BUILDING BETTER PATHWAYS:

An Analysis of Career Trajectories and Occupational Transitions

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Abt Associates

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Table of Contents

List of Exhibits

List of Boxes

Executive Summary

Many employment and training programs focus not just on how to help individuals get a job, but on how to help them advance from low-wage jobs to higher-paying ones and attain self-sufficiency. The growing visibility of the career pathways approach (including in legislation and federal grant programs, as well as among programs) highlights the workforce field's focus on participants' longer-term career outcomes.

The Career Pathways Approach

Career pathways are a workforce development strategy designed to promote long-term earnings advancement for less educated workers. The approach involves a combination of rigorous and high-quality education, training, and other services to support participant success (Workforce Innovation and Opportunity Act, 2014). It has four main tenets (e.g., see Fein, 2012; Werner et al., 2013):

- Offers ***articulated steps*** in an industry sector, offering multiple places to enter and exit training
- Results in ***recognized credentials*** intended to lead to better jobs with higher pay
- Uses ***support services*** and provides ***flexibility*** needed for non-traditional students
- Relies on ***employer connections*** and partnerships

To help inform the occupations for which they develop programs and the content of those programs, career pathways programs often rely on labor market information. That information describes the occupations themselves but does not describe what happens to individuals who hold those jobs over time, including whether they see increases in wages.

This Career Trajectories and Occupational Transitions (CTOT) Study, sponsored by the U.S. Department of Labor and conducted by Abt Associates, has developed novel information on workers' actual economic advancement prospects and pathways. The information is intended to support training programs' design decisions aimed at promoting participants' advancement over the course of their careers. This report focuses on "mid-level" occupations—occupations that typically require education or experience beyond a high school diploma or equivalent, but less than a four-year college degree.

Study Approach

This study's research questions focus on understanding workers' career trajectories and occupational transitions as they occur in the labor market. Specifically, this report addresses the following research question:

(1) *From which occupations do entrants tend to go on to experience higher-than-average wage increases over time (i.e., which are more reliable "launchpads" to advancement)?*

a. *Which characteristics distinguish launchpad occupations?*

b. *To what extent is there variation in whether occupations are launchpads for workers with different backgrounds or experiences?*

The study used panel surveys that follow individuals for decades to examine wage growth 10 years after workers entered these occupations. From that data, the trajectories analyses describe several patterns related to career trajectories:

- Variation in trajectories: how much of a difference exists among occupations in the wage growth that "entrants" go on to experience, and which occupations tend to be more promising launchpads for wage growth over time.
- Characteristics of occupations: factors that predict wage growth, such as occupational cluster and skill and licensing requirements.
- Characteristics of workers: demographic and other factors that predict wage growth, including identifying disparities in wage growth among workers with different backgrounds.

Summary of Findings

The study yields findings about variation in wage growth from mid-level occupations, characteristics that distinguish launchpad occupations, and variation in wage growth among workers with different backgrounds and experiences. The findings are summarized as such:

- There is meaningful variation in wage growth trajectories among workers starting in mid-level occupations. Assuming a starting wage of $20, entrants to launchpad occupations earn about $7.20 more per hour after 10 years compared to those who enter lower-wage-growth occupations.
- Several characteristics distinguish launchpad occupations:
    - Though launchpad occupations can be found across occupational clusters, workers who enter occupations in "Knowledge" clusters such as Information Technology, Management/Finance, and Engineering/Science/Architecture see the highest average wage growth.
    - Launchpad occupations emphasize transferrable skills such as problem solving and two-way communication.
    - Problem solving is not just foundational for advancement, but also a skill that becomes more important as workers advance occupationally. Skills in managing people also become more important as workers advance to higher paying occupations.
- The following career experiences are associated with wage growth:
    - Frequent job changes (seven or more over a 10-year period) are associated with lower wage growth.
    - Leaving the starting occupational cluster is associated with greater wage growth.
- Wage growth varies for workers with different backgrounds or experiences in the following ways:
    - Among workers who start in the same mid-level occupation:

  - Women tend to experience lower wage growth than men do.
  - Hispanic and Black workers tend to experience lower wage growth than White non-Hispanic workers do.
  - Workers with higher levels of education tend to experience higher wage growth than those without a high school diploma or equivalent.
  - Workers who have a parent with a college degree tend to experience higher wage growth than those whose parents do not have a college degree.
- Workers that experience lower wage growth also spend fewer months working.
- When they make an occupational transition, women and Black and Hispanic workers are less likely to advance to higher-level jobs, and more likely to stay in the same occupational cluster.

Implications of Findings for Programs and Policy and for Future Research

The study findings lead to several general implications for policymakers and those designing and implementing career pathways, as well as other employment and training programs with similar employment goals for participants.

Focus training more on occupations that tend to be stronger launchpads for wage growth. Programs have many considerations to weigh when determining occupations for which to offer training. Given how much occupations differ in the typical wage growth that entrants experience, incorporating career trajectories data into those considerations may help career pathways programs achieve their aims to promote participants' long-term career advancement and self-sufficiency. Because launchpad occupations can be found across many occupational clusters, there are likely to be opportunities to target launchpad jobs in any local labor market.

Design programs to build participants' broader transferable skills, not just specialized technical skills. Career pathways programs must consider which skills to emphasize. The findings suggest that designing programs to help participants build key transferable skills such as problem solving and communication may better position them to advance along a range of different advancement pathways.

Consider structural and other barriers facing specific demographic groups. The study finds disparities in wage trajectory by gender, race/ethnicity, and socioeconomic status of workers' family of origin—even among workers starting in the same occupation and who are otherwise similar. Though the study is not designed to determine causality, it is important for programs to consider that, once placed in a job, participants of different backgrounds are likely to face different career advancement challenges. Strategies to address these barriers could include interventions at the program-level, such as longer-term services to assist workers in making upward transitions beyond their first mid-level step, or broader policies, such as policies that directly address wage disparities (e.g., minimum-wage increases, unionization) or those that address broader barriers directly related to gender, race/ethnicity, or socioeconomic status.

As a supplement to existing labor market information, it may be valuable to build data systems that can provide workforce practitioners occupation-specific wage trajectory estimates with large samples that can be updated over time. Such estimates could be produced by merging larger sources of nationally representative data on workers' occupations with longitudinal data on earnings from tax or Unemployment Insurance files. These data files would permit estimates for smaller occupations and more localized labor markets.

These findings also imply several directions for further research, including research on the following questions:

- What can workers' experiences in the labor market tell us about barriers to advancement? How might career pathways programs address those disparities?
- How do individual-level skills associate with advancement?
- How does individual workers' labor market knowledge associate with advancement? How might COVID-19 influence patterns of trajectories and transitions?

This report's companion volume *Appendix on Occupational Cluster Findings for Healthcare, Early Care and Education, Information Technology, and Production* https://www.dol.gov/agencies/oasp/evaluation/currentstudies/Career-Pathways-Descriptive-and-Analytical-Study and the accompanying *Career Trajectories and Occupational Transitions Dashboard* https://www.dol.gov/agencies/oasp/evaluation/resources/career-trajectories-and-occupational-transitions-dashboard also provide more detailed information about career trajectories and occupational transitions for specific occupational clusters and occupations.

Together with traditional labor market information, this new kind of labor market information can inform design of training programs in ways that could enhance their ability to generate more positive economic outcomes for participants over time.

Glossary

Destination occupation: When a worker transitions between occupations, the new occupation is the "destination" occupation. Compare with *source occupation*.

Entrant: A worker who takes a job in an occupation for the first time. Most career pathways program completers are likely to be occupation entrants.

Industry sector: A group of industries that share common attributes. For example, the hospital industry, pharmaceutical industry, and laboratory testing industry share a common focus on wellness; they are all inside the "Healthcare" industry sector. Other industry sectors include Financial Services, Retail, and Manufacturing**.** Industry sector and *occupational cluster* are related but not the same. Industry sector is about the employer; occupational cluster is about the job. For instance, although most Healthcare sector jobs are with healthcare employers, not all are. Nurses working in an emergency room or physician practice represent healthcare occupations in the Healthcare industry sector. But school nurses are a healthcare occupation outside the Healthcare industry sector. Similarly, nearly every company, not just those in the Information Technology sector, has employees who work in occupations related to information technology.

Job: A specific role of employment (e.g., Retail Salesperson at a department store). An individual might transition from one job to another job in the same occupation (e.g., to Retail Salesperson at a car dealership). Compare with *occupation.*

Launchpad occupation: An occupation from which entrants go on to experience higher-than-average wage growth.

Mid-level occupation: An occupation that requires some postsecondary preparation (whether formal or informal) but does not necessarily require a four-year college degree.

Occupation: A set of jobs with a common role and set of characteristics (e.g., Registered Nurse). An individual might transition from one job (e.g., Registered Nurse at a hospital) to another job in the same occupation (e.g., Registered Nurse at a different hospital or nursing home). (A Registered Nurse who returns to school for a business degree and transitions to a Hospital Administrator job has changed occupations.) Compare with *job.*

Occupational cluster: Set of related occupations in the same field (e.g., Healthcare or Construction), typically defined using major occupational categories from the Census and Standard Occupational Classification (SOC) System. Occupational cluster and *industry sector* are often related but are not the same. Occupational cluster is about the job; industry sector is about the employer. Clusters can fall within or across industry sectors. For example, most workers in Healthcare occupations (e.g., Registered Nurses, Nursing Assistants, Medical Assistants, etc.) are employed in the healthcare industry (e.g., in a hospital or physician practice). But some workers in Healthcare occupations are employed outside the healthcare industry; for example, School Nurse is a Healthcare occupation, but school nurses are employed in the education industry.

Source occupation: When a worker transitions between occupations, the original occupation is the "source" occupation. Compare with *destination occupation*.

Starting occupation: For purposes of this study in analyzing career trajectories, the occupation an individual is working in during the beginning of the observation period.

Trajectory: Where entrants are in the years after they first start a job in an occupation; described in terms of wage growth as well as other outcomes such as time spent not working, new degrees obtained, and whether they stay in the same occupational cluster.

Transition: A job change from working in one occupation (the “source” occupation) to working in a different occupation (the “destination” occupation).

Wage growth: For purposes of this study, the amount an entrant’s wage increases over the 10-year period this study examines. *High wage growth* refers to wage increases that are higher than average; *low wage growth* refers to wage increases that are lower than average but are still an increase from the entrant’s starting wage. In this report, high-wage-growth occupations are termed *launchpad occupations*.

Wage trajectory: The course that workers’ wages take over time as they change jobs and occupations.

Chapter 1. Introduction

Many employment and training programs focus not just on how to help individuals get a job, but on how to help them advance from low-wage jobs to higher-paying ones and attain self-sufficiency.[1] The growing visibility of the career pathways approach (including in legislation and federal grant programs, as well as among programs) highlights the workforce field's focus on participants' longer-term career outcomes. But labor market shifts in recent decades have changed the landscape of economic opportunity and introduced challenges to workers' career advancement prospects. Over the last 40 years, adults with a high school education or less have experienced stagnating wages and relatively high unemployment, whereas those with postsecondary credentials have experienced economic gains (Autor, 2015; Carnevale et al., 2016). Shifts in the occupational structure have also changed which skills are valued in the labor market (Acemoglu & Restrepo, 2021; Deming, 2017).

Career pathways programs, as well as other employment and training programs, often rely on labor market information to help inform the occupations for which they develop programs and the content of those programs. This information is valuable for identifying occupations where job opportunities are likely to be available. In fact, many training programs succeed in increasing the receipt of occupational credentials for their participants and in helping them enter an occupation in the targeted field (Peck et al., 2021). But programs have to date been less successful in improving earnings, particularly over the longer term (Peck et al., 2021; Gardiner & Juras, 2019).[2] One factor that could contribute to this result is that some occupations may be more promising entry points for career pathways programs than others because those occupations provide a more effective path to long-term career advancement. However, existing labor market information generally describes characteristics within each occupation, rather than the likely paths a worker's career will take from those occupations.

Sponsored by the U.S. Department of Labor and conducted by Abt Associates, this **Career Trajectories and Occupational Transitions (CTOT) Study** has developed **novel information on workers' actual economic advancement prospects and pathways**. The information is intended to support training programs' design decisions aimed at promoting participants' advancement over the course of their careers. This report focuses on "mid-level" occupations—occupations that typically require education or experience beyond a high school diploma or equivalent, but less than a four-year college degree.

The report presents study findings on:

- the magnitude of the differences between occupations in the career outcomes that entrants go on to experience within 10 years after entering
- which occupations are associated with high wage growth
- what traits of occupations predict higher wage growth

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1 See Holzer (2021) for a review of workforce development approaches, including those that focus on advancement.

2 Studies vary in the time frame at which they measure impacts, but a meta-analysis for this project (Peck et al., 2021) found a lower likelihood of impacts beyond three years.

The report also examines how career outcomes of entrants to an occupation vary among entrants with different characteristics.

About the Descriptive & Analytical Career Pathways Project

Career pathways are a workforce development strategy designed to promote long-term earnings advancement for less educated workers. The approach involves a combination of rigorous and high-quality education, training, and other services to support participant success (Workforce Innovation and Opportunity Act, 2014). It has four main tenets (e.g., see Fein, 2012; Werner et al., 2013):

- ***articulated steps*** in an industry sector (or occupational cluster), offering multiple places to enter and exit training and jobs
- ***recognized credentials*** intended to lead to better jobs with higher pay
- ***support services*** and ***flexibility*** needed for non-traditional students
- employer connections and partnerships

The Workforce Innovation and Opportunity Act emphasizes the use of career pathways programs and requires the U.S. Department of Labor (DOL) to conduct a study to develop, implement, and build upon career advancement models and practices. In order to respond to the need for information and evidence in the field due to this growing emphasis, DOL's Chief Evaluation Office, in collaboration with the Employment and Training Administration, contracted with Abt Associates to conduct the Descriptive & Analytical Career Pathways Project. The project's purpose is to advance the evidence base in the career pathways field by addressing key research gaps, drawing primarily on existing data, to inform career pathways systems and program development to help meet the needs of both participants and employers.

The project builds on earlier work Abt Associates conducted for DOL under the **Career Pathways Design Study** (see Sarna & Strawn, 2018; Schwartz et al., 2018), which scanned career pathways research and practice, interviewed stakeholders, and pointed to ways to fill evidence gaps (Peck et al., 2018).

1.1 Background on the Career Trajectories and Occupational Transitions Study

What sets the CTOT Study apart is that it describes the reality of how workers advance in the labor market. Specifically, it examines the actual ***career trajectories*** that entrants to an occupation go on to experience over 10 years and the specific ***occupational transitions*** that workers make as they move from one occupation to another (see box on **Key Concepts**.) The study's analyses of trajectories focus particularly on wage growth, but also consider length of unemployment and how many workers return to school to earn postsecondary degrees. The trajectories analyses help identify which occupations appear to be more reliable launchpads for career advancement. The study's transitions analyses help uncover common pathways to show how workers typically advance.

Key Concepts

Career trajectory. This term describes where entrants to an occupation end up in the years after they first take a job in the occupation. The analysis focuses particularly on how much wage growth workers go on to experience, but also considers how much formal education they go on to obtain, how much unemployment they experience, how many job changes they make, and how likely they are to stay within the same occupational sector. Advancement in wage growth could be steady, or there could be periods of earnings instability, including unemployment.

Occupational transition. The term describes a change a worker makes from one occupation to another at a particular point in their career. Occupational transitions provide an opportunity for wage growth, though not all transitions are to higher-paying jobs. In general, career pathways programs seek to put participants an on upward trajectory by targeting a defined series of occupational transitions, often with the expectation that entering one occupation (e.g., Certified Nursing Assistant) will lead to subsequent transitions to higher-paying occupations within the same field (e.g., Licensed Practical Nurse, Registered Nurse).

Occupational cluster. We use this term to describe a set of related occupations. Our set of "occupational clusters" is based on the broad occupational categories used by the Census and Standard Occupational Classification (SOC) System. For purposes of this study, some of our clusters are combinations of more than one broad category, when useful for coherence or sample size. For example, our "Healthcare" cluster includes both Healthcare Practitioners and Technical Occupations (SOC 29) and Healthcare Support Occupations (SOC 31).

1.1.1 OCCUPATIONAL INFORMATION FOR EMPLOYMENT AND TRAINING PROGRAMS

The CTOT Study is part of the Descriptive & Analytical Career Pathways Project (see **About** box on previous page), the purpose of which is to inform career pathways systems and program development to help meet the needs of workers and employers. The CTOT Study aims to fill a research gap identified by the study team under the Career Pathways Design Study[3] by providing more information about how workers move through their careers, particularly in occupational clusters typically targeted by career pathways programs. CTOT's analysis yields insights about medium- to long-term (up to 10 years) experiences of workers in the labor market generally that could help career pathways and other employment and training programs target occupations and design programs to support participants' advancement.

Recent evaluations of career pathways programs underscore the need for such labor market information. Studies show career pathways programs commonly succeed in helping participants complete the first step of an education pathway—training needed to enter a new occupation (Gardiner & Juras, 2019; Strawn & Sarna, 2018). But the pay in those first-step occupations typically is not very high, and programs have had less success in helping participants to advance subsequently to additional training, higher-level credentials, and higher-paying jobs. For example, a meta-analysis of 46 career pathways programs (completed as part of this project) found that though career pathways programs were effective at increasing educational progress and employment in the targeted sector, on average, program participants made only small or negligible gains in employment and earnings, particularly in the medium/long term (Peck et al., 2021).[4]

[3] See Peck et al. (2018). Full reports from the Career Pathways Design Study can be found on the website of DOL's Chief Evaluation Office: https://www.dol.gov/agencies/oasp/evaluation/completedstudies.

[4] Peck and colleagues classify "short term" as earnings through the first 35 months after program entry and "medium/long term" as earnings measured after 36 or more months.

These findings raise two important questions:

- Could career pathways programs and other employment and training programs be more effective in promoting participants' long-run wage growth if they targeted occupations where entrants (in the typical labor market) tend to go on to experience stronger wage growth?
- Could career pathways and other employment and training programs improve outcomes for workers if more information on the specific occupational steps associated with advancement were available?

Career pathways and other employment and training programs use a range of labor market information. Available sources of labor market information, such as *Occupational Outlook Handbook*, the Occupational Employment and Wage Statistics (OEWS) program, and O*Net Online, focus on the occupation itself.[5] For example, these sources may describe the median wages in an occupation, how many job openings exist, and how many new jobs are expected to be available in the occupation in the future. That is valuable information for training programs to have, to help ensure that they are training participants for occupations where they are likely to be able to find a job and to access information about likely wages.

But career pathways programs focus not just on the occupation that participants will enter immediately after finishing a training, but on their advancement over the course of their careers.[6] Programs structure their training and related services with some assumptions about how participants are likely to advance through the labor market (either on their own or with additional training). Without data on what typically happens after an individual enters a given occupation, however, those assumptions may be off base. It may be that prospects for advancement vary across occupations—some may typically be strong launchpads for future growth whereas others tend to be dead ends.

For example, a program may be targeting one occupation based on its entry wages or the number of job opportunities available, when a different, similar occupation actually leads to higher wage growth over time. Or a program may identify a certain occupation as the second step in a pathway from a particular entry-level (first-step) occupation, when one or more other occupations are actually more common (and possibly more feasible) upward steps for workers who leave the entry-level occupation. Exhibit 1-1 describes how such information differs from and can supplement the information traditionally available.

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[5] These traditional sources of labor market information can be found at https://www.bls.gov/ooh/, https://www.bls.gov/oes/, and https://www.onetonline.org/, respectively.

[6] As described in subsequent sections, this analysis focuses on outcomes over the 10 years after which an individual enters an occupation.

Exhibit 1-1. Limitations of Traditional Labor Market Information

What type of labor market information do programs typically have?	What additional occupational information might programs potentially need or find useful?
Data that describe the occupation and its incumbents: For example: • Median wages in the occupation • Number of jobs in the occupation • Projected number of job openings in the occupation • Characteristics of workers who are currently in the occupation	Data that show workers' economic outcomes in the years after they first enter an occupation, irrespective of whether they stay in that occupation. For example: • How much wage growth do entrants to the occupation typically experience over time? • How many leave the occupation? • When they change occupations, where do they go? • How often does advancement involve going back to earn more credentials?

Note: Typical sources of labor market information include Occupational Outlook Handbook, the Occupational Employment and Wage Statistics (OEWS) program, and O*Net Online.

1.1.2 CTOT STUDY OVERVIEW AND RESEARCH QUESTIONS

The CTOT Study was designed to describe the ways in which workers advance in the labor market generally, outside of career pathways interventions, generating information to inform future career pathways program development. This study analyzes the patterns of career progress of workers in large, mid-level occupations—occupations that require some education or experience beyond high school, but less than a four-year college degree. Those often are the kinds of occupations for which training programs aim to prepare participants.

This study's research questions focus on understanding workers' career trajectories and occupational transitions as they occur in the labor market. Specifically, this report addresses the following research question:

(1) *From which occupations do entrants tend to go on to experience higher-than-average wage increases over time (i.e., which are more reliable "launchpads" to advancement)?*

   a. *Which characteristics distinguish launchpad occupations?*

   b. *To what extent is there variation in whether occupations are launchpads for workers with different backgrounds or experiences?*

This report's companion volume *Appendix on Occupational Cluster Findings for Healthcare, Early Care and Education, Information Technology, and Production* https://www.dol.gov/agencies/oasp/evaluation/currentstudies/Career-Pathways-Descriptive-and-Analytical-Study and the accompanying *Career Trajectories and Occupational Transitions Dashboard* https://www.dol.gov/agencies/oasp/evaluation/resources/career-trajectories-and-occupational-transitions-dashboard also address a second research question:

(2) *What are the common patterns of transitions from occupations?*

   a. *How do occupations vary in how likely it is that workers move to a higher-paying occupation when they leave?*

   b. *For any given occupational transition, which common destinations represent upward wage mobility?*

The CTOT Study aims to provide labor market information about potential transitions and pathways to target. This information can be used for program design in conjunction with other information, such as indicators of local demand. No study or data source could specify occupations that are *certain* to lead to career advancement for participants of career pathways or other training programs. Integrating information from this study, however, could lead to approaches that are better informed by workers' real-world experiences.

1.2 Insights from Prior Research

Career pathways and other employment and training programs often work with individuals who are earning low incomes or are currently working in low-paying[7] jobs to help them advance to "mid-level" jobs—jobs that require some education or training beyond high school but less than a four-year degree. Research on the changing composition of the labor market and patterns of upward mobility provide context for the CTOT Study. Much existing research focuses on overall labor market conditions, including worker mobility generally, the value and importance of training and education, and which factors are linked to workers' experiences.

Defining a "Mid-Level" Job

In this report, we refer to "mid-level" jobs as those that require education or training beyond high school, but less than a four-year degree.

Other literature refers to these jobs as "middle-skill," but many jobs commonly referred to as "low-skill" do indeed require substantial skills of a kind (Lowrey, 2021), though maybe not formal preparation or experience. For that reason, this report uses the term *level* rather than *skill.*

However, in this section's discussion of existing literature we sometimes use "low-skill" or "middle-skill" to preserve the study authors' original intent.

1.2.1 CHANGES IN THE STRUCTURE OF OCCUPATIONS

Existing research on overall labor market trends for workers in low-wage jobs has potential implications for career pathways initiatives. As described in this section, the literature (spanning the past two decades) reflects three broad themes that are important to this study. First, there are many job opportunities in occupations that require little or no education or training beyond high school, but they often pay low wages. Second, it is often difficult for workers to advance from those occupations. Finally, there are fewer occupations now than in the 1970s and 1980s that can propel workers to the middle class that do not require at least some postsecondary education.

The availability of jobs that can support a household and require only a high school education has shrunk.

In the first half of the 20th century, the U.S. labor market included a substantial number of jobs that offered family-sustaining wages and did not require any education beyond high school, particularly in the manufacturing sector (Carnevale, Cheah, et al., 2019; Novta & Pugacheva, 2019). But in recent decades those kinds of jobs have increasingly disappeared, and lower-paying service jobs have grown in their place (Autor & Dorn, 2013). Access to jobs that pay a family-sustaining wage tend to require at least some education beyond a high school credential (Carnevale, Strohl, et al., 2018).

[7] For more information on target populations for career pathways programs, including common designations around incomes, see Schwartz et al. (2018).

Implications for This Analysis

- Labor demand changes have made it difficult for workers to achieve self-sufficiency without postsecondary education or training
- Mid-level occupations may be a route to economic opportunity, but their promise likely varies across fields and types of credentials
- Employers are demanding different skills than in the past
- It is important to understand disparities in the career trajectories of workers from different demographic or socioeconomic backgrounds.

Mid-level occupations may be a route to the middle class, though the prospects are unclear.

A four-year college degree is often emphasized as the route to economic opportunity,[8] but some researchers have argued that many occupations that require less than four years of postsecondary training represent promising entry points to careers with family-sustaining wages (e.g., Fuller et al., 2014; Carnevale, Strohl, et al., 2018). Other research finds that that the pool of "middle-skill" jobs may be shrinking, rather than growing (Autor, 2010). Analyses differentiating among middle-skill occupations show heterogeneity, with some newer middle-skill occupations expanding, while older ones decline (Holzer, 2015; Autor, 2019).

Prospects for growth in middle-skill jobs in the future are uncertain. The technological changes that have driven many labor demand trends in recent decades are expected to continue to influence changes in occupations and wages (Dubina et al., 2020). Though some of the COVID-19 pandemic's impacts on employment in different occupations are likely to be temporary, it has accelerated the adoption of new technologies that may have more lasting impacts on occupational growth and opportunity (McKay et al., 2019; Sedik & Yoo, 2021).

Regardless of whether the number of mid-level jobs grows or shrinks, a job in a mid-level occupation could be a stepping-stone to a job in a higher-level one. But it is unclear how often jobs in mid-level occupations are an entry point to advancement to higher-level occupations and how often they are a destination. Nor is it clear how much wage growth workers in mid-level occupations experience if they stay in those jobs.

Postsecondary credentials to help enter mid-level occupations are associated with positive career outcomes, relative to a high school diploma, but returns may be uneven.

An associate's degree or occupational credential is required to enter some mid-level occupations. Those educational credentials are key predictors of earnings and advancement. For example, one study found that median lifetime earnings are 30 percent higher for workers with associate's degrees, compared to workers with only a high school diploma (Carnevale et al., 2011). However, there is substantial variation in earnings depending on sector (Jepsen et al., 2014).

Occupational certificates can also have positive returns, but those returns appear to vary depending on the length of the training and the occupational cluster (Belfield & Bailey, 2017). Some research shows that long-term certificates (defined as those that require six months of training or more) appear to be associated with improved labor market outcomes (Carnevale, Ridley, et al., 2018; Jacobson & Mokher, 2009). Further, some research suggests that certificates may have a higher payoff for young, low-income workers, on average increasing earnings after completion by almost 20 percent relative to previous earnings (Carnevale, Strohl, et al., 2018). One study found that certificates in healthcare occupations were associated with the highest growth in wages, whereas business certificates were associated with

[8] The high cost of four-year degrees—in money and time—makes those degrees harder to attain for individuals from low-income backgrounds, as indicated by the fact that low-income students with top-quartile math scores are no more likely to graduate college than are high-income students whose math scores are in the second-to-lowest quartile (Kena et al., 2015).

the highest overall earnings (Carnevale, Ridley, et al., 2018). Evidence also suggests, however, that short-term certificates do not result in the strong labor market improvements of longer-term certificates (Dadgar & Trimble, 2012; Jepsen et al., 2014). Compared to certificates, however, associate's degrees are more likely to be associated with increases in employment, living wages, and continued growth in earnings (Belfield & Bailey, 2017; Dadgar & Trimble, 2012; Jepsen et al., 2014; Minaya & Scott-Clayton, 2017).

1.2.2 FACTORS ASSOCIATED WITH CAREER ADVANCEMENT

Though workers in low-wage jobs face challenges in advancing to higher-paying jobs, some factors indicate whether advancement is more or less likely. As described in this section, research on how workers advance from low-wage jobs can help identify the factors associated with that advancement. Existing evidence indicates several related factors: job/occupation changes and industry conditions, additional education and training, and worker characteristics.

Workers appear likely to need to change occupations to achieve wage growth.

For low-wage workers, changing occupations and industries results in greater relative upward mobility, more so than just changing jobs within the same occupation (Boushey, 2005). Some industries may offer greater potential for upward mobility than others. Mitnik and Zeidenberg (2007) found that of the jobs in 10 different service industry sectors, three of those sectors (banking, hospitals, and schools) offer a high proportion of higher-wage jobs. The proportion of workers in poverty-wage jobs in these three sectors is less than 18 percent. In contrast, they found that more than 50 percent of jobs in the service sector (e.g., restaurant, grocery, and childcare) pay poverty-level wages. The nursing, hotel, and retail clusters also have a higher percentage of poverty-wage jobs (40 percent) than middle-wage jobs (less than 30 percent).

But even in industries where workers have greater room to move up, whether those in lower-wage occupations in those industries can advance to higher-wage occupations is an open question. Higher- and lower-wage occupations are very different in the skills required. For example, in the finance industry, lower-wage jobs may be clerical, whereas higher-wage jobs may be in analysis and require much higher levels of education and very different skills.

Other research focuses on advancement prospects by occupational cluster. Jobs within an occupational cluster may be more similar in skill requirements than are jobs within an industry. Schultz's (2019) analysis found that service jobs, across industries, had the least mobility of low-wage work. For the purposes of informing the selection of occupational training by career pathways programs, findings on advancement from mid-level occupations are most relevant. Analyses by the non-profit Jobs for the Future suggest that middle-skill manufacturing has become one of the most unfavorable occupational clusters, with more than 60 percent of workers in static, low-wage jobs (Lamback et al., 2018).

The types of skills that the labor market rewards are shifting.

Across occupations, the types of skills required may be an important factor in how likely a job is to offer advancement opportunities. Work that consists of routinized tasks is increasingly performed by machines, meaning there are fewer occupations where specific routinized skills are needed (Autor et al., 2003). In contrast, non-routine skills such as problem solving and advanced communication may be comparatively more important, as tasks that require these skills cannot be done by machines (Levy & Murnane, 2013).

Jobs in science, technology, engineering, and mathematics (STEM) fields have featured prominently in the public discourse about areas of economic opportunity (Jacobson & Mokher, 2009). But social skills may be as or more important than specific technical skills for accessing opportunity. Since 1980, the share of jobs in occupations with a low social skills emphasis have declined over time; that includes jobs that require low social skills and high math skills (Deming, 2017). Concurrently, wages have grown in occupations that require more social skills, whereas wages have not grown in occupations that require high math skills without requiring social skills. Occupations that require good judgment and decision-making have also seen more job and wage growth (Deming, 2021). This aligns with what employers say they want from workers coming out of postsecondary education and training programs—specifically, that they need workers with occupation-specific knowledge and broad transferable skills in critical thinking, creativity, and communication (Hart Research Associates, 2013; National Association of Colleges and Employers, 2020).

As noted above, the COVID-19 pandemic may have accelerated automation, as employers sought to limit the number of in-person workers, likely resulting in some industries seeing greater and longer-lasting shifts in employment opportunities than others (Holzer, 2021). As a result, skills needed for non-routine tasks may be increasingly more valuable.

Workers of color and women face barriers to advancement.

Workers' labor market outcomes, such as employment rates, wages, and overall earnings, are heavily conditioned by gender, race/ethnicity, age, and socioeconomic background (Bertrand & Mullainathan, 2003; Boushey, 2005; Carnevale, Strohl, et al., 2018; Neumark et al., 2017; Quillian et al., 2017; Young, 2013; Schultz, 2019; Pager, 2003; The Pew Charitable Trusts, 2010). To some degree, those disparities are driven by differences in which occupations individuals of different races and genders hold (Goldin, 2014; Gould et al., 2016). For example, gender differences in wages between occupations reflect the composition of the workforce in those occupations; female-dominated fields pay less when accounting for job characteristics (Foster et al., 2020) and specific skills (Bol & Heisig, 2021).

However, disparities may also exist in career advancement outcomes along those same axes among entrants to a given occupation. Possible reasons for such disparities include bias in staff development and promotion (Pager et al., 2009), differences in likelihood of obtaining further educational credentials (Landivar & Berkhusen, 2019), or systematic differences in social networks and access information about labor market options that support transitions to higher-paying jobs (Pedulla & Pager, 2019).

Many experts believe that if the pandemic has increased automation, it could hit women and workers of color especially hard due to the occupations in which they tend to work (Albanesi & Kim, 2021; Broady et al., 2021; Sedik & Yoo, 2021). Proposed federal investments in physical and caregiving infrastructure may also affect occupations and workers in different ways. At the time of this report's writing, however, it is not clear how those investments may unfold.

1.3 How the Report Is Organized

This report primarily addresses the study's first research question: *From which occupations do entrants tend to go on to experience higher-than-average wage increases over time (i.e., which are more reliable "launchpads" to advancement)?* Accordingly, the remainder of this report consists of the following:

- Study Approach, Methodology, and Overview of Data (Chapter 2)
- Characteristics that Distinguish Launchpad Occupations (Chapter 3)
- Wage Growth Variation for Workers with Different Backgrounds or Experiences (Chapter 4)

- Discussion & Implications (Chapter 5)

The report also includes the following technical appendices that provide more detail on data, methods, and findings:

- A: Data Sources
- B: Dataset Construction
- C: Analytic Methods
- D: Three-, Five-, and 10-Year Regression Estimates of Predictors of Wage Growth and Other Outcomes
- E: Map of Occupational Codes to Clusters
- F: Full List of Occupations by Starting Wage and 10-Year Wage Growth Percentile Quadrant
- G: Estimates of 10-Year Wage Growth Predictors, with Other Trajectory Outcomes as Predictors

The report's companion volume *Appendix on Occupational Cluster Findings for Healthcare, Early Care and Education, Information Technology, and Production* addresses the study's second research question: *What are the common patterns of transitions from occupations?*

More details at the occupational cluster and individual occupation levels are also available through the CTOT Study's accompanying Career Trajectories and Occupational Transitions Dashboard at https://www.dol.gov/agencies/oasp/evaluation/resources/career-trajectories-and-occupational-transitions-dashboard.

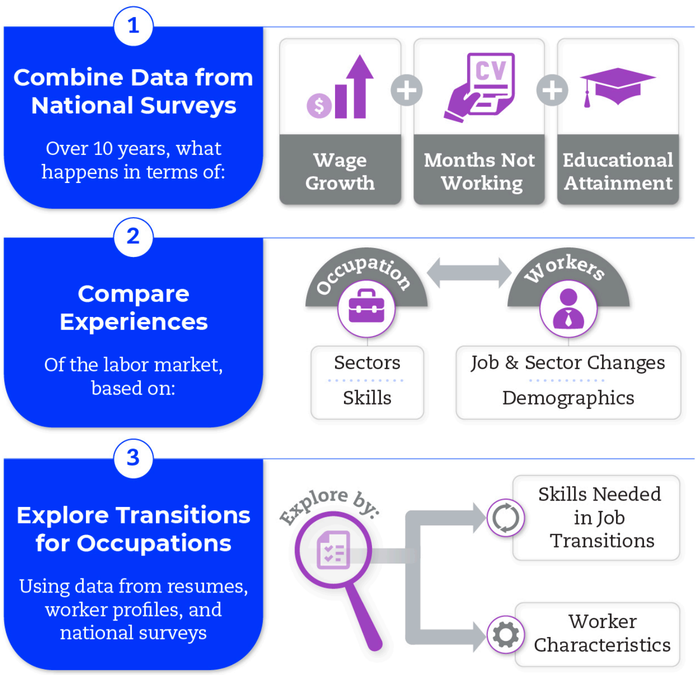
Chapter 2. Study Approach, Methodology, and Overview of Data

This CTOT Study analyzes the patterns of career progress of workers in large, mid-level occupations—occupations that require some education or experience beyond high school, but less than a four-year college degree. Those often are the kinds of occupations that training programs aim to prepare participants for.

The study used panel surveys that follow individuals for decades to examine wage growth 10 years after workers entered these occupations. From that data, the trajectories analyses describe several patterns in career trajectories:

- Variation in trajectories: how much of a difference exists among occupations in the wage growth that "entrants" go on to experience, and which occupations tend to be more promising launchpads for wage growth over time.
- Characteristics of occupations: factors that predict wage growth, such as occupational cluster and skill and licensing requirements.
- Characteristics of workers: demographic and other factors that predict wage growth, including identifying disparities in wage growth among workers with different backgrounds.

Exhibit 2-1. Overview of Data Approach



To better understand the mechanisms behind these career trajectories patterns, the study also documents other details of aspects of workers' experiences after they first take a job in an occupation: the number of months spent without a job, and how many entrants earn a postsecondary degree during the observation period.

This chapter describes the study's approach and research design. (Full details of the analytic methods we use are elaborated in this report's technical appendices A-G.) Section 2.1 gives an overview of the data that the study uses. Section 2.2 describes how the study analyzes workers' **career trajectories**. Section 2.3 describes how the study analyzes **occupational transitions**.[9] Together these analyses produce

[9] The transitions findings presented in this report are used to explore possible mechanisms that explain variation in workers' trajectories; the same data set and analytical approach is used to describe transitions associated with individual occupations in this report's Appendix on Occupational Cluster Findings for Healthcare, Early Care and Education, Information Technology and Production and the accompanying Career Trajectories and Occupational Transitions Dashboard.

insights into career advancement patterns in the labor market that are relevant to program design choices faced by career pathways and other employment, education, and training programs.

2.1 Overview of Data Sources

The ideal data source to examine career trajectories and occupational transitions would contain longitudinal data on individual job histories and wages. The sample of workers would be very large, nationally representative, and as current as possible. Because no single data source meets all those requirements, we brought together multiple data sources to provide the most complete picture possible. Our data sources are summarized in Exhibit 2-2 and described in detail in Appendix A:

Exhibit 2-2. Data Sources

Dataset	Source	Years	Content (other than occupation)	Sample Size	Nationally Rep.	Length of Panel / Occupational History
Panel Study of Income Dynamics (PSID)[a]	University of Michigan	2003–2017	Wages, education, demographic characteristics	24,000 individuals from 10,000 families	Yes	14 years
National Longitudinal Survey of Youth, 1997 (NLSY97)[a]	U.S. Bureau of Labor Statistics	1997–2018	Wages, education, demographic characteristics	8,984 individuals	Yes	20 years
Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS)[b]	U.S. Bureau of Labor Statistics and U.S. Census Bureau	2003–2016	Wages, education, demographic characteristics	98,000 households/year	Yes	1 year
Survey of Income and Program Participation (SIPP)[b]	U.S. Census Bureau	2003–2013	Wages, education, demographic characteristics	Households:[c] 2004 panel: 51,363 2008 panel: 52,031	Yes	2004 panel: 4 years 2008 panel: 5 years
Emsi occupational matrices[b]	Emsi	Through 2019[d]	None	128 million workers' profiles	No	n/a

Note: We also use data from the Occupational Employment and Wage Statistics (OEWS) survey to describe job characteristics; it is not included here because we did not use it as a source to examine transitions themselves.
[a] Data source was used in career trajectories analyses.
[b] Data source was used in occupational transitions analyses.
[c] These are the original sample sizes. Substantial sample attrition occurs over the length of the panel.
[d] The Emsi data of occupational transition counts aggregate from Emsi's 2019 microdata on 128 million unique workers. The transitions represented can have taken place at any point during the workers' careers; as such, they are not a current or recent snapshot, but instead cover a longer period. They represent transitions, not workers.
Source: Abt Associates

The first four sources provide publicly available data collected from national surveys, each with a different purpose but that can be used to provide information about labor market experiences of a cross section of workers. The PSID and NLSY97 are the richest sources of data on advancement over time because of the longer length of those panels and greater detail on individual-level backgrounds and experiences, but they have smaller sample sizes than the other data sources. The CPS, by contrast, provides a much larger sample, but we can observe a given individual for only a year. The SIPP provides a middle ground; it is larger than PSID or NLSY97, but smaller than the CPS. However, it has a longer panel length than the CPS (three to four years), which provides a longer time to observe occupational transitions.

The Emsi data are of a fundamentally different type. Emsi provided the study team with a matrix of counts of transitions between occupations observed in online resumes and career profiles.[10] Unlike the CPS's and SIPP's, the Emsi samples are not necessarily representative,[11] but the data have nationwide coverage and the underlying sample sizes are very large, making the data particularly useful for exploring transitions in occupations too small to be well covered by the other data sources.

The study supplemented those data with data from the following three sources:

- *Occupational Outlook Handbook*: We use its information on licensing to analyze how licensing requirements of an occupation predict entrants' wage growth.
- Occupational Employment and Wage Statistics (OEWS): We use OEWS data on median wages within occupations for the analyses of career trajectories that use Emsi data.
- O*NET: We use the O*NET Job Zone measures to identify which occupations are mid-level. We use O*NET skills and abilities importance measures to create the scales used to analyze which skill requirements of occupations predict wage growth over a trajectory and within a transition.

2.2 Analyses of Career Trajectories

The career trajectories analyses have two primary aims:

- Examine how mid-level occupations vary in typical wage growth and other career outcomes (remaining in the same occupation or occupational cluster,[12] earning additional postsecondary degrees, or spending time not employed) experienced by entrants in the years after first taking a job in those occupations.
- Understand which characteristics of occupations and workers predict wage growth.

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[10] Emsi (https://www.economicmodeling.com) provides labor market data compiled from government sources, job postings, and online profiles and resumes. The study team licensed the data for the specific purposes of this analysis.

[11] Although the online job profiles data include workers from across the country, the types of workers and occupations represented may not be nationally representative because workers in some occupations might be more likely to post resumes or job profiles (e.g., LinkedIn job histories or resumes on recruitment sites) than are workers in other occupations.

[12] Our set of "occupational clusters" is based on the broad occupational categories used by the Census and SOC systems. For purposes of this study, some of our clusters are combinations of more than one broad category, when useful for coherence or sample size. For example, our "Healthcare" cluster includes both Healthcare Practitioners and Technical Occupations (SOC 29) and Healthcare Support Occupations (SOC 31).

Managerial occupations are the one exception to the rule that our occupational clusters follow major Census occupational categories. The Census (and SOC) classification system places Management occupations in their own category. However, most of those Management occupations correspond directly to one of our occupational clusters. For instance, the category Medical and Health Services Managers is substantively part of healthcare, so we categorize it in our Healthcare cluster.

This all has consequences in our analyses of whether occupational transitions are within or outside of a cluster. For example, changing from working as a Registered Nurse to working as a Director of Nursing (Medical and Health Services Manager category) would in our scheme be a change within the same occupational cluster (Healthcare), even though it is a change to a different broad occupational category as classified by the Census or SOC.

Appendix E contains full details of how our occupational clusters map to Census occupational codes.

Our trajectories analyses cover the 10-year period after a worker enters an occupation, to examine where workers subsequently end up in the medium to longer term and the steps involved in getting there. Because career pathways programs aim to alter long-term career advancement, this report focuses on 10-year outcomes; additional results from three- and five-year periods are reported in Appendix D. In particular, these findings identify occupations associated with more upwardly mobile outcomes; therefore, they may be useful for practitioners seeking to identify occupations that may be promising foci of training programs.

This is a retrospective analysis, covering trajectories from 1997 through 2018. The descriptions of these trajectories are not intended to be predictive, as occupations and opportunity structures shift over time. However, the patterns are likely informative of what to expect for workers going forward (though, as discussed in Chapter 5, this information should also be considered alongside information on labor market projections).

2.2.1 UNIT OF ANALYSIS

The primary unit of analysis is *career trajectory*, defined as the occupation, earnings, employment status, additional educational attainment, and wage outcomes of each entrant to an occupation in the 10 years after the entrant first starts working in that occupation as their "main" or "primary" job. Each trajectory begins at the point in time when the individual reports a new occupation, and it continues by month until the end of the observed data for that individual.[13] Therefore, the data would contain more than one observation for an individual if they worked in more than one occupation during the observed data period. The data then allow us to observe outcomes for at least 10 years after the individual entered each of those occupations.

Because this report focuses on 10-year outcomes, the analyses in Chapters 3 and 4 of the report include trajectory observations only for which the data include information on the individual for at least 10 years after entering the occupation. As noted, Appendix D includes outcomes measured at three years and five years, which include more observations corresponding to the period we examine.[14]

2.2.2 COMBINING AND WEIGHTING DATA SOURCES

The primary data sources we use for the analyses of career trajectories are the PSID and NLSY97. These data allow us to look at the entire length of a worker's career to date. Because the PSID and NLSY97 oversample certain categories based on socioeconomic characteristics and because the demographic and educational composition of the workforce changes over time, we generated weights using standard techniques to create a sample that is representative of employed persons ages 18-34 in

[13] See Appendix D for details on measure construction.

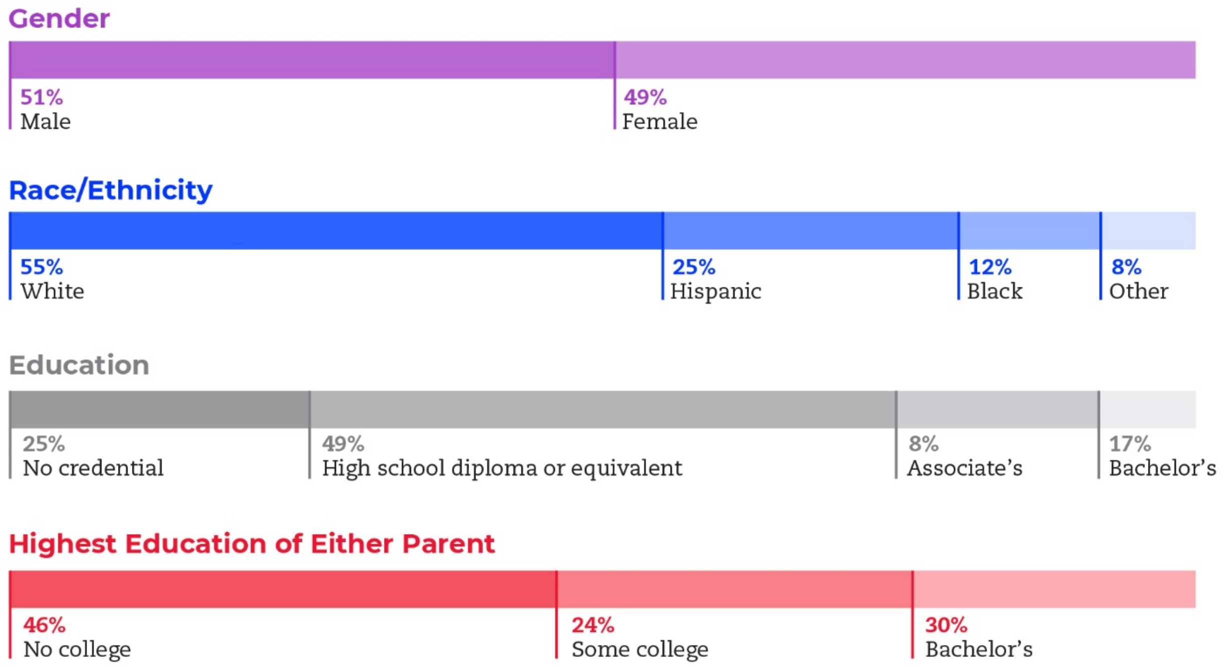
[14] The shorter the observation period, the larger the sample sizes available. This is because there are fewer trajectories for which we have 10 years of outcomes than three or five years of outcomes. For example, suppose the data series for an individual ends in 2018. If the individual started a job in a new occupation in 2013, we would be able to report on five-year outcomes (2013-2018) or three-year outcomes (2015-2018), but not on 10-year outcomes (2008-2018). Another implication of this is that the set of entrants for whom we can observe 10-year trajectory outcomes is younger than the set of entrants for whom we can observe five-year outcomes, because our analysis is based on the age at which they entered the occupation.

2020[15] on gender, race/ethnicity, and educational attainment in 2020. Details about weighting, variable construction, and how we handled missing data are included in Appendix B.

2.2.3 DESCRIPTION OF SAMPLE CHARACTERISTICS

Exhibit 2-3 shows the demographic characteristics at the start of the observation period of the career trajectories study sample (*N*=31,813).[16] The study limits the analysis to trajectories that start when the individual is age 34 or younger, because this is the oldest that entrants could be to allow for 10-year follow-up in the NLSY97 and because the median age for career pathways program participants tends to be early 30s. The study then weights trajectories to align with the 2020 U.S. population within age groupings of 18-24, 25-29, and 30-34. The gender, race/ethnicity, and educational attainment of the sample reflect that of similarly aged populations working in mid-level occupations in 2020.[17]

Exhibit 2-3. Trajectory Study Sample Demographics



Note: *N*=31,813. In the race/ethnicity classification above, all individuals who report identifying as Hispanic or Latinx are classified as Hispanic. Thus, the remaining race/ethnic groups are composed solely of individuals who do not self-identify as Hispanic or Latinx. The Other race/ethnicity category includes individuals who identify as Asian, Pacific Islander, American Indian/Native American, Other, or Multiple Races. Of those who identify ethnically as Hispanic or Latinx in the sample, 45% identify racially as White, 3% as Black, <1% as Asian or Pacific

15 We used March 2020 CPS/ASEC data as the benchmark for workforce composition as it was the most recently available data at the time of the dataset construction. Prior research has found that the March 2020 ASEC experienced uniquely high nonresponse bias (Rothbaum & Bee, 2021). However, the study team compared demographic composition of workers aged 18-34 from the most recent four ASEC samples (2018-2021) and found that the 2020 sample was similar in composition to the surrounding years. Because the benchmark population estimates are similar irrespective of the ASEC year that is chosen, the choice to use the 2020 ASEC, rather than a different recent ASEC year would not be consequential for the findings presented here.

16 Because not all trajectories end with a period in which the worker is employed, and thus earning wages, the sample sizes for analyses of wage changes is smaller, 25,038. See Appendix B.

17 Based on estimates from the March 2020 Current Population Survey.

Islander, 1% as American Indian/Native American, and 48% as Other/Multiple Races. Of those who identify ethnically as non-Hispanic and reported an Other race, 57% identify as Asian or Pacific Islander, 8% as American Indian/Native American, and 32% as Other/Multiple Races.
Source: Authors' tabulations of trajectories observations constructed from weighted NLSY97 and PSID data

Exhibit 2-4 shows the starting wage and 10-year trajectory outcomes of the trajectory sample. The typical starting wage is fairly low (around $12 per hour) but grows substantially over the 10 years. Returning to school to obtain a first or subsequent postsecondary degree is relatively common.[18] The median trajectory includes nearly a year of not being employed over the 10-year span, though that may include time voluntarily out of the labor market due to full-time schooling or other obligations.

Exhibit 2-4. Ten-Year Trajectory Study Sample Outcomes

Trajectory Outcome	% or Median
Starting hourly wage	$12.55
Wage increase	$7.31
Months not employed	8
Earned new postsecondary degree	28%

Note: *N*=31,813 for all but the wage increase measure. *N*=25,038 for the wage increase measure because those who report not being employed for pay or who fail to report their wages at the end of the 10-year trajectory are excluded from the wage increase descriptive. Wages are inflation adjusted to 2020 dollars.
Source: Authors' tabulations of trajectories observations constructed from weighted NLSY97 and PSID data

Exhibit 2-5 shows the most common occupational clusters in which entrants began their trajectories, with the three largest clusters being Office and Administrative Support, Sales, and Personal Service.

2.2.4 ANALYTIC APPROACHES

To identify which occupations tend to be the stronger launchpads for subsequent wage growth, we calculate median wage growth by entrant's occupation for all entrants. Occupations with fewer than 40 trajectory observations are omitted. The larger the number of trajectory observations, the more precise the estimates are (that is, the margin of error is smaller). We set the inclusion threshold at 40 observations in order to balance precise estimates versus estimates for as many occupations as reasonably possible. Those analyses also do not adjust for the characteristics of entrants or characteristics of occupations. Differences among occupations in trajectory outcomes therefore reflect variation given who enters the occupation. Who enters an occupation is likely partially a function of the occupation's characteristics and requirements.

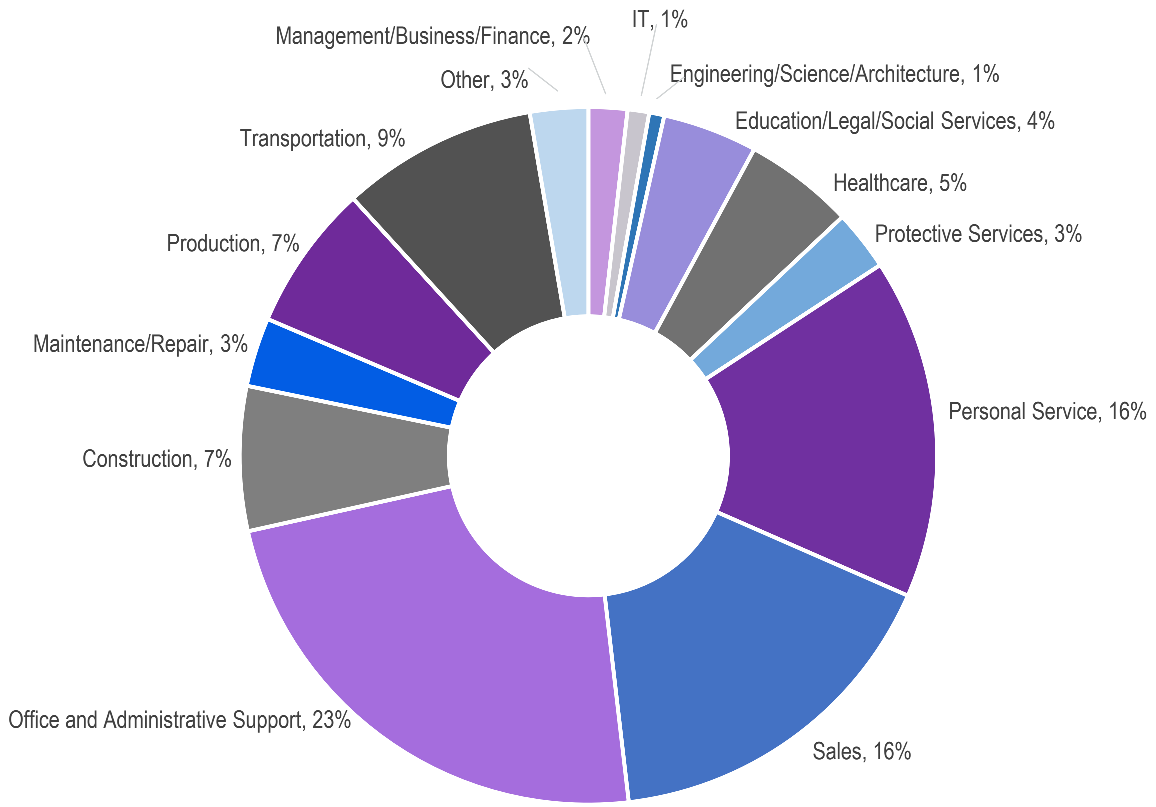
Next, we use regression methods to examine individual-level and occupation-level characteristics that predict wage growth during a trajectory. The analyses of individual-level predictors are set up such that comparisons are among individuals who enter the same occupation.[19] The analyses of occupation-level predictors include controls for the worker' starting wage upon entering the occupation.

[18] For example, non-first-time students comprise more than 50% of students enrolled in public, two-year institutions and 47% of students enrolled in public four-year institutions (McFarland et al., 2019).

[19] In technical terms, the analyses do this by employing "fixed effects" for occupation at trajectory start. Substantial variation can exist among job titles and responsibilities within an occupation as classified using Census definitions by NLSY97 and PSID (Martin-Caughey, 2021). As such, occupation fixed effects do not fully guarantee that estimates of worker-level predictors or trajectory outcomes are based on comparisons among entrants starting in exactly the same type of job. Controls for wage and educational attainment at trajectory will net out some, but not all, of that within-occupation variation in jobs.

Appendix C provides technical details on our analytic specifications.

Exhibit 2-5. Most Common Occupational Clusters Among Starting Occupations



Note: *N*=31,813. Our set of occupational clusters (shown here) is based on the broad occupational categories of the Census (which carry over to SOC). For purposes of this study, some of our clusters are combinations of more than one broad category, when useful for coherence or sample size. For example, our "Healthcare" cluster includes both Healthcare Practitioners and Technical Occupations (SOC 29) and Healthcare Support Occupations (SOC 31). Managerial occupations are the one exception. For more, see Appendix E, which contains full details of how our occupational clusters map to Census occupational codes.
Source: Authors' tabulations of trajectories observations constructed from weighted NLSY97 and PSID data

2.3 Analyses of Occupational Transitions and Job Changes

The analyses of career trajectories described in Section 2.2 help identify which occupations are associated with more promising subsequent career trajectories. The occupational transitions analyses provide detail on the specific occupational steps that workers commonly take along the course of their careers—in particular, what the common upward transitions are.

2.3.1 OCCUPATIONAL TRANSITIONS

Two different data sources are used in the study's analyses of occupational transitions: one is the Emsi matrix of occupational transitions, the other is CPS/SIPP. The first analysis that uses transitions data is an exploration of what occupational characteristics—in particular, what occupational skill requirements—most commonly characterize an *upward transition* (defined as a transition in which the wage earned in the destination occupation is higher than the wage was for the source occupation). The unit of analysis is *occupational transition*, defined as moving from the end of a primary job (the source occupation) to the beginning of a primary job that is in a different occupation (the destination occupation).

The dataset is limited to transitions where the source occupation is a mid-level occupation. That is, we examine where workers go when they leave a mid-level occupation. The destination could be any type of occupation—including occupations that require four-year college degrees or occupations that do not require any preparation beyond high school. These transitions can be immediate, when an individual reports one primary occupation in one month and a different primary occupation in the next month; or there could be a period of time of not working between the two occupations. Because the unit of analysis is transition, the dataset may include multiple transitions related to the same worker.

The study uses the Emsi data to examine the relationship between skills and advancements in the occupational transitions. These data were used for the analysis presented in Exhibit 2-6. One limitation of the Emsi data is that they provide only counts of occupational transitions. We do not know the demographic composition of the sample as a whole or of the individuals who make particular transitions. Thus, it is not possible to weight the data by worker characteristics. But the sample size is very large (128 million workers) and comes from online data sources with nationwide coverage.[20] Its large, nationwide sample allows for more detailed analysis of common transitions and the range of upward pathways from any given occupation. To examine expected wage changes associated with an occupational transition, we use estimates of the median wage for each source occupation and destination occupation from the OEWS program.

Exhibit 2-6. Descriptives of the Emsi Transitions Data

Characteristic (of transitions)	% or Median
Number of transitions per source and destination occupation pairing	11,061
Transitioned from source occupation with no licensing requirements to destination occupation with licensing requirements	29%
Wage Characteristic	
Median wage of source occupation	$19.82
Change in median hourly wage from source to destination occupation	$4
Median wage increased by at least $2 per hour	59%

Note: Median wage is from the Occupational Employment and Wage Statistics estimates for 2019. The unit of observation is a transition from a job in one occupation to a job in another occupation. The same individual may have multiple observations in the dataset.

Several other analyses use the combined CPS/SIPP data to explore relationships between worker characteristics and the nature of transitions (presented in Chapter 4, Exhibits 4-9, 4-10, 4-11, and 4-12). The appended set of CPS and SIPP occupational transitions is weighted in a similar way as the trajectory data to make the sample reflect the workforce population (for more detail, see Appendix B). The dataset includes transitions made between the ages of 18 and 44.

Exhibit 2-7 describes the characteristics of the transitions sample.

20 Although the online job profiles data include workers from across the country, the types of workers and occupations represented may not be nationally representative because workers in some occupations might be more likely to post resumes or job profiles (e.g., LinkedIn job histories or resumes on recruitment sites) than are workers in other occupations.

Exhibit 2-7. Descriptives of the CPS/SIPP Transitions Data

Characteristic	% or Median
Gender	
Male	51.4%
Female	48.6%
Age	
18-24 years	22.6%
25-29 years	21.8%
30-34 years	19.3%
35-39 years	19.1%
40-44 years	17.1%
Race/Ethnicity	
White non-Hispanic	55.6%
Black non-Hispanic	14.2%
Hispanic, any race	22.3%
Other non-Hispanic	7.8%
Wage and Job Level Changes Associated With Transitions	
Source wage	$13.03
Source occupation median wage	$17.40
Change to job in same occupational cluster	39.5%
Change to job in O*Net Job Zone 4 or 5	16.6%
Change to job with higher wage	35.4%
Change to job in occupation with higher median wage	40.0%

Note: The Other race/ethnicity category includes individuals who identify racially as Asian, Pacific Islander, American Indian/Native American, Other, or Multiple Races and do not identify ethnically as Hispanic or Latinx. The SIPP data do not permit disaggregation of finer race/ethnicity categories within the Other group. Missing reports of individual-level wages that cannot be imputed reduces sample sizes for those wage measures. O*Net describes zone 4 as occupations that require “considerable” preparation and level 5 as occupations that require “extensive” preparation. “Change to job with higher wage” is defined as changing to a job that pays at least $2 per hour more; Change to Job in Occupation with Higher Median Wage is defined as changing to an occupation with an average wage of at least $2 per hour more than previous.

2.3.2 SOURCE: AUTHORS’ TABULATIONS OF TRANSITIONS OBSERVATIONS CONSTRUCTED FROM WEIGHTED CPS AND SIPP DATA JOB CHANGES

For one analysis, we also use transitions data to explore whether demographic characteristics are associated with the likelihood of moving to a different occupation when an individual does change jobs. For that analysis (see Exhibit 4-8), the dataset also included job changes in which the source and destination occupations were the same. That analysis uses only SIPP data because the Emsi data do not include demographic characteristics and the CPS data do not include job changes within the same occupation.

Exhibit 2-8. Descriptives of the SIPP Job Changes Data

Characteristic	% or Median
Gender	
Male	52.4%
Female	47.6%
Age	
18-24 years	24.7%
25-29 years	21.8%
30-34 years	18.8%
35-39 years	18.4%
40-44 years	16.4%
Race/Ethnicity	
White non-Hispanic	58.1%
Black non-Hispanic	12.9%
Hispanic, any race	21.6%
Other non-Hispanic	7.3%
Wage and Job Level Changes Associated With Transitions	
Source wage	$12.56
Source occupation median wage	$16.81
Change to job in same occupation	25.9%

Note: The Other race/ethnicity category includes individuals who identify racially as Asian, Pacific Islander, American Indian/Native American, Other, or Multiple Races and do not identify ethnically as Hispanic or Latinx. The SIPP data do not permit disaggregation of finer race/ethnicity categories within the Other group. Missing reports of individual-level wages that cannot be imputed reduces sample sizes for those wage measures.
Source: Authors' tabulations of transitions observations constructed from weighted SIPP data

2.3.3 ANALYTIC APPROACHES

The occupational transitions analyses used to identify worker-level predictors of transition outcomes use ordinary least squares (OLS) specifications of a similar form as described for the trajectories analyses in Section 2.2.4 above. Similar limitations apply as those described in footnote 20. Analyses of which differences between source and destination occupations predict upward transitions in occupational median wage are based solely on aggregated occupation-level data. Appendix C describes the analytical approach in detail.

Chapter 3. Characteristics that Distinguish Launchpad Occupations

Highlights

Assuming a starting wage of $20, entrants to launchpad occupations earn about $7.20 more per hour after 10 years compared to those who enter lower-wage-growth occupations.

Launchpad occupations are spread across industry sectors.

Which occupational characteristics distinguish launchpad occupations?

- "Knowledge" sectors such as Information Technology, Management/Finance, and Engineering/Science/Architecture see the highest wage growth.
- Launchpad occupations emphasize skills such as problem solving and two-way communication.
- Problem solving is also an important skill when considering upward transitions from launchpad occupations, as is managing people.

This chapter examines patterns of career trajectories and occupational transitions found in the CTOT Study, focusing on the characteristics of occupations. First, the chapter explores how greatly entrants' 10-year wage growth (their "wage trajectories") varies by starting occupation. The study identifies which occupations appear to be more reliable launchpads for wage growth, and which occupational clusters tend to have more launchpad occupations. After providing a high-level overview of how much occupations vary in wage trajectories, we explore occupational characteristics that may be related to that variation—focusing particularly on which skill requirements of occupations predict greater subsequent wage growth. We then use transitions data to analyze how differences in skill and licensing requirements of source and destination occupations predict wage growth.

3.1 How Much Do Wage Trajectories Vary Among Occupations?

This section provides more detail on how widely occupations vary in the wage growth that typical "entrants" (a worker starting their first job in a given occupation) go on to experience. If mid-level occupations do not vary greatly in this dimension, then it may not be particularly important to consider data on wage trajectories when considering which occupations to target for training or job placement. But if some occupations do tend more than others to be much more reliable launchpads for wage growth, then having details on typical wage trajectories for individual occupations becomes more important.

3.1.1 EXTENT OF WAGE TRAJECTORY VARIATION AMONG OCCUPATIONS

Future wage prospects can vary dramatically across occupations. In our sample of workers in mid-level occupations, workers earned a median wage of $13.51 per hour in their starting occupation. Over 10

Key Finding

The wage growth that entrants to mid-level occupations experience varies considerably across occupations. After 10 years:

1. An entrant to a high-growth occupation sees a 73 percent increase in wages.
2. Their counterpart in a low-wage-growth occupation sees only a 37 percent increase.

Assuming a starting wage of $20 per hour, this amounts to a difference of around $7.20 per hour (about $15,000 more annually for full-time work).

years, wages grew by a median of $7.36 per hour.[21] But across all mid-level occupations, how much variation exists in entrants' later wage growth?

To answer that question, we designate the occupation in which the wage growth rate is greater than that of 25 percent of all occupations as the cut-off for "**low-wage-growth**"; the one that is greater than 50 percent of all occupations as the cut-off for "**medium-wage-growth**"; and the one that is greater than 75 percent of all occupations as the cut-off for "**high-wage-growth**."

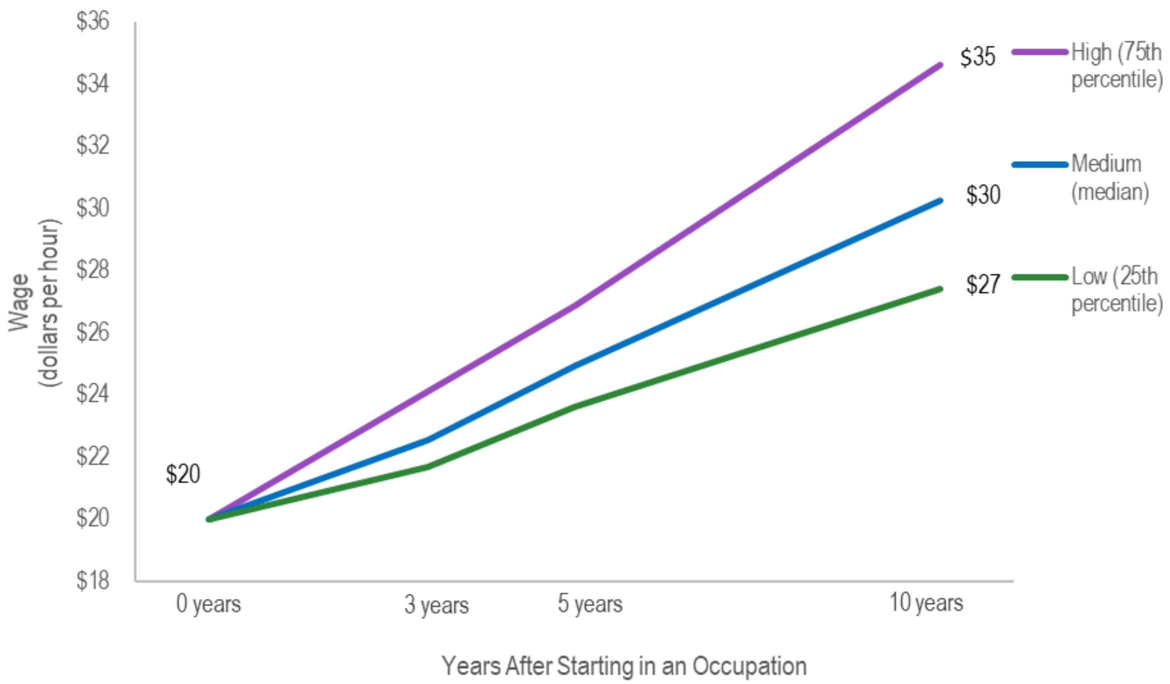
Our analysis refers to medium- and high-wage-growth occupations as **launchpads**, from which entrants go on to experience higher-than-average wage growth. For simplicity, we define launchpad occupations as those at the 50th percentile or above. Among launchpad occupations, there is a gradation in effect, with high-wage-growth occupations being stronger launchpads than medium-wage-growth ones. Our analyses reflect an occupation's strength as a launchpad along a continuum, rather than describing occupations as either a launchpad or not.

Exhibit 3-1 illustrates how wage growth varies among occupations over three years, five years, and 10 years after starting in the occupation. Occupations also vary in starting wage, of course. For purposes of the exhibit, however, we assume the same starting wage ($20 per hour) to better illustrate the difference that different wage growth trajectories make in workers' actual earnings.

As expected, wages grow over time. But the wage growth that entrants to an occupation experience varies a lot across occupations. At each time point, the wage growth for the typical high-wage-growth occupation is more than double that for the typical low-wage-growth occupation. After 10 years, wages of the typical entrant to a 75th percentile occupation have grown by 73 percent. By contrast, wages of the typical counterpart entrant to a 25th percentile occupation has seen wage growth of only 37 percent. In fact, entrants to the high-wage-growth occupation experience similar wage growth after five years (34 percent) as do entrants to the low-wage-growth occupation after 10 years (37 percent).

21 The median wages and wage growth reported here differ slightly from the figures reported in Exhibit 2-4, because these figures exclude trajectories for which reported wages for workers who reported being employed were $0, whereas for the regression analyses for which summary statistics are reported in Exhibit 2-4, wages reported as $0 were bottom-coded to $7.25.

Exhibit 3-1. Wage Growth for Low-, Medium-, and High-Wage-Growth Occupations with the Same Starting Wage



Note: *N*=164 occupations at three years, *N*=157 occupations at five years, and *N*=130 occupations at 10 years. Wage growth percentiles are based on rank ordering of occupations with observations for at least 40 entrants. The graph is based on a starting wage of $20 per hour for illustrative purposes; that wage was chosen for ease of interpretation among the range of plausible mid-level starting wages. Of course, occupations vary in starting wage, but for purposes of the exhibit we assume the same starting wage to better illustrate the difference that different wage growth trajectories make in workers' actual earnings.
Source: NLSY:97 and PSID. Wages on the graph are rounded, so calculated percentages do not line up precisely with text.

3.1.2 OCCUPATIONS THAT OFFER STRONG STARTING WAGES AND STRONG WAGE GROWTH

Key Finding

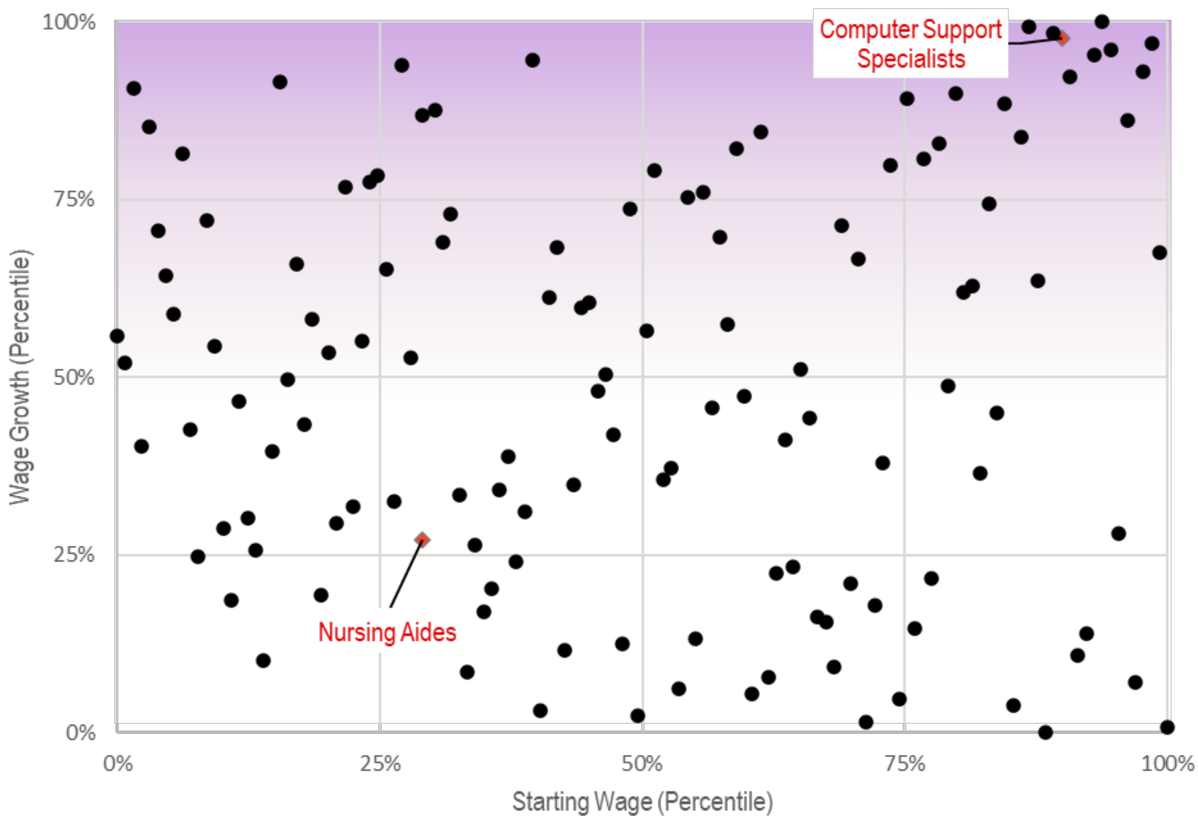
High-and medium-wage-growth ("launchpad") occupations are spread across occupational clusters and occupations with higher and lower starting wages.

The above results indicate that career pathways program decisions about which occupations to target for training workers could have important implications for participants' earnings over the long term. A program that trains participants to work in an occupation in which entrants typically do not experience much wage growth might not be expected to improve participants' earnings much long term. That is particularly true if the occupation also has low starting wages.

The preceding section provided a high-level view of the extent to which occupations can vary in the longer-term wage growth that typical entrants experience. It did not discuss specific occupations. Exhibit 3-2 ranks every occupation in our analyses by their median starting wage and median absolute 10-year wage growth (in dollars) and plots their percentile on the combination of those two measures. The location of each dot represents the given occupation's combination of starting wage and wage growth. Dots to the right of the chart are for occupations that have high starting wages. Dots higher up on the chart are for occupations whose entrants experience greater wage growth over 10 years.

As noted, for simplicity we have defined occupations at the 50th percentile or above in typical wage growth as "launchpads." Of course, as indicated by the shading in the upper half of the exhibit, there is a gradation, with occupations toward the top tending to be stronger launchpads.

Exhibit 3-2. Scatter Plot of Mid-Level Occupations' Ranked by Starting Wages and 10-Year Wage Growth (in Dollars)



Note: *N*=22,834 trajectories across 130 occupations. Analyses include only occupations with data for at least 40 entrants. "Nursing Aides" reflects the full Census occupational category of "Nursing, Psychiatric, and Home Health Aides."
Source: NLSY:97 and PSID

For illustration, Exhibit 3-2 labels two occupations that career pathways programs typically train for—Computer Support Specialists and Nursing, Psychiatric, and Home Health Aides (labeled "Nursing Aides" in the exhibit).

Entrants to occupations in the top-right quadrant tend to go on to the highest long-term earnings, because those occupations combine higher starting wages and higher wage growth. That combination would make those occupations potentially promising targets for training programs. Along with Computer Support Specialists, occupations in the top-right quadrant include occupations such as Registered Nurses, Drafters, Paralegals, Bookkeeping Clerks, and Electricians, representing a range of occupational clusters. The full list of occupations in each quadrant are included in Appendix F.

An important aspect of career pathways programs is meeting participants where they are, and not all participants are likely to be ready immediately to train for occupations with higher starting wages, which tend to also have higher skill requirements. Career pathways programs may find it important to consider some occupations with lower starting wages—those to the left side of the exhibit—which tend to have lower skill requirements. However, if participants enter a lower-wage occupation, a training program with the goal of career advancement would want them to have a good chance of increasing their wages over time, rather than permanently getting stuck in lower-wage work. Occupations in the top left quadrant of the exhibit are ones that tend to be better launchpads for higher wage growth, even though the starting wages are lower than occupations on the right. They include occupations such as Automotive Body and Related Repairers, Customer Service Representatives, File Clerks, and Teacher Assistants.

This report's companion volume *Appendix on Occupational Cluster Findings for Healthcare, Early Care and Education, Information Technology, and Production* provides more detail on career trajectories for occupations in those clusters.

3.2 What Traits Characterize Stronger "Launchpad" Occupations?

The patterns described in the prior section raise questions of why certain occupations function as launchpads whereas others do not. Determining causal relationships is not possible with this analysis but examining which characteristics of occupations predict greater wage growth is. Doing that allows us to identify mechanisms that might explain why entrants' career trajectories differ across mid-level occupations.

It may be that some occupations simply happen to be in occupational clusters that contain more advancement opportunities. Or it may be that the occupation involves—and in turn may help develop—highly transferable skills that are helpful in qualifying for higher-paying occupations. We also explore the role of licensing. Though licensing may make entering an occupation more difficult, it also may serve to elevate wage growth opportunities having entered the occupation. Opportunities for advancement may be generally more common within certain occupational clusters. Section 3.2.1 explores how wage trajectories and time spent not working vary among clusters. In theory, the skills developed within an occupation and licensing required to enter that occupation may better position workers for upward mobility. Section 3.2.2 examines how the skill content of an occupation and the presence of licensing requirements associate with subsequent skill growth. We also use transitions data to examine which skills become more important in the higher-paying jobs that workers advance to from mid-level occupations.

3.2.1 OCCUPATIONAL CLUSTER

Key Finding

Occupations in "knowledge" clusters, such as Information Technology, Management/Finance, and Engineering, Science and Architecture are more likely to be launchpads for growth.

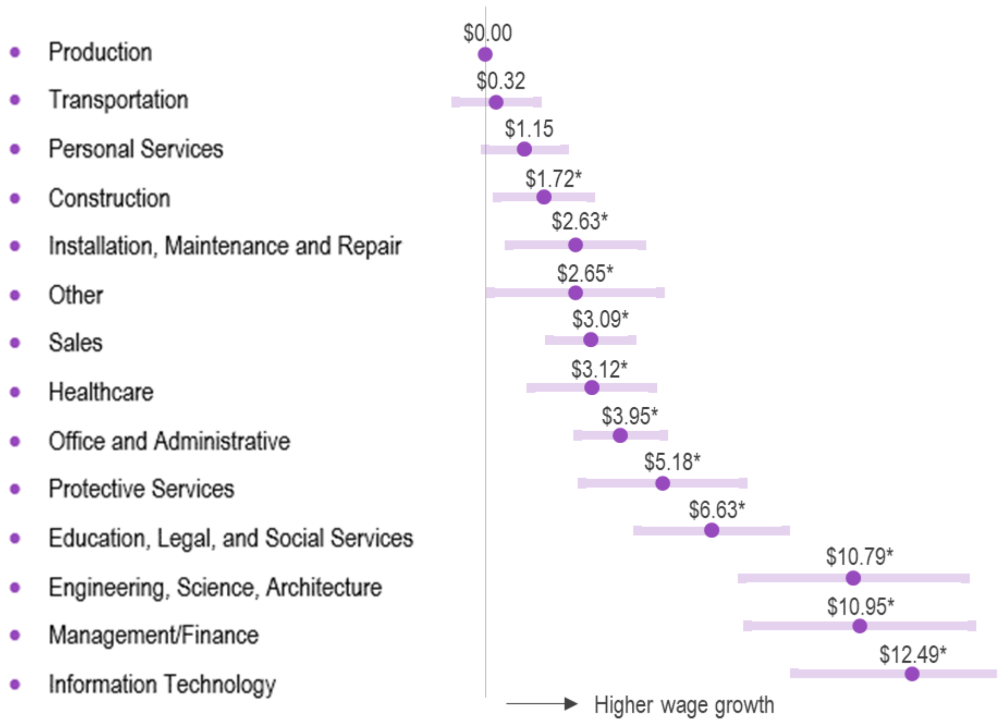
Exhibit 3-3 shows how occupational clusters vary in entrants' wage growth trajectories. Because starting wage may vary across clusters, the analyses adjust for starting wage. The wage growth differences are all relative to Production occupations—the occupations with the lowest wage growth. As indicated by the dots on the graph, **the differences are substantively meaningful, with estimated wage growth for the highest-wage-growth clusters being more than $12 per hour greater than for the lowest-wage-growth clusters.**

The light purple bars indicate the "95 percent confidence intervals," an indicator of the precision of the estimates. The bar represents the range of values within which we are 95 percent statistically confident the actual value falls. The shorter the bar, the more precise the estimate; this exhibit's bars show that these estimates are not highly precise. For example, we estimate the 10-year wage growth for entrants in

Information Technology occupations is $12.49 per hour greater than for entrants in Production occupations (assuming the same starting wages). The confidence interval, however, indicates that the actual wage difference could range between $9.06 and $15.93 per hour.

Still, there are some clear patterns in which occupational clusters are associated with the strongest 10-year wages. **Clusters typically considered to include "knowledge" occupations tend to be associated with the highest wage growth, whereas wage growth for entrants to "manual labor" sectors tends to be much weaker. Service occupations tend to fall in the middle**. Many occupations in manual sectors, such as Maintenance/Repair/Installation, Construction, and Transportation, offer decent starting wages but do not function as launchpads because entrants do not tend to go on to experience as much wage growth as they might in other sectors (see Appendix Exhibit F-3). Of course, as we saw in Section 3.1, exceptions exist, and some manual occupations are launchpads.

Exhibit 3-3. Ten-Year Wage Growth Differences Among Occupational Clusters



How to Read This Graph: The purple dots on this graph indicate the difference between wage growth in hourly wages 10 years after entering an occupation, in comparison to the reference category (in this case, Production). That is, the average entrant to a job in Information Technology sees $12.49 per hour more in wage growth 10 years later than does the average entrant to a Production occupation that has the same starting wage. The bars indicate how precise our estimates are (the 95 percent "confidence interval"); the actual wage difference could fall anywhere in that range, though it is more likely to fall toward the middle of the range than the ends. Asterisks (*) indicate that the average wage growth for the cluster is statistically different from that of the lowest wage growth cluster (Production) at the .05 level.
Note: The Other category includes small occupations in fields not covered elsewhere, such as agriculture, athletics, and the arts. Estimates are drawn from OLS regressions that include controls for starting wage, data source, and indicators for each sector (omitting Production).
Source: NLSY:97 and PSID

Time Spent Not Working, by Cluster

Key Finding

Entrants to sectors that have many launchpad occupations also spend fewer months not employed.

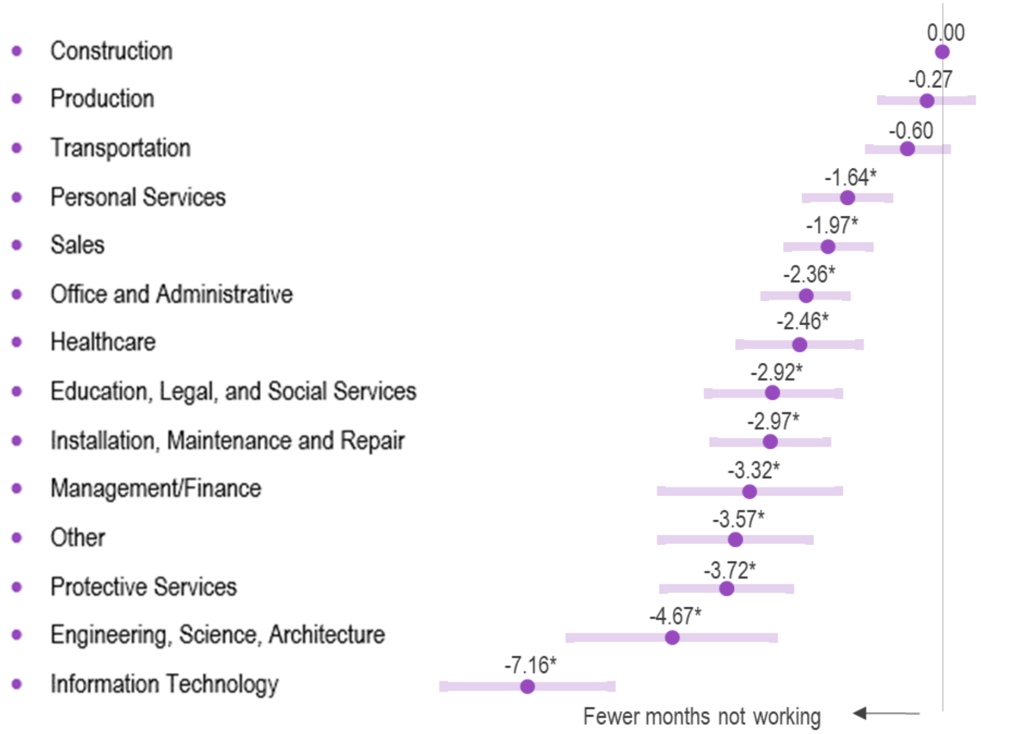
One factor that may be linked to wage growth is spells of unemployment and time voluntarily spent out of the labor market. It may be that some occupations and clusters see more volatility in employment, and workers have less time to accumulate the experience needed to earn higher wages. On the other hand, we might see higher wage growth in clusters with more instability if wage growth compensates for the greater risk of job loss.

Our analyses refer to months not working. Those may be months being unable to find a job (unemployment) or short voluntary spells away from the labor market, but time spent in school is excluded. Below we examine how occupational clusters vary in how many months entrants experience not working in the 10 years after starting in an occupation in that cluster.[22]

As shown in Exhibit 3-4, **entrants to higher-wage-growth occupational clusters spend fewer months not working**. Entrants to Information Technology (IT); Engineering, Science, and Architecture; and Protective Services have the fewest months not working. The clusters where entrants go on to spend the most months not working are Construction, Production, and Transportation. Compared to entrants to Construction occupations, entrants to IT occupations spend, on average, seven fewer months not working during the 10 years after starting in the occupation.

[22] To avoid the influence of extreme values, such as someone stopping working altogether, we cap the maximum number of months at 24. Months not working does not include time spent as a full-time student but would cover looking for work; leaving the workforce temporarily due to disability, health issues, or caregiving responsibilities; and other time spent not working voluntarily or involuntarily.

Exhibit 3-4. Ten-Year Months Not Working Differences, by Occupational Cluster



How to Read This Graph: The purple dots on this graph indicate the difference in number of months spent not working over the course of a 10-year period, in comparison to the reference category (in this case, Construction). That is, the average entrant to a job in construction spends seven more months not working than the average entrant to a job in IT. The bars indicate how precise our estimates are (the 95 percent "confidence interval"); the actual difference could fall anywhere in that range, though it is more likely to fall toward the middle of the range than the ends. Months not working may include being unable to find a job (unemployment) or short voluntary spells away from the labor market, but time spent in school is excluded.

Note: Estimates are drawn for OLS regressions that include controls for starting wage, data source, and indicators for each cluster (omitting Construction). Asterisks (*) indicate a statistically significant difference at the .05 level.

Source: NLSY97 and PSID

3.2.2 TRANSFERABLE SKILLS

As noted above, there may be transferable skills (as opposed to specific technical or other occupation-specific skills) present in some entry occupations that are especially valuable as **foundations** to help workers progress on to higher-paying jobs. To examine this, the study analyzes how the skill content of the mid-level occupation in which an entrant starts predicts later wage growth. Alternatively, this can be characterized as an analysis of which skills are common in occupations that are stronger launchpads.

Other transferable skills, while not foundational for growth, may become increasingly important to develop as workers advance to higher-paying occupations. A second set of analyses examines which *gains* in skills are most commonly involved in upward occupational transitions, by comparing skills that are important in the destination occupation versus skills that are important in the source occupation. If a skill is newly important in the destination occupation, it suggests that the transition involves the acquisition of that skill. Thus, this analysis allows us to identify which skills appear to be important to making a transition to higher-paying jobs.

We also examine how licensing requirements of the starting occupation of a trajectory—and differences in licensing requirements between source and destination occupations in a transition—predict wage growth.

Transferable Skills That Distinguish Launchpad Occupations

Exhibit 3-5 shows our analysis of transferable skill requirements of occupations that are most closely associated with how strong of a wage growth launchpad the occupation is. The dots indicate how much additional wage growth is associated with an occupation scoring one point higher on that skill index (which reflects a meaningful difference in skills).[23]

Key Findings

Occupations where problem solving and communication are important tend to be stronger launchpads.

Jobs that require licenses seem to have some positive association with later wage growth, but it is not a strong one.

The results suggest that entrants to occupations that require more problem solving and two-way communication skills tend to go on to experience particularly high wage growth. Those skills are highly relevant for many knowledge occupations and are also readily transferable. By contrast, occupations in which fine motor skills and gross motor skills are important tend to be associated with lower wage growth over time.

One point the findings highlight is that participants are likely to benefit if training programs focus not just on developing specific technical skills for an occupation but also on broader transferable skills, especially problem solving and two-way communication.

Entrants to occupations that require a license[24] also seem to go on to experience higher wage growth. However, the estimated 10-year wage growth difference between occupations with and without licensing requirements is modest (about $0.80 per hour).

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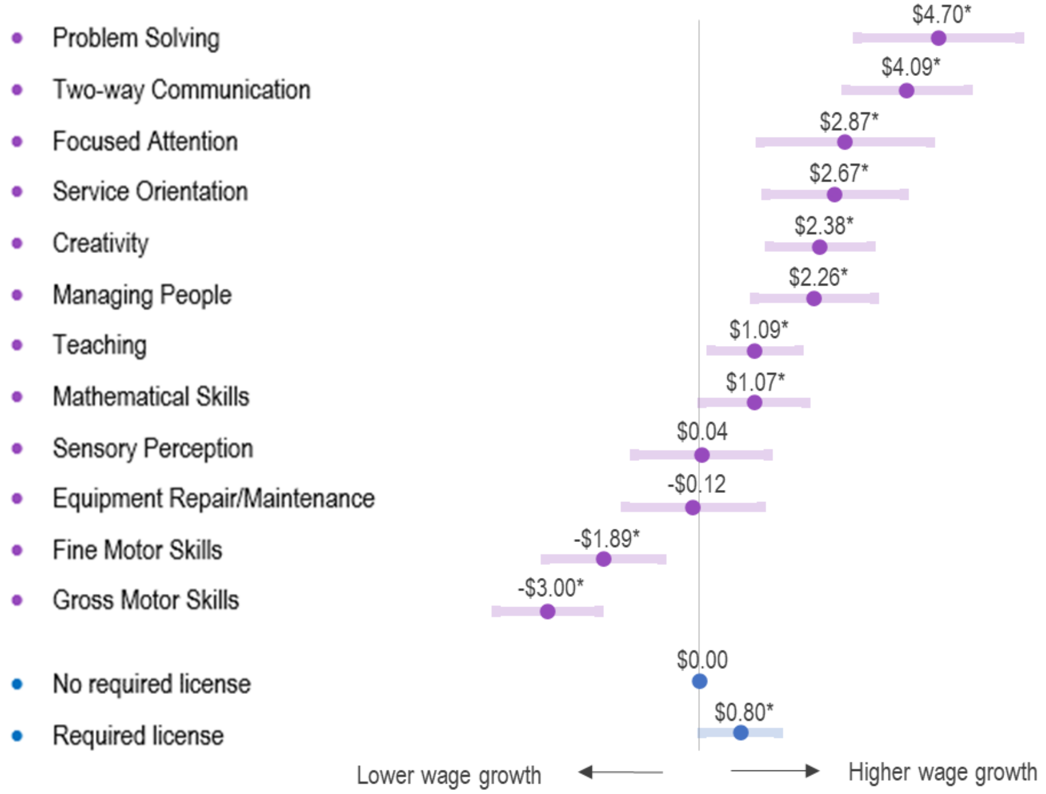
23 The skill measures are indices composed of combinations of O*Net measures that rate how important particular skills and abilities are to work in the occupation (see Appendix C for details of measure construction). Each item is measured on a 1-7 scale, with higher values indicating skills that are more important for the occupation. As an average of those items, each skill scale also has a minimum value of 1 and a maximum value of 7. The coefficient reflects how much 10-year wage growth is associated with a one-point increase in the skill index.

24 An occupation was determined to require a license if the *Occupational Outlook Handbook* description of the occupation referenced required licenses, certifications, or registrations. Because the *Handbook* descriptions are narrative, we manually reviewed the text to try to capture all references.

Exhibit 3-5. Ten-Year Wage Growth Differences, by Transferable Skill and Licensing Requirements



How to Read This Graph: The purple dots on this graph indicate the difference between wage growth in hourly wages 10 years after entering an occupation based on the importance of each skill for the starting occupation. That is, if two occupations differ by one point in their emphasis on problem solving, the average entrant to the occupation that emphasizes problem solving will see $4.70 per hour more in wage growth after 10 years, or makes $4.70 more per hour assuming the same starting wage. The bars indicate how precise our estimates are (the 95 percent "confidence interval"); the actual wage difference could fall anywhere in that range, though it is more likely to fall toward the middle of the range than the ends.
Note: Estimates are drawn from OLS regressions that include controls for starting wage, data source, occupational cluster, and one of the above occupational characteristics. Asterisks (*) indicate a statistically significant difference at the .05 level.
Source: NLSY97 and PSID

Transferable Skill Gains as Predictors of Upward Transitions

Key Finding

Problem solving stands out as the skill most associated with upward transitions.

In this section we briefly examine which skill gains most commonly characterize upward occupational transitions that occur in the broader labor market. For the analysis in this section, we draw on resume and worker profile data licensed from Emsi that provides millions of observed occupational transitions. Again, we focus on source occupations that are mid-level. The analyses help suggest skills that may be most key for participants to develop for the purposes of ongoing career advancement.

Specifically, among a set of 89,758,736 observed transitions from a mid-level source occupation to any destination occupation, we examine how differences in the transferable skill requirements between destination and source occupations predict differences in the median wages between those occupations. The findings in Exhibit 3-6 indicate that among the skills examined, increases in median wages between source and destination occupations are most strongly predicted by increases in required problem solving and people management skills.

Exhibit 3-6. Occupational Skill Requirement Differences between Source and Destination Occupations that Predict Median Wage Differences

How to Read This Graph: The purple dots on this graph indicate the difference between hourly wages before and after a job transition that are associated with a one-point increase in importance of the particular skill between the source and destination occupation. That is, transitions in which the destination occupation differs by one-point from the source occupation in the importance of problem solving, predicts an increase of $23.56 in the median wage between the occupations.
Note: Because of the very large sample sizes, all estimates are statistically different from zero. Confidence intervals are omitted because they are so narrow that they are not meaningful to present.
Estimates are drawn from OLS regressions that include controls for median wage of the source occupation, change in Job Zones as indicated by O*Net, and one of the above occupational characteristics. Asterisks (*) indicate a statistically significant difference at the .05 level.
Source: Emsi occupational matrices

The earlier analysis shown in Exhibit 3-5 examines the extent to which a foundation in certain transferable skills in the starting occupation predicts later wage growth. By contrast the analysis for Exhibit 3-6 explores which skills may be important for workers to acquire to transition to higher-paying jobs, but do not necessarily need to have been acquired previously.

Both are relevant for career pathways programs in considering skills beyond the narrow immediate technical requirements of the first job. **As in Exhibit 3-5, the top skills in Exhibit 3-6 are intellectual and social-emotional, rather than physical or technical. Problem solving again is highest on the list.** Managing people ranks higher in Exhibit 3-6 than in Exhibit 3-5. This is consistent with expectations that management is a skill that is not necessarily foundational but becomes more important to develop over time. By contrast, two-way communication is lower in Exhibit 3-6 than in Exhibit 3-5. That is a skill widely required for success in most occupations. Without strong communication skills a worker may find it difficult to advance, but it may not be a skill that grows in importance as a worker moves into higher-paying occupations.

3.3 Conclusion

The findings in this chapter show that mid-level occupations vary considerably in terms of workers' later wage growth. The key findings are these:

- Workers entering some occupations go on to experience very low wage growth. Other occupations appear to be launchpads, with workers entering them going on to experience very high wage growth.
- Occupations in "knowledge" clusters such as Information Technology, Management/Finance, and Engineering/Science/Architecture are more likely to be launchpads. For example, given the same starting wage, entrants to IT are expected to out earn entrants to Production occupations by more than $12 per hour after 10 years.
- Entrants to occupational clusters that are more likely to include launchpad occupations also spend fewer months not employed.
- Mid-level occupations that require transferable skills such as problem solving and communication are more likely to be launchpads for entrants' future wage growth.
- Over the course of a career, problem solving and people management skills are likely to become increasingly important for workers to advance in terms of wage growth.

We discuss the implications of these findings in Chapter 5.

Chapter 4. Wage Growth Variation for Workers With Different Backgrounds or Experiences

Highlights

Does the extent to which occupations are launchpads vary for workers with different backgrounds or experiences?

(1) Frequent job changes (seven or more over a 10-year period) are associated with lower wage growth.
(2) Leaving the starting occupational cluster is associated with greater wage growth.
(3) Among workers who start in the same mid-level occupation:
   a. Women tend to experience lower wage growth than men do.
   b. Hispanic and Black non-Hispanic workers tend to experience lower wage growth than White non-Hispanic workers do.
   c. Workers with higher levels of education tend to experience higher wage growth than those without a high school diploma or equivalent.
   d. Workers who have a parent with a college degree tend to experience higher wage growth than those whose parents do not have a college degree.
(4) Groups that experience lower wage growth also spend fewer months working.
(5) When they make an occupational transition, women and Black and Hispanic workers are less likely to advance to higher-level jobs, and more likely to stay in the same occupational cluster.

This chapter explores how experiences vary among entrants to the same occupations in terms of worker experiences and backgrounds. First, we examine whether changing jobs or occupational clusters is associated with higher wage growth. Second, we examine the relationship between workers' demographic characteristics and wage growth, as the same occupations may be less likely to be launchpads for some workers than for others. All the findings in the chapter are presented as associations, not causal relationships. Relationships between a given predictor and wage growth may reflect factors beyond those measured in the CTOT Study.

4.1 Job and Occupational Cluster Changes as Predictors of Wage Growth

Key Findings

Compared to zero to two job changes over 10 years, three to four job changes may be associated with slightly higher wage growth, but seven or more job changes are associated with lower wage growth.

Changing clusters is associated with about $1/hour more wage growth.

Career pathways frameworks generally assume that career advancement will occur as workers change occupations within an occupational cluster or industry sector.[25] We analyze how wage growth relates to the frequency of job changes and whether workers typically remain in the same occupational cluster 10 years after starting in an occupation (Exhibit 4-1).

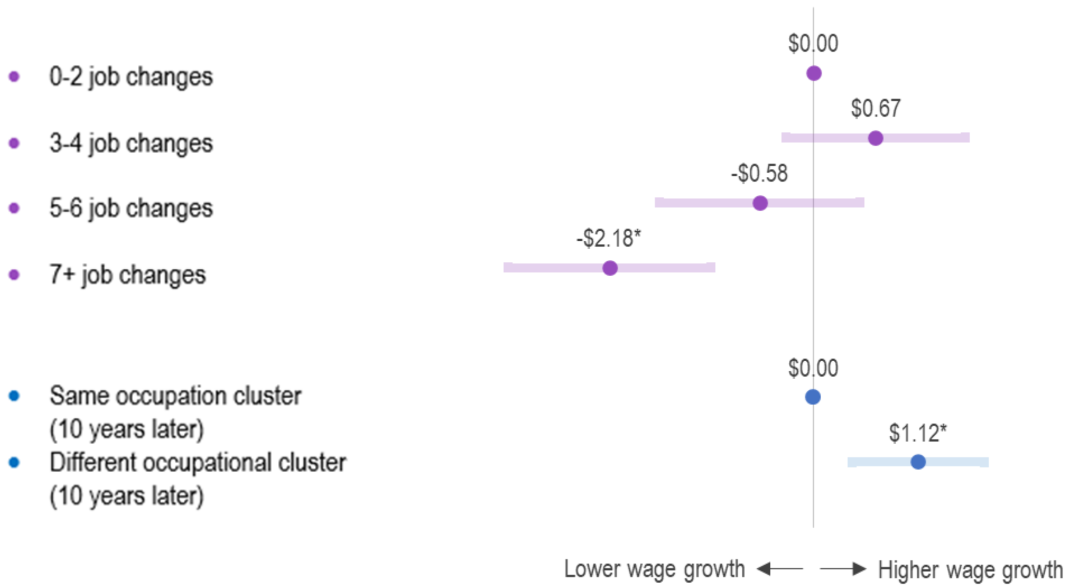
In general, a high number of job changes is associated with lower wage growth. It may be that frequent job changes reflect other factors that cause lower wage growth, rather than the changes themselves. For example, barriers to employment, unstable life circumstances, or skill deficits may make it difficult for individuals to keep a job; those same problems may inhibit career advancement more generally. There is no significant difference in wage growth by number of job changes among workers who made fewer than seven changes, suggesting that changing jobs is not strongly associated with wage growth changes until it occurs more frequently.

Workers who remain in the same occupational cluster 10 years after starting a job in that cluster experienced slightly less wage growth ($1.12) compared to those who work in a different cluster 10 years later. Career pathways programs typically envision wage growth occurring via advancement within an occupational cluster. But these findings indicate that advancement can be found at least as readily through movement across occupations. It may be that this pattern varies among occupational clusters depending on how transferable the skill sets are that workers develop in that cluster. Broadly, however, these results indicate that when programs advise program participants about future career options, it may be too limiting to discuss only occupations within the same sector or occupational cluster.

However, it is possible that those patterns vary by cluster. For instance, leaving a cluster with a highly specialized knowledge base, such as Healthcare, may have different wage implications than does leaving a Service cluster where the set of required skills may be more transferable rather than specialized. We examine the association between leaving an occupational cluster and wage growth by cluster in the report's companion volume *Appendix on Occupational Cluster Findings for Healthcare, Early Care and Education, Information Technology, and Production* and the accompanying Career Trajectories and Occupational Transitions Dashboard.

[25] See, for example, the career pathways model at https://career-pathways.org/about-career-pathways/

Exhibit 4-1. Ten-Year Wage Growth Differences, by Job and Occupational Cluster Changes During the 10-Year Trajectory



How to Read This Graph: The purple dots on this graph indicate the estimated difference in wage growth in hourly wages 10 years after entering an occupation experienced by entrants who made the stated number of changes, in comparison to the reference category (entrants who made two or fewer job changes). For example, entrants who change jobs seven or more times over 10 years experience, on average, $2 per hour less in wage growth over that same period than do otherwise similar entrants who make two or fewer job changes. The blue dots indicate the average difference in 10-year hourly wage growth between entrants who are working in an occupational cluster different than the one they had entered 10 years prior, in comparison to those who were still working in the same occupational cluster. The bars indicate how precise our estimates are (the 95 percent "confidence interval"); the actual wage difference could fall anywhere in that range, though it is more likely to fall toward the middle of the range than the ends.
Note: Estimates are drawn from OLS regressions that include controls for starting wage, data source, age, gender, race/ethnicity, starting education, parent education, and starting occupation. Asterisks (*) indicate a statistically significant difference at the .05 level.
Source: NLSY97 and PSID

4.2 Demographic Characteristics as Predictors of Trajectories

In this section we compare outcomes for workers by demographic categories, controlling for starting wage and occupation. We then explore factors that may contribute to differences in wage growth: time spent not working and receipt of a postsecondary degree. Then, using transitions data, we explore the extent to which demographic characteristics predict the likelihood of moving to jobs that pay higher wages.

4.2.1 WAGE GROWTH, BY WORKER CHARACTERISTICS

Exhibits 4-2 and 4-3 compare wage growth among workers of different characteristics who started in the same mid-level occupation.[26] Exhibit 4-2 shows how wage growth varies based on education-related measures—workers' own education and whether either of their parents has some college or a bachelor's degree. Exhibit 4-3 shows how wage growth varies among workers by their age, gender, and race/ethnicity.

Key Findings

There are significant differences in future wage growth by workers' background characteristics, suggesting that occupations may not function as launchpads for all workers equally effectively:

- Workers with **higher levels of educational attainment** upon entering the occupation experience more wage growth than those with lower levels.
- Workers who have a **parent with a four-year college degree** tend to experience more wage growth than whose parents have less education.
- **Women** tend to experience lower wage growth than **men** do.
- **Black non-Hispanic** workers and **Hispanic** workers each tend to experience lower wage growth than White non-Hispanic workers.
- **Age** is not associated with differences in wage growth.

Meaningfully large and statistically significant differences in wage growth are evident among workers from different backgrounds. The higher the level of education the worker has attained, the more wage growth they tend to experience. Workers with a high school diploma or associate's degree each experience more wage growth than do those without a high school diploma (by $2.47 and $3.79 per hour, respectively). Those with a bachelor's degree experience by far the most 10-year wage growth—$9.96 per hour more than workers who do not have a high school diploma. This is unsurprising given well-documented labor market returns associated with credentials. Because the comparisons here are among entrants to the same mid-level occupation, it may often be the case that entrants with more education are taking jobs in occupations for which they are educationally overqualified while they continue to search for a job in a higher-level (and likely higher-paying) occupation that requires the level of education they have attained.

Workers with at least one parent who has a four-year college degree experience, on average, $3.66 per hour more in wage growth than their otherwise similar peers who do not have a parent with a four-year college degree. This difference remains after accounting for the worker's own educational attainment—suggesting the potential value of resources that stem from their socioeconomic background.

When we compare wage growth for workers from different demographic subgroups, we also find disparities in wage growth. Women tend to experience less wage growth than men do. Black non-Hispanic workers and Hispanic workers each tend to experience less wage growth than White non-Hispanic workers do. The largest estimated differences are between women and men ($3.61 per hour) and between Black workers and White workers ($3.07 per hour). Workers of "Other" racial identities—a heterogeneous group that includes non-Hispanic workers who identify as American Indian, Asian, Pacific

[26] Of course, some of the occupational categories are broad enough that jobs within those occupations may vary, and the particular jobs held within an occupation could differ among workers with different backgrounds (Martin-Caughey, 2021). Adjustment for starting wage in these analyses should at last partially net out effects of within-occupation differences in level and type of jobs held.

Islander, Other, or Multiple Races—experience higher average wage growth than White workers do ($2.73 per hour). No statistically significant difference was detected by age group.[27]

Again, these findings are based on comparisons among workers who were starting from the same occupation. This highlights that for career pathways and other training programs, helping someone enter a new occupation is only one factor putting them on a path to upward mobility. Even after successfully becoming employed in a mid-level occupation, entrants may differ by background in their access to resources or in the barriers they face, including systemic biases; and that difference may affect their future wage growth. For example, workers whose parents have a bachelor's degree may have more access to information, social and professional networks, and financial resources (e.g., for further training) that puts them in a better position to get ahead. White non-Hispanic workers may tend to have more access to many of those same resources. Women and workers of color may face barriers to advancement within many industry sectors or occupational clusters. For example, women may face more challenges to advancement in occupational clusters that have traditionally been dominated by men.

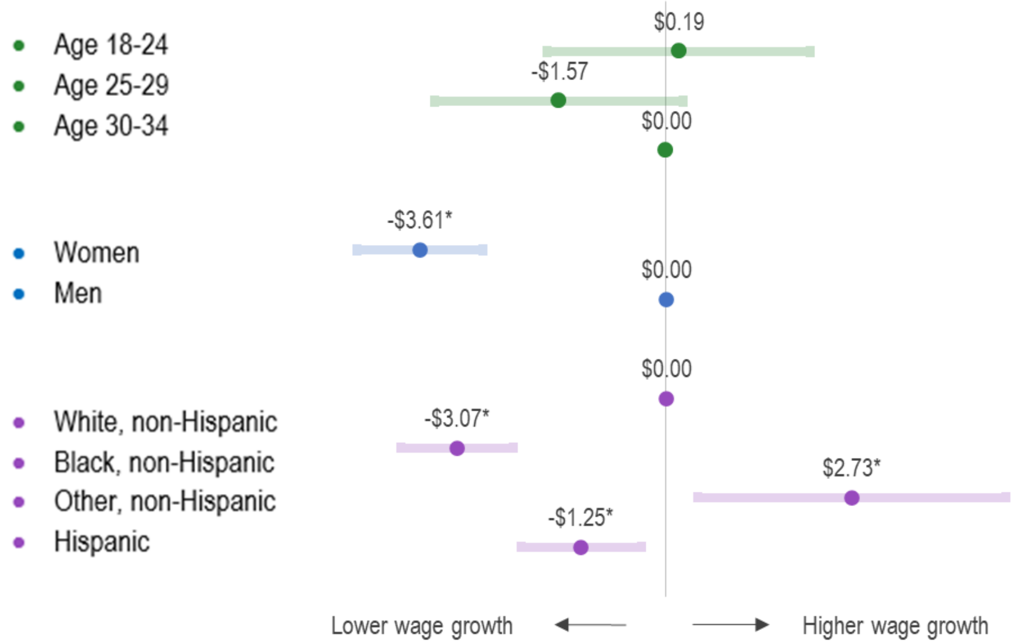
Another paper from the Descriptive and Analytical Career Pathways Project explores patterns of wage growth disparities in more detail—including how disparities vary among occupational clusters (Clarkwest et al., 2021). Program administrators may find it important to consider those potential barriers and resources to address them when designing approaches to meet the career advancement needs of the full range of participants they serve.

[27] It is worth noting that the analysis was restricted to workers who were younger than age 34 at the beginning of the trajectory, meaning the analysis cannot describe disparities for older workers.

Exhibit 4-2. Ten-Year Wage Growth Differences Among Entrants to the Same Starting Occupation, by Worker's Education Background and Parent's Education Background

How to Read This Graph: The dots represent the estimated difference in average wage growth for members of the given category, compared to members of the reference category who are otherwise similar (same starting occupation, starting wage, and demographic characteristics other than the one in question). Dots on the zero line are for the reference category itself (Own education=Has no degree; Parental education=Neither parent has any college). Dots to the right indicate that, on average, entrants from that demographic group experience more wage growth than do otherwise similar entrants from the reference category. For instance, entrants to an occupation who have at least a bachelor's degree experience, on average, $9.96 per hour more in wage growth in the 10 years after entering the occupation than do otherwise similar entrants who have no degree. The bars indicate how precise our estimates are (the 95 percent "confidence interval"); the actual wage difference could fall anywhere in that range, though it is more likely to fall toward the middle of the range than the ends.
Note: Estimates are drawn from OLS regressions that include controls for the worker's starting wage, data source, starting occupation (occupation fixed effects), age, gender, race/ethnicity, and the individual-level characteristics above. Asterisks (*) indicate a statistically significant difference at the .05 level.
Source: NLSY97 and PSID

Exhibit 4-3. Ten-Year Wage Growth Differences Among Entrants to the Same Starting Occupation, by Worker's Demographic Characteristics



How to Read This Graph: The dots represent the estimated difference in average wage growth for members of the given category, compared to members of the reference category who are otherwise similar (same starting occupation, starting wage, and demographic characteristics other than the one in question). Dots on the zero line are for the reference category itself (Age=30-34; Gender=Men; Race/ethnicity=White non-Hispanic). Dots to the right indicate that, on average, entrants from that demographic subgroup experience more wage growth than do otherwise similar entrants from the reference category. For instance, 18- to 24-year-old entrants to an occupation experience, on average, experience $0.19 per hour more in wage growth in the 10 years after entering the occupation than do otherwise similar 30- to 34-year-olds. The bars indicate how precise our estimates are (the 95 percent "confidence interval"); the actual wage difference could fall anywhere in that range, though it is more likely to fall toward the middle of the range than the ends.
Note: Estimates are drawn from OLS regressions that include controls for the worker's starting wage, data source, starting occupation (occupation fixed effects), starting education, parents' education, and the individual-level characteristics above.
The race/ethnicity category Other non-Hispanic includes Asian Americans, Pacific Islanders, American Indian/Native Americans, workers who report multiple racial identities, and workers who report no racial identity or no Hispanic ethnicity. Those workers are grouped only because sample sizes are insufficient to consider each separately. Asterisks (*) indicate a statistically significant difference at the .05 level.
Source: NLSY97 and PSID

4.2.2 TIME SPENT NOT WORKING, BY WORKER CHARACTERISTICS

The wage growth differences described above may understate disparities among workers from different backgrounds because they include only workers who are employed at the end of the career trajectory. In this section we examine the extent to which workers from different backgrounds vary in how many months they spend not working over the 10-year period we examine. In these analyses, time spent not working includes time out of the labor force as well as time spent looking for work, but excludes time spent in school.

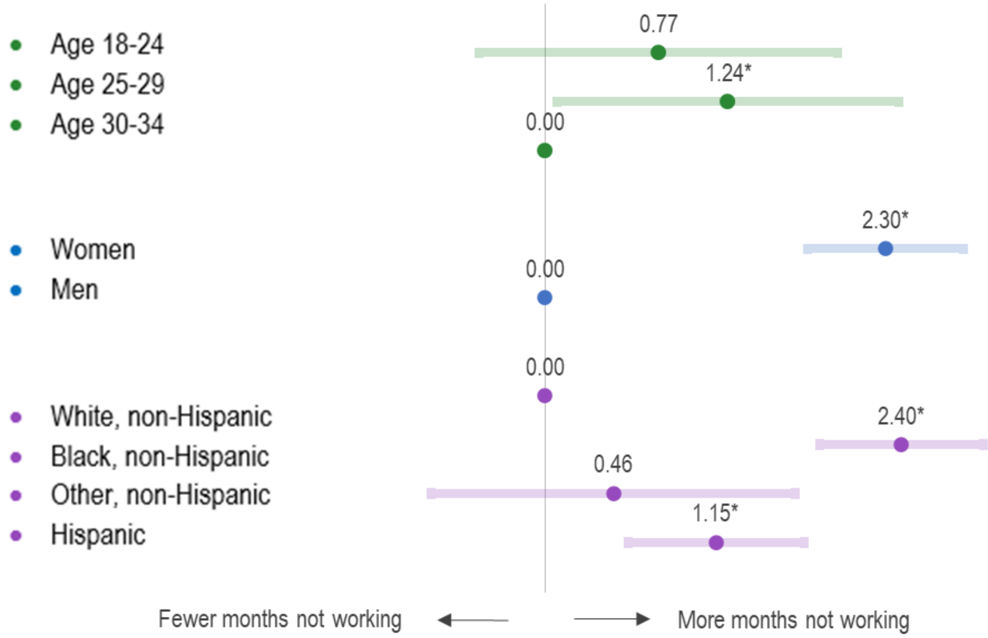
Key Finding

Disparities in time spent not working mirror disparities in wage growth, with the same groups experiencing higher wage growth also spending fewer months not working.

In general, disparities in time not working are consistent with disparities in wage growth. As Exhibit 4-4 shows, over a 10-year period, women spent more months not working than men, and Black non-Hispanic workers spent about two and a half more months not working than White non-Hispanic workers. Workers with higher levels of education themselves or with parents who have higher levels of education spent fewer months not working.

As discussed in the analyses of cross-cluster differences of entrants in months spent not working (see Exhibit 3-4 in Chapter 3), workers may miss out on wage increases during that time and will accrue less total work experience, which may lead to lower wage growth.

Exhibit 4-4. Months Spent Not Working Over 10 Years, by Worker Demographic Characteristics



How to Read This Graph: The dots represent the estimated difference in months spent not employed for members of the given category, compared to members of the reference category who are otherwise similar (same starting occupation, starting wage, and demographic characteristics other than the one in question). Dots on the zero line are for the reference category itself (Age=30-34; Gender=Men; Race/ethnicity=White non-Hispanic). Dots to the right indicate that, on average, entrants from that demographic group experience more months not working than do otherwise similar entrants from the reference category. For instance, 18- to 24-year-old entrants to an occupation spend, on average, 0.77 more months not employed in the 10 years after entering the occupation than do otherwise similar 30- to 34-year-olds. The bars indicate how precise our estimates are (the 95 percent "confidence interval"); the actual difference could fall anywhere in that range, though it is more likely to fall toward the middle of the range than the ends.
Note: Estimates are drawn from OLS regressions that include controls for the worker's starting wage, data source, starting occupation, starting education, parents' education, and the individual-level characteristics above. Asterisks (*) indicate a statistically significant difference at the .05 level.
Source: NLSY97 and PSID

Exhibit 4-5. Months Spent Not Working Over 10 Years, by Worker's Education Background and Parent's Education Background

How to Read This Graph: The dots represent the estimated difference in months spent not employed for members of the given category, compared to members of the reference category who are otherwise similar (same starting occupation, starting wage, and demographic characteristics other than the one in question). Dots on the zero line are for the reference category itself (Own education=Has no degree; Parental education=Neither parent has any college). Dots to the right indicate that, on average, entrants from that demographic group experience more months not working than do otherwise similar entrants from the reference category. For instance, entrants to an occupation with at least a bachelor's degree spend, on average, four and a half fewer months not employed in the 10 years after entering the occupation than do otherwise similar entrants with no degree. The bars indicate how precise our estimates are (the 95 percent "confidence interval"); the actual difference could fall anywhere in that range, though it is more likely to fall toward the middle of the range than the ends.
Note: Estimates are drawn from OLS regressions that include controls for the worker's starting wage, data source, starting occupation, age, gender, race/ethnicity, and the individual-level characteristics above. Asterisks (*) indicate a statistically significant difference at the .05 level.
Source: NLSY97 and PSID

4.2.3 NEW POSTSECONDARY DEGREE ATTAINMENT, BY WORKER CHARACTERISTICS

Next, we look at educational attainment, defined here as how likely workers were to earn a postsecondary degree within 10 years after entering the occupation. Returning for more education could be seen in a positive or negative light in this context. On the one hand, if workers are returning to earn additional degrees of their own volition to move up, that is a positive sign. On the other hand, returning for more education could be a sign of having encountered unfavorable career outcomes (displacement or hitting a dead end). And, of course, additional school involves a tradeoff with acquiring work experience that could itself lead to higher wage growth. Exhibit 4-6 displays those findings.

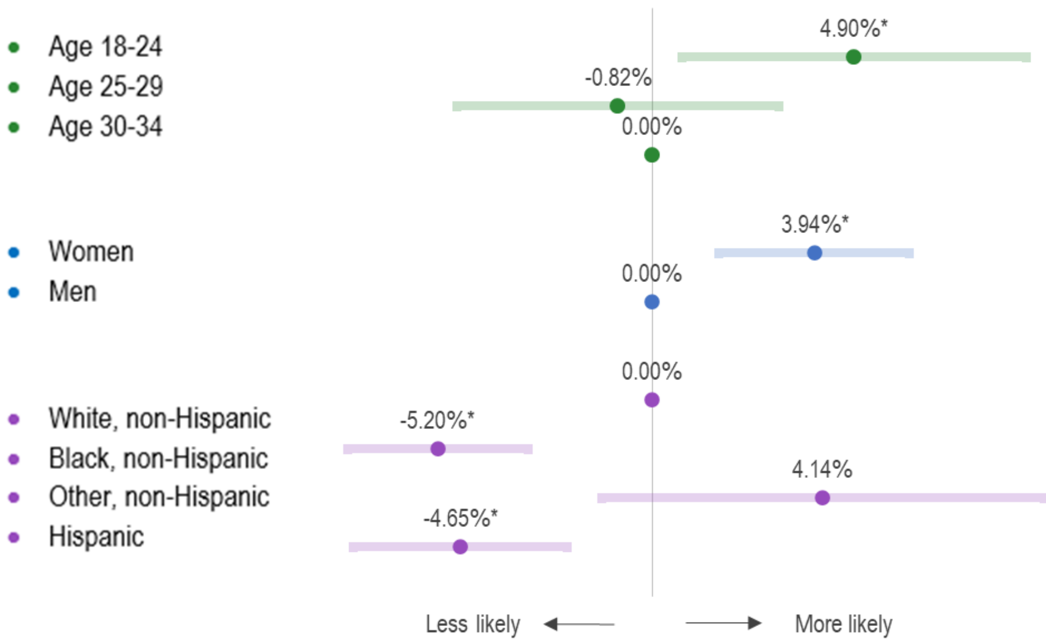
Key Findings

Black non-Hispanic and Hispanic workers are less likely than White non-Hispanic workers to earn a postsecondary degree; women are more likely to do so than men.

Younger workers and workers whose parents have more education are more likely to earn a postsecondary degree. Workers age 18-24 are almost 5 percentage points more likely to earn a postsecondary degree than those age 30-34. Workers with a parent with a bachelor's degree are more than 23 percentage points more likely to earn a postsecondary degree than workers without. Women are nearly 4 percentage points more likely than men to earn a postsecondary degree, too. Black non-Hispanic and Hispanic workers are each about 5 percentage points less likely to earn a postsecondary degree than are White non-Hispanic workers.

Taken as a whole, disparities in educational attainment mirror the disparities we see in wage growth in some instances, but not others. This implies the need to look at patterns for each demographic group separately, though with an intersectional lens (e.g., Black non-Hispanic women may have a different experience than either Black non-Hispanic men or women of other races/ethnicities). It also implies value in understanding the reasons that workers return to college and the barriers to doing so. That having a parent with a college degree so strongly predicts whether the worker goes back to earn a degree indicates how information, expectations, and material resources contribute to whether workers can or want to obtain additional education.

Exhibit 4-6. Likelihood of Earning a Postsecondary Degree, Over 10 Years, by Worker Demographic Characteristics

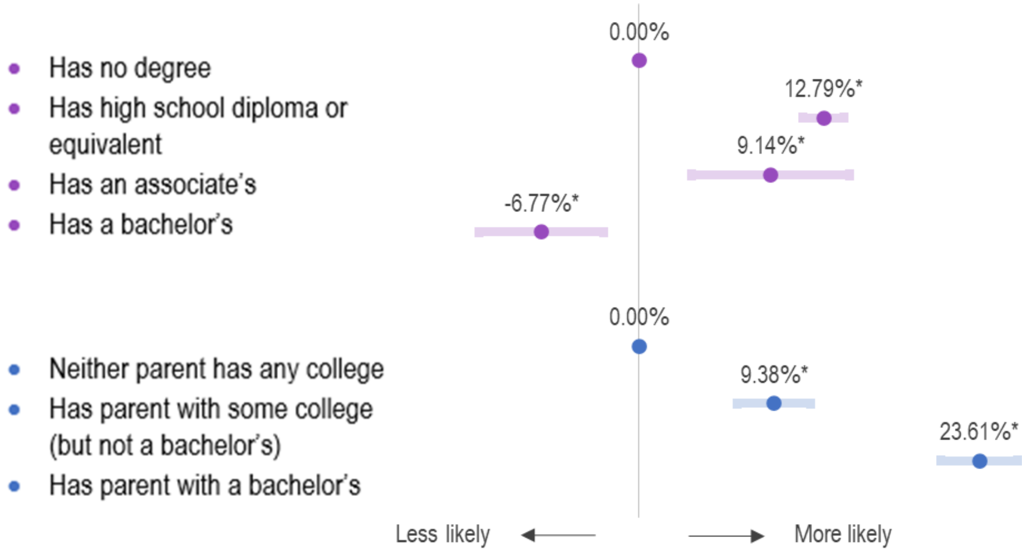


How to Read This Graph: The dots represent the estimated difference in the percentage of entrants from the given group who earn a postsecondary degree, compared to members of the reference category who are otherwise similar (same starting occupation, starting wage, and demographic characteristics other than the one in question). Dots on the zero line are for the reference category itself (Age=30-34; Gender=Men; Race/ethnicity=White non-Hispanic). Dots to the right indicate that, on average, a higher percentage of entrants from that demographic group earn a college degree during the 10-year trajectory than do otherwise similar entrants from the reference category. For instance, 18- to 24-year-old entrants to an occupation are almost 5 percentage points more likely to earn a college degree in the 10 years after entering the occupation than are 30- to 34-year-olds who are otherwise similar. The bars indicate how precise our estimates are (the 95 percent "confidence interval"); the actual difference could fall anywhere in that range, though it is more likely to fall toward the middle of the range than the ends.

Note: Estimates are drawn from OLS regressions that include controls for the worker's starting wage, data source, starting occupation, starting education, parents' education, and the individual-level characteristics above. Asterisks (*) indicate a statistically significant difference at the .05 level.

Source: NLSY97 and PSID

Exhibit 4-7. Likelihood of Earning a Postsecondary Degree, Over 10 Years, by Worker's Education Background and Parent's Education Background



How to Read This Graph: The dots represent the estimated difference in the percentage of entrants from the given group who earn a postsecondary degree, compared to members of the reference category who are otherwise similar (same starting occupation, starting wage, and demographic characteristics other than the one in question). Dots on the zero line are for the reference category itself (Own education=Has no degree; Parental education=Neither parent has any college). Dots to the right indicate that, on average, a higher percentage of entrants from that demographic group earn a college degree during the 10-year trajectory than do otherwise similar entrants from the reference category. For instance, entrants to an occupation who have a high school diploma or equivalent are almost 13 percentage points more likely to earn a college degree in the 10 years after entering the occupation than are otherwise similar entrants with no degree. The bars indicate how precise our estimates are (the 95 percent "confidence interval"); the actual difference could fall anywhere in that range, though it is more likely to fall toward the middle of the range than the ends.
Note: Estimates are drawn from OLS regressions that include controls for the worker's starting wage, data source, starting occupation, age, gender, race/ethnicity, and the individual-level characteristics above. Asterisks (*) indicate a statistically significant difference at the .05 level.
Source: NLSY97 and PSID

4.2.4 JOB CHANGES AND OCCUPATIONAL TRANSITIONS, BY WORKER CHARACTERISTICS

Key Findings

Hispanic workers are more likely to stay in the same occupation when changing jobs. Younger workers are less likely to do so.

Women and workers of color are more likely to stay in the same occupational cluster when changing jobs.

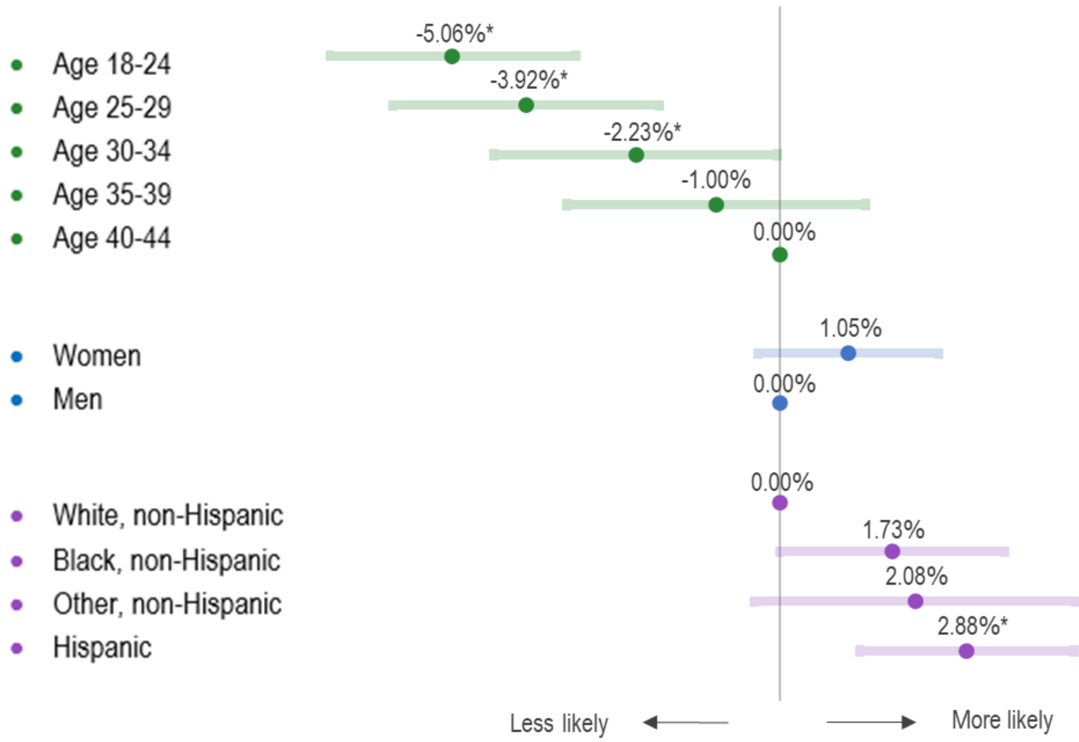
The disparities we find in the analyses of wage growth, time spent not working, and educational attainment highlight the need to understand how workers of different backgrounds move in the labor market. In this subsection, we explore how workers' demographic characteristics predict the nature of job changes they make. First, we explore mobility across occupations and occupational clusters when workers make job changes. Then we explore the likelihood of job changes reflecting advancement, looking both at the likelihood of moving to a job that requires more preparation and at the likelihood of moving into higher-paying jobs. It is worth noting that all analyses in this section are limited to what happens when a worker changes jobs and do not reflect the likelihood of staying in the same job.

Likelihood of Job Changes Remaining in Same Occupation or Occupational Cluster

One factor that might explain differences in wage trajectories is whether workers remain in the same occupation when they change jobs. Transitions within the same occupation could reflect workers moving to higher-paying employers or otherwise preferable roles. However, it could also reflect workers making lateral moves versus advancing to a next, higher career step. The analysis shown in Exhibit 4-8 examines the likelihood of a job change involving switching to a different occupation; it uses the job changes dataset described in Section 2.3.2 in Chapter 2.[28] The other analyses in this section are limited to transitions that involve switching occupations.

Job changes made by workers who are younger are more likely to involve leaving the occupation. Job changes made by Hispanic workers are more likely to involve staying in the same occupation. No statistically significant differences by gender were detected (see Exhibit 4-8).

Exhibit 4-8. Likelihood of Workers Changing Jobs Staying Within the Same Occupation

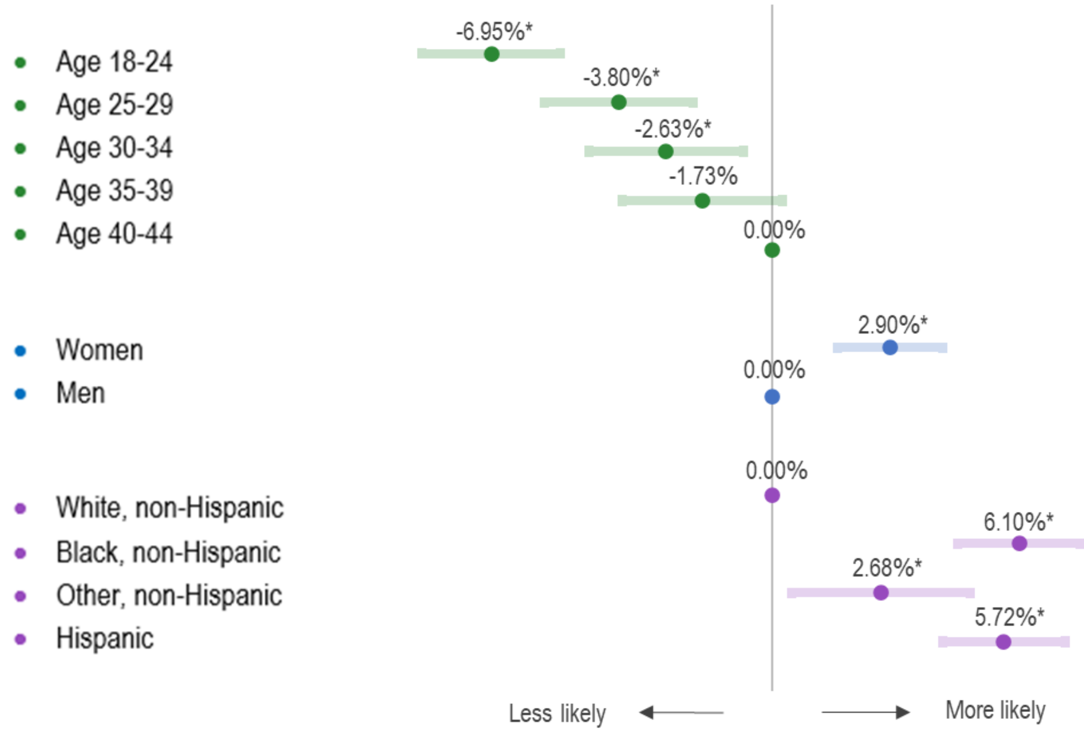


How to Read This Graph: The dots represent the estimated difference in the likelihood that a job change made by a worker from the group in question will be to a job in the same occupation, compared to the likelihood for an otherwise similar worker from the reference category (Age=40-44; Gender=Men; Race/ethnicity=White non-Hispanic). Analysis considers only instances in which a worker changes jobs; it does not consider the likelihood of staying in the same job. Dots for each reference category are found on the vertical line. Dots to the left of the line reflect a lower likelihood. For example, compared to otherwise similar 40- to 44-year-old workers, 18- to 24-year-old workers are, on average, 5 percentage points less likely to stay in the same occupation when making a job change. The bars indicate how precise our estimates are (the 95 percent "confidence interval"); the actual difference could fall anywhere in that range, though it is more likely to fall toward the middle of the range than the ends.
Note: Estimates are drawn from OLS regressions that include controls for starting wage, data source, starting occupation (occupation fixed effects), and all individual-level characteristics above. Asterisks (*) indicate a statistically significant difference at the .05 level.
Source: SIPP

[28] As Section 2.3.2 explains, all job changes are included in this data set, regardless of whether the source and destination occupations are the same. The analysis uses only SIPP data because the Emsi data do not include demographic characteristics and the CPS data do not include job changes within the same occupation.

Women and workers of color are more likely to remain in the starting occupational cluster when changing occupations. Given that these workers tend to experience lower wage growth, this is consistent with our earlier finding in the analysis of 10-year trajectories that remaining in the starting occupational cluster is associated with lower wage growth (see Exhibit 4-1). As shown in Exhibit 4-9, **workers younger than age 35 making a job change are less likely to remain in the starting occupational cluster** than are workers ages 40-44 making a change.

Exhibit 4-9. Likelihood of Workers Changing Occupations Staying Within the Starting Occupational Cluster

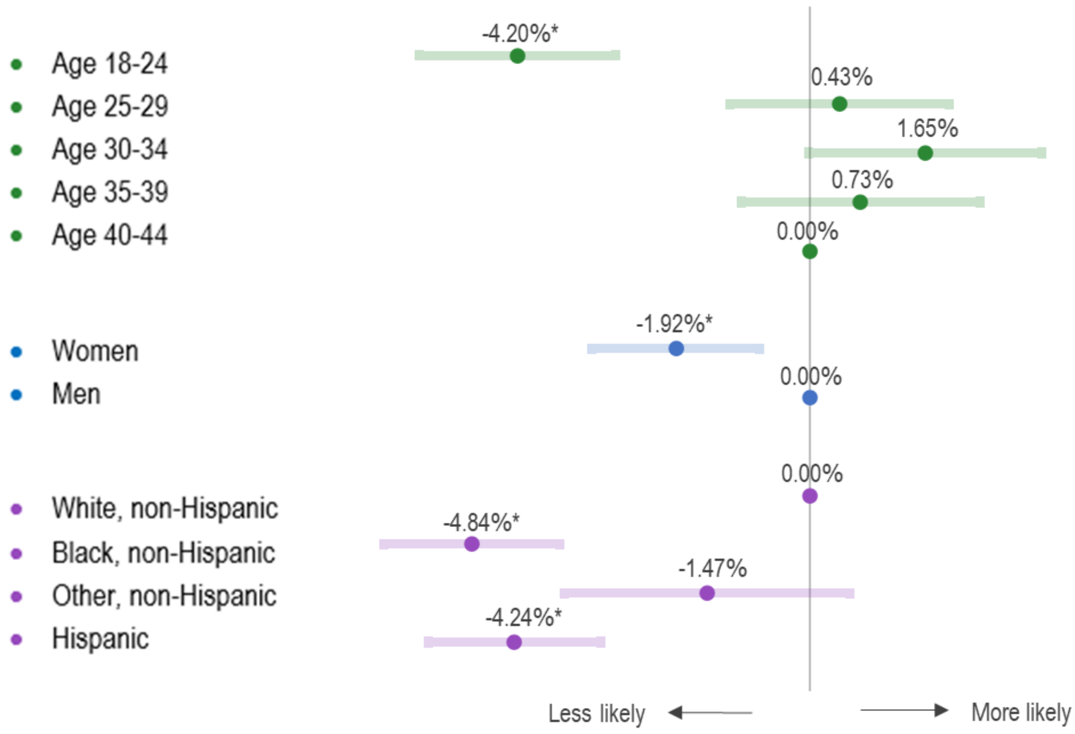


How to Read This Graph: The dots represent the estimated difference in the likelihood that an occupational change made by a worker from the group in question will be to an occupation in the same occupational cluster, compared to the likelihood for an otherwise similar worker from the reference category (Age=40-44; Gender=Men; Race/ethnicity=White non-Hispanic). Dots for each reference category are found on the vertical line. Dots to the left of the line reflect a lower likelihood. For example, compared to otherwise similar 40- to 44-year-old workers, 18- to 24-year-old workers are, on average, 7 percentage points less likely to stay in the same occupational cluster when making an occupational transition. The bars indicate how precise our estimates are (the 95 percent "confidence interval"); the actual difference could fall anywhere in that range, though it is more likely to fall toward the middle of the range than the ends.
Note: Estimates are drawn from OLS regressions that include controls for starting wage, data source, starting occupation, and the individual-level characteristics above. Asterisks (*) indicate a statistically significant difference at the .05 level.
Source: CPS and SIPP

Likelihood of Occupational Transitions Representing Advancement to a Higher-Level Job

This analysis has focused on career trajectories and occupational transitions for workers who start by entering mid-level jobs. One potential mechanism for advancement to higher wages is by transitioning from mid-level jobs to ones that require a higher level of preparation (defined in O*NET as those that require "considerable or extensive" preparation, generally a bachelor's degree or more). Consistent with our findings on wage growth disparities, women and workers of color who make a job change from mid-level jobs are less likely to move to high-level jobs (Exhibit 4-10). This is particularly notable because women are slightly more likely to earn a postsecondary degree within 10 years of starting in a mid-level occupation, as seen in Exhibit 4-6.

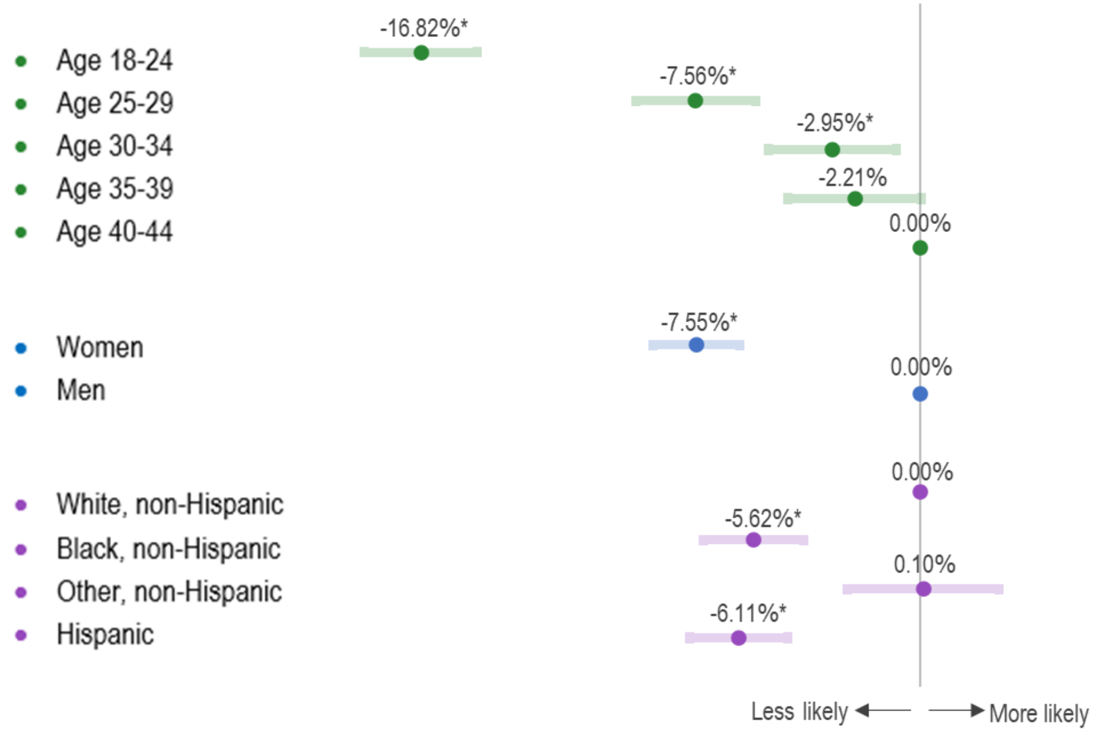
Exhibit 4-10. Likelihood of Job Changes Being to a Higher-Level Job



<u>How to Read This Graph:</u> The dots represent the estimated difference in the likelihood that an occupational transition made by a worker from the group in question is to a job that typically requires at least a four-year college degree (a high-level job), compared to the likelihood for an otherwise similar worker from the reference category (Age=40-44; Gender=Men; Race/ethnicity=White non-Hispanic). All job changes are from mid-level jobs. Dots for each reference category are found on the vertical line. Dots to the left of the line reflect a lower likelihood. For example, compared to job changes made by otherwise similar men, job changes made by women are 2 percentage points less likely to be to a job in a high-level occupation. The bars indicate how precise our estimates are (the 95 percent "confidence interval"); the actual difference could fall anywhere in that range, though it is more likely to fall toward the middle of the range than the ends.
Note: Estimates are drawn from OLS regressions that include controls for starting wage, data source, starting occupation, and the individual-level characteristics above. Asterisks (*) indicate a statistically significant difference at the .05 level.
Source: CPS and SIPP

Occupational transitions for women, Black non-Hispanic, and Hispanic workers and for younger workers are less likely to involve wage increases. Exhibits 4-11 and 4-12 both explore the relationship between demographic characteristics and whether occupational transitions are to destination occupations that pay more. Exhibit 4-11 examines disparities in the likelihood that an occupational transition will be to a job that pays at least $2 per hour more than the job the worker is coming from.

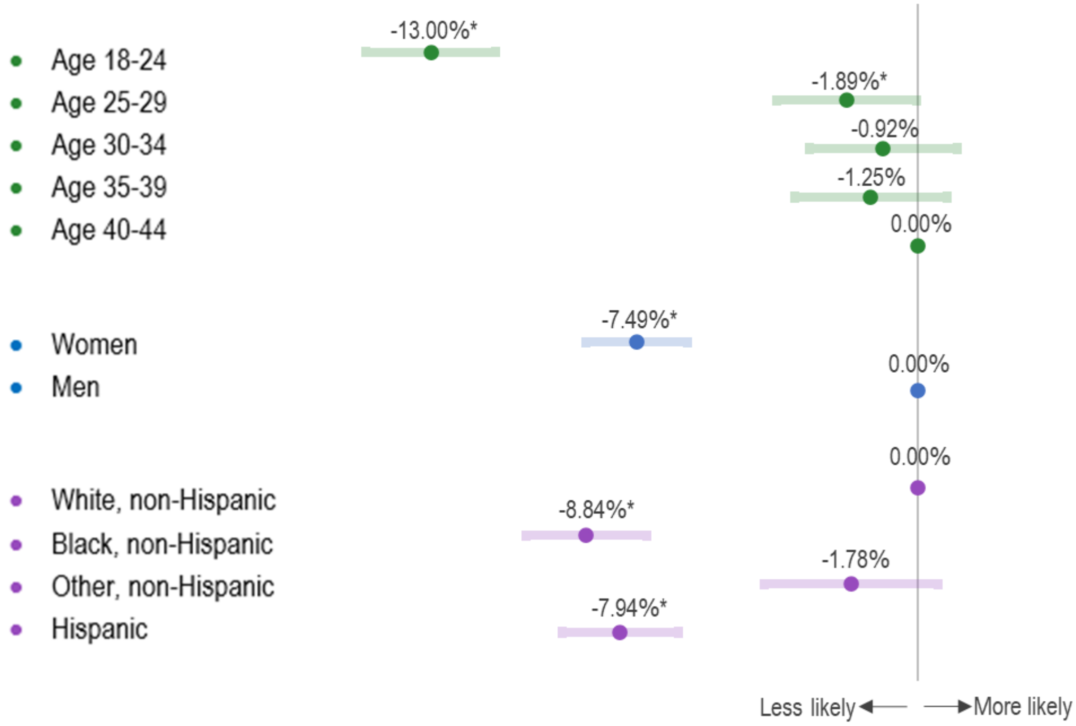
Exhibit 4-11. Likelihood That an Occupational Transition Involves a Wage Increase (at Least $2 per Hour)



How to Read This Graph: The dots represent the estimated difference in the likelihood that a job change made by a worker from the group in question is to a job that pays at least $2 more per hour than the source job, compared to the likelihood for an otherwise similar worker from the reference category (Age=40-44; Gender=Men; Race/ethnicity=White non-Hispanic). Dots for each reference category are found on the vertical line. Dots to the left of the line reflect a lower likelihood. For example, compared to job changes made by otherwise similar men, job changes made by women are almost 8 percentage points less likely to be to a higher-paying job. The bars indicate how precise our estimates are (the 95 percent "confidence interval"); the actual difference could fall anywhere in that range, though it is more likely to fall toward the middle of the range than the ends.
Note: Estimates are drawn from OLS regressions that include controls for starting wage, data source, starting occupation, and the individual-level characteristics above. Asterisks (*) indicate a statistically significant difference at the .05 level.
Source: CPS and SIPP

Women and Black and Hispanic workers are less likely to transition to occupations with higher median wages when they change jobs. The finding discussed in the prior paragraph, in relation to Exhibit 4-11, could be because those workers are less likely to move to higher-paying occupations (relative to job changes made by men; White non-Hispanic workers; and older workers). Or it could be that they are making similar occupational moves, but receiving smaller wage increases when making those transitions. To better understand this, Exhibit 4-12 examines median wages for occupations, rather than individual wages. This analysis shows that transitions for workers age 18-29 are also less likely to be to occupations with higher median wages, but there are no differences detected for workers age 30 and older. With respect to women and Black and Hispanic workers, the lower likelihood of transitioning to jobs with higher median wages suggests that part of the reason they are less likely to see higher wages when changing jobs is that they are transitioning to occupations that pay less (relative to the occupations men and White non-Hispanic workers transition to).

Exhibit 4-12. Likelihood That an Occupational Transition Is to a Higher Median Wage Occupation



How to Read This Graph: The dots represent the estimated difference in the likelihood that an occupational transition made by a worker from the group in question is to an occupation with a median wage at least $2 more per hour than the source occupation, compared to the likelihood for an otherwise similar worker from the reference category (Age=40-44; Gender=Men; Race/ethnicity=White non-Hispanic). Dots for each reference category are found on the vertical line. Dots to the left of the line reflect a lower likelihood. For example, compared to occupational transitions made by otherwise similar men, occupational transitions made by women are almost 8 percentage points less likely to be to a destination occupation with a higher median wage (by at least $2 per hour) than the occupation they came from. The bars indicate how precise our estimates are (the 95 percent "confidence interval"); the actual difference could fall anywhere in that range, though it is more likely to fall toward the middle of the range than the ends.
Note: Estimates are drawn from OLS regressions that include controls for starting wage, data source, starting occupation, and the individual-level characteristics above. Asterisks (*) indicate a statistically significant difference at the .05 level.
Source: CPS and SIPP

4.3 Conclusion

The findings in this chapter show that the trajectory and transition outcomes for workers in mid-level occupations vary considerably among workers of different backgrounds:

- Workers who are women, Black non-Hispanic, and from families where parents do not have four-year college degrees all experience lower wage growth in the 10 years after entering a mid-level occupation than do their counterparts who are men, White non-Hispanic, or who have parents with more education. Workers who are women, Black non-Hispanic, and from families where parents do not have four-year college degrees also tend to spend more time not employed, but that does not fully explain their lower wage growth.
- Women who enter mid-level occupations are more likely than their counterparts who are men to subsequently earn a postsecondary degree during their 10-year trajectory. Despite that, when

making an occupational transition, women are less likely than men to transition to a higher-level job (one that is expected to require at least a bachelor's degree).

- The job changes made by workers who are women or who are Black non-Hispanic or Hispanic are less likely to be to destination jobs that pay more than the jobs they are leaving, relative to men and White non-Hispanic workers, respectively. Younger workers are also less likely to move to jobs that pay more, relative to workers age 40-44.

The next chapter discusses implications from Chapter 3 and this Chapter 4.

Chapter 5. Discussion & Implications

In Chapters 3 and 4 we described this CTOT Study's findings in depth. Here we discuss limitations of the analysis and implications for practice, policy, and further research. This report's companion volume *Appendix on Occupational Cluster Findings for Healthcare, Early Care and Education, Information Technology, and Production* discusses additional findings at the cluster level.

5.1 Limitations

Though this analysis describes patterns between various occupational and worker characteristics and wage growth, it is descriptive in nature and thus does not determine to what extent any of those characteristics *cause* higher or lower wage growth. Additionally, there are many factors that affect wage growth that the study could not explore. In particular, the analysis did not explore regional differences in trajectories, nor the role of some occupational characteristics that might be of interest such as unionization.

The findings are also for a particular historical period. The 10-year trajectories began between 1997 and 2008. Thus, they reflect labor market conditions from 1997 to 2018. They are subject to being affected both by cyclical changes in the economy and by trends in occupational structures during that time period. Future periods will differ. That said, there is a fair amount of stability in many occupational structures—though likely more so in some occupational clusters than others. Although the past is not perfectly predictive of the present, economic structures change slowly enough that past patterns likely can inform expectations for the future.

5.2 Implications for Practice

Together with other data sources, the results reported here (and in the *Appendix on Occupational Cluster Findings for Healthcare, Early Care and Education, Information Technology, and Production*) and accessible through the accompanying Career Trajectories and Occupational Transitions Dashboard https://www.dol.gov/agencies/oasp/evaluation/resources/career-trajectories-and-occupational-transitions-dashboard can be used to develop programs that are responsive to the real-world experiences of workers. For example, a program might use labor market projections to identify a sector or occupational cluster for training; trajectories data to identify potential launchpad occupations within that cluster; and transitions data to develop potential pathways from occupations associated with lower wage growth to those associated with higher subsequent wage growth.

These findings also lead to several more general implications for those designing and implementing career pathways as well as other employment and training programs with similar employment goals for participants:

Focus training on occupations that tend to be stronger launchpads for wage growth. Programs have many considerations to weigh when determining occupations for which to offer training. Given how much occupations differ in the typical wage growth that entrants experience, incorporating career trajectories data into those considerations may help career pathways programs achieve their aims to promote participants' long-term career advancement and self-sufficiency.

Focusing training on occupations that are stronger launchpads does not mean limiting training to one or two occupational clusters. Programs often focus on a particular occupational area or industry due to its importance in the local labor market or the availability of high-quality training options. Our findings suggest that there are opportunities to target launchpad jobs in a variety of occupational clusters.

Design programs to build participants' broader transferable skills, not just specialized technical skills. Career pathways programs must consider which skills to emphasize. The findings suggest that designing programs to help participants build key transferable skills such as problem solving and communication may better position them to advance along a range of different advancement pathways.

Consider structural and other barriers facing specific demographic groups. The study finds disparities in wage trajectory by gender, race/ethnicity, and socioeconomic status of workers' family of origin—even among workers starting in the same occupation and who are otherwise similar. Though the study is not designed to determine causality, it is important for programs to consider that, once placed in a job, participants of different backgrounds are likely to face different career advancement challenges. To increase their advancement from initial mid-level occupations, programs should consider what barriers certain workers may face and ways to tailor support for workers who are women, Black non-Hispanic and Hispanic, and whose parents do not have four-year degrees. Support may include longer-term services to assist workers in making upward transitions beyond their first mid-level step. This could include employer education around disparities and biases in mentoring or performance assessment, or additional training for workers on asking for raises or promotions.

5.3 Implications for Policy

Implications for policy to help address barriers that lead to those wage advancement disparities go beyond increasing access to entry to an occupational cluster. In particular, policies that directly address wage disparities (e.g., minimum-wage increases, unionization) or those that address broader barriers directly related to gender, race/ethnicity, or socioeconomic status may be important. For example, addressing childcare issues, which disproportionately affect women (Pal & Waldfogel, 2016) or transportation issues (which disproportionately affect Black non-Hispanic and Hispanic workers) (McLafferty & Preston, 2019; Probst et al., 2007) might also be an essential part of supporting workers to remain employed and thus in a better position for advancement.

As noted above, though the findings from this analysis help give a more nuanced picture of the range of likely experiences after beginning a job in a targeted occupation, there are many other factors that may affect workers' experiences that the analysis could not address. To further support career pathways programs and other training providers with useful labor market information, policymakers may find it valuable to build systems accessible by practitioners that allow occupation-specific wage trajectory estimates with large samples that can be updated over time. Such estimates could be produced by merging larger sources of nationally representative data on workers' occupations, such as the American Community Survey (ACS) or the Current Population Survey (CPS),[29] with longitudinal data on earnings from tax data (IRS or Social Security Administration) or Unemployment Insurance files (National Directory

[29] The CPS has the advantage that it is possible to observe a subset of people entering an occupation—as we have done in our transitions analyses. The ACS or a single cross section of the CPS has the disadvantage that it is not clear when the individual worker started their trajectory. If linked with the National Directory of New Hires, it may be possible to estimate the trajectory start date based on detail about when employment first began with the primary employer at the time of survey interview.

of New Hires). These data files, which are much larger than panel sources such as the NLSY97 or PSID, would permit estimates for smaller occupations and more localized labor markets. Similar approaches have been used by researchers to better understand how factors such as work experience affect the gender wage gap (see Foster et al., 2020).

5.4 Implications for Further Research

These findings also imply several directions for further research, including research on the following questions:

What can workers' experiences in the labor market tell us about barriers to advancement? How might career pathways programs address those disparities? A related paper for the Descriptive & Analytical Career Pathways Project examines how racial, ethnic, and gender disparities vary by occupational cluster, offering additional insights as to possible reasons behind disparities (Clarkwest et al., 2021). An additional avenue for research could include qualitative studies of workers' experiences to understand barriers to advancement in particular sectors in greater detail, with a specific focus on understanding differences in the experiences of workers of different backgrounds.

Research should also focus on understanding the experiences of workers of color and women in career pathways programs over the longer run. As noted in this project's meta-analysis report (Peck et al., 2021), more consistent reporting on outcomes by participant characteristics over a longer period of time would allow researchers to determine whether there are differences in impacts among career pathways participants according to race, ethnicity, or gender and how they evolve over time. This area of research could also include qualitative studies focused on what existing programs are doing to support women workers and workers of color to advance in the labor market, and which of those practices appear to be promising for increasing advancement and reducing disparities.

The meta-analysis of career pathways program impact estimates also finds that programs that serve a higher proportion of Black non-Hispanic participants tend to have larger positive impacts on labor market impacts (Peck et al., 2021). This may suggest that programs are having some success in helping Black participants overcome advancement barriers, though the meta-analysis was not able to estimate impacts for participants by race due to data limitations. Long-term follow-up studies of career pathways evaluations would help confirm the extent to which wage growth disparities over time really are narrower among career pathways participants than in the broader labor market.

How do individual-level skills associate with advancement? The analyses in this report examine certain transferable, occupational skill requirements as predictors of wage trajectories, in the assumption that they proxy for skills that individuals either bring with them when they enter the starting occupation or else develop while employed in the occupation. But both transferable and technical job skill levels vary among workers in an occupation and are likely to be important determinants of advancement. Unfortunately, existing data that can be used to examine employment outcomes typically provide either no data on individual workers' skills or, at best, data on basic skills such as reading or math. Studies that systematically assess technical skills of training program participants and their broader skills—such as communication and problem solving—could be highly useful as part of longer-term impact studies to help understand which skills are particularly important for programs to help participants develop in order to promote wage growth and self-sufficiency.

How does individual workers' labor market knowledge associate with advancement? The analyses in this report have highlighted that workers often experience similar or even greater wage advancement when they change occupations across clusters than when they stay within an occupational cluster. Further analyses at the occupation level (see *Appendix on Occupational Cluster Findings for Healthcare, Early Care and Education, Information Technology, and Production* and the accompanying Career Trajectories and Occupational Transitions Dashboard) show workers tend to move into many different occupations. Together, this suggests that from any given mid-level occupation there is no single dominant pathway to advancement. Rather, there are many different destination occupations that workers transition into that represent upward moves. Which transitions are the best fit for any given worker likely depends on their own personal strengths and preferences. By acquainting participants with a broader range of pathway options that they could pursue in the future, programs may help a larger percentage of those participants go on from their "first-step" occupation to advance to a higher step.

How might COVID-19 influence patterns of trajectories and transitions? The COVID-19 pandemic has had major impacts on employment and the labor market, raising questions as to whether and how workers' trajectories may be shifting and whether some occupations are affected more than others. For instance, it may have accelerated trends in growth and decline of certain occupations, which may lead to some shifts in which certain occupations or occupational clusters become stronger wage growth launchpads. The pandemic has also disproportionately affected the employment of women and workers of color, which could translate into larger disparities in wage growth over time. Changes could be analyzed using large data sources such as the ACS and CPS or data from online job profiles. The survey sources have the virtue of being nationally representative; but in the near term, the online sources are easier to acquire. Within sectors, there may be additional opportunities in obtaining data from licensing registries or large employers.

5.5 Conclusion

This study has developed labor market information that complements other existing types of labor market information to specifically align with career pathways frameworks. That novel information goes beyond consideration of the availability and wages of occupations that training participants could be placed into now. It also considers how occupations compare regarding the longer-term wage growth that their entrants go on to experience. The CTOT Study is also producing detail on the variety of occupational transitions that workers make from individual occupations. This new kind of labor market information can inform design of training programs in ways that could enhance their ability to generate more positive economic outcomes for participants over time.

Appendix A: Data Sources

This appendix provides additional detail on each of the data sources we used in the analyses included in the CTOT Study. Exhibit A-1 summarizes the data sources.

Exhibit A-1. Career Trajectories and Occupational Transitions: Data Sources

Dataset	Source	Years	Content (other than occupation)	Sample Size	Nationally Rep.	Length of Panel / Occupational History
Panel Study of Income Dynamics (PSID)[a]	University of Michigan	2003–2017	Wages, education, demographic characteristics	24,000 individuals from 10,000 families	Yes	14 years
National Longitudinal Survey of Youth, 1997 (NLSY97)[a]	U.S. Bureau of Labor Statistics	1997–2018	Wages, education, demographic characteristics	8,984 individuals	Yes	20 years
Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS)[b]	U.S. Bureau of Labor Statistics and U.S. Census Bureau	2003–2016	Wages, education, demographic characteristics	98,000 households/year	Yes	1 year
Survey of Income and Program Participation (SIPP)[b]	U.S. Census Bureau	2003–2013	Wages, education, demographic characteristics	Households:[c] 2004 panel: 51,363 2008 panel: 52,031	Yes	2004 panel: 4 years 2008 panel: 5 years
Emsi occupational matrices[b]	Emsi	Through 2019[d]	None	128 million workers' profiles	No	n/a

Note: We also use data from the Occupational Employment and Wage Statistics (OEWS) survey to describe job characteristics; it is not included here because we did not use it as a source to examine transitions themselves.
[a] Data source was used in career trajectories analyses.
[b] Data source was used in occupational transitions analyses.
[c] These are the original sample sizes. Substantial sample attrition occurs over the length of the panel.
[d] The Emsi data of occupational transition counts aggregate from Emsi's 2019 microdata on 128 million unique workers. The transitions represented can have taken place at any point during the workers' careers; as such, they are not a current or recent snapshot, but instead cover a longer period. They represent transitions, not workers.
Source: Abt Associates

Panel Study of Income Dynamics (PSID)

The PSID is a nationally representative survey collecting data on economic, health, education, family formation, and other key outcomes of individuals, families, and households. It has been following a set of households and subsets of their descendants for more than 50 years. The PSID launched with a nationally representative sample of 18,000 individuals in 5,000 households in 1968. The survey oversamples low-income families. Over time, the PSID has added sample members from immigrant groups to maintain the representativeness of the sample as the composition of the U.S. population changes. The current sample includes about 24,000 individuals from 10,000 families.[30]

[30] A brief summary of the PSID is available at https://psidonline.isr.umich.edu/Guide/Brochures/PSID.pdf. A detailed description is available at https://psidonline.isr.umich.edu/data/Documentation/UserGuide2017.pdf.

The PSID survey is conducted biennially. Our analysis uses data from 2003 to 2017 survey waves. Most of the occupational data required for this study's purposes is available only for heads of households or spouses from the family-level survey. Therefore, our PSID sample includes only individuals who were surveyed as a head of household or a spouse during the period between 2003 and 2017.[31]

National Longitudinal Survey of Youth (NLSY)

Our analyses also use data from the NLSY, which is similar to the PSID in many respects. The NLSY is a nationally representative survey that follows a cohort of youth through their early careers. Among other subjects, it contains extensive individual-level data on their socioeconomic background and education and training.[32]

Our trajectories dataset uses the 1997 cohort (NLSY97), which is composed of youth born between 1980 and 1984. There have been 18 waves of interviews with this cohort released (as of the time of this report's writing), including annual surveys from 1997 to 2012 plus three rounds of biennial surveys from 2013 to 2018. In wave 18, which took place in 2017 and 2018, sample members were between the ages of 33 and 38. Compared to our other data sources, the NLSY sample is relatively small at about 9,000.

Current Population Survey (CPS)

The CPS Annual Social and Economic Supplement is a national survey covering about 98,000 U.S. households. The monthly CPS is the government's main source of information for some important economic topics, such as U.S. unemployment and poverty rates.[33] The CPS collects employment-related data from all household members age 15 or older. The sample is designed to be nationally representative. It is mainly cross-sectional in design, but it contains two distinct types of longitudinal components. First, the basic monthly survey of households interviews people in a sample household in each of four successive months, then not for eight months, then again for four months.[34] Second, the Annual Social and Economic Supplement (ASEC) connected to the March survey, also known as the "March CPS Supplement," asks about work in the prior year and current work.

The study uses CPS data from 2003-2016, particularly the annual March supplement to the CPS that provides detailed social and economic information. The March supplement provides information on current job occupation, wage, and hours worked, as well as occupation code, wage, and hours of an individual's primary job in the previous year (defined as the individual's longest job in the last year).

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31 Until the 2017 wave, "Spouses" could only be female, and "Heads" could only be female if no male partner existed. That is, no same-sex partners of sampled respondents were surveyed as spouses before 2017.

32 A description of the NLSY97 is available at https://www.bls.gov/nls/nlsy97.htm

33 A description of the CPS is available at https://www.census.gov/programs-surveys/cps/about.html.

34 The merging of monthly data often focuses on Outgoing Rotation Groups (ORG), or the last of the four monthly interviews. Because these ORG surveys include more detail on wages, wage changes can be analyzed for a fraction of the data. In addition to being found on the Census Bureau page, data on the CPS ORG are maintained by the National Bureau of Economic Research at https://www.nber.org/data/morg.html.

Survey of Income and Program Participation (SIPP)

The SIPP is a nationally representative panel survey that collects data on economic well-being of households and household members' program participation. Each panel is run for a period of three to five years, after which the SIPP is updated to reflect changes in the policy, economic, and social environment and a new panel is selected. The SIPP follows all sample members who remain in the household, as well as any sample members who subsequently form new households.[35] All household members age 15 or older are interviewed.

The study uses data from the 2004 and 2008 SIPP panels.

Emsi Occupational Transitions Matrix

Abt entered into an agreement with Emsi to access occupational transitions data, provided to the study team in an aggregated form. Emsi's underlying "worker profiles" microdata come from resumes and other worker-provided job histories (e.g., LinkedIn profiles), made available to it through partnerships and by downloading from various websites. These underlying data cover a large sample of workers (128 million records). Emsi has worked to de-duplicate the data to ensure that each observation is unique: one profile per person, using the most recent available.[36] With total U.S. employment at 157 million workers in 2019 (Bureau of Labor Statistics, 2020), the Emsi database likely contains a large share of active U.S. workers.

Emsi processed (or "parsed") the data in worker profile records into a sequence of individual jobs and educational experiences. Using automated procedures, Emsi tagged each job in each profile with an O*NET occupational code, based on the job title and description. The O*NET occupational codes are eight-digit codes that are based on 2010 SOC codes, but they sub-divide some of the SOC codes into multiple sub-codes. Given the 1,073 unique O*Net occupation codes, there are in theory approximately 1.15 million possible combinations of *source-occupation*-to-*destination-occupation* pairs. In the Emsi matrices, we observe 690,689 different source-occupation-to-destination-occupation pairs among the roughly 254 million unique job transitions in the underlying data file. Some of those transitions are very rare (e.g., the transition from Electronic Equipment Installers and Repairers, Motor Vehicles to Judicial Law Clerks occurs exactly once in the Emsi data). The remaining 460,000 or so occupation-to-occupation transitions that are not included in the matrices are ones that are never observed to occur (and may simply be ones that never occur in the real-world labor market).

The Emsi dataset we licensed aggregates all the transitions observed in the 128 million unique worker profiles to produce counts of how many transitions occur between every possible pairing of source and destination occupations.[37] Emsi provided the counts to Abt in the form of a two-dimensional matrix: source occupation by destination occupation. The matrix lists O*NET-defined occupations. For each occupation in O*NET, the matrix reports a count of the transitions to all other O*NET occupations. In each cell of this two-dimensional matrix is the count of the number of transitions from that source to that destination.

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35 A description of the SIPP is available at: https://www.census.gov/sipp/.

36 The Emsi data include people who may not be considered part of the current labor force: some of the sample may have left work or may not be looking for work.

37 For instance, if a particular worker profile contains a sequence of occupations moving from A to B to C, the table counts A to B as one transition and B to C as one transition.

For example, if there were only three occupations in the U.S. economy, the matrix might look something like Exhibit A-2 below. According to our hypothetical matrix, 217 people moved from occupation B to occupation C, for example. Although the Emsi matrix contains same-occupation job transition counts, our analyses focus solely on transitions between occupations, omitting same-occupation transitions.

Exhibit A-2. Hypothetical Emsi Two-Dimensional Occupational Transitions Matrix

	Destination Occupation		
Source Occupation	Occupation A	Occupation B	Occupation C
Occupation A	4,912	1,815	320
Occupation B	412	2,520	217
Occupation C	221	163	884

Source: Abt Associates

Though covering a large proportion of the U.S. labor force, the Emsi data are not strictly nationally representative. To the extent that workers in some occupations are less likely to have online job profiles, the Emsi data will be less representative of those occupations. The quality of occupational counts also depends on the accuracy and completeness of the job descriptions provided on the profiles.

Unlike our other data sources, the Emsi dataset lacks reliable information on demographics or any information on individual-level wages. All wage-related analyses using the Emsi data rely on aggregate (median) wages for the occupation from the Occupational Employment and Wage Statistics (OEWS) program.

Occupational Employment and Wage Statistics (OEWS) Survey as a Supplement to the Emsi Matrix

Conducted by the Bureau of Labor Statistics, the OEWS survey produces estimates of employment and wages for more than 800 occupations using information from 1.1 million establishments, produced by aggregating data from surveying about 180,000 to 200,000 establishments every six months.[38]

Because the Emsi data lack detail on wages of an occupation's incumbents, we supplemented them with data from the OEWS survey. The OEWS data provide median hourly wages for each occupational code, which allowed us to observe the change in median wages across transitions. The difference in wages between two occupations as calculated from the OEWS medians may not accurately reflect the actual change in wages experienced by individuals in the Emsi data who move between occupations. For instance, workers who move from a typically lower-wage occupation to an occupation that typically has higher wages may tend to be among the higher-performing and higher-paid incumbents in the source occupation. In that example, examining differences in median wages of the source and destination occupations may overstate the actual wage changes typically experienced by workers who make those moves. Again, longitudinal data will provide us with a more accurate sense of the wage growth that is typically associated with occupational transitions.

[38] A description of the OEWS program is available at https://www.bls.gov/oes/home.htm.

Additional Supplementary Sources

Our analyses also made use of a few other sources to provide additional information on occupations' typical requirements to help describe the occupations themselves and between-occupation transitions.

O*NET

Managed by DOL's Employment and Training Administration, O*NET is the most comprehensive source of data on occupational characteristics. Through surveys of experts and incumbents in each occupation, O*NET provides data on a variety of descriptors of occupations. The study used the following measures from O*NET data:

- **Required preparation.** O*NET categorizes occupations into groupings ("Job Zones") with similar education, experience, and on-the-job training requirements. These groupings range from Job Zone 1 (occupations that require little or no preparation) to Job Zone 5 (occupations that require extensive preparation).[39] The study uses those data to identify "mid-level" occupations—occupations that require some education or experience beyond high school but do not necessarily require a four-year college degree.

- **Important skills and abilities.** O*NET includes data on dozens of skills and abilities, rating how important each skill or ability is to performing a given occupation's tasks. From analyses of the large number of O*Net items, we constructed a set of scale measures for the following 12 types of skills (described in further detail in Appendix C): creativity, equipment repair/maintenance, fine motor, focused attention, gross motor, mathematical reasoning, managing people, problem solving, sensory perception, service orientation, teaching, and two-way communication.

OCCUPATIONAL OUTLOOK HANDBOOK (OOH)

As part of a larger narrative text for each occupation, the OOH provides descriptions of licensing and certification requirements. The study uses the OOH for information on whether licenses are typically required to work in a given occupation. Specifically, if the OOH contains any text in the field for licensing, we code the occupation as being one that potentially requires a license.

[39] More detail on Job Zones is available at https://www.onetonline.org/help/online/zones.

Appendix B: Dataset Construction

This appendix describes how the study constructed the three datasets used in the CTOT Study analyses: (1) the trajectories dataset, (2) the job changes dataset, and (3) the transitions dataset.

Trajectories Dataset

We compiled the trajectories dataset from the 1997 National Longitudinal Survey of Youth (NLSY) and the Panel Study of Income Dynamics (PSID). Both datasets are intended to be nationally representative of the U.S. population, but the NLSY specifically focuses on individuals born between 1980 and 1984 and follows one cohort over time, whereas the PSID covers all ages. The two surveys also have different methods and levels of detail and frequency for tracking information for individuals across time. Therefore, we made adjustments to the datasets separately to create the monthly trajectories before combining them into the full trajectories dataset.

NATIONAL LONGITUDINAL SURVEY OF YOUTH (NLSY)

Demographic information from the NLSY data include the individual's date of birth, gender, race, ethnicity, and parents' educational attainment. Unlike the PSID (outlined below), none of these variables was reported separately in each survey, so there were no discrepancies over time to resolve. The NLSY also includes measures of educational attainment for the surveyed individual at the time of survey and monthly school enrollment statuses, which are allowed to vary over time.

The NLSY collects employment status and job indicators by week since the time of the last survey and links those jobs to an employment roster for the year. The employment roster houses additional job information for each job worked during that year, including the 2002 Census occupation code, hours worked per week, and wages.

NLSY Missing Data

Educational attainment was sometimes reported only at certain time periods or not at all for an individual. To fill in periods of missing data, we first carried forward any previously reported education. If there were periods of missing education at the beginning of the observed data, we used a combination of age and degrees reported in later periods. Specifically, any individual with observed data starting at age 18 to 23 was assumed to start with a high school diploma or equivalent if they reported any degrees later in time. If the individual did not report any degrees in the observed data, then they were imputed as starting with no degree. Individuals with observed data starting after age 23 were imputed as having their earliest reported educational attainment at the beginning of their observed data. For individuals with no reported educational attainment throughout the observed data (less than 1% of NLSY trajectories), we used the Job Zone[40] of their reported occupations to impute education. Individuals with occupations in Job Zone 1 were assumed to have no degree; individuals with occupations between Job Zone 1 and 2.75 were assumed to have a high school diploma or equivalent; individuals with occupations between 2.75 and 3.75 were assumed to have an associate's degree; and individuals with occupations above Job Zone 3.75 were assumed to have at least a bachelor's degree.

[40] See Job Zone descriptions in the O*NET section of Appendix A for more information.

Because respondents could report on multiple jobs per month, we selected the primary job for a given month to be the job for which the individual had the highest earnings in that period. If the identified primary job was missing an occupation code, we used the most recent primary job occupation code instead. If there were no previous non-missing occupation codes, we used the next available primary job occupation code. Individuals with no occupation codes available across all surveys are excluded from the dataset.

Due to the format of the yearly employment roster, we linked weekly-reported employer codes to the yearly employment roster in order to compile the monthly employment data characteristics. However, occasionally a job was reported worked during the year that was not included in that year's employment roster. In these cases, we used the associated data from the most recent annual employment roster with that employer code. If the job remained unmatched, then we used the associated data from the next available annual employment roster with that employer code. When wages were not reported for a primary job, we assumed a linear progression of wages from the most recently reported wage data to the next available wage data. The top 1 percent of wages were top-coded and values converted to December 2019 dollars prior to imputation.

PANEL STUDY OF INCOME DYNAMICS (PSID)

Demographic information from the PSID data includes the individual's age, gender, race, ethnicity,[41] educational attainment, any additional training the individual received, and parents' educational attainment. All of these fields except for age are reported separately at the time of each survey.

An individual's educational attainment was recorded as a combination of years of education up until age 16, after which any additional education was recorded in one code for postgraduate work, college degrees earned within the United States, and degrees earned outside of the United States. Education within and outside the United States was combined into a single variable of either no degree, a high school diploma or equivalent, an associate's degree, a bachelor's degree, or a graduate degree. Other training reported such as certificates, licenses, or other diplomas were also included and linked to the month received in the trajectory data.

Mother's and father's educational attainment was reported separately for education received within the United States and outside of the United States. For schooling completed within the United States, both parents were coded as completing up to five grades, six to eight grades, nine to 11 grades, 12 grades or high school, 12 grades plus nonacademic training, some college but less than a bachelor's, a bachelor's degree, or an advanced degree. Schooling completed outside of the United States was simply coded in years of schooling for both parents. These two measures of education were collapsed into one summary variable for both parents that indicated if either parent had at least a bachelor's degree (reported directly for education received in the United States and calculated as more than 15 years of education outside of the United States), either parent had at least some college (reported directly for education received in the United States and calculated as more than 12 years of education outside of the United States), or neither parent had any college education.

We used a variety of employment data from the PSID to construct the monthly occupation characteristics. At the time of each survey, the individual reported their employment status as either currently working,

41 A Spanish descent indicator was available beginning in the 2005 wave and was used to supplement data on Hispanic ethnicity for all data thereafter.

temporarily laid off or on leave, unemployed and looking for work, retired, permanently or temporarily disabled, keeping house, student, or something else. The PSID also identified a primary job at the time of the survey that could either be the individual's current primary job or be their most recent primary job if not currently working. Information associated with reported primary jobs included whether or not it was a current job or most recent job, whether or not the individual worked the primary job for each month of the previous year, and the month and year the individual began and finished (if applicable) working the primary job.

We also used more general employment information including whether or not the individual worked at all during the two years prior to the survey, whether or not the individual was unemployed for each month of the previous year, and whether or not the individual was unemployed for each month of the year before the previous year.

Procedures for Addressing PSID Data Inconsistencies Across Surveys

Because the PSID data used in the occupation trajectories follow the same individuals across multiple surveys over a span of more than 10 years and because most of the data are reported separately at the time of each survey, there are some inconsistencies across data collected at different times. Demographic data was collected for every individual at the time of each survey, which required some reconciliation. For race or ethnicity, we aggregated any reported race and ethnicity across all survey waves. If there was inconsistency of reported gender for an individual across waves, we kept the most commonly reported value. If there was more than one most commonly reported value, we kept the most recent value.

Due to the lookback periods, recalled employment data often overlapped data reported in previous surveys and occasionally contained inconsistencies needing reconciliation. Sometimes the reported monthly indicators and job start and end dates conflicted with each other. For the most part, the start and end dates appeared to be more accurate on a monthly basis, and the monthly indicators appeared to be more or less constant throughout a given year. The one exception was the unemployment status by month, which appeared to fluctuate on a monthly basis. Additionally, some variables such as unemployment status were collected for a period that overlapped with the previous survey wave. Occasionally, the data reported in the previous wave conflicted with the lookback data.

We resolved the more common inconsistencies as follows:

1. If the individual indicated that they worked their main job every month of the previous year, but the reported start date of their main job is in the middle of the previous year, the start date was assumed correct.

2. If the individual indicated that they worked their main job every month of the previous year, but the reported end date of their most recent job is in the middle of the previous year, the end date was assumed correct.

3. If the individual indicated that they worked their main job in the previous year, but the reported end date of their most recent job is before the previous year, the end date was assumed correct.

4. If the individual indicated that they worked their main job every month of the previous year, but they also reported being unemployed in the previous year, the unemployed status was assumed correct.

5. If the individual reported being unemployed during the month of the previous survey but they had reported working their main job at the time of the previous survey, the previous survey data was assumed correct (i.e., the assumption was that the contemporaneous reporting was more accurate than the recalled reporting).

PSID Missing Data

The availability of multiple survey waves for the same individual allowed us to minimize missing data (either survey-level or item-level) by filling in data holes from other surveyed periods. Missing item-level or survey-level years of education for the individual and their parents was filled in using the nearest available data. If the most recent and next available data were the same distance away, then we gave priority to the most recent data. The individual’s degree was logically imputed using both years of education and degrees received within and outside the United States. For individuals with periods missing reported degrees, we first carried forward any previously reported degrees, foreign or domestic. For remaining periods of missing data, we imputed no degree if less than 12 years of education, a high school diploma or equivalent if at least 12 years of education, an associate’s degree if at least 14 years of education, a bachelor’s degree if at least 16 years of education, and a master’s degree if at least some postgraduate work was reported. Others reporting at least some postgraduate work were assumed to only have a bachelor’s degree. Missing item-level data for reported additional training received was filled in with the most recent available data, or the next available data if no previous data existed. We assumed reports of being a student at the time of the survey carried across that academic year (August–July). If a survey had missing employment information for the four months (the length of a typical academic term) before the individual reported receiving an additional training degree or certificate, we assumed that the individual was not working and a full-time student during that period.

We also carried primary job information across waves for an individual. The 2017 occupation data were coded in terms of 2010 Census occupation codes, whereas all other waves used 2000 Census occupation codes. Therefore, we converted the 2017 occupation data to 2000 Census codes prior to carrying the information across to other time periods. We marked an individual as working a given job in months that fell between the start and end dates for the job and where there was no other indication of unemployment during that month. For individuals that reported multiple primary occupations that overlapped in time, we gave priority to the data from the next wave with non-missing job data, and then prioritized data from the closest previous wave with non-missing job data. Missing hours per week worked we first filled in with any reported data of hours per week worked for the same occupation in the past five years (giving the most recent data priority), and then filled in with any reported data for the same occupation in the next five years (prioritizing next available data). For remaining missing hours worked data, we repeated the same process to fill in hours from the past and next five years reported for any occupation. Remaining missing hours per week worked we assumed were 40.

The wage data exhibited small unavoidable gaps due to the frequency with which wage information is reported, but we imputed earnings data where possible to avoid larger gaps due to missing data. The gaps due to reporting frequency occurred because wages were only reported in the year of and prior to the survey, whereas employment and occupation statuses were typically reported by month and coded across surveys by start and end date. If an individual reported earnings by salary instead of hourly wages, then we assumed the wage was equal to the salary divided by 52 weeks per year and the number of hours per week worked. The top 1 percent of wages were top-coded to avoid outliers. We imputed remaining missing wages in the middle of an individual’s observed data based on the reported wages immediately before and after the missing period, assuming a linear wage trajectory, including both wage increases and decreases over time. We adjusted all wages and salaries to December 2019 dollars prior to imputation.

COMBINED NLSY AND PSID

After separately processing the NLSY and PSID data, we combined them into a single trajectories dataset and weighted the data within each of three age categories (18-24, 25-29, and 30-34) to make the sample reflect the gender, race/ethnicity, and educational composition of the workforce for workers in those age categories in 2020.[42]

Each trajectory begins when the individual reports a new non-missing occupation,[43] then continues by month until the end of the observed data period for that individual. Therefore, an individual may have more than one trajectory if they worked more than one mid-level occupation during the period. Each trajectory varies in length, depending on the number of years observing the worker's occupation and wage after they first took a job in the given occupation. Because the PSID trajectories were constructed from job start and end dates, some reported jobs began well before the observed data period.

We omitted PSID trajectories where the observed data period began more than two years after the reported job start date. For example, we dropped the trajectory for a job beginning in 1970 because the first occupation data available do not start until the 2000s,[44] making it impossible to correctly evaluate growth from the true beginning of the trajectory. By definition, a trajectory begins with a valid job, so we omitted months not working or missing data before a trajectory. Similarly, a trajectory ends either with a valid job or with a valid not working or student status, so we omitted months with missing data at the end of a trajectory. We also omitted trajectories beginning with missing wage data (after applying imputation procedures as described earlier) because wage growth analyses could not be conducted in those cases. Similarly, we trimmed trajectories ending in missing wage information (unless it is a period of not working) to end at the month with the most recently reported wage, so there is valid wage data at the end of the trajectory. We excluded completely trajectories missing wages across all months.

We then created three-year, five-year, and 10-year data files. For the three-year file, each trajectory observation that was at least three years in length was trimmed to three years; trajectories shorter than three years in length were omitted from the file. We used analogous procedures for the five-year and 10-year files, but trimming at five and 10 years, respectively. The 10-year file has the smallest sample because fewest of the trajectory observations covered that long of a period. The three-year file has the largest sample. For all files, the sample is limited to trajectories that began when the worker was between the ages of 18 and 34.

We weighted the trajectories to align with the 2020 U.S. population within age groupings of 18-24, 25-29, and 30-34. Within each age group, we weighted each trajectory by gender (male or female); race/ethnicity category (Hispanic of any race, White non-Hispanic, Black non-Hispanic, Native American non-Hispanic,

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[42] Based on estimates from the March 2020 Current Population Survey.

[43] Since most of the raw data classify occupations according to the 2000/2002 Census code scheme, all trajectory data is defined by 2002 Census codes. 2002 Census codes only differ from 2000 Census codes by a factor of 10 to begin the conversion of earlier 3-digit codes to 4-digit codes used in future Census code schemes.

[44] The start of the observed data periods vary by individual due to when an individual entered the sample or due to non-responses or missing data.

Asian non-Hispanic, Pacific Islander non-Hispanic, or other non-Hispanic/missing race/multiracial); and college degree attainment (has at least a bachelor's degree, does not have a bachelor's degree).

Finally, for analysis, we limited the dataset to include only mid-level occupations. To determine the Job Zone we used the U.S. Bureau of Labor Statistics' O*NET Job Zone classifications to classify job levels. Because NLSY97 and PSID use different systems to classify occupations, crosswalks are required. O*NET's occupational classifications are finer grained than Census classifications. As such, in some cases multiple O*NET codes correspond to a single Census code. In those cases, the Job Zone for the Census occupation is calculated as the simple average of the Job Zones for the set of corresponding O*NET codes. The study defined mid-level jobs as those with Job Zones of at least 2 but less than or equal to 3.8. This means that mid-level occupations typically require some postsecondary preparation but not a four-year college degree. High-level occupations are those with an average Job Zone higher than 3.8, meaning that they require more extensive preparation.

We bottom-coded starting wages to the federal minimum wage of $7.25 per hour and top-coded starting wages to the 98th percentile to avoid the influence of outliers on wage growth. Months not working were also capped at 24 months for certain analyses to try to home in on involuntary unemployment rather than long-term voluntary unemployment.

The final 10-year trajectory analysis dataset includes 31,813 trajectories, whereas the three- and five-year analysis datasets include 43,037 and 46,789 trajectories, respectively. Exhibit B-1 lists the number of observations for which we observe trajectories of that length (Dataset N) and the number for which we can measure wage growth between the start and end of the trajectory (Measure N). All trajectories have a wage at the start. The two Ns differ principally because the individual was not employed (and thus did not have wages) at the end of the trajectory period. Exhibit B-1 describes the observations for which wage data are not available. Analyses of outcomes such as months spent not working during the trajectory can include observations that are not included in the wage growth analyses.

Exhibit B-1. Trajectories Missing Data Frequencies

Measure	Dataset (N)	Measure (N)	Description of Observations without End-of-Trajectory Wage Data
Three-year wage change	46,789	36,789	If the individual is a student or otherwise not working after three years, they are missing the three-year wage change measure.
Five-year wage change	43,037	33,808	If the individual is a student or otherwise not working after five years, they are missing the five-year wage change measure.
Ten-year wage change	31,813	25,038	If the individual is a student or otherwise not working after 10 years, they are missing the 10-year wage change measure.

Job Changes Dataset

The study uses transitions data to explore whether demographic characteristics are associated with the likelihood of moving to a different occupation when an individual does change jobs. The job changes dataset uses data from the CPS and the SIPP. Both sources are intended to be nationally representative at the time of survey. The CPS is a cross-sectional dataset; observations are at an individual level, and an individual is represented only once. The SIPP is a longitudinal survey; observations are at the individual-month level, and an individual is represented for the length of a panel (12 waves/48 months for the 2004 panel; 16 waves/64 months for the 2008 panel). Because the study's job changes analyses look at individuals only at the moment they transition from one occupation to another, that the units of analysis differ for the two source datasets is not a concern. The majority of the annual and monthly sources for both surveys classify occupations according to the 2010 Census code scheme, so all of the occupations are classified that way.

CURRENT POPULATION SURVEY (CPS)

Within the CPS data, the study observes an occupational transition when an individual's longest job in the previous year has a different code than their current job. CPS data do not provide detail on when the transition occurred, only that it did occur. Once we identify a transition, we also look at hourly wage and hours worked at the previous and current job, as well as demographic information for the individual making the transition.

The CPS data observe a transition only if the individual transitions between two different occupational codes. If they change jobs within the same occupational code, the CPS does not provide enough detail to capture that. If the individual experiences an unemployment spell either in the previous year or at the time of the survey, we do not include that as a complete occupational transition.

SURVEY OF INCOME AND PROGRAM PARTICIPATION (SIPP)

Because of the additional details the SIPP data provide, the study can observe occupational changes at the job level instead of the occupational code level. To identify occupational changes, the study looks at the "primary" job reported in each month (defined as the job providing the highest monthly wages, for individuals reporting multiple jobs), and compares the start and end dates of the individual's primary jobs. This additional detail allows the study to report job changes that occur within an occupation code, as well as between two different occupation codes.

Because SIPP is a longitudinal survey, individuals are observed in the data for multiple years. This means that some individuals are not included in the job changes dataset (if they never change jobs in that time period), are included one time (if they make one job change), or are included multiple times (if they make multiple job changes). Because the study is most interested in information at the job change level and because we reweight the data to reflect the workforce population, multiple observations for an individual do not cause an issue.

The SIPP data also can observe unemployment spells between jobs. Because this study does not include unemployment spells in job changes, it includes a job change only once the individual starts a new job.

COMBINED CPS AND SIPP

The CPS and SIPP data combined create the job changes dataset. The study team applied weights to the combined dataset to make the sample reflect the age, gender, race/ethnic, and educational composition of the workforce for workers in 2020. Because the job changes dataset is intended to align with the 10-year trajectory analyses and because the trajectories dataset includes data for entrants age 18 to 34, we restricted job changes to only those that occur for workers age 18 to 44. Similarly, we included only job changes starting from an occupation in Job Zones 2 to 3.8 (mid-level occupations). As we did for trajectories, we bottom-coded starting wages to $7.25 per hour and top-coded to the 98th percentile.

The final job changes analysis dataset includes 43,350 job changes. There are small amounts of missing data as reported in Exhibit B-2.

Exhibit B-2. Job Changes Missing Data Frequencies

Measure	Dataset (N)	Measure (N)	Missing Data Description
Source wage	43,350	42,116	Missing data.
Destination wage	43,350	38,144	Missing data.
Change to job with higher wage	43,350	37,250	This measure is available only if both the source and the destination wages are non-missing.
Source occupation median wage	43,350	43,350	No missing data.
Destination occupation median wage	43,350	43,229	Missing data.
Change to job in an occupation with a higher median wage	43,350	43,229	This measure is available only if both the source and destination occupation median wages are non-missing.
Change to job in same occupation	43,350	29,009	Only the SIPP data contain information on same-occupation job changes; the CPS data are excluded from this measure.

Transitions Dataset

The transitions dataset uses data combined from Emsi and OEWS. It does not include the same person-level data as the job changes dataset but represents a larger number of transitions.

COMBINED EMSI AND OEWS

In order to combine the Emsi transition matrix data and the OEWS wage data, we converted occupation codes to a consistent classification scheme (2018 SOC codes). The OEWS data contain fewer occupation codes than does Emsi because OEWS uses six-digit SOC codes, whereas Emsi data extends the O*NET codes to eight digits. The two codes are effectively identical in most cases; for example, the OEWS code for Marketing Managers is 11-2021, and the O*NET code is 11-2020.00. In other cases, O*NET codes add further granularity; for example, OEWS has a single code for Transportation, Storage, and Distribution Managers (11-3071), but O*NET has three sub-codes for Transportation Managers (11-3071.01), Storage and Distribution Managers (11-3071.02), and Logistics Managers (11-3071.03).

To apply OEWS wage data to Emsi occupations, we assumed that the wages at the six-digit occupation level apply the same to each of the eight-digit codes that shares the same first six digits. Where median wages for an occupation were missing, we imputed as 81.5 percent of the mean hourly wage for that occupation. If no hourly wage data were available, then the median wages for an occupation were assumed to be the annual median salary for an individual working full-time (40 hours per week) for 10 months of the year (43 weeks).

This dataset defines “transitions” as switching from one occupation to another, so there are no same-occupation steps included.

The final transitions analysis dataset includes 256,831 pairings of mid-level source occupations to destination occupations, representing 89,758,736 transitions. There are no missing data among the variables of interest in the analysis dataset.

Appendix C: Analytic Methods

This appendix describes the full analytic methods, first describing the development of the skills and abilities scales, and then describing the trajectories, job changes, and transitions analyses.

Skills and Abilities Scales

The study conducted a factor analysis on the large number of O*Net importance rating on skills and abilities to identify sets of items related to common factors. After identifying 12 factors, we then created a summative skill index for each factor, averaging the importance ratings across the items that loaded most strongly (at least 0.4) on each factor. For example, the index for two-way communication came from averaged ratings from the “oral comprehension” and “oral expression” abilities and the “speaking” and “active listening” skills. Each of the 12 indices created from those items have an internal consistency (Cronbach’s alpha) of more than 0.70. Most have internal consistency of 0.90 or greater. We then were able to merge the created scales onto the rest of our datasets by occupation code.

The sections below describe the items that compose a given scale and the internal consistency of the scale. We applied a name to each scale, based on the set of items that compose it.

- **Creativity**: The Creativity scale is composed of ratings on originality, fluency of ideas, and visualization abilities. Cronbach’s alpha is 0.74 for this scale.
- **Equipment repair/maintenance**: The Equipment Repair/Maintenance scale is composed of ratings on repair, equipment maintenance, equipment selection, installation, troubleshooting, and quality control analysis skills. Cronbach’s alpha is 0.95 for this scale.
- **Fine motor**: The Fine Motor scale is composed of ratings on finger dexterity, arm-hand steadiness, manual dexterity, visual color discrimination, and control precision abilities. Cronbach’s alpha is 0.94 for this scale.
- **Focused attention**: The Focused Attention scale is composed of auditory attention, flexibility of closure, perceptual speed, selective attention, and speed of closure abilities. Cronbach’s alpha is 0.82 for this scale.
- **Gross motor**: The Gross Motor scale is composed of gross body coordination, stamina, dynamic strength, gross body equilibrium, trunk strength, dynamic flexibility, extent flexibility, static strength, and explosive strength abilities. Cronbach’s alpha is 0.97 for this scale.
- **Mathematical reasoning**: The Mathematical Reasoning scale is composed of mathematical reasoning and number facility abilities, as well as mathematics skills. Cronbach’s alpha is 0.98 for this scale.
- **Managing people**: The Managing People scale is composed of management of personnel resources, time management, and coordination skills. Cronbach’s alpha is 0.87 for this scale.
- **Problem solving**: The Problem Solving scale is composed of inductive reasoning, deductive reasoning, and problem sensitivity abilities, as well as complex problem solving, critical thinking, and judgement and decision-making skills. Cronbach’s alpha is 0.97 for this scale.

- **Sensory perception**: The Sensory Perception scale is composed of peripheral vision, night vision, sound localization, spatial orientation, and glare sensitivity abilities. Cronbach's alpha is 0.98 for this scale.
- **Service orientation**: The Service Orientation scale is composed of service orientation, persuasion, and social perceptiveness skills. Cronbach's alpha is 0.90 for this scale.
- **Teaching**: The Teaching scale is composed of instructing and learning strategies skills. Cronbach's alpha is 0.95 for this scale.
- **Two-Way communication**: The Two-Way Communication scale is composed of oral comprehension and oral expression abilities, as well as speaking and active listening skills. Cronbach's alpha is 0.97 for this scale.

TRAJECTORIES ANALYSES

The trajectories enabled us to evaluate wage growth across workers in a particular occupation as well as determining how many of those workers remained in the same occupation after a certain number of years. We could then aggregate wage growth at three, five, and 10 years after starting in the occupation to describe a typical progression for a given starting occupation. For example, we ranked occupations by percentile of starting wage and wage growth after 10 years to identify "launchpad" occupations, or high-wage-growth occupations.

We used ordinary least squares (OLS) regression analyses to identify predictors of wage growth based on starting occupation characteristics. We used the trajectories in two sets of OLS regressions: (1) regressions focusing on the worker- (entrant-) level characteristics that predict trajectory outcomes and (2) regressions focusing on the occupation where characteristics of the occupation predict outcomes.

Regressions examining worker-level predictors take the following form:

$$(1)\quad y_{ij} = \beta X_{ij} + \delta_1 c_1 + \delta_2 c_2 + \cdots + \delta_{k-1} c_{k-1} + u_{ij}$$

where *y* is the trajectory-level outcome such as wage growth (measured at the end of the trajectory period). X_{ij} is a vector of worker characteristics (*i*) measured at the start of the trajectory (*j*), such as age, race/ethnicity, wage at trajectory start, etc. Recall that an individual may have more than one observation if their job history includes multiple mid-level occupations for which sufficient follow-up period is available to observe a trajectory of the designated length (three, five, or 10 years). The specification includes a set of *k*–1 indicators for occupation at trajectory start (occupation fixed effects), *C*, where *k* is the total number of unique starting occupations among the trajectory observations. The specification uses robust standard errors clustered at the individual level to account for non-independence among the observations for an individual who has more than one observation in the data.

Regressions examining occupation-level predictors of workers' trajectory outcomes take the following form:

$$(2)\quad y_{ij} = \beta X_{ij} + \gamma Z_c + u_{ij}$$

Equation (2) shares many terms with Equation (1). Z_c is a vector of occupation-level characteristics (e.g., skill requirements, occupational cluster). The parameters of primary interest in these analyses are the vector of coefficients, γ, which reflect the linear association between the occupation-level characteristics, Z_c, and trajectory outcomes y_{ij}.

JOB CHANGES ANALYSES

We used the job changes dataset to evaluate individual person-level job pathways. OLS regressions controlling for data source, starting wage, starting age, gender, race/ethnicity, and origin occupation predicted whether job changes resulted in occupation changes, cluster changes, moving to an occupation in a higher Job Zone, moving to a job with higher wages (defined as at least $2 per hour more than the origin job), and moving to an occupation with higher median wages (defined as at least $2 per hour more than the origin occupation). The results from these analyses allowed us to describe labor market movements that enhanced understandings of wage growth predictions from the trajectories analyses.

The OLS regressions that use data from the CPS and SIPP to examine predictors of worker-level predictors of worker-level transition outcomes use specifications of the same form as Equation (1) above. The analyses of difference in skills and licensing requirements between source and destination occupations that are most strongly associated with transitions to higher-wage occupations take the following form:

$$(3)\ \ y_i = \beta X_i + u_i$$

The data are drawn from a matrix of counts of transitions among every source-occupation/destination-occupation pair. The unit of analysis is the source/destination pair. The analyses weight each observation by the count of transitions observed for each pair, resulting in analyses that are analogous to what would result from analyses of a dataset of individual observed transitions with an N equal to the sum of the frequency weights used in the analyses, for which standard errors were clustered by source/destination occupation pair.

TRANSITIONS ANALYSES

The transitions dataset does not include the same person-level data as the job changes dataset but represents a larger number of transitions. Therefore, it is more appropriate for describing and predicting transitions themselves rather than individual person pathways.

To describe transitions at the occupation level, we ordered the top 30 largest transitions for each origin occupation, from most common (largest count of transitions) to least common (smallest count of transitions), and identified each as either an upward, downward, or lateral move. We classified transitions as upward, downward, or lateral according to the following: (1) upward transitions were transitions moving to an occupation with a median wage of $2 per hour or more than the origin occupation's median wage, (2) downward transitions were transitions moving to an occupation with a lower median wage than the origin occupation, and (3) lateral transitions were transitions with median wage changes between zero and $2 per hour.

We also used the large sample size in the transitions dataset to predict wage changes at the transition level. OLS regressions used characteristics of the origin occupation such the importance of skills and abilities and required licenses to predict changes in the median wage resulting from a transition. These analyses produced much more precise results than either the trajectories or job changes dataset would allow on how the skills and abilities valued in an origin occupation can predict moving to a higher-wage occupation.

Appendix D: Three-, Five-, and 10-Year Regression Estimates of Predictors of Wage Growth and Other Outcomes

This appendix presents full regression estimates of wage growth, months not working, and likelihood of earning a postsecondary degree at three, five, and 10 years.

Exhibit D-1. Three-, Five-, and 10-Year Wage Growth Differences, by Worker Characteristic

	After 3 Years			After 5 Years			After 10 Years		
Outcome: Wage Growth	**Estimate**	**95% Confidence Interval**	***p*-Value**	**Estimate**	**95% Confidence Interval**	***p*-Value**	**Estimate**	**95% Confidence Interval**	***p*-Value**
Age									
Age 18-24	-$1.26	[-$1.73, -$0.78]	0.00	-$0.94	[-$1.64, -$0.25]	0.01	$0.19	[-$1.74, $2.12]	0.85
Age 25-29	-$1.07	[-$1.54, -$0.60]	0.00	-$1.00	[-$1.66, -$0.34]	0.00	-$1.57	[-$3.40, $0.26]	0.09
Age 30-34	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
Gender									
Women	-$1.66	[-$2.02, -$1.31]	0.00	-$2.20	[-$2.69, -$1.70]	0.00	-$3.61	[-$4.54, -$2.69]	0.00
Men	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
Race/Ethnicity									
White non-Hispanic	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
Black non-Hispanic	-$1.02	[-$1.34, -$0.70]	0.00	-$1.46	[-$1.89, -$1.03]	0.00	-$3.07	[-$3.89, -$2.25]	0.00
Other non-Hispanic	$0.83	[-$0.05, $1.72]	0.07	$0.92	[-$0.31, $2.15]	0.14	$2.73	[$0.47, $4.99]	0.02
Hispanic	-$0.10	[-$0.47, $0.27]	0.60	-$0.29	[-$0.80, $0.22]	0.27	-$1.25	[-$2.12, -$0.37]	0.01
Starting Education									
No degree	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
High school diploma or equivalent	$1.29	[$1.00, $1.57]	0.00	$1.62	[$1.26, $1.98]	0.00	$2.47	[$1.92, $3.01]	0.00
Associate's degree	$1.76	[$1.13, $2.39]	0.00	$2.78	[$1.79, $3.77]	0.00	$3.79	[$2.19, $5.40]	0.00
Bachelor's degree or more	$4.95	[$4.36, $5.55]	0.00	$6.27	[$5.47, $7.06]	0.00	$9.96	[$8.37, $11.54]	0.00

Outcome: Wage Growth	After 3 Years Estimate	After 3 Years 95% Confidence Interval	After 3 Years *p*-Value	After 5 Years Estimate	After 5 Years 95% Confidence Interval	After 5 Years *p*-Value	After 10 Years Estimate	After 10 Years 95% Confidence Interval	After 10 Years *p*-Value
Parent Education									
Neither parent has any college	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
At least one parent has some college	$0.20	[-$0.14, $0.53]	0.26	$0.64	[$0.16, $1.11]	0.01	$0.74	[-$0.11, $1.59]	0.09
At least one parent has a bachelor's degree	$0.69	[$0.31, $1.07]	0.00	$1.49	[$0.96, $2.01]	0.00	$3.66	[$2.68, $4.64]	0.00

Note: The table rows represent the estimated difference in average wage growth for members of the given category, compared to members of the reference category who are otherwise similar (same starting occupation, starting wage, and demographic characteristics other than the one in question). Each demographic group has its own (omitted) reference category, indicated by *italics*. The confidence intervals indicate how precise our estimates are; the actual wage difference could fall anywhere in that range, though they are more likely to fall toward the middle.
Estimates are drawn from OLS regressions that include controls for data source, starting wage, starting occupation, and all of the individual-level characteristics above. "Other non-Hispanic" includes Asian Americans, Pacific Islanders, Native Americans, workers who report multiple racial identities, and workers who report no racial identity or Hispanic ethnicity. Those workers are grouped only because sample sizes are insufficient to consider each separately.
Source: NLSY97 and PSID

Exhibit D-2. Three-, Five-, and 10-Year Months Spent Not Working Differences, by Worker Characteristic

Outcome: Months Not Working	After 3 Years			After 5 Years			After 10 Years		
	Estimate	95% Confidence Interval	*p*-Value	Estimate	95% Confidence Interval	*p*-Value	Estimate	95% Confidence Interval	*p*-Value
Age									
Age 18-24	-$0.09	[-$0.40, $0.22]	0.57	$0.12	[-$0.50, $0.74]	0.70	$0.77	[-$0.44, $1.97]	0.21
Age 25-29	$0.70	[$0.40, $1.00]	0.00	$1.03	[$0.43, $1.63]	0.00	$1.24	[$0.08, $2.39]	0.04
Age 30-34	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
Gender									
Women	$0.73	[$0.49, $0.96]	0.00	$1.36	[$0.99, $1.72]	0.00	$2.30	[$1.77, $2.82]	0.00
Men	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
Race/Ethnicity									
White non-Hispanic	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
Black non-Hispanic	$1.46	[$1.20, $1.71]	0.00	$2.04	[$1.67, $2.41]	0.00	$2.40	[$1.85, $2.96]	0.00
Other non-Hispanic	$0.68	[$0.10, $1.25]	0.02	$0.93	[$0.04, $1.81]	0.04	$0.46	[-$0.77, $1.69]	0.46
Hispanic	$0.73	[$0.46, $1.01]	0.00	$1.02	[$0.61, $1.42]	0.00	$1.15	[$0.56, $1.74]	0.00
Starting Education									
No degree	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
High school diploma or equivalent	-$1.70	[-$1.95, -$1.46]	0.00	-$2.32	[-$2.65, -$1.99]	0.00	-$2.71	[-$3.10, -$2.32]	0.00
Associate's degree	-$2.42	[-$2.94, -$1.90]	0.00	-$3.45	[-$4.27, -$2.64]	0.00	-$4.76	[-$5.93, -$3.59]	0.00
Bachelor's degree or more	-$2.28	[-$2.66, -$1.90]	0.00	-$3.27	[-$3.85, -$2.69]	0.00	-$4.51	[-$5.37, -$3.64]	0.00
Parent Education									
Neither parent has any college	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
At least one parent has some college	-$0.49	[-$0.75, -$0.22]	0.00	-$0.65	[-$1.05, -$0.25]	0.00	-$0.95	[-$1.53, -$0.38]	0.00
At least one parent has a bachelor's degree	-$0.78	[-$1.04, -$0.52]	0.00	-$1.17	[-$1.57, -$0.78]	0.00	-$1.40	[-$2.00, -$0.79]	0.00

Note: The table rows represent the estimated difference in months not working for members of the given category, compared to members of the reference category who are otherwise similar (same starting occupation, starting wage, and demographic characteristics other than the one in question). Each demographic group has its own (omitted) reference category, indicated by *italics*. The confidence intervals indicate how precise our estimates are (at 95 percent confidence level); the actual difference could fall anywhere in that range, though they are more likely to fall toward the middle of the range than the ends.

Estimates are drawn from OLS regressions that include controls for data source, starting wage, starting occupation, and all of the individual-level characteristics above. "Other non-Hispanic" includes Asian Americans, Pacific Islanders, Native Americans, workers who report multiple racial identities, and workers who report no racial identity or Hispanic ethnicity. Those workers are grouped only because sample sizes are insufficient to consider each separately.

Source: NLSY97 and PSID

Exhibit D-3. Three-, Five-, and 10-Year Likelihood of Earning a Postsecondary Degree Differences, by Worker Characteristic

Outcome: Likelihood of Earning a New Postsecondary Degree	After 3 Years				After 5 Years				After 10 Years			
	Estimate	95% Confidence Interval		*p*-Value	Estimate	95% Confidence Interval		*p*-Value	Estimate	95% Confidence Interval		*p*-Value
Age												
Age 18-24	$0.03	[$0.02,	$0.04]	0.00	$0.06	[$0.04,	$0.08]	0.00	$0.05	[$0.01,	$0.09]	0.02
Age 25-29	$0.01	[-$0.00,	$0.02]	0.08	$0.00	[-$0.02,	$0.02]	0.94	-$0.01	[-$0.05,	$0.03]	0.68
Age 30-34	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*
Gender												
Women	$0.01	[$0.00,	$0.02]	0.03	$0.02	[$0.01,	$0.04]	0.00	$0.04	[$0.02,	$0.06]	0.00
Men	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*
Race/Ethnicity												
White non-Hispanic	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*
Black non-Hispanic	-$0.01	[-$0.02,	-$0.01]	0.00	-$0.04	[-$0.05,	-$0.02]	0.00	-$0.05	[-$0.07,	-$0.03]	0.00
Other non-Hispanic	$0.01	[-$0.01,	$0.03]	0.33	$0.00	[-$0.03,	$0.03]	0.94	$0.04	[-$0.01,	$0.10]	0.13
Hispanic	-$0.02	[-$0.03,	-$0.01]	0.00	-$0.04	[-$0.05,	-$0.02]	0.00	-$0.05	[-$0.07,	-$0.02]	0.00
Starting Education												
No degree	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*
High school diploma or equivalent	$0.10	[$0.10,	$0.11]	0.00	$0.15	[$0.14,	$0.16]	0.00	$0.13	[$0.11,	$0.14]	0.00
Associate's degree	$0.12	[$0.09,	$0.14]	0.00	$0.14	[$0.11,	$0.18]	0.00	$0.09	[$0.04,	$0.15]	0.00
Bachelor's degree or more	$0.01	[-$0.01,	$0.02]	0.34	$0.00	[-$0.03,	$0.02]	0.79	-$0.07	[-$0.11,	-$0.02]	0.00
Parent Education												
Neither parent has any college	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*
At least one parent has some college	$0.03	[$0.02,	$0.03]	0.00	$0.05	[$0.04,	$0.07]	0.00	$0.09	[$0.07,	$0.12]	0.00
At least one parent has a bachelor's degree	$0.07	[$0.06,	$0.09]	0.00	$0.14	[$0.12,	$0.16]	0.00	$0.24	[$0.21,	$0.26]	0.00

Note: The table rows represent the estimated difference in average likelihood of earning an additional postsecondary degree for members of the given category, compared to members of the reference category who are otherwise similar (same starting occupation, starting wage, and demographic characteristics other than the one in question). Each demographic group has its own

(omitted) reference category, indicated by *italics*. The confidence intervals indicate how precise our estimates are (at 95 percent confidence level); the actual difference could fall anywhere in that range, though they are more likely to fall toward the middle of the range than the ends.
Estimates are drawn from OLS regressions that include controls for data source, starting wage, starting occupation, and all of the individual-level characteristics above. “Other non-Hispanic” includes Asian Americans, Pacific Islanders, Native Americans, workers who report multiple racial identities, and workers who report no racial identity or Hispanic ethnicity. Those workers are grouped only because sample sizes are insufficient to consider each separately.
Source: NLSY97 and PSID

Exhibit D-4. Three-, Five-, and 10-Year Wage Growth Differences, by Job and Occupation Cluster Changes During the Trajectory

Outcome: Wage Growth	After 3 Years			After 5 Years			After 10 Years		
	Estimate	95% Confidence Interval	*p*-Value	Estimate	95% Confidence Interval	*p*-Value	Estimate	95% Confidence Interval	*p*-Value
Number of Job Changes									
0-2	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
3-4	-$0.05	[-$0.37, $0.27]	0.75	-$0.26	[-$0.66, $0.13]	0.19	$0.67	[-$0.30, $1.63]	0.18
5-6	-$0.27	[-$0.75, $0.22]	0.28	-$0.65	[-$1.16, -$0.15]	0.01	-$0.58	[-$1.65, $0.50]	0.29
7 or more	-$0.61	[-$1.43, $0.22]	0.15	-$1.28	[-$1.98, -$0.59]	0.00	-$2.18	[-$3.27, -$1.10]	0.00
Occupational Cluster Change									
No cluster change	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
Changed to a different cluster	-$0.05	[-$0.32, $0.21]	0.69	$0.06	[-$0.28, $0.41]	0.73	$1.12	[$0.41, $1.83]	0.00

Note: The table rows represent the estimated difference in average wage growth for members of the given category, compared to members of the reference category who are otherwise similar (same starting occupation, starting wage, and demographic characteristics). Each group has its own (omitted) reference category, indicated by *italics*. The confidence intervals indicate how precise our estimates are (at 95 percent confidence level); the actual wage difference could fall anywhere in that range, though they are more likely to fall toward the middle of the range than the ends. Estimates are drawn from OLS regressions that include controls for data source, starting wage, starting occupation, age, gender, race/ethnicity, starting education, parent education, and all of the characteristics above.
Source: NLSY97 and PSID

Exhibit D-5. Three-, Five-, and 10-Year Wage Growth Differences, by Occupational Cluster

	After 3 Years			After 5 Years			After 10 Years		
Outcome: Wage Growth	Estimate	95% Confidence Interval	*p*-Value	Estimate	95% Confidence Interval	*p*-Value	Estimate	95% Confidence Interval	*p*-Value
Occupational Cluster									
Production	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
Transportation	$0.25	[-$0.25, $0.74]	0.33	-$0.02	[-$0.67, $0.63]	0.95	$0.32	[-$0.88, $1.52]	0.60
Personal Services	-$0.23	[-$0.73, $0.26]	0.36	-$0.22	[-$0.88, $0.43]	0.50	$1.15	[-$0.01, $2.31]	0.05
Construction	$0.31	[-$0.25, $0.88]	0.28	$0.88	[$0.11, $1.65]	0.03	$1.72	[$0.35, $3.09]	0.01
Installation, Maintenance, and Repair	$1.08	[$0.33, $1.84]	0.00	$1.64	[$0.66, $2.62]	0.00	$2.63	[$0.68, $4.57]	0.01
Other	$0.67	[-$0.28, $1.63]	0.17	$2.33	[$0.97, $3.70]	0.00	$2.65	[$0.16, $5.13]	0.04
Sales	$1.12	[$0.62, $1.62]	0.00	$1.57	[$0.89, $2.24]	0.00	$3.09	[$1.88, $4.29]	0.00
Healthcare	$1.66	[$0.92, $2.41]	0.00	$2.70	[$1.68, $3.73]	0.00	$3.12	[$1.33, $4.91]	0.00
Office and Administrative Support	$0.81	[$0.37, $1.25]	0.00	$1.57	[$0.94, $2.20]	0.00	$3.95	[$2.70, $5.21]	0.00
Protective Services	$2.37	[$1.52, $3.22]	0.00	$2.96	[$1.92, $3.99]	0.00	$5.18	[$2.83, $7.53]	0.00
Education, Legal, and Social Services	$1.69	[$0.88, $2.51]	0.00	$2.91	[$1.75, $4.07]	0.00	$6.63	[$4.47, $8.79]	0.00
Engineering, Science, Architecture	$4.18	[$2.13, $6.22]	0.00	$4.44	[$2.42, $6.46]	0.00	$10.79	[$7.51, $14.06]	0.00
Management, Business, Finance	$3.78	[$2.78, $4.78]	0.00	$4.55	[$3.26, $5.83]	0.00	$10.95	[$7.66, $14.24]	0.00
Information Technology	$7.09	[$5.37, $8.82]	0.00	$9.04	[$6.65, $11.42]	0.00	$12.49	[$9.06, $15.93]	0.00

Note: The table rows represent the estimated difference in average wage growth for entrants to the given occupational cluster, compared to members of the reference cluster who have the same starting wage. The reference cluster is indicated by *italics*. The confidence intervals indicate how precise our estimates are (at 95 percent confidence level); the actual wage difference could fall anywhere in that range, though they are more likely to fall toward the middle of the range than the ends.
Estimates are drawn from OLS regressions that include controls for data source and starting wage.
Source: NLSY97 and PSID

Exhibit D-6. Three-, Five-, and 10-Year Months Not Working Differences, by Occupational Cluster

Outcome: Months Not Working	After 3 Years			After 5 Years			After 10 Years		
	Estimate	95% Confidence Interval	*p*-Value	Estimate	95% Confidence Interval	*p*-Value	Estimate	95% Confidence Interval	*p*-Value
Occupational Cluster									
Construction	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
Production	-$0.14	[-$0.56, $0.28]	0.52	-$0.10	[-$0.65, $0.46]	0.73	-$0.27	[-$1.05, $0.51]	0.50
Transportation	-$0.28	[-$0.67, $0.10]	0.15	-$0.30	[-$0.80, $0.21]	0.25	-$0.60	[-$1.27, $0.07]	0.08
Personal Services	-$1.33	[-$1.71, -$0.95]	0.00	-$1.47	[-$1.99, -$0.96]	0.00	-$1.64	[-$2.35, -$0.93]	0.00
Sales	-$1.64	[-$2.02, -$1.27]	0.00	-$1.83	[-$2.33, -$1.32]	0.00	-$1.97	[-$2.67, -$1.27]	0.00
Office and Administrative Support	-$1.86	[-$2.23, -$1.49]	0.00	-$2.19	[-$2.69, -$1.69]	0.00	-$2.36	[-$3.06, -$1.65]	0.00
Healthcare	-$1.91	[-$2.40, -$1.42]	0.00	-$2.26	[-$2.93, -$1.58]	0.00	-$2.46	[-$3.49, -$1.43]	0.00
Education, Legal, and Social Services	-$1.62	[-$2.28, -$0.97]	0.00	-$2.28	[-$3.06, -$1.50]	0.00	-$2.92	[-$4.05, -$1.80]	0.00
Installation, Maintenance, and Repair	-$1.65	[-$2.18, -$1.12]	0.00	-$1.96	[-$2.68, -$1.24]	0.00	-$2.97	[-$3.96, -$1.99]	0.00
Management, Business, Finance	-$2.28	[-$2.84, -$1.72]	0.00	-$3.18	[-$3.98, -$2.39]	0.00	-$3.32	[-$4.86, -$1.79]	0.00
Other	-$2.68	[-$3.18, -$2.18]	0.00	-$3.11	[-$3.94, -$2.29]	0.00	-$3.57	[-$4.85, -$2.30]	0.00
Protective Services	-$2.14	[-$2.69, -$1.59]	0.00	-$2.85	[-$3.57, -$2.13]	0.00	-$3.72	[-$4.82, -$2.63]	0.00
Engineering, Science, Architecture	-$2.89	[-$3.66, -$2.12]	0.00	-$3.26	[-$4.79, -$1.74]	0.00	-$4.67	[-$6.43, -$2.91]	0.00
Information Technology	-$3.30	[-$3.94, -$2.65]	0.00	-$4.83	[-$5.80, -$3.87]	0.00	-$7.16	[-$8.61, -$5.71]	0.00

Note: The table rows represent the estimated difference in months not working for entrants to the given occupational cluster, compared to members of the reference cluster who have the same starting wage. The reference cluster is indicated by *italics*. The confidence intervals indicate how precise our estimates are (at 95 percent confidence level); the actual difference could fall anywhere in that range, though they are more likely to fall toward the middle of the range than the ends.
Estimates are drawn from OLS regressions that include controls for data source and starting wage.
Source: NLSY97 and PSID

Exhibit D-7. Three-, Five-, and 10-Year Likelihood of Earning a Postsecondary Degree Differences, by Occupational Cluster

Outcome: Likelihood of Earning a New Postsecondary Degree	After 3 Years Estimate	After 3 Years 95% Confidence Interval	After 3 Years *p*-Value	After 5 Years Estimate	After 5 Years 95% Confidence Interval	After 5 Years *p*-Value	After 10 Years Estimate	After 10 Years 95% Confidence Interval	After 10 Years *p*-Value
Occupational Cluster									
Transportation	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
Construction	$0.00	[-$0.01, $0.01]	0.93	$0.01	[-$0.01, $0.02]	0.46	$0.00	[-$0.03, $0.03]	0.99
Production	$0.00	[-$0.01, $0.01]	0.70	$0.00	[-$0.01, $0.02]	0.62	$0.00	[-$0.03, $0.03]	0.99
Installation, Maintenance, and Repair	$0.01	[-$0.01, $0.02]	0.43	$0.02	[-$0.01, $0.04]	0.15	$0.04	[-$0.00, $0.08]	0.08
Sales	$0.03	[$0.02, $0.05]	0.00	$0.07	[$0.06, $0.09]	0.00	$0.12	[$0.10, $0.15]	0.00
Office and Administrative Support	$0.06	[$0.05, $0.07]	0.00	$0.11	[$0.09, $0.12]	0.00	$0.15	[$0.13, $0.17]	0.00
Protective Services	$0.06	[$0.03, $0.08]	0.00	$0.09	[$0.06, $0.12]	0.00	$0.16	[$0.11, $0.21]	0.00
Healthcare	$0.07	[$0.06, $0.09]	0.00	$0.11	[$0.09, $0.14]	0.00	$0.16	[$0.12, $0.20]	0.00
Personal Services	$0.05	[$0.04, $0.06]	0.00	$0.10	[$0.09, $0.12]	0.00	$0.17	[$0.14, $0.19]	0.00
Other	$0.07	[$0.05, $0.10]	0.00	$0.13	[$0.10, $0.16]	0.00	$0.19	[$0.14, $0.24]	0.00
Management, Business, Finance	$0.11	[$0.07, $0.14]	0.00	$0.14	[$0.09, $0.18]	0.00	$0.19	[$0.12, $0.27]	0.00
Information Technology	$0.08	[$0.04, $0.11]	0.00	$0.14	[$0.09, $0.19]	0.00	$0.22	[$0.13, $0.30]	0.00
Engineering, Science, Architecture	$0.13	[$0.07, $0.19]	0.00	$0.22	[$0.15, $0.29]	0.00	$0.31	[$0.20, $0.41]	0.00
Education, Legal, and Social Services	$0.17	[$0.14, $0.20]	0.00	$0.27	[$0.23, $0.30]	0.00	$0.37	[$0.32, $0.42]	0.00

Note: The table rows represent the estimated difference in average likelihood of earning an additional postsecondary degree for entrants to the given occupational cluster, compared to members of the reference cluster who have the same starting wage. The reference cluster is indicated by *italics*. The confidence intervals indicate how precise our estimates are (at 95 percent confidence level); the actual difference could fall anywhere in that range, though they are more likely to fall toward the middle of the range than the ends.
Estimates are drawn from OLS regressions that include controls for data source and starting wage.
Source: NLSY97 and PSID

Exhibit D-8. Three-, Five-, and 10-Year Wage Growth Differences, by Transferable Skill and Licensing Requirements

Outcome: Wage Growth	After 3 Years				After 5 Years				After 10 Years			
	Estimate	95% Confidence Interval		*p*-Value	Estimate	95% Confidence Interval		*p*-Value	Estimate	95% Confidence Interval		*p*-Value
Skill												
Problem Solving	$3.42	[$2.84,	$3.99]	0.00	$3.69	[$2.94,	$4.44]	0.00	$4.70	[$3.10,	$6.31]	0.00
Two-Way Communication	$2.50	[$2.03,	$2.97]	0.00	$2.82	[$2.20,	$3.43]	0.00	$4.09	[$2.88,	$5.29]	0.00
Focused Attention	$2.10	[$1.41,	$2.79]	0.00	$2.35	[$1.50,	$3.20]	0.00	$2.87	[$1.20,	$4.54]	0.00
Service Orientation	$2.03	[$1.49,	$2.58]	0.00	$2.03	[$1.33,	$2.73]	0.00	$2.67	[$1.31,	$4.03]	0.00
Creativity	$1.98	[$1.57,	$2.39]	0.00	$1.99	[$1.47,	$2.51]	0.00	$2.38	[$1.38,	$3.38]	0.00
Managing People	$1.83	[$1.41,	$2.25]	0.00	$1.70	[$1.17,	$2.24]	0.00	$2.26	[$1.07,	$3.45]	0.00
Teaching	$0.95	[$0.61,	$1.29]	0.00	$0.89	[$0.45,	$1.34]	0.00	$1.09	[$0.22,	$1.97]	0.01
Mathematical Skills	$0.73	[$0.36,	$1.10]	0.00	$1.22	[$0.74,	$1.69]	0.00	$1.07	[$0.05,	$2.09]	0.04
Sensory Perception	$0.13	[-$0.36,	$0.63]	0.60	-$0.09	[-$0.73,	$0.55]	0.79	$0.04	[-$1.28,	$1.36]	0.95
Equipment Repair/Maintenance	-$0.17	[-$0.72,	$0.37]	0.53	$0.07	[-$0.63,	$0.78]	0.84	-$0.12	[-$1.46,	$1.22]	0.86
Fine Motor Skills	-$0.99	[-$1.45,	-$0.53]	0.00	-$1.06	[-$1.67,	-$0.46]	0.00	-$1.89	[-$3.03,	-$0.75]	0.00
Gross Motor Skills	-$1.29	[-$1.71,	-$0.86]	0.00	-$1.81	[-$2.35,	-$1.28]	0.00	-$3.00	[-$4.01,	-$1.99]	0.00
Licensing												
License required	$0.50	[$0.20,	$0.81]	0.00	$0.62	[$0.24,	$0.99]	0.00	$0.80	[$0.05,	$1.56]	0.04

Note: The table rows represent the estimated difference between wage growth in hourly wages in the years after entering an occupation based on the importance of each skill for the starting occupation. That is, if two occupations differ by one point in their emphasis on problem solving, the average entrant to the occupation that emphasizes problem solving will see $4.69 per hour more in wage growth after 10 years or makes $4.69 more per hour assuming the same starting wage. The confidence intervals indicate how precise our estimates are (at 95 percent confidence level); the actual wage difference could fall anywhere in that range, though they are more likely to fall toward the middle of the range than the ends.
Estimates are drawn from OLS regressions that include controls for data source and starting wage.
Source: NLSY97 and PSID

Appendix E: Map of Occupational Codes to Clusters

This appendix shows how individual occupations map to occupational clusters.

Exhibit E-1. Occupations Codes in Standard Occupational Clusters

Occupational Cluster	Occupations Included (2002 Census Occupation Code)
Management/Business/Finance	General businesses management occupations (0010-0020, 0430), Public relations/purchasing/marketing management occupations (0050-0060, 0150), Financial managers (0120), Human resources managers (0130), Property, real estate, and community association managers (0410), Business and financial operations occupations (0500-0950)
Information Technology	Computer and mathematical occupations (1000-1110), Computer and information systems managers (0110)
Engineering/Science/Architecture	Drafters (1540), Engineering technicians (1550), Surveying and mapping technicians (1560), Life/physical/social science technicians (1900-1960), Engineering and natural science managers (300, 360)
Education/Legal/Social Services	Legal support workers (2140-2150), Education, training, and library occupations (2200-2550), Legislators (0030), Education administrators (0230), Social and community service managers (0420)
Healthcare	Healthcare practitioner and technical occupations (3130, 3200-3540), Healthcare support occupations (3600-3650), Medical and health services managers (0350)
Protective Services	Protective service occupations (3700-3950)
Personal Service	Food preparation and serving related occupations (4000-4160), Building and grounds cleaning and maintenance occupations (4200-4250), Personal care and service occupations (4300-4650), Personal service managers (0310-0340)
Sales	Retail, wholesale, and services sales workers/agents/representatives and cashiers/clerks (4700-4960), Advertising and promotions managers (0040)
Office and Administrative Support	Communication equipment operators (5010-5030), Information/record clerks and related occupations (5100-5420), Postal service related occupations (5500-5630), Administrative assistants, general office clerks, typists/keyers, and office/administrative support workers (5700-5930), Administrative services managers (0100, 5000), Postmasters and mail superintendents (0400)
Construction	Carpenters and construction laborers (6200-6260, 6600-6660), Equipment operators and internal installation workers (6300-6460), Roofers and metal workers (6500-6530), Miscellaneous construction and related workers (6700-6760), Oil/gas/mining extraction workers (6800-6940), Managers of construction trades and extraction workers (0220, 6200)
Maintenance/Repair	Installation, maintenance, and repair occupations (7000-7620)
Production	Machine and perishable foods production occupations (7700-8960), Industrial production managers (0140)
Transportation	Transportation and material moving occupations (9000-9750), Transportation, storage, and distribution managers (0160)
Other	Arts, design, entertainment, sports, and media occupations (2600-2960), Agriculture workers including supervisors (6000-6050), Fishing and hunting, and forest and logging workers (6100-6130), Farmers and ranchers (0210), Farm, ranch, and other agricultural managers (0200)

Exhibit E-2. Occupational Codes in Alternatively Used Occupational Clusters

Alternative Occupational Cluster	Occupations Included
Education/ECE	Education, training, and library occupations (2200-2550), Education administrators (0230)
Arts/Entertainment	Arts, design, entertainment, sports, and media occupations (2600-2960)
Agriculture	Agriculture workers including supervisors (6000-6050), Fishing and hunting, and forest and logging workers (6100-6130), Farmers and ranchers (0210), Farm, ranch, and other agricultural managers (0200)

Full lists of Census occupations are available on the Census website: https://www.census.gov/content/dam/Census/about/about-the-bureau/adrm/data-linkage/HUDMetadata/HUD-MTO/IndustryOccupationCodes/2002%20Census%20Occupation%20Codes.pdf

Appendix F: Full List of Occupations by Starting Wage and 10-Year Wage Growth Percentile Quadrant

Exhibit F-1. Occupations by Starting Wage and 10-Year Wage Growth Percentile Quadrant, High Starting Wage/High Wage Growth (Upper Right) Quadrant

	After 3 Years			After 5 Years			After 10 Years		
Occupation	N	Starting Wage Percentile	Wage Growth Percentile	N	Starting Wage Percentile	Wage Growth Percentile	N	Starting Wage Percentile	Wage Growth Percentile
Registered nurses	333	99%	52%	280	99%	62%	152	99%	67%
Securities, commodities, and financial services sales agents	95	98%	89%	88	98%	99%	59	98%	97%
Police and sheriff's patrol officers	140	97%	96%	127	97%	97%	77	98%	93%
Sales representatives, wholesale and Production	360	95%	86%	315	96%	69%	201	96%	86%
Claims adjusters, appraisers, examiners, and investigators	85	93%	58%	75	94%	70%	42	95%	96%
Drafters	67	92%	91%	64	93%	84%	46	94%	100%
Network systems and data communications analysts	189	93%	100%	163	94%	98%	104	93%	95%
Human resources, training, and labor relations specialists	326	91%	97%	282	92%	86%	172	91%	92%
Computer support specialists	227	90%	94%	190	90%	93%	115	90%	98%
Miscellaneous legal support workers	118	89%	87%	106	89%	100%	61	89%	98%
Real estate brokers and sales agents	132	87%	62%	115	88%	5%	71	88%	64%
Other business operations specialists	98	86%	29%	87	87%	56%	41	87%	99%
Wholesale and retail buyers, except farm products	76	85%	38%	65	87%	22%	43	86%	84%
Engineering technicians, except drafters	121	84%	94%	111	85%	88%	67	84%	88%
Production, planning, and expediting clerks	147	82%	74%	136	83%	79%	83	83%	74%
Designers	240	80%	38%	223	81%	74%	151	81%	63%
Radio and telecommunications equipment installers and repairers	95	83%	7%	87	85%	26%	56	81%	62%
Artists and related workers	67	78%	75%	63	79%	97%	40	80%	90%

Occupation	After 3 Years N	After 3 Years Starting Wage Percentile	After 3 Years Wage Growth Percentile	After 5 Years N	After 5 Years Starting Wage Percentile	After 5 Years Wage Growth Percentile	After 10 Years N	After 10 Years Starting Wage Percentile	After 10 Years Wage Growth Percentile
Computer, automated teller, and office machine repairers	149	77%	92%	135	79%	71%	95	78%	83%
Other teachers and instructors	442	75%	45%	412	78%	55%	305	77%	81%
Clinical laboratory technologists and technicians	75	74%	78%	70	76%	47%	45	75%	89%
Paralegals and legal assistants	105	74%	98%	95	76%	58%	56	74%	80%
Bookkeeping, accounting, and auditing clerks	424	67%	22%	383	69%	33%	274	71%	67%
Electricians	184	66%	89%	165	68%	83%	112	69%	71%
Billing and posting clerks and machine operators	183	60%	54%	169	62%	50%	111	65%	51%
Athletes, coaches, umpires, and related workers	222	56%	71%	210	58%	94%	163	61%	84%
Heating, air conditioning, and refrigeration mechanics and installers	102	55%	74%	91	56%	90%	56	59%	82%
Inspectors, testers, sorters, samplers, and weighers	377	54%	52%	342	56%	75%	234	58%	57%
Secretaries and administrative assistants	1,018	53%	63%	927	55%	64%	645	57%	70%
Data entry keyers	362	50%	42%	344	52%	78%	279	56%	76%
Drywall installers, ceiling tile installers, and tapers	86	51%	28%	81	53%	34%	67	54%	75%
Tour and travel guides	56	47%	13%	52	49%	87%	42	51%	79%
Automotive service technicians and mechanics	278	46%	50%	256	48%	68%	170	50%	57%

Quadrants are defined by starting wage and wage growth after 10 years.
Source: NLSY97 and PSID

Exhibit F-2. Occupations by Starting Wage and 10-Year Wage Growth Percentile Quadrant, Low Starting Wage/High Wage Growth (Upper Left) Quadrant Occupations

	After 3 Years			After 5 Years			After 10 Years		
Occupation	N	Starting Wage Percentile	Wage Growth Percentile	N	Starting Wage Percentile	Wage Growth Percentile	N	Starting Wage Percentile	Wage Growth Percentile
Sheet metal workers	77	45%	50%	72	47%	52%	49	49%	74%
Interviewers, except eligibility and loan	207	41%	73%	194	43%	69%	143	47%	50%
Customer service representatives	1,363	40%	66%	1,243	42%	61%	920	45%	60%
Photographers	102	38%	20%	95	40%	22%	61	44%	60%
Tellers	304	38%	56%	283	40%	81%	241	42%	68%
Preschool and kindergarten teachers	364	37%	50%	337	39%	41%	228	41%	61%
Word processors and typists	141	36%	87%	138	37%	92%	117	40%	95%
File clerks	352	28%	80%	333	29%	87%	278	32%	73%
Couriers and messengers	153	28%	90%	139	29%	72%	106	31%	69%
Office clerks, general	508	27%	83%	464	28%	92%	360	30%	88%
Taxi drivers and chauffeurs	76	25%	65%	70	26%	60%	42	29%	87%
Security guards and gaming surveillance officers	621	25%	49%	577	27%	62%	395	28%	53%
Residential advisors	70	25%	81%	68	27%	91%	55	27%	94%
Receptionists and information clerks	1,025	23%	68%	963	24%	58%	756	26%	65%
Teacher assistants	463	22%	69%	427	23%	79%	310	25%	78%
Miscellaneous vehicle and mobile equipment mechanics, installers, and repairers	82	21%	77%	71	22%	41%	53	24%	78%
Waiters and waitresses	1,542	21%	49%	1,478	22%	37%	1,213	23%	55%
Recreation and fitness workers	370	19%	93%	335	20%	89%	267	22%	77%
Automotive body and related repairers	68	17%	71%	62	17%	99%	44	20%	53%
Hotel, motel, and resort desk clerks	204	16%	76%	189	17%	73%	141	19%	58%
Parking lot attendants	86	15%	98%	80	15%	94%	60	17%	66%
Miscellaneous personal appearance workers	70	13%	99%	60	14%	91%	43	16%	91%
Stock clerks and order fillers	1,395	9%	69%	1,309	9%	58%	1,036	9%	54%

	After 3 Years			After 5 Years			After 10 Years		
Occupation	N	Starting Wage Percentile	Wage Growth Percentile	N	Starting Wage Percentile	Wage Growth Percentile	N	Starting Wage Percentile	Wage Growth Percentile
Retail salespersons	2,319	7%	84%	2,180	7%	74%	1,769	9%	72%
Service station attendants	145	5%	91%	131	5%	83%	107	6%	81%
Library assistants, clerical	64	4%	53%	63	4%	15%	58	5%	59%
Childcare workers	1,050	4%	88%	994	4%	82%	782	5%	64%
Counter and rental clerks	179	3%	72%	172	3%	67%	142	4%	71%
Lifeguards and other protective service workers	138	2%	85%	136	3%	85%	124	3%	85%
Library technicians	51	1%	53%	48	1%	85%	44	2%	91%
Cashiers	2,573	0%	80%	2,477	0%	63%	2,163	1%	52%
Ushers, lobby attendants, and ticket takers	75	0%	72%	73	0%	51%	63	0%	56%

Quadrants are defined by starting wage and wage growth after 10 years.
Source: NLSY97 and PSID

Exhibit F-3. Occupations by Starting Wage and 10-Year Wage Growth Percentile Quadrant, High Starting Wage/Low Wage Growth (Bottom Right) Quadrant Occupations

	After 3 Years			After 5 Years			After 10 Years		
Occupation	N	Starting Wage Percentile	Wage Growth Percentile	N	Starting Wage Percentile	Wage Growth Percentile	N	Starting Wage Percentile	Wage Growth Percentile
Dancers and choreographers	51	99%	1%	47	99%	0%	41	100%	1%
First-line supervisors/managers of mechanics, installers, and repairers	111	96%	4%	92	97%	1%	48	97%	7%
First-line supervisors/managers of construction trades and extraction workers	230	94%	18%	191	95%	18%	105	95%	28%
Licensed practical and licensed vocational nurses	106	91%	43%	93	92%	29%	58	92%	14%
Industrial and refractory machinery mechanics	89	90%	48%	78	91%	8%	49	91%	11%
Musicians, singers, and related workers	83	89%	1%	79	89%	31%	54	88%	0%
Telecommunications line installers and repairers	77	85%	30%	66	86%	57%	47	85%	4%
Loan interviewers and clerks	85	82%	17%	78	84%	30%	53	84%	45%
First-line supervisors/managers of production and operating workers	209	81%	26%	171	83%	17%	91	82%	36%
First-line supervisors/managers of office and administrative support workers	568	79%	54%	491	80%	44%	283	79%	49%
Operating engineers and other construction equipment operators	118	76%	21%	103	78%	11%	66	78%	22%
Bailiffs, correctional officers, and jailers	140	75%	15%	129	77%	7%	69	76%	15%
Bartenders	333	72%	9%	307	74%	3%	209	74%	5%
Pipelayers, plumbers, pipefitters, and steamfitters	183	69%	39%	167	71%	78%	117	73%	38%
Bus and truck mechanics and diesel engine specialists	81	68%	67%	69	70%	45%	40	72%	18%
Brick masons, block masons, and stonemasons	73	67%	2%	66	69%	4%	46	71%	2%
Supervisors, transportation and material moving workers	129	66%	41%	103	68%	12%	56	70%	21%
Maintenance and repair workers, general	130	64%	59%	114	66%	35%	68	68%	9%
Welding, soldering, and brazing workers	193	64%	25%	176	65%	3%	119	67%	16%
Insurance claims and policy processing clerks	172	63%	44%	149	65%	13%	106	67%	16%

	After 3 Years			After 5 Years			After 10 Years		
Occupation	N	Starting Wage Percentile	Wage Growth Percentile	N	Starting Wage Percentile	Wage Growth Percentile	N	Starting Wage Percentile	Wage Growth Percentile
Carpenters	582	62%	24%	535	64%	48%	389	66%	44%
Chefs and head cooks	133	60%	34%	117	62%	36%	86	64%	23%
Dispatchers	121	59%	23%	101	61%	53%	60	64%	41%
Order clerks	89	58%	29%	82	60%	45%	63	63%	22%
Personal care and service workers, all other	113	58%	9%	106	60%	1%	73	62%	8%
Weighers, measurers, checkers, and samplers, recordkeeping	68	57%	40%	64	59%	24%	48	60%	5%
First-line supervisors/managers of retail sales workers	1,094	55%	31%	973	57%	39%	657	60%	47%
Carpet, floor, and tile installers and finishers	113	52%	47%	104	54%	65%	83	57%	46%
Dental assistants	81	52%	68%	75	53%	44%	47	55%	13%
Metalworkers and plastic workers, all other	155	50%	19%	138	51%	13%	98	53%	6%
Driver/sales workers and truck drivers	868	48%	60%	786	50%	42%	578	53%	37%
Bill and account collectors	207	48%	47%	184	49%	38%	128	52%	36%

Quadrants are defined by starting wage and wage growth after 10 years.
Source: NLSY97 and PSID

Exhibit F-4. Occupations by Starting Wage and 10-Year Wage Growth Percentile Quadrant, Low Starting Wage/Low Wage Growth (Bottom Left) Quadrant Occupations

	After 3 Years			After 5 Years			After 10 Years		
Occupation	N	Starting Wage Percentile	Wage Growth Percentile	N	Starting Wage Percentile	Wage Growth Percentile	N	Starting Wage Percentile	Wage Growth Percentile
Construction laborers	949	39%	27%	886	41%	48%	700	43%	35%
Painters, construction and maintenance	286	31%	45%	274	33%	47%	219	34%	26%
Roofers	127	44%	6%	120	46%	10%	88	47%	42%
Nursing, psychiatric, and home health aides	921	26%	15%	830	28%	17%	589	29%	27%
Health diagnosing and treating practitioner support technicians	187	33%	63%	169	35%	77%	109	37%	39%
Medical assistants and other healthcare support occupations	495	34%	25%	447	36%	42%	294	38%	24%
Telephone operators	57	43%	5%	55	45%	12%	47	46%	48%
Reservation and transportation ticket agents and travel clerks	109	33%	77%	103	34%	26%	86	36%	20%
Shipping, receiving, and traffic clerks	392	29%	46%	361	30%	40%	266	33%	33%
Mail clerks and mail machine operators, except postal service	94	11%	40%	90	12%	21%	62	13%	26%
Office machine operators, except computer	56	23%	33%	56	24%	49%	46	26%	33%
Food service managers	311	35%	34%	287	37%	46%	188	39%	31%
First-line supervisors/managers of food preparation and serving workers	593	18%	20%	529	19%	14%	363	21%	29%
Cooks	1,271	2%	64%	1,206	2%	43%	991	2%	40%
Food servers, nonrestaurant	171	12%	10%	158	13%	25%	122	15%	40%
Hosts and hostesses, restaurant, lounge, and coffee shop	374	6%	93%	357	6%	68%	315	7%	43%
Nonfarm animal caretakers	91	6%	60%	80	6%	38%	59	8%	25%
Hairdressers, hairstylists, and cosmetologists	211	37%	17%	198	38%	4%	130	40%	3%
Personal and home care aides	471	14%	16%	423	15%	28%	256	16%	50%

	After 3 Years			After 5 Years			After 10 Years		
Occupation	N	Starting Wage Percentile	Wage Growth Percentile	N	Starting Wage Percentile	Wage Growth Percentile	N	Starting Wage Percentile	Wage Growth Percentile
Electrical, electronics, and electromechanical assemblers	94	30%	37%	88	31%	25%	67	35%	17%
Miscellaneous assemblers and fabricators	573	20%	35%	527	21%	21%	406	22%	32%
Bakers	101	8%	57%	93	8%	54%	72	10%	29%
Cutting, punching, and press machine setters, operators, and tenders, metal and plastic	81	45%	26%	70	47%	6%	44	50%	2%
Packaging and filling machine operators and tenders	242	12%	42%	221	12%	33%	167	14%	10%
Photographic process workers and processing machine operators	78	9%	60%	76	10%	65%	60	12%	30%
Helpers–production workers	61	36%	79%	59	38%	63%	50	43%	12%
Production workers, all other	596	32%	39%	550	33%	14%	406	36%	34%
Telemarketers	522	17%	18%	510	18%	28%	461	19%	19%
Industrial truck and tractor operators	378	44%	21%	344	46%	32%	234	48%	12%
Cleaners of vehicles and equipment	464	10%	79%	446	11%	52%	367	12%	47%
Laborers and freight, stock, and material movers, hand	1,647	15%	66%	1,540	16%	51%	1,259	18%	43%
Packers and packagers, hand	414	10%	56%	391	10%	19%	302	11%	19%
Refuse and recyclable material collectors	82	24%	13%	76	25%	9%	59	33%	9%

Quadrants are defined by starting wage and wage growth after 10 years.
Source: NLSY97 and PSID

Appendix G: Estimates of 10-Year Wage Growth Predictors, With Other Trajectory Outcomes as Predictors

The tables below compare how estimated wage growth disparities differ after adjusting for other trajectory outcomes. These analyses aim to help identify pathways through which wage growth disparities may occur. However, in no cases do the additional controls alter the estimate substantively.

Exhibit G-1. Ten-Year Wage Growth Differences, by Worker Characteristic With and Without Controls for Job and Occupational Cluster Changes During the 10-Year Trajectory

	Not Controlling for Cluster or Job Changes				Controlling for Cluster and Job Changes			
Ten-Year Wage Growth	Estimate	95% Confidence Interval		*p*-Value	Estimate	95% Confidence Interval		*p*-Value
Age								
Age 18-24	$0.19	[-$1.74,	$2.12]	0.85	$0.16	[-$1.76,	$2.08]	0.87
Age 25-29	-$1.57	[-$3.40,	$0.26]	0.09	-$1.58	[-$3.41,	$0.24]	0.09
Age 30-34	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*
Gender								
Women	-$3.61	[-$4.54,	-$2.69]	0.00	-$3.49	[-$4.40,	-$2.57]	0.00
Men	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*
Race/Ethnicity								
White non-Hispanic	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*
Black non-Hispanic	-$3.07	[-$3.89,	-$2.25]	0.00	-$2.90	[-$3.71,	-$2.08]	0.00
Other non-Hispanic	$2.73	[$0.47,	$4.99]	0.02	$2.51	[$0.24,	$4.78]	0.03
Hispanic	-$1.25	[-$2.12,	-$0.37]	0.01	-$1.26	[-$2.14,	-$0.38]	0.01
Starting Education								
No degree	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*
High school diploma or equivalent	$2.47	[$1.92,	$3.01]	0.00	$2.12	[$1.57,	$2.67]	0.00
Associate's degree	$3.79	[$2.19,	$5.40]	0.00	$3.23	[$1.63,	$4.83]	0.00
Bachelor's degree or more	$9.96	[$8.37,	$11.54]	0.00	$9.18	[$7.57,	$10.80]	0.00
Parent Education								
Neither parent has any college	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*
At least one parent has some college	$0.74	[-$0.11,	$1.59]	0.09	$0.78	[-$0.07,	$1.63]	0.07
At least one parent has a bachelor's degree	$3.66	[$2.68,	$4.64]	0.00	$3.70	[$2.71,	$4.68]	0.00

The table rows represent the estimated difference in average wage growth for members of the given category, compared to members of the reference category who are otherwise similar (same starting occupation, starting wage, and demographic characteristics other than the one in question). Each demographic group has its own (omitted) reference category, indicated by *italics*. Estimates in green indicate that, on average, entrants from that demographic group experience more wage growth than do otherwise similar entrants from the reference category. Likewise, estimates in red indicate that, on average, entrants from that demographic group experience less wage growth than do otherwise similar

entrants from the reference category. For instance, Black non-Hispanic entrants to an occupation see, on average, $2.90 per hour less in wage growth 10 years after entering the occupation compared to the otherwise similar White non-Hispanic entrant when controlling for cluster and job changes, versus $3.07 per hour less when not controlling for cluster and job changes. The confidence intervals indicate how precise our estimates are (at 95 percent confidence level); the actual wage difference could fall anywhere in that range, though they are more likely to fall toward the middle of the range than the ends.
Estimates are drawn from OLS regressions that include controls for data source, starting wage, starting occupation, and all of the individual-level characteristics above. “Other non-Hispanic” includes Asian Americans, Pacific Islanders, Native Americans, workers who report multiple racial identities, and workers who report no racial identity or Hispanic ethnicity. Those workers are grouped only because sample sizes are insufficient to consider each separately.
Source: NLSY97 and PSID

Exhibit G-2. Ten-Year Wage Growth Differences, by Worker Characteristic with and without Controls for Months Not Working during the Ten-Year Trajectory

Ten-Year Wage Growth	Not Controlling for Months Not Working				Controlling for Months Not Working			
	Estimate	95% Confidence Interval		*p*-Value	Estimate	95% Confidence Interval		*p*-Value
Age								
Age 18-24	$0.19	[-$1.74,	$2.12]	0.85	$0.46	[-$1.46,	$2.39]	0.64
Age 25-29	-$1.57	[-$3.40,	$0.26]	0.09	-$1.21	[-$3.02,	$0.60]	0.19
Age 30-34	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*
Gender								
Women	-$3.61	[-$4.54,	-$2.69]	0.00	-$3.35	[-$4.27,	-$2.43]	0.00
Men	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*
Race/Ethnicity								
White non-Hispanic	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*
Black non-Hispanic	-$3.07	[-$3.89,	-$2.25]	0.00	-$2.56	[-$3.38,	-$1.74]	0.00
Other non-Hispanic	$2.73	[$0.47,	$4.99]	0.02	$2.87	[$0.60,	$5.14]	0.01
Hispanic	-$1.25	[-$2.12,	-$0.37]	0.01	-$0.99	[-$1.85,	-$0.12]	0.03
Starting Education								
No degree	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*
High school diploma or equivalent	$2.47	[$1.92,	$3.01]	0.00	$1.95	[$1.40,	$2.49]	0.00
Associate's degree	$3.79	[$2.19,	$5.40]	0.00	$2.85	[$1.28,	$4.41]	0.00
Bachelor's degree or more	$9.96	[$8.37,	$11.54]	0.00	$9.16	[$7.56,	$10.77]	0.00
Parent Education								
Neither parent has any college	*$0.00*	*N/A*		*N/A*	*$0.00*	*N/A*		*N/A*
At least one parent has some college	$0.74	[-$0.11,	$1.59]	0.09	$0.60	[-$0.24,	$1.44]	0.16
At least one parent has a bachelor's degree	$3.66	[$2.68,	$4.64]	0.00	$3.47	[$2.49,	$4.45]	0.00

The table rows represent the estimated difference in average wage growth for members of the given category, compared to members of the reference category who are otherwise similar (same starting occupation, starting wage, and demographic characteristics other than the one in question). Each demographic group has its own (omitted) reference category, indicated by *italics*. Estimates in green indicate that, on average, entrants from that demographic group experience more wage growth than do otherwise similar entrants from the reference category. Likewise, estimates in red indicate that, on average, entrants from that demographic group experience less wage growth than do otherwise similar entrants from the reference category. For instance, Black non-Hispanic entrants to an occupation see, on average, $2.56 per hour less in wage growth 10 years after entering the occupation compared to the otherwise similar White non-Hispanic entrant when controlling for months not working, versus $3.07 per hour less when not controlling for months not working. The confidence intervals indicate how precise our estimates are (at 95 percent confidence level); the actual wage difference could fall anywhere in that range, though they are more likely to fall toward the middle of the range than the ends.

Estimates are drawn from OLS regressions that include controls for data source, starting wage, starting occupation, and all of the individual-level characteristics above. "Other non-Hispanic" includes Asian Americans, Pacific Islanders, Native Americans, workers who report multiple racial identities, and workers who report no racial identity or Hispanic ethnicity. Those workers are grouped only because sample sizes are insufficient to consider each separately.

Source: NLSY97 and PSID

Exhibit G-3. Ten-Year Wage Growth Differences, by Worker Characteristic with and without Controls for Earning an Additional Postsecondary Degree during the 10-Year Trajectory

Ten-Year Wage Growth	Not Controlling for Additional Postsecondary Degrees			Controlling for Additional Postsecondary Degrees		
	Estimate	95% Confidence Interval	p-Value	Estimate	95% Confidence Interval	p-Value
Age						
Age 18-24	$0.19	[-$1.74, $2.12]	0.85	-$0.16	[-$2.09, $1.76]	0.87
Age 25-29	-$1.57	[-$3.40, $0.26]	0.09	-$1.54	[-$3.37, $0.28]	0.10
Age 30-34	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
Gender						
Women	-$3.61	[-$4.54, -$2.69]	0.00	-$3.94	[-$4.85, -$3.03]	0.00
Men	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
Race/Ethnicity						
White, non-Hispanic	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
Black, non-Hispanic	-$3.07	[-$3.89, -$2.25]	0.00	-$2.77	[-$3.58, -$1.97]	0.00
Other, non-Hispanic	$2.73	[$0.47, $4.99]	0.02	$2.51	[$0.23, $4.79]	0.03
Hispanic	-$1.25	[-$2.12, -$0.37]	0.01	-$0.93	[-$1.80, -$0.05]	0.04
Starting Education						
No degree	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
High school diploma or equivalent	$2.47	[$1.92, $3.01]	0.00	$1.68	[$1.15, $2.22]	0.00
Associates degree	$3.79	[$2.19, $5.40]	0.00	$3.21	[$1.63, $4.80]	0.00
Bachelor's degree or more	$9.96	[$8.37, $11.54]	0.00	$10.43	[$8.83, $12.03]	0.00
Parent Education						
Neither parent has any college	*$0.00*	*N/A*	*N/A*	*$0.00*	*N/A*	*N/A*
At least one parent has some college	$0.74	[-$0.11, $1.59]	0.09	$0.15	[-$0.68, $0.99]	0.72
At least one parent has a bachelor's degree	$3.66	[$2.68, $4.64]	0.00	$2.19	[$1.19, $3.20]	0.00
Additional Postsecondary Degree						
No new postsecondary degree	*N/A*			*$0.00*	*N/A*	*N/A*
Earned additional postsecondary degree	N/A			$6.06	[$5.19, $6.94]	0.00

The table rows represent the estimated difference in average wage growth for members of the given category, compared to members of the reference category who are otherwise similar (same starting occupation, starting wage, and demographic characteristics other than the one in question). Each demographic group has its own (omitted) reference category, indicated by *italics*. Estimates in green indicate that, on average, entrants from that demographic group experience more wage growth than do otherwise similar entrants from the reference category. Likewise, estimates in red indicate that, on average, entrants from that demographic group experience less wage growth than do otherwise similar entrants from the reference category. For instance, Black non-Hispanic entrants to an occupation see, on average, $2.77 per hour less in wage growth 10 years after entering the occupation compared to the otherwise similar White non-Hispanic entrant when controlling for earning an additional postsecondary degree, versus $3.07 per hour less when not controlling for earning an additional postsecondary degree. The confidence intervals indicate how precise our estimates are (at 95 percent confidence level); the actual wage difference could fall anywhere in that range, though they are more likely to fall toward the middle of the range than the ends.
Estimates are drawn from OLS regressions that include controls for data source, starting wage, starting occupation, and all of the individual-level characteristics above. “Other non-Hispanic” includes Asian Americans, Pacific Islanders, Native Americans, workers who report multiple racial identities, and workers who report no racial identity or Hispanic ethnicity. Those workers are grouped only because sample sizes are insufficient to consider each separately.
Source: NLSY97 and PSID

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