,544,536	4
Indiana	$ 118,700,000	$ 307,200,000	$ 313,300,000	$ 79,420,000	$ 79,420,000	$ 313,300,000	$ 173,556,368	4
Iowa	$ 33,470,000	$ 39,640,000	$ 22,890,000	$ 36,390,000	$ 22,890,000	$ 39,640,000	$ 32,423,083	3
Kansas	$ 22,680,000	$ 107,300,000	$ 20,550,000	$ 39,270,000	$ 20,550,000	$ 107,300,000	$ 37,435,089	3
Kentucky	$ 127,800,000	$ 158,900,000	$ 65,040,000	$ 186,500,000	$ 65,040,000	$ 186,500,000	$ 125,279,073	4
Louisiana	$ 6,548,000	$ 21,620,000	$ 3,855,000	$ 7,278,000	$ 3,855,000	$ 21,620,000	$ 7,938,715	2
Maine	$ 10,210,000	$ 5,789,000	$ 5,556,000	$ 2,685,000	$ 2,685,000	$ 10,210,000	$ 5,449,215	1
Maryland	$ 28,030,000	$ 20,180,000	$ 21,270,000	$ 8,597,000	$ 8,597,000	$ 28,030,000	$ 17,933,484	2
Massachusetts	$ 48,690,000	$ 46,200,000	$ 23,020,000	$ 24,640,000	$ 23,020,000	$ 48,690,000	$ 33,609,105	3
Michigan	$ 179,000,000	$ 406,900,000	$ 219,300,000	$ 145,600,000	$ 145,600,000	$ 406,900,000	$ 219,601,439	4
Minnesota	$ 43,040,000	$ 48,640,000	$ 46,200,000	$ 45,460,000	$ 43,040,000	$ 48,640,000	$ 45,791,441	3
Mississippi	$ 14,390,000	$ 7,449,000	$ 4,982,000	$ 12,080,000	$ 4,982,000	$ 14,390,000	$ 8,962,050	2
Missouri	$ 88,840,000	$ 58,570,000	$ 143,200,000	$ 112,600,000	$ 58,570,000	$ 143,200,000	$ 95,706,469	4
Montana		$ 887,000			$ 887,000	$ 887,000	$ 887,000	1
Nebraska	$ 68,490,000	$ 13,210,000	$ 38,270,000	$ 42,900,000	$ 13,210,000	$ 68,490,000	$ 34,910,931	3
Nevada	$ 1,476,000		$ 9,423,000	$ 7,832,000	$ 1,476,000	$ 9,423,000	$ 4,775,836	1
New Hampshire	$ 13,600,000	$ 4,440,000	$ 9,261,000	$ 4,628,000	$ 4,440,000	$ 13,600,000	$ 7,132,525	2
New Jersey	$ 33,510,000	$ 24,500,000	$ 22,450,000	$ 34,160,000	$ 22,450,000	$ 34,160,000	$ 28,168,822	3
New Mexico				$ 2,259,000	$ 2,259,000	$ 2,259,000	$ 2,259,000	1
New York	$ 44,320,000	$ 70,490,000	$ 59,040,000	$ 73,900,000	$ 44,320,000	$ 73,900,000	$ 60,761,644	3
North Carolina	$ 57,850,000	$ 47,540,000	$ 83,970,000	$ 80,070,000	$ 47,540,000	$ 83,970,000	$ 65,575,126	3
North Dakota	$ 2,030,000	$ 1,141,000		$ 4,726,000	$ 1,141,000	$ 4,726,000	$ 2,220,369	1
Ohio	$ 270,800,000	$ 258,100,000	$ 540,500,000	$ 636,200,000	$ 258,100,000	$ 636,200,000	$ 393,737,253	4
Oklahoma	$ 26,230,000	$ 10,730,000	$ 4,909,000	$ 28,780,000	$ 4,909,000	$ 28,780,000	$ 14,121,163	2
Oregon	$ 34,400,000	$ 55,960,000	$ 33,510,000	$ 19,580,000	$ 19,580,000	$ 55,960,000	$ 33,523,999	3
Pennsylvania	$ 44,840,000	$ 62,710,000	$ 63,560,000	$ 122,200,000	$ 44,840,000	$ 122,200,000	$ 68,361,939	3
Rhode Island	$ 1,264,000		$ 6,307,000		$ 1,264,000	$ 6,307,000	$ 2,823,482	1
South Carolina	$ 35,180,000	$ 49,530,000	$ 95,350,000	$ 83,470,000	$ 35,180,000	$ 95,350,000	$ 61,024,442	3
South Dakota	$ 1,576,000	$ 2,251,000	$ 1,617,000	$ 13,670,000	$ 1,576,000	$ 13,670,000	$ 2,975,792	1
Tennessee	$ 69,890,000	$ 75,340,000	$ 140,200,000	$ 831,200,000	$ 69,890,000	$ 831,200,000	$ 157,388,701	4
Texas	$ 79,100,000	$ 67,730,000	$ 80,150,000	$ 114,900,000	$ 67,730,000	$ 114,900,000	$ 83,809,892	4
Utah	$ 16,140,000	$ 33,860,000	$ 11,460,000	$ 12,950,000	$ 11,460,000	$ 33,860,000	$ 16,875,678	2
Vermont	$ 3,137,000	$ 1,388,000	$ 4,529,000	$ 4,293,000	$ 1,388,000	$ 4,529,000	$ 3,033,310	1
Virginia	$ 18,940,000	$ 26,480,000	$ 31,090,000	$ 30,210,000	$ 18,940,000	$ 31,090,000	$ 26,197,953	3
Washington	$ 23,140,000	$ 100,800,000	$ 150,300,000	$ 68,320,000	$ 23,140,000	$ 150,300,000	$ 69,957,242	4
West Virginia	$ 1,331,000	$ 6,243,000	$ 8,400,000	$ 6,828,000	$ 1,331,000	$ 8,400,000	$ 4,672,357	1
Wisconsin	$ 136,300,000	$ 131,100,000	$ 361,800,000	$ 111,300,000	$ 111,300,000	$ 361,800,000	$ 163,781,773	4
Wyoming	$ 15,690,000		$ 1,931,000		$ 1,931,000	$ 15,690,000	$ 5,504,306	1

APPENDIX E

IRB Approval Confirmation

From: no-reply=kuali.co@mx3.kuali.co <no-reply=kuali.co@mx3.kuali.co> **On Behalf Of** Kuali Notifications
Sent: April 22, 2025 2:11 PM
To: Freshwater,Scott <Scott.Freshwater@colostate.edu>
Subject: IRB Not Human Research Determination

Gloeckner, Gene,

This is your formal notification that a Not Human Research Determination was made for Protocol 6842 MAPPING THE IMPACT OF ROBOTIC INVESTMENT ON THE U.S. MANUFACTURING INDUSTRY: A MULTI-LEVEL LONGITUDINAL ANALYSIS OF EMPLOYMENT, INDUSTRY FIRM COMPOSITION, AND OCCUPATIONAL CHANGE.

The IRB determined that the proposed activity is not research involving human subjects as defined by DHHS and FDA regulations. IRB review and approval by CSU IRB is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these activities are research involving human subjects, please submit a new request to the IRB for a determination.

APPENDIX F

Supplemental Tables and Figures

Table A.1

NAICS 3-digit industry quartiles.

NAICS	Capex Quartile	CAPEX 2018	CAPEX 2019	CAPEX 2020	CAPEX 2021
311	4	423,600,000	326,700,000	442,600,000	296,600,000
312	3	41,810,000	19,650,000	50,180,000	100,500,000
313	1	3,938,000	4,274,000	3,300,000	2,401,000
314	1	981,000		1,904,000	4,744,000
315	1	98,000		999,000	
316	1	259,000		105,000	
321	2	5,619,000	20,780,000	43,080,000	24,670,000
322	3	86,720,000	75,460,000	120,800,000	77,870,000
323	1	7,114,000	7,827,000	6,602,000	10,430,000
324	2	18,650,000	9,997,000	7,318,000	12,440,000
325	3	80,820,000	95,720,000	126,500,000	137,500,000
326	4	301,600,000	240,400,000	200,800,000	241,600,000
327	4	50,530,000	287,100,000	118,900,000	82,470,000
331	3	109,000,000	45,750,000	47,610,000	39,610,000
332	4	261,900,000	230,100,000	248,300,000	304,500,000
333	4	189,100,000	208,900,000	261,100,000	330,300,000
334	4	65,940,000	115,000,000	375,100,000	421,100,000
335	3	50,400,000	67,820,000	165,600,000	87,580,000
336	4	865,500,000	1,298,000,000	1,095,000,000	1,496,000,000
337	2	26,520,000	29,990,000	47,840,000	22,000,000
339	3	34,350,000	104,100,000	46,360,000	65,420,000

Table A.1

Mean employment by CAPEX quartile and 3-digit NAICS sub-industry (2018–2021)

CAPEX Quartile | NAICS Code	Quartile 1	Quartile 2	Quartile 3	Quartile 4
1 | 313	86023			
1 | 314	107626			
1 | 315	74387			
1 | 316	25426			
1 | 323	414642			
2 | 321		412689		
2 | 324		111764		
2 | 337		360220		
3 | 312			267982	
3 | 322			341709	
3 | 325			834524	
3 | 331			371293	
3 | 335			342839	
3 | 339			544913	
4 | 311				1614185
4 | 326				795045
4 | 327				396756
4 | 332				1431651
4 | 333				1051305
4 | 334				797007
4 | 336				1617836

Note. Table summarizes average employment across NAICS 311–339 industries, categorized by mean CAPEX quartile. Employment values reflect national industry means from 2018 to 2021.

Table A.2

One-way ANOVA summary table for mean employment by CAPEX quartile (3-digit NAICS industries, 2018–2021)

Anova: Single Factor

Summary

Groups	*Count*	*Sum*	*Average*	*Variance (Millions)*
Quartile 1	5	708,104	141,621	24,202
Quartile 2	3	884,673	294,891	25,840
Quartile 3	6	2,703,260	450,543	43,880
Quartile 4	7	7,703,785	1,100,541	220,709

ANOVA

Source of Variation	*SS (Millions)*	*df*	*MS (Millions)*	*F*	*P-value*	*F crit*
Between Groups	3,200,490	3	1,066,830	10.71781427	0.00034331	3.19677684
Within Groups	1,692,146	17	99,538			
Total	4,892,636	20				

Note. This table summarizes the results of a one-way analysis of variance (ANOVA) comparing mean employment across industries grouped by CAPEX quartile. The analysis yielded a statistically significant difference in mean employment, $F(3, 17) = 10.72$, $p = .0003$. Group statistics are reported for each quartile, including count, sum, average employment, and within-group variance. The critical F value at $\alpha = .05$ was 3.20

Table A.3

CAPEX and Firm Count Changes by Industry, Including Pearson Correlation Results (2018–2021)

ID	CAPEX 2018	CAPEX 2021	Firm Count_2018	Firm Count_2021	CAPEX Δ (2018–2021)	CAPEX % Δ($M)	Firm Count Δ (2018 – 2021)
311	423,600,000	296,600,000	23,288	24,992	-127000000	-127.00	1,704
312	41,810,000	100,500,000	9,372	10,907	58690000	58.69	1,535
313	3,938,000	2,401,000	1,765	1,600	-1537000	-1.54	-165
314	981,000	4,744,000	5,545	5,024	3763000	3.76	-521
315	98,000		5,411	4,790	-98000	-0.10	-621
316	259,000		1,128	1,055	-259000	-0.26	-73
321	5,619,000	24,670,000	12,392	11,672	19051000	19.05	-720
322	86,720,000	77,870,000	2,444	2,271	-8850000	-8.85	-173
323	7,114,000	10,430,000	23,402	21,342	3316000	3.32	-2,060
324	18,650,000	12,440,000	934	872	-6210000	-6.21	-62
325	80,820,000	137,500,000	9,906	10,375	56680000	56.68	469
326	301,600,000	241,600,000	9,135	8,529	-60000000	-60.00	-606
327	50,530,000	82,470,000	9,265	8,786	31940000	31.94	-479
331	109,000,000	39,610,000	3,196	2,821	-69390000	-69.39	-375
332	261,900,000	304,500,000	50,801	49,442	42600000	42.60	-1,359
333	189,100,000	330,300,000	20,387	19,220	141200000	141.20	-1,167
334	65,940,000	421,100,000	10,433	9,896	355160000	355.16	-537
335	50,400,000	87,580,000	4,753	4,524	37180000	37.18	-229
336	865,500,000	1,496,000,000	9,218	9,074	630500000	630.50	-144
337	26,520,000	22,000,000	14,045	13,857	-4520000	-4.52	-188
339	34,350,000	65,420,000	24,049	22,531	31070000	31.07	-1,518
				Pearson r			-0.09
				t-statistic			-0.37
				p-value (2-tailed)			0.71

Note. This table presents changes in capital investment and firm count by 3-digit NAICS industry from 2018 to 2021. The final rows show the Pearson correlation coefficient (r), calculated t-statistic, and two-tailed p-value, derived from Excel formulas

Table A.4

, 2018–2021

ID	CAPEX 2018	CAPEX 2021	Firm Count 2018	Firm Count 2021	% CAPEX Change	% Firm Count Change	Change Category
311	423,600,000	296,600,000	23,288	24,992	-29.98	7.32	Expansion
312	41,810,000	100,500,000	9,372	10,907	140.37	16.38	Expansion
313	3,938,000	2,401,000	1,765	1,600	-39.03	-9.35	Consolidation
314	981,000	4,744,000	5,545	5,024	383.59	-9.40	Consolidation
315	98,000	0	5,411	4,790	-100.00	-11.48	Consolidation
316	259,000	0	1,128	1,055	-100.00	-6.47	Consolidation
321	5,619,000	24,670,000	12,392	11,672	339.05	-5.81	Consolidation
322	86,720,000	77,870,000	2,444	2,271	-10.21	-7.08	Consolidation
323	7,114,000	10,430,000	23,402	21,342	46.61	-8.80	Consolidation
324	18,650,000	12,440,000	934	872	-33.30	-6.64	Consolidation
325	80,820,000	137,500,000	9,906	10,375	70.13	4.73	Expansion
326	301,600,000	241,600,000	9,135	8,529	-19.89	-6.63	Consolidation
327	50,530,000	82,470,000	9,265	8,786	63.21	-5.17	Consolidation
331	109,000,000	39,610,000	3,196	2,821	-63.66	-11.73	Consolidation
332	261,900,000	304,500,000	50,801	49,442	16.27	-2.68	Restructuring
333	189,100,000	330,300,000	20,387	19,220	74.67	-5.72	Consolidation
334	65,940,000	421,100,000	10,433	9,896	538.61	-5.15	Consolidation
335	50,400,000	87,580,000	4,753	4,524	73.77	-4.82	Consolidation
336	865,500,000	1,496,000,000	9,218	9,074	72.85	-1.56	Restructuring
337	26,520,000	22,000,000	14,045	13,857	-17.04	-1.34	Restructuring
339	34,350,000	65,420,000	24,049	22,531	90.45	-6.31	Consolidation

Note. This appendix table lists 3-digit NAICS manufacturing industries, their percentage changes in capital expenditures and firm counts between 2018 and 2021, and the assigned structural change category: Expansion (>+3%), Consolidation (<–3%), or Restructuring (–3% to +3%).

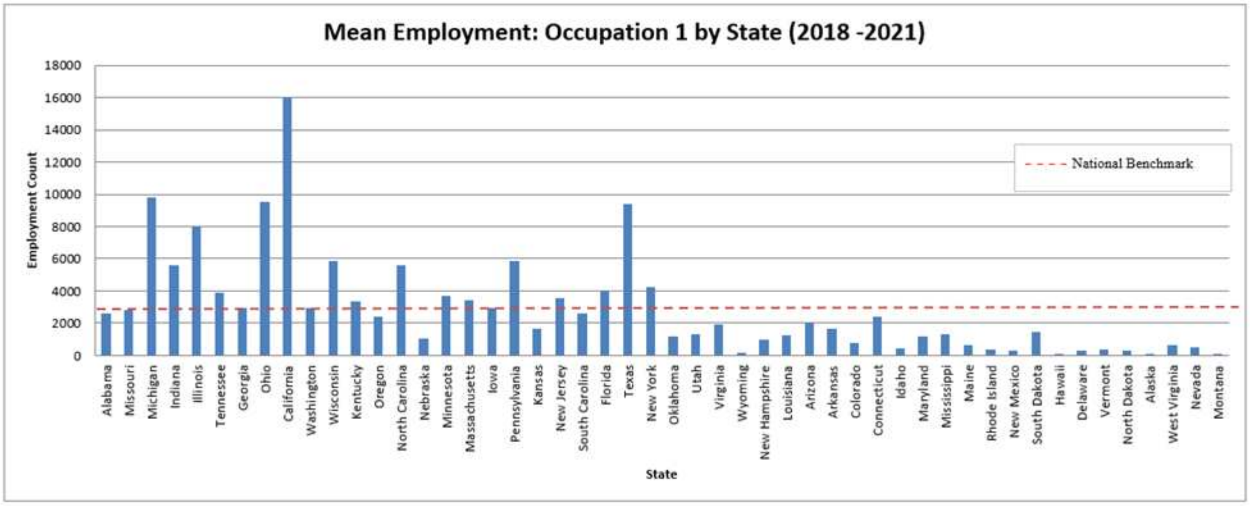

Figure A.1.

Mean employment for Occupation 1 (industrial production managers) by state, sorted by CAPEX quartile (2018–2021).

Note. Bars represent 4-year average employment Industrial Production Managers (SOC 11-3051) in NAICS 31–33 manufacturing across U.S. states. States are organized by capital expenditure quartile from highest (Q4) to lowest (Q1).

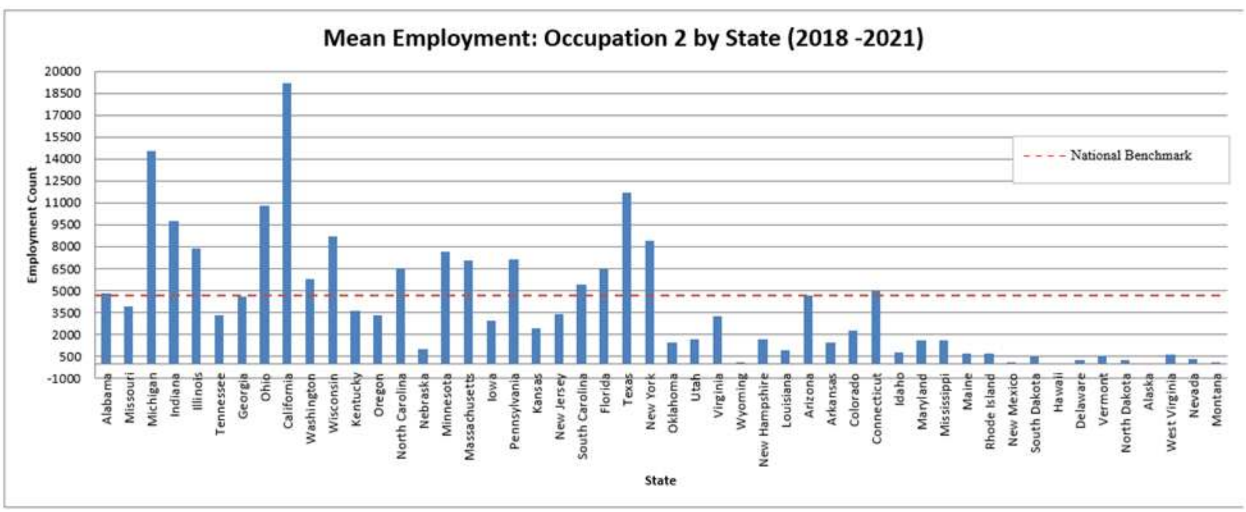

Figure A.2.

Mean employment for Occupation 2 (industrial engineers) by state, sorted by CAPEX quartile (2018–2021).

Note. Bars reflect average employment levels for engineers, including industrial, mechanical, and electrical engineers (e.g., SOC 17-2112), across states in the manufacturing sector (NAICS 31–33). States are grouped by CAPEX quartile

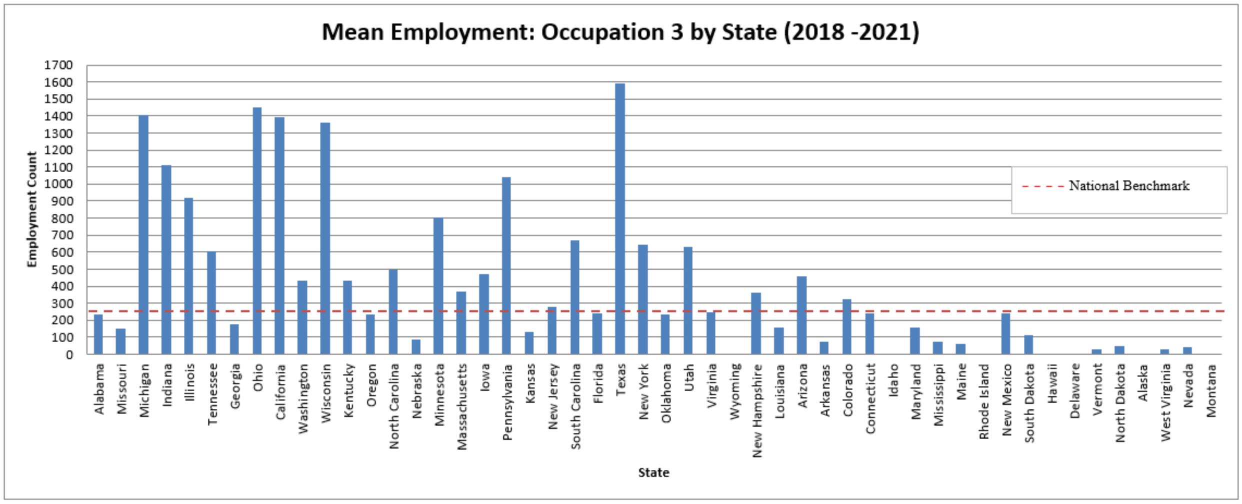

Figure A.3. *Mean employment for Occupation 3 (engineering technicians) by state, sorted by CAPEX quartile (2018–2021).*
Note. Bars reflect average employment levels for engineers, mechanical engineering technologists and technicians (e.g., SOC 17-3027), across states in the manufacturing sector (NAICS 31–33). States are grouped by CAPEX quartile.

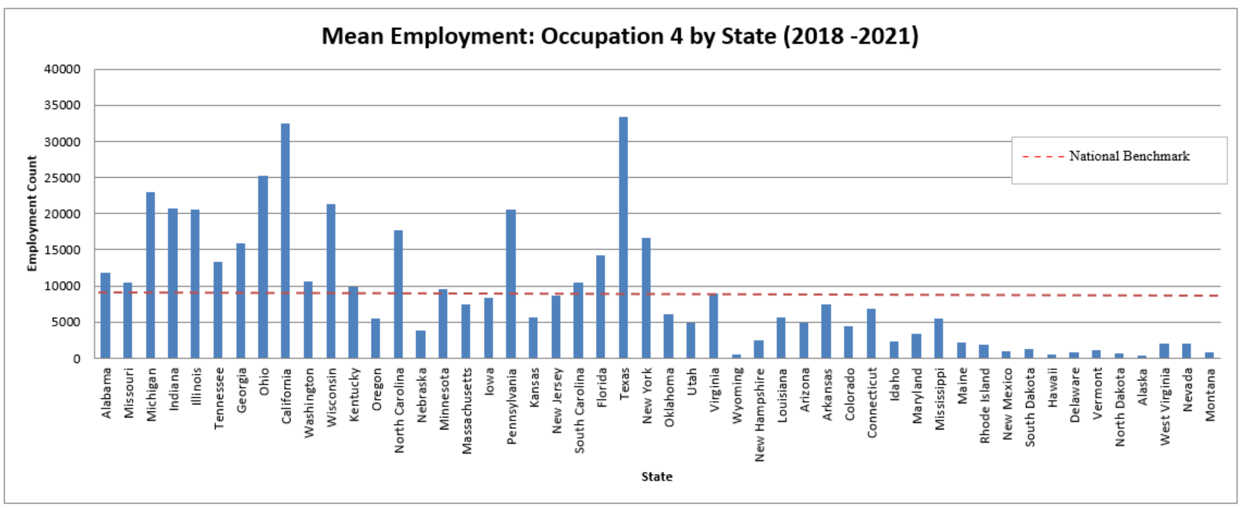

Figure A.4. *Mean employment for Occupation 4 (first line supervisors) by state, sorted by CAPEX quartile (2018–2021).*
Bars indicate average employment for first-line production supervisors (SOC 51-1011) across the manufacturing sector. States are grouped by CAPEX quartile to show the relationship between investment intensity and supervisory employment.