AI-Accelerated Occupational Decline and the Mobility Trap

By Xi Song, Jennie E. Brand, Sukie Xiuqi Yang, and Michael Lachanski*

Economic transformation poses challenges that extend beyond the creation, destruction, or redistribution of jobs across occupations (Autor et al., 2024). It raises a related question: can workers successfully navigate this disruption by switching occupations, or do these transitions – be they proactive or reactive – result in lower wages or worse career prospects? In *When Work Disappears*, William Julius Wilson (1996) showed how manufacturing's decline, driven by globalization and technology, triggered widespread poverty and social deterioration in American cities. We now face a new wave of labor market disruption from artificial intelligence that differs from earlier shifts in two ways: it is unfolding more rapidly, and it reaches beyond factories into professional, clerical, and service work.

This paper examines how recent occupational restructuring, driven in part by the post-2018 acceleration of Transformer-based AI, shapes worker mobility. We propose and test a mobility trap hypothesis: we ask whether workers in high AI-exposure declining occupations are effectively "trapped," unable to transition into high-growth occupations, and whether those who do switch nonetheless struggle to achieve upward mobility.

Existing methods for measuring occupational restructuring are ill-equipped to capture this mobility dynamic. Traditional indices, derived from the marginal distributions of mobility tables, are both backward-looking and often distorted in survey data (e.g., Erikson and Goldthorpe 1992; Kambourov and Manovskii 2008; Sørensen and Grusky 1996). They document changes that have already occurred but fail to account for the forward-looking decisions workers must make based on projected growth. They also cannot distinguish between permanent, AI-driven transformation and transient economic cycles.

To overcome these limitations, our study introduces a novel, predictive methodology. We integrate detailed administrative data from the Bureau of Labor Statistics, including both short-term employment changes and ten-year occupational projections, with individual worker transition data from the Current Population Survey (2018–2024). This allows us to evaluate the impact of AI-accelerated restructuring through three interrelated analyses: who moves, where they move, and their subsequent economic outcomes.

Our findings support a pronounced "mobility trap." Workers in high AI-exposure declining occupations show significantly higher mobility rates than their peers in growing fields. Moreover, those who manage to leave declining occupations are 5.2 times more likely to transition into another declining occupation than into a growing occupation. These moves are frequently lateral or downward, with almost 70% resulting in lower occupational status based on occupation-level income. This evidence confirms that significant barriers are hardening within the labor market. Ongoing occupational restructuring threatens not merely job displacement but entrenching the marginal position of vulnerable workers, deepening existing disadvantages and echoing the inequalities Wilson documented during the decline of manufacturing.

I. Measuring Occupational Growth and Decline

We conceptualize "occupational restructuring" along two dimensions: short-term realized change and long-term projected change in the number of jobs. Occupational growth and decline are measured using administrative data from the Bureau of Labor Statistics' Occupational Outlook Handbook (OOH). The OOH tracks how an occupation's size changes over time and treats these changes as indicators of shifting structural opportunity in the labor market. Because the OOH was historically

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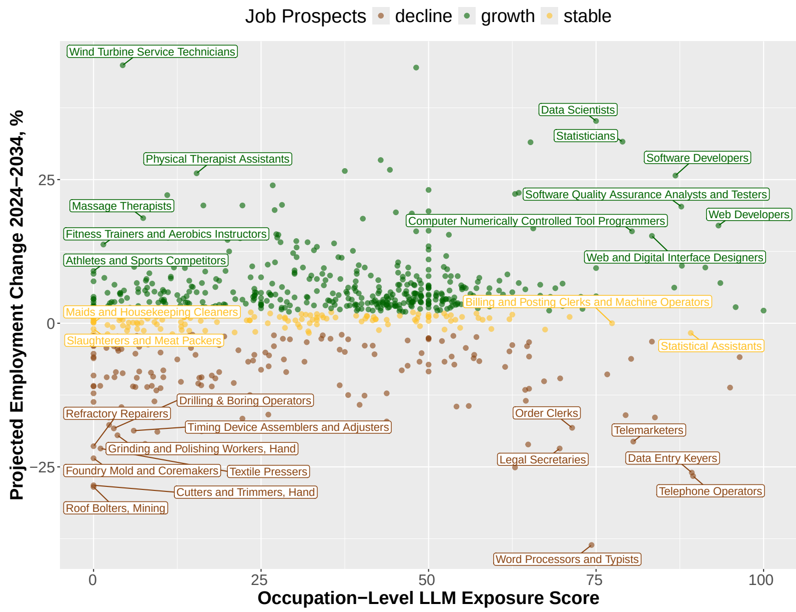

FIGURE 1. THE DISTRIBUTION OF OCCUPATIONS BY 10-YEAR PROJECTED OCCUPATIONAL GROWTH RATES AND OCCUPATION-LEVEL LLM EXPOSURE SCORE

Note: The figure presents 10-year employment projections (2024–2034) from the OOH, highlighting occupations with the fastest and slowest projected growth as well as those with very high or low exposure to Large Language Models (LLMs). LLM exposure is measured using the beta score developed by Eloundou et al. (2024), which quantifies the potential impact of LLMs on occupational tasks. See *Appendix* Table A1 for definitions of growing, stable, and declining occupation categories.

updated biennially since 1949, the short-term measure is constructed over two-year intervals, aligning with the spacing of historical OOH editions.

Short-term occupational growth (or decline) is measured as the percent change in an occupation's employment size between consecutive OOH years. This measure is intended to capture immediate labor-market turbulence, such as cyclical expansions or contractions, that can influence job availability and workers' propensity to move. To reduce contamination from discontinuities arising from changes in occupational definitions or coding, we drop occupations whose employment size changes by more than 400% between two OOH years.

Long-term occupational growth and decline are measured using the OOH's ten-year employment projections. These projections are designed to reflect expected structural trends, such as technological change, demographic shifts, and globalization, rather than short-run fluctuations. We use both a continuous projected growth-rate measure (the projected percent change over the next decade) and a categorical outlook measure based on BLS projection categories. Because the detailed BLS outlook categories are not consistently available across all years, we collapse them into three harmonized groups – growing, stable, and declining – so that the measure is comparable over the 2018–2024 period. Together, these measures allow us to distinguish between recent realized contraction/expansion and forward-looking expectations about where jobs are likely to grow or disappear.

Figure 1 plots each occupation's LLM exposure score (recently developed by Eloundou et al. (2024)) against its OOH projected employment change from 2024–2034. Overall, the plot shows no simple one-to-one relationship between AI exposure and projected growth: occupations with similar exposure scores (roughly 3.0-4.5 on the x-axis) span the full range of projected outcomes, from substantial decline to strong growth (about -40% to +40% on the y-axis). For example, several high-exposure, information/health occupations (e.g., Information Security Analysts, Statisticians) appear alongside high-exposure occupations projected to shrink (e.g., Telephone Operators, Word Processors and Typists). The results indicate that AI applications to work tasks do not necessarily lead to

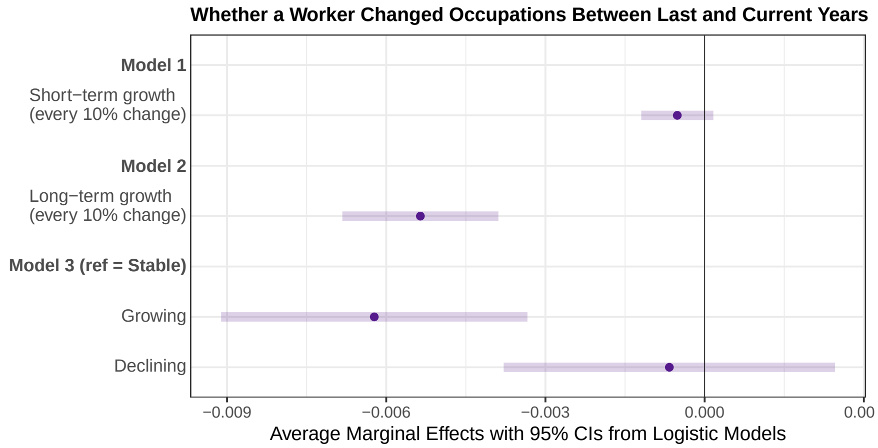

FIGURE 2. AVERAGE MARGINAL EFFECTS FROM LOGISTIC REGRESSIONS PREDICTING WORKERS' CHANGES BETWEEN OCCUPATIONS USING SHORT-TERM AND LONG-TERM OCCUPATIONAL GROWTH RATES AND CATEGORIES

Note: This plot displays the average marginal effects of occupational growth on the probability that a worker changes occupations between the last and current year. The logistic regression results are presented in *Appendix* Table F3. Error bars represent 95% confidence intervals for the average marginal effects. The continuous growth variables capture the effect of a 10% change in growth rates on this probability.

job disappearance. Instead, for many occupations, high LLM exposure leads to work transformation and augmentation rather than replacement. While rapidly growing occupations may attract worker inflows, this figure does not reveal the destinations of existing workers. Answering this question requires microdata tracking individual workers' occupational transitions over time.

II. Data

This paper links three data sources: administrative occupation-level employment trends, individual worker occupational transitions, and occupation characteristics (earnings and AI exposure levels) from 2018 to 2024. We first measure occupational restructuring using archived editions of the Bureau of Labor Statistics' Occupational Outlook Handbooks, which provide employment levels and 10-year projections for hundreds of detailed occupations. Next, to observe actual worker occupational transitions, we use the Current Population Survey Annual Social and Economic Supplement, which asks respondents whether their current job differs from their longest job in the prior year and, if so, to identify the previous occupation. This allows us to measure one-year occupational mobility. We code occupations using the 2010 Census classification and link them to OOH occupations via crosswalks. To focus on AI-accelerated restructuring, we restrict analyses to high-AI-exposure occupations (exposure score > 0.5) using the task-based measure from Eloundou et al. (2024), which quantifies the share of tasks exposed to LLMs or LLM-enabled tools (see *Appendix* C for additional details).

To evaluate mobility outcomes, we merge occupation-level median earnings from BLS Occupational Employment and Wage Statistics (OEWS), defining upward mobility as transitions to occupations with earnings at least 5% higher than the origin occupation. We also incorporate education data from O*NET to characterize occupations by typical credential requirements (less than high school through advanced degree). We discuss our modeling strategies in the online *Appendix* E.

III. Results

Our analyses proceed in three steps: (1) identify who moves by comparing mobility rates in growing versus declining high AI-exposure occupations; (2) determine where workers move by modeling destination choices; and (3) assess what they gain by evaluating whether transitions lead to upward mobility.

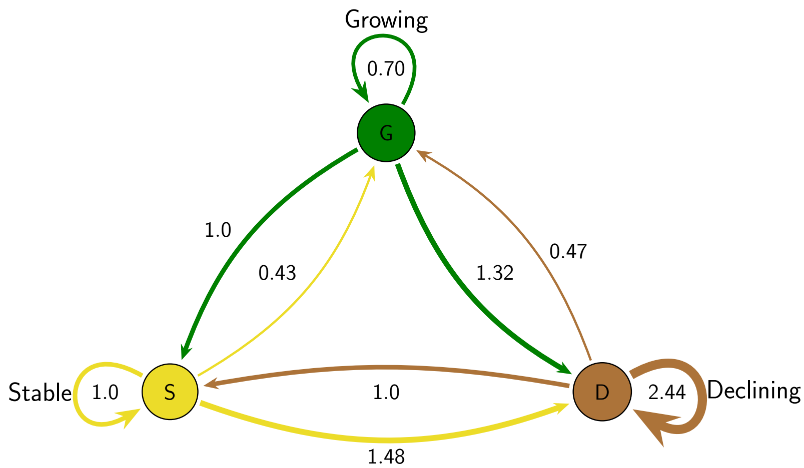

FIGURE 3. ODDS RATIOS FROM DISCRETE CHOICE MODELS PREDICTING OCCUPATIONAL TRANSITIONS BETWEEN DIFFERENT TYPES OF PROJECTED OCCUPATIONAL GROWTH CATEGORIES

Note: This plot displays odds ratios derived from the model estimates presented in *Appendix* Table F4, Model 4. For each origin group, the reference group consists of individuals who transition into stable occupations. By definition, the odds of transitioning from a growing or declining origin into a stable destination serve as the reference within each origin group and are set to 1.0. For example, OR = odds(Growing vs. Stable destination | Declining origin)/odds(Growing vs. Stable destination | Stable origin) = 0.47. That is, workers in declining occupations have 0.47 times the odds of moving to a growing (rather than stable) occupation compared to workers in stable occupations.

A. *Who Moves: Higher Mobility in Declining than Growing Occupations*

Figure 2 presents logistic regression results on how short-term (two-year) and long-term (ten-year projected) occupational growth affect workers' likelihood of changing occupations, controlling for demographics. Short-term growth shows no significant effect on mobility (see Appendix Table F3). Long-term growth reveals a notable pattern: when measured continuously, higher projected growth is associated with lower mobility, suggesting workers in fast-growing occupations tend to stay. Our categorical measure confirms this: workers in growing occupations are less likely to move than those in stable occupations, whereas workers in declining occupations show mobility similar to those in stable occupations. Compared to workers in stable occupations (10.1% annual mobility), those in growing occupations exhibit a slightly lower rate (9.5%), while those in declining occupations show an identical rate (10.1%). These findings indicate modest differences in mobility between growing and declining occupations. During 2000–2020, workers in growing and declining occupations were more mobile than those in stable occupations (Song et al., 2025). Recent data reveal a reversal: workers in growing occupations now exhibit lower mobility than those in stable or declining occupations, suggesting a shift from opportunity-seeking to stability-seeking behavior in the labor market.

B. *Where Workers Move: Trapped in Declining Occupations*

Next, we test whether occupational restructuring shapes where movers go, thereby creating different destination patterns for workers starting in growing versus declining occupations. Using discrete choice models of destination occupation (among workers who changed occupations in the CPS), we predict where individuals move as a function of both short- and long-term occupational growth, while controlling for worker characteristics and year effects. We also incorporate opportunity constraints by weighting destinations by occupation size (as a proxy for vacancy availability). As the results from short-term and long-term measures are similar (see *Appendix* F4), we present only the long-term measure results for year 2024 in Figure 3.

Two main patterns emerge from the long-term (10-year outlook) categories. First, mobility barriers exist between growing versus stable and declining occupations: workers are significantly less likely

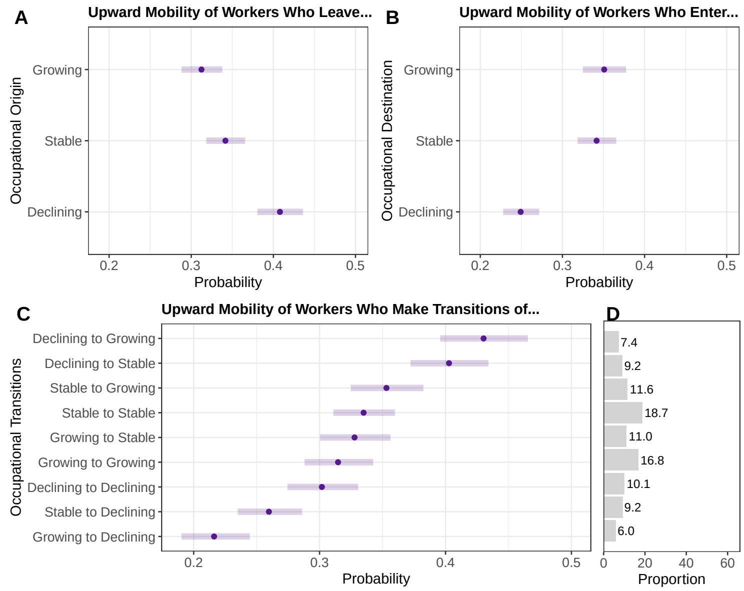

FIGURE 4. PREDICTED UPWARD MOBILITY PROBABILITIES FOR WORKERS IN DIFFERENT PROJECTED OCCUPATIONAL OUTLOOK CATEGORIES

Note: This graph reports predicted upward-mobility probabilities from Models 3 and 4 in *Appendix* Table F5, along with the share of workers making each type of move. The probabilities are estimated for non-Hispanic white workers who changed occupations within the last year, had a high school diploma as their highest level of education, and were in their prime working ages (between 35 and 56) in 2024.

to move into growing occupations than into stable or declining ones. For example, among workers coming from a stable occupation, the odds of moving into a growing destination relative to moving into a stable one are 0.43. Yet the odds of moving into a declining occupation rather than another stable occupation is 1.48.

Second, workers in declining occupations are “trapped.” They are far less likely to transition into growing occupations than to move laterally into other declining jobs. Substantively, the odds of moving from a declining origin into another declining destination are 5.2 times of the odds of moving from a declining origin into a growing destination ($= 2.44/0.47$, using stable destinations as the within-origin reference). Overall, the results confirm our mobility opportunity trap hypothesis: declining occupations are associated with constrained, largely lateral moves within declining sectors.

C. *Mobility Outcomes: Limited Upward Mobility for Workers in Declining Occupations*

Finally, we examine mobility outcomes of workers who successfully changed occupations using logistic models described in *Appendix* E. Results summarized in Figure 4 show that occupational transitions produce unequal economic returns depending on whether workers move into growing or declining fields. Upward mobility is defined as moving to a destination occupation whose median earnings are at least 5% higher than the origin occupation’s median earnings. As a reference, we estimate upward mobility probabilities for 2024 among non-Hispanic White workers with a high school education who are ages 35–56. On average, workers leaving declining occupations show a higher probability of upward mobility (about 41%) than workers leaving stable (about 34%) or growing occupations (about 31%). However, entering a declining occupation substantially reduces the chances of upward mobility: movers who enter declining fields are upwardly mobile about 25% of the time, compared to roughly 34% for movers entering growing or stable occupations.

Looking at transition types provides evidence consistent with the mobility trap hypothesis. Moves from declining origins to growing destinations are associated with the highest probability of upward mobility (43%), whereas moves from growing to declining destinations have the lowest probability (22%). Among workers who move from declining to declining occupations, only 30% experience upward mobility; 70% are downwardly mobile or experience no occupational earnings gains. At the same time, a substantial share of workers remain within the declining sectors: based on labor-force shares, 38% of workers who start in declining occupations and change occupations transition into another declining occupation, rather than into stable or growing destinations. Because transitions into declining destinations yield markedly lower chances of upward mobility than transitions into stable or growing destinations, this pattern suggests that workers in declining occupations face both constrained pathways and lower returns when they move.

IV. Discussion

Our findings suggest that the current wave of technological disruption has entrenched profound disparities across the labor market. The key implication is a pervasive "mobility trap" that challenges a traditional view that mobility primarily reflects moves to opportunity or the openness and fluidity of a society (Durlauf, Kourtellos and Tan, 2022; Erikson and Goldthorpe, 1992; Hout and DiPrete, 2006). While traditional economic models predict that workers should reallocate from contracting sectors to expanding ones (DiPrete, 1993), our evidence reveals the opposite: workers in declining occupations face substantial structural barriers to occupational opportunity. They are nearly 5.2 times more likely to transition into another declining field than into a high-growth occupation. This pattern suggests an increasingly bifurcated labor market, with "islands" of growth and "basins" of decline, with only limited and uneven bridges between them.

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Online Appendix

AI-Accelerated Occupational Decline and the Mobility Trap

This PDF file includes:

Supplementary Text

Figs. A1 to B1

Tables A1 to F5

References

Contents

Appendix A: Occupational Outlook Handbook

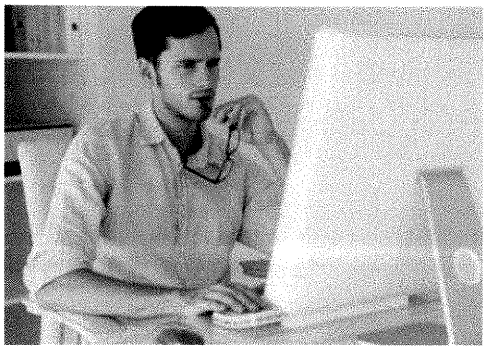
The Occupational Outlook Handbook (OOH) is a career resource with detailed job information designed to assist individuals in making decisions about their future work lives. Updated biennially, the OOH has been developed and maintained by the Office of Occupational Statistics and Employment Projections in the Bureau of Labor Statistics since 1949.

The OOH organizes occupational profiles in a standardized format to facilitate easy comparisons between occupations, although there are slight format variations from year to year. Using the OOH 2020-2030 as an example, each profile starts with key information such as median pay, entry-level education, job count, job outlook (growth rate), and employment size changes expected in the next decade. More detailed descriptions include job definitions, typical duties, work environment, work schedules, educational requirements, training, licenses, median pay, and other relevant characteristics. Figure A1 illustrates pages from the profile of computer programmers in the 2020–2030 Edition of OOH. Information used in our analysis includes the median pay, the number of jobs, projected employment change, and the job outlook percentage and its classification.

Computer Programmers

Summary

Quick Facts: Computer Programmers	
2020 Median Pay	$89,190 per year $42.88 per hour
Typical Entry-Level Education	Bachelor's degree
Work Experience in a Related Occupation	None
On-the-job Training	None
Number of Jobs, 2020	185,700
Job Outlook, 2020-30	-10% (Decline)
Employment Change, 2020-30	-18,300



Programmers spend most of their time writing and testing computer code.

What Computer Programmers Do

Computer programmers write and test code that allows computer applications and software programs to function properly.

Work Environment

Programmers usually work in offices, most commonly in the computer systems design and related services industry.

How to Become a Computer Programmer

Most computer programmers have a bachelor's degree; however, some employers hire workers with an associate's degree. Most programmers specialize in a few programming languages.

Computer programmers write programs in a variety of computer languages, such as C++ and Java.

Pay

The median annual wage for computer programmers was $89,190 in May 2020.

Job Outlook

Employment of computer programmers is projected to decline 10 percent from 2020 to 2030.

Despite declining employment, about 9,700 openings for computer programmers are projected each year, on average, over the decade. All of those openings are expected to result from the need to replace workers who transfer to other occupations or exit the labor force, such as to retire.

What Computer Programmers Do

Computer programmers write and test code that allows computer applications and software programs to function properly. They turn the program designs created by software developers and engineers into instructions that a computer can follow. In addition, programmers test newly created applications and programs to ensure that they produce the expected results. If they do not work correctly, computer programmers check the code for mistakes and fix them.

Duties

Computer programmers typically do the following:

- Write programs in a variety of computer languages, such as C++ and Java
- Update and expand existing programs
- Test programs for errors and fix the faulty lines of computer code
- Create and test code in an integrated development environment (IDE)
- Use code libraries, which are collections of independent lines of code, to simplify the writing

Programmers work closely with software developers, and in some businesses their duties overlap. When such overlap occurs, programmers can do work that is typical of developers, such as designing programs. Program design entails planning the software initially, creating models and flowcharts detailing how the code is to be written, writing and debugging code, and designing an application or systems interface.

A program's purpose determines the complexity of its computer code. For example, a weather application for a mobile device will require less programming than a social-networking application. Simpler programs can be written in less time. Complex programs, such as computer operating systems, can take a year or more to complete.

Software-as-a-service (SaaS), which consists of applications provided through the Internet, is a growing field. Although programmers typically need to rewrite their programs to work on different system platforms, such as Windows or OS X, applications created with SaaS work on all platforms. Accordingly, programmers writing SaaS applications may not have to rewrite as much code as other programmers do and can instead spend more time writing new programs.

Work Environment

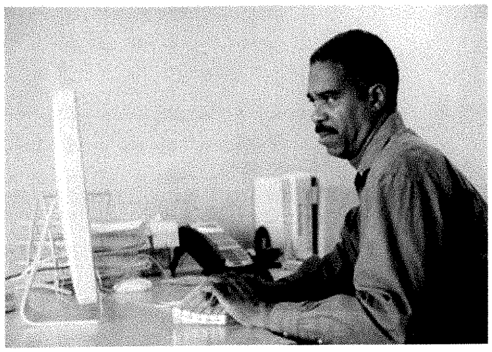
Computer programmers held about 185,700 jobs in 2020. The largest employers of computer programmers were as follows:

Computer systems design and related services	36%
Finance and insurance	8
Manufacturing	6
Software publishers	6
Self-employed workers	2

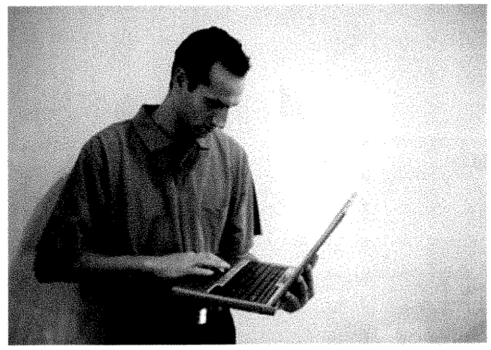
Programmers normally work alone, but sometimes work with other computer specialists on large projects. Because writing code can be done anywhere, many programmers work from their homes.

Work Schedules

Most computer programmers work full time.



Most programmers work independently in offices.



Most programmers have a degree in computer science or a related field.

How to Become a Computer Programmer

Most computer programmers have a bachelor's degree in computer science or a related subject; however, some employers hire workers with an associate's degree. Most programmers specialize in a few programming languages.

Education

Computer programmers typically need a bachelor's degree in computer and information technology or a related field, such as mathematics. However, some employers hire workers who have other degrees or experience in specific programming languages. Programmers who work in specific fields, such as healthcare or accounting, may take classes in that field to supplement their computer-related degree. In addition, employers value experience, which many students gain through internships.

Most programmers learn a few computer languages while in school. However, a computer science degree gives students the skills needed to learn new computer languages easily. Students get hands-on experience writing code, testing programs, fixing errors, and doing many other tasks that they will perform on the job.

To keep up with changing technology, computer programmers may take continuing education classes and attend professional development seminars to learn new programming languages or about upgrades to programming languages they already know.

Licenses, Certifications, and Registrations

Programmers can become certified in specific programming languages or for vendor-specific programming products. Some companies require their computer programmers to be certified in the products they use.

Advancement

Programmers who have general business experience may become computer systems analysts. With experience, some programmers may become software developers. They may also be promoted to managerial positions. For more information, see the profiles on computer systems analysts, software developers, and computer and information systems managers.

Important Qualities

Analytical skills. Computer programmers must understand complex instructions in order to create computer code.

Concentration. Programmers must focus their attention on their work as they write code or check existing code for errors.

Detail oriented. Computer programmers must closely examine the code they write because a small mistake can affect the entire computer program.

Troubleshooting skills. An important part of a programmer's job is to check the code for errors and fix any they find.

Pay

The median annual wage for computer programmers was $89,190 in May 2020. The median wage is the wage at which half the workers in an occupation earned more than that amount and half earned less. The lowest 10 percent earned less than $51,440, and the highest 10 percent earned more than $146,050.

In May 2020, the median annual wages for computer programmers in the top industries in which they worked were as follows:

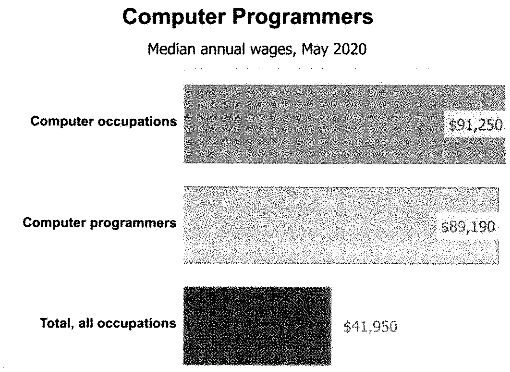
Software publishers	$103,710
Finance and insurance	92,390
Manufacturing	89,530
Computer systems design and related services	88,510

Most computer programmers work full time.

Job Outlook

Employment of computer programmers is projected to decline 10 percent from 2020 to 2030.

Despite declining employment, about 9,700 openings for computer programmers are projected each year, on average, over the decade. All of those openings are expected to result

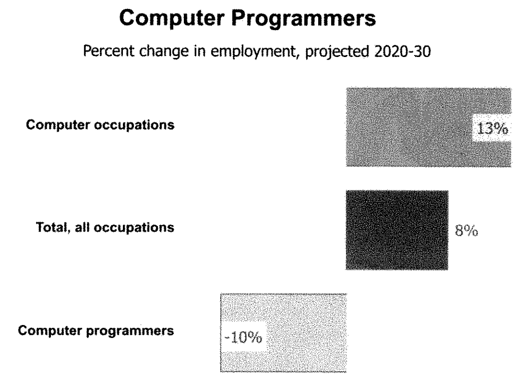


Note: All Occupations includes all occupations in the U.S. Economy.
Source: U.S. Bureau of Labor Statistics, Occupational Employment Statistics.

from the need to replace workers who transfer to other occupations or exit the labor force, such as to retire.

Employment

Computer programming can be done from anywhere in the world, so companies sometimes hire programmers in countries where wages are lower. This ongoing trend is projected to limit employment growth for computer programmers in the United States. However, the high costs associated with managing projects given to overseas programmers sometimes offsets the savings from the lower wages, causing some companies to bring back or keep programming jobs in the United States.



Note: All Occupations includes all occupations in the U.S. Economy.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Occupational Title	SOC Code	Employment, 2020	Projected Employment, 2030	Change, 2020-30	
				Percent	Numeric
Computer programmers	15-1251	185,700	167,300	-10	-18,300

Contacts for More Information

For more information about computer programmers, visit

➤ Association for Computing Machinery
➤ CompTIA
➤ IEEE Computer Society

For information about opportunities for women pursuing information technology careers, visit

➤ National Center for Women & Information Technology

Figure A1. Occupational Profile of Computer Programmers Described in the Occupation Outlook Handbook 2020–2030 Edition

Employment Estimates

Employment estimates for the current year in the OOH predominantly rely on data from the OEWS survey. For example, an estimated 52,000 individuals were employed as reporters, correspondents, and broadcast news analysts in 2019, as shown in Figure A1. The BLS administers the OEWS survey to about 400,000 establishments across all states and industries. The OEWS survey has been fielded as a nationally representative survey since 1996, superseding smaller surveys of establishments at the state and local levels. The OEWS is completed by the owners and management of selected firms. Large firms are categorized by industry according to the North American Industry Classification System (NAICS).

Each NAICS receives a different survey. Those surveys allow the management of large establishments to specify the number of employees and individual employee wages by occupation. The occupation list in the survey from which employers specify employee counts is establishment-specific. Establishments in different industries are given different potential occupation lists. The length of the occupation list ranges from 50 to 225, varying by the industry of the establishment. Small establishments simply list the occupations of their employees or list the tasks that employees complete on the job, with the BLS coding these tasks into occupations. All establishments specify interval wages for each employee.

Starting in 2002, the OEWS was run biannually, with 200,000 establishments sampled in May and 200,000 establishments sampled in November. Overall, about 1.1 million establishments are sampled over a three-year period. Certain firms are sampled with certainty once every three years, and no establishment is sampled more than once over that time period. Annual OEWS data releases are model-based estimates constructed from the previous three years of data. The OEWS estimates are weighted to be nationally representative. Weights are derived from broad industry and establishment-size groups using the Quarterly Census of Employment and Wages (QCEW) as a reference. The OEWS compares favorably with the Current Population Survey as a source of occupational employment statistics because establishment managers are likely more accurate in assessing employees' occupations than the workers themselves. The survey was not originally designed for time series use but can be adapted for such use with minor modifications (Spletzer and Handwerker 2014). The OEWS typically has a 20% nonresponse rate and published estimates rely on imputation.

Weighted estimates are believed to be representative by occupation, industry, and geography. Approximately 830 occupations are represented in the OEWS in a given year. Valid employment and wage estimates are available for all 3-digit industries, most 4-digit industries, and selected 5- and 6-digit industries. Estimates for employment and wages are also available for all states and MSAs, nonmetropolitan areas, and territories. The OEWS ignores self-employed workers, owners, and partners in unincorporated firms, household workers, or unpaid family workers.

Employment Projections

The OOH publications contain BLS's National Employment Matrix (NEM), which presents current employment and projected employment in the next ten years for SOC occupations.

Data in the NEM are primarily constructed from the establishment-based Occupational Employment and Wage Statistics (OEWS) Survey, which collects employment information of wage and salary workers by occupation and industry except for agricultural and self-employed workers. The NEM data also draw on estimates of the number of self-employed and unpaid family workers in each occupation from the Current Population Survey (CPS). Data from other sources may also be combined with OEWS and CPS to provide estimates of total employment in each OOH occupation. For example, the Office of Personnel Management (OPM) provides employment data on Federal Government workers. Some OOH occupations combine several SOC occupations in the NEM. For these reasons, employment numbers in the OOH are often different from employment data from OEWS, CPS, or other employment surveys.

Below we describe employment forecast procedures used in BLS's Occupational Employment Projections Data program. The OOH's typical range for forecasts is ten years, with alternative forecasts with a range of 1 to 13 years appearing occasionally. The Bureau of Labor Statistics (BLS) forecasts require six interrelated steps relying on assumptions and model input from the labor force, aggregated economy, gross domestic product by sector and product, industry output, industry employment, and job openings by occupation (Hogan and Roberts 2015). Figure A2 illustrates these steps. First, the BLS projects the size and demographic composition of the labor force. Second, they use a macroeconomic model to forecast aggregate economic growth. Third, they forecast each industry's final demand. Fourth, input-output relationships estimated from a separate model generate intermediate industry output. Fifth, industry-specific demands are used to estimate industry-specific employment. Finally, using estimated overall industry demand and employment and a matrix translating industry employment to occupational employment, the BLS estimates occupational employment trajectories. Each step is based on separate procedures, models, and related assumptions. BLS analysts approach the six inputs sequentially, as the results produced by each step are key inputs to the following steps and therefore must be reviewed and revised in order. In addition, the sequence may be repeated multiple times to allow feedback and ensure consistency of results. Each step is discussed in more detail below. These steps are summarized from the descriptions of the "Projections Methodology" in the 2018–2019 and 2020–2021 editions of the OOH.

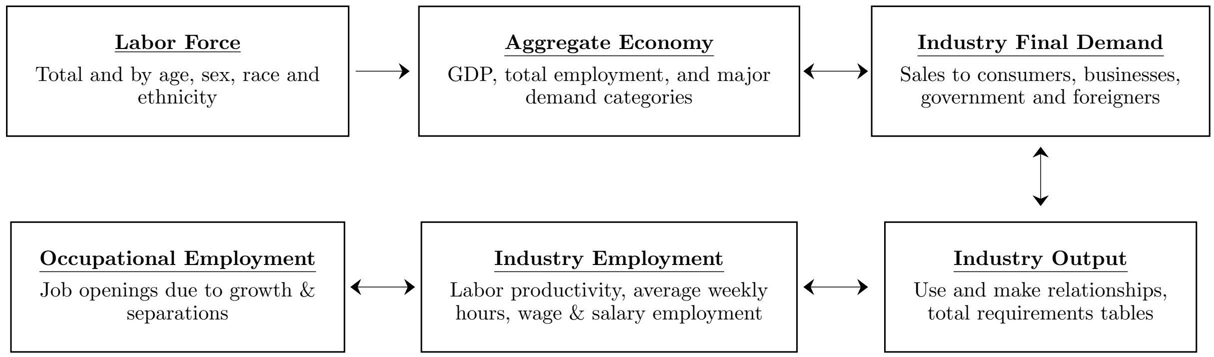


Figure A2. BLS's Flow Chart that Illustrates the Six-Step Process of the Projections of Occupational Employment

Notes: Double-headed arrows indicate the possibility of repeating certain steps multiple times, enabling feedback between the steps and ensuring consistent estimation. Further information regarding this process can be found in the BLS Handbook of Methods (2022).

Step 1: Project Labor Force Size To estimate the expected civilian labor force, the BLS starts with resident population projections produced by the Census Bureau and converts them to projections of the civilian, noninstitutional population. These projections (by age, sex, race, and ethnicity) are then multiplied by projected labor force participation rates for the corresponding demographic groups, estimated using the Current Population Survey. Summing across groups yields the projected total civilian labor force.

Step 2: Forecast Aggregate Economic Growth Starting with the 2012–22 projections, the BLS has used the MA/US model, licensed from Macroeconomic Advisers and distributed by IHS Markit (an information services provider). The MA/US system is designed to provide estimates of the GDP, the number of people engaged in productive activities within the economy, and other major demand categories such as spending by households on durable goods, nondurable goods, and services; business spending on physical capital such as new machinery, equipment, software, and the construction of new buildings or houses; expenditures by federal, state, and local governments on goods and services, such as public servant salaries, infrastructure, and defense; and a country's total exports and imports (Richards and Terkanian 2013).

Step 3: Forecast Industry Final Demand Using the macro model, the BLS forecasts aggregate gross domestic product (GDP) and its composition across major final-demand categories. These GDP projections constrain a "final demand" matrix that maps demand categories to commodity groups. The resulting commodity-level final demand is then aggregated to the industry level to produce initial estimates of industry demand. The BLS subsequently adjusts these estimates using internal research and review by industry experts.

Step 4: Estimate Industry Output GDP captures only the value of final goods and services purchased by final users, but many industries produce intermediate inputs that never appear as final demand. To translate projected final demand into the total (direct and indirect) production required across industries, the BLS uses an input–output (I–O) model.

The BLS I–O system includes a *use* matrix (inputs required by each industry) and a *make* matrix (commodities produced by each industry). Initial I–O estimates are based on historical relationships and the projected final demand matrix, and the BLS reviews and revises them to reflect evolving production technologies and input structures. For occupational projections, the I–O system is effectively used "in reverse": given projected final demand (from Step 3), the inverted I–O relationships produce implied intermediate and basic industry output levels across industries.

Step 5: Project Industry Employment Next, the BLS projects the industry employment required to produce the projected industry output from Step 4. Industry output is used in regression models to estimate total hours worked. The BLS then projects output per hour (labor productivity) for both wage-and-salary and salaried workers, drawing on evidence about technological and productivity trends. Combining projected output, projected hours, and projected productivity yields projected employment by industry.

Step 6: Project Occupational and Self-Employment Finally, the BLS converts projected industry employment into projected occupational employment using an industry–occupation staffing matrix. From 2004 onward, this mapping is referred to as the "National Employment Matrix." Employment patterns are primarily based on the Occupational Employment Statistics survey (collected on a multi-year cycle) and CPS-based estimates of self-employment. In more recent projection rounds, additional inputs come from the Quarterly Census of Employment and Wages (QCEW).

The treatment of self-employment differs across projection years. Prior to the 2012 OOH projections, self-employment was estimated separately using CPS data rather than being embedded in the industry–occupation matrix. From 2012 onward, the matrix is constructed to include detailed occupations covering wage-and-salary workers as well as the self-employed and private household workers.

For the projected year, BLS analysts review both quantitative evidence and qualitative information to identify structural changes (e.g., shifting technologies or employment practices) and to adjust occupational employment patterns accordingly. Projected self-employment is typically produced at a more aggregated occupational level than wage-and-salary employment.

Table A1. OOH Definitions of a Standard Set of Growth Adjectives

		A Standard Set of Occupational Growth Adjectives to Describe the 10-Year Employment Projection							
		Growing Occupations			Stable Occupations		Declining Occupations		
OOH Publication Year	Projected Employment Change Between	Much faster than average	Faster than average	As fast as average	Slower than average	Little or no change	Decline	Decline slowly or moderately	Decline rapidly
2019	2018-2028	Increase 11 percent or more	Increase 7 to 10 percent	Increase 4 to 6 percent	Increase 2 to 3 perccent	Decrease 1 percent to increase 1 percent	Decrease 2 percent or more	-	-
2020	2019-2029	Increase 8 percent or more	Increase 5 to 7 percent	Increase 3 to 4 percent	Increase 1 to 2 percent	Remain largely unchanged	Decrease 1 percent or more	-	-
2021	2020-2030	Increase 16 percent or more	Increase 11 to 15 percent	Increase 6 to 10 percent	Increase 2 to 5 percent	Decrease 1 percent to increase 1 percent	Decrease 2 percent or more	-	-
2022	2021-2031	Increase 11 percent or more	Increase 8 to 10 percent	Increase 4 to 7 percent	Increase 2 to 3 percent	Decrease 1 percent to increase 1 percent	Decrease 2 percent or more	-	-
2023	2022-2032	Increase 9 percent or more	Increase 5 to 8 percent	Increase 2 to 4 percent	-	Decrease 1 percent to increase 1 percent	Decrease 2 percent or more	-	-
2024	2023-2033	Increase 9 percent or more	Increase 6 to 8 percent	Increase 3 to 5 percent	Increase 1 to 2 percent	Increase less than 1 percent to decrease less than 1 percent	Decrease 1 percent or more	-	-
2025	2024-2034	Increase 7 percent or more	Increase 5 to 6 percent	Increase 3 to 4 percent	Increase 1 to 2 percent	Decrease less than 1 percent to increase less than 1 percent	Decrease 1 percent or more	-	-

Data sources: Occupational Outlook Handbook 2018-2019 Edition, 2019-2029 Edition, 2020-2021 Edition, 2020-2030 Edition, 2021-2031 Edition, 2022-2032 Edition, 2023-2033 Edition, and 2024-2034 Edition.

Notes: These growth adjectives are used by BLS to compare growth rates among different occupations within the same year. For some years, the growth adjective definitions do not differentiate between decline, decline slowly or moderately, and decline rapidly. The dash sign (-) means that the definitions of these growth adjectives are not available for that year. The employment size and projection data being referred to in the publication were collected two years before the publication year.

Appendix B: Occupational Classifications and Crosswalks

Occupational Classifications in the OOH

The OOH is widely used by career counselors, urban and local planners, workforce development agencies, policymakers, occupational organizations, and job seekers due to its detailed occupational classification scheme. Between 2018 and 2024, all occupations were assigned to consistent occupational classification codes based on the Standard Occupational Classification (SOC). Our analyses focus on 2018—2024, but we also use 2016 data to calculate the short-term (two-year) occupational change measure for 2018.

Each occupation receives a six-digit code: the first two digits identify the major group, the third digit the minor group, the fourth and fifth digits the broad occupation, and the sixth digit the detailed occupation. For example, “Family and General Practitioners” is coded as 29-1062: “29” denotes the major group “Healthcare Practitioners and Technical Occupations,” “1” denotes the minor group “Health Diagnosing and Treating Practitioners,” “06” denotes the broad occupation “Physicians and Surgeons,” and the final digit specifies the detailed occupation. The SOC has been updated periodically, with editions released in 1977, 1980, 2000, 2010, and 2018. The classification system has expanded over time. The number of major occupation groups increased from 21 in 1977 to 23 in 2018, while the number of detailed occupations grew from 662 in 1977 to 867 in 2018.

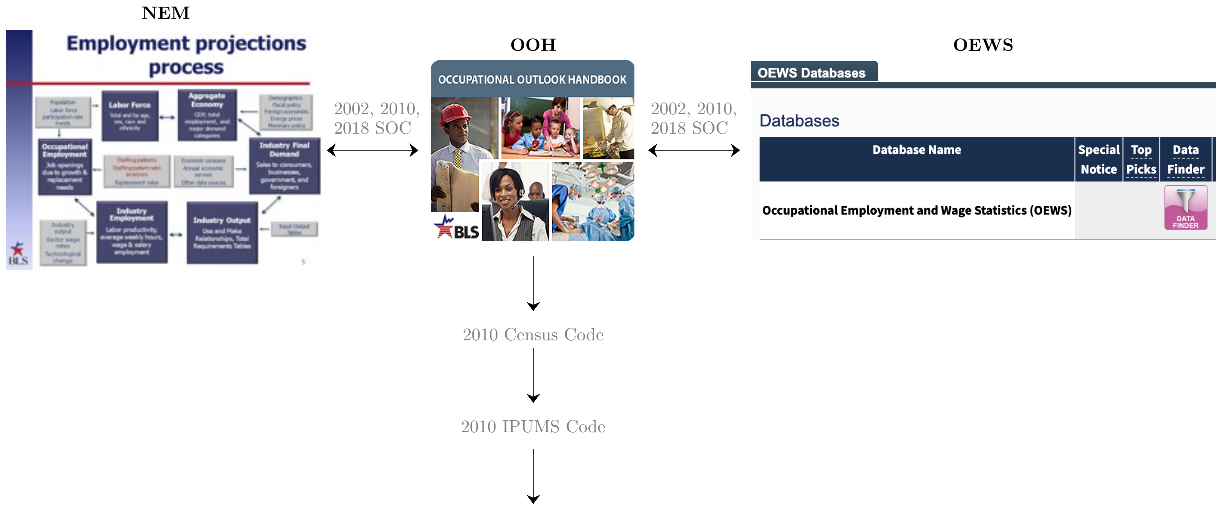


Table 1 – I&O Details for Current Job (Basic CPS) and Longest Job (ASEC Supplement)

Subject		Current Job (Basic CPS data)	Longest Job Last Year (ASEC data)
		Variable Name	
Industry	4-digit code	PEIOIND	INDUSTRY
	2-digit recode (detailed groups)	A_DTIND	WEIND
	2-digit recode (major groups)	A_MJIND	WEMIND
Occupation	4-digit code	PEIOOCC	OCCUP
	2-digit recode (detailed groups)	A_DTOCC	POCCU2
	2-digit recode (major groups)	A_MJOCC	WEMOCG
Class of Worker	Class of Worker	A_CLSWKR	LJCW

IPUMS Harmonized CPS-ASEC

Figure B1. Data Linking Procedures for Occupational Outlook Handbook (OOH), Occupational Employment and Wage Statistics (OEWS), National Employment Matrix (NEM), and the IPUMS Current Population Survey–Annual Social and Economic Supplement (CPS-ASEC)

Notes: The published OOH already integrates information from both NEW and OEWS. Our data linkage involves only crosswalking SOC codes in the OOH with the 2010 IPUMS occupation codes used in the CPS-ASEC.

Crosswalking OOH Occupations to Census Occupations

To merge the OOH occupation data with CPS occupation codes (Figure B1), we convert the occupational codes used in the OOH into the Census occupational codes used in the IPUMS CPS. The procedure involves the following steps.

Step 1: Attach SOC2010 and SOC2018 codes using OOH-SOC codes Because the SOC was updated in 2010 and 2018, the OOH 2016–2024 files contain a mix of SOC versions. Using the Census Bureau's 2010 and 2018 SOC code lists, we append the corresponding SOC2010 and SOC2018 codes as two separate variables to the OOH file.

Step 2: Impute missing SOC codes caused by minor coding differences Some OOH codes do not match the Census code lists exactly due to small differences (often in the last digit). In these cases, we harmonize by treating the OOH code as equivalent to the closest Census code. For instance, the OOH may list 13-1031 ("Claims Adjusters, Appraisers, Examiners, and Investigators"), whereas the Census SOC list includes 13-1030 for the same title; we treat 13-1031 as 13-1030.

Step 3: Fill in missing SOC2010 codes using SOC2018 crosswalks Some SOC occupations with valid SOC2018 codes may have missing SOC 2010 codes. We use crosswalk files prepared by the Census Bureau to update missing SOC2010 codes with non-missing SOC2018 codes.

Step 4: Convert SOC2010 to Census 2010 occupation codes CPS uses the Census occupational classification, which is based on SOC occupations but does not perfectly align with SOC codes. We therefore merge in Census 2010 occupation codes using the Census Bureau crosswalk file "2010-occ-codes-with-crosswalk-from-2002-2011,"[1] producing variables for the Census 2010 code (CEN2010) and its title.

Step 5: Convert Census 2010 codes to IPUMS-modified Census 2010 codes (OCC2010) The IPUMS CPS harmonizes CPS occupations using OCC2010, a standardized coding scheme based on Census 2010 codes. In some cases, OCC2010 collapses multiple Census detailed occupations to improve comparability over time. For example, Census codes 4700 ("First-Line Supervisors of Non-Retail Sales Workers") and 4710 ("First-Line Supervisors of Retail Sales Workers") are combined into OCC2010 code 4700 ("First-Line Supervisors of Sales

[1]The file can be download from https://www2.census.gov/programs-surveys/demo/guidance/industry-occupation/2010-occ-codes-with-crosswalk-from-2002-2011.xls (Accessed December 27, 2025.

Workers"). Following IPUMS guidance[2], we constructed a crosswalk between CEN2010 and OCC2010 by downloading IPUMS CPS data (2011–2019) containing both variables (OCC and OCC2010) and using the observed mappings to build the crosswalk. The final crosswalk is provided in the Excel file "crosswalk_CPS_OOH2002_2020.xlsx" on the project website.

[2] https://forum.ipums.org/t/occ2010-really-2010-census-occupations/3792

Appendix C: Measuring Occupation-Level AI Exposure

To measure AI exposure, we use the task-based exposure score developed by Eloundou et al. (2024), which assesses the extent to which large language models (LLMs) and LLM-enabled tools can reduce the time required to complete occupational tasks by at least 50% while maintaining equivalent quality. In Elnoundou et al.'s rubric, tasks are labeled E0 (no exposure), E1 (direct exposure via an LLM interface such as ChatGPT), or E2 (exposure via complementary LLM-powered software, e.g., tools that retrieve up-to-date information, search databases with internal company data, or process long documents). Task labels are assigned by both human annotators and GPT-4 and aggregated to occupations using weighted averages. We use the E1+E2 measure, which is interpreted as the share of tasks in an occupation exposed under full LLM and complementary software integration.

The exposure score ranges from 0 to 1 and is available for 932 O*NET-SOC occupations (mean $= 0.547$). After aggregating to Census occupations, the mean exposure score is 0.499. The original exposure data are available at https://github.com/openai/GPTs-are-GPTs/tree/main (accessed December 28, 2025), and our Census code-level aggregation is available on the project website. We define high AI-exposure occupations as those with scores above 0.5 and restrict our mobility analyses to workers whose origin occupations fall in this high-exposure group.

Appendix D: Measuring Workers' Occupational Mobility Using the Current Population Survey

Data Description

Our mobility analyses use microdata from the Current Population Survey Annual Social and Economic Supplement (CPS–ASEC) for 2018–2024 published through IPUMS (Flood et al. 2020). The CPS–ASEC has been extensively used in prior research on occupational mobility (e.g., Cheng and Park 2020; Ebenstein et al. 2013; Lin and Hung 2022). The CPS is a monthly household survey conducted jointly by the U.S. Bureau of Labor Statistics and the Census Bureau. It samples approximately 60,000 occupied households each month to provide nationally representative data on the civilian, noninstitutionalized U.S. population aged 15 and older (excluding those in the Armed Forces, prisons, long-term care hospitals, and nursing homes). The survey employs a rotating panel design: each household is interviewed for four consecutive months, rotates out for eight months, then returns for four additional months.

The CPS collects detailed information on labor force participation, employment status, unemployment, earnings, hours worked, and demographic characteristics. The Annual Social and Economic Supplement (ASEC), administered in February through April each year, extends the basic monthly survey with additional questions about the prior calendar year. The ASEC asks respondents to report their main (longest) job from the previous calendar year, which allows us to observe occupational changes over one-year periods.

Coding Issues

Kambourov and Manovskii (2013) identify several sources of bias in mobility estimates derived from the monthly CPS. The CPS employs two different occupational coding methods depending on interview timing. In the first and fifth months of a household's participation, respondents describe their main job activities (tasks and duties), and trained coders assign Census occupational codes based on these descriptions. During the remaining months (second through fourth and sixth through eighth), the CPS uses dependent coding: respondents are asked whether they (1) changed companies, (2) experienced changes in usual work activities and duties, and (3) confirm that the previous month's job description remains accurate. This dependent coding procedure substantially reduces observed occupational mobility rates.

However, Kambourov and Manovskii (2013) note that dependent coding can introduce systematic biases. Only individuals who remain with the same company, report no changes in work activities, and confirm the accuracy of their previous job description receive the same occupation code as the prior month. All others, including those who changed companies but not occupations, those reporting changed duties, and those indicating inaccuracies in previous descriptions, are coded independently. Because CPS interviews often rely on proxy respondents (household members answering for others), inaccuracies are common, leading to a substantial share of the sample being independently coded. This can result in overestimation of occupational mobility rates.

To avoid these measurement problems, we do not link monthly CPS data across waves. Instead, we use the CPS Annual Social and Economic Supplement (ASEC), which has employed dependent coding since 1970 but with a more reliable structure for measuring mobility. The ASEC asks respondents whether their longest job in the prior calendar year is the same as their current job (Question 46). If not, respondents provide details about that previous job, including occupation, industry, and class of worker (Question 47). This retrospective design yields more accurate measures of occupational transitions than linking independently coded monthly observations.

Appendix E: Models

Part I: Estimating Mobility Rates Using Logistic Regression Models

First, we follow DiPrete and Nonnemaker's (1997) regression method to examine who moves. Let P denote the probability that worker k in year t changes occupations and $\mathbf{X}$ denote the vector of possible individual-level characteristics known to affect occupational mobility rates. We assume that worker k is from occupation i, where $\mathbf{Z}_i$ denotes occupation-level characteristics for occupation i. The parameters α and β refer to the vectors of coefficients for the variables in $\mathbf{Z}_i$ and $\mathbf{X}$, including an intercept term. We specify the following equation to estimate the additive effects of structural dynamics and individual-level characteristics on the log odds of the probability of occupational mobility.

$$\frac{P}{1-P} = e^{\mathbf{Z}_i'\alpha + \mathbf{X}'\beta} \tag{1}$$

where the variables $\mathbf{Z}_i$ include (1) net change rate of occupational size (i.e., the net change in size of occupation i from time $t-2$ to time t, divided by the size of occupation i in time $t-2$), (2) projected growth rate over the next ten years, and (3) OOH definitions of occupational growth (i.e., outlook categories). Given that the value of z_{it} tends to be very small, we adjust the scale of these variables to reflect a 10% change. This transformation enhances the interpretability of the regression coefficients.

Part II: Estimating Discrete Choice Models with Occupational Size Constraints

We model occupational transitions using a discrete choice framework, which represents decision-making situations in which individuals select one option from a finite set of alternatives. The standard assumption is that individuals choose the alternative that yields the highest utility. This approach was introduced by McFadden (1973; 1974; 1978) and further developed in Ben-Akiva and Lerman (1985), Louviere et al. (2000), and Train (2003). In our setting, the choice set is the set of occupations (defined by SOC or Census codes), and the model characterizes how destination occupations are selected from the available alternatives.

Model Structure and Data Format

We implement a single-choice discrete choice model in which each individual selects one destination occupation. Table E1 illustrates the required data structure. Each individual (k) currently employed in occupation i is represented by multiple rows (J), where each row corresponds to a potential destination alternative. This creates a "person-alternative" data structure in which the J alternatives constitute the individual's choice set. Individual-level characteristics (X_k), such as education, remain constant across all rows for a given person, while alternative-specific attributes (Z_{ij}), such as occupational outlook and median earnings, vary across destination options.

Table E1. Data Structure for Estimating Discrete Choice Models

Person ID	Origin Occupation	Alternative Occupations	Destination Occupation	Origin Outlook	Alternative Outlook	Origin Earnings	Alternative Earnings	Education	Choice
1	200	1	210	Growing	Growing	60000	80000	HS	0
1	200	2	210	Growing	Growing	60000	70000	HS	0
...	...	...	...	...	...	...	...	...	...
1	200	210	210	Growing	Stable	60000	65000	HS	1
...	...	...	...	...	...	...	...	...	...
1	200	1000	210	Growing	Declining	60000	40000	HS	0
2	200	1	530	Declining	Growing	35000	80000	Below HS	0
2	520	2	530	Declining	Growing	35000	70000	Below HS	0
...	...	...	...	...	...	...	...	...	...
2	520	530	530	Declining	Stable	35000	35000	Below HS	1
...	...	...	...	...	...	...	...	...	...
2	520	1000	530	Declining	Declining	35000	40000	Below HS	0

Sample Construction

We restructured the CPS individual-level mobility data into discrete choice format. The original dataset contains 46,765 movers (workers who changed occupations) and 454 possible destination occupations. After reshaping, each mover is represented by 454 rows (one for each potential destination), yielding 454 * 46,765 person-alternative observations. We then restricted the sample by excluding observations from odd years and cases with missing occupational characteristics, resulting in a final analytical sample of 2,024,618 person-alternative observations.

Model Specification

In standard discrete choice models, the outcome Y_{kij} is an indicator variable denoting whether individual k currently in occupation i chooses destination occupation j. Let U_{kij} represent the latent utility that individual k derives from choosing occupation j, and let P_{kij} denote the probability of this choice, where $\sum_{j \in J} P_{kij} = 1$.

Utility depends on occupation characteristics (potentially interacted with individual sociodemographic traits) and unobserved factors. Occupation characteristics $\mathbf{Z}_{ij}$ include occupational outlook and median earnings. Individual characteristics $\mathbf{X}_k$ include demographic attributes such as age, sex, race, ethnicity, and education. The term $\boldsymbol{\phi}_{kij}$ captures unobserved factors affecting individual k's preference for occupation j. Thus, individual utility can be expressed as:

$$U_{kij} = F(\mathbf{Z}_{ij}, \mathbf{X}_k, \boldsymbol{\phi}_{kij}) \tag{2}$$

Standard estimation assumes that unobserved characteristics $\boldsymbol{\phi}_{kij}$ follow a type I extreme value (Gumbel) distribution, yielding the multinomial logit probability:

$$P_{kij} = \frac{\exp(\mathbf{Z}_{ij}\boldsymbol{\gamma} + \mathbf{X}_k\boldsymbol{\beta}_j)}{\sum_{j \in J} \exp(\mathbf{Z}_{ij}\boldsymbol{\gamma} + \mathbf{X}_k\boldsymbol{\beta}_j)} \tag{3}$$

Incorporating Occupational Size Constraints

A limitation of the standard discrete choice model for occupational mobility is that it ignores variation in occupation size or job vacancies, implicitly assuming these are irrelevant to the mobility process. However, the availability of job opportunities, whether occupations are growing or declining, can substantially affect mobility decisions and outcomes.

To address this, we introduce destination occupation size constraints $\mathbf{D}_{kj}$ into the model. We assume that occupational mobility probability is proportional to the *product* of destination opportunities and worker preferences:

$$P_{kij} \propto \underbrace{\mathbf{D}_{kj}}_{\substack{\text{destination}\\ \text{size constraints}}} \cdot \underbrace{U_{kij}}_{\substack{\text{worker}\\ \text{utility}}} \tag{4}$$

This multiplicative specification modifies equation (3) as follows:

$$P_{kij} = \frac{\mathbf{D}_{kj} \cdot \exp(\mathbf{Z}_{ij}\boldsymbol{\gamma} + \mathbf{X}_k\boldsymbol{\beta}_j)}{\sum_{j \in J} \mathbf{D}_{kj} \cdot \exp(\mathbf{Z}_{ij}\boldsymbol{\gamma} + \mathbf{X}_k\boldsymbol{\beta}_j)} \tag{5}$$

We refer to equation (5) as the occupational mobility model with opportunity constraints. This represents a weighted mixed logit model in which utility $\exp(\mathbf{Z}_{ij}\boldsymbol{\gamma}+\mathbf{X}_k\boldsymbol{\beta}_j)$ is weighted by the opportunity structure $\mathbf{D}_{kj}$. The model can be estimated using standard mixed logit software by including $\log(\mathbf{D}_{kj})$ as an offset variable with its coefficient fixed at 1. In our main analysis, we use occupation-level employment size as the empirical measure of $\mathbf{D}_j$.

Part III: Estimating Upward Mobility Using Logistic Regression Models

Finally, we explore the vertical aspect of mobility by determining the type of occupational movements that result in upward mobility (versus downward mobility or immobility). We categorize downward mobility and mobility to another occupation with similar median earnings as the reference category because these moves generally do not involve positive consequences for workers' living conditions and are often involuntary. We model whether an individual moves from a lower-paying to a higher-paying job using a binary logistic regression. Upward mobility is defined as moving to a destination occupation whose median earnings are at least 5% higher than the origin occupation's median earnings.

Let $P(y = \text{upward})$ denote the probability that worker k in year t achieves upward mobility following an occupational change. Let $\mathbf{X}$ be a vector of individual-level characteristics associated with occupational mobility, and $\mathbf{Z}_i$ be occupation-level characteristics of the origin occupation i. The parameter vectors α and β correspond to the coefficients on $\mathbf{Z}_i$ and $\mathbf{X}$, respectively. Following the modeling strategy in Part I, we estimate the following model:

$$\frac{P(y = \text{upward})}{1 - P(y = \text{upward})} = e^{\mathbf{Z}_i'\alpha + \mathbf{X}'\beta} \tag{6}$$

where variables in $\mathbf{Z}_i$ include (1) net change rate of occupational size (i.e., the net change in size of occupation i from time $t-2$ to time t, divided by the size of occupation i in time $t-2$), (2) projected growth rate over the next ten years, and (3) OOH definitions of occupational growth (i.e., outlook categories). Given that the value of z_{it} tends to be very small, we adjust the scale of these variables to reflect a 10% change. Except for the outcome variable and the analytic sample, the model specification is identical to that in equation (1).

Appendix F: Main Analyses

Table F1. Occupational and Demographic Characteristics of Workers in the Current Population Survey

	All Workers	Stayers	Movers
	A. Occupational Characteristics		
Occupational Growth Rate Over the Last Two Years, %	0.26	0.29	-0.08
	(18.12)	(18.14)	(17.93)
Projected Occupational Growth Rate Over the Next Decade, %	3.02	3.09	2.35
	(8.32)	(8.31)	(8.47)
Projected Occupational Outlook Categories, %			
Growing	36.60	36.92	33.76
Stable	38.93	38.86	39.54
Declining	24.47	24.22	26.70
Occupation-Level Earnings in 2024 Dollars	91,465.50	92,656.01	80,615.29
	(48,443.61)	(48,784.81)	(43,747.85)
	B. Demographic Characteristics		
Age Group, %			
15–35	31.97	30.91	41.68
36–56	50.73	51.47	43.99
56–65	17.30	17.63	14.33
Gender, %			
Male	47.12	47.27	45.75
Female	52.88	52.73	54.25
Race, %			
White	78.96	79.35	75.34
Black	9.52	8.97	14.49
Asian and Others	11.53	11.68	10.17
Hispanics, %			
Yes	14.94	14.83	15.96
No	85.06	85.17	84.04
Levels of Education, %			
Below High School	3.07	2.88	4.75
High School	18.23	17.66	23.46
Some College	24.91	24.50	28.70
BA and Above	53.78	54.96	43.10
N	244,262	220,111	24,151

Data sources: Occupational Outlook Handbook 2018–2024; Occupational Employment and Wage Statistics 2018–2024. Current Population Survey Annual Social and Economic Supplement (CPS-ASEC) 2018–2024.

Notes: Numbers in parentheses are standard deviations for continuous variables. All workers include workers who did not change occupations (stayers), those who changed occupations (movers), and those who became unemployed or exited the labor force. Movers refer to workers who reported occupational changes between the last and current calendar years in CPS-ASEC. The occupational growth rate over the last two years is defined as the percent employment change between two OOH years. The projected occupational growth rate over the next decade is defined as the projected percent change in employment over the projection's decade. The OOH crosswalks between projected occupational growth rate and growth categories (growing, stable, and declining occupations) are included in Appendix Table A1.

Table F2. Occupational and Demographic Characteristics of Workers in the Current Population Survey

	Occupational Characteristics		
	Growing	**Stable**	**Declining**
Occupational Growth Rate Over the Last Two Years, %	0.87	1.79	-3.06
	(17.95)	(13.05)	(10.68)
Projected Occupational Growth Rate Over the Next Decade, %	11.04	2.63	-9.12
	(6.85)	(1.98)	(6.31)
Current Employment Size	410,173	337,998	275,437
	(646,649)	(600,539)	(635,674)
Projected Employment Size	451,638	346,958	257,355
	(706,282)	(616,323)	(595,867)
Occupation-Level Earnings in 2024 Dollars	71,162.30	65,626.64	49,817.66
	(34,057.81)	(33,783.52)	(19,838.94)
Number of Occupation-Years	870	1,102	629

Data sources: Occupational Outlook Handbook 2018–2024; Occupational Employment and Wage Statistics 2018–2024.

Notes: Numbers in parentheses are standard deviations for continuous variables. The occupational growth rate over the last two years is defined as the percent employment change between two OOH years. The projected occupational growth rate over the next decade is defined as the projected percent change in employment over the projection's decade. The OOH crosswalks between projected occupational growth rate and growth categories (growing, stable, and declining occupations) are included in Appendix Table A1.

Table F3. Coefficients from Logistic Regression Models Predicting Occupational Changes Using Occupation-Level and Workers' Characteristics

	Whether a Worker Changed Occupations Between Last and Current Calendar Years		
	(1)	(2)	(3)
Occupational Growth Rate Over the Last Two Years	-0.006		
	(0.004)		
Projected Occupational Growth Rate Over the Next Decade		-0.061***	
		(0.009)	
Projected Occupational Outlook Categories (ref: Stable)			
Growing			-0.071***
			(0.017)
Declining			-0.007
			(0.018)
Workers' Characteristics	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Number of Observations	244,262	244,262	244,262

Data sources: Current Population Survey Annual Social and Economic Supplement 2018–2024; Occupational Outlook Handbook 2018–2024; Occupational Employment and Wage Statistics 2018–2024. We keep only even years as the OOHs were published every other year.
Notes: The occupational growth rates over the last two years and over the next decades are quantified by increments of 10 percent. All models include workers' characteristics and year dummies as controls. Workers' characteristics include age, gender, race, ethnicity, and education.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; two-tailed tests.

Table F4. Coefficients from Discrete Choice Models Predicting Occupational Destinations Using Occupation-Level and Workers' Characteristics

	Whether a Worker Moved into an Occupation in the Choice Set			
	(1)	(2)	(3)	(4)
Occ. Dest. Growth Rate Over the Last Two Years	-0.426***			
	(0.049)			
Occ. Dest. Projected Growth Over the Next Decade		-0.659***		
		(0.051)		
Occ. Dest. Projected Outlook Category (ref: Stable)				
Growing			-0.765***	-0.848***
			(0.096)	(0.097)
Declining			0.537***	0.392***
			(0.091)	(0.093)
Occ. Origin t *** Occ. Dest.** $t+1$				
Growing * Growing				0.493***
				(0.037)
Growing * Declining				-0.111*
				(0.044)
Declining * Growing				0.084*
				(0.042)
Declining * Declining				0.501***
				(0.041)
Workers' Characteristics	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Occupational Size Constraint	Yes	Yes	Yes	Yes
Number of Workers	24,027	24,027	24,027	24,027
Number of Observations	10,458,628	10,458,628	10,458,628	10,458,628

Data sources: Current Population Survey Annual Social and Economic Supplement 2018–2024; Occupational Outlook Handbook 2018–2024; Occupational Employment and Wage Statistics 2018–2024. We keep only even years as the OOHs were published every other year.
Notes: The discrete choice models are described in equations (3)-(5). The occupational growth rates over the last two years and over the next decades are quantified by increments of 10 percent. All models control for workers' characteristics and year dummies, which are added as interactions between these variables and the characteristics of occupations in the choice set. Workers' characteristics include age, gender, race, ethnicity, and education.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; two-tailed tests.

Table F5. Coefficients from Logistic Regression Models Predicting Upward Mobility Using Occupation-Level and Workers' Characteristics

	Whether a Mover Experienced Upward Mobility (5% or More Increase in Occupation-Level Earnings)			
	(1)	(2)	(3)	(4)
Occ. Origin Growth Rate Over the Last Two Years	-0.028***			
	(0.008)			
Occ. Dest. Growth Rate Over the Last Two Years	0.003***			
	(0.0004)			
Occ. Origin Projected Growth Rate Over the Next Decade		-0.216***		
		(0.017)		
Occ. Dest. Projected Growth Rate Over the Next Decade		0.302***		
		(0.017)		
Occ. Origin Projected Outlook Categories (ref: Stable)				
Growing			-0.133***	-0.033
			(0.033)	(0.051)
Declining			0.284***	0.292***
			(0.034)	(0.053)
Occ. Dest. Projected Outlook Categories (ref: Stable)				
Growing			0.041	0.080
			(0.032)	(0.050)
Declining			-0.447***	-0.361***
			(0.036)	(0.056)
Occ. Origin t *** Occ. Dest.** $t+1$				
Growing * Growing				-0.140*
				(0.071)
Growing * Declining				-0.208*
				(0.091)
Declining * Growing				0.033
				(0.081)
Declining * Declining				-0.083
				(0.083)

…continued

	Whether a Mover Experienced Upward Mobility (5% or More Increase in Occupation-Level Earnings)			
	(1)	(2)	(3)	(4)
Workers' Characteristics	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Intercept	-0.976***	-0.967***	-0.933***	-0.962***
	(0.080)	(0.081)	(0.082)	(0.084)
Number of Observations	24,151	24,151	24,151	24,151

Data sources: Current Population Survey Annual Social and Economic Supplement 2018–2024; Occupational Outlook Handbook 2018–2024; Occupational Employment and Wage Statistics 2018–2024. We keep only even years as the OOHs were published every other year.

Notes: Upward mobility is defined by whether the destination occupation's median earnings are at least 5% higher than the origin occupation's median earnings. The occupational growth rates over the last two years and over the next decades are quantified by increments of 10 percent. All models include workers' characteristics and year dummies as controls. Workers' characteristics include age, gender, race, ethnicity, and education.

$^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; two-tailed tests.

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