



Hochschule für
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Berlin School of Economics and Law

**THE DEMAND-SIDE SHOCK OF RAPID AI-DRIVEN
LABOR DISPLACEMENT: INCOME, CONSUMPTION, AND
AGGREGATE DEMAND DURING THE TRANSITION
PERIOD IN THE UNITED STATES**

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Contents

LIST OF FIGURES	II
LIST OF TABLES	IV
LIST OF ABBREVIATIONS	V
I. INTRODUCTION	1
II. THEORETICAL BACKGROUND	3
III. LITERATURE REVIEW	5
IV. CONCEPTUAL FRAMEWORK	15
4.1 THE DISPLACEMENT CHANNEL	15
4.2 THE INCOME CHANNEL	16
4.3 THE CONSUMPTION CHANNEL	17
4.4 THE AGGREGATE DEMAND CHANNEL	17
5. SCOPE AND LIMITATIONS.....	19
5.1 SCOPE OF THE STUDY	19
5.2 LIMITATIONS	20
6. METHODOLOGY AND DATA	21
6.1 DATA SOURCES	21
6.2 THE AI OCCUPATIONAL EXPOSURE (AIOE) INDEX	21
6.3 MERGING THE AIOE INDEX WITH BLS EMPLOYMENT AND WAGE DATA	24
6.4 CONSTRUCTING THE VULNERABLE LABOUR POOL	25
6.5 CONSTRUCTING THE LOWER-TIER REEMPLOYMENT POOL	28
6.6 BASELINE PARAMETERS	30
6.7 OLS REGRESSION SPECIFICATION.....	31
6.8 SCENARIO MODEL SPECIFICATION	31
6.8.1 Step I: Income Loss	31
6.8.2 Step II: Consumption Shock.....	32
6.8.3 Step III: Aggregate Demand Contraction.....	32
7. RESULTS AND ANALYSIS	33
7.1 AI EXPOSURE AND WAGES: OLS REGRESSION RESULTS (FIGURE 1)	33
7.2 AI EXPOSURE AND RECENT EMPLOYMENT GROWTH: OLS REGRESSION RESULTS (FIGURE 2)	35
7.3 AI EXPOSURE AND PROJECTED EMPLOYMENT GROWTH: BINNED SCATTER ANALYSIS (FIGURE 3).....	36
7.4 CALIBRATED SCENARIO MODELLING RESULTS	38
7.4.1 STRUCTURE OF RESULTS	39
8. DISCUSSION	40
8.1 CONTEXTUALIZING THE MODELLED MAGNITUDES	40
8.2 THE VALLEY BETWEEN DISPLACEMENT AND REINSTATEMENT	42
8.3 WHAT THE TRANSITION PERIOD ACTUALLY LOOKS LIKE.....	43
8.4 THE HIRING CYCLE HAS DECOUPLED FROM THE BUSINESS CYCLE	44
8.5 CONDITIONS THAT COULD DAMPEN THE DEMAND SHOCK	45
8.6 POLICY IMPLICATIONS	46
9. CONCLUSION.....	48
LIST OF REFERENCES	51
APPENDICES.....	56

List of Figures

Figure 1. Theoretical AI Capability and Observed Exposure by Occupational Category: Share of job tasks that large language models could theoretically perform (Eloundou et al. capability score, blue area) compared to tasks observed in actual Claude usage (observed exposure, red area), averaged across broad US occupational categories.

Source: Massenkoff, M. and McCrory, P. (2026) 'Labor market impacts of AI: A new measure and early evidence', Anthropic Economic Research Report, 5 March [Online]. Available at: <https://www.anthropic.com/research/labor-market-impacts> (Accessed: [date]). p. [X]

Figure 2. Headcount Over Time by Age Group in Computer Occupations (Normalized), 2021–2025: Normalized employment headcount by age cohort in computer and AI-exposed occupations; dashed line marks mid-2022 (widespread generative AI availability).

Source: Brynjolfsson, B., Chandar, A. and Chen, Y. (2025) 'Canaries in the Coal Mine? Six Facts About the Recent Employment Effects of Artificial Intelligence.' Stanford Digital Economy Lab Working Paper. Used with permission. p. [X]

Figure 3. Change in Job Postings by AI Impact Type, Post-ChatGPT (November 2022 – March 2025): Percentage change in US job postings for occupations classified as automation-prone (displacement) versus augmentation-prone (complementarity) following the public launch of ChatGPT.

Source: Srinivasan, S., Chen, W.X. and Zakerinia, S. (2024, updated 2025) 'Displacement or Complementarity? The Labor Market Impact of Generative AI', Harvard Business School Working Paper, No. 25-038. Summarised in: Azpúrua, A.E. (2026) HBS Working Knowledge, 20 February [Online]. Available at: <https://www.library.hbs.edu/working-knowledge/enhance-or-eliminate-how-ai-will-likely-change-these-jobs> (Accessed: [date]). p. [X]

Figure 4. The Four-Channel Transmission Mechanism from AI-Driven Labour Displacement to Aggregate Demand Contraction: Schematic diagram of the displacement → income → consumption → aggregate demand causal chain specified in Chapter 4, with amplifying and dampening factors indicated.

Source: Author's elaboration, based on Acemoglu and Restrepo (2018, 2019); Jacobson, LaLonde and Sullivan (1993); Friedman (1957); Mian, Straub and Sufi (2021); Keynes (1936). p. [X]

Figure 5. AI Occupational Exposure (AIOE) Score vs. Annual Median Wage, 2025: Scatterplot of all ~760 BLS occupations with 20-bin bin averages (blue dots); positive correlation indicates higher wages are associated with higher AI exposure.

Source: Felten, E., Raj, M. and Seamans, R. (2021, 2023) AI Occupational Exposure Index; Bureau of Labor Statistics (2025) Occupational Employment and Wage Statistics. Author's elaboration. p. [X]

Figure 6. AI Occupational Exposure (AIOE) Score vs. Employment Change, 2021–2025: OLS Linear Regression (Slope = 2.00): Scatterplot of AIOE score against observed employment change with OLS fit line; slope is positive but relationship is weak.

Source: Felten, E., Raj, M. and Seamans, R. (2021, 2023) AI Occupational Exposure Index; Bureau of Labor Statistics (2025) Occupational Employment and Wage Statistics. Author's elaboration. p. [X]

Figure 7. AI Occupational Exposure (AIOE) Score vs. Projected Employment Change, 2024–2034: Binned Scatter (20 Bins), Weighted OLS Fit (Slope = 0.06): Employment-weighted binned scatterplot showing slight positive relationship between AI exposure and BLS projected employment growth.

Source: Felten, E., Raj, M. and Seamans, R. (2021, 2023) AI Occupational Exposure Index; Bureau of Labor Statistics (2025) Employment Projections, 2024–2034. Author's elaboration. p. [X]

Figure 8. Total Demand Contraction (\$ Billions) by Displacement Rate (δ) and Reemployment Rate (ρ): Three-line chart showing demand vulnerability across nine modelling scenarios; higher displacement and lower reemployment produce larger contractions.

Source: Author's elaboration. p. [X]

List of Tables

- Table 1. Top 15 Occupations by AI Occupational Exposure (AIOE) Score.
Source: Felten, E., Raj, M. and Seamans, R. (2021, 2023). See full citation in text. p. [X]
- Table 2. Top 15 Occupations with Lowest (Negative) AIOE Scores.
Source: Felten, E., Raj, M. and Seamans, R. (2021, 2023). See full citation in text. p. [X]
- Table 3. Top 14 Highest-AIOE Occupations: Merged AIOE, Employment, Wage, and Projection Data.
Sources: Felten et al. (2021, 2023); BLS OEWS (2025); BLS Employment Projections (2024–2034). Author's elaboration. p. [X]
- Table 4. Top 25 Occupations in the Potentially AI-Driven Declining Pool (out of 81 total), Ranked by Projected Employment Decline, 2024–2034.
Sources: Felten et al. (2021, 2023); BLS OEWS (2025); BLS Employment Projections (2024–2034); Harvard Business School automation score. Author's elaboration. p. [X]
- Table 5. Lower-Tier Growing Occupations Used as the Reemployment Pool (25 occupations shown).
Sources: BLS OEWS (2025); BLS Employment Projections (2024–2034). Author's elaboration. p. [X]
- Table 6. Baseline Parameters for the Calibrated Scenario Model.
Sources: BLS OEWS (2025); BLS Employment Projections (2024–2034). Author's elaboration. p. [X]
- Table 7. Macroeconomic Shock Scenario Matrix: Income Loss, Consumption Shock, and Total Demand Contraction across Displacement Rate (δ) and Reemployment Rate (ρ) Scenarios.
Source: Author's elaboration. p. [X]

List of Abbreviations

AD	Aggregate Demand
AI	Artificial Intelligence
AIOE	AI Occupational Exposure (index, Felten, Raj and Seamans, 2021, 2023)
BEA	Bureau of Economic Analysis (US Department of Commerce)
BLS	Bureau of Labor Statistics (US Department of Labor)
CBPP	Center on Budget and Policy Priorities
CBO	Congressional Budget Office
CES	Consumer Expenditure Survey (BLS)
EIA	US Energy Information Administration
FRED	Federal Reserve Economic Data (Federal Reserve Bank of St. Louis)
GDP	Gross Domestic Product
GPT	Generative Pre-trained Transformer (e.g. ChatGPT, GPT-4)
HBS	Harvard Business School
IMF	International Monetary Fund
LLM	Large Language Model
MPC	Marginal Propensity to Consume
O*NET	Occupational Information Network (US Department of Labor)
OECD	Organisation for Economic Co-operation and Development
OEWS	Occupational Employment and Wage Statistics (BLS)
OLS	Ordinary Least Squares (regression)
PCE	Personal Consumption Expenditure
PIH	Permanent Income Hypothesis
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SOC	Standard Occupational Classification
UBI	Universal Basic Income
UI	Unemployment Insurance
UN SNA	United Nations System of National Accounts
US / USA	United States of America

I. Introduction

In recent years, the rapid advancement and diffusion of AI technologies have intensified debates around technological unemployment, the future of work, and the macroeconomic consequences of automation at scale. Much of the existing literature has focused on the micro-level impacts: which occupations are exposed, which tasks are at risk, what productivity gains accrue at the firm level, and how AI complements or substitutes individual workers. These are important questions. But a larger and less studied question emerges when these micro-level effects begin to aggregate: what happens when AI starts to reshape the economy as a whole?

Unlike earlier technological disruptions, which primarily targeted routine physical labour, AI possesses the capability to replace both physical and cognitive work. It can automate not only routine tasks, but increasingly complex cognitive and decision-making processes, the kind of work that was previously considered insulated from automation. Some studies do treat AI as a macro-critical transition rather than a standard technological shock, but this remains a minority position in a literature.

This thesis is concerned with one specific macro-level risk that has received limited attention: the demand-side consequences of AI-driven labour displacement. While AI increases productivity and reduces labour costs at the firm level, and efficiency gains on the supply side are evident, the risk emerges on the income and demand side of the macroeconomy. At a micro level, it is perfectly rational for an individual firm to adopt AI, cut labour costs, and optimize supply-side efficiency. However, if businesses do this collectively, a macroeconomic coordination problem emerges: widespread job displacement strips away aggregate labour income, workers lose purchasing power, aggregate consumer demand declines, and ultimately the very firms that automated their workforces see their consumer markets erode. The feedback loop runs as follows: AI-driven labour displacement reduces wages and employment, causing a contraction in aggregate consumer demand, which depresses corporate revenue and macroeconomic stability - what this thesis terms the AI demand paradox.

Historically, similar concerns arose during the Industrial Revolution, and in those cases, economies eventually adjusted through job creation, reskilling, and sectoral shifts, what economists call the reinstatement effect. However, AI may represent a structurally different type of technological shift. First, the speed of adoption is substantially faster, fueled by competition between technology companies, which means that policy responses and reskilling systems cannot keep pace. Second, the breadth of exposure is wider than in any previous wave of automation: AI is moving into cognitive, analytical, and decision-making roles that were previously considered safe. Autor et al. (2024) find that displacement has intensified over the past four decades while the creation of new work has not consistently kept pace, and early evidence suggests the current wave is disproportionately affecting entry-level workers (Brynjolfsson et al., 2025).

This thesis therefore focuses on the interim transition period: the window in which AI-induced job losses may generate significant demand contraction before reemployment and reinstatement effects can materialize. The central research question is: in the short-term adjustment process, how might AI-driven widespread job displacement impact aggregate consumer demand through the income and consumption channels, and what are the broader macroeconomic implications for the United States economy during the transition period before reinstatement effects materialize? Two sub-questions operationalize this. First, what do AI exposure metrics reveal about recent and projected employment trends and wages across occupations? Second, under what combinations of displacement risk and reemployment rate does AI labour automation pose a measurable threat to aggregate consumer demand, and how sensitive is the magnitude of that contraction to the wage quality of reemployment? The focus is deliberately on the short run, as the transition period is where the demand risk is most acute and least studied.

This thesis contributes to the emerging literature on the macroeconomic implications of AI by examining whether AI-induced labour displacement, under plausible assumptions about displacement and reemployment rates, generates aggregate demand constraints, and by the scale of that risk through calibrated scenario modelling grounded in real occupational and wage data.

The remainder of this thesis is structured as follows. Chapter 2 presents the theoretical background, situating the AI displacement problem within existing theories of technological

unemployment and automation. Chapter 3 reviews the relevant empirical literature. Chapter 4 describes the conceptual framework, specifying the four transmission channels through which displacement propagates into aggregate demand. Chapter 5 presents scope and limitations of the thesis. Chapter 6 presents the methodology and data. Chapter 7 presents the results and analysis, covering both the OLS regression findings and the calibrated scenario modelling outcomes. Chapter 8 discusses the results and their implications. Chapter 9 offers concluding remarks and directions for future research.

II. Theoretical Background

To understand the current disruptive role of AI in economies, it is necessary to situate it within the broader theoretical tradition on automation, technological unemployment, and the relationship between labour-saving technology and aggregate economic outcomes.

Automation corresponds to the development and adoption of technologies that enable capital to be substituted for labour across a range of tasks, with the displacement effect implying a reduction in the labour share of value added (Acemoglu and Restrepo, 2018). The concern that machines could permanently displace human labour is not new. Keynes (1930, p.3), in “Economic Possibilities for Our Grandchildren”, identified what he termed “technological unemployment”, defined as unemployment arising from the “discovery of means of economizing the use of labour outrunning the pace at which we can find new uses for labour.” Wassily Leontief raised comparable concerns decades later, writing that labour would become progressively less important as workers were replaced by machines, and expressing skepticism that new industries could absorb all those seeking employment (Curtis, 1983, as cited in Acemoglu and Restrepo, 2020). These early contributions established the theoretical possibility that technological progress, under certain conditions, could generate persistent rather than transitional unemployment.

The Austrian school offers the principal counter-argument: that free markets naturally adapt through entrepreneurship and competition, generating new activities and roles that absorb displaced workers over time. Historical evidence from the Industrial Revolution is frequently cited in support of this view. Early automation of artisan tasks in spinning and weaving caused significant short-run displacement and social unrest, including the Luddite riots, before labour markets eventually rebalanced through the creation of new occupations

(Mokyr, 1990; Mantoux, 1928, as cited in Acemoglu and Restrepo, 2019). The long-run record of technological transitions thus supports the view that adjustment occurs, but does not resolve the question of how long adjustment takes or what the aggregate demand consequences are during the transition.

Brynjolfsson and McAfee (2014), in “The Second Machine Age”, revived the technological unemployment debate in the context of digital automation, arguing that digital technologies replace activities previously considered insulated from automation and that the resulting income inequality represents both an economic and a societal challenge. Korinek and Stiglitz (2017) extend this argument, emphasising that AI can, in the long run, shift income distribution and exacerbate unemployment in the absence of adequate policy responses. These contributions are significant because they move the analysis beyond task substitution at the firm level toward the distributional and macroeconomic consequences of automation at scale.

Acemoglu and Autor's (2011) task-based framework provides the most influential contemporary treatment of the automation-labour relationship. Their model, further expanded by Acemoglu and Restrepo (2018, 2019), formalizes a race between a displacement effect, in which automation directly substitutes for labour in specific tasks, and a reinstatement effect, in which new tasks are created in which labour retains a comparative advantage. Their long-run equilibrium assumes these effects roughly offset over time, leaving employment and wages broadly stable. The framework does not, however, model the transition period between displacement and reinstatement, the interval in which income and demand effects may be significant. This thesis takes Acemoglu and Restrepo's framework as its theoretical starting point, and examines the macroeconomic consequences of a scenario in which displacement is rapid and reinstatement lags behind, the transitory interval before reinstatement effects materialize.

Taken together, these theoretical strands establish that automation is not merely a technical substitution phenomenon. It penetrates demand processes, alters income distributions, and can affect the stability of markets and macroeconomic institutions. Chapter 4 builds on these foundations to develop the conceptual framework through which this thesis models the transmission from AI-driven displacement to aggregate demand contraction.

III. Literature Review

The economic literature on artificial intelligence and labour markets has, until recently, been dominated by a task-based framework in which technology is understood not as a single force that either destroys or creates jobs, but as a bundle of forces acting on the tasks that make up an occupation. Acemoglu and Autor (2011) laid the conceptual groundwork for this approach, showing that the wage and employment effects of automation depend on which tasks are reallocated from labour to capital and which new tasks are created in which labour retains a comparative advantage. Empirically, Acemoglu and Restrepo (2018) used US data to argue that recent wage stagnation, skill mismatches and employment pressure reflect not merely slow productivity growth but a specific mismatch: automation has accelerated while the creation of new tasks has not kept pace. Acemoglu and Restrepo (2019a) extend this to AI directly, noting that whether the technology proves predominantly labour-displacing or labour-complementing is not a fixed property of AI itself but depends on whether firms and researchers direct it toward automating existing tasks or augmenting new ones.

Acemoglu and Restrepo (2020, p. 3-5) sharpen the normative implication, distinguishing “right” automation, which raises productivity sufficiently to fund new task creation, from “so-so” automation or “wrong” kind of AI driven by tax distortions or a capital bias that displaces labour without commensurate gains, a distinction that anticipates the demand-side concerns explored later in this review.

Building on this task-based tradition, a growing body of work has sought to measure the exposure of occupations to large language models (LLMs) specifically, rather than to automation in general. The most widely cited contribution is Eloundou, Manning, Mishkin and Rock (2024, pp. 1306-1308), which combined human expert judgement with GPT-4-assisted classification to estimate that around 80% of the United States workforce could have at least 10% of their tasks affected by LLMs, and that roughly 19% of workers could see at least half of their tasks affected; when LLM-powered software and tooling are considered rather than the models alone, the share of substantially affected tasks rises considerably. Crucially, the authors found that exposure is not concentrated among low-wage occupations, as earlier waves of automation research tended to assume, but spans the wage distribution and, if anything, skews towards higher-income, more cognitively demanding jobs. This finding has been broadly corroborated by Felten, Raj and Seamans (2021, pp. 2195-2217),

whose dataset linking AI capabilities to O*NET task descriptions likewise found exposure concentrated in white-collar, non-routine cognitive occupations previously considered insulated from automation, and by their later study using large language models directly (Felten, Raj and Seamans, 2023), which extended the methodology to generative AI and reached similar conclusions.

Webb (2020) constructs a measure of the task exposure to automation, using the overlap between the text of job descriptions and the text of patents. He finds that while robots primarily replaced low-skill "muscle" tasks and software impacted middle-skill routine processing, AI is uniquely directed at high-skilled applications requiring judgment and pattern recognition. Under the assumption that historical substitution patterns will persist, the study concludes that AI is likely to reduce overall wage inequality by displacing high-earning professionals, such as laboratory technicians and engineers, rather than low-wage manual labourers. Webb empathizes that labour market adjustments to General Purpose Technologies (GPTs) like AI are often gradual, and "if history is a guide, the main impacts on the labour market may not appear for three decades" (Jovanovic and Rousseau 2005; Yates 2005, as quoted in Webb, 2020, p. 45).

Handa et al. (2025), reporting on Anthropic's analysis of millions of Claude¹ conversations, add an important empirical refinement to this theoretical exposure literature: actual usage is heavily concentrated in software development, writing and administrative support tasks, and a large share of observed use is augmentative rather than fully automating, suggesting that theoretical exposure estimates such as Eloundou et al.'s (2024) may overstate near-term displacement if usage patterns remain skewed toward complementary use. This distinction between theoretical capability and observed, revealed use is taken further in Anthropic's own labour-market research report (Massenkoff and McCrory, 2026), which introduces an "observed exposure" measure combining O*NET task data, Eloundou et al.'s (2024)

¹ Claude is a large language model (LLM) and AI assistant developed by Anthropic, PBC. It is available via a consumer-facing chat interface (claude.ai) and a developer API. Multiple versions of Claude have been released since 2023; the versions relevant to the studies cited in this thesis (Handa et al., 2025; Massenkoff and McCrory, 2026) are those active during 2024 and 2025. Usage data from Claude conversations, analysed via the Anthropic Economic Index, forms part of the empirical basis for the observed exposure measure introduced by Massenkoff and McCrory (2026).

capability ratings, and real Claude usage data. That report's central finding is that actual AI adoption remains a small fraction of theoretical capability (Figure 1), and that, to date, there is no systematic economy-wide rise in unemployment among highly exposed workers, although the authors note suggestive evidence that hiring of younger workers has slowed in the most exposed occupations.

Theoretical capability and observed usage by occupational category

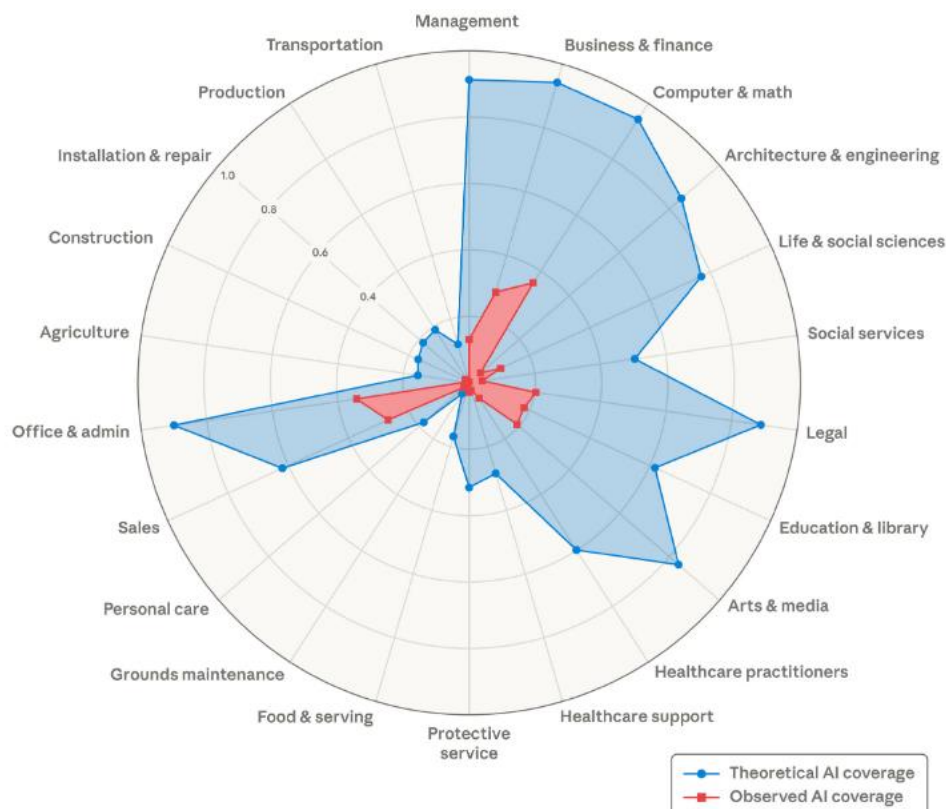


Figure 1. Theoretical AI Capability and Observed Exposure by Occupational Category: Share of job tasks that large language models could theoretically perform (Eloundou et al. capability score, blue) compared to tasks observed in actual Claude usage (observed exposure, red), averaged across broad US occupational categories. Source: Massenkoff, M. and McCrory, P. (2026) 'Labor market impacts of AI: A new measure and early evidence', Anthropic Economic Research Report, 5 March [Online].

Empirical evidence on realised, rather than theoretical, labour market impacts remains limited by the short time that generative AI tools have been widely available, but a small number of studies using high-frequency administrative or platform data have begun to emerge. Stanford research group led by Brynjolfsson, Chandar and Chen (2025) analysing payroll records covering millions of United States workers, report that early-career workers

aged 22-25 in the occupations most exposed to generative AI, particularly software development and customer support, have experienced a roughly 16% relative decline in employment since the widespread adoption of generative AI in late 2022 (Figure 2), even after controlling for firm-level shocks, while employment for older workers in the same occupations has continued to grow.

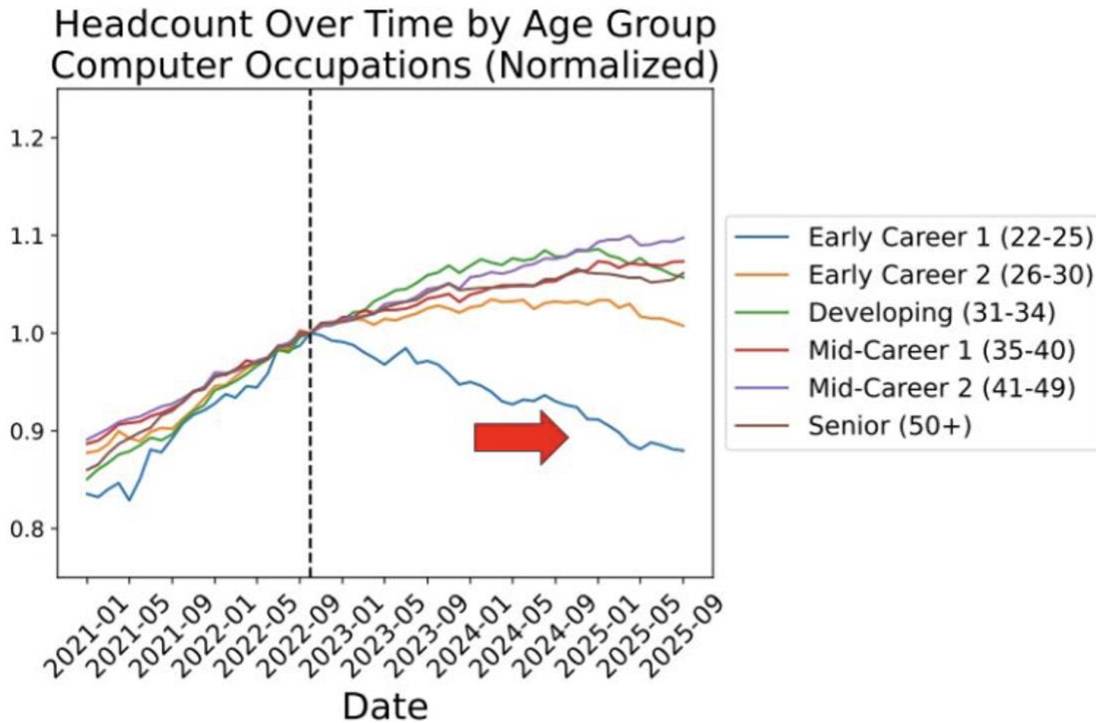


Figure 2. Headcount Over Time by Age Group in Computer Occupations (Normalized), 2021–2025.
Source: Brynjolfsson, B., Chandar, A. and Chen, Y. (2025) 'Canaries in the Coal Mine? Six Facts About the Recent Employment Effects of Artificial Intelligence.' Stanford Digital Economy Lab Working Paper. Used with permission.

The authors interpret this age gradient as consistent with AI substituting for the codified, explicit knowledge that entry-level workers typically supply while complementing the tacit, experience-based knowledge held by more senior employees.

Further early evidence comes from the Harvard Business School (HBS) report: Srinivasan, Chen and Zakerinia (2024, pp.9-18), examined generative AI's labour market impact directly, by assessing job postings from 2019 through June 2024 (later extended through March 2025), across a dataset, covering “nearly all US vacancies”, to see how employer demand shifted

following the public launch of ChatGPT in November 2022. Their findings reveal an asymmetric pattern: postings for occupations with high automation potential (displacement) fell by 17%, while demand for roles likely to be augmented by AI (complementarity) grew by 22% (Figure 3). The effect is heterogeneous and depends on each occupation's task composition. Roles consisting primarily of routine cognitive tasks face displacement and a simplification of required skills, while occupations that combine automatable tasks with complex human judgement see rising labour demand and upward pressure on skill requirements. The automation susceptibility scores that Srinivasan, Chen and Zakerinia constructed in the course of this analysis are incorporated into the labour pool filtering methodology in Chapter 6.

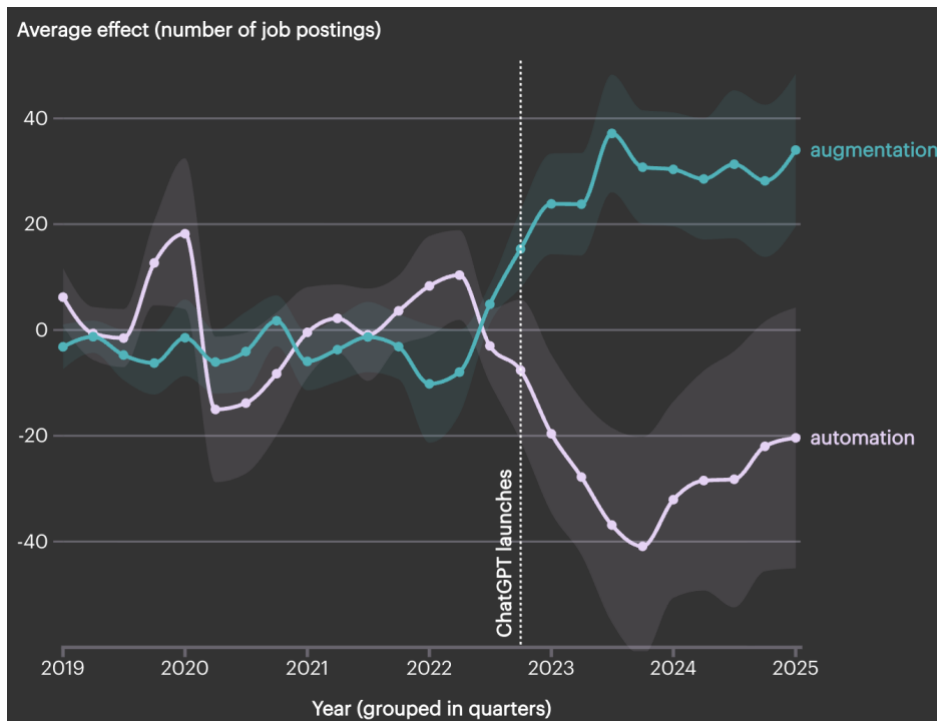


Figure 3. Change in Job Postings by AI Impact Type, Post-ChatGPT (November 2022 – March 2025): Percentage change in US job postings for occupations classified as automation-prone (displacement) versus augmentation-prone (complementarity) following the public launch of ChatGPT in November 2022. Displacement-prone postings fell by 13–17%; augmentation-prone postings grew by 20–22%.

Source: Srinivasan, S., Chen, W.X. and Zakerinia, S. (2024, updated 2025) 'Displacement or Complementarity? The Labor Market Impact of Generative AI', Harvard Business School Working Paper, No. 25-038 [Online]. Summarised in: Azpúrua, A.E. (2026) 'Enhance or Eliminate? How AI Will Likely Change These Jobs', HBS Working Knowledge, 20 February [Online]

This is broadly consistent with the effects reported by Hui, Reshef and Zhou (2024), who examined an online freelancing marketplace and found that generative AI tools reduced job postings and earnings for automatable writing and graphic design tasks.

Choi and Leigh (2024), using online job postings and patent data across United States metropolitan areas, similarly document that AI adoption both creates new labour demand in AI-complementary occupations and displaces demand in occupations whose tasks AI can perform, with the net local effect depending on each metropolitan area's existing industry mix and innovation capacity.

Drawing on detailed online job vacancy data from 2010 to 2018, Acemoglu, Autor, Hazell and Restrepo (2022) show that while AI-exposed establishments are hiring AI workers and changing their skill requirements, the displacement consequences currently outweigh any positive productivity or complementarity effects, leading to a measurable decline in their overall hiring. These effects are not yet visible at the industry or occupation level simply due to the relatively small scale of current AI adoption across the total economy.

At the stock market and firm-value level, Eisfeldt, Schubert, Zhang and Taska (2023) constructed a measure of firms' workforce exposure to generative AI and found that, following the public release of ChatGPT, firms with more exposed workforces experienced abnormally positive stock returns, an effect the authors attribute primarily to anticipated labour-cost savings, where firms are expected to increase profitability by replacing human workers with more efficient, lower-cost technology.

Taken together, these firm- and market-level studies suggest that the task-based displacement and reinstatement dynamics theorised by Acemoglu and Restrepo (2018, 2019) are already visible in early data, but that their distributional consequences fall disproportionately on younger and more codifiable segments of the workforce, a pattern with direct implications for aggregate labour income even where headline employment figures remain stable.

It is this last point, the disjuncture between stable aggregate employment and a possible erosion of aggregate labour income and demand, that is at the centre of this thesis, has become

the focus of a distinct and growing strand of the literature. A number of contributions² from 2025 and 2026 engage this problem directly, and warrant detailed attention here given their relevance to the argument developed in this thesis. Occhipinti and colleagues have advanced this argument across two closely related contributions. In an earlier working paper, Occhipinti et al. (2024) frame the concern explicitly against Adam Smith's account of the market's self-correcting "invisible hand," arguing that although each individual firm's automation decision may be privately rational and welfare-improving, the aggregation of many such decisions across an economy can generate a self-reinforcing macroeconomic externality that no single firm has an incentive to internalise; drawing on International Labour Organization and World Health Organization data, the authors further argue that the resulting job insecurity constitutes a documented risk to population mental health in its own right, independent of its purely economic costs, so that the demand-side risks reviewed in this thesis carry a social-wellbeing dimension as well as a narrowly macroeconomic one. The peer-reviewed elaboration of this argument, Occhipinti et al. (2025), formalises the mechanism as a system dynamics model calibrated to Australian national accounts and labour-force data, in which the key driver is the rate of increase in the AI-capital-to-labour ratio. The authors show that beyond a certain rate of this capital deepening, which they term a socioeconomic tipping point, even historically high rates of new job creation become insufficient to prevent a self-reinforcing cycle of labour underutilisation, falling disposable income and depressed consumption, a cycle that conventional labour-market policy instruments such as retraining alone cannot correct without sustained government intervention.

A closely related but more formally game-theoretic treatment is offered by Falk and Tsoukalas (2026), who model automation decisions among competing firms in a shared product market and show that even fully rational, forward-looking firms cannot unilaterally avoid over-automating: because each firm captures the full cost saving from replacing workers but bears only a fraction of the resulting fall in aggregate consumer demand, a demand externality traps the whole industry in an automation arms race that displaces labour

² Falk and Tsoukalas (2026), Bayraktar (2026), Chen (2026), and Occhipinti et al. (2025) are cited from working-paper or arXiv preprint versions that had not completed formal peer review at the time of writing. Where available, the most recent publicly accessible version has been used. Readers should note that conclusions may be revised in forthcoming published versions.

well beyond the collectively optimal level. This results in a deadweight loss, where both workers (through lost income) and firm owners (through eroded total profits) are worse off than they would be under a cooperative agreement.

Their analysis is notable for systematically testing a range of proposed remedies, including wage adjustments, capital income taxes, worker equity participation, universal basic income and Coasian bargaining, and concluding that none of these fully corrects the demand externality, because they do not change the underlying “competitive incentives” that drive over-automation. Only a Pigouvian tax on automation, in their model, aligns private incentives with the collective interest. Bayraktar (2026) reaches a similar conclusion from a heterogeneous-agent general equilibrium model in which households differ by skill and wealth: automation is found to raise aggregate output and welfare when productivity gains are strong and ownership of capital is broadly distributed, but becomes "excessive," in the sense of reducing welfare despite raising measured output, when exposure falls disproportionately on low-wealth, high-marginal-propensity-to-consume households whose spending underpins aggregate demand, while the returns to automation accrue mainly to concentrated capital owners.

Chen (2026) formalises an overlapping but distinct mechanism under the label of a "displacement spiral": as firms substitute AI for labour, aggregate labour income and therefore aggregate demand fall, which in turn accelerates further AI adoption as firms seek to protect margins in a weakening market; a feedback loop whose stability depends on the relative speed of AI capability growth, diffusion and task reinstatement. Chen (2026, p.10-11) further introduces the concept of "Ghost GDP³," in which AI-generated output substitutes for labour-generated output in a way that can inflate measured production even as consumption-relevant household income stagnates. Stiefenhofer (2025) arrives at a related but more speculative endpoint using a production-function approach building on Cobb-Douglas foundations: as autonomous AI agents operating at near-zero marginal cost substitute for human labour, the marginal productivity, and hence market wage, of labour is

³ Chen (2026) defines Ghost GDP as AI-generated output that substitutes for labour-generated output in national accounts, inflating measured production even as labour income and household consumption stagnate. The concept is related to but distinct from standard discussions of labour productivity: it identifies a wedge between GDP growth and the consumption-relevant income of households whose spending drives aggregate demand.

pushed toward zero, producing a paradox in which firms can produce more but a shrinking share of consumers can afford to buy it; concentrated ownership of AI and capital further entrenches wealth inequality and reduced social mobility in the author's model, a dynamic Stiefenhofer argues will ultimately require a renegotiated social contract involving instruments such as universal basic income, public or cooperative ownership of AI, or progressive capital taxation. Read together, these contributions converge on the same feedback loop, from AI-driven displacement to reduced labour income to reduced aggregate demand, while emphasising different mechanisms and remedies: a product-market externality (Falk and Tsoukalas, 2026), a wealth-and-ownership distribution problem (Bayraktar, 2026), a capability-diffusion race (Chen, 2026), and a wage-collapse endpoint (Stiefenhofer, 2025); their shared conclusion is that standard labour-market policy is unlikely on its own to prevent the harm they each model. Heinz (2025) synthesises much of this reasoning under the heading of an "AI consumption spiral," combining theoretical model-building with a review of international labour and income data to argue that falling real wages, despite rising nominal wages, combined with rising income inequality and a widening gap between the consumption propensities of low- and high-income households, are already eroding the demand base of advanced economies, and that conventional labour-market instruments such as retraining or a modest basic income are insufficient on their own to break the cycle.

A further body of evidence, drawing on historical comparisons and demand-side industrial organisation rather than macroeconomic modelling, offers a more explicitly cautionary counterweight to the demand-spiral literature.

Bessen (2018) argues that the impact of technology on industry employment is fundamentally determined by the price elasticity of demand. He demonstrates that automation has historically coincided with rising industry employment when demand is elastic (greater than one), because falling prices expand the market volume enough to more than offset the labor-saving effect of the technology. Conversely, technology-driven productivity gains result in job losses within an industry only when demand for its output becomes inelastic (less than one). This dynamic is illustrated by the inverted U" pattern observed in the textile, steel, and automotive industries, which experienced decades of job growth alongside rapid technical change until their markets eventually reached satiation.

Acemoglu (2025, pp. 13-58) argues, on the basis of a calibrated task-based growth model, that even optimistic assumptions about AI capability, translate into comparatively modest gains in total factor productivity and GDP over a ten-year horizon, because many economically valuable tasks lie outside AI's current capability frontier or generate more modest productivity gains than headline claims suggest once general-equilibrium adjustment costs, including the demand and reallocation frictions emphasised elsewhere in this review, are taken into account. The research further suggests that while AI may not exacerbate demographic inequality as severely as prior technologies, it is likely to widen the gap between capital and labour income without significantly boosting wages for low-skill workers.

At the policy-research level, the OECD (Green, 2024) reports that AI is reshaping the demand for skills within the global labour market, and suggests a complex shift where AI exposure may eventually reduce the need for certain traditional office and cognitive skills while potentially boosting demand for physical, blue-collar competencies through productivity gains. Ultimately, it serves as a policy guide to help training agencies and employment services prepare the workforce for a future where AI acts as a primary catalyst for workplace reorganization.

Reconciling these strands, the literature as a whole suggests a field in an early and unsettled stage of development, in which the theoretical mechanisms linking AI-driven labour displacement to a shortfall in aggregate demand are increasingly well specified, drawing on established task-based automation theory (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2019, 2020), but for which direct, large-sample empirical confirmation of a self-reinforcing macroeconomic spiral remains limited, resting so far on early payroll and platform-level evidence of age- and task-specific displacement (Brynjolfsson, Chandar and Chen, 2025; Hui, Reshef and Zhou, 2024), on system dynamics simulations calibrated to a single national context (Occhipinti et al., 2025), and on theoretical general-equilibrium and game-theoretic models whose predictions have not yet been tested against realised macroeconomic outcomes (Falk and Tsoukalas, 2026; Bayraktar, 2026; Chen, 2026; Stiefenhofer, 2025). What does appear consistent across nearly all perspectives, optimistic and pessimistic alike, is the recognition that the distributional pattern of AI-driven displacement, and in particular whether the income losses of displaced workers are offset by

new task creation, redistribution or broadly shared capital ownership, matters at least as much as the aggregate scale of automation in determining whether labour income and consumer demand are eroded in practice.

IV. Conceptual Framework

This chapter develops the conceptual framework through which the thesis models the macroeconomic transmission of AI-driven labour displacement. The framework is grounded in the definition of AI as a general-purpose technology, as established by the UN System of National Accounts (2025), the IMF, and the OECD, and as operationalized in the labour market context by Eloundou et al. (2023). As a general-purpose technology, AI has the potential to permeate across sectors simultaneously, unlike sector-specific technological innovations, and to both displace and complement labour within the same occupation in ways that previous technologies have not. This dual nature, combining automation and augmentation, and the deep uncertainty surrounding the pace and distribution of its effects, makes scenario-based modelling the appropriate methodological response, as the thesis adopts in Chapter 6.

The thesis isolates the transmission mechanism operating during the transition period, and specifies four sequential channels through which AI-driven displacement propagates into aggregate consumer demand: the displacement channel, the income channel, the consumption channel, and the aggregate demand channel.

4.1 The Displacement Channel

The framework first distinguishes between automation exposure and actual displacement. Exposure refers to the technical susceptibility of an occupation's task content to AI, as measured by indices such as the AI Occupational Exposure Index developed by Felten, Raj, and Seamans (2021, 2023). Displacement, by contrast, is the realized event in which a worker's task set is substituted by AI and the worker exits employment or experiences a substantial reduction in hours or wages.

The gap between exposure and displacement is governed by the pace of adoption. This thesis models a scenario in which displacement is rapid and simultaneous across many occupations while reinstatement, reskilling infrastructure, and policy response lag behind, a pattern that

early empirical evidence suggests is already underway. This lag between the speed of AI diffusion and the speed of institutional adaptation is the defining feature of the transition period that is the focus of this study.

4.2 The Income Channel

Job displacement does not merely interrupt income, it typically imposes a persistent earnings penalty even after reemployment. The foundational evidence comes from Jacobson, LaLonde, and Sullivan (1993), who found that displaced workers in Pennsylvania suffered earnings losses of approximately 25% that persisted for years after job loss, driven by the erosion of firm- and industry-specific human capital. More recent work on the cyclicity of earning losses (Lachowska, Mas & Woodbury, 2020), confirms that individuals who lost their jobs during the Great Recession experienced sustained reductions in income even after reemployment. While losing a high-paying firm is a factor, most of the income drop stems from the destruction of unique worker-employer matches, where specialized skills and tenure no longer translate to the new role.

This is theoretically significant for the AI displacement scenario because mass, simultaneous displacement across multiple sectors would replicate the labour-market slack conditions under which scarring effects are most severe. The very speed and scale assumed in this thesis's transition-period scenario would amplify the income channel beyond what isolated, idiosyncratic displacement events typically produce. Formally, expected income loss for a displaced worker can be expressed as:

$$\Delta Y = w_0 \times \delta,$$

where w_0 is the worker's pre-displacement wage and δ is the earnings loss ratio drawn from the displacement literature, commonly estimated between 0.15 and 0.40 depending on tenure, sector, and labour market conditions at the time of displacement. Aggregating across the displaced population yields total income loss as a function of the displacement rate and the wage distribution of exposed occupations, which, as demonstrated in the results section, are concentrated in middle- to high-skill, white-collar roles.

4.3 The Consumption Channel

The transmission from income loss to consumption decline depends on the marginal propensity to consume (MPC) of displaced workers. This effect is reinforced by the empirical literature on heterogeneous MPCs. Lower- and middle-income households, who make up the majority of those in automatable occupations, exhibit higher MPCs, compared to substantially lower MPCs among high-income and capital-owning households (Mian, Straub, and Sufi, 2021). This asymmetry matters because the AI displacement shock is not income-neutral in its incidence: it strikes labour income concentrated among high-MPC households while potentially increasing capital income accruing to firms and asset owners. The result is a redistribution from high-MPC to low-MPC agents, which depresses aggregate consumption even if aggregate income is held constant.

4.4 The Aggregate Demand Channel

The final channel applies the Keynesian multiplier. A primary decline in consumption generates a secondary contraction in aggregate demand through the multiplier effect:

$$\Delta AD = \Delta C \times (1 / (1 - MPC)).$$

In a transition-period scenario where displacement is concentrated, rapid, and concurrent across sectors, this multiplier effect risks compounding through a feedback loop: reduced consumer demand lowers firm revenue, which can trigger further layoffs, including in non-automatable sectors dependent on consumer spending, reinforcing the original shock. This dynamic is analogous to a demand-side recession, distinguishing it from a supply-side productivity shock, which is the implicit framing of most long-run automation literature.

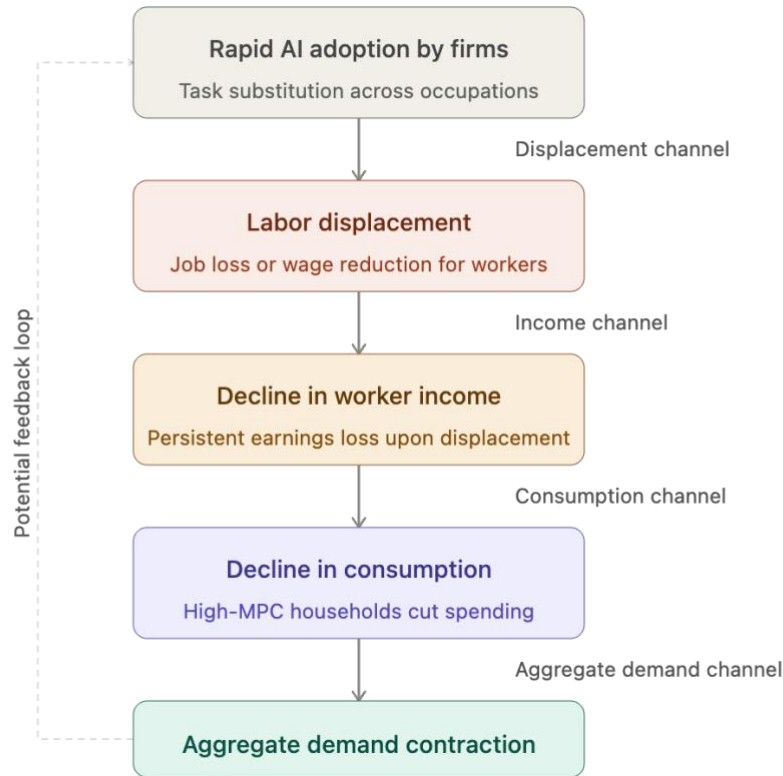


Figure 4. The Four-Channel Transmission Mechanism from AI-Driven Labor Displacement to Aggregate Demand Contraction.

Source: Author's elaboration, based on Acemoglu and Restrepo (2018, 2019); Jacobson, LaLonde and Sullivan (1993); Friedman (1957); Mian, Straub and Sufi (2021); Keynes (1936).

These four channels together yield the thesis's core proposition: that the magnitude of demand-side disruption during an AI-driven transition period is a function not merely of the displacement rate, but of its speed, its income distribution incidence, and the responsiveness of policy buffers. This framework is operationalized in Chapter 6 through calibrated scenario modelling, in which displacement rate, earnings loss ratio, MPC, and multiplier estimates are combined to generate quantitative estimates of aggregate demand contraction under varying transition-period conditions.

5. Scope and Limitations

5.1 Scope of the Study

This thesis focuses on the United States labour market and economy. The US is an appropriate primary case for this analysis for three reasons: it has among the highest rates of AI adoption and technology investment globally; its labour market is characterized by relatively high flexibility, making it a leading indicator of displacement dynamics; and the majority of AI occupational exposure literature, including the primary data sources used in this study, is US-based. The temporal scope covers the present to the near-future horizon of 2024 to 2034, aligned with the BLS employment projection data used in the empirical analysis, and specifically targets the transition period in which displacement may precede reemployment and reinstatement at scale.

Within aggregate demand, this thesis focuses exclusively on the consumer consumption component, to be precise, consumption out of wages. The focus is justified on two grounds. First, consumer consumption is the largest single component of US aggregate demand, consistently accounting for approximately 67 to 70 percent of GDP (Federal Reserve Bank of St. Louis, 2026). Second, the transmission mechanism modelled in this thesis, from labour income loss to reduced household spending, operates directly through the consumption component. Investment, government expenditure, and net exports may be affected indirectly, but those secondary effects are outside the scope of this study. This is a deliberate scope boundary: the aim is to isolate and quantify the direct consumption channel of the demand shock, holding other components constant.

It is also important to note that this thesis does not contest the long-run macroeconomic case for AI. Long-term effects may well be positive in aggregate: AI-driven productivity growth could stimulate investment, generate new occupations, and expand net exports through technological comparative advantage. There will be winners and losers, but the net long-run macroeconomic trajectory may be positive. The contribution of this thesis is specifically to quantify the short-to-medium run demand risk during the current transition period.

5.2 Limitations

Several limitations of this study must be acknowledged explicitly. First, AI is a rapidly evolving technology and many firms remain in early stages of adoption. The scenario model captures a hypothetical but plausible transition-period shock: it is not a forecast, and the actual pace and breadth of displacement will depend on adoption dynamics that remain uncertain.

Second, there is currently no publicly available occupational-level microdata linking individual workers' spending patterns to specific job titles. The Consumer Expenditure Survey reports spending by income quintile and broad occupation category, but is not granular enough to isolate the consumption behavior of workers in high-AI-exposure occupations specifically. This thesis, therefore, estimates consumption impact using an aggregate MPC derived from the CES, applied to the modelled income loss. This is a standard methodological approach in macroeconomic simulation but introduces approximation error at the occupational level.

Third, this is a partial equilibrium simulation. The model does not capture firm behavior, price adjustment, or monetary policy response. It does not model job creation on the reinstatement side. The analysis is deliberately designed to isolate the demand shock from displacement, holding other equilibrating forces constant, in order to establish a clear estimate of the direct demand effect before secondary adjustments occur. A general equilibrium treatment is a natural extension for future work.

Fourth, since the thesis focuses exclusively on the US economy and does not extend to cross-country comparisons, the structural features of other economies, labour market institutions, social protection systems, consumption patterns, would produce different transmission dynamics, making direct generalization inappropriate without further analysis.

Despite these limitations, the scenario modelling framework provides a consistent and empirically grounded estimate of the order of magnitude of aggregate demand contraction under plausible transition-period conditions. The findings are intended to quantify the potential scale and extent of the demand impact, not to predict a specific outcome, but to establish the conditions under which the risk becomes macroeconomically significant.

6. Methodology and Data

This thesis employs a two-stage empirical design combining econometric analysis with macroeconomic scenario simulation. The first stage uses Ordinary Least Squares (OLS) regression to evaluate correlations between AI occupational exposure, wages, and employment trends. The second stage applies a calibrated scenario model to project aggregate income loss and demand contraction under varying displacement and reemployment conditions. The use of scenario modelling is appropriate here because, under conditions of deep uncertainty, as characterize the current stage of AI diffusion, it is more methodologically defensible to model a range of plausible outcomes than to produce a single point estimate.

6.1 Data Sources

The empirical analysis draws on four primary data sources. The first is the AI Occupational Exposure (AIOE) index developed by Felten, Raj, and Seamans (2021, 2023), which covers approximately 760 US occupations. The second is the US Bureau of Labour Statistics (BLS) Occupational Employment and Wage Statistics (OEWS), providing current employment counts and median wages at the occupational level. The third is the BLS Employment Projections dataset for the 2024–2034 period, used to identify occupations with projected employment growth or decline. The fourth is the BLS Consumer Expenditure Survey (CES), from which the marginal propensity to consume is derived. Additionally, the automation susceptibility scores constructed by the Harvard Business School (HBS) research team are incorporated into the data filtering process described in Section 6.4. These datasets are merged using Standard Occupational Classification (SOC) codes as the common identifier.

6.2 The AI Occupational Exposure (AIOE) Index

To capture AI exposure at the occupational level, this thesis uses the AI Occupational Exposure index developed by Felten, Raj, and Seamans (2021, 2023). The AIOE index grades approximately 760 unique US occupations by matching O*NET⁴ job task profiles

⁴ O*NET (Occupational Information Network) is a publicly available US Department of Labor database that describes the tasks, knowledge, skills, and abilities associated with approximately 900 occupations. Felten, Raj and Seamans (2021, 2023) match O*NET task descriptions to nine AI capability areas, including abstract reasoning, natural language processing, and image recognition, to construct the AIOE score for each occupation.

against specific AI application categories, assessing the extent to which core job tasks can be automated or augmented by AI. A higher AIOE score indicates greater theoretical exposure to AI, while a negative score indicates minimal or no exposure.

An important caveat applies to the interpretation of AIOE scores. A high AIOE score does not necessarily indicate that a worker will be displaced, it may equally indicate that AI will augment the worker's productivity without eliminating the role. Whether AI automates or augments depends on the specific task composition of the occupation and the economic incentives of individual firms. However, the index remains a reliable basis for identifying which occupations are most exposed to AI-driven change, and this distinction between exposure and realized displacement is addressed explicitly in the conceptual framework in Chapter 4.

Tables 1 and 2 present the 15 occupations with the highest and lowest AIOE scores, respectively, to illustrate the distributional properties of the index. As Table 1 shows, the most exposed occupations are predominantly high-skill, high-wage, white-collar roles: genetic counselors, actuaries, financial examiners, budget analysts, judges, and accountants. This is consistent with the argument developed in Chapter 4 that the AI demand risk operates through the income channel of high-earning workers, not the low-wage, routine-physical labour that previous automation waves primarily targeted. Conversely, as Table 2 shows, the least exposed occupations are physically embodied, human-centric roles: dancers, fitness trainers, construction helpers, and manual trade workers, which are structurally resistant to AI substitution.

Top 15 Occupations by AI Occupational Exposure (AIOE) Score.

SOC Code	Occupation Title	AIOE Score
29-9092	Genetic Counselors	1.528
13-2061	Financial Examiners	1.526
15-2011	Actuaries	1.516

A full description of the matching methodology and the complete AIOE dataset are available at <https://github.com/AIOE-Data/AIOE>.

SOC Code	Occupation Title	AIOE Score
13-2031	Budget Analysts	1.503
23-1023	Judges, Magistrate Judges, and Magistrates	1.496
43-3061	Procurement Clerks	1.488
13-2011	Accountants and Auditors	1.482
15-2021	Mathematicians	1.472
23-1012	Judicial Law Clerks	1.463
11-9033	Education Administrators, Postsecondary	1.461
19-3033	Clinical, Counseling, and School Psychologists	1.456
11-3031	Financial Managers	1.446
13-1141	Compensation, Benefits, and Job Analysis Specialists	1.441
43-4041	Credit Authorizers, Checkers, and Clerks	1.440
25-1125	History Teachers, Postsecondary	1.437

Table 1. Top 15 Occupations by AI Occupational Exposure (AIOE) Score.

Source: Felten, E., Raj, M. and Seamans, R. (2021) 'Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses.' Strategic Management Journal, 42(12), pp. 2195–2217; Felten, E.W., Raj, M. and Seamans, R. (2023) 'How Will Language Modelers Like ChatGPT Affect Occupations and Industries?' SSRN Electronic Journal. <https://doi.org/10.2139/ssrn.4375268>.

Top 15 Occupations with Lowest (Negative) AIOE Scores.

SOC Code	Occupation Title	AIOE Score
27-2031	Dancers	-2.670
39-9031	Fitness Trainers and Aerobics Instructors	-2.112
47-3014	Helpers—Painters, Paperhangers, Plasterers, and Stucco Masons	-2.045
47-2171	Reinforcing Iron and Rebar Workers	-1.971
51-6021	Pressers, Textile, Garment, and Related Materials	-1.950
47-3011	Helpers—Brickmasons, Blockmasons, Stonemasons, and Tile and Marble Setters	-1.942
35-9011	Dining Room and Cafeteria Attendants and Bartender Helpers	-1.927
47-4031	Fence Erectors	-1.902
47-3016	Helpers—Roofers	-1.898
51-3023	Slaughterers and Meat Packers	-1.835
37-3011	Landscaping and Groundskeeping Workers	-1.824

SOC Code	Occupation Title	AIOE Score
27-2021	Athletes and Sports Competitors	-1.814
45-4021	Fallers	-1.795
47-2221	Structural Iron and Steel Workers	-1.780

Table 2. Top 15 Occupations with Lowest (Negative) AIOE Scores.

Source: Felten, E., Raj, M. and Seamans, R. (2021) 'Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses.' Strategic Management Journal, 42(12), pp. 2195–2217; Felten, E.W., Raj, M. and Seamans, R. (2023) 'How Will Language Modelers Like ChatGPT Affect Occupations and Industries?' SSRN Electronic Journal. <https://doi.org/10.2139/ssrn.4375268>.

6.3 Merging the AIOE Index with BLS Employment and Wage Data

To extend the AIOE index into an empirically grounded dataset for regression and scenario analysis, it is merged with BLS Occupational Employment and Wage Statistics and Employment Projections data using SOC codes as the common identifier. The merged dataset includes, for each occupation: the AIOE score, employment levels in 2021 and 2025, annual median wages in 2025, the percentage employment change from 2021 to 2025, and the projected percentage employment change from 2024 to 2034. Table 3 presents a sample of this merged dataset for the 14 highest-AIOE occupations.

A notable feature of the merged data is the divergence between recent observed employment trends and forward-looking BLS projections. Most high-AIOE occupations grew in employment between 2021 and 2025, financial managers increased by 23.6%, clinical psychologists by 30.8%, and compensation specialists by 28%. This is consistent with the finding in the empirical literature that AI-driven displacement is not yet observable in aggregate occupational data. However, the forward-looking projections tell a more mixed story: budget analysts are projected to grow by only 1% over 2024–2034, procurement clerks are projected to decline by 8.7%, and mathematicians by 7%. The divergence between current employment growth and deteriorating forward projections is the empirical basis for treating this as a forward-looking risk rather than a presently observable crisis.

Top 14 Highest-AIOE Occupations: Merged AIOE, Employment, Wage, and Projection Data.

SOC Code	Occupation Title	AIOE	Employment 2025	Median Wage 2025 (\$)	Employment 2021	Change 2021–2025 (%)	Projected Change 2024–2034 (%)
29-9092	Genetic Counselors	1.528	3,740	100,040	2,740	36.50%	9.3
13-2061	Financial Examiners	1.526	67,830	94,160	60,750	11.65%	18.5
15-2011	Actuaries	1.516	26,670	130,000	23,040	15.76%	21.8
13-2031	Budget Analysts	1.503	47,160	91,640	47,440	-5.90%	1.0
43-3061	Procurement Clerks	1.488	55,810	50,580	61,930	-9.88%	-8.7
13-2011	Accountants and Auditors	1.482	1,449,500	83,680	1,318,550	9.93%	4.6
15-2021	Mathematicians	1.472	2,030	126,710	1,770	14.69%	-7.0
23-1012	Judicial Law Clerks	1.463	13,290	64,920	14,800	-10.20%	2.5
11-9033	Education Administrators, Postsecondary	1.461	180,470	104,590	155,990	15.69%	1.7
19-3033	Clinical, Counseling, and School Psychologists	1.456	75,990	100,580	58,100	30.79%	11.2
11-3031	Financial Managers	1.446	841,710	166,570	681,070	23.59%	14.8
13-1141	Compensation, Benefits, and Job Analysis Specialists	1.441	112,380	78,210	87,750	28.07%	5.3
43-4041	Credit Authorizers, Checkers, and Clerks	1.440	12,030	50,080	16,820	-2.85%	-6.2
25-1125	History Teachers, Postsecondary	1.437	18,790	83,820	18,590	1.08%	-0.2

Table 3. Top 14 Highest-AIOE Occupations: Merged AIOE, Employment, Wage, and Projection Data.
Sources: Felten et al. (2021, 2023) (see Table 1); Bureau of Labor Statistics (2025) Occupational Employment and Wage Statistics [online]; Bureau of Labor Statistics (2025) Employment Projections, 2024–2034 [online].
Author's elaboration.

6.4 Constructing the Vulnerable Labour Pool

The scenario model requires isolating the occupations that constitute the vulnerable, potentially AI-displaced labour pool. This is not simply the set of occupations with the highest AIOE scores, since high exposure does not necessarily imply displacement. Instead, a three-criterion filter is applied to the full merged dataset. First, an occupation must have a projected employment decline or stagnant growth, defined as a BLS projected employment

change of 2% or less over 2024–2034. Second, it must have a positive AIOE score, indicating meaningful AI exposure. Third, it must have an HBS automation score⁵ above 0.35, which is above the mean automation score of 0.316 across all occupations and is used here to distinguish occupations with high automation potential from those where the AIOE score primarily reflects augmentation rather than substitution.

The HBS automation score was constructed by a Harvard Business School research team using GPT-4 to evaluate over 19,000 job tasks across more than 900 occupations, assessing the proportion of tasks within each occupation that are susceptible to automation through AI. Occupations above the mean score of 0.316, such as word processors, data entry keyers, and telemarketers, are treated as having a higher likelihood of realized displacement. Occupations below the mean, such as food preparation workers, dancers, and forensic science technicians, are treated as having low automation potential, even if they carry some degree of AI exposure. Human judgement regarding task content is also applied to borderline cases.

The application of this three-criterion filter to the full dataset yields 81 occupations that constitute the vulnerable, potentially AI-displaced declining pool. Table 4 presents the top 25 of these occupations by magnitude of projected employment decline, along with their AIOE scores, current employment, median wages, projected employment change, and HBS automation scores. These are the occupations whose contractions are most plausibly being accelerated or driven by cognitive automation, including word processors and typists, data entry keyers, telemarketers, payroll and timekeeping clerks, and a range of clerical and administrative roles.

⁵ The automation susceptibility scores used here were constructed by Srinivasan, Chen and Zakerinia (2024, 2025) at Harvard Business School, using GPT-4 to evaluate the automation potential of over 19,000 tasks drawn from O*NET task profiles for more than 900 occupations. The mean score across all occupations is 0.316; the threshold of 0.35 applied in this thesis is above that mean but deliberately conservative, excluding borderline cases where the balance of evidence does not clearly support treating displacement as the more likely outcome than augmentation.

**Top 25 Occupations in the Potentially AI-Driven Declining Pool (81 occupations total),
Ranked by Projected Employment Decline, 2024–2034.**

SOC Code	Occupation Title	AIOE	Employment 2025	Median Wage 2025 (\$)	Projected Change 2024–2034 (%)	Automation Score (HBS)
43-9022	Word Processors and Typists	0.622	35,010	49,280	-36.1	0.72
43-2021	Telephone Operators	1.020	3,430	41,740	-27.5	0.52
43-2011	Switchboard Operators, Including Answering Service	0.983	34,280	38,630	-26.3	0.48
43-9021	Data Entry Keyers	0.311	127,080	41,340	-25.9	0.46
41-9041	Telemarketers	1.118	58,430	35,450	-22.1	0.73
43-4151	Order Clerks	0.839	75,200	46,170	-17.2	0.72
43-3051	Payroll and Timekeeping Clerks	1.258	153,140	58,260	-16.7	0.70
43-4071	File Clerks	0.284	73,440	43,600	-15.9	0.49
25-1191	Adult Literacy, Remedial Education, and GED Teachers and Instructors	1.349	37,310	61,540	-13.7	0.45
43-3071	New Accounts Clerks	1.175	36,860	47,670	-13.2	0.48
43-3071	Tellers	0.473	329,480	43,030	-12.9	0.36
43-4111	Interviewers, Except Eligibility and Loan	1.297	148,060	45,920	-11.6	0.65
43-3011	Bill and Account Collectors	1.272	158,830	47,030	-10.5	0.70
43-4011	Brokerage Clerks	1.145	35,940	65,750	-9.5	0.59
43-3061	Procurement Clerks	1.488	55,810	50,580	-8.7	0.66
41-3021	Insurance Appraisers, Auto Damage	0.663	11,560	78,240	-8.2	0.37
13-1071	Human Resources Specialists	1.353	90,220	50,610	-7.1	0.68
25-4031	Library Technicians	0.038	68,690	44,580	-6.8	0.45
41-3011	Advertising Sales Agents	1.163	91,700	64,820	-6.4	0.63
43-4041	Credit Authorizers, Checkers, and Clerks	1.440	12,030	50,080	-6.2	0.63
43-3031	Bookkeeping, Accounting, and Auditing Clerks	1.040	1,373,680	50,670	-5.8	0.68

SOC Code	Occupation Title	AIOE	Employment 2025	Median Wage 2025 (\$)	Projected Change 2024–2034 (%)	Automation Score (HBS)
43-6012	Legal Secretaries	1.015	156,280	55,570	-5.8	0.53
43-4021	Correspondence Clerks	1.150	4,290	46,800	-5.6	0.86
43-4051	Customer Service Representatives	0.956	2,595,750	44,770	-5.5	0.57
27-3011	Radio and Television Announcers	0.849	21,240	47,340	-5.5	0.53

Table 4. Top 25 Occupations in the Potentially AI-Driven Declining Pool (out of 81 total), by Projected Employment Decline. Sources: Felten et al. (2021, 2023); BLS Occupational Employment and Wage Statistics; BLS Employment Projections (2024–2034); Harvard Business School automation score. Author's elaboration.

6.5 Constructing the Lower-Tier Reemployment Pool

The scenario model also requires a specification of where displaced workers are assumed to find reemployment. As discussed in the conceptual framework, the literature on previous technological transitions finds that displaced workers, particularly those without access to rapid reskilling, tend to transition into lower-tier, lower-wage occupations rather than immediately moving into newly created high-skill roles. In the short-term adjustment period that is the focus of this thesis, it is not plausible to assume that displaced typists or payroll clerks become network architects or data scientists.

The lower-tier reemployment pool is therefore constructed from BLS-projected growing occupations that have negative or near-zero AIOE scores, indicating low AI exposure and therefore stability, and that represent roles accessible without significant reskilling. These include taxi drivers, stock clerks and order fillers, construction labourers, couriers, food batchmakers, and personal care aides. Table 5 presents the 25 occupations used to construct this pool. Their median wages range from approximately \$32,600 to \$59,050, substantially below the weighted average wage of the declining pool.

Lower-Tier Growing Occupations Used as the Reemployment Pool (25 occupations shown).

SOC Code	Occupation Title	AIOE	Employment 2025	Median Wage 2025 (\$)	Projected Change 2024–2034 (%)
53-3054	Taxi Drivers and Chauffeurs	-0.632	41,050	42,100	11.1
53-3031	Driver/Sales Workers	-0.729	409,180	38,770	8.8
53-7065	Stock Clerks and Order Fillers	-0.789	2,833,810	37,330	8.5
43-5021	Couriers and Messengers	-0.959	68,640	39,200	8.2
39-5091	Makeup Artists, Theatrical and Performance	-0.460	2,340	97,150	8.1
47-2061	Construction Labourers	-1.623	1,096,780	47,120	7.3
53-3033	Truck Drivers, Light or Delivery Services	-1.121	983,300	44,860	7.3
39-5092	Manicurists and Pedicurists	0.034	152,770	35,760	7.0
51-3092	Food Batchmakers	-0.379	174,520	42,290	6.9
53-3053	Shuttle Car Operators	-1.352	248,530	37,290	6.7
39-9099	Personal and Home Care Aides	-0.574	60,420	41,600	6.4
39-3093	Locker Room, Coatroom, and Dressing Room Attendants	-0.345	15,560	36,300	6.4
35-9011	Dining Room and Cafeteria Attendants and Bartender Helpers	-1.927	542,750	33,980	6.3
39-3092	Costume Attendants	-0.453	6,510	50,400	5.9
35-3011	Bartenders	-0.616	756,390	34,340	5.9
33-9092	Lifeguards, Ski Patrol, and Other Recreational Protective Service Workers	-0.472	157,550	33,580	5.8
47-3016	Helpers—Roofers	-1.898	6,030	44,160	5.7
49-3093	Tire Repairers and Changers	-1.551	108,410	37,710	5.7
51-3022	Meat, Poultry, and Fish Cutters and Trimmers	-1.106	145,700	38,300	5.5
39-5093	Shampooers	-0.905	8,070	32,600	5.5
51-6011	Laundry and Dry-Cleaning Workers	-1.054	198,040	34,890	5.4

SOC Code	Occupation Title	AIOE	Employment 2025	Median Wage 2025 (\$)	Projected Change 2024–2034 (%)
47-3015	Helpers—Pipelayers, Plumbers, Pipefitters, and Steamfitters	-1.679	44,330	42,360	4.9
47-3012	Helpers—Carpenters	-1.425	21,680	43,780	4.5
51-9111	Packaging and Filling Machine Operators and Tenders	-0.979	379,060	43,220	4.5
53-3052	Bus Drivers, Transit and Intercity	-0.605	159,240	59,050	4.3

Table 5. Lower-Tier Growing Occupations Used as the Reemployment Pool. Sources: BLS Occupational Employment and Wage Statistics; BLS Employment Projections (2024–2034). Author's elaboration.

6.6 Baseline Parameters

The application of the filtering criteria described in Sections 6.4 and 6.5 yields the baseline parameters that serve as inputs to the scenario model. These are summarized in Table 6. The total vulnerable, potentially AI-induced declining pool encompasses approximately 19.6 million workers, with a weighted average annual median wage of \$57,183.56. The lower-tier reemployment pool, comprising 29.7 million workers, carries a weighted average wage of \$38,354.91. The resulting wage deficit per reemployed worker, the difference between the wage lost in the declining occupation and the wage earned in the reemployment occupation, is \$18,828.65. This wage deficit is a key structural feature of the model: it means that even workers who are successfully reemployed suffer a substantial income loss, and that this income loss generates consumption and demand contraction regardless of whether the displaced worker finds new employment or remains unemployed.

Parameter	Value
Total declining pool (potentially AI-induced)	19,595,360 workers
Total lower-tier growing pool	29,739,900 workers
Weighted average wage - declining pool (w_d)	\$57,183.56
Weighted average wage - lower-tier growing pool (w_l)	\$38,354.91
Wage deficit per reemployed job ($w_d - w_l$)	\$18,828.65

Table 6. Baseline Parameters for the Scenario Model. Sources: BLS Occupational Employment and Wage Statistics; BLS Employment Projections (2024–2034). Author's elaboration.

6.7 OLS Regression Specification

The first stage of the empirical analysis uses OLS regression to evaluate two structural relationships. The first regression examines whether an occupation's AIOE score explains observed employment changes from 2021 to 2025, controlling for initial wage levels. The second regresses wages on AIOE scores across all occupations to assess the correlation between AI exposure and earning levels. A binned scatterplot approach is also used to visualize the relationship between AIOE score and projected employment change from 2024 to 2034, weighting bins by current employment levels to account for the large variation in occupational size. These regressions address the first sub-question of the thesis and provide the empirical grounding for the scenario model's occupational classification.

6.8 Scenario Model Specification

The second stage of the methodology applies a calibrated scenario model to quantify the aggregate demand implications of AI-driven labour displacement. The model operates through three sequential steps: income loss, consumption shock, and aggregate demand contraction, each governed by a specific equation and calibrated to real-world data.

6.8.1 Step I: Income Loss

The income loss from displacement is calculated as follows:

$$\Delta Y = L \times \delta \times [(1 - \rho) \times w_d + \rho \times (w_d - w_l)]$$

where L is the total employment in the potentially AI-affected declining pool (19.6 million workers); δ is the displacement rate, modelled at 10%, 25%, and 50%, drawn from the empirical literature including Eloundou et al. (2023); ρ is the reemployment rate, representing the share of displaced workers who find new employment in lower-tier roles, modelled at 20%, 50%, and 80%; w_d is the weighted average wage in the declining pool (\$57,183.56); and w_l is the weighted average wage in the lower-tier reemployment pool (\$38,354.91). The term $(1 - \rho)$ captures the income loss of workers who remain unemployed and lose their full wage. The term $\rho \times (w_d - w_l)$ captures the wage deficit incurred by workers who find reemployment but at lower pay. Both terms contribute to income loss: the formula therefore models a situation in which even successful reemployment generates aggregate income

contraction, because the wage quality of available reemployment occupations is lower than the wage quality of the occupations being lost.

The three displacement rates and three reemployment rates produce a 3×3 scenario matrix of nine distinct outcomes. The displacement rate values of 10%, 25%, and 50% are selected to span a low, moderate, and high displacement range, consistent with estimates in the AI exposure literature. The three reemployment rates provide a similar low, moderate, and high range for labour market reabsorption. Together, these nine scenarios provide a systematic picture of aggregate demand risk across a realistic range of transition-period conditions.

6.8.2 Step II: Consumption Shock

Income loss is translated into a consumption shock using the general consumption function, excluding autonomous consumption, since the analysis focuses specifically on the consumption derived from labour income, in other words, consumption out of wages:

$$\Delta C = \Delta Y \times \text{MPC}$$

The marginal propensity to consume (MPC) is set at 0.80, derived from the BLS Consumer Expenditure Survey. Empirical estimates using CES microdata consistently show that the aggregate MPC for middle- and lower-income US households, who are disproportionately represented in the vulnerable labour pool identified in Section 6.4, falls in the range of 0.60 to 0.90. A value of 0.80 is selected as a conservative central estimate within this range. Since no publicly available dataset reports consumption expenditure at the level of individual occupational categories, the aggregate MPC is applied uniformly across the displaced population, constituting a standard approximation in macroeconomic simulation of this type.

6.8.3 Step III: Aggregate Demand Contraction

The final step incorporates the Keynesian multiplier to capture the macroeconomic feedback effect, in which the primary consumption decline triggers secondary reductions in output and income as the spending of displaced workers constitutes the income of other workers and firms:

$$\Delta \text{AD} = \Delta C \times k, \text{ where } k = 1 / (1 - \text{MPC})$$

A theoretical multiplier of $1 / (1 - 0.80) = 5$ is not used, as real-world leakages through imports, taxation, and precautionary saving substantially compress the effective multiplier in an open economy. Based on empirically estimated multiplier ranges in the macroeconomic literature, which typically fall between 1.2 and 1.5 for the United States, a conservative value of $k = 1.35$ is used. This is applied uniformly across all nine scenarios. The output of this step which is total aggregate demand contraction in billions of dollars, is the primary outcome variable of the scenario model and is reported in full in the results section.

7. Results and Analysis

This results and analysis section presents the findings from the OLS regression analysis and the calibrated scenario modelling. The empirical results address the first two sub-questions of this thesis: what AI exposure metrics reveal about the relationship between occupational AI exposure, wages, and recent and projected employment trends; and under what combinations of displacement risk and reemployment rate does AI-driven labour automation pose a threat to aggregate consumer demand. The scenario modelling results then quantify the potential macroeconomic implications in terms of income loss, consumption shock, and total demand contraction.

7.1 AI Exposure and Wages: OLS Regression Results (Figure 1)

Figure 2 presents a scatterplot that visualizes the relationship between AI Occupational Exposure (AIOE) scores and annual median wages in 2025 across all approximately 760 BLS occupations.

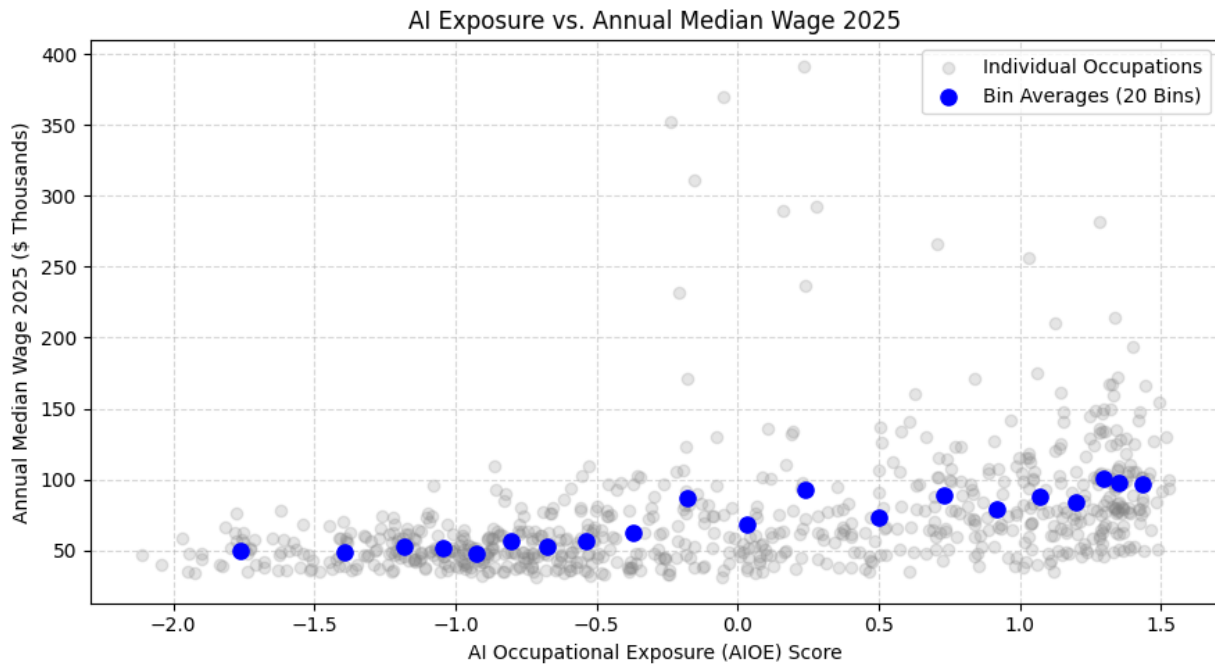


Figure 5. *AI Occupational Exposure (AIOE) Score vs. Annual Median Wage, 2025: All BLS Occupations (~760) with Bin Averages (20 Bins).*

Source: Felten, E., Raj, M. and Seamans, R. (2021, 2023) *AI Occupational Exposure Index*; Bureau of Labor Statistics (2025) *Occupational Employment and Wage Statistics*. Author's elaboration.

To clarify the underlying trend, all occupations were grouped into 20 equally sized bins based on their AIOE score, and the average AIOE score for each bin was plotted against the median wage of the occupations within that bin. Individual occupations are shown as grey dots, while the bin averages are shown as blue dots.

The analysis reveals a clear positive correlation between AI exposure and wages. As the AIOE score increases, indicating greater theoretical exposure to AI automation or augmentation, the median annual wage of the occupation also tends to rise. Occupations with negative AIOE scores, indicating minimal or no AI exposure, cluster predominantly below \$50,000 in annual median wages. By contrast, occupations in the highest-exposure bins, with AIOE scores above 1.0, show a notably higher and upward-stepping wage profile, with bin averages consistently approaching or exceeding \$100,000.

This finding carries a significant implication for the demand-side argument of this thesis. Contrary to the pattern observed in earlier waves of automation, which predominantly displaced low-wage, routine manual workers, AI exposure appears most concentrated among

high-skill, white-collar occupations. The most exposed workers are not at the margins of consumer spending; they are among those who contribute disproportionately to aggregate demand. If AI inflicts severe labour displacement, the job losses will not be concentrated in low-wage sectors as in the past, but in high-earning white-collar brackets. The demand contraction risk is therefore larger per displaced worker than a simple headcount of affected occupations would suggest.

7.2 AI Exposure and Recent Employment Growth: OLS Regression Results (Figure 2)

Figure 3 presents an OLS linear regression examining whether higher AI occupational exposure is correlated with recent employment growth. The x-axis shows the AIOE score and the y-axis shows the percentage employment change between 2021 and 2025, based on observed BLS Occupational Employment and Wage Statistics data. The red line represents the OLS fit across all approximately 760 occupations.



Figure 6. AI Occupational Exposure (AIOE) Score vs. Employment Change, 2021–2025: OLS Linear Regression (Slope = 2.00).

Source: Felten, E., Raj, M. and Seamans, R. (2021, 2023) AI Occupational Exposure Index; Bureau of Labor Statistics (2025) Occupational Employment and Wage Statistics. Author's elaboration

The estimated slope of the OLS fit is 2.00, indicating a slightly positive association between AI exposure and recent employment growth. However, this result must be interpreted with

considerable caution. The scatter of individual occupation data points is extremely wide, and the overall explanatory power of the model is very low. The positive slope is driven largely by the broad variance in the data and does not represent a reliable or systematic relationship. In practical terms, the regression provides no robust evidence that AI-exposed occupations have experienced meaningfully faster or slower employment growth than low-exposure occupations over this period.

This finding is consistent with the early empirical evidence reviewed in the literature section, including Brynjolfsson et al. (2025) and Massenkoff and McCrory (2026), which similarly found limited evidence of aggregate AI-driven unemployment to date, while identifying early signals in specific sub-groups such as entry-level and early-career workers. The absence of a strong signal in the 2021 to 2025 employment data does not, however, diminish the forward-looking concern. As noted by Massenkoff and McCrory (2026), the gap between AI's theoretical capability and its observed deployment in the workplace remains wide, meaning the labour market effects of AI diffusion are likely still in early stages. The demand-side risk examined in this thesis is therefore better characterized as a forward-looking risk than a currently measurable crisis.

7.3 AI Exposure and Projected Employment Growth: Binned Scatter Analysis (Figure 3)

Figure 4 shifts the analysis from observed to projected employment outcomes. The x-axis again shows the AIOE score, while the y-axis now shows the BLS projected employment change from 2024 to 2034. This is presented as a binned scatterplot with 20 equally sized bins; each data point represents the average AIOE score and projected employment growth for the occupations within that bin. The dashed regression line is weighted by current employment levels, so larger occupational groups carry more influence in the fit.

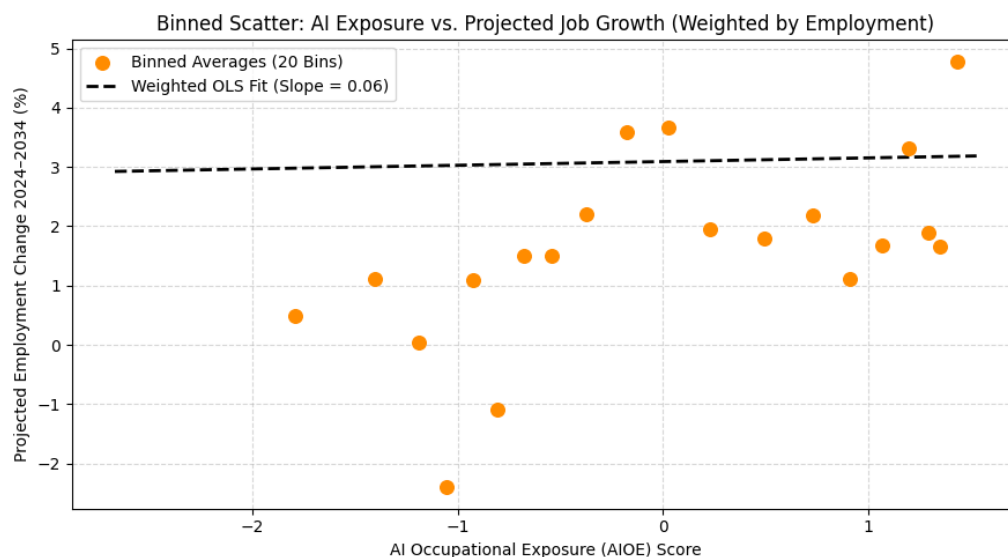


Figure 7. *AI Occupational Exposure (AIOE) Score vs. Projected Employment Change, 2024–2034: Binned Scatter (20 Bins), Weighted OLS Fit (Slope = 0.06).*

Source: Felten, E., Raj, M. and Seamans, R. (2021, 2023) *AI Occupational Exposure Index*; Bureau of Labor Statistics (2025) *Employment Projections, 2024–2034*. Author's elaboration.

The weighted OLS slope is 0.06, meaning that for every 10-percentage point increase in AI exposure, the BLS projected employment growth rate rises by approximately 0.6 percentage points. This is a positive but very small effect. Taken at face value, the BLS projections do not suggest that high-exposure occupations are expected to contract more than low-exposure ones over the next decade. In fact, the highest-exposure bin shows the strongest projected growth, driven by a small number of rapidly expanding AI-adjacent roles, such as in data science, actuarial work, and technology management.

However, several important qualifications apply. First, the relationship is weak and the variance across bins is large, particularly in the middle of the AIOE distribution, scores between approximately negative 0.5 and positive 0.5, where projected growth ranges from contraction to moderate expansion across different occupational groups. Second, BLS projections are produced using established methodological frameworks that may not fully incorporate the pace and breadth of AI diffusion anticipated over the 2024 to 2034 period. Third, and most critically for this thesis, aggregate projected growth at the occupational level masks the within-occupation distributional dynamics: even in occupations projected to grow overall, AI may reduce the number of workers needed per unit of output, depressing labour income without necessarily reducing headcount proportionally.

Taken together, the three figures establish a coherent empirical baseline. AI exposure is most concentrated among high-wage, white-collar workers. Recent employment data shows no aggregate displacement signal, consistent with the early stage of AI diffusion. Forward-looking projections suggest a slightly positive, but highly uncertain, employment trajectory for high-exposure occupations. This combination of high wage exposure, limited current displacement, and significant forward uncertainty provides the empirical grounding for the calibrated scenario modelling presented in the following section.

7.4 Calibrated Scenario Modelling Results

This section presents the results of the calibrated scenario model, which quantifies the potential macroeconomic impact of AI-driven labour displacement on aggregate income, consumer spending, and total demand. As outlined in the methodology section, the model is structured around two key parameters: the displacement rate (δ), representing the share of workers in the potentially AI-affected declining occupational pool who lose their jobs as a result of AI automation, and the reinstatement rate (ρ), representing the share of those displaced workers who successfully find reemployment, albeit in lower-tier growing occupations. Three values are modelled for each parameter: displacement rates of 10%, 25%, and 50%, and reinstatement rates of 20%, 50%, and 80%, producing a 3×3 scenario matrix of nine distinct outcomes. The results are reported in Table 1 below.

Displacement Rate (δ)	Reemployment Rate (ρ)	Income Loss (-\$B)	Consumption Shock (-\$B)	Total Demand Contraction (-\$B)
10%	20%	97.022	77.617	104.783
10%	50%	74.474	59.579	80.432
10%	80%	51.927	41.542	56.081
25%	20%	242.554	194.043	261.959
25%	50%	186.186	148.949	201.081
25%	80%	129.817	103.854	140.203
50%	20%	485.108	388.087	523.917
50%	50%	372.372	297.897	402.161
50%	80%	259.635	207.708	280.406

Table 7. Macroeconomic Shock Scenario Matrix: Income Loss, Consumption Shock, and Total Demand Contraction across Displacement Rate (δ) and Reemployment Rate (ρ) Scenarios. Source: Author's elaboration.

7.4.1 Structure of Results

Total demand contraction ranges from \$56.081 billion to \$523.917 billion. Even workers who are successfully reinstated ($p = 0.80$) transition into lower-tier growing occupations with a weighted average wage of \$38,354.91, compared to the \$57,183.56 weighted average wage of the declining pool. The wage deficit per reemployed worker is therefore \$18,828.64. This means that reemployment in this model does not restore full income, it merely reduces the extent of income loss relative to full unemployment. No reinstatement rate, including the most optimistic 80% scenario, is sufficient to offset the aggregate income decline, because the wage gap between declining and growing lower-tier occupations is large enough to generate income loss in every scenario.

This is a substantively important result. It suggests that even in a labour market that reabsorbs most displaced workers relatively quickly, aggregate consumer income, and therefore aggregate demand, still contracts if the quality of reemployment is materially lower than the quality of the jobs lost. The macroeconomic feedback loop modelled in this thesis does not require mass long-term unemployment to operate. A broad wage downgrade, affecting millions of workers, is sufficient to generate demand contraction. This shows that the wage gap between office work and low-tier service work creates a lasting deficit in aggregate demand that reemployment alone cannot fix. Even when the reemployment rate increases to 80% within that high-displacement bracket, the contraction only drops to \$280.406 billion. This means that finding new jobs does not fix the problem if those jobs are low-tier, low-paying positions. The wage deficit, the difference between what workers earned before and what they earn after ($w_d - w_l$) drives a persistent drain on the economy. The data proves that reemployment alone cannot stop a demand contraction if it forces workers down the income ladder.

Critical insight from the data is that the rate of displacement acts as the main driver of economic loss, while the reemployment mechanism (p) acts as a minor buffer and relatively weak in preventing demand destruction. Moving from a low pessimistic reemployment rate (20%) to a highly optimistic reemployment rate ($p = 80\%$) under a fixed 25% displacement rate only reduces the total demand contraction from \$261.959 billion to \$140.203 billion. This marginal improvement highlights the wage down-levelling built into the model. Because

high-exposure white-collar workers are forced into lower-tier, low-wage service roles upon displacement, finding a job does not preserve their original purchasing power.

8. Discussion

The scenario modelling results presented in Chapter 7 are stylized by design, they are not forecasts. They are boundary conditions. Their purpose is to establish the range and structure of the aggregate demand risk associated with AI-driven labour displacement, and to determine the conditions under which that risk becomes macroeconomically significant. This discussion section situates those results in the broader empirical and theoretical context, contextualizes the modelled magnitudes against US macroeconomic aggregates, engages with the labour market dynamics currently visible in the transition period, and draws out the policy implications that follow.

8.1 Contextualizing the Modelled Magnitudes

The scenario matrix produces total demand contraction estimates ranging from \$56.1 billion in the most conservative scenario - 10% displacement, 80% reemployment, to \$523.9 billion in the most severe - 50% displacement, 20% reemployment. To interpret what these figures mean in macroeconomic terms, we must compare them against relevant US economic aggregates. US personal consumption expenditure stood at \$19.8 trillion in 2024, representing 67.9% of GDP in that year (Federal Reserve Bank of St. Louis, 2025). A demand contraction of \$56.1 billion represents approximately 0.3% of personal consumption, and at the severe end, \$523.9 billion represents approximately 3%, a contraction of a magnitude that, if sustained over the short-to-medium run, would constitute a substantial drag on GDP growth. For context, during the Great Recession of 2007-2009, real US GDP fell by roughly 4.3% from peak to trough. However, it must be noted that GDP effects are ambiguous because productivity gains may offset the demand contraction in measured output (the Ghost GDP mechanism, as discussed by Chen et al, 2026). , in which falling consumption coexists with a stable or rising GDP.

It is important to note, however, that the relationship between demand contraction and GDP is not straightforward. As Chen (2026) demonstrates, AI-driven productivity gains can sustain or increase measured output even as labour income and household consumption decline, because AI-generated value substitutes for labour-generated value in national

accounts without a corresponding gain in the disposable income of workers. This wedge between GDP growth and consumption-relevant household income means that stable or rising GDP figures may coexist with a deteriorating demand base, a pattern Chen (2026) terms the displacement spiral, of which the GDP measurement distortion is one consequence. Standard macroeconomic indicators may therefore understate the demand-side risk at precisely the moment it is building.

Demand destruction is a substantial challenge to fiscal stability. The Congressional Budget Office estimated that the 2020 CARES Act stimulus, which was designed to offset a demand collapse, delivered approximately \$2.3 trillion in fiscal support, out of which \$610 billion were direct payments and unemployment benefits to households. (2020). The upper-bound scenario in this thesis models a demand shock that is roughly of that scale, not from an external pandemic shock but from an endogenous transformation of the labour market. This comparison is offered to establish that the modelled magnitudes are not negligible and fall within the range of macroeconomic events that have historically prompted policy responses.

The productivity gains narrative complicates this picture and must be engaged directly. The standard argument is that AI-driven productivity growth will expand output, lower prices, increase real wages, and ultimately generate sufficient economic surplus to offset displacement-driven income losses. This argument is not wrong in principle, and this thesis does not contest it as a long-run proposition. However, productivity gains and labour income losses are not distributed symmetrically across time or across agents. Productivity gains accrue primarily to capital owners and high-skill workers who complement AI, while labour income losses are concentrated among cognitive, white-collar workers in the transition period.

The result is a redistribution from high-MPC workers to low-MPC capital owners, which, by definition, depresses aggregate consumption even if aggregate income is held constant, a mechanism that standard productivity narratives do not adequately account for.

As summarised by Nigar et al. (2025, p. 3), Acemoglu (2025) argues that “AI-induced productivity growth remains insufficient to reduce labor-income inequality, instead, it would likely widen the capital-labor income gap”.

8.2 The Valley Between Displacement and Reinstatement

This thesis's findings are not inconsistent with the long-run optimism of Acemoglu and Restrepo's (2018, 2019) reinstatement framework. Their model is compelling as a description of how technological transitions have eventually resolved in the past. The concern that this thesis raises is not about where the economy ends up in 50 years, but it is about the transition period, valley between displacement and reinstatement. How long and how deep could that valley be?

The historical evidence on technological transitions suggests that the adjustment period is rarely smooth or short. The Industrial Revolution generated decades of labour market disruption before new occupations and industries absorbed the displaced workforce at scale. McKinsey Global Institute (2017) documents that average real wages in England stagnated for decades during the Industrial Revolution even as productivity rose, with wage growth eventually catching up only after substantial policy reforms. What is different about the current AI transition is the speed of displacement relative to the speed of institutional adaptation. Reskilling systems, educational institutions, labour market infrastructure, and policy frameworks all operate on timescales that are measured in years to decades. AI capabilities are advancing on a timescale measured in months. The asymmetry between the speed of displacement and the speed of adaptation is the defining feature of the transition period, and it is this asymmetry, that generates the demand-side risk modelled in this thesis.

Autor et al. (2024, p. 7) find that “demand-eroding effects of automation innovation have intensified in the last four decades, while the demand-increasing effects of augmentation innovations have not”, in other words, the creation of new work has not consistently kept pace with displacement over the past four decades, even before the current AI wave. If the reinstatement effect is operating more slowly than the displacement effect, and the early labour market evidence reviewed in this thesis suggests it is, then the valley between displacement and reinstatement may be deeper and longer than historical precedent implies. The scenario model quantifies what that valley could cost in aggregate demand terms: between \$56 billion and \$524 billion in total demand contraction, depending on the pace and quality of labour market reabsorption. These are the stakes of getting the transition management wrong.

8.3 What the Transition Period Actually Looks Like

The aggregate employment statistics present a superficially reassuring picture. US unemployment has remained near historic lows. GDP growth has been positive and, since the pandemic recovery, has been accompanied by record stock market valuations. Corporate earnings have been strong, reflecting in part the cost efficiency gains from AI adoption and the repricing of technology assets. On paper, the economy appears healthy. The risk identified in this thesis is precisely that this surface-level reading obscures structural dynamics that are already operating beneath it.

The empirical evidence reviewed in Chapter 3 points to a set of early signals that are difficult to explain without reference to AI-driven labour market restructuring. Brynjolfsson et al. (2025), and Anthropic's research report find that entry-level hiring in AI-exposed occupations has slowed markedly since late 2022. Firms are replacing the functions typically performed by junior workers, drafting, summarizing, coding, data entry, research with AI tools, while retaining experienced workers whose judgment, client relationships, and institutional knowledge are harder to replicate. The result is not mass unemployment but a narrowing of the entry-level pipeline.

This matters for reasons that extend well beyond the current cohort of job seekers. Research finds that graduating into a weak job market carries earnings consequences that persist for decades (Kahn, 2010). If entry-level hiring in high-exposure occupations continues to contract, because firms are substituting AI for junior labour, the current generation of graduates in exposed fields may face permanently lower earnings trajectories.

A related and underappreciated dimension of the transition period is the weakening of workers' bargaining power. Even in the absence of realized unemployment, the credible threat of AI substitution shifts the balance of power between employers and employees. Workers in exposed occupations are less able to negotiate wages, resist workload increases, or demand improved conditions when their employers can plausibly substitute their functions with AI tools. This suppresses wage growth without generating observable unemployment, it is a form of income loss that does not appear in headline statistics but operates through the same consumption channel modelled in this thesis. Therefore, the aggregate demand risk does not require only mass unemployment to materialize, most importantly it requires that

income growth for high-MPC households is depressed relative to what it would otherwise have been.

The institutional response to these dynamics has been slow and, in some important respects, miscalibrated. Universities and colleges are not updating curricula at the speed required to prepare graduates for AI-transformed job markets. Employers are simultaneously demanding AI-ready skills while reducing the entry-level positions that historically served as the primary vehicle through which those skills were developed on the job. Policy makers and labour market institutions are largely responding to the aggregate employment statistics rather than to the distributional and structural dynamics beneath them. The result is a growing mismatch between the signals that policy instruments are calibrated to detect, unemployment, inflation, GDP growth, and the labour market transformation that is actually underway.

8.4 The Hiring Cycle Has Decoupled from the Business Cycle

This mismatch has a further implication that bears directly on the adequacy of traditional policy responses. Historically, the hiring cycle tracked the business cycle closely: when interest rates fell and corporate budgets expanded, firms hired more workers, unemployment fell, and consumer demand recovered. This transmission mechanism is the foundation of conventional monetary policy as a demand management tool. There are strong reasons to believe it is weakening in the current environment.

Corporate budgets among large technology companies and AI-adopting firms are not constrained in the traditional sense. Many of these firms are sitting on substantial cash reserves, have access to historically low-cost capital, and are generating record earnings. The barrier to hiring is not financial, but strategic decision. Company executives are directing available capital toward AI investment rather than labour, and signalling that choice explicitly to investors to appear innovative and as evidence of operational discipline. Lowering interest rates would expand the budgets of firms that are already resource-abundant. It does not follow that expanding them further will induce more hiring, as it has historically during recessions when firms were credit-constrained and demand-limited. The channel through which monetary easing traditionally stimulates employment has been disrupted by the very productivity dynamics that the AI optimism narrative celebrates.

This decoupling of the hiring cycle from the business cycle makes it impossible to use historical relationships between interest rates, GDP growth, and employment to predict what will happen next or to conclude optimistically that hiring will naturally recover as macro conditions improve. The tools that policy makers have available are largely calibrated to cyclical downturns, not structural technological transitions. That mismatch is the policy problem that this thesis is ultimately pointing toward.

8.5 Conditions That Could Dampen the Demand Shock

The scenario model is a partial equilibrium exercise that isolates the demand shock from displacement while holding other equilibrating forces constant. It is therefore important to be explicit about the conditions under which the demand shock could be materially smaller than the modelled estimates suggest. Three dampening mechanisms are most relevant.

The first is a strong and rapid fiscal response. If governments respond to AI-driven displacement with substantial income support, enhanced unemployment insurance, direct cash transfers, or universal basic income, the consumption decline modelled in this thesis would be partially or fully offset. The MPC of transfer recipients in the income range of displaced workers is high, meaning that well-targeted fiscal transfers would be effective at sustaining consumption. The dampening effect of fiscal policy depends critically on its speed and targeting: transfers that arrive after the displacement wave has already contracted demand are less effective than transfers that are pre-positioned as automatic stabilizers. The Alaska Permanent Fund, which distributes a share of state oil revenues as an annual dividend to all residents, provides a relevant analogy, adapted to the AI context (Alaska Department of Revenue, 2025). An AI revenue fund sourced from levies on firms capturing the productivity gains from AI automation and redistributed as a transition dividend to displaced or vulnerable workers could in principle close the income gap at the speed the transition requires.

The second dampening mechanism is high-quality, rapid reemployment, specifically, reemployment into occupations that do not carry a large wage deficit relative to the displaced occupation. As the scenario matrix makes clear, the persistence of demand contraction across all modelled scenarios is driven not by displacement per se but by the wage quality of available reemployment. If accelerated reskilling programs or hiring incentive structures

were to enable displaced workers to transition into comparably paid or better-paid roles, rather than into the lower-tier occupations modelled as the default reemployment destination, the income loss and associated demand contraction would be substantially reduced. The policy implication is direct: the objective of labour market transition policy should not be reemployment at any wage, but reemployment at wages that preserve the consumption capacity of the affected workforce.

The third dampening mechanism is the possibility that AI-driven productivity gains are more rapidly and broadly shared than the current distributional patterns suggest, for instance, through competitive pressures that pass productivity gains to consumers as lower prices, or through labour market institutions that capture a share of productivity gains as wage increases for non-displaced workers. These channels exist in principle but are not currently operating at the scale required to offset the income losses in the vulnerable occupational pool.

8.6 Policy Implications

The policy implications of this analysis do not point toward restricting AI adoption. Slowing the technology would forfeit the real and substantial productivity gains that AI offers and would ultimately be neither effective nor desirable. The policy objective, rather, is to ensure that the speed and wage quality of labour market adjustment matches the speed of the technology, and that the institutions and instruments designed to support workers through technological transitions are rebuilt for the pace and structure of the current one.

Several specific policy directions follow from the analysis. First, enhanced and restructured unemployment insurance is necessary but not sufficient. Current US unemployment insurance is designed for cyclical job loss, short-duration income replacement while workers seek re-entry into a stable labour market. It is not adapted to situations of displacement of workers into a labour market that may not offer employment opportunities comparable to their previous conditions (von Wachter, 2019; CBPP, 2023).

By extending the duration and expanding the coverage of benefits specifically for workers displaced by structural automation, the government can keep aggregate consumption from collapsing while workers retrain.

Similarly, in light of AI-disrupted labour market, Universal Basic Income (UBI) has also emerged as a potential solution, that addresses the demand-side risk by maintaining a floor of disposable income for displaced workers. However, this has been raising questions regarding the high fiscal cost, and, for being the universal transfers, rather than targeted tool towards the displaced workers.

On the other hand, a case for an AI revenue levy merits serious policy consideration. If a share of the productivity gains captured by AI-adopting firms were redirected into a dedicated transition fund, analogous to the Alaska Permanent Fund but applied at the federal level and calibrated to AI adoption rates, it would create a mechanism for distributing the gains from AI more broadly across the workforce.

Firms that adopt AI benefit from aggregate consumer demand. If AI adoption erodes the income base that sustains that demand, firms face the paradox identified at the outset of this thesis: their individual efficiency gains undermine the collective market they depend on. An “AI transition fund” would partially internalize that externality.

Third, hiring incentive structures, tax credits, subsidy schemes, or public employment guarantees in AI-adjacent roles, could be used to counteract the strategic preference for AI investment over labour investment that is currently observable among large technology firms. The objective would not be to prevent AI adoption but to create a countervailing financial incentive for maintaining or expanding the entry-level labour pipeline that is currently contracting.

Finally, and perhaps most urgently, the educational and institutional response to AI-driven labour market restructuring needs to accelerate substantially. Universities, vocational training systems, and professional credentialing bodies are operating on timescales that are misaligned with the pace of AI diffusion. The mismatch between what employers demand, AI-ready skills, and what educational institutions are currently delivering is not a temporary gap that will close naturally, it is a problem that requires active institutional redesign. Policy makers who treat the current labour market statistics as evidence that no intervention is required are reading the wrong indicators. The aggregate employment rate is a lagging measure of a dynamic that is already well underway. By the time it registers in headline statistics, the window for preventive action will have narrowed considerably.

The core argument of this thesis is ultimately a simple one: AI-driven labour displacement poses a measurable, quantifiable demand-side risk to aggregate consumer spending, and that risk is largest precisely when it is hardest to see: in the transition period before displacement registers in aggregate unemployment statistics, before policy makers have mobilized a response, and before the reinstatement effect has had time to operate. Quantifying that risk, establishing its conditions, and identifying the policy instruments that can dampen is a necessary complement to the productivity optimism that currently dominates the public and academic discourse, and a prerequisite for managing the transition in a way that does not leave a generation of workers to absorb its costs alone. That is the question this thesis has attempted to put numbers on, and the one that policy needs to take more seriously before the transition period is already over.

9. Conclusion

This thesis set out to examine a specific macroeconomic risk that has received limited attention in the AI-labour literature: the demand-side consequences of AI-driven labour displacement during the transition period, before reinstatement and reemployment effects have time to offset displacement at scale. The central concern, what this thesis terms the AI demand paradox, is that AI adoption is individually rational for each firm but potentially self-defeating in aggregate: if businesses collectively replace workers with AI, the labour income that sustains consumer spending contracts, and the very markets that AI-equipped firms depend on begin to erode.

The empirical analysis establishes three baseline findings. First, the OLS regression of wages on AIOE scores across approximately 760 US occupations reveals a clear positive correlation: the occupations most exposed to AI are predominantly high-wage, high-skill, white-collar roles, not the low-wage, routine-manual workers targeted by earlier automation waves. Second, the OLS regression of recent employment change on AIOE scores finds no displacement signal in observed 2021–2025 data, confirming that the demand risk is forward-looking rather than currently measurable, and consistent with the early empirical evidence from Brynjolfsson et al. (2025) and Massenkoff and McCrory (2026), who find signals in entry-level hiring and among younger workers rather than in aggregate unemployment. Third, the binned scatter of BLS projected employment change on AIOE scores shows a

weak positive relationship, with a weighted OLS slope of 0.06, indicating that high-exposure occupations are not uniformly projected to contract, but that the projections carry substantial uncertainty and may not fully capture the pace of AI diffusion anticipated over 2024–2034.

The calibrated scenario model, applied to a vulnerable declining pool of approximately 19.6 million workers with a weighted average wage of \$57,183, produces total demand contraction estimates ranging from \$56.1 billion in the most conservative scenario, 10% displacement, 80% reemployment into lower-tier roles, to \$523.9 billion in the most severe 50% displacement, 20% reemployment. Critically, all nine scenarios in the 3×3 matrix produce positive demand contraction, because the wage deficit between the declining pool and the lower-tier reemployment pool (\$18,829 per reemployed worker) is large enough to generate income loss even when most displaced workers find new jobs. The displacement rate is the primary driver of the magnitude of contraction; the reemployment rate moderates the outcome but cannot eliminate demand contraction within the current model's reemployment assumptions. This finding directly answers the second sub-question: AI labour automation poses a measurable demand-side threat across all modelled combinations of displacement and reemployment rates, with severity determined primarily by the breadth of displacement and secondarily by the wage quality of labour market reabsorption.

The discussion contextualizes these results against US macroeconomic aggregates: the lower bound of \$56.1 billion represents approximately 0.3% of 2024 personal consumption expenditure (\$19.8 trillion), while the upper bound approaches 3%, a contraction that, if sustained, would constitute a substantial drag on growth. Beneath the headline statistics, early signals are already visible: entry-level hiring in AI-exposed occupations has slowed, institutions — universities, labour market policy, reskilling infrastructure, are operating on timescales

misaligned with the pace of AI diffusion. And the hiring cycle has decoupled from the business cycle in ways that make conventional monetary policy responses, including interest rate cuts aimed at expanding corporate budgets, inadequate instruments for the current problem. The valley between displacement and reinstatement, to use the framing developed in Chapter 8, may be deeper and longer than historical technological transitions imply.

These findings highlight that the severity of the "valley" between job displacement and task reinstatement depends on the speed and wage quality of labour reabsorption. To build upon this baseline, future research should expand and quantify alternative adjustment scenarios, most importantly, evaluating a rapid reinstatement framework where displaced workers are rapidly retrained into high-wage, AI-ready occupations such as AI architects, systems engineers, and domain-specific data specialists, thereby determining how accelerated reskilling into expanding technical roles alters aggregate demand trajectories. Additionally, future macroeconomic studies should incorporate general equilibrium adjustments to model how corporate profit redistribution, price deflators, and automated capital depth dynamically offset household consumption shocks over time. Finally, empirical research must evaluate the regional and sectoral concentration of AI displacement to determine whether localized demand contractions trigger compounding multiplier effects in geographically exposed labour markets. Ultimately, managing the transition requires policymakers to recognize that maintaining aggregate demand is just as vital as fostering technological innovation.

List of References

- Acemoglu, D. (2025) The Simple Macroeconomics of AI, *Economic Policy*, Volume 40, Issue 121, January 2025, Pages 13–58, <https://doi.org/10.1093/epolic/eiae042>
- Acemoglu, D. and Autor, D. (2011) 'Skills, tasks and technologies: Implications for employment and earnings', in Ashenfelter, O. and Card, D. (eds.) *Handbook of Labor Economics*, Vol. 4B. Amsterdam: Elsevier, pp. 1043–1171.
- Acemoglu, D. and Restrepo, P. (2018) 'The race between man and machine: Implications of technology for growth, factor shares, and employment', *American Economic Review*, 108(6), pp. 1488–1542. <https://doi.org/10.1257/aer.20160696>
- Acemoglu, D. and Restrepo, P. (2019a) 'Artificial intelligence, automation, and work', in Agrawal, A., Gans, J. and Goldfarb, A. (eds.) *The Economics of Artificial Intelligence: An Agenda*. Chicago: University of Chicago Press, pp. 197–236.
- Acemoglu, D. and Restrepo, P. (2019b) 'Automation and new tasks: How technology displaces and reinstates labor', *Journal of Economic Perspectives*, 33(2), pp. 3–30. <https://doi.org/10.1257/jep.33.2.3>
- Acemoglu, D. and Restrepo, P. (2020) 'The wrong kind of AI? Artificial intelligence and the future of labour demand', *Cambridge Journal of Regions, Economy and Society*, 13(1), pp. 25–35. <https://doi.org/10.1093/cjres/rsz022>
- Acemoglu, D., Autor, D., Hazell, J. and Restrepo, P. (2022) 'Artificial intelligence and jobs: Evidence from online vacancies', *Journal of Labor Economics*, 40(S1), pp. S293–S340. <https://doi.org/10.1086/718327>
- Alaska Department of Revenue, Permanent Fund Dividend Division (2025) About us [Online]. Available at: <https://pfd.alaska.gov/Division-Info/about-us> (Accessed: [July 2, 2026]).
- Appel, R., Massenkoff, M., McCrory, P., McCain, M., Heller, R., Neylon, T. and Tamkin, A. (2026) 'Anthropic Economic Index report: Economic primitives', *Anthropic Research Report* [Online]. Available at: <https://www.anthropic.com/economic-index> (Accessed: [April 4, 2026]).
- Autor, D., Chin, C., Salomons, A. and Seegmiller, B. (2022) 'New frontiers: The origins and content of new work, 1940–2018', *Quarterly Journal of Economics*, 139(3), pp. 1399–1465. <https://doi.org/10.1093/qje/qjae008> Available at: <https://economics.mit.edu/sites/default/files/2023-12/New%20Frontiers%20-%20The%20Origins%20and%20Content%20of%20New%20Work%201940-2018.pdf> (Accessed: May 12, 2026).
- Azpúrua, A.E. (2026) 'Enhance or eliminate? How AI will likely change these jobs', *HBS Working Knowledge*, 20 February [Online]. Available at: <https://www.library.hbs.edu/working->

- [knowledge/enhance-or-eliminate-how-ai-will-likely-change-these-jobs](#) (Accessed: [June 19, 2026]).
- Bayraktar, E. (2026) 'The Demand Externality of Automation', (Version 1). arXiv. <https://doi.org/10.48550/ARXIV.2605.05127> [Online]. Available at: [\[https://arxiv.org/pdf/2605.05127\]](https://arxiv.org/pdf/2605.05127) (Accessed: [April 23, 2026]).
- Bessen, J.E. (2018) 'AI and jobs: The role of demand', NBER Working Paper No. 24235 [Online]. Available at: <https://www.nber.org/papers/w24235> (Accessed: [May 5, 2026]).
- Brynjolfsson, E. and McAfee, A. (2014) *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: W.W. Norton & Company.
- Brynjolfsson, E., Chandar, B. and Chen, R. (2025) 'Canaries in the coal mine? Six facts about the recent employment effects of artificial intelligence', Stanford Digital Economy Lab Working Paper [Online]. Available at: https://digitaleconomy.stanford.edu/app/uploads/2025/11/CanariesintheCoalMine_Nov25.pdf (Accessed: [April 2, 2026]).
- Bureau of Economic Analysis (BEA). (2025) Personal consumption expenditures. U.S. Department of Commerce [Online]. Available at: <https://www.bea.gov/data/consumer-spending/main> (Accessed: [June 8, 2026]).
- Bureau of Labor Statistics (BLS). (2025a) Occupational Employment and Wage Statistics (OEWS). U.S. Department of Labor [Online]. Available at: <https://www.bls.gov/oes/tables.htm> (Accessed: [April 5, 2026]).
- Bureau of Labor Statistics (BLS). (2025b) Employment Projections, 2024–2034. U.S. Department of Labor [Online]. Available at: <https://www.bls.gov/emp/tables/emp-by-major-occupational-group.htm> (Accessed: [April 5, 2026]).
- Bureau of Labor Statistics (BLS) (2022–2023) Consumer Expenditure Survey (CES). U.S. Department of Labor [Online]. Available at: <https://www.bls.gov/cex/> (Accessed: [April 5, 2026]).
- Center on Budget and Policy Priorities (CBPP) (2023) Unemployment insurance system unprepared for another recession [Online]. Available at: <https://www.cbpp.org/research/economy/unemployment-insurance-system-unprepared-for-another-recession> (Accessed: [July 9, 2026]).
- Choi, T., & Leigh, N. G. (2024). Artificial intelligence's creation and displacement of labor demand. *Technological Forecasting and Social Change*, 209, 123824. <https://doi.org/10.1016/j.techfore.2024.123824>
- Congressional Budget Office (CBO) (2020) The Effects of Pandemic-Related Legislation on Output. [Online]. Available at: <https://www.cbo.gov/publication/56334> (Accessed: [July 9, 2026])

- Congressional Budget Office (CBO) (2020) H.R. 748, CARES Act, Public Law 116-136 [Cost estimate] [Online]. Available at: <https://www.cbo.gov/publication/56334> (Accessed: [July 9, 2026]).
- Curtis, G. (1983) *The Political Economy of Japan*. New York: St Martin's Press.
- Eisfeldt, A., Schubert, G., Zhang, M. and Taska, B. (May 2, 2023) The Labor impact of Generative AI and Firm Value, Working Paper [Online]. Journal of Finance forthcoming, Available at SSRN: <https://ssrn.com/abstract=4436627> or <http://dx.doi.org/10.2139/ssrn.4436627> (Accessed: [May 10, 2026]).
- Eloundou, T., Manning, S., Mishkin, P. and Rock, D. (2023, published 2024) 'GPTs are GPTs: An early look at the labor market impact potential of large language models', *Science*, 384(6702), pp. 1306–1308. <https://doi.org/10.1126/science.adj0998>
- Falk, A. and Tsoukalas, J. (2026) 'Automation, market competition, and the demand externality', Working Paper [Online]. Available at: <https://arxiv.org/abs/2603.20617> (Accessed: [April 27, 2026]).
- Federal Reserve Bank of St. Louis (FRED) (2025) Shares of gross domestic product: Personal consumption expenditures [DPCERE1A156NBEA] [Online]. Available at: <https://fred.stlouisfed.org/series/DPCERE1A156NBEA> (Accessed: [June 13, 2026]).
- Federal Reserve Bank of St. Louis (FRED) (2026) Personal consumption expenditures: Total for United States [Online]. Available at: <https://fred.stlouisfed.org/series/USPCE> (Accessed: [June 13, 2026]).
- Felten, E., Raj, M. and Seamans, R. (2021) 'Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses', *Strategic Management Journal*, 42(12), pp. 2195–2217. <https://doi.org/10.1002/smj.3286>
- Felten, E.W., Raj, M. and Seamans, R. (2023) 'How will language modelers like ChatGPT affect occupations and industries?', *SSRN Electronic Journal* [Online]. Available at: <https://doi.org/10.2139/ssrn.4375268> (Accessed: [April 2, 2026]).
- Friedman, M. (1957) *A Theory of the Consumption Function*. Princeton, NJ: Princeton University Press.
- Green, A. (2024) Artificial intelligence and the changing demand for skills in the labour market', *OECD AI Papers No. 14*. Correct. Paris: OECD Publishing. <https://doi.org/10.1787/88684e36-en>
- Handa, K., Tamkin, A., McCain, M., Huang, S., Durmus, E., Heck, S., Mueller, J., Hong, J., Ritchie, S., Belonax, T., Troy, K.K., Amodei, D., Kaplan, J., Clark, J. and Ganguli, D. (2025) 'Which economic tasks are performed with AI? Evidence from millions of Claude conversations',

Anthropic Research Report [Online]. Available at: <https://www.anthropic.com/economic-index> (Accessed: [date]).

Heinz, K.J. (2025) “The AI Consumption Spiral: An Underestimated Systemic Risk for Economy and Society,” *International Journal of Research and Review*, 12(10), pp. 77–87. Available at: <https://doi.org/10.52403/ijrr.20251009>.

Hui, X., Reshef, O. and Zhou, L. (2023) *The Short-Term Effects of Generative Artificial Intelligence on Employment: Evidence from an Online Labor Market*, Social Science Research Network. Rochester, NY. Available at: <https://doi.org/10.2139/ssrn.4544582>.

Jacobson, L.S., LaLonde, R.J. and Sullivan, D.G. (1993) 'Earnings losses of displaced workers', *American Economic Review*, 83(4), pp. 685–709.

Kahn, L.B. (2010) 'The long-term labor market consequences of graduating from college in a bad economy', *Labour Economics*, 17(2), pp. 303–316. <https://doi.org/10.1016/j.labeco.2009.09.002>

Keynes, J.M. (1930) 'Economic possibilities for our grandchildren', in Keynes, J.M. (1931) *Essays in Persuasion*. London: Macmillan, pp. 358–373.

Korinek, A. and Stiglitz, J.E. (2017) 'Artificial intelligence and its implications for income distribution and unemployment', NBER Working Paper No. 24174 [Online]. Available at: <https://www.nber.org/papers/w24174> (Accessed: [May 17, 2026]).

Lachowska, M., Mas, A. and Woodbury, S.A. (2020) 'Sources of displaced workers' long-term earnings losses', *American Economic Review*, 110(10), pp. 3231–3266. <https://doi.org/10.1257/aer.20180652>

Mantoux, P. (1928) *The Industrial Revolution in the Eighteenth Century*. London: Jonathan Cape. [As cited in Acemoglu and Restrepo, 2019b.]

Massenkoff, M. and McCrory, P. (2026) 'Labor market impacts of AI: A new measure and early evidence', *Anthropic Economic Research Report*, 5 March [Online]. Available at: <https://www.anthropic.com/research/labor-market-impacts> (Accessed: [April 7, 2026]).

McKinsey Global Institute (2017) *Jobs Lost, Jobs Gained. Workforce Transitions in a Time of Automation* [Online]. Available at: <https://www.mckinsey.com/~media/mckinsey/featured%20insights/future%20of%20organizations/what%20the%20future%20of%20work%20will%20mean%20for%20jobs%20skills%20and%20wages/mgi-jobs-lost-jobs-gained-report-december-6-2017.pdf> (Accessed: [June 29, 2026]).

Mian, A. and Sufi, A. (2014) *House of Debt: How They (and You) Caused the Great Recession, and How We Can Prevent It from Happening Again*. Chicago: University of Chicago Press.

- Mian, A., Straub, L. and Sufi, A. (2021) 'Indebted demand', *Quarterly Journal of Economics*, 136(4), pp. 2243–2307. <https://doi.org/10.1093/qje/qjab007>
- Mokyr, J. (1990) *The Lever of Riches: Technological Creativity and Economic Progress*. New York: Oxford University Press.
- Nigar, N., Juli, R., Golder, T., Alam, M. and Hossain, M. (2025) 'Artificial intelligence, automation, and technological unemployment: A systematic review', *Technology in Society*, 80, article 102553. <https://doi.org/10.1016/j.techsoc.2025.102553>
- Occhipinti, JA., Hynes, W., Prodan, A. et al. (2024) 'The invisible hand of AI: Coordination failure, aggregate demand, and the macroeconomic externality of automation', *arXiv preprint [Online]*. Available at: <https://arxiv.org/abs/2407.01545> (Accessed: [April 24, 2026]).
- Occhipinti, JA., Hynes, W., Prodan, A. et al. (2025) Generative AI may create a socioeconomic tipping point through labour displacement. *Sci Rep* 15, 26050 (2025). <https://doi.org/10.1038/s41598-025-08498-x>
- Srinivasan, S., Chen, W.X. and Zakerinia, S. (2024, updated 2025) 'Displacement or complementarity? The labor market impact of generative AI', *Harvard Business School Working Paper*, No. 25-038 [Online]. Available at: <https://www.hbs.edu/faculty/Pages/item.aspx?num=67045> (Accessed: [June 19, 2026]).
- Stiefenhofer, P. (2025). *Artificial General Intelligence and the End of Human Employment: The Need to Renegotiate the Social Contract* (arXiv:2502.07050). arXiv. <https://doi.org/10.48550/arXiv.2502.07050>
- von Wachter, T. (2019) 'Unemployment insurance reform', *The ANNALS of the American Academy of Political and Social Science*, 686(1), pp. 121–146. <https://doi.org/10.1177/0002716219885339>
- Webb, M. (2020) 'The impact of artificial intelligence on the labor market', *SSRN Working Paper [Online]*. Available at: <https://doi.org/10.2139/ssrn.3482150> (Accessed: [May 15, 2026])

Appendices

Appendix A. Full Declining Pool Dataset (81 Occupations).

SOC Code	Occupation Title	AIOE	Employment_2025	Annual_Median_wage_2025	Employment_2021	employment change 2021-2025 (%)	Projected Employment change, percent, 2024–2034	Automation Score based on HBS study (0-0.9)
11-2011	Word Processors and Typists	0.622	35010	49280	41930	-16.50%	-36.1	0.72
11-9031	Telephone Operators	1.02	3430	41740	3870	-11.37%	-27.5	0.52
11-9032	Switchboard Operators, Including Answering Service	0.983	34280	38630	48190	-28.86%	-26.3	0.48
11-9131	Data Entry Keyers	0.311	127080	41340	147170	-13.65%	-25.9	0.46
13-1031	Telemarketers	1.118	58430	35450	115130	-49.25%	-22.1	0.73
13-1032	Order Clerks	0.839	75200	46170	133850	-43.82%	-17.2	0.72
13-1051	Payroll and Timekeeping Clerks	1.258	153140	58260	149290	2.58%	-16.7	0.70
13-1075	File Clerks	0.284	73440	43600	85460	-14.07%	-15.9	0.49
13-2041	Adult Literacy, Remedial Education, and GED Teachers and Instructors	1.349	37310	61540	38260	-2.48%	-13.7	0.45
13-2053	New Accounts Clerks	1.175	36860	47670	40500	-8.99%	-13.2	0.48
13-2081	Tellers	0.473	329480	43030	364210	-9.54%	-12.9	0.36
15-1232	Interviewers, Except Eligibility and Loan	1.297	148060	45920	169840	-12.82%	-11.6	0.65
15-1242	Bill and Account Collectors	1.272	158830	47030	212900	-25.40%	-10.5	0.70
15-1244	Brokerage Clerks	1.145	35940	65750	39980	-10.11%	-9.5	0.59
15-2021	Procurement Clerks	1.488	55810	50580	61930	-9.88%	-8.7	0.66
19-3022	Insurance Appraisers, Auto Damage	0.663	11560	78240	11430	1.14%	-8.2	0.37
19-3092	Human Resources Assistants, Except Payroll and Timekeeping	1.353	90220	50610	102770	-12.21%	-7.1	0.68
19-3094	Library Technicians	0.038	68690	44580	73000	-5.90%	-6.8	0.45
23-1021	Advertising Sales Agents	1.163	91700	64820	96660	-5.13%	-6.4	0.63
25-1124	Credit Authorizers, Checkers, and Clerks	1.44	12030	50080	16820	-28.48%	-6.2	0.63
25-1125	Bookkeeping, Accounting, and Auditing Clerks	1.04	1373680	50670	1509370	-8.99%	-5.8	0.68
25-2021	Legal Secretaries	1.015	156280	55570	155250	0.66%	-5.8	0.53
25-2022	Correspondence Clerks	1.15	4290	46800	7060	-39.24%	-5.6	0.86
25-2031	Customer Service Representatives	0.956	2595750	44770	2787070	-6.86%	-5.5	0.57
25-3011	Radio and Television Announcers	0.849	21240	47340	24580	-13.59%	-5.5	0.53
25-3099	Survey Researchers	1.427	8290	69460	8850	-6.33%	-5.2	0.57
25-4031	Claims Adjusters, Examiners, and Investigators	1.274	324230	78000	278140	16.57%	-5.1	0.48

25-9021	First-Line Supervisors/Managers of Retail Sales Workers	0.02	1121800	48520	1143260	-1.88%	-5	0.40
27-3011	Medical Transcriptionists	1.063	41550	40410	55830	-25.58%	-4.9	0.74
27-3023	Credit Analysts	1.345	64390	83510	68770	-6.37%	-4.4	0.58
27-3092	Cost Estimators	1.368	224220	78740	208950	7.31%	-4.2	0.50
31-9094	Network and Computer Systems Administrators	0.79	314340	99130	316760	-0.76%	-4.2	0.47
41-3011	Broadcast News Analysts, Reporters and Correspondents	1.164	39250	62200	39080	0.44%	-3.9	0.54
41-9011	Insurance Claims and Policy Processing Clerks	1.24	214260	49230	218300	-1.85%	-3.7	0.68
41-9041	Computer User Support Specialists	0.299	717190	61860	654310	9.61%	-3.7	0.49
41-9091	Postmasters and Mail Superintendents	0.823	13810	96660	12750	8.31%	-3.5	0.46
43-1011	Political Scientists	1.419	5540	142080	5650	-1.95%	-3.1	0.56
43-2011	Geographers	1.436	1400	102040	1440	-2.78%	-3.1	0.38
43-2021	Insurance Underwriters	1.327	105420	81370	107690	-2.11%	-2.6	0.57
43-3011	Statistical Assistants	1.39	4710	50330	6190	-23.91%	-2.5	0.60
43-3021	Farm and Home Management Advisors	0.86	8220	60220	10620	-22.60%	-2.5	0.45
43-3031	Education Administrators, Preschool and Child Care Center/Program	0.838	73660	59300	56430	30.53%	-2.5	0.42
43-3051	Loan Interviewers and Clerks	1.364	164790	50020	238610	-30.94%	-2.3	0.70
43-3061	Advertising and Promotions Managers	1.294	21470	133660	22520	-4.66%	-2.2	0.43
43-3071	Middle School Teachers, Except Special and Vocational Education	1.286	620090	64370	592000	4.74%	-2	0.39
43-4011	Production, Planning, and Expediting Clerks	0.70	390160	59650	367200	6.25%	-1.8	0.60
43-4041	Tax Examiners, Collectors, and Revenue Agents	1.367	56610	62370	52270	8.30%	-1.8	0.50
43-4051	Executive Secretaries and Administrative Assistants	1.08	459910	76590	466910	-1.50%	-1.6	0.68
43-4071	Secretaries, Except Legal, Medical, and Executive	1.099	1706790	47540	1825980	-6.53%	-1.6	0.62
43-4111	Dispatchers, Except Police, Fire, and Ambulance	1.235	202810	50340	194330	4.36%	-0.9	0.62
43-4131	Mathematicians	1.472	2030	126710	1770	14.69%	-0.7	0.64
43-4141	Database Administrators	1.285	69990	104620	85870	-18.49%	-0.7	0.57
43-4151	Administrative Law Judges, Adjudicators, and Hearing Officers	1.375	16370	117860	13840	18.28%	-0.7	0.43
43-4161	Proofreaders and Copy Markers	1.288	4580	51120	5340	-14.23%	-0.6	0.66
43-5032	Billing and Posting Clerks and Machine Operators	1.333	404060	48500	429080	-5.83%	-0.4	0.48
43-5061	Court Reporters	0.835	12870	72420	12300	4.63%	-0.3	0.57

43-6011	First-Line Supervisors/Managers of Office and Administrative Support Workers	1.039	1436680	69500	1443630	-0.48%	-0.3	0.55
43-6012	Foreign Language and Literature Teachers, Postsecondary	1.334	19830	79350	19640	0.97%	-0.2	0.45
43-6014	History Teachers, Postsecondary	1.437	18790	83820	18590	1.08%	-0.2	0.44
43-9021	Teachers and Instructors, All Other	1.325	113790	66140	164650	-30.89%	-0.1	0.67
43-9022	Labor Relations Specialists	1.335	64810	95420	63810	1.57%	-0.1	0.55
43-9041	Demonstrators and Product Promoters	0.124	64520	39320	40680	58.60%	-0.1	0.45
43-9081	Receptionists and Information Clerks	1.01	910180	38010	983150	-7.42%	0	0.64
43-9111	Receptionists and Information Clerks	1.01	910180	38010	983150	-7.42%	0	0.64
41-1011	English Language and Literature Teachers, Postsecondary	1.42	57720	78760	58480	-1.30%	0	0.49
43-4171	First-Line Supervisors/Managers of Non-Retail Sales Workers	1.32	214390	87520	243920	-12.11%	0	0.41
25-1123	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	0.82	1238190	72080	1242490	-0.35%	0.3	0.49
41-1012	Editors	1.13	91690	77920	88780	3.28%	0.6	0.53
43-4171	Philosophy and Religion Teachers, Postsecondary	1.36	20460	80260	20850	-1.87%	0.7	0.49
41-4012	Technical Writers	1.18	45500	90390	47620	-4.45%	0.9	0.51
27-3041	Eligibility Interviewers, Government Programs	1.23	154800	54210	151340	2.29%	1	0.59
25-1126	Budget Analysts	1.50	47160	91640	47440	-0.59%	1	0.55
27-3042	Interpreters and Translators	1.11	52060	60170	52170	-0.21%	1.7	0.80
13-2031	Loan Officers	1.39	274330	76690	340170	-19.36%	1.7	0.58
43-4061	Librarians and Media Collection Specialists	1.04	133790	68270	127790	4.70%	1.7	0.53
13-2072	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	0.89	284800	104920	266160	7.00%	1.9	0.62
27-3091	Title Examiners, Abstractors, and Searchers	1.28	48580	58650	51040	-4.82%	2	0.59
25-4022	Historians	1.10	3450	76750	2910	18.56%	2.2	0.59
41-4011	Travel Agents	1.13	55110	50160	37190	48.18%	2.2	0.56
23-2093	Judicial Law Clerks	1.46	13290	64920	14800	-10.20%	2.5	0.53
41-3041	Reservation and Transportation Ticket Agents and Travel Clerks	0.23	118710	44390	100860	17.70%	2.8	0.57

Appendix B. Full Lower-Tier Reemployment Pool Dataset

SOC Code	Occupation Title	AIOE	Employment_2025	Annual_Median_wage_2025	Employment_2021	employment change 2021-2025 (%)	Projected Employment change, percent, 2024-2034
53-3054	Taxi Drivers and Chauffeurs	-0.632	41050	42100	13950	194.27%	11.1
53-3031	Driver/Sales Workers	-0.729	409180	38770	477020	-14.22%	8.8
53-7065	Stock Clerks and Order Fillers	-0.789	2833810	37330	2451430	15.60%	8.5
43-5021	Couriers and Messengers	-0.959	68640	39200	68310	0.48%	8.2
39-5091	Makeup Artists, Theatrical and Performance	-0.460	2340	97150	1960	19.39%	8.1
47-2061	Construction Laborers	-1.623	1096780	47120	968760	13.21%	7.3
53-3033	Truck Drivers, Light or Delivery Services	-1.121	983300	44860	1010040	-2.65%	7.3
39-5092	Manicurists and Pedicurists	0.034	152770	35760	120540	26.74%	7
51-3092	Food Batchmakers	-0.379	174520	42290	155240	12.42%	6.9
53-3053	Shuttle Car Operators	-1.352	248530	37290	175660	41.48%	6.7
39-9099	Personal and Home Care Aides	-0.574	60420	41600	72030	-16.12%	6.4
39-3093	Locker Room, Coatroom, and Dressing Room Attendants	-0.345	15560	36300	9670	60.91%	6.4
35-9011	Dining Room and Cafeteria Attendants and Bartender Helpers	-1.927	542750	33980	336970	61.07%	6.3
39-3092	Costume Attendants	-0.453	6510	50400	3380	92.60%	5.9
35-3011	Bartenders	-0.616	756390	34340	485330	55.85%	5.9

33-9092	Lifeguards, Ski Patrol, and Other Recreational Protective Service Workers	-0.472	157550	33580	114320	37.81%	5.8
47-3016	Helpers--Roofers	-1.898	6030	44160	6830	-11.71%	5.7
49-3093	Tire Repairers and Changers	-1.551	108410	37710	93180	16.34%	5.7
51-3022	Meat, Poultry, and Fish Cutters and Trimmers	-1.106	145700	38300	132100	10.30%	5.5
39-5093	Shampooers	-0.905	8070	32600	9560	-15.59%	5.5
51-6011	Laundry and Dry-Cleaning Workers	-1.054	198040	34890	157400	25.82%	5.4
47-3015	Helpers--Pipelayers, Plumbers, Pipefitters, and Steamfitters	-1.679	44330	42360	45930	-3.48%	4.9
47-3012	Helpers--Carpenters	-1.425	21680	43780	27540	-21.28%	4.5
51-9111	Packaging and Filling Machine Operators and Tenders	-0.979	379060	43220	358640	5.69%	4.5
53-3052	Bus Drivers, Transit and Intercity	-0.605	159240	59050	145720	9.28%	4.3
53-7121	Tank Car, Truck, and Ship Loaders	-1.388	10700	58870	12090	-11.50%	4.3
53-3032	Truck Drivers, Heavy and Tractor-Trailer	-1.149	2062040	58640	1903420	8.33%	4
53-7061	Cleaners of Vehicles and Equipment	-1.630	380430	35830	351960	8.09%	3.9
47-2141	Painters, Construction and Maintenance	-1.588	225190	49400	214220	5.12%	3.8
35-0000	Combined Food Preparation and Serving Workers, Including Fast Food	-0.531	13680750	35050	11201480	22.13%	3.5

39-3091	Amusement and Recreation Attendants	-0.525	397830	32150	262170	51.75%	3.4
35-3041	Food Servers, Nonrestaurant	-0.727	293900	35360	243030	20.93%	3
47-3014	Helpers-- Painters, Paperhangers, Plasterers, and Stucco Masons	-2.045	7490	40470	8940	-16.22%	2.3
49-9098	Helpers-- Installation, Maintenance, and Repair Workers	-1.347	95580	39630	88480	8.02%	2.3
35-9000	Counter Attendants, Cafeteria, Food Concession, and Coffee Shop	-0.485	1537520	34080	1121960	37.04%	2.2
51-3021	Butchers and Meat Cutters	-0.971	136430	40140	145930	-6.51%	1
53-7081	Refuse and Recyclable Material Collectors	-1.283	147240	49690	126050	16.81%	0.9
33-9032	Security Guards	-0.391	1283470	38020	1057100	21.41%	0.4
37-2012	Maids and Housekeeping Cleaners	-1.481	860670	35510	723430	18.97%	0.4

Appendix C. Python Code and Data Sources

<https://github.com/arna-t/Thesis-Appendix>

```
import pandas as pd
import numpy as np

# Load Declining Pool Data
df_declining = pd.read_csv("declining_jobs_blsProj_hbsAutom..csv")
df_growing_all = pd.read_csv("growing.lower_tier.csv")

# Clean data formats
for df in [df_declining, df_growing_all]:
```

```

df['Wage_Clean'] = pd.to_numeric(df['Annual_Median_wage_2025'].astype(str).str.replace(',', ''),
errors='coerce')
df['Emp_Clean'] = pd.to_numeric(df['Employment_2025'].astype(str).str.replace(',', ''), errors='coerce')

# Drop any row missing vital 2025 metric data
df_declining = df_declining.dropna(subset=['Wage_Clean', 'Emp_Clean'])
df_growing = df_growing_all.dropna(subset=['Wage_Clean', 'Emp_Clean'])

# Compute baseline parameters for declining pool
total_jobs_lost = df_declining['Emp_Clean'].sum()
total_jobs_gained = df_growing['Emp_Clean'].sum()

# Headcount-Weighted Wage Average = Sum(Wage * 2025_Employment) / Total_2025_Employment
weighted_wage_declining = (df_declining['Wage_Clean'] * df_declining['Emp_Clean']).sum() / total_jobs_lost
weighted_wage_low_tier = (df_growing['Wage_Clean'] * df_growing['Emp_Clean']).sum() / total_jobs_gained

# Calculate the wage deficit per job
wage_deficit_per_job = weighted_wage_declining - weighted_wage_low_tier

# Macro Transmission Weights
mpc = 0.80
multiplier = 1.35

# 3x3 Simulation Grids
displacement_risk = [0.10, 0.25, 0.50]    # Delta
low_tier_reemployment = [0.20, 0.50, 0.80] # p (probability of sliding into low-tier service)

two_tier_results = []

for delta in displacement_risk:
    for p in low_tier_reemployment:
        # Applying Equation:  $\Delta Y = L * \text{delta} * [(1-p)*w_{\text{dec}} + p*(w_{\text{dec}} - w_{\text{low}})]$ 
        unemployment_destruction_effect = (1 - p) * weighted_wage_declining
        wage_compression_effect = p * (weighted_wage_declining - weighted_wage_low_tier)

        income_loss = total_jobs_lost * delta * (unemployment_destruction_effect + wage_compression_effect)

```

```

# Transmission to aggregate consumption and demand
direct_consumption_drop = income_loss * mpc
total_macro_demand_impact = direct_consumption_drop * multiplier

two_tier_results.append({
    'Displacement Rate (Delta)': f"{delta*100}%",
    'Low-Tier Reemployment Rate (p)': f"{p*100}%",
    'Aggregate Income Loss ($B)': round(income_loss / 1e9, 3),
    'Direct Consumption Shock ($B)': round(direct_consumption_drop / 1e9, 3),
    'Total Demand Contraction ($B)': round(total_macro_demand_impact / 1e9, 3)
})

df_simulation_matrix = pd.DataFrame(two_tier_results)

print("\n===== MACROECONOMIC SHOCK SCENARIO MATRIX =====")
print(df_simulation_matrix.to_string(index=False))

# 4. PRINT Baseline parameters
print(f"Total Declining Base Pool (2025): {total_jobs_lost:,.0f} workers")
print(f"Total Growing Base Pool (2025): {total_jobs_gained:,.0f} workers")
print(f"Weighted Baseline Declining Wage: ${weighted_wage_declining:,.2f}")
print(f"Weighted Baseline Growing Wage: ${weighted_wage_low_tier:,.2f}")
print(f"Structural Wage Deficit Per Job: ${wage_deficit_per_job:,.2f}")

```

Appendix D. OLS Regression

OLS Regression Results

```

=====
Dep. Variable:   Wage_Growth_2022_2025   R-squared:                1.000
Model:          OLS   Adj. R-squared:      nan
Method:         Least Squares   F-statistic:      nan
Date:           Fri, 31 Jul 2026   Prob (F-statistic):      nan
Time:           21:34:32   Log-Likelihood:      101.98
No. Observations:      3   AIC:              -198.0
Df Residuals:          0   BIC:              -200.7
Df Model:             2

```

Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
AIOE_Score	0.8000	inf	0	nan	nan	nan
Education_Level	-0.0144	inf	-0	nan	nan	nan
Remote_Work_Potential	-0.5000	inf	-0	nan	nan	nan

Omnibus:	nan	Durbin-Watson:	0.065
Prob(Omnibus):	nan	Jarque-Bera (JB):	0.526
Skew:	0.700	Prob(JB):	0.769
Kurtosis:	1.500	Cond. No.	2.51e+03

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 2.51e+03. This might indicate that there are strong multicollinearity or other numerical problems.

(.venv) (base) arna.togayeva@Arnas-MacBook-Air python_may2026 %

```
OLS Regression Results
=====
Dep. Variable:    Wage_Growth_2022_2025    R-squared:        1.000
Model:            OLS                      Adj. R-squared:    nan
Method:           Least Squares            F-statistic:       nan
Date:             Fri, 31 Jul 2026          Prob (F-statistic): nan
Time:             21:34:32                  Log-Likelihood:    101.98
No. Observations: 3                       AIC:               -198.0
Df Residuals:     0                       BIC:               -200.7
Df Model:         2
Covariance Type:  nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
AIOE_Score      0.8000         inf         0         nan         nan         nan
Education_Level -0.0144         inf        -0         nan         nan         nan
Remote_Work_Potential -0.5000         inf        -0         nan         nan         nan
=====
Omnibus:            nan    Durbin-Watson:      0.065
Prob(Omnibus):      nan    Jarque-Bera (JB):  0.526
Skew:               0.700    Prob(JB):       0.769
Kurtosis:           1.500    Cond. No.       2.51e+03
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 2.51e+03. This might indicate that there are strong multicollinearity or other numerical problems.

(.venv) (base) arna.togayeva@Arnas-MacBook-Air python_may2026 %

AI Directory

No.	AI tool	Purpose of use	Affected Sections	Remarks, Procedure, Prompts
	<i>Information about the AI tool (Name, URL)</i>	<i>Task for which the AI tool was used</i>	<i>Reference to the section(s) or chapter(s) of the work</i>	<i>Further explanations Prompts; alternatively, reference to the prompt log</i>
1	Claude AI	Data visualization, data manipulation, brainstorming, structuring, formatting	Conceptual Framework, Chapters 1-7	Prompt log 1
2	Gemini Code Assist, Claude Code	Coding assistance, built in Visual Studio Code IDE.	Methods	Prompt log 2,3
3	Research Rabbit	Search for literature and relevant papers	Literature review	Search for relevant literature based on 2 literature papers
4	Grammarly	text formulation, grammar check	Chapters 1-9	Prompt log 4
5	Notebook LM	Literature summary, asking specific questions based on the uploaded literature	Literature review	
6	DeepL Translate	Translation	Chapters 1-9	Translation support (Russian to English)
7	Claude AI	Data manipulation, brainstorming	Chapters 2-7	
8	Elicit	Ask specific questions about the content of my uploaded .pdf doc (articles), look up terms	Literature review	
9	Cite.ai	Citation management	List of References	

Examples for column 3 (Purpose of use):

brainstorming and topic identification / research questions / conception / structuring / literature research and analysis / literature management and citation management / selection of methods and models / data collection and analysis / programming / visualisation / interpretation and validation / text formulation / translation / final proofreading / formatting of work / others

Prompt-Log

Nr.	Date	Prompts/Input
	<i>Date</i>	<i>List the prompts used, if not already documented in the AI directory or in footnotes. Separate multiple prompts of a chat with [...].</i>
1	July 12	create a simple diagram of the four-channel causal chain (displacement -> income -> consumption -> aggregate demand) as a figure.
2	May	Generate a code to plot the relationship between the "AIOE" on x-axis, and "Annual_Median_wage_2025" on the y-axis, for each occupation, where occupations are grouped into 20 equal-sized bins based on AIOE score. Median salary should be in plotted as follows: if median salary is 30000, then plot it as 30.
3	May	Generate a code to create a binned scatter plot with 20 equally-sized bins, with the AIOE Score on the X-axis and the Projected % Job Change (2024–2034) on the Y-axis. Plot solid dots to show the average observed exposure and projected

		employment change for one of the bins. Please create a dashed line simple linear regression fit, weighted by the employment levels (2025).
4	July	Please help me to correct and improve my texts, preserving my writing style. Correct my spelling and grammar use.
5		

Declaration of Authorship

I hereby declare

- that I have written the submitted academic work entirely by myself without anyone else's assistance, and that I have not used any sources or aids other than those stated. Wherever I have drawn on literature or other sources, either in direct quotes, or in paraphrasing such material, I have given, in accordance with academic standards, the reference to the original author or authors and to the source where it appeared.
- that if I have used AI-based tools that were classified as reportable at the time of submission of my paper, I have fully listed them in the "AI directory" section with the product name, the source (e.g., URLs), the purpose of use, details of the parts of the academic work affected, as well as the inputs/prompts. In addition, I have indicated the use of AI in the respective sections in the main text.

I am aware

- that the use of quotations, or of close paraphrasing, from books, magazines, newspapers, the internet or other sources, which are not marked as such, or the use of AI tools without detailed documentation, will be considered as an attempt at misconduct, and that the academic work will be graded with a fail. I have notified the

examiners and the board of examiners in the case that I have submitted the academic work, either in whole or in part, for other examination purposes.

- that AI tools do not constitute scientific sources and therefore cannot be cited as such.
- that if I have used AI-based tools to create this academic work, I am responsible for any incorrect or biased content, incorrect references, as well as violations of data protection, copyright, or plagiarism that may have been generated by the AI.

I hereby declare that I

- ☒ have used AI-based tools in my submitted academic work and documented their use in accordance with the above requirements.
- ☐ have not used any AI-based tools in my submitted academic work.

Berlin, July 31, 2026 Anna Togayeva
place, date, signature