The Labor Market Impact of Artificial Intelligence: Local vs. Aggregate Effect*

Yueling Huang†

May 17, 2025

Abstract

Abstract

How does Artificial Intelligence (AI) affect local and aggregate labor markets? I show that US commuting zones with higher AI adoption experienced stronger declines in employment and wage. The distributional impact is similar as routine-biased technological change. However, local estimates only identify relative effects and may differ from aggregate effects. To infer the latter, I quantify a general equilibrium multi-region model with technology adoption disciplined by local estimates. Depending on AI cost savings, one firm adopting AI out of every thousand changes the employment-to-population ratio by -0.20 to 0.15 percentage points and wage by -0.8 to 1.0 percent.

Keywords: Artificial intelligence, technology, labor, local labor markets, shift share, aggregate effect

*I would like to thank Alexandre Balduino Sollaci, Corina Boar, Yoro Diallo, Jiajia Gu, Florence Jaumotte, Florian Misch, Ting Lan, Jin Liu, Giovanni Melina, Mohamed Norat, Augustus Panton, Adrian Peralta Alva, Carlo Pizzinelli, Ippei Shibata, Manmohan Singh, Marina Tavares, Alberto Tumino, and seminar participants at the IMF for helpful comments and discussions. The paper was previously circulated under the title "The Labor Market Impact of Artificial Intelligence: Evidence from US Regions". The views expressed in this paper are those of the author and should not be attributed to the IMF, its Executive Board, or its management. All errors are my own.

†International Monetary Fund. Email: yhuang5@imf.org.

1 Introduction

The rapid and ongoing development in Artificial Intelligence (AI) since the last decade, and in particular the advent of generative AI technologies such as ChatGPT or DeepSeek since November 2022, have spurred much debate on the labor market implications of AI. A natural question arises: how does AI affect employment? Theoretically, the answer is ambiguous (Acemoglu and Restrepo (2019), Webb (2020), Acemoglu (2025)). On the one hand, AI can expand the set of automatable tasks, thereby displacing workers. On the other hand, AI can boost productivity and income, thereby increasing labor demand in non-automated tasks. AI can also create new tasks and jobs such as machine learning engineer, data engineer, or data scientist. While most research tackle this question at the establishment, firm, or individual level (Acemoglu et al. (2022b), Copestake et al. (2023), Hui et al. (2023), Abis and Veldkamp (2024), Babina et al. (2024), Hampole et al. (2025), Jiang et al. (2025)), this paper focuses on macro-level effects.

In this paper, I study the effect of AI on local labor markets and the aggregate US economy. Throughout the paper, I define AI as any of the following five technologies: machine learning, machine vision, natural language processing, voice recognition software, and automated-guided vehicles (AGVs) (McElheran et al. (2024)). I ask three main questions: (*i*) how do changes in the overall employment-to-population ratio and the average wage in high AI exposure commuting zones compare with those in low AI exposure commuting zones during 2010-2021?[1] (*ii*) is the employment effect unequally distributed across population subgroups? (*iii*) what do the relative regional estimates of the employment and wage effects imply for the aggregate effects in the US economy? Aggregate effects can be different from relative regional effects, as the former takes into account national general equilibrium effects such as aggregate income effect and sectoral/regional reallocation, which are differenced out in cross-regional regressions.

To answer the three questions, I first exploit variations in AI adoption across US commuting zones using a shift-share instrumental variable approach to estimate the labor market effects of high AI exposure commuting zones relative to low AI exposure commuting zones. I then develop and calibrate a general equilibrium multi-region model to infer

[1]The main period of analysis is 2010-2021. Therefore, the paper does not focus on generative AI due to the recency of generative AI technology and limited data availability. However, the framework developed in this paper can be easily applied to assess the effects of generative AI when more data become available.

the aggregate implications of AI. The model delivers a structural relationship between AI exposure and changes in employment or wage across regions. The relative regional estimates from the empirical analysis are used to discipline model parameters. Due to the recency of technological change and data availability, the analysis so far does not extend beyond 2022. However, the paper offers a tractable framework to gauge the aggregate labor market effects of AI using only publicly available data. The framework presented in this paper can therefore be applied to assess the aggregate impact of future waves of technological change and in other countries, as long as local labor markets and industry-level AI adoption rates data are available.

There are two key empirical challenges in the cross-regional estimation. First, data on AI adoption at the commuting zone level is scarce. To address this, I construct a measure of AI exposure for US commuting zones, combining 2010 local employment shares with nationwide AI adoption data from the Annual Business Survey (ABS) Technology module. The second challenge is the endogeneity of AI exposure. Unobserved positive local demand shocks may induce firms to adopt AI and demand more workers, leading to an upward bias in the OLS estimates. Moreover, AI adoption is likely to be anticipated or dependent on previous technologies. Commuting zones that have adopted more ICT, software, and robotics are also more likely to adopt AI. If anticipation or past technologies affect labor market outcomes, using local industry specialization patterns after the ICT revolution for AI exposure can suffer from simultaneity bias.

To address these endogeneity concerns, I instrument the AI exposure measure using local employment share in 1990 and industry-level AI adoption in the EU, under the reasonable assumption that ICT only started to proliferate since the second half of 1990s (Colecchi and Schreyer (2002)). I also use 1995 local employment share and average local employment share in 1990-1995 to compute the IV as robustness checks. EU industry-level AI adoption allows to capture global technological advances and isolate US-specific factors. For example, idiosyncratic US-specific factors such as positive US-specific industry demand shocks can increase both AI adoption and local labor demand, resulting in a positive bias of the simple OLS estimate. The first-stage F-statistic shows that the instrument is relevant. Furthermore, I control for a comprehensive set of initial commuting zone characteristics and commuting zone exposures to the concurrent labor market shocks of robotization and import competition. I perform falsification tests that regress *past* changes in overall employment-to-population ratio and average wage in 1980-2010 on AI exposure in 2010-2021. Results indicate that long-run common factors are unlikely to drive both the changes in labor market outcomes and AI adoption.

I find that commuting zones with a higher share of AI-adopting firms have experienced a stronger decline in the overall employment-to-population ratio and average wage during 2010-2021. The estimates suggest that a one standard deviation increase in AI exposure in the local labor market leads to 0.976 percentage points lower employment-to-population and 2.34% lower wage. Furthermore, the estimated effect implies that employment-to-population in commuting zones at the 75th percentile of AI exposure declines by 1.25 percentage points more than in commuting zones at the 25th percentile of AI exposure, and average wage declines by 3% more.

The negative effect is heterogeneous. It is primarily borne by the manufacturing and low-skill services sectors, middle-skill workers, non-STEM occupations, and individuals at the two ends of the age distribution. The adverse impact is also more pronounced on men than women. These unequal effects of AI are similar as previous waves of labor market shocks, such as routine-biased technological change (RBTC) (Autor et al. (2006), Goos et al. (2014) for skill group), offshoring (Goos et al. (2014) for skill group), industrial robots usage (Acemoglu and Restrepo (2020) for skill group and gender), and import competition (Traiberman (2019) for age). These findings may appear surprising, as high-skill occupations are more exposed to AI, and these occupations were largely insulated from previous shocks such as RBTC or offshoring (Webb (2020), Eloundou et al. (2023), Cazzaniga et al. (2024), Huang (2025)). However, higher exposure does not imply lower employment. Employment or hours worked can increase if AI complements human labor (Cazzaniga et al. (2024), Jiang et al. (2025)) or if the dispersion of task exposure to AI within an occupation is high (Hampole et al. (2025)). For policymakers, these findings underscore the unequal distributional consequences of labor market shocks and the need for social safety nets and job retraining programs. The main findings are robust across several alternative specifications, such as using alternative definition of US industry-level AI adoption, constructing AI exposure measure and its IV with local employment shares in alternative years, and using 2019 as the end year to address concerns about the potential employment impact of Covid-19.

However, local labor market estimates only identify relative effects, as general equilibrium effects are differenced out in cross-regional regressions. Therefore, to gauge the aggregate implications of AI on the US economy, I develop and calibrate a general equilibrium multi-region model with inter-regional trade in goods that accounts for cross-region spillovers and national-level aggregates. One key novelty of the model is that it features endogenous technology adoption in an otherwise standard task-based framework of automation à la Acemoglu and Restrepo (2020). AI adoption involves paying an upfront fixed-cost of adoption in return for a lower marginal cost of production. Adding endogenous technology adoption decision in the model ensures a tight link with the empirical analysis, as the main AI exposure measure in this paper is the percentage of firms adopting AI in a given industry. The model delivers a structural relationship between AI exposure and changes in employment or wage across regions. The relative regional estimates from the empirical analysis are used as targets to match model parameters. The calibrated model exactly matches both the relative regional employment and wage effects estimated from the commuting zone data.

Equipped with the calibrated model, I infer the aggregate implications of AI. Two main takeaways stand out. First, it is important to clarify the unit of analysis when discussing the impacts of AI. Specifically, the relative regional effect and aggregate effect can be quite different. Under the baseline calibration with a relatively optimistic view on the cost savings capacity of AI (27%), one additional AI-adopting firm per thousand firms translates into a 0.14 percentage point increase in the aggregate employment-to-population ratio and a 0.99% increase in aggregate wage. Both changes are positive. By contrast, the relative regional effects are negative. This is because changes in objects that affect all commuting zones equally (such as aggregate output or non-labor income from capital or profits, are absorbed by the constant term in the long-difference regression. The estimated effects are therefore only relative: comparing labor market outcomes between high-exposure commuting zones versus low-exposure commuting zones. However, gauging the aggregate effect requires take into account of all variables affected by the AI shock. For example, a rise in national income induced by AI technological improvement can boost demand in non-tradables and non-automated tasks, pushing up aggregate employment and wage.

Second, the direction and size of the aggregate effects depend crucially on the degree of cost savings from AI. As AI becomes more cost effective, the employment and wage effects of AI are more positive. This result suggests that the worker displacement effect of AI dominates when cost savings are small. However, as technology advances and cost savings become larger, higher income and lower prices induce stronger demand for non-automable labor, resulting in a positive net effect on employment and wage. In the empirically relevant case where AI cost savings are less than 30%, an increase in the fraction of AI-adopting firms by 0.1 percentage point results in a change in the aggregate employment-to-population ratio between -0.2 to 0.15 percentage points, and a change in aggregate wage between -0.8 to 1 percent. Aggregate output increases between 2.3-5.5%. This finding echos Korinek and Suh (2024), who underscore the importance of scenario analysis given the highly uncertain nature of AI's future path.

Related literature. This paper contributes to several strands of literature. First, the paper directly speaks to the burgeoning debate on the labor market impact of AI. Several studies leverage information on the occupational task content to compute occupational exposure to AI (Frey and Osborne (2017), Webb (2020), Felten et al. (2021), Eloundou et al. (2023), Eisfeldt et al. (2023)). However, as Cazzaniga et al. (2024) and Hampole et al. (2025) emphasize, higher exposure does not imply lower employment if AI complementarity or productivity effects are strong. My paper directly estimates the employment effect. Moreover, using firms' AI adoption as the main measure of AI exposure allows me to exploit country-level variations to construct the IV.

Most empirical works on the employment impact of AI are at the micro level. This paper provides a more macro-level assessment focusing on labor labor markets and the aggregate US economy. For studies at the micro-level, the most common ones use vacancy data (Acemoglu et al. (2022b), Copestake et al. (2023), Babina et al. (2024)). Findings are mixed.[2] The empirical analysis on local labor markets is closely related to Bonfiglioni et al. (2025), who also find a stronger negative impact in more AI exposed commuting zones. One key distinction is that I use the empirical estimates to discipline a general equilibrium multi-region model and quantify the aggregate impacts of AI. Another difference is on the measure of AI exposure. Bonfiglioni et al. (2025) use changes in commuting zone employment share of AI-related professions for AI exposure. There are 19 AI professions, which essentially correspond to "Computer and Mathematical Occupations" in SOC 2018, excluding actuaries. In this paper, I directly leverage information

[2] Acemoglu et al. (2022b) and Copestake et al. (2023) find negative effect of AI adoption on non-AI jobs and overall hiring in US and India establishments, respectively. Hui et al. (2023) examine the short-run employment effect of generative AI using data on freelancers from Upwork and find that generative AI reduces overall labor demand for all types of knowledge workers in the short-term. However, Babina et al. (2024) show that AI-investing US public firms experience higher growth in sales and employment. They further argue that the positive growth stems from stronger product innovation of AI-investing firms.

on AI adoption from a nationally representative survey of firms. Doing so has several advantages. First, AI adoption can more intuitively capture the concept of AI exposure when examining the employment impact. There are many non-AI occupations such as managers (Copestake et al. (2023)), economists (Korinek (2023)), financial analysts (Abis and Veldkamp (2024)), even customer support agents (Brynjolfsson et al. (2025)) whose job contents are transformed by AI. It is also highly possible that AI production (which heavily relies on computer and mathematical occupations) is geographically concentrated and does not take place in the same local labor market as AI adoption. Second, using AI adoption allows for instrumenting US industry-level adoption with EU data to capture global technological advances, thereby isolating US-specific shocks.

This paper also contributes to the extensive literature on the macroeconomic impact of technological change and automation. Theoretically, Acemoglu and Restrepo (2019) highlight the main economic forces of automation on employment in a task-based framework. Acemoglu (2025) applies the logic to AI. I extend the framework with endogenous technology adoption to deliver a structural counterpart of the cross-regional empirical specification, so that relative regional estimates serve as targets in model calibration. Empirically, this paper analyzes the impacts of a different and new technology on local labor markets. I borrow the identification strategy from Acemoglu and Restrepo (2020), who investigate the employment and wage impacts of industrial robots in 1990-2007. The key difference is the exposure measure, which arises naturally as AI cannot be counted in the same way as robots. Specifically, Acemoglu and Restrepo (2020) use the number of robots per thousand workers for robots exposure, whereas I use the fraction of AI-adopting firms for AI exposure. Finally, this paper also examines the distributional impact of AI. It is therefore related to the literature on job polarization (Acemoglu and Autor (2011), Autor et al. (2006), Goos et al. (2014)) and trade (Traiberman (2019)).

Methodologically, this paper uses causal estimates from regional data to discipline macroeconomic models and explores the aggregate implications. Nakamura and Steinsson (2018) discuss the use of cross-regional variation to estimate relative regional effects and then infer aggregate, macroeconomic effects from regional estimates. One direct application on the topic of technological change is Acemoglu and Restrepo (2020) for industrial robots.

The rest of the paper is organized as follows. Section 2 introduces the data sources. Section 3 describes the empirical strategy. Section 4 presents the main empirical findings and discusses robustness checks. Section 5 explores the aggregate implications of AI using a calibrated multi-region model with endogenous technology adoption. Section 6 concludes.

2 Data Sources

2.1 AI Adoption Data

For industry-level AI adoption, I use data from the Annual Business Survey (ABS) in the United States and its European counterpart, the ICT Usage in Enterprises. The main purpose of using the European data is to isolate US-specific shocks and construct an instrument for US AI adoption, so that the AI adoption "shock" captures global technological advances.[3]

Annual Business Survey (ABS). The ABS is an annual survey on US businesses and business owners. The survey introduces a new technology module for the years 2018, 2019, and 2021. The module is conducted by the US Census Bureau in partnership with the National Center for Science and Engineering Statistics (NCSES). The data is publicly available at the 2-digital NAICS level, 3-digit NAICS for manufacturing, and 4-digit NAICS for professional, scientific and technical services. Acemoglu et al. (2022a) and Hubmer and Restrepo (2022) use the 2019 module to study automation at the firm level. In this paper, I use the data in 2021, the latest year available. Specifically, the dataset reports the number of firms that use a given AI technology at the industry level. There are five different AI technologies in the ABS: machine learning, machine vision, natural language processing, voice recognition software, and automated-guided vehicles (AGVs) (McElheran et al. (2024)). Together with information on the total number of firms by industry, I calculate the percentage of firms in a given industry that adopt a given AI technology, and then take the average industry-level adoption rate across AI technologies

[3] I choose to use AI adoption in the EU for two reasons. First, industry-level AI adoption data is scant. While it would be interesting to obtain data from other large AI-adopting countries, such as China, such data is not easy to acquire. Second, since we are talking about AI adoption (rather than AI production or innovation), Europe still ranks highly in this regard, as indicated by the IMF AI preparedness index (https://www.imf.org/external/datamapper/datasets/AIPI). To alleviate the concern that shocks to some commuting zones (e.g., Silicon Valley) may affect global trends of AI adoption in certain industries, I conduct an additional test by excluding the top 1% commuting zone in terms of AI exposure. The results remain robust (Table 2).

to obtain the baseline industry-level measure of adoption in AI overall.

ICT Usage in Enterprises. The European Commission collects annual data from national statistical institutes of EU member countries on ICT (Information and Communication Technologies) usage and e-commerce in enterprises. The data is publicly available under NACE Rev. 2 industry classification. I use the percentage of enterprises that use at least one of the following AI technologies (text mining, speech recognition, natural language processing, machine learning, AI-based software robotic process automation, and autonomous robots/vehicles/drones) in 2021 as the baseline measure of industry AI adoption in the EU.

The ABS and the ICT Usage of Enterprises use different industry classification schemes. Appendix A.1 and the fourth column of Appendix A.2 list the final industry classification for the US and the EU. There are 47 industries in the ABS and 27 industries in the ICT Usage in Enterprises data.[4] Both datasets cover manufacturing as well as services.

2.2 Commuting Zone Level Data

There are two main sources of commuting zone level data: the American Community Survey (ACS) and the County Business Patterns (CBP). Both datasets are aggregated to the commuting zone level using the crosswalks of Autor and Dorn (2013). There are 722 commuting zones in total.

American Community Survey (ACS). I use the ACS 5% sample from IPUMS (Ruggles et al. (2024)) to compute commuting zone characteristics such as population, employment, demographics (e.g., share of female population, share of population aged 65 and above, share of white/black/American Indian or Alaskan native/Asian population, share of population with college degrees and above, share of foreign born), industry and occupation compositions. Specifically, I use the crosswalks of Autor and Dorn (2013) to map counties (for the year 1980) or PUMAs (Public Use Microdata Areas, for the years 1990 and beyond) to commuting zones. I drop individuals in the military. Annual wage income is converted in real terms, to 1999 constant US dollars. I exclude observations with top-coded wage income and trim at the 1% level. The main outcome variables are annual wage

[4] As the EU adoption data is mainly used to construct the IV, I do not need to impose any assumptions on the mapping between US and EU industries. The first-stage F statistic suggests that the IV is relevant, so having coarser industry in the EU data is less concerning.

income and employment-to-population and average annual wage income. Employment-to-population ratio is defined as the number of employed working-age individuals (aged 16-65), divided by the total working-age population. Both outcome variables are calculated using census weights.

County Business Patterns (CBP). I use county-level industry employment from the CBP to obtain local employment share. I use the local employment share to construct Bartik-style commuting zone exposure to AI, detailed in Section 3.1 below. I also use the CBP to compute commuting zone Bartik exposure to industrial robot penetration and Chinese import competition during 2010-2021.

2.3 Additional Data Sources

One identification challenge is to ensure that commuting zones with higher AI exposure are comparable to those with lower AI exposure. Differences in initial conditions across commuting zones may affect both AI adoption and employment outcomes. For example, local labor market trends may differ by the share of foreign born for reasons other than AI due to cultural differences - foreign borns are more likely to be employed. If commuting zones with a higher share of foreign born are more likely to adopt AI, the estimates will be upward biased without controlling for the initial share of foreign born. Therefore, I compute a wide range of initial commuting zone demographic characteristics and industrial structure from the ACS. Section 3.1 provides a comprehensive list of controls in the regression analysis.

Another type of confounding factor is concurrent labor market shocks during 2010-2021 (the period of analysis). For example, Acemoglu and Restrepo (2020) document that robotization reduces the employment-to-population ratio. If commuting zones with higher AI adoption are also more exposed to robotization, the estimated effect cannot be attributable to AI adoption alone. Using data on industrial robots from the International Federation of Robotics (IFR), I follow Acemoglu and Restrepo (2020) to compute Bartik exposure to robotics in 2010-2021. Similarly, I compute Bartik exposure to Chinese import competition in 2010-2021 using data from CEPII BACI (Gaulier and Zignago (2010)), which provides information on bilateral trade flows at the HS 6-digit product level.

In Section 4.1, I perform falsification tests and provide support that after controlling for a wide range of commuting zone covariates, AI adoption in 2010-2021 does not affect *past* changes in the employment-to-population ratio in 1980-2010. This implies that commuting zones with low vs. high AI exposures are reasonably similar to begin with.

3 Empirical Strategy

3.1 Empirical Specification

The main goal of the empirical analysis is to estimate the impact of AI on employment and wage. The empirical strategy borrows from Acemoglu and Restrepo (2020). In particular, I exploit commuting zone level variation in AI adoption to estimate its local employment/wage effect. The baseline empirical specification is:

$$\Delta_{2010}^{2021} Y_i = \alpha_{d(i)} + \beta AIExposure_i + \gamma X_i + \epsilon_i \tag{1}$$

where i denotes commuting zones, $d(i)$ refers to the census division of commuting zone i. $\alpha_{d(i)}$ is the census division fixed effect. Y_i refers to labor market outcomes in commuting zone i, such as the overall employment-to-population ratio, or the employment-to-population ratio by subgroups (e.g, occupation, industry), or average wage. The dependent variable is the long difference of Y_i between 2010 and 2021. I set 2010 as the start year. The underlying assumption is that there was no AI adoption in 2010.[5] To alleviate concerns that 2021 may be related to Covid-19 and affects employment patterns in a special way, I also explore the long-differences using 2019 as an alternative for the end year in Appendix A.6.

The coefficient of interest is β, which captures the effect of commuting zone level AI exposure on local labor market outcomes. I provide more details on the construction of $AIExposure_i$ during 2010-2021 in Section 3.2 below. The baseline specification controls for commuting zone level covariates X_i that may potentially influence the change in labor market outcomes between 2010 and 2021. These covariates are initial demographic characteristics (i.e, log of population size, share of female population, share of population

[5] The Electronic Frontier Foundation (EFF) published measurements on the progress of AI research (`https://www.eff.org/ai/metrics`) until 2019. The measurement covers a range of AI applications, and there has been little progress in 2010/2011. Felten et al. (2021) chooses 10 AI applications from the AI Progress Measurement to calculate occupational exposure to AI. This is also the start year chosen in Babina et al. (2024), who study the impact of AI investment on firm growth in 2010-2018.

aged above 65, share of white/black/American Indian or Alaskan native/Asian population, share of foreign born, share of college-educated workers), initial industrial structure (i.e, manufacturing share, light manufacturing share), initial share of routine occupations to proxy for exposure to routine-biased technological change,[6] initial share of high offshorability occupations,[7] as well as Bartik exposures to robotization and Chinese import competition.

3.2 Commuting Zone Level Exposure to AI

Ideally, to determine the causal effect of AI exposure on local employment and wage, $AIExposure_i$ should be exogenous. However, there are several challenges in measuring $AIExposure_i$. First, there is no readily available data of AI adoption at the county (and therefore commuting zone) level. Second, AI adoption is unlikely to be exogenous because of unobserved local demand shocks, anticipation of AI arrival, and the path dependent nature of technological change.

US Exposure to AI. To address the first challenge, I compute a Bartik-style measure of AI exposure in the US in 2010-2021, $USExposure_i$:

$$USExpsoure_i = \sum_j \frac{L_{ij2010}}{L_{i2010}} \Delta_{2010}^{2021} AIAdoption_j^{US} \tag{2}$$

which is a weighted sum of nationwide industry-specific change in AI adoption in 2010-2021 in the US from the ABS,[8] $\Delta_{2010}^{2021} AIAdoption_j^{US}$ ("shift"). Weights are computed as the local employment share of industry j in commuting zone i, $\frac{L_{ij2010}}{L_{i2010}}$ ("share"). Autor et al. (2013) use a similar measure for commuting zone exposure to Chinese import competition in 1990-2007 and Acemoglu and Restrepo (2020) for exposure to industrial robots in 1990-2007.

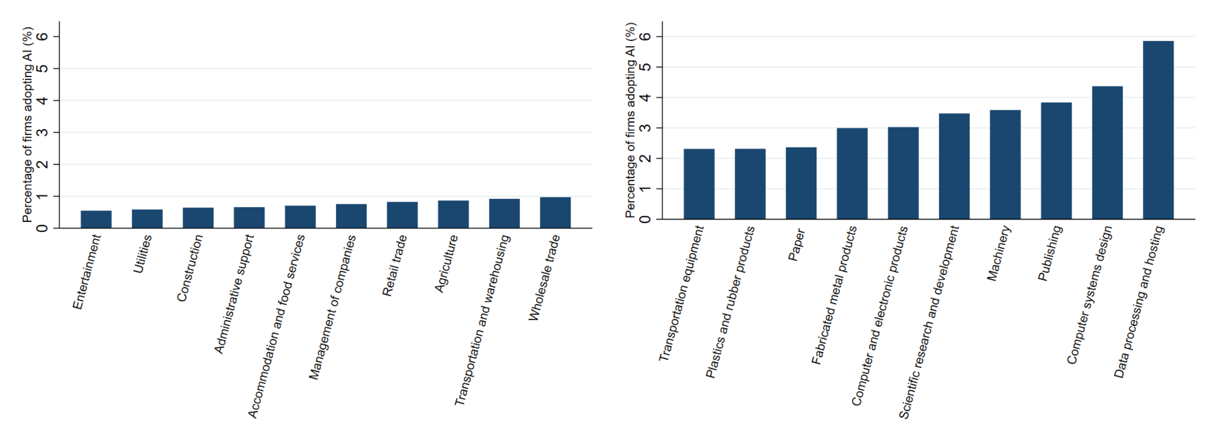
Figure 1 depicts the top and bottom 10 industries of AI adoption in the US. The baseline measure of industry-level AI adoption is the average percentage of adopting firms across

[6] Acemoglu and Autor (2011) calculate routine task scores from data on occupation task content from O*NET. I define routine occupations as occupations with a routine task score above the 66th percentile, as in Autor and Dorn (2013).

[7] Data on offshorability of occupations is from Autor and Dorn (2013). I define offshorable occupations as occupations with an offshorability score above the 66th percencile.

[8] I leverage the industry AI adoption data in 2021, so the implicit assumption is that AI adoption in the US is zero across all industries in 2010.

the five different AI technologies (AGV, machine learning, voice recognition, speech recognition, text mining). I also present robustness results using the maximum adoption rate across the five AI technologies for a given industry as an alternative measure for industry-level AI adoption in Appendix A.5. Not surprisingly, the data processing, hosting, and related services industry, an industry in the information sector, has the highest AI adoption rate at 6%. The second and third industries of AI adoption are computer systems design and publishing. There are also several manufacturing industries with high AI adoption, such as machinery, computer and electronic products, paper products, plastic and rubber products, and transportation equipment. Scientific research and development is also intensive in AI adoption.



(a) bottom 10 industries

(b) top 10 industries

Figure 1: Bottom and Top 10 Industries of AI Adoption in the US

Sources: ABS (2021) and author's calculations.
Notes: Each blue bar represents the average percentage of adopting firms across the five different AI technologies (AGV, machine learning, voice recognition, speech recognition, text mining) for the bottom 10 industries (Panel (a)) and top 10 industries (Panel (b)) in the US. Industry classification is according to Appendix A.1.

However, neither the share nor the shift component of $USExposure_i$ is likely to be exogenous. Local employment share in 2010 can incorporate the anticipation effect of AI arrival, resulting in simultaneity bias. Similarly, technological change can be fairly path dependent. Commuting zones that have adopted more ICT, software, and robotics since the 1990s are also more likely to adopt AI. To the extent that anticipation or past technologies affect employment outcomes, using local industry specialization patterns after the proliferation of ICT to construct AI exposure may suffer from simultaneity bias. As for the shift component, idiosyncratic US-specific factors such as US-specific industry demand shocks can increase both AI adoption and local labor demand, resulting in a positive bias of the simple OLS estimate.

Instrumental Variable. I construct the following instrumental variable (IV) for $USExposure_i$, denoted as $EUExposure_i$:

$$EUExpsoure_i = \sum_j \frac{L_{ij1990}}{L_{i1990}} \Delta_{2010}^{2021} AIAdoption_j^{EU} \tag{3}$$

This IV is in the same spirit as in Acemoglu and Restrepo (2020), who use 1970 local employment share interacted with EU industry-level industrial robot penetration to instrument for 1990 US robot penetration. I use the local employment share in 1990 to mitigate concerns of AI anticipation and path dependence of technological change. This is because in 1990, technologies such as ICT and robotization are only at burgeoning stages at best.[9] I also perform robustness checks using local employment shares in 1995 and average local employment shares in 1990-1995. For the shift component, I use industry-level AI adoption in the EU to capture global technological advances, similar to Autor et al. (2013) and Acemoglu and Restrepo (2020). Figure 2 shows a strong positive relationship between industry-level AI adoption in the US versus the EU, suggesting that EU AI adoption is a relevant instrument for US AI adoption.[10] Moreover, as shown in Table 1, the F-statistic is 58.2, well above 10, indicating that $EUExposure_i$ is a strong instrument.

AI Exposure vs. AI Adoption. To clarify, I use the terms "AI exposure" and "AI adoption" interchangeably when referring to *commuting zone level* AI exposure. I only use the term "AI adoption" (but not "AI exposure") when referring to *industry-level* AI adoption, as AI adoption is the main variable that is used in the "shift" component of commuting zone level AI exposure measures ($USExposure_i$, $EUExposure_i$).

[9] I do not choose earlier periods such as 1980 due to the concern that local employment share in 2010 may have changed too much, resulting in the problem of weak instrument.

[10] The scales of US and EU adoption are different, because the two measures use different definitions. The baseline definition for industry-level AI adoption in the US data is the average industry-level adoption rate across five AI technologies (machine learning, machine vision, natural language processing, voice recognition software, and AGVs). The definition for industry-level AI adoption in the EU data is the percentage of enterprises that use at least one of the following AI technologies (text mining, speech recognition, natural language processing, machine learning, AI-based software robotic process automation, and autonomous robots/vehicles/drones).

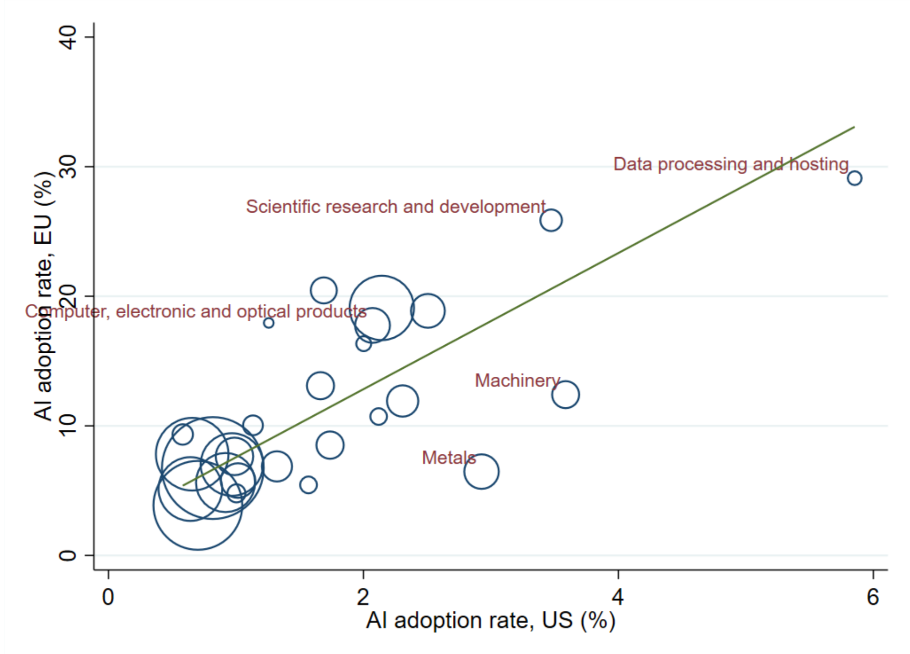


Figure 2: Correlation of Industry-Level AI Adoption in US vs. EU

Sources: ABS (2021), Eurostat (2021), BLS OEWS (2010), and author's calculations.
Notes: Each blue circle represents an industry according to the industry classification in Appendix A.2. The x-axis is AI adoption in the US. The y-axis is AI adoption in the EU. The green line is the linear regression fit, with coefficient of 5.255 and standard error of 0.874. The size of the blue circle is the US industry share in 2010.

AI Exposure by Commuting Zone. Figure 3 plots the geographic distribution of AI exposure across US commuting zones. Darker color indicates that the commuting zone is more exposed to AI. Consistent with intuition, San Francisco, Los Angeles, San Antonio, Seattle, Pittsburgh, New York, Washington D.C., and Boston have high exposure to AI under both $USExposure_i$ and $EUExposure_i$.

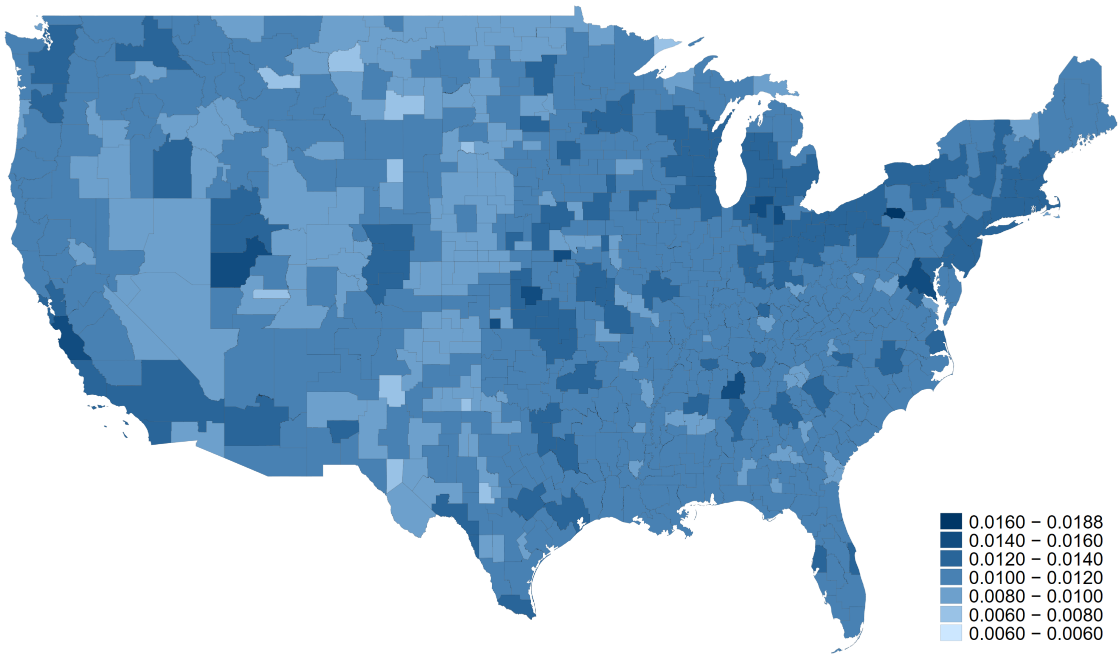
3.3 Instrumental Variable Approach

Given specification (1) and the IV, the main empirical approach of the paper is a two-stage least-squares (2SLS) regression. The first stage is:

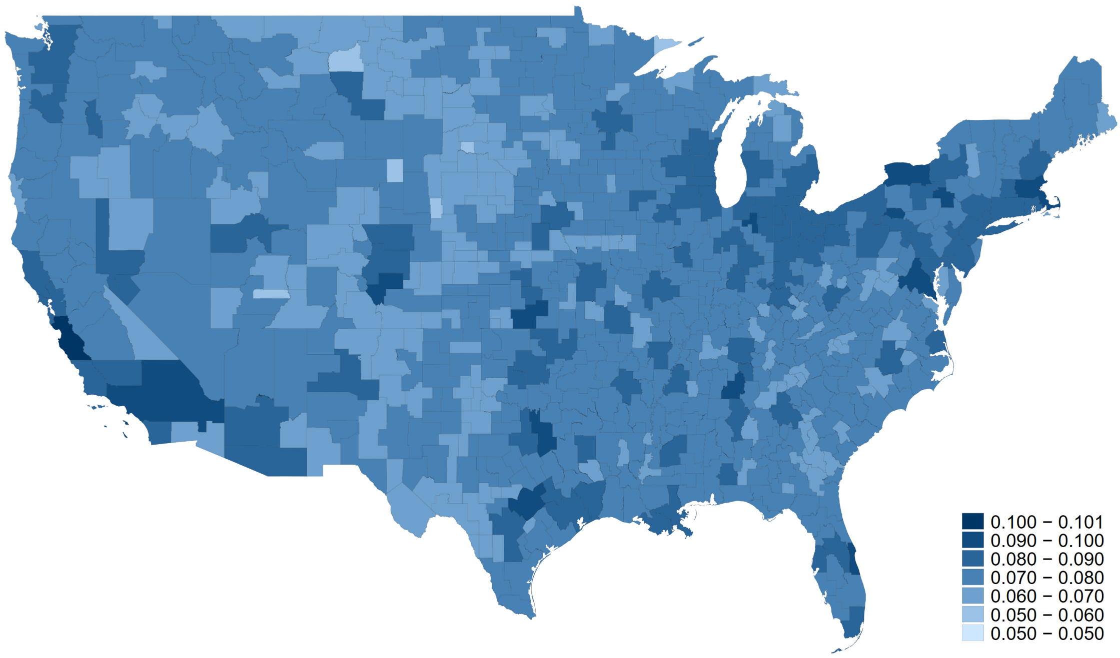
$$USExposure_i = \tilde{\alpha}_{d(i)} + \tilde{\beta} EUExposure_i + \tilde{\gamma} X_i + \tilde{\epsilon}_i \tag{4}$$

The second stage is:

$$\Delta_{2010}^{2021} Y_i = \alpha_{d(i)} + \beta \widehat{USExposure}_i + \gamma X_i + \epsilon_i \tag{5}$$



(a) $USExposure_i$



(b) $EUExposure_i$

Figure 3: AI Exposure by US Commuting Zone

Sources: ABS (2021), Eurostat (2021), CBP (1990, 2010), and author's calculations.

Notes: Each cell represents a commuting zone. Darker color indicates a higher value for $USExposure_i$ (Panel (a)) or $EUExposure_i$ (Panel (b)).

where $\widehat{USExposure_i}$ is the first-stage estimate from equation (4). Each regression is weighted by commuting zone population in 2010. Standard errors are clustered at the state-level to account for potential serial correlation in the error term within state.

4 Empirical Results

4.1 Effect on the Overall Employment-to-Population Ratio

Table 1 presents the second-stage estimates β from equation (5), which explores the impact of AI exposure on overall employment-to-population ratio at the commuting zone level. I find that commuting zones with higher AI exposure have experienced a more negative change in the employment-to-population ratio during 2010-2021.

The baseline IV uses local employment share in 1990, as shown in equation (3). Under the reasonable assumption that ICT have not yet proliferated,[11] I also use local employment share in 1995 and average local employment share in 1990-1995 to compute the IV for robustness. I refrain from using later years such as the 2000s due to concerns that ICT and robotization have become more prevalent by then, resulting in an invalid instrument. The first stage F-statistic is consistently above 50, indicating that the IV is relevant.

Column (1) is the baseline specification, where I use 1990 as the local employment share to compute the IV, and examine the effect of AI exposure on change in employment-to-population ratio in 2010-2021. The estimate suggests that a one standard deviation increase in AI exposure implies 0.976 percentage points lower employment-to-population ratio. Furthermore, the estimate also implies that the employment-to-population ratio in commuting zones at the 75th percentile of AI exposure declines by 1.25 percentage points more than in commuting zones at the 25th percentile of AI exposure. Column (2) presents the second-stage estimate using 1995 local employment share to compute the IV. Similarly, column (3) uses average local employment share in 1990-1995 to compute the IV, so that I do not rely on the local employment share in any particular year. The estimated effects of AI exposure on change in employment-to-population ratio in 2010-2021 from both specifications remain significantly negative.

[11] Colecchi and Schreyer (2002) show that the rate of growth in IT equipment in the 1990s doubled with respect to the 1980s in the US. ICT investment accelerated particularly in the second half of the 1990s.

I first perform a falsification test, where I regress *past* changes in the overall employment-to-population ratio in 1980-2010 on *future* AI exposure in 2010-2021. The coefficients are insignificant in columns (4)-(6). These results suggest that after controlling for initial commuting zone characteristics, concurrent labor market shocks, and census division fixed effects, AI exposure in 2010-2021 only affects outcomes for the period 2010-2021, but not for the earlier period of 1980-2010. Hence, long-run common factors are unlikely to drive both the change in employment-to-population and AI adoption.

One potential concern is that shocks to some commuting zones (e.g., Silicon Valley) may affect global trends of AI adoption in certain industries, undermining the exogeneity of EU adoption. To address this concern, I remove the top 1% of commuting zones in terms of AI exposure ($USExposure_i$). Table 2 reports the results. The negative effect on the employment-to-population ratio remains robust.

The baseline outcome variable is the employment-to-population ratio. However, if the commuting zones that are early adopters of AI are also the richest in the country, their population may have increased by more than the national average over time. As a result, the employment-to-population ratio could have decreased for reasons other than AI exposure. I show that the negative effect in the employment-to-population ratio is indeed driven by the negative effect on employment (the numerator). Specifically, I use the change in the log of overall employment *level* in 2010-2021 as the main outcome variable and include changes in the log of working-age population as an additional control. Table 3 shows that conditional on changes in working-age population, commuting zones with higher exposure to AI experience stronger declines in the employment level.

Table 4 runs similar regressions, with average annual and hourly wage as the main outcome variables. Falsification tests (Columns (3) and (4)) indicate that AI exposure in 2010-2021 does not drive wage outcomes during the earlier period of 1980-2010. Columns (1) and (2) suggest that commuting zones with a higher share of AI-adopting firms have experienced a more negative effect on average annual wage income during 2010-2021. A one standard deviation increase in AI exposure in the local labor market results in 2.34% lower average annual wage income. Average wage in commuting zones at the 75th percentile of AI exposure declines by 3% more than in commuting zones at the 25th percentile of AI exposure. However, the wage effects are less precisely estimated than employment effects. Indeed, wage information contains more measurement error and noise than employment information. Therefore, for the next section on heterogeneity, I focus only on changes in employment.

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990-1995 Average 2010-2021 (3)	1990 Share 1980-2010 (4)	1995 Share 1980-2010 (5)	1990-1995 Average 1980-2010 (6)
$USExposure$	-7.511**	-5.699*	-8.375***	2.217	-1.199	0.716
	(3.067)	(2.979)	(3.129)	(4.739)	(5.402)	(5.075)
Observations	722	722	722	722	722	722
R-squared	0.28	0.30	0.26	0.56	0.55	0.55
First-stage coefficient	0.075***	0.084***	0.086***	0.075***	0.084***	0.086***
	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)
First-stage F-statistic	58.2	52.8	57.3	58.2	52.8	57.3

Table 1: Effect of AI on Employment-to-Population Ratio: 2SLS Estimates

Notes: The table reports the second stage estimates β from equation (5). The dependent variable is the change in the employment-to-population ratio in 1980-2010 (for columns (4)-(6)) and 2010-2021 (for columns (1)-(3)). Columns (1) and (4) use local employment share in 1990 to compute the IV $EUExposure_i$. Columns (2) and (5) use local employment share in 1995 to compute the IV $EUExposure_i$. Columns (3) and (6) use the average local employment share in 1990-1995 to compute the IV $EUExposure_i$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

4.2 Heterogeneity

In this section, I examine the effect of AI exposure on changes in employment by various subgroups, such as the broad sector, occupation, education, age, and gender. The goal is to explore potential heterogeneous effects of AI adoption and investigate the subgroups that contribute to the negative impact of AI exposure on employment. There are four main findings. First, the manufacturing and low-skill services sectors are negatively affected. Second, similar to routine-biased technological change, one of the main drivers behind job polarization[12] in the 1990s (Autor et al. (2006), Goos et al. (2014)), the negative impact of AI exposure also falls mainly on middle-skill workers. Third, AI exposure

[12]Job polarization is a labor market phenomenon in the US and EU since the 1990s where middle-skill occupations are in decline in terms of employment and wage.

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990-1995 Average 2010-2021 (3)	1990 Share 1980-2010 (4)	1995 Share 1980-2010 (5)	1990-1995 Average 1980-2010 (6)
$USExposure$	-8.968**	-6.345	-10.054***	2.409	-2.533	-0.024
	(4.156)	(3.912)	(4.225)	(6.220)	(7.361)	(6.900)
Observations	714	714	714	714	714	714
R-squared	0.24	0.29	0.22	0.55	0.55	0.55
First-stage coefficient	0.060***	0.066***	0.067***	0.060***	0.066***	0.067***
	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)
First-stage F-statistic	41.5	43.1	43.0	41.5	43.1	43.0

Table 2: Effect of AI on Employment-to-Population Ratio (Excluding Top 1% $USExposure_i$): 2SLS Estimates

Notes: The table reports the second stage estimates β from equation (5). The dependent variable is the change in the employment-to-population ratio in 1980-2010 (for columns (4)-(6)) and 2010-2021 (for columns (1)-(3)). The sample excludes commuting zones with top 1% $USExposure_i$. Columns (1) and (4) use local employment share in 1990 to compute the IV $EUExposure_i$. Columns (2) and (5) use local employment share in 1995 to compute the IV $EUExposure_i$. Columns (3) and (6) use the average local employment share in 1990-1995 to compute the IV $EUExposure_i$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

reduce the employment-to-population ratio of individuals at the two ends of the age distribution (those aged 16-25 and above 46). Fourth, the adverse impact is more pronounced on men than women.

Broad sector. Table 5 shows the second-stage estimates of AI exposure on changes in sectoral employment-to-population ratio during 2010-2021. The results reported here use the baseline IV, where local employment shares are from 1990. Manufacturing, and especially low-skill services, stand out as the sectors contributing to the negative impact of AI exposure on employment. The effect on agriculture is mildly positive, consistent with the finding in Bonfiglioni et al. (2025). One possible explanation could be that workers in low-skill services and manufacturing switch into agriculture, as the agriculture sector has a relatively low skill requirement.

Occupation. Table 6 explores the impact of AI exposure on employment for two classifications of occupation groups: whether the occupation is STEM or not (Columns (1)-(2)),

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990-1995 Average 2010-2021 (3)	1990 Share 1980-2010 (4)	1995 Share 1980-2010 (5)	1990-1995 Average 1980-2010 (6)
USExposure	-10.970**	-8.759*	-12.351***	2.162	-3.237	-0.269
	(4.856)	(4.701)	(4.951)	(7.190)	(8.245)	(7.605)
Observations	722	722	722	722	722	722
R-squared	0.95	0.95	0.95	0.99	0.98	0.99
First-stage coefficient	0.075	0.084	0.086	0.075	0.084	0.086
First-stage F-statistic	59.5	53.2	58.0	59.4	54.2	59.5

Table 3: Effect of AI on Log Employment Level: 2SLS Estimates

Notes: The table reports the second stage estimates β from equation (5). The dependent variable is the change in the change in log employment level in 1980-2010 (for columns (4)-(6)) and 2010-2021 (for columns (1)-(3)). In addition, the right-hand side also controls for the change in log working age population in 1980-2010 (for columns (4)-(6)) and 2010-2021 (for columns (1)-(3)). Columns (1) and (4) use local employment share in 1990 to compute the IV $EUExposure_i$. Columns (2) and (5) use local employment share in 1995 to compute the IV $EUExposure_i$. Columns (3) and (6) use the average local employment share in 1990-1995 to compute the IV $EUExposure_i$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

and whether the occupation is high-skill, middle-skill, or low-skill (Columns (3)-(5)). The estimates suggest that the negative employment impact is due to non-STEM and middle-skill occupations. This is finding is consistent with the firm-level evidence documented in Babina et al. (Forthcoming). They find that firms with higher initial shares of more educated workers tend to invest more in AI, which in turn shift these AI-investing firms towards a more educated and more specialized workforce in STEM fields and IT skills.

Education. I compute the employment-to-population ratio by four education groups: below high school, high school graduate, some college, college and above. The estimates in Table 7 suggest that the employment of individuals with middle levels of education, namely those with some college education (but not reaching Bachelors degree) and in particular high school graduates, are negatively affected by AI exposure. Together with the previous finding that middle-skill occupations drive the negative employment impact of AI, these results indicate that similar to routine-biased technological change, one of the main drivers behind job polarization in the 1990s, the negative impact of AI exposure also falls primarily on middle-skill workers.

	2010-2018 Annual Wage (1)	2010-2018 Hourly Wage (2)	1980-2010 Annual Wage (3)	1980-2010 Hourly Wage (4)
Exposure to AI	-18.053*	-12.782	3.719	5.051
	(9.297)	(9.034)	(18.550)	(17.953)
Observations	722	722	722	722
R-squared	0.53	0.53	0.64	0.59
First-stage coefficient	0.075***	0.075***	0.075***	0.075***
First-stage F-statistic	58.2	58.2	58.2	58.2

Table 4: Effect of AI on Wage: 2SLS Estimates

Notes: The table reports the second stage estimates β from equation (5). The dependent variable is the change in the log residual annual (for columns (1) and (3))/hourly (for columns (2) and (4)) wage in 1980-2010 (for columns (3)-(4)) and 2010-2021 (for columns (1)-(2)). Columns (1) and (4) use local employment share in 1990 to compute the IV $EUExposure_i$. Columns (2) and (5) use local employment share in 1995 to compute the IV $EUExposure_i$. Columns (3) and (6) use the average local employment share in 1990-1995 to compute the IV $EUExposure_i$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Age. I divide the working-age population by 10-year age bins (16-25, 26-35, 36-45, 46-55, 56-65) and calculate their respective employment-to-population ratios. Columns (1)-(5) in Table 8 show that the negative impact of AI on employment falls primarily on individuals at the two ends of the age distribution: the very young (aged 16-25) and older workers (aged above 46). Intuitively, the low employment-to-population ratio of young individuals can be attributed to two reasons. First, as technological change tends to replace simple tasks, more individuals aged 16-25 stay in school for longer to acquire more technical skills and remain competitive in the labor market. Second, young individuals who are already in the labor force are less likely to have attended college, and therefore tend to work in lower skill occupations, which are more at risk of displacement under technological change. Older workers (those aged 46 and above) are negatively hit by AI as their skills may have become obsolete upon the arrival of new frontier technologies and these workers are also less adaptable to learn new technologies (Cazzaniga et al. (2024)). Older workers also have a higher opportunity cost to switch jobs because of the large amount of *specific* human capital they have accumulated over time. Higher switching

	Agriculture	Manufacturing	Construction	Low-Skill Services	High-Skill Services
	(1)	(2)	(3)	(4)	(5)
$USExposure$	0.914**	-5.118*	1.047	-5.292***	0.939
	(0.460)	(2.782)	(1.091)	(2.039)	(1.635)
Observations	722	722	722	722	722

Table 5: Effect of AI on Employment-to-Population Ratio by Broad Sector: 2SLS Estimates

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in sectoral employment-to-population ratio in 2010-2021. Manufacturing includes manufacturing and mining. Low-skill services are wholesale trade, retail trade, utilities, transportation, information, real estate, administrative support and waste management, arts and entertainment, accommodation and food services, and other services. High-skill services are finance and insurance, professional scientific and technical services, management of companies and enterprises, education, health, and social assistance. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

	Non-STEM	STEM	Low-Skill	Middle-Skill	High-Skill
	(1)	(2)	(3)	(4)	(5)
$USExposure$	-6.997***	-0.514	-0.230	-4.936*	-2.345
	(2.881)	(1.049)	(0.980)	(2.559)	(1.701)
Observations	722	722	722	722	722

Table 6: Effect of AI on Employment-to-Population Ratio by Occupation: 2SLS Estimates

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in occupational (STEM vs. non-STEM occupations; low, middle, high-skill occupations) employment-to-population ratio in 2010-2021. The list of STEM occupations are from O*NET. High-skill occupations are management, business and financial occupations, professionals, and technicians. Middle-skill occupations are office and administration, sales, construction and extraction, mechanics and repairers, production, transportation and material moving. Low-skill occupations are personal services and agriculture occupations. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

cost and lower job mobility are also found among older workers under import competition (Traiberman (2019)) or trade liberalization (Dix-Carneiro (2014)).

	Below High School	High School	Some College	College and Above
	(1)	(2)	(3)	(4)
$USExposure$	-2.598	-9.723***	-6.216*	-0.550
	(5.850)	(3.935)	(3.729)	(2.401)
Observations	722	722	722	722

Table 7: Effect of AI on Employment-to-Population Ratio by Education: 2SLS Estimates

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by education levels (below high school, high school, some college, college and above) in 2010-2021. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Gender. Columns (6) and (7) in Table 8 summarize the findings on male and female employment. Both gender groups experienced a stronger decline in employment in more AI-exposed commuting zones during 2010-2021. However, the negative impact on male employment is more pronounced than female employment. Cazzaniga et al. (2024) argue that although women are more likely to be employed in high AI exposure occupations,[13] these occupations also tend to be more complementary to AI. Therefore, AI also presents greater opportunities for women. The complementary nature of occupations held by women may be the reason for the relatively smaller adverse employment impact of AI on women than men.

Use 1995 local share or 1990-1995 average local share in IV. I perform robustness checks by using 1995 local employment share and 1990-1995 average local employment share to compute the IV. Results are in Appendix A.3 and Appendix A.4. The findings are robust. The negative employment effect is primarily borne by manufacturing and low-skill services, middle-skill workers, non-STEM occupations, and individuals at the two ends of the age distribution. The adverse impact is also more pronounced on men than women.

[13] AI occupation exposure (AIOE) is from Felten et al. (2021). An occupation with a higher AIOE score implies that this occupation requires more abilities on which AI technologies have made more progress.

	16-25	26-35	36-45	46-55	56-65	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$USExposure$	-11.519**	-2.962	-5.576	-7.746**	-7.969*	-9.191**	-5.581*
	(5.606)	(3.423)	(4.007)	(3.750)	(4.108)	(4.214)	(3.089)
Observations	722	722	722	722	722	722	722

Table 8: Effect of AI on Employment-to-Population Ratio by Age and Gender: 2SLS Estimates

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by 10-year age bin (16-25, 26-35, 36-45, 46-55, 56-65) or gender (male, female) in 2010-2021. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

4.3 Robustness

I conduct three robustness exercises. First, as mentioned in Section 3.2, I use the maximum adoption rate across the five AI technologies for a given industry as an alternative measure of US industry-level AI adoption $AIAdoption_j^{US}$ (Appendix A.5). Second, I use 2019 as the end year of the long-difference to mitigate the concern that employment patterns in 2021 may be related to Covid-19 (Appendix A.6). Third, I use local employment shares in 2005 instead of 2010 for $USExposure_i$ (Appendix A.7) to mitigate potential AI anticipation or mean reversion from the 2007-2009 Great Recession. The findings are very consistent across these alternative specifications.

5 Inferring Aggregate Effect from Relative Regional Estimates

How do the relative regional estimates of the labor market effect of AI translate into *aggregate* effects in the US economy? I answer this question through a general equilibrium multi-region model with inter-regional trade in goods that accounts for cross-region spillovers. Crucially, the empirically estimated relative regional effects of AI on employment and wage are used to discipline the multi-region model. Section 5.1 describes a closed economy model *with AI adoption*. The key purpose of this section is to illustrate how AI technological advance in a given industry affects the fraction of AI-adopting firms and the labor share in that industry. Section 5.2 modifies the model to incorporate cross-region spillovers through trade. Section 5.3 describes the parameterization procedure and presents the aggregate implications of AI.

5.1 Closed Economy Model

Since the main AI exposure measure is the percentage of firms adopting AI in a given industry, the model should feature an extensive margin of AI adoption to ensure a tight link with the empirical analysis. To this end, I extend the task-based framework from Acemoglu and Restrepo (2020) with heterogeneous firms and endogenous technology adoption. AI adoption involves paying an upfront fixed-cost of adoption in return for a lower marginal cost of production.[14] The marginal cost of production is lower, because a set of tasks can now be automated by AI at a lower cost than human labor. Firms are heterogeneous in productivity. As firm profit increases with productivity, AI adoption follows a cut-off rule. Technological advance in AI for a given industry is captured by an expansion in the set of AI-automable tasks. Below I describe the model and its implications in closed economy in more detail. I show that labor share in a given industry is shaped by three forces as technology advances: a negative direct effect, a positive productivity effect, and an industry composition effect.

Production. The economy consists of I commuting zones, indexed by i. Each commuting zone has preferences over a final good, which is a CES aggregate over industry j:

$$Y_i = \Big(\sum_j \nu_j^{\frac{1}{\sigma}} Y_{ij}^{\frac{\sigma-1}{\sigma}}\Big)^{\frac{\sigma}{\sigma-1}}, \sigma > 0 \text{ and } \sum_j \nu_j = 1 \tag{6}$$

where σ is the elasticity of substitution across industries, ν_j measures the importance of industry j's good in the final good. Therefore, demand for industry j goods in commuting zone i is:

$$Y_{ij} = \nu_j \Big(\frac{P_{ij}^X}{P_i}\Big)^{-\sigma} Y_i \tag{7}$$

The ideal price index of the final good P_i is normalized to 1 in each commuting zone:

$$P_i = \Big(\sum_j \nu_j P_{ij}^{X 1-\sigma}\Big)^{\frac{1}{1-\sigma}} = 1 \tag{8}$$

[14]The model is similar in spirit as Stapleton and Webb (2023), who model both firm-level offshoring and automation decisions subject to fixed costs.

In autarky equilibrium, industry demand Y_{ij} equals its production X_{ij} in each commuting zone i. Each industry j in commuting zone i consists of a continuum of monopolistically competitive firm. Each firm produces a differentiated variety ω and differs in terms of productivity $z(\omega)$. The production function of industry j in commuting zone i is:

$$X_{ij} = \alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)} A_{ij} \Big(\underbrace{\Big(\int_0^1 x_{ij}(\omega)^{\frac{\eta_j - 1}{\eta_j}} d\omega \Big)^{\frac{\eta_j}{\eta_j - 1}}}_{:= \tilde{X}_{ij}} \Big)^{\alpha} K_{ij}^{1-\alpha} \tag{9}$$

where $1-\alpha$ is the share of non-AI capital K_{ij}. $\eta_j > 1$ is the elasticity of substitution across varieties in industry j, which implies a constant markup of $\frac{\eta_j}{\eta_j - 1}$. $\tilde{X}_{ij}$ is a CES aggregator over heterogeneous producers, which use either human labor or AI as factor inputs. The production function of heterogeneous producer is given below in equation (10). $\alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)}$ is a scaling factor. A_{ij} denotes the productivity of industry j in commuting zone i and shapes the local industry employment composition.

The part of the output of variety producer ω that can be either performed by human labor or AI is given by $x_{ij}(\omega)$, a CES aggregate over a continuum of tasks $s \in [0,1]$:

$$x_{ij}(\omega) = z_{ij}(\omega) \min_{s \in [0,1]} \{x_{ij}(\omega, s)\} \tag{10}$$

AI can replace human labor in the set of tasks $s \in [0, \theta_j]$:

$$x_{ij}(\omega, s) = \begin{cases} \gamma_M M_{ij}(s) + \gamma_L L_{ij}(s), & \text{if } s \le \theta_j \\ \gamma_L L_{ij}(s), & \text{if } s > \theta_j \end{cases} \tag{11}$$

Tasks are ordered such that $\frac{\gamma_L(s)}{\gamma_M(s)}$ increases in s, so that larger s corresponds to a more complex task that cannot be easily replaced by AI. To model the extensive margin, assume that AI adoption involves an upfront fixed cost f_M but lower marginal cost of production. I further assume that the fixed cost of AI adoption does not increase with the number of AI-replacing tasks, so that firms adopt AI on all tasks that can be feasibly replaced by AI. This assumption gives tractability by abstracting from the endogenous choice of θ_j (Acemoglu et al. (2020), Hubmer and Restrepo (2022)) and is also used in Stapleton and Webb (2023).

Define the cost savings from AI (relative to human labor) as $\Delta_i := 1 - \frac{R_i^M/\gamma_M}{w_i/\gamma_L} \ge 0$

(so that AI will not be adopted if $\frac{R_i^M}{\gamma_M} > \frac{w_i}{\gamma_L}$).[15] For example, if $\frac{R_i^M}{\gamma_M}$ is 30% of $\frac{w_i}{\gamma_L}$, then the cost saving Δ_i is 0.7. Technological advance in AI for industry j is captured by $d\theta_j$. The idea of the model is to study the effect of $d\theta_j$ on employment and wage.

Household. To close the model, assume that a representative household in commuting zone i exhibits the following preference:

$$u(C_i, L_i) = \frac{C_i^{1-\psi} - 1}{1-\psi} - \frac{B}{1+\varepsilon} L_i^{1+\varepsilon} \tag{12}$$

where ψ determines the income elasticity of labor supply, and ε is the inverse of the wage elasticity of labor supply. The household budget constraint is $C_i \leq w_i L_i + \Pi_i$, where w_i denotes wage, and Π_i is non-labor (capital and profits) income. For example, the household owns the firms. Therefore, profits of monopolistic competitive producers ω are rebated lump-sum to the household and captured by Π_i.

Investment. I follow Acemoglu and Restrepo (2020)) by modeling the production of AI as $M_i = D(1+\kappa) I_i^{\frac{1}{1+\kappa}}$, where I_i denotes investment (in units of final good).[16] $\kappa > 0$, implying an upward-sloping AI capital supply curve[17] The rental price of AI capital is R_i^M. Non-AI capital supply is fixed at K_i. The price of capital equals to R_i^K.

Equilibrium. An equilibrium is a set of factor prices $\{w_i, R_i^M, R_i^K\}$, factor supplies $\{L_i, M_i\}$, and output Y_i such that in all commuting zones, (i) factor supplies satisfy the household's and AI production maximization problems; (ii) factor prices satisfy the ideal price index condition; and (iii) factor markets clear for labor, AI capital, and non-AI capital. Appendix B.1.3 characterizes the equilibrium.

Lemma 1 (cut-off rule of AI adoption): *In closed economy, firm's adoption decision follows a cut-off rule z_{ij}^*, where firms with productivity $z_{ij}(\omega) \geq z_{ij}^*$ adopt AI and those with productivity $z_{ij}(\omega) < z_{ij}^*$ do not. The cut-off value of productivity z_{ij}^* is:*

$$z_{ij}^* = \left(\frac{f_M}{\Omega_{ij} P_{ij}^{\tilde{X}\alpha(1-\sigma)-1+\eta_j} Y_i^{1+(1-\alpha)(1-\sigma)} ((\theta_j(1-\Delta_i) + (1-\theta_j))^{1-\eta_j} - 1)} \right)^{\frac{1}{\eta_j - 1}} \frac{w_i}{\gamma_L} \tag{13}$$

[15] The model can be easily extended to incorporate industry-level scale effects of AI adoption due to cross-firm spillover, such that industry production function (9) is depends on the share of AI-adopting firms $1 - G(z^*)$. However, the degree of such spillover is unclear.

[16] Local digital infrastructure is an example of such investment.

[17] Higher κ implies more inelastic AI supply curve. When $\kappa = 0$, AI capital supply is perfectly elastic and follows $R^M = \frac{1}{D}$.

where $\Omega_{ij} := \eta_j^{-\eta_j}(\eta_j - 1)^{\eta_j-1}\alpha(1-\alpha)^{(1-\alpha)(1-\sigma)}\nu_j A_{ij}^{\sigma-1} K_i^{-(1-\alpha)(1-\sigma)}$. (See Appendix B.1.1, equation (29) for derivations).

Denote the cumulative distribution of productivity as $G(z)$, so the fraction of firms that adopt AI in industry j and commuting zone i is $1 - G(z^*_{ij})$. A lower value of z^*_{ij} implies a higher fraction of AI adoption firms. Proposition 1 implies that a higher fraction of firms adopt AI if the fixed cost of adoption f_M is lower but final output Y_i (which suggests positive income effect) and cost saving from AI Δ_i are higher.

For the remainder of the paper, assume that productivity z follows a Pareto distribution such that the cumulative distribution $G(z) = 1 - z^{-\phi_j}, \phi_j > \max\{\eta_j - 1, 1\}$,[18] ϕ_j is the shape parameter. A lower value indicates a fatter tail of the distribution and hence higher dispersion.

Define the labor share (net of non-AI capital) in industry j and commuting zone i as s^L_{ij}:

$$s^L_{ij} := \frac{w_i L_{ij}}{P^{\tilde{X}}_{ij}\tilde{X}_{ij}} = \frac{w_i L_{ij}}{\alpha P^X_{ij} X_{ij}}$$

which is a revenue-weighted share of firm-level labor share:

$$s^L_{ij} = \frac{w_i L_{ij}}{P^{\tilde{X}}_{ij}\tilde{X}_{ij}} = \frac{\int_0^1 w_i L_{ij}(\omega)d\omega}{\int_0^1 p_{ij}(\omega)x_{ij}(\omega)d\omega} = \int_0^1 \underbrace{\frac{w_i L_{ij}(\omega)}{p_{ij}(\omega)x_{ij}(\omega)}}_{\text{firm-level labor share}} \underbrace{\frac{p_{ij}(\omega)x_{ij}(\omega)}{\int_0^1 p_{ij}(\omega)x_{ij}(\omega)d\omega}}_{\text{revenue share}} d\omega$$

Lemma 2 (labor share s^L_{ij}): *The labor share of industry j in commuting zone i, s^L_{ij}, is:*

$$s^L_{ij} = \Big(\frac{\eta_j - 1}{\eta_j}\Big)\Big(\frac{1 + ((1-\theta_j)\Gamma_{ij}^{-\eta_j} - 1)z_{ij}^{*\eta_j-\phi_j-1}}{1 + (\Gamma_{ij}^{1-\eta_j} - 1)z_{ij}^{*\eta_j-\phi_j-1}}\Big) \tag{14}$$

(See Appendix B.1.2 for derivations).

Lemma 3 (partial equilibrium effect of $d\theta_j$ on AI adoption cut-off z^*_{ij} and the

[18]This condition ensures that average firm productivity and $P^{\tilde{X}}_{ij}$ are finite.

labor share s_{ij}^L): *Taking prices as given,*

$$d\ln z_{ij}^* = -\frac{\Delta_i}{\Gamma_{ij}(1-\Gamma_{ij}^{\eta_j-1})}d\theta_j + \frac{\alpha(1-\sigma)-1+\eta_j}{1-\eta_j}d\ln P_{ij}^{\tilde{X}} + \frac{1+(1-\alpha)(1-\sigma)}{1-\eta_j}d\ln Y_i \tag{15}$$

where $\Delta_i = 1 - \frac{R_i^M/\gamma_M}{w_i/\gamma_L}$ *and* $\Gamma_{ij} = \theta_j(1-\Delta_i) + (1-\theta_j)$.

$$d\ln s_{ij}^L = \Gamma_{ij}^{-2\eta_j} z_{ij}^{*\eta_j-\phi_j-1}(\Delta_i - 1)\Big)\Xi_{ij}d\theta_j + (\phi_j - \eta_j + 1)\theta_j(1-\Delta_i)\Gamma_{ij}^{-\eta_j}\Xi_{ij}d\ln z_{ij}^* \tag{16}$$

where $\Xi_{ij} := \frac{z_{ij}^{*\eta_j-\phi_j-1}}{(1+((1-\theta_j)\Gamma_{ij}^{-\eta_j}-1)z_{ij}^{*\eta_j-\phi_j-1})(1+(\Gamma_{ij}^{1-\eta_j}-1)z_{ij}^{*\eta_j-\phi_j-1})} > 0$. (See Appendices B.1.1 and B.1.2 for derivations).

Equation (15) indicates that there are three forces shaping the fraction of AI-adopting firms in response to technological advance in AI. The first term captures the direct effect. As technology advances ($d\theta_j > 0$), z_{ij}^* is lower, which implies that a higher fraction of firms adopt AI. The second term captures the industry composition effect. Profit increases as industry price is higher, hence more firms can afford to adopt AI. The third term captures the positive productivity effect of AI, which leads to higher commuting zone level final output and higher share of AI-adopting firms. Equation (16) suggests that labor share in industry j commuting zone i shrinks with AI technological advance and the fraction of AI-adopting firms.

5.2 Open Economy Model

The closed economy model described in Section 5.1 abstracts from trade in goods and services across commuting zones. Therefore, the closed economy model does not incorporate potential cross-region spillover effects, which is a key difference from relative regional effect estimated at the commuting zone level and aggregate effect on the US economy. The multi-region part of the model largely follows the seminal work of Acemoglu and Restrepo (2020).

Household. The representative household's consumption is now a composite of a tradable good C_i and a non-tradable good (service) S_i:

$$u(C_i, L_i) = \frac{(C_i^{\chi}S_i^{1-\chi})^{1-\psi} - 1}{1-\psi} - \frac{B}{1+\varepsilon}L_i^{1+\varepsilon}$$

where $\chi \in (0,1)$ is the expenditure share on the tradable good. Assume that the production of non-tradable good is $S_i = L_i^S$. Labor market clearing requires that $L_i^C = L_i - L_i^S$. Household budget constraint becomes $C_i + P_i^S S_i \leq w_i L_i + \chi_i^{\Pi}\Pi$, as the price of tradable good is the numeraire and χ_i^{Π} denotes the share of non-labor income allocated to commuting zone i (so that $\sum_i \chi_i^{\Pi} = 1$).

Tradable good production. Each region i produces a differentiated tradable good, but labor is immobile across regions. P_i denotes the price of tradable good produced in region i and normalized to 1. The production function of the tradable final good in commuting zone i is the same as (6). Industry tradable good in commuting zone i follows similar CES structure as in the closed economy model, given by (9). The only modification is that industry production now incorporates industry inputs sourced from all commuting zones k:

$$Y_{ij} = \left(\sum_k \nu_{kj}^{\frac{1}{\lambda}} X_{kij}^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}}, \lambda > 0 \text{ and } \sum_k \nu_{kj} = 1 \tag{17}$$

where ν_{kj} is the weight associated with input from commuting zone k for industry j. Trade is subject to iceberg trade cost t_{ik}, such that $t_{ii} = 1$ and $t_{ik} \geq 1$ for $i \neq k$. This implies that in order for 1 unit of the good produced in i to be delivered in k, region i must ship t_{ik} units of the good. Therefore, the price of good from region k in region i, P_{ki}, equals to $t_{ki}P_k$. I make the extreme assumption of no trade costs ($\pi_{ik} = 1, \forall i, k$), which implies that the price of tradable good is equalized across commuting zones. Setting the price of (aggregate) tradable good to be the numeraire gives $P_i = 1, \forall i$.

Tradable goods market clearing requires:

$$X_{ij} = \sum_k X_{ikj}, \forall i, j \tag{18}$$

Capital. Capital is assumed to be freely mobile across commuting zones. Therefore, $R_i^K = R^K, \forall i$.

The rest of the economy is similar to the closed economy version.

Equilibrium. An equilibrium is a set of prices $\{w_i, R_i^M\}$, factor supplies $\{L_i, R_i^M\}$, and national aggregates $\{Y, R^K, \Pi\}$ such that (i) factor supplies satisfy the household's and AI production maximization problems; (ii) factor prices satisfy the ideal price index conditions for the aggregate and industry tradable goods; (*iii*) factor markets clear for labor, AI capital, and non-AI capital; and (*iv*) non-labor income Π follows from national final goods market clearing. Appendix B.2.1 characterizes the equilibrium.

Assumption 1 (conditions for $z^*_{ij} = z^*_j, \forall i$): *If (i) $\frac{\gamma_M}{\gamma_L} \propto \frac{R^M_i}{w_i}$, (ii) $\nu_{ij} \propto A^{1-\lambda}_{ij}$, (iii) $f_M \propto w_i^{\alpha(1-\lambda)}$, then $z^*_{ij} = z^*_j$ for all i. Moreover, $s^L_{ij} = s^L_j$ for all i.* (See Appendix B.2.2 for derivations).

Assumption 1 allows the model to deliver analytical expressions linking the change in employment or wage with the change in the fraction of AI adoption firms. These analytical expressions mirror the empirical regression counterpart (1). The first condition assumes that the relative productivity of AI to human labor is proportional to the local relative factor price of AI to human labor. Intuitively, this condition implies that the marginal productivity gain from AI diminishes as AI technology deepens (so that $\frac{R^M_i}{w_i}$ is lower). The second condition suggests that the weight associated with industry good j sourced from commuting zone i in the production function is inversely proportional to the productivity of commuting zone i in industry j (as typically $\lambda > 1$). This is possible if commuting zone i produces higher quality industry good, which is more desirable but more difficult to produce. The third condition requires that the fixed cost of AI adoption is inversely proportional to the commuting zone wage rate. This could be the case if the adoption is easier in high wage commuting zones, which are typically richer and benefit more from technology.

Assumption 2 (conditions for $z^*_{ij} = z^*, \forall i, j$): *If (i) $\frac{\gamma_M}{\gamma_L} \propto \frac{R^M_i}{w_i}$, (ii) $\nu_{ij} \propto A^{1-\lambda}_{ij}$, (iii) $f_M \propto w_i^{\alpha(1-\lambda)}$, (iv) $\theta_j = \theta_0$, $\eta_j = \eta$, $\phi_j = \phi$, (v) $\nu_j \propto P_j^{Y\sigma-\lambda}$, then $z^*_{ij} = z^*$ for all i and j. Moreover, $s^L_{ij} = s^L$ for all i and j.* (See Appendix B.2.2 for derivations).

Under Pareto distribution, the share of AI-adopting firms in industry j is $\pi^f_j := 1 - G(z^*_j) = z_j^{*-\phi}$, hence $d\ln\pi^f_j = -\phi d\ln z^*_j$ and $d\pi^f_j = -\phi\pi^f d\ln z^*_j = -\phi z^{*-\phi} d\ln z^*_j$. Commuting zone i's AI exposure corresponds to $\sum_i l_{ij} d\pi^f_j$.

Proposition 1 (effect of $d\pi^f_j$ on $d\ln L_i$ and $d\ln w_i$): *Under Assumption 2, equations (72), (73), (78), (79), (80) define a system of 5 linear equations with 5 unknowns: $d\ln L_i$, $d\ln w_i$, $d\ln R^K$, $d\ln R^M_i$, $d\ln M_i$. The solution of the system of equations is the equilibrium outcome. The equation linking $d\ln L$ to AI exposure is given by (112) in Ap-*

pendix B.3.3. (See Appendices B.2.3 and B.3.3 for derivations).

Define aggregate (average) US employment and wage as $d\ln L = \sum_i \chi_i^w d\ln L_i$ and $d\ln w = \sum_i \chi_i^w d\ln w_i$, where χ_i^w is the share of national wage bill for commuting zone i. Similarly, $d\ln R^M = \sum_i \chi_i^w d\ln R_i^M$ and $d\ln M = \sum_i \chi_i^w d\ln M_i$.

Proposition 2 (effect of $d\pi_j^f$ on $d\ln L$ and $d\ln w$): *Under Assumption 2, and suppose that the initial allocation of non-labor income satisfies $\chi_i^\Pi = \frac{w_i L_i}{\sum_k w_k L_k}$, the equations (84), (85), (89), (90), (91), (92) define a system of 6 linear equations with 6 unknowns: $d\ln L$, $d\ln w$, $d\ln R^K$, $d\ln R^M$, $d\ln M$, $d\ln Y$. The solution of the system of equations is the equilibrium outcome. The equation linking $d\ln L$ to AI exposure is given by (99) in Appendix B.2.4.* (See Appendix B.2.4 for derivations).

5.3 Inferring Aggregate Effect from Relative Regional Estimates

Proposition 2 provides analytical expressions describing the relationship between AI exposure and aggregate employment and wage for the US economy. The basic idea about the back-of-the-envelope calculation is similar to the standard approach in quantitative macroeconomics. Crucially, the estimated relative regional effects of AI on employment (Table 1) and wage (Table 4) are used to discipline the multi-region model. The calibrated model is able to exactly reproduce the estimated relative regional effects. Equipped with all the parameter values, I then compute the aggregate implications of AI, by solving the system of equations in Proposition 2.

5.3.1 Parameterization

Table 9 summarizes the parameter values and their source/target. I group the parameters in three blocs: production, preference, and AI-related. In this section, I first describe the assigned parameters, followed by calibrated parameters. For standard production parameters, I set σ to 1, so that the production of the tradable final good is Cobb-Douglas. The elasticity of substitution between traded varieties sourced from different commuting zones λ is set to 5, the standard value used in the trade literature (Head and Mayer (2014), Simonovska and Waugh (2014)) and adopted by Acemoglu and Restrepo (2020) in their multi-region model of robotics. I choose η to be 6[19] to match a markup of 1.2. This value is roughly in the middle of the wide range of markup estimates in the literature (Basu

[19] $\eta = \frac{1.2}{1.2-1} = 6$, as $\frac{\eta}{\eta-1} = 1.2$.

(2019)).

For the AI-related parameters, I adopt the value estimated by Acemoglu and Restrepo (2020) for κ, which equals to 0.79. I perform sensitivity analysis by varying the values for κ in Figure 4. I set the cost savings of AI Δ to 0.27, in line with the baseline value in Acemoglu (2025). This value of cost savings is the average of two estimates from experimental studies of AI: Noy and Zhang (2023) and Brynjolfsson et al. (2025). Specifically, Noy and Zhang (2023) find a 40% faster completion in writing tasks among white-collar workers with high ChatGPT-3.5 usage than those with low usage. Brynjolfsson et al. (2025) show that AI increases the speed of customer service completion by 15% on average. Hence, $\gamma = 1 - \Delta = 0.73$. Due to the wide range of estimates, and because this paper focuses on pre-generative AI, I also experiment with higher values of γ (implying lower cost savings). Figure 4 depicts the results and indicates that the degree of cost savings is an essential determinant of the direction and size of the aggregate effects.

I have the following parameters to calibrate: $\{\phi, \alpha, \chi, \psi, \varepsilon\}$. First, I assume that initially, 0.001% of firms adopt AI across all industries in 2010,[20] so that $\pi_j^f = \pi_0^f = 10^{-5}$. Given this assumption, the five calibrated parameters are determined in a loop. In the outer loop, θ_0 is pinned down by matching the IV estimate of the employment effect of AI, i.e., $\hat{\beta}_L^{IV} = -7.511$. Appendix B.3.3 derives the structural equation of $\hat{\beta}_L^{IV}$. Given π_j^f and θ_0, the shape parameter ϕ of the Pareto productivity distribution can be solved by targeting the 2010 mean-to-standard-deviation ratio of firm sales, which equals to 0.212 according to Compustat. This results in an $\phi = 10.13$.[21] Details on the calibration of ϕ is in Appendix B.3.1. Given $\{\phi,\ \eta,\ \gamma,\ \theta_0,\ \pi_0^f\}$,[22] s^L can be calculated according to equation (37). α is pinned down by targeting an overall labor share of $\alpha s^L = 0.6$ in 2010 (Karabarbounis (2024)), so that $\alpha = 0.72$.

For preference parameters, I follow Acemoglu and Restrepo (2020) by setting the tradable employment share $\rho = \frac{\alpha\chi}{1-\chi+\alpha\chi}$ equal to the manufacturing employment share of 0.18, so that $\chi = \frac{\rho}{\alpha+\rho-\alpha\rho} = 0.23$. ψ and ε are determined according to equations (109) and (108) in Appendix B.3.2, which equal to 0.05 and 0.49, respectively.

[20] The initial π_j^f must be greater than zero to ensure that the problem is bounded.

[21] ϕ must be greater than $2(\eta - 1)$ for the standard deviation to be bounded.

[22] Details on the value of γ are elaborated in the next paragraph on AI-related parameters.

Parameter	Description	Value	Source/Target
Production:			
σ	Elasticity of substitution (industries)	1	Cobb-Douglas production
λ	Elasticity of substitution (traded varieties)	5	Standard
η	Elasticity of substitution (firms)	6	Markup = 1.2
ϕ	Pareto distribution, shape parameter	10.13	$\frac{\text{Average firm sales}}{\text{Standard Deviation of firm sales}} = 0.212$
α	Labor and AI capital share	0.72	Labor share = 0.6
Preference:			
χ	Tradable sector share	0.23	$\rho = \frac{\text{Manufacturing Employment}}{\text{Total employment}} = 0.18$
ψ	Degree of risk aversion	0.05	Marginal propensity of leisure = $\frac{\psi}{\varepsilon}\omega^L = 0.1$
ε	Inverse of Frisch elasticity of labor supply	0.49	Household labor supply = equation (72), $\hat{\beta}_w^{IV} = -18.053$
AI:			
κ	Inverse of supply elasticity of AI	0.79	Acemoglu and Restrepo (2020)
γ	cost savings of AI	0.73	Acemoglu (2025)
Initial conditions:			
π_0^f	Initial fraction of AI-adoption firms	10^{-5}	Assumption
θ_0	Initial set of AI-automable tasks	0.065	$\hat{\beta}_L^{IV} = -7.511$

Table 9: Parameter Values

5.3.2 Aggregate Implications

Baseline Results. Equipped with the parameters in Table 9, I solve the equilibrium for the aggregate US economy according to Proposition 2. I find that one additional AI-adopting firm per thousand firms translates into a 0.14 percentage point increase in the aggregate employment-to-population ratio and a 0.99% increase in aggregate wage. Aggregate output increases by 5.45%. Non-labor income increases by 29.57%.[23] Investment-to-output ratio increases by 0.53 percentage points. These results highlight the difference between relative regional effect and aggregate effect. When exploiting regional variation of AI exposure across commuting zones, changes in objects that affect all commuting zones equally (such as Y or Π) are absorbed by the constant term in the long-difference regression. Hence, the estimated effects are merely relative: comparing labor market outcomes between high-exposure commuting zones versus low-exposure commuting zones. However, gauging the aggregate effect requires take into account of all variables possibly affected by the AI shock. These variables include, for example, changes in aggregate output and

[23] The model does not feature heterogeneous skills and abstracts from worker transition costs, which are beyond the scope of this paper. Transition costs may lower aggregate output and non-labor income in the short run, resulting in lower wage and employment.

non-labor income. Intuitively, a rise in income induced by AI technological improvement can boost demand in non-tradables and non-automated tasks, generating positive effects on aggregate employment-to-population and wage.

Importance of AI cost savings Δ. The baseline value for AI cost savings $\Delta = 1 - \gamma$ is taken from experimental studies of generative AI. Since this paper focuses on pre-generative AI and because the baseline value of AI cost savings is also on the upper side of the wide range of estimates found in the literature, I further investigate how aggregate outcomes vary with alternative values of cost savings. I also test for the sensitivity of the results to alternative values of AI supply elasticity $1/\kappa$. Figure 4 plots the relationship between AI cost savings and changes in aggregate outcomes in response to one additional AI-adopting firm per thousand firms under various degrees of AI capital supply elasticity κ.

First, the degree of cost savings is an essential determinant shaping the direction and size of the aggregate effects. As AI becomes more cost effective, the employment and wage effects of AI are more positive. This suggests that the worker displacement effect of AI dominates when cost savings are small. However, as technology advances and cost savings become larger, higher income and lower prices induce stronger demand for non-automable labor, resulting in a positive net effect on employment and wage. In the empirically relevant case ($\Delta < 0.3$), as the fraction of AI-adopting firms increases by 0.1 percentage point, change in aggregate employment-to-population ratio ranges between -0.2 to 0.15 percentage points, and change in aggregate wage ranges between -0.8 to 1 percent. Aggregate output increases between 2.3-5.5%. Non-labor income increases between 18.9-29.6%. The investment-to-output ratio increases by 0.53 percentage points. This value does not vary much by AI cost savings, as the initial investment-to-output ratio (ι) is close to zero.

Second, aggregate labor market outcomes are fairly robust to alternative values of κ. When κ is smaller, implying a more elastic AI capital supply, the economy invests more heavily in AI capital, which pushes up output. However, aggregate employment-to-population and wage are lower. Non-labor income is also lower because gains from AI capital is lower when supply is more elastic (smaller κ).

Sensitivity Analysis: Varying π_0^f. Table 10 presents changes in aggregate outcomes in response to one additional AI-adopting firm per thousand firms under other plausible assumptions on π_0^f. The effects are reasonably robust to alternative values on π_0^f. Overall, the magnitude of aggregate effects slightly diminishes as the initial fraction of AI-adopting firms is higher.

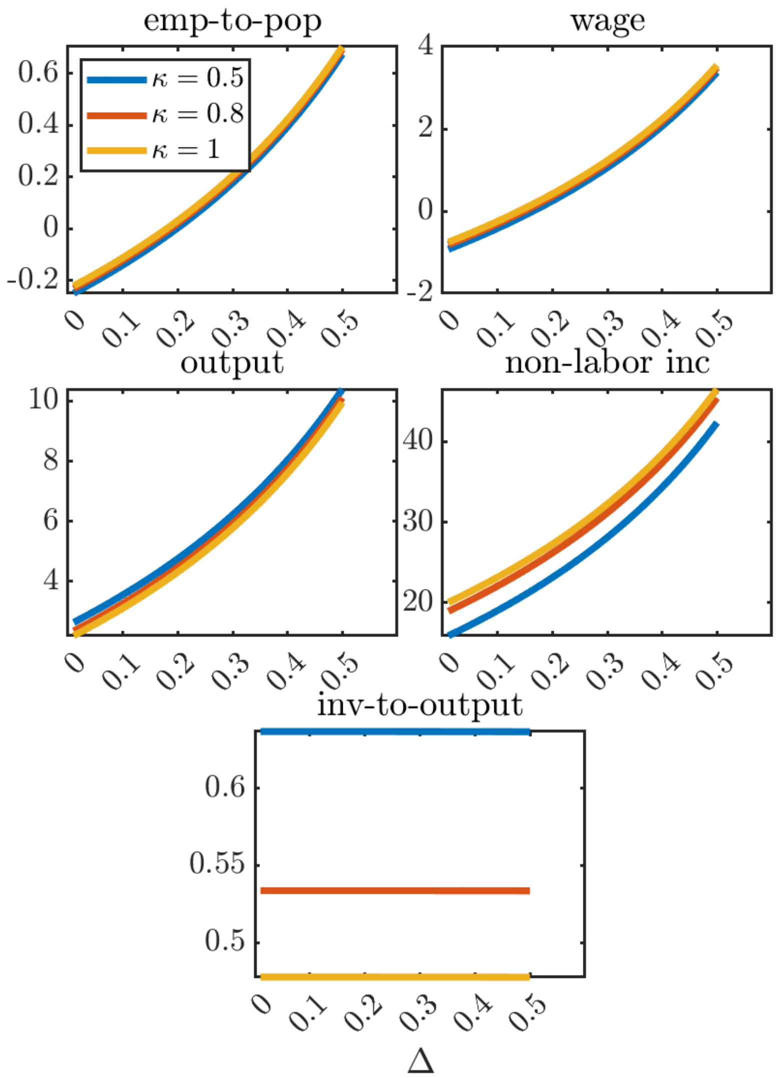


Figure 4: Aggregate Implications: Importance of AI cost savings Δ

Notes: The y-axis are percentage point or percent changes of aggregate outcomes in response to one additional AI-adopting firm per thousand firms under $\kappa = 0.5$ (blue line), $\kappa = 0.8$ (red line), $\kappa = 0.5$ (orange line).

	$\pi_0^f = 10^{-7}$	$\pi_0^f = 10^{-6}$	$\pi_0^f = 10^{-5}$	$\pi_0^f = 10^{-4}$
	(1)	(2)	(3)	(4)
Change in aggregate outcomes (%):				
Employment-to-population ratio	0.17	0.16	0.14	0.10
Wage	1.03	1.00	0.99	0.72
Output	5.68	5.62	5.45	5.11
Non-labor income	30.34	30.13	29.57	28.46
Investment-to-output ratio	0.53	0.53	0.53	0.53

Table 10: Sensitivity Analysis: Varying π_0^f

6 Conclusion

Rapid and ongoing development in AI since the last decade, and in particular the advent of generative AI technologies such as ChatGPT and DeepSeek since November 2022, have spurred much debate on the labor market implications of AI. Most empirical research has studied this question at the firm or individual level. This paper delves into a macro-level analysis focusing on local labor markets and the aggregate US economy. I exploit variation in AI adoption across US commuting zones using a shift-share approach to investigate the employment and wage impacts of AI in 2010-2021. In particular, to address endogeneity concerns, I instrument AI exposure using data on local employment share in 1990 and industry-level AI adoption in the EU.

I find that commuting zones with higher AI adoption have experienced stronger declines in the employment-to-population ratio and wage during 2010-2021. The distributional impact is similar to previous labor market shocks such as RBTC and import competition: the negative employment effect is primarily borne by manufacturing and low-skill services, middle-skill workers, non-STEM occupations, males, and workers at the two ends of the age distribution.

However, aggregate effects can be different from local labor market effects, as the former takes into account national general equilibrium effects such as aggregate income effect and sectoral/regional reallocation, which are differenced out in cross-regional regressions. To this end, I develop and calibrate a general equilibrium multi-region model with endogenous technology adoption which exactly matches the local labor market evidence.

The model suggests depending on the degree of AI cost savings, a 0.1 percentage point increase in fraction of AI-adopting firms leads to a change in the aggregate employment-to-population ratio between -0.2 to 0.15 percentage points, and a change in aggregate wage between -0.8 to 1 percent.

Currently, there are two main constraints in the research on the labor market impact of AI. First, reliable data is scant, in particular large-scale, up-to-date micro-level *panel* data on AI adoption.[24] The ABS does not extend to the generative-AI era, proliferated by the launch of ChatGPT in 2022. It is therefore difficult to precisely gauge the aggregate effects of generative AI. However, this paper provides a tractable framework to gauge the aggregate effects of AI from publicly available data on local labor markets and industry-level AI adoption. The aggregate effects of new waves of AI or in other countries can be gauged upon availability of local labor markets and industry-level adoption data. Second, the direction of AI technological change is rapid and highly uncertain. This uncertainty poses a challenge to researchers. As argued by this paper and Korinek and Suh (2024), scenario analysis may be useful given the highly uncertain nature of AI's future path.

The paper suggests several avenues for future research. First, given the importance of AI cost savings in shaping the direction and size of aggregate effects, more studies are needed to determine the precise extent of AI cost savings. Second, AI production can be quite different from AI usage or adoption, which is the focus of this paper. Local labor markets can specialize in or outsource AI production. Investigating the geographical specialization in the AI "value chain", spanning from AI production to AI usage is also a fruitful dimension for research. Third, the empirical analysis can be extended to other outcome variables, such as inequality, housing prices, and political views.

[24] The panel dimension allows researchers to exploit the time variation.

References

Abis, Simona and Laura Veldkamp (2024) "The Changing Economics of Knowledge Production," *The Review of Financial Studies*, 37 (1), 89–118.

Acemoglu, Daron (2025) "The Simple Macroeconomics of AI," *Economic Policy*, 40 (121), 13–58.

Acemoglu, Daron, Gary Anderson, David Beede et al. (2022a) "Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey," Manuscript, Boston University.

Acemoglu, Daron and David H. Autor (2011) "Skills, Tasks and Technologies: Implications for Employment and Earnings," in *Handbook of Labor Economics*, 4, Chap. 12, 1043–1171: Elsevier.

Acemoglu, Daron, David Autor, Jonathan Hazell, and Pascual Restrepo (2022b) "Artificial Intelligence and Jobs: Evidence from Online Vacancie," *Journal of Labor Economics*, 40 (S1), 293–340.

Acemoglu, Daron, Andrea Manera, and Pascual Restrepo (2020) "Does the U.S. Tax Code Favor Automation?" *Brookings Papers on Economic Activity*, Spring, 231–300.

Acemoglu, Daron and Pascual Restrepo (2019) "Automation and New Tasks: How Technology Displaces and Reinstates Labor," *Journal of Economic Perspectives*, 33 (2), 3–30.

——— (2020) "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, 128 (6), 2188 – 2244.

Autor, David and David Dorn (2013) "The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market," *American Economic Review*, 103 (5), 1553–1597.

Autor, David, David Dorn, and Gordon Hanson (2013) "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103 (6), 2121–2168.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney (2006) "The Polarization of the U.S. Labor Market," *American Economic Review*, 96 (2), 189–194.

Babina, Tania, Anastassia Fedyk, Alex He, and James Hodson (2024) "Artificial Intelligence, Firm Growth, and Product Innovation," *The Journal of Financial Economics*, 151, 1–26.

——— (Forthcoming) "Firm Investments in Artificial Intelligence Technologies and Changes in Workforce Composition," *NBER Volume on Technology, Productivity, and Economic Growth*.

Basu, Susanto (2019) "Are Price-Cost Markups Rising in the United States? A Discussion of the Evidence," *Journal of Economic Perspectives*, 33 (3), 3–22.

Bonfiglioni, Alessandra, Rosario Crinò, Gino Gancia, and Ioannis Papadakis (2025) "Artificial Intelligence and Jobs: Evidence from US Commuting Zones," *Economic Policy*, 40, 145–194.

Brynjolfsson, Erik, Danielle Li, and Lindsey R. Raymond (2025) "Generative AI at Work," *The Quarterly Journal of Economics*, 1–54.

Cazzaniga, Mauro, Florence Jaumotte, Longji Li, Giovanni Melina, Augustus J Panton, Carlo Pizzinelli, Emma J Rockall, and Marina Mendes Tavares (2024) "Gen-AI: Artificial Intelligence and the Future of Work," IMF Staff Discussion Notes No. 2024/001.

Colecchi, Alessandra and Paul Schreyer (2002) "ICT Investment and Economic Growth in the 1990s: Is the United States a Unique Case?" *Review of Economic Dynamics*, 5 (2), 408–442.

Copestake, Alex, Ashley Pople, Katherine Stapleton, and Max Marczinek (2023) "AI and Services-Led Growth: Evidence from Indian Job Adverts," Manuscript, International Monetary Fund.

Dix-Carneiro, Rafael (2014) "Trade Liberalization and Labor Market Dynamics," *Econometrica*, 82 (3), 825–885.

Eisfeldt, Andrea L., Gregor Schubert, and Ben Miao Zhang (2023) "Generative AI and Firm Values," NBER Working Paper 31222.

Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock (2023) "GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models," Working Paper.

Felten, Edward, Manav Raj, and Robert Seamans (2021) "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses," *Strategic Management Journal*, 42, 2195–2217.

Frey, Carl Benedikt and Michael A. Osborne (2017) "The Future of Employment: How Susceptible are Jobs to Computerisation?" *Technological Forecasting and Social Change*, 114, 254–280.

Gaulier, Guillaume and Soledad Zignago (2010) "BACI: International Trade Database at the Product-Level. The 1994-2007 Version.," CEPII Working Paper, N°2010-23.

Goos, Maarten, Alan Manning, and Anna Salomons (2014) "Explaining Job Polarization: Routine-Biased Technological Change," *American Economic Review*, 104 (8), 2509–2526.

Hampole, Menaka, Dimitris Papanikolaou, Lawrence D.W.Schmidt, and Bryan Seegmiller (2025) "Artificial Intelligence and the Labor Market," NBER Working Paper 33509.

Head, Keith and Thierry Mayer (2014) "Gravity Equations: Workhorse,Toolkit, and Cookbook," in *Handbook of International Economics*, 4, Chap. 3, 131–195: Elsevier.

Huang, Yueling (2025) "Is the Impact of AI Different from IT? ," IMF Research Perspectives.

Hubmer, Joachim and Pascual Restrepo (2022) "Not a Typical Firm: Capital-Labor Substitution and Firms' Labor Shares," Manuscript, Boston University.

Hui, Xiang, Oren Reshef, and Luofeng Zhou (2023) "The Short-Term Effects of Generative Artificial Intelligence on Employment: Evidence from an Online Labor Market," CESifo Working Paper.

Imbens, Guido W., Donald B. Rubin, and Bruce I. Sacerdote (2001) "Estimating the Effect of Unearned Income on Labor Earnings, Savings, and Consumption: Evidence from a Survey of Lottery Players," *American Economic Review*, 91 (4), 778–794.

Jiang, Wei, Junyoung Park, Rachel (Jiqiu) Xiao, and Shen Zhang (2025) "AI and the Extended Workday: Productivity, Contracting Efficiency, and Distribution of Rents," NBER Working Paper 33536.

Karabarbounis, Lukas (2024) "Perspectives on the Labor Share," *Journal of Economic Perspectives*, 38 (2), 107–136.

Korinek, Anton (2023) "Generative AI for Economic Research: Use Cases and Implications for Economists," *Journal of Economic Literature*, 61 (4), 1281–1317.

Korinek, Anton and Donghyun Suh (2024) "Scenarios for the Transition to AGI," NBER Working Paper 32255.

McElheran, Kristina, J. Frank Li, Erik Brynjolfsson, Zachary Kroff, Emin Dinlersoz, Lucia Foster, and Nikolas Zolas (2024) "AI Adoption in America: Who, What, and Where," *Journal of Economics and Management Strategy*, 33 (2), 375–415.

Nakamura, Emi and Jón Steinsson (2018) "Identification in Macroeconomics," *Journal of Economic Perspectives*, 32 (3), 59–86.

Noy, Shakked and Whitney Zhang (2023) "Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence," *Science*, 381 (6654), 187–192.

Ruggles, Steven, Sarah Flood, Matthew Sobek et al. (2024) "IPUMS USA: Version 15.0,": Minneapolis, MN: IPUMS, https://doi.org/10.18128/D010.V15.0.

Simonovska, Ina and Michael E. Waugh (2014) "The Elasticity of Trade: Estimates and Evidence," *Journal of International Economics*, 92 (1), 34–50.

Stapleton, Katherine and Michael Webb (2023) "Automation, Trade and Multinational Acitivity: Micro Evidence from Spain," Working Paper.

Traiberman, Sharon (2019) "Occupations and Import Competition: Evidence from Denmark," *American Economic Review*, 109 (12), 4260–4301.

Webb, Michael (2020) "The Impact of Artificial Intelligence on the Labor Market," Manuscript.

Online Appendix

A Data Appendix

A.1 Industry Classification in the ABS

Industry	Description	NAICS
1	Agriculture, forestry, fisheries	11
2	Mining, extraction, and support activities	21
3	Utilities	22
4	Construction	23
5	Food, beverages, tobacco	311-312
6	Textile, apparel, leather products	313-316
7	Wood products	321
8	Paper products	322
9	Printing and related support activities	323
10	Coke and refined petroleum products	324
11	Chemicals and chemical products	325
12	Rubber and plastic products	326
13	Nonmetallic mineral products	327
14	Basic metals	331
15	Fabricated metal products	332
16	Machinery	333
17	Computer and electronic products	334
18	Electrical equipment, appliances, and components	335
19	Transportation equipment	336
20	Furniture and related products	337
21	Miscellaneous manufacturing	339
22	Wholesale trade	42
23	Retail trade	44
24	Transportation and storage	48
25	Accommodation and food services	72
26	Publishing	511
27	Telecommunications	517

28	Data processing, hosting, and related services	518
29	Other information	519
30	Finance and insurance	52
31	Real estate	53
32	Legal services	5411
33	Accounting, tax preparation, bookkeeping, and payroll services	5412
34	Architectural, engineering, and related services	5413
35	Specialized design services	5414
36	Computer systems design	5415
37	Management, scientific, and technical consulting services	5416
38	Scientific research and development services	5417
39	Advertising, public relations, and related services	5418
40	Other professional, scientific and technical services	5419
41	Management of companies and enterprises	55
42	Administrative and support service	56
43	Education	61
44	Health care	621
45	Social assistance	624
46	Arts, entertainment, and recreation	71
47	Other services	81

A.2 Crosswalk of NAICS and NACE Rev. 2

Industry	Description	NAICS	NACE Rev. 2
1	Food, beverages, tobacco	311-312	C10-C12
2	Textile, wearing apparel, leather and related products	313	C13-15
3	Wood products, paper products, printing and related support activities	321-323	C16-C18
4	Coke and refined petroleum products	324	C19
5	Chemicals and chemical products	325 (ex. 3254)	C20
6	Basic pharmaceutical products and pharmaceutical preparations	3254	C21
7	Rubber and plastic products, other non-metallic mineral products	326-327	C22-C23
8	Basic metals and fabricated metal products, except machinery and equipment	331-332	C24-C25
9	Computer, electronic and optical products	334, 339	C26
10	Electrical equipment	335	C27
11	Machinery and equipment n.e.c.	333	C28
12	Motor vehicles, trailers and semi-trailers, other transport equipment	336	C29-C30
13	Furniture and related products	337	C31-C33
14	Utilities, water supply and waster management	22	D, E
15	Construction	23	F
16	Wholesale trade	42	G46
17	Retail trade	44	G47
18	Transportation and storage	48	H
19	Accommodation and food service	72	I
20	Publishing activities	511, 519	J58-J60
21	Telecommunications	517	J61
22	Computer programming, data processing, hosting and related activities	518	J62-J63
23	Real estate	53	L68
24	Legal and accounting activities, activities of head offices, management consultancy activities,	5411-5416	M69-M71

	architectural and engineering activities,		
	technical testing and analysis		
25	Scientific research and development	5417	M72
26	Advertising, public relations, and related services	5418-5419	M73-M75
	Other professional, scientific, technical activities		
27	Administrative and support service	56	N

A.3 Heterogeneous Effects with 1995 Local Share in IV

This section presents the second-stage estimates of heterogeneous effects of employment by subgroups using 1995 local share to calculate the IV $EUExposure_i$.

A.3.1 Broad Sector

	Agriculture	Manufacturing	Construction	Low-Skill Services	High-Skill Services
	(1)	(2)	(3)	(4)	(5)
$USExposure$	0.866*	-4.069*	1.671	-6.058***	1.890
	(0.489)	(2.321)	(1.162)	(1.712)	(1.496)
Observations	722	722	722	722	722

Table A.3: Effect of AI on Employment-to-Population Ratio by Broad Sector: 1995 Share in IV

Notes: The table reports the second stage estimates β from equation (5), using 1995 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in sectoral employment-to-population ratio in 2010-2021. Manufacturing includes manufacturing and mining. Low-skill services are wholesale trade, retail trade, utilities, transportation, information, real estate, administrative support and waste management, arts and entertainment, accommodation and food services, and other services. High-skill services are finance and insurance, professional scientific and technical services, management of companies and enterprises, education, health, and social assistance. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.3.2 Occupation

	Non-STEM	STEM	Low-Skill	Middle-Skill	High-Skill
	(1)	(2)	(3)	(4)	(5)
$USExposure$	-6.045**	-0.346	-0.394	-4.020	-1.285
	(2.821)	(1.019)	(1.239)	(2.491)	(1.750)
Observations	722	722	722	722	722

Table A.4: Effect of AI on Employment-to-Population Ratio by Occupation: 1995 Share in IV

Notes: The table reports the second stage estimates β from equation (5), using 1995 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in occupational (STEM vs. non-STEM occupations; low, middle, high-skill occupations) employment-to-population ratio in 2010-2021. The list of STEM occupations are from O*NET. High-skill occupations are management, business and financial occupations, professionals, and technicians. Middle-skill occupations are office and administration, sales, construction and extraction, mechanics and repairers, production, transportation and material moving. Low-skill occupations are personal services and agriculture occupations. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.3.3 Education

	Below High School	High School	Some College	College and Above
	(1)	(2)	(3)	(4)
$USExposure$	-5.527	-8.665**	-3.586	0.272
	(6.209)	(3.502)	(3.815)	(2.494)
Observations	722	722	722	722

Table A.5: Effect of AI on Employment-to-Population Ratio by Education: 1995 Share in IV

Notes: The table reports the second stage estimates β from equation (5), using 1995 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by education levels (below high school, high school, some college, college and above) in 2010-2021. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.3.4 Age and Gender

	16-25	26-35	36-45	46-55	56-65	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$USExposure$	-11.499**	-1.458	-6.657*	-6.620*	-0.826	-6.613*	-4.596
	(5.260)	(3.860)	(3.789)	(3.853)	(3.980)	(3.758)	(3.273)
Observations	722	722	722	722	722	722	722

Table A.6: Effect of AI on Employment-to-Population Ratio by Age and Gender: 1995 Share in IV

Notes: The table reports the second stage estimates β from equation (5), using 1995 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by 10-year age bins (16-25, 26-35, 36-45, 46-55, 56-65) or gender (male, female) in 2010-2021. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.4 Heterogeneous Effects with 1990-1995 Average Local Share in IV

This section presents the second-stage estimates of heterogeneous effects of employment by subgroups using average 1990-1995 local share to calculate the IV $EUExposure_i$.

A.4.1 Broad Sector

	Agriculture	Manufacturing	Construction	Low-Skill Services	High-Skill Services
	(1)	(2)	(3)	(4)	(5)
$USExposure$	0.878*	-4.976*	1.260	-6.432***	0.895
	(0.453)	(2.605)	(1.126)	(1.743)	(1.484)
Observations	722	722	722	722	722

Table A.7: Effect of AI on Employment-to-Population Ratio by Broad Sector: 1990-1995 Average Share in IV

Notes: The table reports the second stage estimates β from equation (5), using 1990-1995 average local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in sectoral employment-to-population ratio in 2010-2021. Manufacturing includes manufacturing and mining. Low-skill services are wholesale trade, retail trade, utilities, transportation, information, real estate, administrative support and waste management, arts and entertainment, accommodation and food services, and other services. High-skill services are finance and insurance, professional scientific and technical services, management of companies and enterprises, education, health, and social assistance. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.4.2 Occupation

	Non-STEM	STEM	Low-Skill	Middle-Skill	High-Skill
	(1)	(2)	(3)	(4)	(5)
$USExposure$	-7.781***	-0.594	-0.559	-5.090**	-2.726
	(2.838)	(1.096)	(1.124)	(2.504)	(1.814)
Observations	722	722	722	722	722

Table A.8: Effect of AI on Employment-to-Population Ratio by Occupation: 1990-1995 Average Share in IV

Notes: The table reports the second stage estimates β from equation (5), using 1990-1995 average local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in occupational (STEM vs. non-STEM occupations; low, middle, high-skill occupations) employment-to-population ratio in 2010-2021. The list of STEM occupations are from O*NET. High-skill occupations are management, business and financial occupations, professionals, and technicians. Middle-skill occupations are office and administration, sales, construction and extraction, mechanics and repairers, production, transportation and material moving. Low-skill occupations are personal services and agriculture occupations. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.4.3 Education

	Below High School	High School	Some College	College and Above
	(1)	(2)	(3)	(4)
$USExposure$	-7.109	-10.546***	-5.820	-1.555
	(5.782)	(3.703)	(3.873)	(2.553)
Observations	722	722	722	722

Table A.9: Effect of AI on Employment-to-Population Ratio by Education: 1990-1995 Average Share in IV

Notes: The table reports the second stage estimates β from equation (5), using 1990-1995 average local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by education levels (below high school, high school, some college, college and above) in 2010-2021. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.4.4 Age and Gender

	16-25	26-35	36-45	46-55	56-65	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$USExposure$	-13.546***	-3.810	-7.546*	-9.109**	-4.921	-9.945***	-6.534**
	(5.441)	(3.609)	(3.967)	(3.972)	(3.898)	(4.099)	(3.309)
Observations	722	722	722	722	722	722	722

Table A.10: Effect of AI on Employment-to-Population Ratio by Age and Gender: 1990-1995 Average Share in IV

Notes: The table reports the second stage estimates β from equation (5), using 1990-1995 average local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by 10-year age bins (16-25, 26-35, 36-45, 46-55, 56-65) or gender (male, female) in 2010-2021. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.5 Alternative Measure of Industry-Level AI Adoption

This section presents the second-stage estimates using the maximum over AI technologies for $AIAdopt_j^{US}$.

A.5.1 Overall employment-to-population ratio

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990-1995 Average 2010-2021 (3)	1990 Share 1980-2010 (4)	1995 Share 1980-2010 (5)	1990-1995 Average 1980-2010 (6)
$USExposure$	-3.785**	-2.897*	-4.325***	1.117	-0.610	0.370
	(1.628)	(1.584)	(1.740)	(2.403)	(2.746)	(2.622)
Observations	722	722	722	722	722	722
R-squared	0.20	0.25	0.16	0.55	0.55	0.55
First-stage coefficient	0.149	0.165	0.166	0.149	0.165	0.166
First-stage F-statistic	33.2	29.2	30.7	33.2	29.2	30.7

Table A.11: Effect of AI on Employment-to-Population Ratio: Use Maximum for $AIAdoption_j^{US}$

Notes: The table reports the second stage estimates β from equation (5). The dependent variable is the change in the employment-to-population ratio in 1980-2010 (for columns (4)-(6)) and 2010-2021 (for columns (1)-(3)). Columns (1) and (4) use local employment share in 1990 to compute the IV $EUExposure_i$. Columns (2) and (5) use local employment share in 1995 to compute the IV $EUExposure_i$. Columns (3) and (6) use the average local employment share in 1990-1995 to compute the IV $EUExposure_i$. $USExposure_i$ is computed using the maximum over AI technologies for $AIAdopt_j^{US}$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.5.2 Broad Sector

	Agriculture	Manufacturing	Construction	Low-Skill Services	High-Skill Services
	(1)	(2)	(3)	(4)	(5)
$USExposure$	0.461*	-2.579*	0.527	-2.667**	0.473
	(0.243)	(1.472)	(0.551)	(1.048)	(0.827)
Observations	722	722	722	722	722

Table A.12: Effect of AI on Employment-to-Population Ratio by Broad Sector: Use Maximum for $AIAdoption_j^{US}$

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in sectoral employment-to-population ratio in 2010-2021. Manufacturing includes manufacturing and mining. Low-skill services are wholesale trade, retail trade, utilities, transportation, information, real estate, administrative support and waste management, arts and entertainment, accommodation and food services, and other services. High-skill services are finance and insurance, professional scientific and technical services, management of companies and enterprises, education, health, and social assistance. $USExposure_i$ is computed using the maximum over AI technologies for $AIAdopt_j^{US}$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.5.3 Occupation

	Non-STEM	STEM	Low-Skill	Middle-Skill	High-Skill
	(1)	(2)	(3)	(4)	(5)
$USExposure$	-3.526**	-0.259	-0.116	-2.487*	-1.182
	(1.509)	(0.534)	(0.495)	(1.327)	(0.871)
Observations	722	722	722	722	722

Table A.13: Effect of AI on Employment-to-Population Ratio by Occupation: Use Maximum for $AIAdoption_j^{US}$

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in occupational (STEM vs. non-STEM occupations; low, middle, high-skill occupations) employment-to-population ratio in 2010-2021. The list of STEM occupations are from O*NET. High-skill occupations are management, business and financial occupations, professionals, and technicians. Middle-skill occupations are office and administration, sales, construction and extraction, mechanics and repairers, production, transportation and material moving. Low-skill occupations are personal services and agriculture occupations. $USExposure_i$ is computed using the maximum over AI technologies for $AIAdopt_j^{US}$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.5.4 Education

	Below High School	High School	Some College	College and Above
	(1)	(2)	(3)	(4)
$USExposure$	-1.309	-4.900**	-3.132	-0.277
	(2.971)	(2.050)	(1.903)	(1.209)
Observations	722	722	722	722
R-squared	0.25	0.26	0.25	0.24

Table A.14: Effect of AI on Employment-to-Population Ratio by Education: Use Maximum for $AIAdoption_j^{US}$

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by education levels (below high school, high school, some college, college and above) in 2010-2021. $USExposure_i$ is computed using the maximum over AI technologies for $AIAdopt_j^{US}$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.5.5 Age and Gender

	16-25	26-35	36-45	46-55	56-65	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$USExposure$	-5.804**	-1.493	-2.810	-3.904*	-4.016*	-4.631**	-2.812*
	(2.871)	(1.744)	(2.079)	(2.030)	(2.145)	(2.180)	(1.628)
Observations	722	722	722	722	722	722	722

Table A.15: Effect of AI on Employment-to-Population Ratio by Age and Gender: Use Maximum for $AIAdoption_j^{US}$

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by 10-year age bins (16-25, 26-35, 36-45, 46-55, 56-65) or gender (male, female) in 2010-2021. $USExposure_i$ is computed using the maximum over AI technologies for $AIAdopt_j^{US}$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.6 Alternative End Year for the Long-Difference

This section presents the second-stage estimates of AI exposure on employment changes during 2010-2019 rather than 2010-2021.

A.6.1 Overall employment-to-population ratio

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990-1995 Average 2010-2021 (3)	1990 Share 1980-2010 (4)	1995 Share 1980-2010 (5)	1990-1995 Average 1980-2010 (6)
$USExposure$	-7.060**	-6.450**	-8.240***	2.217	-1.199	0.716
	(3.088)	(2.918)	(3.129)	(4.739)	(5.402)	(5.075)
Observations	722	722	722	722	722	722
R-squared	0.37	0.38	0.35	0.56	0.55	0.55
First-stage coefficient	0.075	0.084	0.086	0.075	0.084	0.086
First-stage F-statistic	58.2	52.8	57.3	58.2	52.8	57.3

Table A.16: Effect of AI on Employment-to-Population Ratio: 2019 as End Year

Notes: The table reports the second stage estimates β from equation (5). The dependent variable is the change in the employment-to-population ratio in 1980-2010 (for columns (4)-(6)) and 2010-2019 (for columns (1)-(3)). Columns (1) and (4) use local employment share in 1990 to compute the IV $EUExposure_i$. Columns (2) and (5) use local employment share in 1995 to compute the IV $EUExposure_i$. Columns (3) and (6) use the average local employment share in 1990-1995 to compute the IV $EUExposure_i$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.6.2 Broad Sector

	Agriculture	Manufacturing	Construction	Low-Skill Services	High-Skill Services
	(1)	(2)	(3)	(4)	(5)
$USExposure$	1.160**	-5.771**	1.482	-4.773***	0.842
	(0.474)	(2.504)	(1.107)	(1.561)	(1.590)
Observations	722	722	722	722	722

Table A.17: Effect of AI on Employment-to-Population Ratio by Broad Sector: 2019 as End Year

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in sectoral employment-to-population ratio in 2010-2019. Manufacturing includes manufacturing and mining. Low-skill services are wholesale trade, retail trade, utilities, transportation, information, real estate, administrative support and waste management, arts and entertainment, accommodation and food services, and other services. High-skill services are finance and insurance, professional scientific and technical services, management of companies and enterprises, education, health, and social assistance. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.6.3 Occupation

	Non-STEM	STEM	Low-Skill	Middle-Skill	High-Skill
	(1)	(2)	(3)	(4)	(5)
$USExposure$	-6.259**	-0.801	0.550	-5.114**	-2.496
	(2.909)	(0.808)	(1.098)	(2.347)	(1.529)
Observations	722	722	722	722	722

Table A.18: Effect of AI on Employment-to-Population Ratio by Occupation: 2019 as End Year

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in occupational (STEM vs. non-STEM occupations; low, middle, high-skill occupations) employment-to-population ratio in 2010-2019. The list of STEM occupations are from O*NET. High-skill occupations are management, business and financial occupations, professionals, and technicians. Middle-skill occupations are office and administration, sales, construction and extraction, mechanics and repairers, production, transportation and material moving. Low-skill occupations are personal services and agriculture occupations. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.6.4 Education

	Below High School	High School	Some College	College and Above
	(1)	(2)	(3)	(4)
$USExposure$	-0.320	-7.005**	-7.569**	-2.139
	(5.776)	(3.416)	(3.726)	(2.413)
Observations	722	722	722	722

Table A.19: Effect of AI on Employment-to-Population Ratio by Education: 2019 as End Year

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by education levels (below high school, high school, some college, college and above) in 2010-2019. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.6.5 Age and Gender

	16-25	26-35	36-45	46-55	56-65	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$USExposure$	-11.104**	-4.588	-3.180	-7.393*	-7.938**	-7.685**	-6.242**
	(5.448)	(3.017)	(3.977)	(4.131)	(3.914)	(3.859)	(3.171)
Observations	722	722	722	722	722	722	722

Table A.20: Effect of AI on Employment-to-Population Ratio by Age and Gender: 2019 as End Year

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by 10-year age bins (16-25, 26-35, 36-45, 46-55, 56-65) or gender (male, female) in 2010-2019. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.7 Alternative Share for $USExposure$

This section presents the second-stage estimates using 2005 local employment share to compute $USExpsoure_i$.

A.7.1 Overall employment-to-population ratio

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990-1995 Average 2010-2021 (3)	1990 Share 1980-2010 (4)	1995 Share 1980-2010 (5)	1990-1995 Average 1980-2010 (6)
$USExposure$	-7.109**	-5.160*	-7.840***	2.098	-1.086	0.671
	(2.899)	(2.712)	(2.946)	(4.479)	(4.892)	(4.751)
Observations	722	722	722	722	722	722
R-squared	0.27	0.30	0.25	0.55	0.55	0.55
First-stage coefficient	0.080	0.092	0.092	0.080	0.092	0.092
First-stage F-statistic	57.5	69.4	56.6	57.5	69.4	56.6

Table A.21: Effect of AI on Employment-to-Population Ratio: 2005 Share in $USExposure$

Notes: The table reports the second stage estimates β from equation (5). The dependent variable is the change in the employment-to-population ratio in 1980-2010 (for columns (4)-(6)) and 2010-2021 (for columns (1)-(3)). $USExposure$ uses 2005 local employment share. Columns (1) and (4) use local employment share in 1990 to compute the IV $EUExposure_i$. Columns (2) and (5) use local employment share in 1995 to compute the IV $EUExposure_i$. Columns (3) and (6) use the average local employment share in 1990-1995 to compute the IV $EUExposure_i$. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.7.2 Broad Sector

	Agriculture	Manufacturing	Construction	Low-Skill Services	High-Skill Services
	(1)	(2)	(3)	(4)	(5)
$USExposure$	0.865**	-4.845*	0.991	-5.009**	0.889
	(0.429)	(2.629)	(1.030)	(2.028)	(1.573)
Observations	722	722	722	722	722

Table A.22: Effect of AI on Employment-to-Population Ratio by Broad Sector: 2005 Share in $USExposure$

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in sectoral employment-to-population ratio in 2010-2021. $USExpsoure_i$ uses 2005 local employment share. Manufacturing includes manufacturing and mining. Low-skill services are wholesale trade, retail trade, utilities, transportation, information, real estate, administrative support and waste management, arts and entertainment, accommodation and food services, and other services. High-skill services are finance and insurance, professional scientific and technical services, management of companies and enterprises, education, health, and social assistance. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.7.3 Occupation

	Non-STEM	STEM	Low-Skill	Middle-Skill	High-Skill
	(1)	(2)	(3)	(4)	(5)
$USExposure$	-6.623**	-0.486	-0.217	-4.672*	-2.220
	(2.725)	(0.992)	(0.926)	(2.516)	(1.545)
Observations	722	722	722	722	722

Table A.23: Effect of AI on Employment-to-Population Ratio by Occupation: 2005 Share in $USExposure$

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in occupational (STEM vs. non-STEM occupations; low, middle, high-skill occupations) employment-to-population ratio in 2010-2021. $USExpsoure_i$ uses 2005 local employment share. The list of STEM occupations are from O*NET. High-skill occupations are management, business and financial occupations, professionals, and technicians. Middle-skill occupations are office and administration, sales, construction and extraction, mechanics and repairers, production, transportation and material moving. Low-skill occupations are personal services and agriculture occupations. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.7.4 Education

	Below High School	High School	Some College	College and Above
	(1)	(2)	(3)	(4)
$USExposure$	-2.459	-9.203**	-5.884	-0.520
	(5.484)	(3.920)	(3.693)	(2.260)
Observations	722	722	722	722

Table A.24: Effect of AI on Employment-to-Population Ratio by Education: 2005 Share in $USExposure$

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by education levels (below high school, high school, some college, college and above) in 2010-2021. $USExpsoure_i$ uses 2005 local employment share. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

A.7.5 Age and Gender

	16-25	26-35	36-45	46-55	56-65	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$USExposure$	-10.903*	-2.804	-5.278	-7.332**	-7.543**	-8.699**	-5.283*
	(5.653)	(3.220)	(3.599)	(3.336)	(3.843)	(4.134)	(2.795)
Observations	722	722	722	722	722	722	722

Table A.25: Effect of AI on Employment-to-Population Ratio by Age and Gender: 2005 Share in $USExposure$

Notes: The table reports the second stage estimates β from equation (5), using 1990 local employment share to compute the IV $EUExposure_i$. The dependent variable is the change in employment-to-population ratio by 10-year age bins (16-25, 26-35, 36-45, 46-55, 56-65) or gender (male, female) in 2010-2021. $USExpsoure_i$ uses 2005 local employment share. All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

B Model Appendix

B.1 Closed Economy Model

B.1.1 Production

The price of industry j in commuting zone i, P_{ij}^X, follows from the standard maximization problem of Cobb-Douglas production (9):

$$P_{ij}^X = \frac{1}{A_{ij}} P_{ij}^{\tilde{X}\alpha} R_i^{K 1-\alpha} \tag{19}$$

The composite price $P_{ij}^{\tilde{X}}$ is:

$$P_{ij}^{\tilde{X}} = \Big(\int_0^1 p_{ij}(\omega)^{1-\eta_j} d\omega \Big)^{\frac{1}{1-\eta_j}} \tag{20}$$

The price of firm ω, $p_{ij}(\omega)$, is:

$$p_{ij}(\omega) = \frac{\eta_j}{\eta_j - 1} mc_{ij}(\omega) \tag{21}$$

where the marginal cost of production of firm ω is:

$$mc_{ij}(\omega) = \begin{cases} \frac{1}{z_{ij}(\omega)} \Big(\theta_j \frac{R_i^M}{\gamma_M} + (1-\theta_j) \frac{w_i}{\gamma_L} \Big), & \text{if adopting AI} \\ \frac{1}{z_{ij}(\omega)} \frac{w_i}{\gamma_L}, & \text{if not adopting AI} \end{cases} \tag{22}$$

Demand of firm ω, $x_{ij}(\omega)$, is:

$$x_{ij}(\omega) = \Big(\frac{p_{ij}(\omega)}{P_{ij}^{\tilde{X}}} \Big)^{-\eta_j} \tilde{X}_{ij} \tag{23}$$

Demand of composite output $\tilde{X}_{ij}$ is:

$$\begin{aligned} \tilde{X}_{ij} &= \alpha \frac{P_{ij}^X X_{ij}}{P_{ij}^{\tilde{X}}} \\ &= \alpha \frac{\nu_j P_{ij}^{X 1-\sigma} Y_i}{P_{ij}^{\tilde{X}}} = \alpha \nu_j A_{ij}^{\sigma-1} P_{ij}^{\tilde{X}\alpha(1-\sigma)-1} R_i^{K(1-\alpha)(1-\sigma)} Y_i \\ &= \alpha \nu_j A_{ij}^{\sigma-1} P_{ij}^{\tilde{X}\alpha(1-\sigma)-1} \Big((1-\alpha) \frac{Y_i}{K_i} \Big)^{(1-\alpha)(1-\sigma)} Y_i \\ &= \alpha (1-\alpha)^{(1-\alpha)(1-\sigma)} \nu_j A_{ij}^{\sigma-1} P_{ij}^{\tilde{X}\alpha(1-\sigma)-1} K_i^{-(1-\alpha)(1-\sigma)} Y_i^{1+(1-\alpha)(1-\sigma)} \end{aligned} \tag{24}$$

where the second line follows from (7) and the third line follows from $R_i^K K_i = (1-\alpha)Y_i$.

Profit of firm ω, $\pi_{ij}(\omega)$, is:

$$\pi_{ij}(\omega) = \begin{cases} \frac{1}{\eta_j}\left(\frac{\eta_j}{\eta_j-1}\frac{1}{z_{ij}(\omega)}\left(\theta_j\frac{R_i^M}{\gamma_M} + (1-\theta_j)\frac{w_i}{\gamma_L}\right)\right)^{1-\eta_j} P_{ij}^{\tilde{X}\eta_j}\tilde{X}_{ij} - f_M, & \text{if adopting AI} \\ \frac{1}{\eta_j}\left(\frac{\eta_j}{\eta_j-1}\frac{1}{z_{ij}(\omega)}\frac{w_i}{\gamma_L}\right)^{1-\eta_j} P_{ij}^{\tilde{X}\eta_j}\tilde{X}_{ij}, & \text{if not adopting AI} \end{cases} \tag{25}$$

Therefore, firm ω chooses to adopt AI if:

$$\frac{1}{\eta_j}\Big(\frac{\eta_j}{\eta_j-1}\frac{1}{z_{ij}(\omega)}\Big(\theta_j\frac{R_i^M}{\gamma_M} + (1-\theta_j)\frac{w_i}{\gamma_L}\Big)\Big)^{1-\eta_j} P_{ij}^{\tilde{X}\eta_j}\tilde{X}_{ij} - f_M \geq \frac{1}{\eta_j}\Big(\frac{\eta_j}{\eta_j-1}\frac{1}{z_{ij}(\omega)}\frac{w_i}{\gamma_L}\Big)^{1-\eta_j} P_{ij}^{\tilde{X}\eta_j}\tilde{X}_{ij} \tag{26}$$

Define cost savings from AI (relative to human labor) as $\Delta_i := 1 - \frac{R_i^M/\gamma_M}{w_i/\gamma_L} \geq 0$ (so that AI will not be adopted if $\frac{R_i^M}{\gamma_M} > \frac{w_i}{\gamma_L}$. For example, if $\frac{R_i^M}{\gamma_M}$ is 30% of $\frac{w_i}{\gamma_L}$, then the cost saving Δ_i is 0.7. Then:

$$\theta_j\frac{R_i^M}{\gamma_M} + (1-\theta_j)\frac{w_i}{\gamma_L} = \underbrace{(\theta_j(1-\Delta_i) + (1-\theta_j))}_{:=\Gamma_{ij}}\frac{w_i}{\gamma_L} \leq \frac{w_i}{\gamma_L} \tag{27}$$

where the inequality in (27) follows from $\Delta_i \geq 0$ and implies that AI adoption leads to lower marginal cost of production. A higher Δ_i (hence a lower Γ_{ij}) implies lower marginal cost of production following AI adoption.

Simplifying equation (26):

$$\Omega_{ij}P_{ij}^{\tilde{X}\alpha(1-\sigma)-1+\eta_j}Y_i^{1+(1-\alpha)(1-\sigma)}z_{ij}(\omega)^{\eta_j-1}((\theta_j(1-\Delta_i)+(1-\theta_j))^{1-\eta_j}-1)\Big(\frac{w_i}{\gamma_L}\Big)^{1-\eta_j} \geq f_M \tag{28}$$

where $\Omega_{ij} := \eta_j^{-\eta_j}(\eta_j-1)^{\eta_j-1}\alpha(1-\alpha)^{(1-\alpha)(1-\sigma)}\nu_j A_{ij}^{\sigma-1}K_i^{-(1-\alpha)(1-\sigma)}$.

Therefore, firm's adoption decision follows a cut-off rule z_{ij}^*, where firms with productivity $z_{ij}(\omega) \geq z_{ij}^*$ adopt AI and those with productivity $z_{ij}(\omega) < z_{ij}^*$ do not. The cut-off value of productivity z_{ij}^* is:

$$z_{ij}^* = \Big(\frac{f_M}{\Omega_{ij}P_{ij}^{\tilde{X}\alpha(1-\sigma)-1+\eta_j}Y_i^{1+(1-\alpha)(1-\sigma)}((\theta_j(1-\Delta_i)+(1-\theta_j))^{1-\eta_j}-1)}\Big)^{\frac{1}{\eta_j-1}}\frac{w_i}{\gamma_L} \tag{29}$$

Suppose that the cumulative distribution of productivity is $G(z)$, the fraction of firms that adopt AI is $1 - G(z^*_{ij})$. A lower value of z^*_{ij} implies a higher fraction of AI adoption firms. Therefore, equation (29) implies that a higher fraction of firms adopt AI if the fixed cost of adoption f_M is lower but final output Y_i (which suggests positive income effect) and cost saving from AI Δ_i are higher.

How does technological advance in AI $d\theta_j$ affects the productivity cut-off z^*_{ij}? In *partial equilibrium*, taking factor prices as given and differentiating equation (29) with respect to $d\theta_j$:

$$d\ln z^*_{ij} = -\frac{\Delta_i}{\Gamma_{ij}(1-\Gamma_{ij}^{\eta_j-1})}d\theta_j + \frac{\alpha(1-\sigma)-1+\eta_j}{1-\eta_j}d\ln P^{\tilde{X}}_{ij} + \frac{1+(1-\alpha)(1-\sigma)}{1-\eta_j}d\ln Y_i \tag{30}$$

where $\Delta_i = 1 - \frac{R^M_i/\gamma_M}{w_i/\gamma_L}$ and $\Gamma_{ij} = \theta_j(1-\Delta_i) + (1-\theta_j)$. Equation (30) indicates that there are three forces shaping the fraction of AI-adopting firms in response to technological advance in AI. The first term captures the direct effect. As technology advances ($d\theta_j > 0$), z^*_{ij} is lower, which implies that a higher fraction of firms adopt AI. The second term captures the industry composition effect. Profit increases as industry price is higher, hence more firms can afford to adopt AI. The third term captures the positive productivity effect of AI, which leads to higher commuting zone level final output and higher share of AI-adopting firms.

Assume that productivity z follows a Pareto distribution such that the cumulative distribution $G(z) = 1 - z^{-\phi_j}$, $\phi_j > \max\{\eta_j - 1, 1\}$,[25] ϕ_j is the shape parameter. A lower value indicates a fatter tail of the distribution and hence higher dispersion. Incorporating the AI adoption rule into (20):

$$\begin{aligned} P^{\tilde{X}}_{ij} &= \frac{w_i}{\gamma_L}\frac{\eta_j}{\eta_j-1}\Big(\Big(\int_1^{z^*_{ij}} z^{\eta_j-1}dGz\Big) + \Gamma_{ij}^{1-\eta_j}\Big(\int_{z^*_{ij}}^{\infty} z^{\eta_j-1}dGz\Big)\Big)^{\frac{1}{1-\eta_j}} \\ &= \frac{w_i}{\gamma_L}\frac{\eta_j}{\eta_j-1}\Big(\frac{\phi_j}{\phi_j-\eta_j+1}\Big)^{\frac{1}{1-\eta_j}}\Big(1+(\Gamma_{ij}^{1-\eta_j}-1)z_{ij}^{*\eta_j-\phi_j-1}\Big)^{\frac{1}{1-\eta_j}} \end{aligned} \tag{31}$$

In *partial equilibrium*, taking factor prices as given and differentiating equation (31) with respect to $d\theta_j$:

$$d\ln P^{\tilde{X}}_{ij} = -\frac{\Gamma_{ij}^{-\eta_j} z_{ij}^{*\eta_j-\phi_j-1}\Delta_i}{1+(\Gamma_{ij}^{1-\eta_j}-1)z_{ij}^{*\eta_j-\phi_j-1}}d\theta_j + \Big(\frac{\phi_j}{\eta_j-1}-1\Big)\frac{(\Gamma_{ij}^{1-\eta_j}-1)z_{ij}^{*\eta_j-\phi_j-1}}{1+(\Gamma_{ij}^{1-\eta_j}-1)z_{ij}^{*\eta_j-\phi_j-1}}d\ln z^*_{ij} \tag{32}$$

[25] This condition ensures that average firm productivity and $P^{\tilde{X}}_{ij}$ are finite.

Equation (32) describes how the composite price responds to increase in AI technology. Composite price falls as AI technology advances ($d\theta_j > 0$) or higher fraction of firms adopt AI ($d \ln z^*_{ij} < 0$).

B.1.2 Labor Share

Define the labor share (net of non-AI capital) in industry j and commuting zone i as s^L_{ij}:

$$s^L_{ij} := \frac{w_i L_{ij}}{P^{\tilde{X}}_{ij}\tilde{X}_{ij}} = \frac{w_i L_{ij}}{\alpha P^X_{ij} X_{ij}} \tag{33}$$

which is a revenue-weighted share of firm-level labor share:

$$s^L_{ij} = \frac{w_i L_{ij}}{P^{\tilde{X}}_{ij}\tilde{X}_{ij}} = \frac{\int_0^1 w_i L_{ij}(\omega) d\omega}{\int_0^1 p_{ij}(\omega) x_{ij}(\omega) d\omega} = \int_0^1 \underbrace{\frac{w_i L_{ij}(\omega)}{p_{ij}(\omega) x_{ij}(\omega)}}_{\text{firm-level labor share}} \underbrace{\frac{p_{ij}(\omega) x_{ij}(\omega)}{\int_0^1 p_{ij}(\omega) x_{ij}(\omega) d\omega}}_{\text{revenue share}} d\omega \tag{34}$$

with

$$\frac{w_i L_{ij}(\omega)}{p_{ij}(\omega) x_{ij}(\omega)} = \begin{cases} \frac{\eta_j - 1}{\eta_j} \frac{(1-\theta_j)\frac{w_i}{\gamma_L}}{\theta_j \frac{R^M_i}{\gamma_M} + (1-\theta_j)\frac{w_i}{\gamma_L}}, & \text{if } z_{ij}(\omega) \geq z^*_{ij} \\ \frac{\eta_j - 1}{\eta_j}, & \text{if } z_{ij}(\omega) < z^*_{ij} \end{cases} \tag{35}$$

$$\frac{p_{ij}(\omega) x_{ij}(\omega)}{\int_0^1 p_{ij}(\omega) x_{ij}(\omega) d\omega} = \frac{p_{ij}(\omega) x_{ij}(\omega)}{P^{\tilde{X}}_{ij}\tilde{X}_{ij}} = \frac{p_{ij}^{1-\eta_j} P^{\tilde{X}\eta_j}_{ij} \tilde{X}_{ij}}{P^{\tilde{X}}_{ij}\tilde{X}_{ij}} = \left(\frac{p_{ij}(\omega)}{P^{\tilde{X}}_{ij}}\right)^{1-\eta_j} \tag{36}$$

Plug (35) and (36) into (34):

$$\begin{aligned} s^L_{ij} &= P^{\tilde{X}\eta_j - 1}_{ij} \left(\frac{\eta_j}{\eta_j - 1}\right)^{-\eta_j} \left(\frac{w_i}{\gamma_L}\right)^{1-\eta_j} \left(\int_1^{z^*_{ij}} z^{\eta_j - 1} dGz + (1-\theta_j)\Gamma^{-\eta_j}_{ij} \int_{z^*_{ij}}^{\infty} z^{\eta_j - 1} dGz \right) \\ &= P^{\tilde{X}\eta_j - 1}_{ij} \left(\frac{\eta_j}{\eta_j - 1}\right)^{-\eta_j} \left(\frac{w_i}{\gamma_L}\right)^{1-\eta_j} \left(\frac{\phi_j}{\phi_j - \eta_j + 1}\right) \left(1 + ((1-\theta_j)\Gamma^{-\eta_j}_{ij} - 1) z^{*\eta_j - \phi_j - 1}_{ij}\right) \\ &= \left(\frac{\eta_j - 1}{\eta_j}\right) \left(\frac{1 + ((1-\theta_j)\Gamma^{-\eta_j}_{ij} - 1) z^{*\eta_j - \phi_j - 1}_{ij}}{1 + (\Gamma^{1-\eta_j}_{ij} - 1) z^{*\eta_j - \phi_j - 1}_{ij}}\right) \end{aligned} \tag{37}$$

Assuming $1 + ((1-\theta_j)\Gamma^{-\eta_j}_{ij} - 1) z^{*\eta_j - \phi_j - 1}_{ij} > 0$ ensures that $s^L_{ij} > 0$. Taking prices as given and totally differentiate (37) with respect to $d\theta_j$:

$$
\begin{aligned}
d\ln s^L_{ij} &= \Big(\frac{\Gamma_{ij}^{-\eta_j-1}((1-\theta_j)\eta_j\Delta_i-\Gamma_{ij})}{1+((1-\theta_j)\Gamma_{ij}^{-\eta_j}-1)z_{ij}^{*\eta_j-\phi_j-1}}+\frac{\Gamma_{ij}^{-\eta_j}(1-\eta_j)\Delta_i}{1+(\Gamma_{ij}^{1-\eta_j}-1)z_{ij}^{*\eta_j-\phi_j-1}}\Big)z_{ij}^{*\eta_j-\phi_j-1}d\theta_j \\
&+(\eta_j-\phi_j-1)\Big(\frac{(1-\theta_j)\Gamma_{ij}^{-\eta_j}-1}{1+((1-\theta_j)\Gamma_{ij}^{-\eta_j}-1)z_{ij}^{*\eta_j-\phi_j-1}}-\frac{\Gamma_{ij}^{1-\eta_j}-1}{1+(\Gamma_{ij}^{1-\eta_j}-1)z_{ij}^{*\eta_j-\phi_j-1}}\Big)z_{ij}^{*\eta_j-\phi_j-1}d\ln z^*_{ij} \\
&=\Big(\Gamma_{ij}^{-\eta_j}(1-z_{ij}^{*\eta_j-\phi_j-1})((1-\eta_j)\Delta_i-1)+\Gamma_{ij}^{-\eta_j-1}(1-z_{ij}^{*\eta_j-\phi_j-1})\eta_j\Delta_i(1-\theta_j) \\
&+\Gamma_{ij}^{-2\eta_j}z_{ij}^{*\eta_j-\phi_j-1}(\Delta_i-1)\Big)\Xi_{ij}d\theta_j+(\phi_j-\eta_j+1)\theta_j(1-\Delta_i)\Gamma_{ij}^{-\eta_j}\Xi_{ij}d\ln z^*_{ij} \\
&=\Big(\Gamma_{ij}^{-\eta_j}(1-z_{ij}^{*\eta_j-\phi_j-1})(\Delta_i-1)+\Gamma_{ij}^{-\eta_j}(1-z_{ij}^{*\eta_j-\phi_j-1})\eta_j\Delta_i(\frac{1-\theta_j}{\Gamma_{ij}}-1) \\
&+\Gamma_{ij}^{-2\eta_j}z_{ij}^{*\eta_j-\phi_j-1}(\Delta_i-1)\Big)\Xi_{ij}d\theta_j+(\phi_j-\eta_j+1)\theta_j(1-\Delta_i)\Gamma_{ij}^{-\eta_j}\Xi_{ij}d\ln z^*_{ij}
\end{aligned}
\tag{38}
$$

where $\Xi_{ij} := \frac{z_{ij}^{*\eta_j-\phi_j-1}}{(1+((1-\theta_j)\Gamma_{ij}^{-\eta_j}-1)z_{ij}^{*\eta_j-\phi_j-1})(1+(\Gamma_{ij}^{1-\eta_j}-1)z_{ij}^{*\eta_j-\phi_j-1})} > 0$. Equation (38) suggests that labor share in industry j commuting zone i shrinks with AI technological advance and the fraction of AI-adopting firms.

B.1.3 Equilibrium

The household optimization problem gives:

$$
w_i = BL_i^{\varepsilon}C_i^{\psi} = BL_i^{\varepsilon}(Y_i-I_i)^{\psi} = BL_i^{\varepsilon}(Y_i-I_i)^{\psi} = BL_i^{\varepsilon}(Y_i-D^{-1-\kappa}(1+\kappa)^{-1-\kappa}M_i^{1+\kappa}-\Pi_i)^{\psi} \tag{39}
$$

where the second equality is the final good market clearing condition and third equality is the AI production function.

The first-order condition of AI production gives:

$$
R_i^M = D^{-1-\kappa}(1+\kappa)^{-\kappa}M_i^{\kappa} \tag{40}
$$

The final good in each commuting zone is the numeraire, so the ideal price index is:

$$
P_i = \Big(\sum_j \nu_j P_{ij}^{X1-\sigma}\Big)^{\frac{1}{1-\sigma}} = 1 \tag{41}
$$

Labor demand is:

$$\begin{aligned} w_i L_i &= \sum_i \alpha s_{ij}^L P_{ij}^X X_{ij} = \alpha s_{ij}^L \nu_j P_{ij}^{X1-\sigma} Y_i \\ &= \sum_i \alpha s_{ij}^L \nu_j \Big(\frac{1}{A_{ij}} P_{ij}^{\tilde{X}\alpha} R_i^{K1-\alpha} \Big)^{1-\sigma} Y_i \\ &= \sum_i \alpha s_{ij}^L \nu_j \Big(\frac{1}{A_{ij}} P_{ij}^{\tilde{X}\alpha} \Big(\frac{(1-\alpha)Y_i}{K_i} \Big)^{1-\alpha} \Big)^{1-\sigma} Y_i \end{aligned} \tag{42}$$

AI capital demand is:

$$R_i^M M_i = \sum_i \alpha \Big(\frac{\eta_j - 1}{\eta_j} - s_{ij}^L \Big) \nu_j \Big(\frac{1}{A_{ij}} P_{ij}^{\tilde{X}\alpha} \Big(\frac{(1-\alpha)Y_i}{K_i} \Big)^{1-\alpha} \Big)^{1-\sigma} Y_i \tag{43}$$

Non-AI capital demand is:

$$R_i^K K_i = (1-\alpha) Y_i \tag{44}$$

Therefore, equations (39), (40), (41), (42), (43) and (44) characterize the equilibrium.

B.2 Open Economy Model

B.2.1 Equilibrium

Since the price of tradable good P_i is normalized to 1, household maximization problem gives:

$$S_i = \frac{1-\chi}{w_i} (w_i L_i + \chi_i^\Pi \Pi) \tag{45}$$

where $P_i^S = w_i$ follows from the non-tradable good production function $S_i = L_i^S$.

The consumer price index of the consumption aggregate $C_i^\chi S_i^{1-\chi}$ is:

$$P_i^{CPI} = (1-\chi)^{-(1-\chi)} \chi^{-\chi} w_i^{1-\chi} \tag{46}$$

The labor supply condition derived from the household maximization problem gives:

$$w_i^{\chi + (1-\chi)\psi} = (1-\chi)^{(1-\chi)(\psi-1)} \chi^{\chi(\psi-1)} B (w_i L_i + \chi_i^\Pi \Pi)^\psi L_i^\varepsilon \tag{47}$$

The first-order condition of AI production remains the same as the closed economy model:

$$R_i^M = D^{-1-\kappa} (1+\kappa)^{-\kappa} M_i^\kappa \tag{48}$$

The price of tradable good for industry j in commuting zone i is:

$$P_j^Y = P_{ij}^Y = \Big(\sum_k \nu_{kj} P_{kj}^{X1-\lambda}\Big)^{\frac{1}{1-\lambda}} \tag{49}$$

The price of the aggregate tradable good is the numeraire, and the ideal price index is:

$$1 = \sum_j \nu_j P_j^{Y1-\sigma} \tag{50}$$

Labor demand is:

$$\begin{aligned}
w_i L_i &= \sum_j w_i L_{ij} + w_i L_i^S \\
&= \sum_j \alpha s_{ij}^L P_{ij}^X X_{ij} + (1-\chi)(w_i L_i + \chi_i^\Pi \Pi) \\
&= \sum_j \alpha s_{ij}^L P_{ij}^X \Big(\sum_k X_{ikj}\Big) + (1-\chi)(w_i L_i + \chi_i^\Pi \Pi) \\
&= \sum_j \alpha s_{ij}^L P_{ij}^X \Big(\sum_k \nu_{ij} Y_{kj} P_j^{Y\lambda} P_{ij}^{X-\lambda}\Big) + (1-\chi)(w_i L_i + \chi_i^\Pi \Pi) \\
&= \sum_j \alpha s_{ij}^L P_{ij}^X \Big(\sum_k \nu_{ij}\nu_j Y_k P_j^{Y\lambda-\sigma} P_{ij}^{X-\lambda}\Big) + (1-\chi)(w_i L_i + \chi_i^\Pi \Pi) \\
&= \sum_j \alpha s_{ij}^L \nu_{ij}\nu_j P_j^{Y\lambda-\sigma} P_{ij}^{X1-\lambda} \Big(\sum_k Y_k\Big) + (1-\chi)(w_i L_i + \chi_i^\Pi \Pi) \\
&= \sum_j \alpha s_{ij}^L \nu_{ij}\nu_j P_j^{Y\lambda-\sigma} P_{ij}^{X1-\lambda} Y + (1-\chi)(w_i L_i + \chi_i^\Pi \Pi)
\end{aligned} \tag{51}$$

where the fourth equality follows from optimal demand of commuting zone i's input in industry j sourced by commuting zone k: $X_{ikj} = \nu_{ij}\Big(\frac{P_{ij}^X}{P_j^Y}\Big)^{-\lambda} Y_{kj}$ and the fifth equality follows from optimal demand of $Y_{kj} = \nu_j P_j^{Y-\sigma} Y_k$.

AI capital demand is:

$$R_i^M M_i = \sum_j \alpha\Big(\frac{\eta_j - 1}{\eta_j} - s_{ij}^L\Big)\nu_{ij}\nu_j P_j^{Y\lambda-\sigma} P_{ij}^{X1-\lambda} Y \tag{52}$$

Non-AI capital demand is:

$$R^K K = (1-\alpha) Y \tag{53}$$

Non-labor income (capital and profit gains) is:

$$\Pi = Y - \sum_i w_i L_i - \sum_i D^{-1-\kappa}(1+\kappa)^{-1-\kappa} M_i^{1+\kappa} \tag{54}$$

Therefore, equations (48), (49), (50), (51), (52), (53), (54) characterize the equilibrium.

B.2.2 AI Adoption

In open economy, the price of industry j in commuting zone i, P^X_{ij} is similar as in the closed economy version (equation (19)), except that now $R^K_i = R^K, \forall i$. This is because non-AI capital is freely mobile across commuting zones:

$$P^X_{ij} = \frac{1}{A_{ij}} P^{\tilde{X}\alpha}_{ij} R^{K1-\alpha} \tag{55}$$

Demand of the composite output $\tilde{X}_{ij}$ is:

$$\begin{aligned}
\tilde{X}_{ij} &= \alpha \frac{P^X_{ij} X_{ij}}{P^{\tilde{X}}_{ij}} \\
&= \alpha \frac{\nu_{ij}\nu_j P^{Y\lambda-\sigma}_j P^{X1-\lambda}_{ij} Y}{P^{\tilde{X}}_{ij}} = \alpha \nu_{ij}\nu_j P^{Y\lambda-\sigma}_j A^{\lambda-1}_{ij} P^{\tilde{X}\alpha(1-\lambda)-1}_{ij} R^{K(1-\alpha)(1-\lambda)} Y \\
&= \alpha \nu_{ij}\nu_j P^{Y\lambda-\sigma}_j A^{\lambda-1}_{ij} P^{\tilde{X}\alpha(1-\lambda)-1}_{ij} \Big((1-\alpha)\frac{Y}{K}\Big)^{(1-\alpha)(1-\lambda)} Y \\
&= \alpha(1-\alpha)^{(1-\alpha)(1-\lambda)} \nu_{ij}\nu_j P^{Y\lambda-\sigma}_j A^{\lambda-1}_{ij} P^{\tilde{X}\alpha(1-\lambda)-1}_{ij} Y^{(1-\alpha)(1-\lambda)+1} K^{-(1-\alpha)(1-\lambda)}
\end{aligned} \tag{56}$$

where the second line is derived following the same steps as for equation (51) and the third equality follows from $R^K K = (1-\alpha)Y$.

Same as in the closed economy version, firm ω chooses to adopt AI if:

$$\frac{1}{\eta_j}\Big(\frac{\eta_j}{\eta_j-1}\frac{1}{z_{ij}(\omega)}\Big(\theta_j\frac{R^M_i}{\gamma_M} + (1-\theta_j)\frac{w_i}{\gamma_L}\Big)\Big)^{1-\eta_j} P^{\tilde{X}\eta_j}_{ij}\tilde{X}_{ij} - f_M \geq \frac{1}{\eta_j}\Big(\frac{\eta_j}{\eta_j-1}\frac{1}{z_{ij}(\omega)}\frac{w_i}{\gamma_L}\Big)^{1-\eta_j} P^{\tilde{X}\eta_j}_{ij}\tilde{X}_{ij} \tag{57}$$

Simplifying equation (57):

$$\tilde{\Omega}_j\nu_j\nu_{ij} P^{Y\lambda-\sigma}_j A^{\lambda-1}_{ij} P^{\tilde{X}\alpha(1-\lambda)-1+\eta_j}_{ij} Y^{(1-\alpha)(1-\lambda)+1} z_{ij}(\omega)^{\eta_j-1}((\theta_j(1-\Delta_i)+(1-\theta_j))^{1-\eta_j}-1)\Big(\frac{w_i}{\gamma_L}\Big)^{1-\eta_j} \geq f_M \tag{58}$$

where $\tilde{\Omega}_j := \eta_j^{-\eta_j}(\eta_j-1)^{\eta_j-1}\alpha(1-\alpha)^{(1-\alpha)(1-\lambda)}K^{-(1-\alpha)(1-\lambda)}$.

Therefore, firm's adoption decision follows a cut-off rule z^*_{ij}, where firms with productivity $z_{ij}(\omega) \geq z^*_{ij}$ adopt AI and those with productivity $z_{ij}(\omega) < z^*_{ij}$ do not. The cut-off value of productivity z^*_{ij} is:

$$z^*_{ij} = \Big(\frac{f_M}{\tilde{\Omega}_j\nu_j\nu_{ij} P^{Y\lambda-\sigma}_j A^{\lambda-1}_{ij} P^{\tilde{X}\alpha(1-\lambda)-1+\eta_j}_{ij} Y^{(1-\alpha)(1-\lambda)+1}((\theta_j(1-\Delta_i)+(1-\theta_j))^{1-\eta_j}-1)}\Big)^{\frac{1}{\eta_j-1}} \frac{w_i}{\gamma_L} \tag{59}$$

Recall that:

$$P_{ij}^{\tilde{X}} = \frac{w_i}{\gamma_L}\frac{\eta_j}{\eta_j - 1}\Big(\frac{\phi_j}{\phi_j - \eta_j + 1}\Big)^{\frac{1}{1-\eta_j}}\Big(1 + (\Gamma_{ij}^{1-\eta_j} - 1)z_{ij}^{*\eta_j-\phi_j-1}\Big)^{\frac{1}{1-\eta_j}} \tag{60}$$

$$s_{ij}^{L} = \Big(\frac{\eta_j - 1}{\eta_j}\Big)\Big(\frac{1 + ((1-\theta_j)\Gamma_{ij}^{-\eta_j} - 1)z_{ij}^{*\eta_j-\phi_j-1}}{1 + (\Gamma_{ij}^{1-\eta_j} - 1)z_{ij}^{*\eta_j-\phi_j-1}}\Big) \tag{61}$$

Therefore, if (i) $\frac{\gamma_M}{\gamma_L} \propto \frac{R_i^M}{w_i}$, (ii) $\nu_{ij} \propto A_{ij}^{1-\lambda}$, (iii) $f_M \propto w_i^{\alpha(1-\lambda)}$, then $z_{ij}^* = z_j^*$ and $s_{ij}^L = s_j^L$ for all i.

Under the above three conditions (Assumption 1 in Section 5.2), and let $1 - \Delta_i = \frac{R_i^M \gamma_L}{w_i \gamma_M} = \gamma \leq 1$[26] (by condition (i)), then $\Gamma_{ij} = \Gamma_j = \theta_j\gamma + 1 - \theta_j$. The cut-off value of productivity is $z_{ij}^* = z_j^*$:

$$z_j^* \propto \Bigg(\frac{1}{P_j^{Y\lambda-\sigma}\Big(1 + (\Gamma_j^{1-\eta_j} - 1)z_j^{*\eta_j-\phi_j-1}\Big)^{\frac{\alpha(1-\lambda)-1+\eta_j}{1-\eta_j}} Y^{(1-\alpha)(1-\lambda)+1}(\Gamma_j^{1-\eta_j} - 1)}\Bigg)^{\frac{1}{\eta_j-1}} \tag{62}$$

Moreover,

$$P_{ij}^{\tilde{X}} = \frac{w_i}{\gamma_L}\frac{\eta_j}{\eta_j - 1}\Big(\frac{\phi_j}{\phi_j - \eta_j + 1}\Big)^{\frac{1}{1-\eta_j}}\Big(1 + (\Gamma_j^{1-\eta_j} - 1)z_j^{*\eta_j-\phi_j-1}\Big)^{\frac{1}{1-\eta_j}} \tag{63}$$

$$s_{ij}^{L} = s_j^L = \Big(\frac{\eta_j - 1}{\eta_j}\Big)\Big(\frac{1 + ((1-\theta_j)\Gamma_j^{-\eta_j} - 1)z_{ij}^{*\eta_j-\phi_j-1}}{1 + (\Gamma_j^{1-\eta_j} - 1)z_{ij}^{*\eta_j-\phi_j-1}}\Big) \tag{64}$$

In addition to Assumption 1, together with (i) $\theta_j = \theta_0$, $\eta_j = \eta$, and $\phi_j = \phi$, (ii) $\nu_j \propto P_j^{Y\sigma-\lambda}$, equation (59) becomes:

$$z^* \propto \Big(1 + (\Gamma^{1-\eta} - 1)z^{*\eta-\phi-1}\Big)^{\frac{\alpha(1-\lambda)-1+\eta}{(1-\eta)^2}} Y^{\frac{(1-\alpha)(1-\lambda)+1}{1-\eta}}(\Gamma^{1-\eta} - 1)^{\frac{1}{1-\eta}} \tag{65}$$

where $\Gamma = \theta_0\gamma + 1 - \theta_0$. Equation (65) suggests that $z_{ij}^* = z^*$, for all i and j. Moreover, from (60) and (61), $\frac{P_{ij}^{\tilde{X}}}{P_{kj}^{\tilde{X}}} = \frac{w_i}{w_k}$ and $s_{ij}^L = s^L$ for all i, j, and k.

Note that when $\theta_j = \theta_0$ and $\Delta_i = 1 - \gamma$:

$$d\Gamma_j = -(1-\gamma)d\theta_j \tag{66}$$

[26] $\Delta_i \geq 0$ implies that $\gamma \leq 1$.

Totally differentiating (65):

$$\begin{aligned}
d\ln z_j^* &= \frac{\alpha(1-\lambda)-1+\eta}{(1-\eta)^2}\frac{z^{*\eta-\phi-1}}{1+(\Gamma^{1-\eta}-1)z^{*\eta-\phi-1}}((1-\eta)\Gamma^{-\eta}d\Gamma_j+(\Gamma^{1-\eta}-1)(\eta-\phi-1)d\ln z_j^*) \\
&+\frac{(1-\alpha)(1-\lambda)+1}{1-\eta}d\ln Y+\frac{\Gamma^{-\eta}}{\Gamma^{1-\eta}-1}d\Gamma_j+\frac{\lambda-\sigma}{1-\eta}d\ln P_j^Y \\
&= \frac{\alpha(1-\lambda)-1+\eta}{(1-\eta)^2}\frac{z^{*\eta-\phi-1}}{1+(\Gamma^{1-\eta}-1)z^{*\eta-\phi-1}}((1-\eta)\Gamma^{-\eta}(\gamma-1)d\theta_j+(\Gamma^{1-\eta}-1)(\eta-\phi-1)d\ln z_j^*) \\
&+\frac{(1-\alpha)(1-\lambda)+1}{1-\eta}d\ln Y+\frac{\Gamma^{-\eta}}{\Gamma^{1-\eta}-1}(\gamma-1)d\theta_j+\frac{\lambda-\sigma}{1-\eta}d\ln P_j^Y \\
&= -\Big(\frac{\alpha(1-\lambda)-1+\eta}{1-\eta}\frac{z^{*\eta-\phi-1}}{1+(\Gamma^{1-\eta}-1)z^{*\eta-\phi-1}}+\frac{1}{\Gamma^{1-\eta}-1}\Big)\Gamma^{-\eta}(1-\gamma)d\theta_j \\
&+\frac{\alpha(1-\lambda)-1+\eta}{(1-\eta)^2}\frac{z^{*\eta-\phi-1}}{1+(\Gamma^{1-\eta}-1)z^{*\eta-\phi-1}}(\Gamma^{1-\eta}-1)(\eta-\phi-1)d\ln z_j^* \\
&+\frac{(1-\alpha)(1-\lambda)+1}{1-\eta}d\ln Y+\frac{\lambda-\sigma}{1-\eta}d\ln P_j^Y
\end{aligned} \tag{67}$$

where the second equality follows from equation (66).

Let $\omega^z := \frac{z^{*\eta-\phi-1}}{1+(\Gamma^{1-\eta}-1)z^{*\eta-\phi-1}}$. Rearranging equation (67):

$$d\theta_j = \varphi^z d\ln z_j^* + \varphi^Y d\ln Y + \varphi^{P^Y} d\ln P_j^Y \tag{68}$$

where $\varphi^z := \frac{\frac{\alpha(1-\lambda)-1+\eta}{(1-\eta)^2}\omega^z(\Gamma^{1-\eta}-1)(\eta-\phi-1)-1}{\Lambda_z\Gamma^{-\eta}(1-\gamma)}$, $\varphi^Y := \frac{\frac{(1-\alpha)(1-\lambda)+1}{1-\eta}}{\Lambda_z}$, $\varphi^{P^Y} := \frac{\frac{\lambda-\sigma}{1-\eta}}{\Lambda_z}$, and $\Lambda_z := \frac{\alpha(1-\lambda)-1+\eta}{1-\eta}\omega^z + \frac{1}{\Gamma^{1-\eta}-1}$.

Differentiating equation (60):

$$\begin{aligned}
d\ln P_{ij}^X &= \alpha d\ln P_{ij}^{\tilde{X}} + (1-\alpha)d\ln R^K \\
&= \alpha(d\ln w_i \\
&+\frac{1}{1-\eta}\frac{z^{*\eta-\phi-1}}{1+(\Gamma^{1-\eta}-1)z^{*\eta-\phi-1}}((1-\eta)\Gamma^{-\eta}(\gamma-1)d\theta_j \\
&+(\Gamma^{1-\eta}-1)(\eta-\phi-1)d\ln z_j^*)+(1-\alpha)d\ln R^K \\
&= -\alpha\omega^z\Gamma^{-\eta}(1-\gamma)d\theta_j+\alpha d\ln w_i \\
&+\frac{\alpha}{1-\eta}\omega^z(\Gamma^{1-\eta}-1)(\eta-\phi-1)d\ln z_j^*+(1-\alpha)d\ln R^K \\
&= \alpha\mu^z d\ln z_j^*+\alpha\mu^Y d\ln Y+\alpha\mu^{P^Y}d\ln P_j^Y+\alpha d\ln w_i+(1-\alpha)d\ln R^K
\end{aligned} \tag{69}$$

where $\mu^z := -\omega^z\Gamma^{-\eta}(1-\gamma)\varphi^z + \frac{1}{1-\eta}\omega^z(\Gamma^{1-\eta}-1)(\eta-\phi-1)$, $\mu^Y := -\omega^z\Gamma^{-\eta}(1-\gamma)\varphi^Y$, and $\mu^{P^Y} := -\omega^z\Gamma^{-\eta}(1-\gamma)\varphi^{P^Y}$. The third equality follows from plugging in equation (66).

Differentiating equation (61):

$$
\begin{aligned}
ds_j^L &= \frac{z^{*\eta-\phi-1}}{1+((1-\theta_0)\Gamma^{-\eta}-1)z^{*\eta-\phi-1}}(-\Gamma^{-\eta}d\theta_j-(1-\theta_0)\eta\Gamma^{-\eta-1}d\Gamma_j \\
&+((1-\theta_0)\Gamma^{-\eta}-1)(\eta-\phi-1)d\ln z_j^*) \\
&-\frac{z^{*\eta-\phi-1}}{1+(\Gamma^{1-\eta}-1)z^{*\eta-\phi-1}}((1-\eta)\Gamma^{-\eta}d\Gamma_j+(\Gamma^{1-\eta}-1)(\eta-\phi-1)d\ln z_j^*) \\
&= -\omega^s\Gamma^{-\eta}d\theta_j-(\omega^s(1-\theta_0)\eta\Gamma^{-\eta-1}+(1-\eta)\omega^z\Gamma^{-\eta})d\Gamma_j \\
&+(\eta-\phi-1)(\omega^s((1-\theta_0)\Gamma^{-\eta}-1)-\omega^z(\Gamma^{1-\eta}-1))d\ln z_j^* \\
&= (-\omega^s\Gamma^{-\eta}+(1-\gamma)\omega^s(1-\theta_0)\eta\Gamma^{-\eta-1}+(1-\gamma)(1-\eta)\omega^z\Gamma^{-\eta})d\theta_j \\
&+(\eta-\phi-1)(\omega^s((1-\theta_0)\Gamma^{-\eta}-1)-\omega^z(\Gamma^{1-\eta}-1))d\ln z_j^* \\
&= \tau^z d\ln z_j^*+\tau^Y d\ln Y+\tau^{P^Y}d\ln P_j^Y
\end{aligned} \tag{70}
$$

where $\omega^s := \frac{z^{*\eta-\phi-1}}{1+((1-\theta_0)\Gamma^{-\eta}-1)z^{*\eta-\phi-1}}$, $\tau^z := (-\omega^s\Gamma^{-\eta}+(1-\gamma)\omega^s(1-\theta_0)\eta\Gamma^{-\eta-1}+(1-\gamma)(1-\eta)\omega^z\Gamma^{-\eta})\varphi^z+(\eta-\phi-1)(\omega^s((1-\theta_0)\Gamma^{-\eta}-1)-\omega^z(\Gamma^{1-\eta}-1))$, $\tau^Y := (-\omega^s\Gamma^{-\eta}+(1-\gamma)\omega^s(1-\theta_0)\eta\Gamma^{-\eta-1}+(1-\gamma)(1-\eta)\omega^z\Gamma^{-\eta})\varphi^Y$, and $\tau^{P^Y} := (-\omega^s\Gamma^{-\eta}+(1-\gamma)\omega^s(1-\theta_0)\eta\Gamma^{-\eta-1}+(1-\gamma)(1-\eta)\omega^z\Gamma^{-\eta})\varphi^{P^Y}$.

B.2.3 Relative Regional Effect

Assume that Assumption 2 holds, so that $z_{ij}^* = z^*$ and $s_{ij}^L = s^L$ for all i and j.

Note that the change in household income is:

$$
\begin{aligned}
d\ln(w_iL_i+\chi_i^\Pi\Pi) &= \frac{w_iL_i}{w_iL_i+\chi_i^\Pi\Pi}(d\ln w_i+d\ln L_i)+\left(1-\frac{w_iL_i}{w_iL_i+\chi_i^\Pi\Pi}\right)d\ln\Pi \\
&= \frac{\sum_k w_kL_k}{\sum_k w_kL_k+\Pi}(d\ln w_i+d\ln L_i)+\left(1-\frac{\sum_k w_kL_k}{\sum_k w_kL_k+\Pi}\right)d\ln\Pi \\
&= \left(1-\chi+\chi\frac{\alpha s^L}{1-\iota}\right)(d\ln w_i+d\ln L_i)+\left(\chi-\chi\frac{\alpha s^L}{1-\iota}\right)d\ln\Pi \\
&= \omega^L(d\ln w_i+d\ln L_i)+(1-\omega^L)d\ln\Pi
\end{aligned} \tag{71}
$$

where $\iota = \frac{\sum_i I_i}{Y} = \frac{\alpha(1-s^L)}{1+\kappa}$ is the aggregate investment-to-output ratio and $\omega^L := 1-\chi+\chi\frac{\alpha s^L}{1-\iota}$.

Differentiating equation (47) and plugging in equation (71):

$$
(\chi+(1-\chi)\psi)d\ln w_i = \psi\omega^L(d\ln w_i+d\ln L_i)+\psi(1-\omega^L)d\ln\Pi+\varepsilon d\ln L_i \tag{72}
$$

Differentiating (48):

$$d\ln R_i^M = \kappa d\ln M_i \tag{73}$$

Differentiating (51):

$$\begin{aligned} d\ln w_i + d\ln L_i = \rho d\ln Y + (1-\rho)(\omega^L(d\ln w_i + d\ln L_i) + (1-\omega^L)d\ln \Pi) \\ + \sum_j l_{ij} d\ln s_j^L + (1-\lambda)\sum_j l_{ij} d\ln P_{ij}^X + (\lambda-\sigma)\sum_j l_{ij} d\ln P_j^Y \end{aligned} \tag{74}$$

where ρ is the baseline share of employment in the tradable sector and l_{ij} is the share of employment of industry j in total employment in commuting zone i.

Using the price index (49) and differentiating:

$$\begin{aligned} d\ln P_j^Y &= \sum_k \nu_{kj}\Big(\frac{P_{kj}^X}{P_j^Y}\Big)^{1-\lambda} d\ln P_{kj}^X \\ &= \sum_k \nu_{kj}\Big(\frac{P_{kj}^X}{P_j^Y}\Big)^{1-\lambda}\Big(\alpha\mu^z d\ln z_j^* + \alpha\mu^Y d\ln Y + \alpha\mu^{P^Y} d\ln P_j^Y + \alpha d\ln w_k + (1-\alpha)d\ln R^K\Big) \\ &= \alpha\mu^z d\ln z_j^* + \alpha\mu^Y d\ln Y + \alpha\mu^{P^Y} d\ln P_j^Y + (1-\alpha)d\ln R^K + \sum_k \nu_{kj}\Big(\frac{P_{kj}^X}{P_j^Y}\Big)^{1-\lambda}\alpha d\ln w_k \end{aligned} \tag{75}$$

where the second equality follows from plugging in equation (69).

Rearranging:

$$d\ln P_j^Y = \frac{1}{1-\alpha\mu^{P^Y}}\Big(\alpha\mu^z d\ln z_j^* + \alpha\mu^Y d\ln Y + (1-\alpha)d\ln R^K + \sum_k \nu_{kj}\Big(\frac{P_{kj}^X}{P_j^Y}\Big)^{1-\lambda}\alpha d\ln w_k\Big) \tag{76}$$

Note that under Pareto distribution, the share of AI-adopting firms in industry j is $\pi_j^f := 1-G(z_j^*) = z_j^{*-\phi}$, hence $d\ln \pi_j^f = -\phi d\ln z_j^*$ and $d\pi_j^f = -\phi\pi^f d\ln z_j^* = -\phi z^{*-\phi} d\ln z_j^*$. Therefore, the relationship between the change in the share of AI-adopting firms $d\pi_j^f$ and the adoption productivity cut-off is:

$$d\ln z_j^* = -\frac{1}{\phi} z^{*\phi} d\pi_j^f \tag{77}$$

Plugging equation (76) into (74):

$$
\begin{aligned}
d\ln w_i + d\ln L_i &= \rho d\ln Y + (1-\rho)(\omega^L(d\ln w_i + d\ln L_i) + (1-\omega^L)d\ln\Pi) \\
&+ \sum_j l_{ij}(\tau^z d\ln z_j^* + \tau^Y d\ln Y + \tau^{P^Y} d\ln P_j^Y) \\
&+ (1-\lambda)\sum_j l_{ij}(\alpha\mu^z d\ln z_j^* + \alpha\mu^Y d\ln Y + \alpha\mu^{P^Y} d\ln P_j^Y + \alpha d\ln w_i + (1-\alpha)d\ln R^K) \\
&+ (\lambda-\sigma)\sum_j l_{ij} d\ln P_j^Y \\
&= \rho(1+\tau^Y + (1-\lambda)\alpha\mu^Y)d\ln Y + (1-\rho)(\omega^L(d\ln w_i + d\ln L_i) + (1-\omega^L)d\ln\Pi) \\
&+ (\tau^z + (1-\lambda)\alpha\mu^z)\sum_j l_{ij} d\ln z_j^* + \rho(1-\lambda)\alpha d\ln w_i + \rho(1-\lambda)(1-\alpha)d\ln R^K \\
&+ (\tau^{P^Y} + (1-\lambda)\alpha\mu^{P^Y} + (\lambda-\sigma))\sum_j l_{ij} d\ln P_j^Y \\
&= \rho\Big(1+\tau^Y + (1-\lambda)\alpha\mu^Y + \frac{\tau^{P^Y} + (1-\lambda)\alpha\mu^{P^Y} + (\lambda-\sigma)}{1-\alpha\mu^{P^Y}}\alpha\mu^Y\Big)d\ln Y \\
&+ (1-\rho)(\omega^L(d\ln w_i + d\ln L_i) + (1-\omega^L)d\ln\Pi) \\
&+ \Big(\tau^z + (1-\lambda)\alpha\mu^z + \frac{\tau^{P^Y} + (1-\lambda)\alpha\mu^{P^Y} + (\lambda-\sigma)}{1-\alpha\mu^{P^Y}}\alpha\mu^z\Big)\sum_j l_{ij} d\ln z_j^* \\
&+ \rho(1-\lambda)\alpha d\ln w_i + \rho\Big((1-\lambda)(1-\alpha) + \frac{\tau^{P^Y} + (1-\lambda)\alpha\mu^{P^Y} + (\lambda-\sigma)}{1-\alpha\mu^{P^Y}}(1-\alpha)\Big)d\ln R^K \\
&+ G_{i,US} \\
&= \rho\Big(1+\tau^Y + (1-\lambda)\alpha\mu^Y + \frac{\tau^{P^Y} + (1-\lambda)\alpha\mu^{P^Y} + (\lambda-\sigma)}{1-\alpha\mu^{P^Y}}\alpha\mu^Y\Big)d\ln Y \\
&+ (1-\rho)(\omega^L(d\ln w_i + d\ln L_i) + (1-\omega^L)d\ln\Pi) \\
&- \Big(\tau^z + (1-\lambda)\alpha\mu^z + \frac{\tau^{P^Y} + (1-\lambda)\alpha\mu^{P^Y} + (\lambda-\sigma)}{1-\alpha\mu^{P^Y}}\alpha\mu^z\Big)\frac{z^{*\phi}}{\phi}\sum_j l_{ij} d\pi_j^f \\
&+ \rho(1-\lambda)\alpha d\ln w_i + \rho\Big((1-\lambda)(1-\alpha) + \frac{\tau^{P^Y} + (1-\lambda)\alpha\mu^{P^Y} + (\lambda-\sigma)}{1-\alpha\mu^{P^Y}}(1-\alpha)\Big)d\ln R^K \\
&+ G_{i,US}
\end{aligned} \tag{78}
$$

where $G_{i,US} := \frac{\tau^{P^Y}+(1-\lambda)\alpha\mu^{P^Y}+(\lambda-\sigma)}{1-\alpha\mu^{P^Y}}\sum_j l_{ij}\sum_k \nu_{kj}\left(\frac{P_{kj}^X}{P_j^Y}\right)^{1-\lambda}\alpha d\ln w_k$. The last equality uses equation (77).

Differentiating (52):

$$
\begin{aligned}
d\ln R_i^M + d\ln M_i =& d\ln Y - \frac{1}{\rho}\frac{s^L}{\frac{\eta-1}{\eta}-s^L}\sum_j l_{ij} d\ln s_j^L + \frac{1}{\rho}(1-\lambda)\sum_j l_{ij} d\ln P_{ij}^X + \frac{1}{\rho}(\lambda-\sigma)\sum_j l_{ij} d\ln P_j^Y \\
=& d\ln Y - \frac{1}{\rho}\frac{s^L}{\frac{\eta-1}{\eta}-s^L}\sum_j l_{ij}(\tau^z d\ln z_j^* + \tau^Y d\ln Y + \tau^{P^Y} d\ln P_j^Y) \\
&+\frac{1}{\rho}(1-\lambda)\sum_j l_{ij}(\alpha\mu^z d\ln z_j^* + \alpha\mu^Y d\ln Y + \alpha\mu^{P^Y} d\ln P_j^Y + \alpha d\ln w_i + (1-\alpha) d\ln R^K) \\
&+\frac{1}{\rho}(\lambda-\sigma)\sum_j l_{ij} d\ln P_j^Y \\
=& \Big(1 - \frac{s^L}{\frac{\eta-1}{\eta}-s^L}\tau^Y + (1-\lambda)\alpha\mu^Y\Big) d\ln Y - \frac{1}{\rho}\Big(\frac{s^L}{\frac{\eta-1}{\eta}-s^L}\tau_z - (1-\lambda)\alpha\mu^z\Big)\sum_j l_{ij} d\ln z_j^* \\
&+(1-\lambda)\alpha d\ln w_i + (1-\lambda)(1-\alpha) d\ln R^K \\
&-\frac{1}{\rho}\Big(\frac{s^L}{\frac{\eta-1}{\eta}-s^L}\tau^{P^Y} - (1-\lambda)\alpha\mu^{P^Y} - (\lambda-\sigma)\Big)\sum_j l_{ij} d\ln P_j^Y \\
=& \Big(1 - \frac{s^L}{\frac{\eta-1}{\eta}-s^L}\tau^Y + (1-\lambda)\alpha\mu^Y - \frac{\frac{s^L}{\frac{\eta-1}{\eta}-s^L}\tau^{P^Y} - (1-\lambda)\alpha\mu^{P^Y} - (\lambda-\sigma)}{1-\alpha\mu^{P^Y}}\alpha\mu^Y\Big) d\ln Y \\
-&\frac{1}{\rho}\Big(\frac{s^L}{\frac{\eta-1}{\eta}-s^L}\tau_z - (1-\lambda)\alpha\mu^z + \frac{\frac{s^L}{\frac{\eta-1}{\eta}-s^L}\tau^{P^Y} - (1-\lambda)\alpha\mu^{P^Y} - (\lambda-\sigma)}{1-\alpha\mu^{P^Y}}\alpha\mu^z\Big)\sum_j l_{ij} d\ln z_j^* \\
&+(1-\lambda)\alpha d\ln w_i \\
&+\Big((1-\lambda)(1-\alpha) - \frac{\frac{s^L}{\frac{\eta-1}{\eta}-s^L}\tau^{P^Y} - (1-\lambda)\alpha\mu^{P^Y} - (\lambda-\sigma)}{1-\alpha\mu^{P^Y}}(1-\alpha)\Big) d\ln R^K \\
&-\frac{1}{\rho}H_{i,US} \\
=& \Big(1 - \frac{s^L}{\frac{\eta-1}{\eta}-s^L}\tau^Y + (1-\lambda)\alpha\mu^Y - \frac{\frac{s^L}{\frac{\eta-1}{\eta}-s^L}\tau^{P^Y} - (1-\lambda)\alpha\mu^{P^Y} - (\lambda-\sigma)}{1-\alpha\mu^{P^Y}}\alpha\mu^Y\Big) d\ln Y \\
+&\frac{1}{\rho}\Big(\frac{s^L}{\frac{\eta-1}{\eta}-s^L}\tau_z - (1-\lambda)\alpha\mu^z + \frac{\frac{s^L}{\frac{\eta-1}{\eta}-s^L}\tau^{P^Y} - (1-\lambda)\alpha\mu^{P^Y} - (\lambda-\sigma)}{1-\alpha\mu^{P^Y}}\alpha\mu^z\Big)\frac{z^{*\phi}}{\phi}\sum_j l_{ij} d\pi_j^f \\
&+(1-\lambda)\alpha d\ln w_i \\
&+\Big((1-\lambda)(1-\alpha) - \frac{\frac{s^L}{\frac{\eta-1}{\eta}-s^L}\tau^{P^Y} - (1-\lambda)\alpha\mu^{P^Y} - (\lambda-\sigma)}{1-\alpha\mu^{P^Y}}(1-\alpha)\Big) d\ln R^K \\
&-\frac{1}{\rho}H_{i,US}
\end{aligned} \tag{79}
$$

where $H_{i,US} := \frac{\frac{s^L}{\frac{\eta-1}{\eta}-s^L}\tau^{P^Y}-(1-\lambda)\alpha\mu^{P^Y}-(\lambda-\sigma)}{1-\alpha\mu^{P^Y}} \sum_j l_{ij} \sum_k \nu_{kj} \left(\frac{P^X_{kj}}{P^Y_j}\right)^{1-\lambda} \alpha d\ln w_k$.

Differentiating (53):

$$d\ln R^K = d\ln dY \tag{80}$$

Equations (72), (73), (78), (79), (80) define a system of 5 linear equations with 5 unknowns: $d\ln L_i$, $d\ln w_i$, $d\ln R^K$, $d\ln R^M_i$, $d\ln M_i$.

B.2.4 Aggregate Effect

Define aggregate (average) US employment and wage as $d\ln L = \sum_i \chi^w_i d\ln L_i$ and $d\ln w = \sum_i \chi^w_i d\ln w_i$, where χ^w_i is the share of national wage bill for commuting zone i. Similarly, $d\ln R^M = \sum_i \chi^w_i d\ln R^M_i$ and $d\ln M = \sum_i \chi^w_i d\ln M_i$.

Assume that Assumption 2 holds, so that $z^*_{ij} = z^*$ and $s^L_{ij} = s^L$ for all i and j. Moreover, the initial allocation of non-labor income satisfies $\chi^\Pi_i = \frac{w_i L_i}{\sum_k w_k L_k}$. Then:

$$\begin{aligned} \chi^w_i &= \frac{w_i L_i}{\sum_k w_k L_k} \\ &= \frac{w_i L^T_i}{\sum_k w_k L^T_k} \\ &= \frac{\alpha s^L \sum_j P^X_{ij} X_{ij}}{\alpha s^L Y} \\ &= \frac{\sum_j P^X_{ij} X_{ij}}{Y} \end{aligned} \tag{81}$$

where L^T_i denotes total employment in the tradable sector and Y is aggregate output in the tradable sector.

Aggregating equation (72) over all commuting zones i, weighed by χ^w_i:

$$(\chi + (1-\chi)\psi)d\ln w = \psi\omega^L(d\ln w + d\ln L) + \psi(1-\omega^L)d\ln\Pi + \varepsilon d\ln L \tag{82}$$

Note that $\sum_i w_i L_i + \Pi = Y - I$, differentiating:

$$\omega^L(d\ln w + d\ln L) + (1-\omega^L)d\ln\Pi = \frac{1}{1-\iota}d\ln Y - \frac{\iota}{1-\iota}(1+\kappa)d\ln M \tag{83}$$

where $\omega^L := \frac{\sum_k w_k L_k}{\sum_k w_k L_k + \Pi} = 1 - \chi + \chi \frac{\alpha s^L}{1-\iota}$, with $\iota = \frac{\sum_i I_i}{Y} = \frac{\alpha(\frac{\eta-1}{\eta} - s^L)}{1+\kappa}$.

Plugging (83) into (82):

$$(\chi + (1-\chi)\psi) d\ln w = \frac{\psi}{1 - \frac{\alpha(\frac{\eta-1}{\eta} - s^L)}{1+\kappa}} (d\ln Y - \alpha(\frac{\eta-1}{\eta} - s^L) d\ln M) + \varepsilon d\ln L \tag{84}$$

Aggregating equation (73) over all commuting zones i, weighted by χ_i^w:

$$d\ln R^M = \kappa d\ln M \tag{85}$$

Aggregating equation (74):

$$\begin{aligned} d\ln w + d\ln L = {} & \rho d\ln Y + (1-\rho)(\omega^L(d\ln w + d\ln L) + (1-\omega^L) d\ln \Pi) \\ & + \sum_i \chi_i^w \sum_j l_{ij} d\ln s_j^L + (1-\lambda) \sum_i \sum_j \chi_i^w l_{ij} d\ln P_{ij}^X + (\lambda - \sigma) \sum_i \sum_j \chi_i^w l_{ij} d\ln P_j^Y \end{aligned} \tag{86}$$

Note that:

$$\begin{aligned} \sum_i \sum_j \chi_i^w l_{ij} d\ln P_j^Y &= \rho \sum_i \sum_j \chi_i^w \chi_{ij} d\ln P_j^Y \\ &= \rho \sum_j \sum_i \frac{\sum_h P_{ih}^X X_{ih}}{Y} \frac{P_{ij}^X X_{ij}}{\sum_h P_{ih}^X X_{ih}} d\ln P_j^Y \\ &= \rho \sum_j \sum_i \frac{P_{ij}^X X_{ij}}{Y} d\ln P_j^Y \\ &= \rho \sum_j \frac{P_j^Y Y_j}{Y} d\ln P_j^Y \\ &= 0 \end{aligned} \tag{87}$$

as all tradable industries have the same labor intensity, so $l_{ij} = \rho \chi_{ij}$, where χ_{ij} denotes the value-added share of industry j in the total tradable sector value-added share of commuting zone i. Y_j is the total output of industry j, such that $P_j^Y Y_j = \sum_i P_{ij}^X X_{ij}$. The last equality follows from differentiating the ideal price index (50), which is normalized to 1.

Similarly,

$$\begin{aligned}
\sum_i \sum_j \chi_i^w l_{ij} d\ln P_{ij}^X &= \rho \sum_j \sum_i \chi_i^w \chi_{ij} d\ln P_{ij}^X \\
&= \rho \sum_j \sum_i \frac{\sum_h P_{ih}^X X_{ih}}{Y} \frac{P_{ij}^X X_{ij}}{\sum_h P_{ih}^X X_{ih}} d\ln P_{ij}^X \\
&= \rho \sum_j \sum_i \frac{P_{ij}^X X_{ij}}{Y} d\ln P_{ij}^X \\
&= \rho \sum_j \frac{P_j^Y Y_j}{Y} \sum_i \frac{P_{ij}^X X_{ij}}{P_j^Y Y_j} d\ln P_{ij}^X \\
&= \rho \sum_j \frac{P_j^Y Y_j}{Y} d\ln P_j^Y \\
&= 0
\end{aligned} \tag{88}$$

where the second last line follows from differentiating the price index (49) and the last line follows from differentiating the ideal price index (50).

Hence, by equation (88) and note that $l_{ij} = \rho\chi_{ij}$:

$$\alpha\mu^Y d\ln Y + \alpha d\ln w + (1-\alpha) d\ln R^K = \frac{\alpha\mu^z}{\rho\phi} z^{*\phi} \sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f \tag{89}$$

Moreover, equation (86) becomes:

$$\begin{aligned}
d\ln w + d\ln L = \rho d\ln Y &+ \frac{1-\rho}{1 - \frac{\alpha(\frac{\eta-1}{\eta} - s^L)}{1+\kappa}} (d\ln Y - \alpha(\frac{\eta-1}{\eta} - s^L) d\ln M) \\
&+ \sum_i \chi_i^w \sum_j l_{ij} (\tau^z d\ln z_j^* + \tau^Y d\ln Y + \tau^{P^Y} d\ln P_j^Y) \\
&= \rho(1+\tau^Y) d\ln Y + \frac{1-\rho}{1 - \frac{\alpha(\frac{\eta-1}{\eta} - s^L)}{1+\kappa}} (d\ln Y - \alpha(\frac{\eta-1}{\eta} - s^L) d\ln M) \\
&- \frac{\tau^z}{\phi} z^{*\phi} \sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f
\end{aligned} \tag{90}$$

Aggregating equation (79):

$$
\begin{aligned}
d\ln R^M + d\ln M &= d\ln Y - \frac{1}{\rho}\frac{s^L}{\frac{\eta-1}{\eta}-s^L}\sum_i \chi_i^w \sum_j l_{ij} d\ln s_j^L \\
&= d\ln Y - \frac{1}{\rho}\frac{s^L}{\frac{\eta-1}{\eta}-s^L}\sum_i \chi_i^w \sum_j l_{ij}(\tau^z d\ln z_j^* + \tau^Y d\ln Y + \tau^{P^Y} d\ln P_j^Y) \\
&= (1 - \frac{s^L}{\frac{\eta-1}{\eta}-s^L}\tau^Y) d\ln Y + \frac{\tau^z}{\rho\phi} z^{*\phi} \frac{s^L}{\frac{\eta-1}{\eta}-s^L}\sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f
\end{aligned}
\tag{91}
$$

Finally, differentiating (53):

$$
d\ln R^K = d\ln dY \tag{92}
$$

Equations (84), (85), (89), (90), (91), (92) define a system of 6 linear equations with 6 unknowns: $d\ln L$, $d\ln w$, $d\ln R^K$, $d\ln R^M$, $d\ln M$, $d\ln Y$.

I now solve for the above system of equations. Starting with equation (89) and note that $d\ln R^K = d\ln Y$, express $d\ln Y$ in terms of $d\ln w$:

$$
d\ln Y = \frac{\alpha\mu^z}{\rho\phi(\alpha\mu^Y + 1 - \alpha)} z^{*\phi} \sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f - \frac{\alpha}{\alpha\mu^Y + 1 - \alpha} d\ln w \tag{93}
$$

As $d\ln R^M = \kappa d\ln M$, equation (91) gives:

$$
d\ln M = \frac{1 - \frac{s^L}{\frac{\eta-1}{\eta}-s^L}\tau^Y}{1+\kappa} d\ln Y + \frac{\tau^z}{\rho\phi(1+\kappa)} z^{*\phi} \frac{s^L}{\frac{\eta-1}{\eta}-s^L}\sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f \tag{94}
$$

Therefore,

$$
\begin{aligned}
d\ln Y - \alpha(\frac{\eta-1}{\eta} - s^L) d\ln M &= \Big(1 - \frac{\alpha(\frac{\eta-1}{\eta}-s^L) - \alpha s^L \tau^Y}{1+\kappa}\Big) d\ln Y \\
&\quad - \frac{\alpha s^L \tau^z}{\rho\phi(1+\kappa)} z^{*\phi} \sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f \\
&= -\frac{1+\kappa - \alpha(\frac{\eta-1}{\eta}-s^L) + \alpha s^L\tau^Y}{1+\kappa} \frac{\alpha}{\alpha\mu^Y + 1 - \alpha} d\ln w \\
+\Big(\frac{1+\kappa - \alpha(\frac{\eta-1}{\eta}-s^L) + \alpha s^L\tau^Y}{1+\kappa} &\frac{\alpha\mu^z}{\rho\phi(\alpha\mu^Y+1-\alpha)} - \frac{\alpha s^L\tau^z}{\rho\phi(1+\kappa)}\Big) z^{*\phi} \sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f
\end{aligned}
\tag{95}
$$

Given (93) and (95), rearranging equation (84) gives a relationship between $d\ln w$ and $d\ln L$:

$$
\begin{aligned}
d\ln w &= \frac{\varepsilon}{\chi+(1-\chi)\psi+\frac{\alpha\psi}{\alpha\mu^Y+1-\alpha}\frac{1+\kappa-\alpha(\frac{\eta-1}{\eta}-s^L)+\alpha s^L\tau^Y}{1+\kappa-\alpha(\frac{\eta-1}{\eta}-s^L)}} d\ln L \\
&+ \frac{\frac{\psi}{1+\kappa-\alpha(\frac{\eta-1}{\eta}-s^L)}\left(\alpha\mu^z\frac{1+\kappa-\alpha(\frac{\eta-1}{\eta}-s^L)+\alpha s^L\tau^Y}{\rho\phi(\alpha\mu^Y+1-\alpha)}-\frac{\alpha s^L\tau^z}{\rho\phi}\right)}{\chi+(1-\chi)\psi+\frac{\alpha\psi}{\alpha\mu^Y+1-\alpha}\frac{1+\kappa-\alpha(\frac{\eta-1}{\eta}-s^L)+\alpha s^L\tau^Y}{1+\kappa-\alpha(\frac{\eta-1}{\eta}-s^L)}} z^{*\phi}\sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f \\
&= \zeta^L d\ln L + \zeta^\pi z^{*\phi}\sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f
\end{aligned} \tag{96}
$$

where $\zeta^L := \frac{\varepsilon}{\chi+(1-\chi)\psi+\frac{\alpha\psi}{\alpha\mu^Y+1-\alpha}\frac{1+\kappa-\alpha(\frac{\eta-1}{\eta}-s^L)+\alpha s^L\tau^Y}{1+\kappa-\alpha(\frac{\eta-1}{\eta}-s^L)}}$ and $\zeta^\pi := \frac{\frac{\psi}{1+\kappa-\alpha(\frac{\eta-1}{\eta}-s^L)}\left(\alpha\mu^z\frac{1+\kappa-\alpha(\frac{\eta-1}{\eta}-s^L)+\alpha s^L\tau^Y}{\rho\phi(\alpha\mu^Y+1-\alpha)}-\frac{\alpha s^L\tau^z}{\rho\phi}\right)}{\chi+(1-\chi)\psi+\frac{\alpha\psi}{\alpha\mu^Y+1-\alpha}\frac{1+\kappa-\alpha(\frac{\eta-1}{\eta}-s^L)+\alpha s^L\tau^Y}{1+\kappa-\alpha(\frac{\eta-1}{\eta}-s^L)}}$.

Equation (90) becomes:

$$
\begin{aligned}
d\ln w + d\ln L &= \rho(1+\tau^Y)d\ln Y + \frac{1-\rho}{\psi}((\chi+(1-\chi)\psi)d\ln w - \varepsilon d\ln L) - \frac{\tau^z}{\phi}z^{*\phi}\sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f \\
&= \Big(\frac{(1-\rho)\chi}{\psi} + (1-\rho)(1-\chi) - \frac{\rho(1+\tau^Y)\alpha}{\alpha\mu^Y+1-\alpha}\Big)d\ln w - \frac{(1-\rho)\varepsilon}{\psi}d\ln L \\
&+ \Big(\frac{(1+\tau^Y)\alpha\mu^z}{\phi(\alpha\mu^Y+1-\alpha)} - \frac{\tau^z}{\phi}\Big)z^{*\phi}\sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f
\end{aligned} \tag{97}
$$

where the first equality follows from (84) and the second equality follows from (93).

Rearranging and plugging in equation (96):

$$
\begin{aligned}
d\ln L &= \frac{\psi}{\psi+(1-\rho)\varepsilon}\Big(\frac{(1-\rho)\chi}{\psi} - \chi - \rho + \chi\rho - \frac{\rho(1+\tau^Y)\alpha}{\alpha\mu^Y+1-\alpha}\Big)d\ln w \\
&+ \frac{\psi}{\psi+(1-\rho)\varepsilon}\Big(\frac{(1+\tau^Y)\alpha\mu^z}{\phi(\alpha\mu^Y+1-\alpha)} - \frac{\tau^z}{\phi}\Big)z^{*\phi}\sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f \\
&= \frac{\psi}{\psi+(1-\rho)\varepsilon}\Big(\frac{(1-\rho)\chi}{\psi} - \chi - \rho + \chi\rho - \frac{\rho(1+\tau^Y)\alpha}{\alpha\mu^Y+1-\alpha}\Big)\zeta^L d\ln L + \frac{\psi}{\psi+(1-\rho)\varepsilon} \\
&\Big(\Big(\frac{(1-\rho)\chi}{\psi} - \chi - \rho + \chi\rho - \frac{\rho(1+\tau^Y)\alpha}{\alpha\mu^Y+1-\alpha}\Big)\zeta^\pi + \frac{(1+\tau^Y)\alpha\mu^z}{\phi(\alpha\mu^Y+1-\alpha)} - \frac{\tau^z}{\phi}\Big)z^{*\phi}\sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f
\end{aligned} \tag{98}
$$

This gives a relationship between $d\ln L$ and $\sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f$:

$$
\begin{aligned}
d\ln L &= \frac{\frac{\psi}{\psi+(1-\rho)\varepsilon}\left(\left(\frac{(1-\rho)\chi}{\psi} - \chi - \rho + \chi\rho - \frac{\rho(1+\tau^Y)\alpha}{\alpha\mu^Y+1-\alpha}\right)\zeta^\pi + \frac{(1+\tau^Y)\alpha\mu^z}{\phi(\alpha\mu^Y+1-\alpha)} - \frac{\tau^z}{\phi}\right)}{1 - \frac{\psi}{\psi+(1-\rho)\varepsilon}\left(\frac{(1-\rho)\chi}{\psi} - \chi - \rho + \chi\rho - \frac{\rho(1+\tau^Y)\alpha}{\alpha\mu^Y+1-\alpha}\right)\zeta^L} z^{*\phi} \sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f \\
&= \underbrace{\frac{\left(\frac{(1-\rho)\chi}{\psi} - \chi - \rho + \chi\rho - \frac{\rho(1+\tau^Y)\alpha}{\alpha\mu^Y+1-\alpha}\right)\zeta^\pi + \frac{(1+\tau^Y)\alpha\mu^z}{\phi(\alpha\mu^Y+1-\alpha)} - \frac{\tau^z}{\phi}}{1 + \frac{(1-\rho)(\varepsilon-\chi\zeta^L)}{\psi} + \left(\chi + \rho - \chi\rho + \frac{\rho(1+\tau^Y)\alpha}{\alpha\mu^Y+1-\alpha}\right)\zeta^L} z^{*\phi}}_{\text{aggregate effect}} \sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f
\end{aligned}
\tag{99}
$$

where the coefficient in front of $\sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f$ is the aggregate effect of AI exposure on employment.

The change in investment-to-output ratio $d\iota$ is:

$$
\begin{aligned}
d\iota &= \iota d\ln d\iota \\
&= -\frac{\alpha(\frac{\eta-1}{\eta} - s^L)}{1+\kappa} \frac{s^L}{\frac{\eta-1}{\eta} - s^L} \sum_i \chi_i^w \sum_j l_{ij} d\ln s_j^L \\
&= -\frac{\alpha(\frac{\eta-1}{\eta} - s^L)}{1+\kappa} \frac{s^L}{\frac{\eta-1}{\eta} - s^L} \sum_i \chi_i^w \sum_j l_{ij} (\tau^z d\ln z_j^* + \tau^Y d\ln Y + \tau^{P^Y} d\ln P_j^Y) \\
&= -\frac{\alpha(\frac{\eta-1}{\eta} - s^L)}{1+\kappa} \frac{s^L}{\frac{\eta-1}{\eta} - s^L} \left(\rho\tau^Y d\ln Y - \frac{\tau^z}{\phi} z^{*\phi} \sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f\right)
\end{aligned}
\tag{100}
$$

The change in overall labor share $d\omega^L$ is:

$$
\begin{aligned}
d\omega^L &= \omega^L d\ln \omega^L \\
&= (1 - \chi + \chi\frac{\alpha s^L}{1-\iota})\left(\sum_i \chi_i^w \sum_j l_{ij} d\ln s_j^L + \frac{\iota}{1-\iota} d\ln\iota\right) \\
&= (1 - \chi + \chi\frac{\alpha s^L}{1-\iota})\left(\sum_i \chi_i^w \sum_j l_{ij} (\tau^z d\ln z_j^* + \tau^Y d\ln Y + \tau^{P^Y} d\ln P_j^Y) + \frac{\iota}{1-\iota} d\ln\iota\right) \\
&= (1 - \chi + \chi\frac{\alpha s^L}{1-\iota})\left(\rho\tau^Y d\ln Y - \frac{\tau^z}{\phi} z^{*\phi} \sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f + \frac{\iota}{1-\iota} d\ln\iota\right)
\end{aligned}
\tag{101}
$$

B.3 Parameterization

B.3.1 Shape Parameter of the Pareto Distribution

Sales of a firm with productivity $z_{ij}(\omega)$ is: $r_{ij}(\omega) := p_{ij}(\omega)x_{ij}(\omega) = p_{ij}(\omega)^{1-\eta}P_{ij}^{\tilde{X}\eta}\tilde{X}_{ij}$.

Average sales is:

$$\begin{aligned} E(r) &= P_{ij}^{\tilde{X}\eta}\tilde{X}_{ij}\Big(\frac{w_i}{\gamma_L}\Big)^{1-\eta}\Big(\int_1^{z^*} z^{\eta-1}dG(z) + \Gamma^{1-\eta}\int_{z^*}^{\infty} z^{\eta-1}dG(z)\Big) \\ &= P_{ij}^{\tilde{X}\eta}\tilde{X}_{ij}\Big(\frac{w_i}{\gamma_L}\Big)^{1-\eta}\frac{\phi}{\phi-\eta+1}(1+(\Gamma^{1-\eta}-1)z^{*\eta-\phi-1}) \end{aligned} \tag{102}$$

Note that when $\phi > 2(\eta-1)$:

$$\begin{aligned} E(r^2) &= \Big(P_{ij}^{\tilde{X}\eta}\tilde{X}_{ij}\Big(\frac{w_i}{\gamma_L}\Big)^{1-\eta}\Big)^2\Big(\int_1^{z^*} z^{2\eta-2}dG(z) + \Gamma^{2-2\eta}\int_{z^*}^{\infty} z^{2\eta-2}dG(z)\Big) \\ &= \Big(P_{ij}^{\tilde{X}\eta}\tilde{X}_{ij}\Big(\frac{w_i}{\gamma_L}\Big)^{1-\eta}\Big)^2\frac{\phi}{\phi-2\eta+2}(1+(\Gamma^{2-2\eta}-1)z^{*2\eta-\phi-2}) \end{aligned} \tag{103}$$

Therefore, the standard deviation of sales is:

$$\begin{aligned} SDV(r) &= E(r^2) - E(r)^2 \\ &= P_{ij}^{\tilde{X}\eta}\tilde{X}_{ij}\Big(\frac{w_i}{\gamma_L}\Big)^{1-\eta}\Big(\frac{\phi}{\phi-2\eta+2}(1+(\Gamma^{2-2\eta}-1)z^{*2\eta-\phi-2}) \\ &\quad - \Big(\frac{\phi}{\phi-\eta+1}\Big)^2(1+(\Gamma^{1-\eta}-1)z^{*\eta-\phi-1})^2\Big)^{\frac{1}{2}} \end{aligned} \tag{104}$$

ϕ is chosen to match the 2010 mean-to-standard-deviation ratio of firm sales $\frac{E(r)}{SDV(r)} = 0.212$ from Compustat. Denote π_0^f as the initial fraction of AI-adopting firms, the corresponding adoption cut-off productivity $z^* = \pi_0^{f-\frac{1}{\phi}}$. Moreover, let θ_0 denote the initial value for the set of AI-automable tasks, ϕ solves the following equation:

$$\begin{aligned} &\frac{\frac{\phi}{\phi-\eta+1}(1+(\Gamma^{1-\eta}-1)z^{*\eta-\phi-1})}{\Big(\frac{\phi}{\phi-2\eta+2}(1+(\Gamma^{2-2\eta}-1)z^{*2\eta-\phi-2}) - \Big(\frac{\phi}{\phi-\eta+1}\Big)^2(1+(\Gamma^{1-\eta}-1)z^{*\eta-\phi-1})^2\Big)^{\frac{1}{2}}} \\ =&\frac{\frac{\phi}{\phi-\eta+1}(1+(\Gamma^{1-\eta}-1)\pi_0^{f\,\frac{\phi-\eta+1}{\phi}})}{\Big(\frac{\phi}{\phi-2\eta+2}(1+(\Gamma^{2-2\eta}-1)\pi_0^{f\,\frac{\phi-2\eta+2}{\phi}}) - \Big(\frac{\phi}{\phi-\eta+1}\Big)^2(1+(\Gamma^{1-\eta}-1)\pi_0^{f\,\frac{\phi-\eta+1}{\phi}})^2\Big)^{\frac{1}{2}}} \\ =&0.212 \end{aligned} \tag{105}$$

Under the baseline assumption $\pi_0^f = 10^{-5}$ and the calibrated θ_0, ϕ is 10.13.

B.3.2 Preferences

Household first-order condition implies that (negative) marginal propensity of leisure is:

$$w_i \frac{dL_i}{dC_i} = -\frac{\psi}{\varepsilon}\frac{w_i L_i}{C_i} = -\frac{\psi}{\varepsilon}\omega^L \tag{106}$$

The third equality is from the definition of ω^L (labor share in total value-added). Imbens et al. (2001) estimate that the marginal propensity of leisure (of one additional dollar) is 0.1, therefore $\frac{\psi}{\varepsilon}\omega^L = 0.1$.

As $d\ln L_i = \hat{\beta}_L^{IV} \sum_j l_{ij} d\pi_j^f$ and $d\ln w_i = \hat{\beta}_w^{IV} \sum_j l_{ij} d\pi_j^f$, when $d\ln Y = d\ln \Pi = G_{i,US} = 0$, equation (72) becomes:

$$(\chi + (1-\chi)\psi - \psi\omega^L)\hat{\beta}_w^{IV} = (\psi\omega^L + \varepsilon)\hat{\beta}_L^{IV} \tag{107}$$

Combining with $\frac{\psi}{\varepsilon}\omega^L = 0.1$ yields:

$$\varepsilon = \frac{\chi\hat{\beta}_w^{IV}}{0.1(\hat{\beta}_w^{IV} + \hat{\beta}_L^{IV}) - \frac{0.1(1-\chi)}{\omega^L}\hat{\beta}_w^{IV} + \hat{\beta}_L^{IV}} \tag{108}$$

$$\psi = \frac{0.1}{\omega^L}\frac{\chi\hat{\beta}_w^{IV}}{0.1(\hat{\beta}_w^{IV} + \hat{\beta}_L^{IV}) - \frac{0.1(1-\chi)}{\omega^L}\hat{\beta}_w^{IV} + \hat{\beta}_L^{IV}} \tag{109}$$

B.3.3 Relative Regional Effect

I derive the structural expression for $\hat{\beta}^{IV}$, which helps informing the initial set of AI-automable tasks θ_0.

When $d\ln Y = d\ln \Pi = G_{i,US} = 0$, equation (78) becomes:

$$\begin{aligned}(1-(1-\rho)\omega^L)d\ln L_i = &-\Big(\tau^z + (1-\lambda)\alpha\mu^z + \frac{\tau^{P^Y} + (1-\lambda)\alpha\mu^{P^Y} + (\lambda-\sigma)}{1-\alpha\mu^{P^Y}}\alpha\mu^z\Big)\frac{z^{*\phi}}{\phi}\sum_j l_{ij} d\pi_j^f \\ &+ (\rho(1-\lambda)\alpha - 1 + (1-\rho)\omega^L)d\ln w_i\end{aligned} \tag{110}$$

Equation (72) implies that:

$$(\chi + (1-\chi)\psi - \psi\omega^L)d\ln w_i = (\psi\omega^L + \varepsilon)d\ln L_i \tag{111}$$

Combining equations (110) and (72) give:

$$d \ln L_i = \underbrace{-\frac{\left(\tau^z + (1-\lambda)\alpha\mu^z + \frac{\tau^{P^Y} + (1-\lambda)\alpha\mu^{P^Y} + (\lambda-\sigma)}{1-\alpha\mu^{P^Y}}\alpha\mu^z\right)\frac{z^{*\phi}}{\phi}}{(1-(1-\rho)\omega^L) - \frac{(\psi\omega^L+\varepsilon)(\rho(1-\lambda)\alpha-1+(1-\rho)\omega^L)}{(\chi+(1-\chi)\psi-\psi\omega^L)}}}_{=\hat{\beta}_L^{IV}\text{, relative regional effect}} \sum_j l_{ij} d\pi_j^f \tag{112}$$

Therefore, the calibration procedure requires that θ_0 matches:

$$-\frac{\left(\tau^z + (1-\lambda)\alpha\mu^z + \frac{\tau^{P^Y} + (1-\lambda)\alpha\mu^{P^Y} + (\lambda-\sigma)}{1-\alpha\mu^{P^Y}}\alpha\mu^z\right)\frac{z^{*\phi}}{\phi}}{(1-(1-\rho)\omega^L) - \frac{(\psi\omega^L+\varepsilon)(\rho(1-\lambda)\alpha-1+(1-\rho)\omega^L)}{(\chi+(1-\chi)\psi-\psi\omega^L)}} = \hat{\beta}_L^{IV} = -7.511$$