Vienna University of Technology

Gender Dynamics at Work: Analyzing Trends and Patterns in the US Labor Market

194.147 Interdisciplinary Project in Data Science

Anna Baghumyan
12044943

Supervisors:
Fariba Karimi *(Complexity Science Hub)*
Maria del Rio-Chanona *(Complexity Science Hub)*
Mauritz Cartier van Dissel *(Complexity Science Hub)*
Allan Hanbury *(TU Wien)*

May 16, 2024

Abstract

Gender dynamics in the labor force have long been a topic of interest, often reflecting broader societal trends and inequalities. This project aims to analyze gender dynamics in the US labor market using data spanning 2000 to 2023. In particular, exploratory data analysis and statistical testing are used to examine the trends in gender representation and income disparities across various occupational fields and how they have evolved over time. Furthermore, social network analysis techniques are used to explore occupational mobility for men and women and its connection to income. This analysis provides deeper understanding of gender dynamics in the labor market and offers valuable insights for policy interventions aimed at promoting gender equality in the workforce.

Keywords: *gender dynamics, labor market, gender representation, wage gap, social network analysis, occupational mobility*

Contents

1 Introduction

Gender dynamics in the labor market have long been a subject of academic interest, particularly when considering the broader context of gender equality. Prior research has extensively documented gender disparities, emphasizing the multifaceted factors contributing to them. Notably, persistent occupational segregation has been highlighted, often resulting in gender-specific jobs or "occupational ghettos" [1]. Paradoxically, this segregation was present in higher level in more developed and gender-egalitarian countries [1, 2], where deeply ingrained gender stereotypes and societal beliefs perpetuate this phenomenon [2].

Previous research has also underscores income disparities between genders within the labor market. Studies have delved into international differences in gender wage gaps, attributing variations across countries to differences in labor market institutions like wage-setting mechanisms and family-friendly policies [3, 4]. Comprehensive analyses have provided insights into the extent, trends, and underlying factors of the gender wage gap, emphasizing the roles of occupational segregation, educational attainment, and work experience [5]. Additionally, factors like child-care and household duties, even in countries with family-friendly work policies, contribute to the wage gap [6, 7]. Despite observations indicating a "grand gender convergence" in income levels, progress remains slow and potentially stalled [8].

Examining the interplay between gender dynamics and occupational mobility, a change in a person's occupational status, is crucial for understanding income disparities and gender representation in the labor market. Research highlights the coexistence of individualism and gender essentialism in shaping occupational mobility [9]. While individualism promotes gender equality in career opportunities, gender essentialism suggests innate gender differences. This duality often leads women towards traditionally female-dominated fields, with some gravitating towards male-dominated sectors for upward mobility, particularly those from middle-class backgrounds. Conversely, men exhibit less inclination to transition into traditionally female domains due to a lack of economic incentives [9]. Moreover, occupational similarity emerges as a crucial factor influencing job transitions, with research indicating a strong tendency for people to transition into occupations with similar job tasks [10].

In light of these considerations, our study aims to address three primary research questions regarding gender dynamics, income disparities, and occupational mobility within the US labor market over the years 2000-2023. Firstly, we investigate how gender dynamics interplay with marital status, race, and education. Secondly, we analyze the trends in income disparities between genders and how they have evolved in the past two decades. Lastly, we explore the differences in occupational mobility between men and women and examine its relationship with income disparities. To provide comprehensive insights into these questions, we employ a multifaceted methodology that encompasses exploratory data analysis, hypothesis testing, and social network analysis, allowing us to explore the complexities of the labor market landscape and revealing how gender disparities interact with other socio-economic factors.

The rest of the paper is organized as follows. Section 3 details our methodology, including data retrieval and preprocessing. In Section 3 we present and discuss our results. Finally, in Section 4, we conclude the paper with a brief summary and suggesting avenues for future research.

2 Methodology

In this section, we outline the methodology employed in our study. We begin by detailing the process of data retrieval and preprocessing, including the source of our data, the steps taken to choose the relevant data sample, and how to clean and organize the dataset for analysis. Next, we describe the techniques used for information visualization and statistical analysis, which enable us to explore and visualize the relationships between various socio-demographic factors and gender within the labor market. Finally, we explain the approach used in social network analysis, including the network modeling and centrality measures that were employed for the analysis.

2.1 Data Retrieval and Preprocessing

The data utilized for this study were retrieved from the Integrated Public Use Microdata Series, Current Population Survey (IPUMS CPS) dataset [11]. The IPUMS CPS dataset provides an integrated set of data from the Current Population Survey (CPS) spanning from 1962 forward. The CPS is a monthly U.S. household survey jointly conducted by the U.S. Census Bureau and the Bureau of Labor Statistics to gather information on education, labor force status, demographics, and other aspects of the U.S. population. For this project, we specifically focused on the sample from the Annual Social and Economic Supplement (ASEC) of the CPS, conducted in March. The ASEC provides one set of data for IPUMS CPS and is the most widely used by social scientists and policymakers.

Since the IPUMS CPS dataset provides a wide range of variables and years, we needed to specify the data extract suitable for this study. Our final dataset spans the years 2000 to 2023 and contains 22 variables relevant to our analysis, including household and person identifiers, demographic attributes like age, gender and race, socio-economic indicators such as marital status and educational attainment, as well as occupational details like occupation and wage and salary income. These variables serve as the foundation for our analysis, allowing us to explore gender dynamics, income disparities, and occupational mobility within the U.S. labor market.

The dataset also contains two weight variables - `ASECWT` and `ASECWTCVD` - to ensure the accuracy and representativeness of the analysis. `ASECWT` is a person-level weight that adjusts for various factors such as failure to obtain an interview, oversampling of certain demographic groups, and other considerations. `ASECWTCVD` was introduced for the years 2019-2021 and serves to adjust for nonrandom nonresponse resulting from the COVID-19 pandemic. For all other ASEC years, researchers are advised to utilize `ASECWT`. However, it is important to note that `ASECWT` is comparable throughout the ASEC supplements, except for 2014. In 2014, a redesign of some survey questions provided to a sample of individuals occurred, impacting the comparability of weights for that specific year. Therefore, results obtained for the year 2014 will not be comparable with those from other years.

Another important consideration is the occupational coding scheme changes in CPS data over the years. The original occupational codes are stored in the `OCC` (occupation) and `OCCLY` (occupation last year) variables, but using these introduces inconsistencies in the analysis. Therefore, in our study, we opt for `OCC2010` and `OCC10LY` instead. These variables provide a harmonized occupation coding scheme based on the Census Bureau's 2010 classification, ensuring consistency and comparability throughout our analysis.

Once we have identified the desired variables, we utilize the IPUMS online data extract system to incorporate them into our dataset (a comprehensive list of variables can be found in Table 1). Our data extract encompasses 24 samples spanning the years 2000-2023, with the data format set to .csv and the structure specified as Rectangular (cross-sectional). Following a processing period, the extract becomes available for use. Additionally, accompanying codebook files are provided, featuring the codes and labels of the variables. These are converted to .csv format to facilitate easier access and manipulation of the variable information during the subsequent stages of our analysis.

To gain a broader and more comprehensive understanding of the occupational trends and mobility, we introduced two more variables: occupational field (`OCC_FIELD`) and occupational field last year (OCC_FIELD_LY). These variables use occupation categories from the 2010 scheme, providing a wider perspective on occupation trends over time. Likewise, we adopted a similar approach with the RACE variable by combining racial categories into a new variable called RACE_GROUP. This adjustment was made due to the consistent number of racial groups across the years, despite the rise in the number of racial codes within these groups.

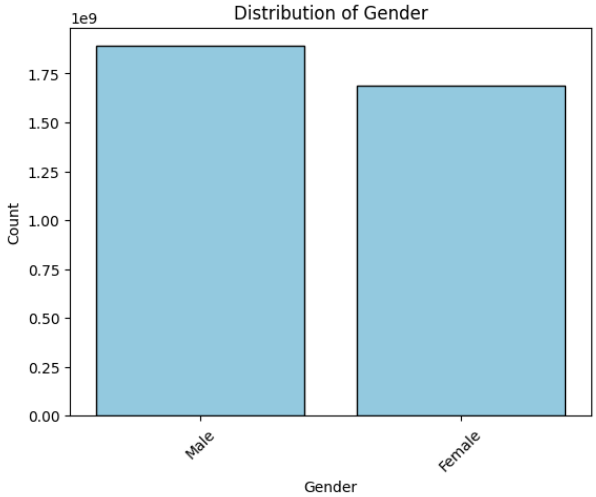


Figure 1: Distribution of gender

For our research, we are interested only in people who are 18 and above and are currently in the labor market. Our dataset predominantly comprises individuals who are White and married. In terms of educational attainment, high school diploma is the most common, followed by a bachelor's degree. Regarding occupational fields, the most prevalent categories include Office and Administrative Support; Management in Business, Science, and Arts; as well as Sales and Related occupations. Additionally, the data reveals a higher representation of men compared to women, as illustrated in Figure 1. The distributions of the other key variables can be found in the appendix.

2.2 Information Visualization and Statistical Analysis

To gain deeper insights into the data, we began our analysis with exploratory data analysis (EDA). In this phase, we computed descriptive statistics, such as means, medians, and standard deviations, for key variables to understand the distribution and central tendencies of the data. Additionally, visualization techniques including histograms, box plots, and line plots were used to identify patterns and trends, and gain a visual overview of the data's characteristics and relationships.

Following the EDA, we conducted hypothesis testing to examine relationships between variables of interest. Utilizing statistical tests like t-tests and chi-square tests, we explored associations between gender and income, marital status, race, and education.

2.3 Social Network Analysis

The final stage of our analysis employed social network analysis to understand the occupational mobility within the labor market. The initial step of our approach was data preparation to build two distinct networks: the occupational field mobility network and the occupational mobility network. For this part we only worked with the sample of individuals in the data who transitioned to a new job. Then, for both men and women, we constructed node lists and edge lists incorporating variables such as occupation, occupational field, and average income. In the occupational mobility network, nodes represent specific occupations, while edges indicate transitions from one occupation to another. The occupational field mobility network is similar, but here the nodes represent occupational fields instead.

To visualize and analyze the constructed networks, we employed Gephi [12], a powerful network analysis and visualization tool. After importing our node lists and edge lists into Gephi, we used different mappings to explore the connections between different nodes and variables. We also applied various layout algorithms and filtering techniques to enhance the clarity and interpretability of the networks.

Additionally, Gephi provided valuable insights into the centrality measures of the nodes, helping us understand the significance of individual nodes within the networks. We focused on several key centrality measures:

- **Degree Centrality**: Degree centrality measures the number of links connected to a node. It can be further divided into in-degree (number of incoming links) and out-degree (number of outgoing links) [13].
- **Weighted Degree Centrality**: This measure takes into account the weight or strength of the connections, providing a more nuanced understanding of node importance based on the strength of connections [13].
- **Closeness Centrality**: Closeness centrality measures how close a node is to all other nodes in the network, indicating nodes that can interact with other nodes most quickly and efficiently [13].
- **Betweenness Centrality**: This measure identifies nodes that act as bridges between different parts of the network. Nodes with high betweenness centrality have the potential to control the flow of information between other nodes [13]. In our case, those will be the occupations that often lie between two non-adjacent occupations and have the potential to facilitate transitions between them.
- **Eigenvector Centrality**: Eigenvector centrality considers both the node's direct links and the links of its neighbors. It reflects a node's influence in the network, considering not just the quantity but also the quality of its connections [14].
- **PageRank**: Originating from Google's search algorithm, PageRank is a variation of eigenvector centrality and measures the importance of nodes based on the number and quality of links to them. It evaluates the 'voting' power of nodes in the network [15].

These centrality measures provided a comprehensive view of the network structures and highlighted key occupations and occupational fields that play significant roles in occupational mobility.

3 Results and Discussion

In this section, we present the results of our analysis. We begin by examining the associations between gender and marital status, race, and education. Next, we explore the trends in income disparities between genders and their evolution over the last two decades. Finally, we investigate the relationship between occupational mobility and gender, uncovering insights into how occupational transitions differ between men and women and their implications for income differentials.

3.1 Relationships with Marital Status, Race, and Education

In our examination of the relationships between gender and other socio-demographic factors, namely marital status, race, and education, we first analyzed the distribution of gender within occupational fields. The data presented in Figure 2 illustrate the gender disparities across different sectors. Based on these proportions, we grouped the occupational fields into male-dominated, female-dominated, and balanced fields, as summarized in Table 3. Furthermore, through the application of a chi-squared test, we assessed the association between gender and occupational field, yielding statistically significant results. This further highlights the phenomenon of occupational gender segregation observed in previous studies, such as that by Charles and Grusky [1], and underscores its presence in the modern US labor market.

Additionally, our analysis highlights the persistent underrepresentation of women in STEM (science, technology, engineering, and math) fields. This phenomenon has been attributed to gender stereotypes, as indicated by Breda et al. [2], who identified beliefs such as "math is not for girls" as influential factors contributing to the gender gap in STEM participation.

Furthermore, our examination of gender representation over the years for each occupational field reveals a stable trend, with minimal changes in gender proportions observed across the years 2000-2023. Figure 3 provides a visual representation of this trend, indicating that gender representation has remained relatively consistent over the past two decades, despite societal and economic shifts.

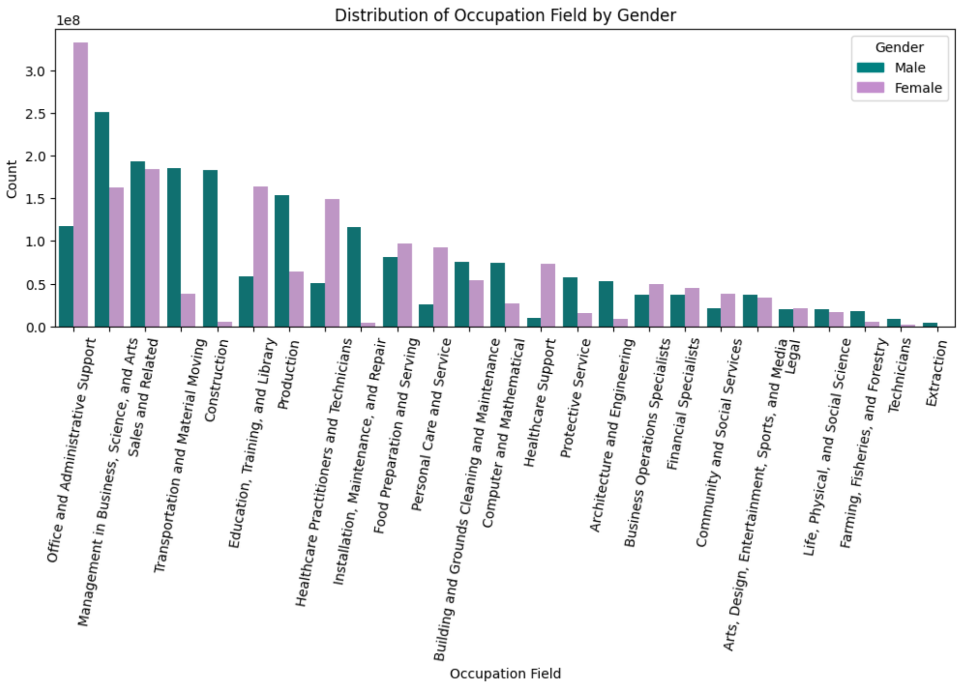


Figure 2: Distribution of gender withing occupational fields

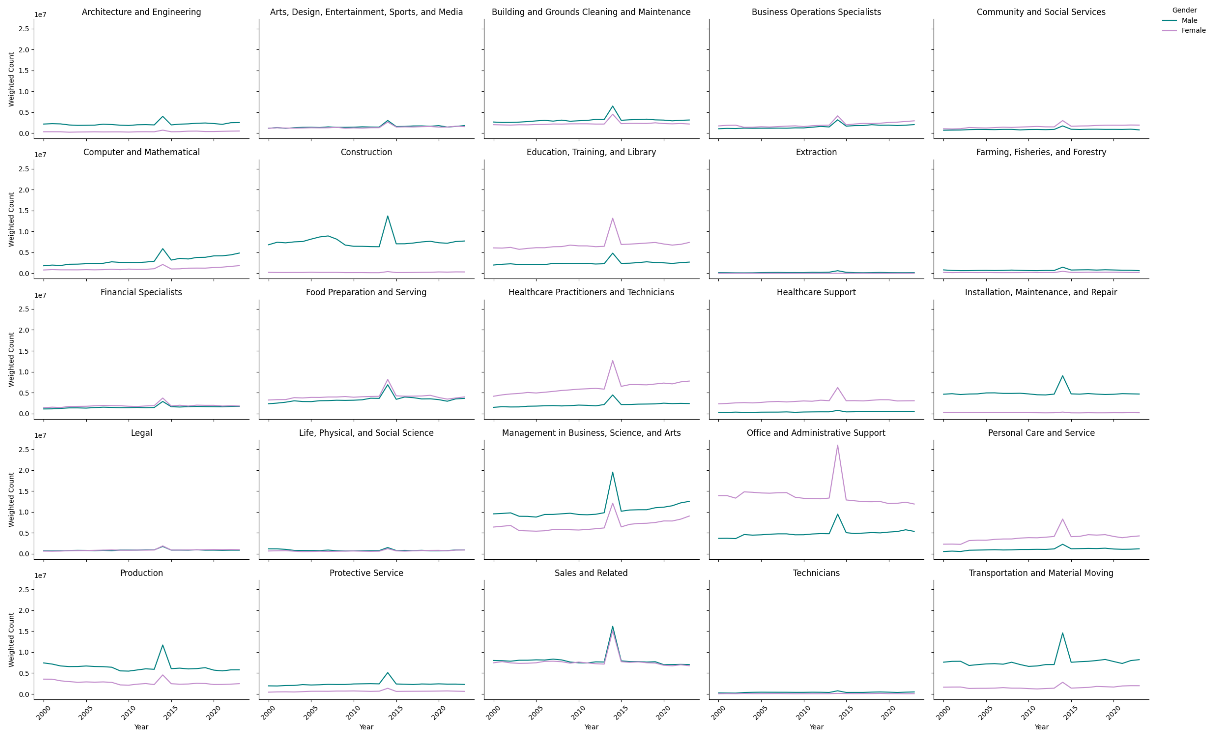


Figure 3: Distribution of gender withing occupational fields Across the Years

3.1.1 Gender and Educational Attainment

Educational attainment often serves as a key determinant of job opportunities, income levels, and career trajectories, so understanding its relationship with gender in the job market can provide insights into the dynamics of opportunity and advancement. Blau and Khan [5] found that while women began with lower average education levels compared to men in 1981, they surpassed men in average schooling by 2011. This shift was accompanied by a higher likelihood of women holding at least a bachelor's degree while men had a slightly higher incidence of having exactly a bachelor's degree.

Our analysis reflects a similar pattern, as depicted in Figure 4. Despite women being underrepresented in our dataset, they demonstrate higher proportions of master's and associate's degrees as their highest educational attainment. This contrasts with the prevalence of men across other education levels, including doctorates and professional school degrees. Interestingly, even within fields traditionally dominated by women, men tend to hold a greater share of advanced degrees.

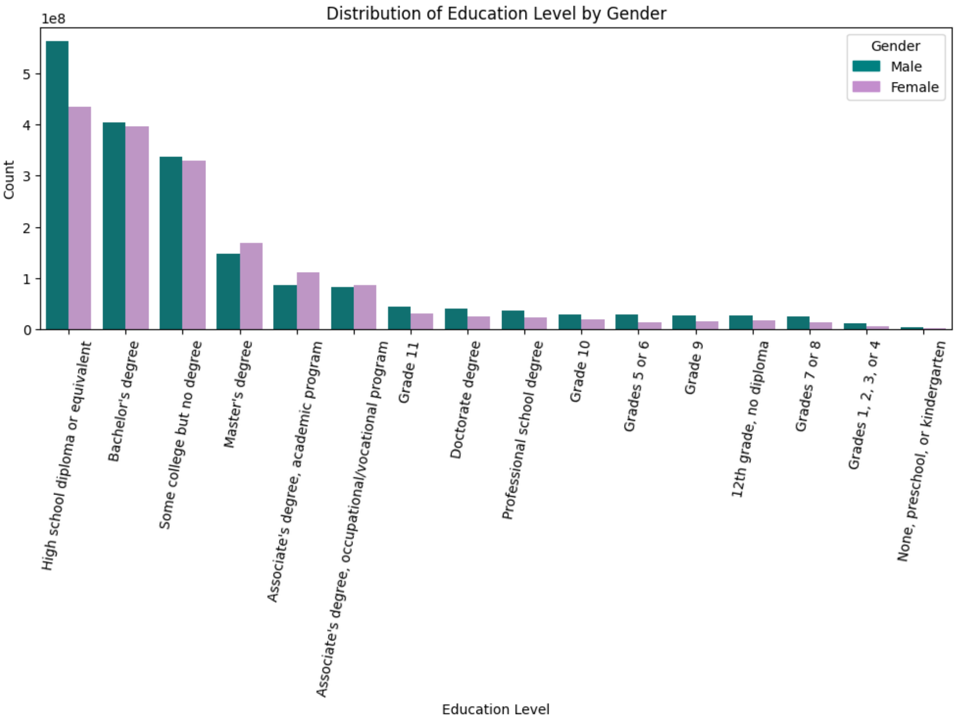


Figure 4: Distribution of educational attainment by gender

3.1.2 Gender and Marital Status

Next, we analyzed the interplay between gender and marital status. As depicted in Figure 5, the majority of the labor force in our dataset comprises married individuals (with present spouses), followed by never married/single individuals. Interestingly, there is a higher proportion of widowed and separated women compared to men. Furthermore, we found that *Food Preparation and Serving* is the only occupational field not predominantly occupied by married individuals for both genders, with single/never married individuals being the highest in this category (see Figure 27). Additionally, women consistently exhibit a concentration in *Office and Administrative Support* roles across all marital statuses. In contrast, men display more variation in their top occupational choices depending on marital status, as illustrated in Figures 6 and 7.

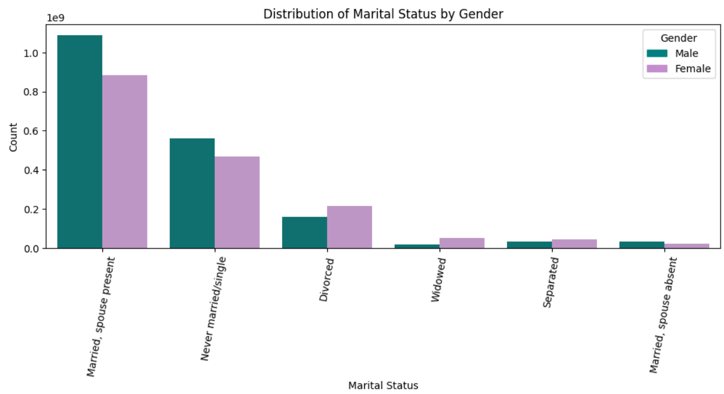


Figure 5: Distribution of marital status by gender

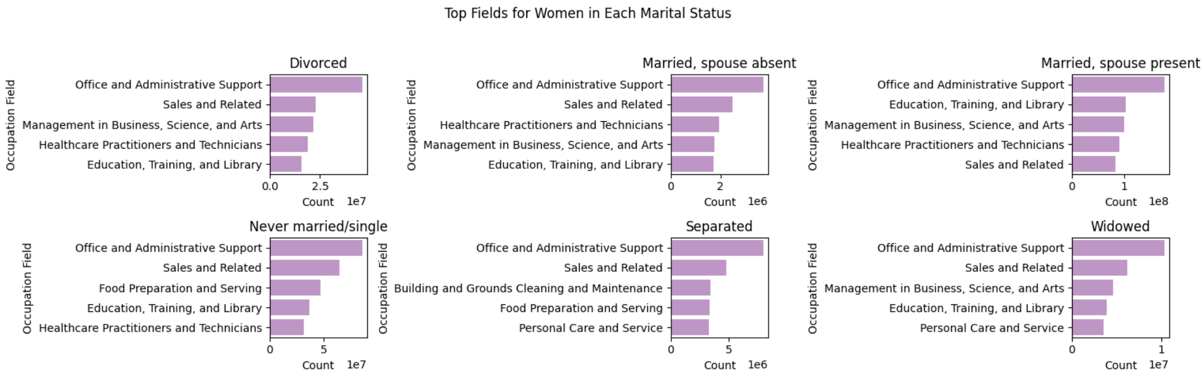


Figure 6: Top 5 fields for women in each marital status

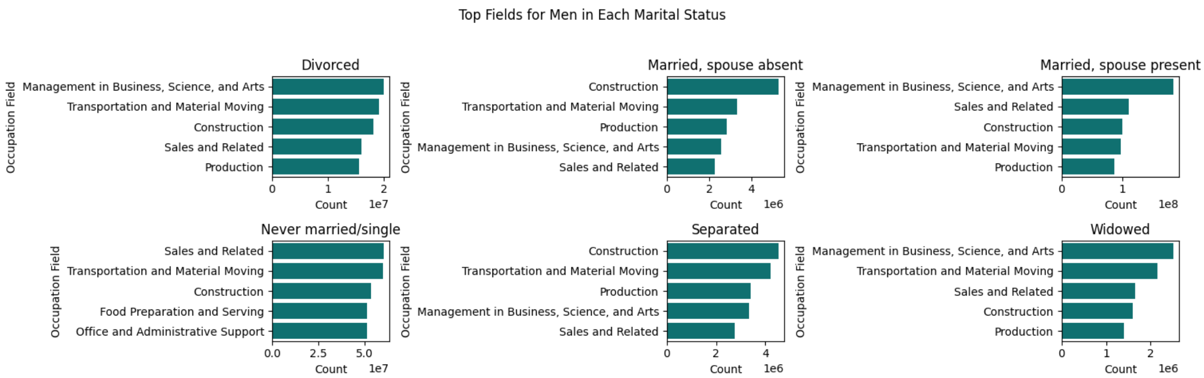


Figure 7: Top 5 fields for men in each marital status

3.1.3 Gender and Race

For the analysis of gender and race dynamics within the labor force, we used the larger race groups as mentioned in Section 2. As depicted in Figure 8, White individuals emerge as the predominant demographic group in the labor force, with significant representation across both genders. Furthermore, our findings indicate a gender disparity within racial categories, with men outnumbering women in the labor force across all racial groups except for Black individuals. This lower employment rate for Black men could potentially be influenced by discrimination in hiring practices, higher rates of incarceration and limited access to education and economic opportunities [16, 17, 18].

Moreover, similar to marital status, our analysis reveals distinct occupational pattern among men and women across different racial categories. While women again exhibit a consistent concentration in *Office and Administrative Support* roles regardless of race, men display greater occupational variation based on racial identity, as shown in Figures 29 and 30. Furthermore, from Figure 9 we can see that individuals of Asian or Pacific islander descent are relatively highly represented in occupational fields such as *Architecture and Engineering; Computer and Mathematical; Life, Physical and Social Science*, regardless of gender, while fields like *Food Preparation and Serving* and *Healthcare Practitioners and Technicians* have higher proportions of men. Similarly, among the Black racial group, both men and women are more prevalent in occupational fields such as *Building and Grounds Cleaning and Maintenance; Community and Social Services; Food Preparation and Serving; Healthcare Support; Installation, Maintenance, and Repair; Office and Administrative Support; Personal Care and Service; Production; Protective Service; Transportation and Material Moving*. On thee other hand, fields like *Business Operations Specialists; Computer and Mathematical; Financial Specialists* and *Healthcare*

Practitioners and Technicians have relatively higher representation of Black women.

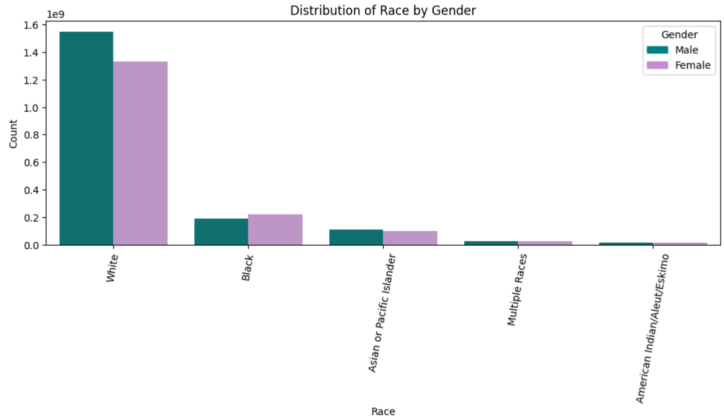


Figure 8: Distribution of race by gender

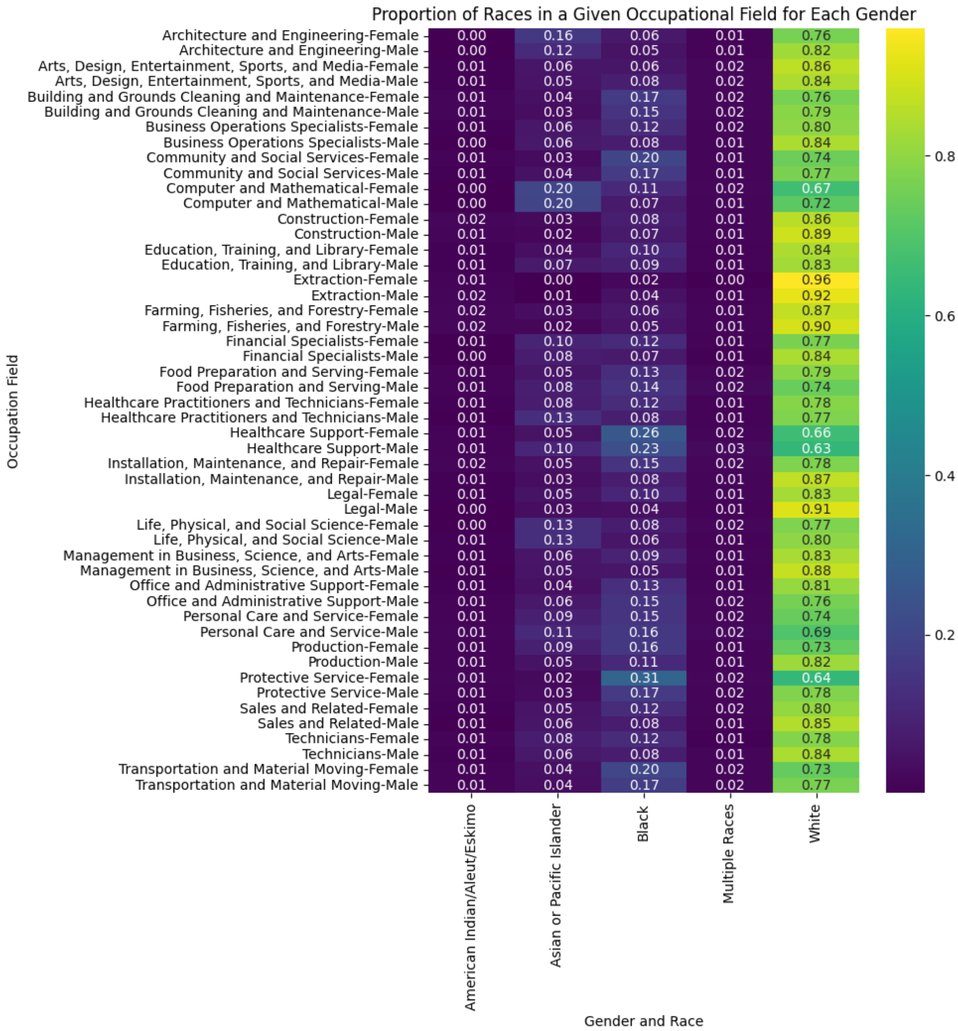


Figure 9: Proportion of races in a given occupational field for each genders

3.2 Income Disparities Between Genders

In examining gender disparities in income, the data reveals significant gaps in both mean and median earnings. Figure 10 illustrates the distribution of income by gender, showing clear differences between male and female income levels. Men have a weighted mean income of $53,200, notably higher than the $36,500 for women. Similarly, the median income for males, at $38,000, surpasses that of females, which stands at $28,000. Moreover, as Figure 11 shows, this wage gap remains consistent across the years, despite efforts to address gender inequality in the workforce. The two-sample t-test also confirms that the income disparities between men and women are statistically significant.

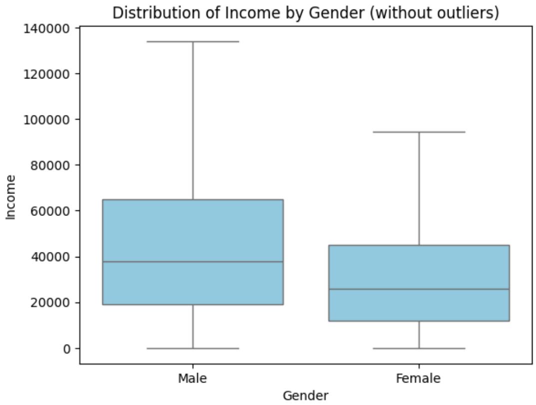


Figure 10: Distribution of income by gender (excluding outliers)

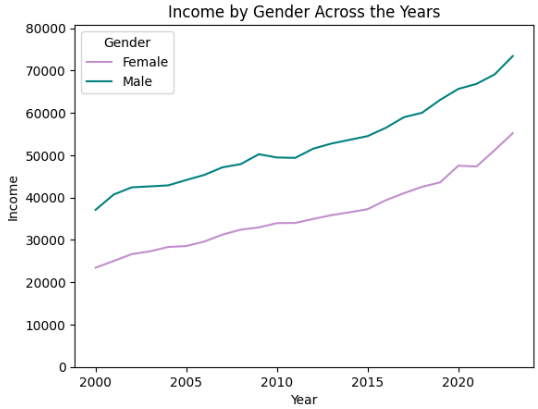


Figure 11: Income by gender over the years

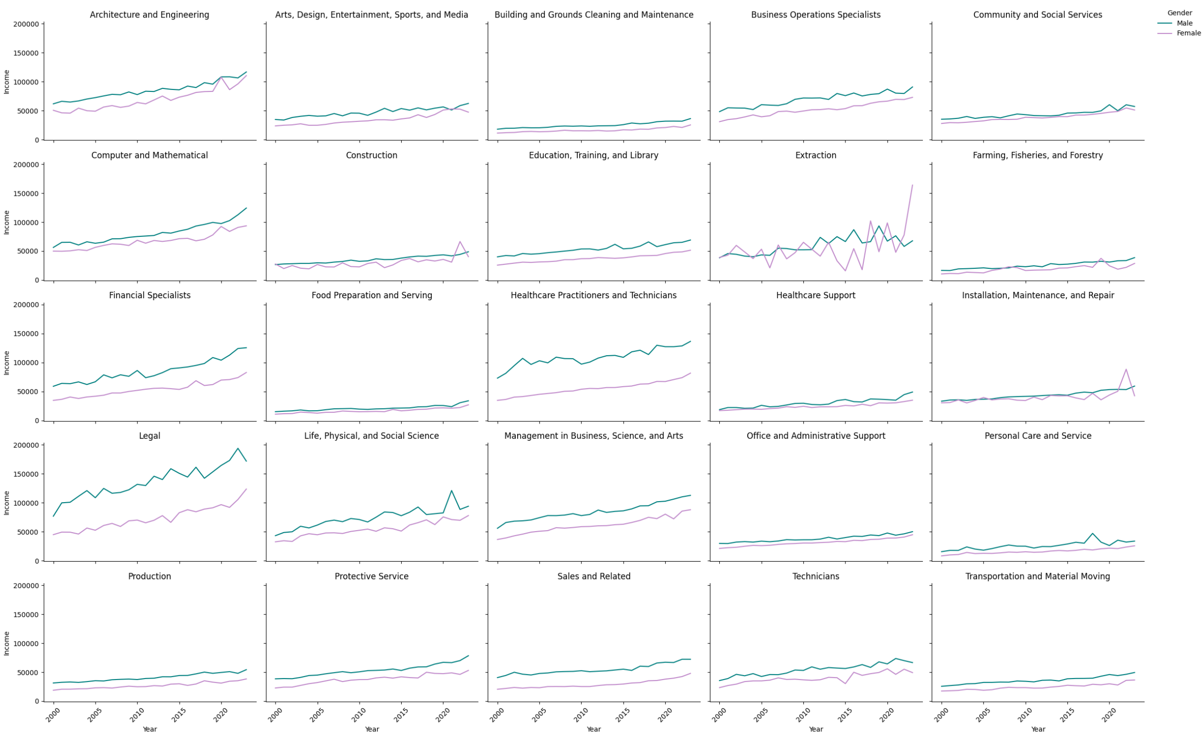


Figure 12: Income by gender over the years for each occupational field

Figure depicts 12 the evolution of average income by gender in 2000-2023 for each occupational field. The figure highlights variations in wage gap across the occupational fields. The gender-based income disparities persist across occupational fields, race, marital status and educational levels, as confirmed by two-sample t-tests. Notably, the income variable used for this analysis reflects an individual's total pre-tax wage and salary income for the previous calendar year, without accounting for hourly wages or working hours. Therefore, while our analysis cannot directly identify gender-based discrimination in hourly wages, as outlined in our introduction, existing literature suggests that differences in working hours between men and women, often influenced by unequal distribution of household and childcare responsibilities, contribute significantly to the wage gap.

3.3 Occupational Mobility and Gender

In this part of our research, we explore patterns of occupational mobility among men and women, aiming to understand how gender influences career trajectories and opportunities for advancement. Firstly, we notice a consistent trend: women exhibit a higher rate of occupational mobility compared to men, as illustrated in Figure 13, and this disparity persists across the years, as depicted in Figure 14.

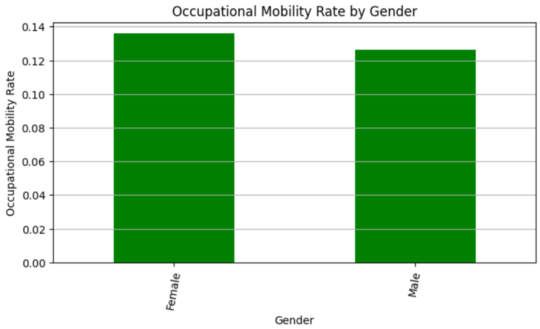


Figure 13: Distribution of occupational mobility rate by gender

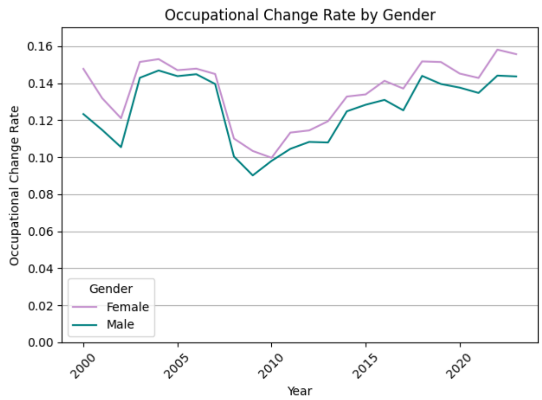
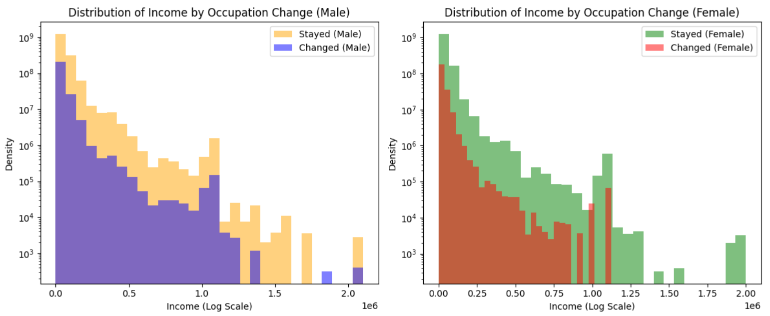


Figure 14: Occupational mobility rate by gender over the years

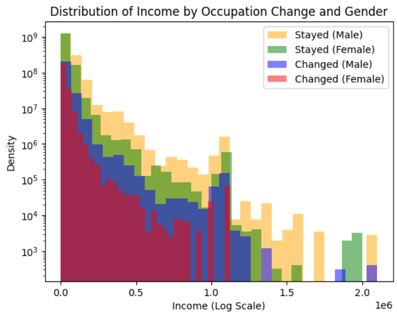
We also observe occupational mobility patterns associated with socio-economic factors. For both men and women, individuals who are never married/single or married (with a spouse absent) are more likely to change their occupations, whereas those who are married (with a present spouse) or divorced exhibit lower occupational mobility rates. Moreover, separated women display a higher occupational mobility rate than widowed women, while the difference between these two categories is less pronounced for men (see Figure 31). Education also plays a role in occupational mobility, as higher educational attainment is associated with lower occupational mobility rates for both men and women (see Figure 32).

Regarding race, individuals in the Black and Multiple Races categories exhibit higher occupational mobility rates, while those in the White or Asian or Pacific Islander categories have relatively lower rates. Additionally, for women, individuals in the American Indian/Aleut/Eskimo category also demonstrate a relatively high mobility rate, which is not the case for men in this category (see Figure 33). Moreover, while certain occupational fields, such as *Sales and Related, Computer and Mathematical*, *Legal*, and *Financial Specialist*, exhibit similar rates of occupational mobility for both men and women, there are notable variations in mobility rates across genders within other fields (see Figure 34).

Continuing our examination of occupational mobility, we now turn our attention to its relationship with income. The results shown in Figure 15 indicate that, for both men and women, individuals with lower incomes are more likely to change their occupation. Notably, the highest income earners tend to be predominantly men who have not changed their occupation, followed



(a) Distribution of income by occupation change for each gender separately



(b) Distribution of income by occupation change and gender

Figure 15: Distribution of income by occupation change for men and women

by women in similar circumstances. However, even among high-income earners, men are more likely to transition to a new occupation compared to women with similar incomes. Furthermore, this pattern generally holds across various occupational fields, as depicted in Figure 36. These findings suggest potential gender disparities in career advancement opportunities and highlights the need for further investigation into the factors contributing to these differences.

3.3.1 Occupational Field Mobility Network

To gain deeper insights into the dynamics of transitions between occupational fields and their relationship with income, we constructed several occupational field mobility networks for both genders.Through our network analysis, we uncovered notable patterns and distinctions between the occupational mobility of men and women. For men, fields such as *Extraction; Farming, Fisheries, and Forestry*, and *Healthcare Support* exhibit the lowest in-degree, indicating that there are few fields from which people transition into these fields (see Figure 38). Conversely, the *Legal* field demonstrates the lowest out-degree, suggesting that there are not many fields that people transition out of this field. On the other hand, for women, the in-degree and out-degree of fields do not show noticeable differences, with *Extraction* ranking the lowest in both categories (see Figure 37). The rest of the fields have relatively high in-degree and out-degree for both genders, indicating a high connectivity between the occupational fields.

Figure 17 reveals that for men, *Sales and Related* has the highest weighted in-degree and out-degree, indicating a high volume of transitions both into and out of the field. Similarly, for women, *Sales and Related* also demonstrates high weighted in-degree and out-degree; however, the highest numbers are observed in the *Office and Administrative Support* field (see Figure 16). Furthermore, women exhibit notably strong transitions between *Sales and Related* and *Office and Administrative Support* fields. Despite these differences, the majority of transitions occur within the same occupational field for both men and women, highlighting a consistent pattern across genders. This finding aligns with the research of Mealy et al. [10], which suggests that individuals are more inclined to transition into occupations with tasks similar to their current occupation.

Furthermore, our analysis highlights significant disparities in average income between occupational fields and genders. The fields such as *Legal; Healthcare Practitioners and Technicians; Architecture and Engineering; Computer and Mathematics; Management in Business, Science and Arts* consistently emerge as the highest-paying fields for both men and women. However, gender-based income gaps are evident, particularly in the *Legal* field. While both men and women in this field earn the highest average income, men earn nearly double that of women, with men averaging approximately $139,000 compared to women's $75,000.

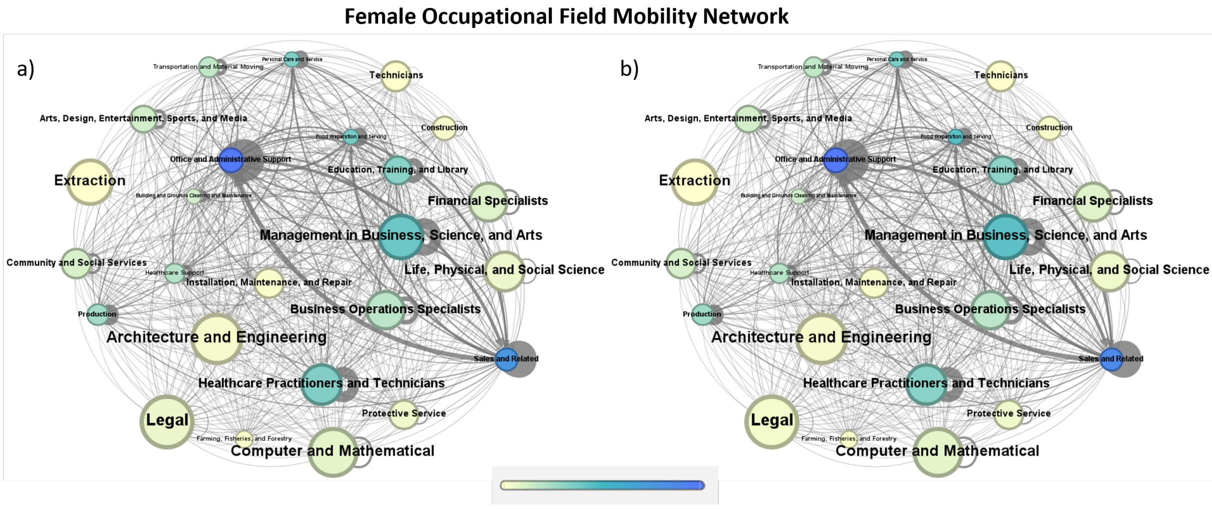


Figure 16: Female occupational field mobility network. Network mappings: node size - weighted average income; color - a) weighted in-degree, b) weighted out-degree

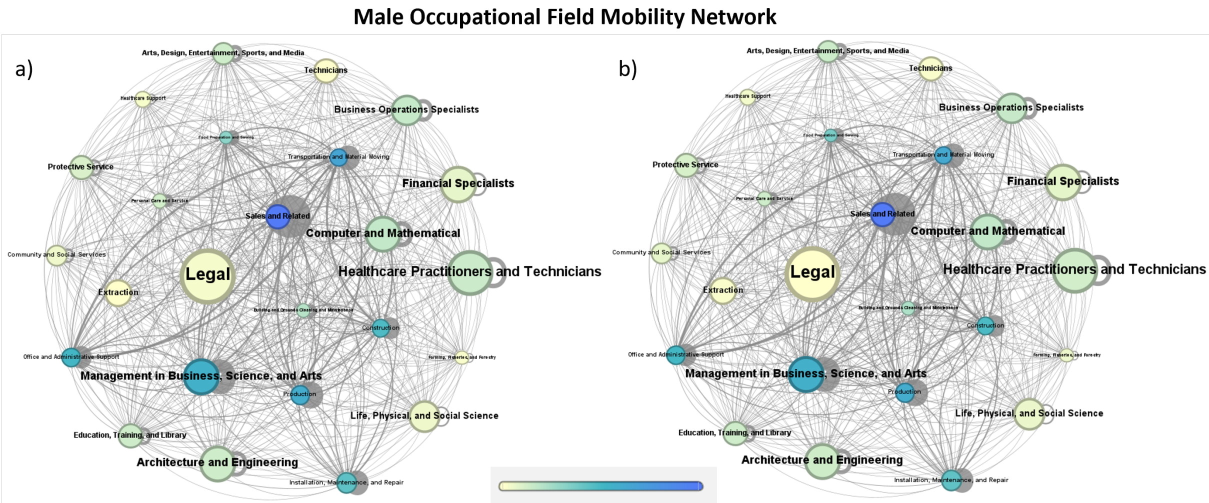


Figure 17: Male occupational field mobility network. Network mappings: node size - weighted average income; color - a) weighted in-degree, b) weighted out-degree

Another curious observation is related to the *Extraction* field. It ranks as the fourth-highest field in terms of average income for women, whereas only ninth for men. Nonetheless, both men and women in this field earn approximately the same average income.

Moreover, as depicted in Figure 18, women are more likely than men to transition to occupational fields experiencing a decrease in average income, suggesting a greater degree of income instability or fewer opportunities for upward mobility among women in their career trajectories.

We utilized centrality measures introduced in Section 2 to identify the most central occupational fields for men and women, summarized in Tables 4 and 5. Our analysis revealed both similarities and differences in career trajectories between genders within the labor market, consistent with our earlier findings. For both genders, roles in *Sales and Related* occupations emerge as highly central. This suggests that sales-related roles play a crucial role in the professional networks and career paths of both men and women. However, for men, other central occupational fields include *Transportation and Material Moving; Production; Building and Grounds Cleaning and Maintenance* and *Business Operations Specialist.* On the other hand, for women the most central

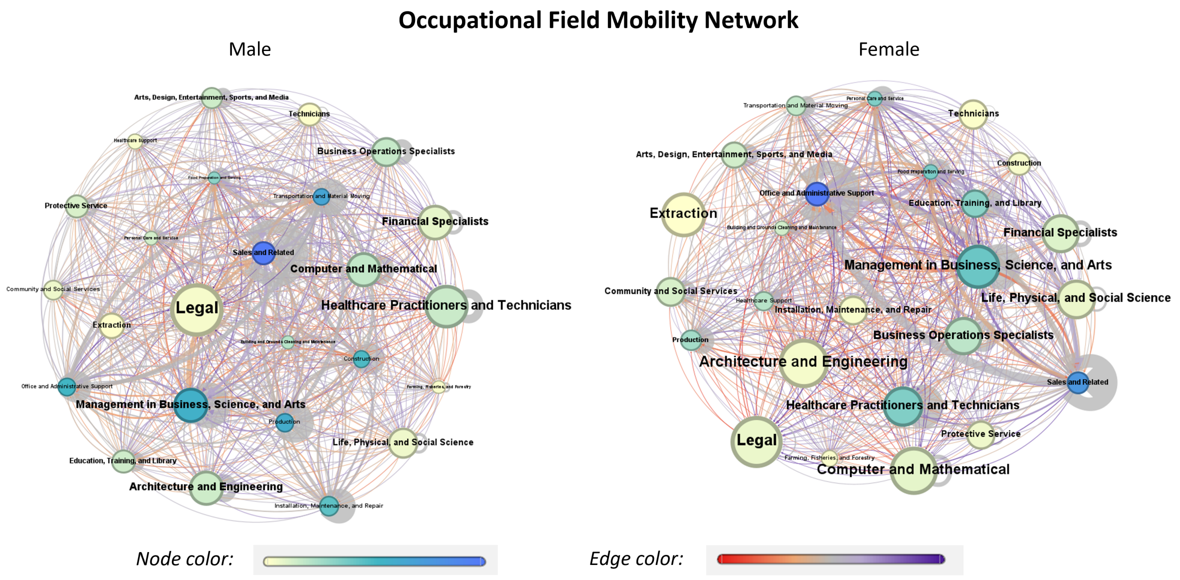


Figure 18: Occupational field mobility network. Network mappings: node size - weighted average income; node color - weighted in-degree; edge color - weighted average income difference

fields are *Management in Business, Science and Arts; Office and Administrative Support* and *Healthcare Practitioners and Technicians.*

3.3.2 Occupational Mobility Network

In our exploration of the occupational mobility network, several noteworthy patterns emerge. Firstly, we utilized network mappings that visualize node size based on weighted average income, with filters applied to focus on fields with incomes exceeding \$50,000 and \$100,000, respectively. Notably, the male network (Figure 20) exhibits greater density and includes significantly more nodes than the female network (Figure 19), indicating potentially broader career options for men with high pay.

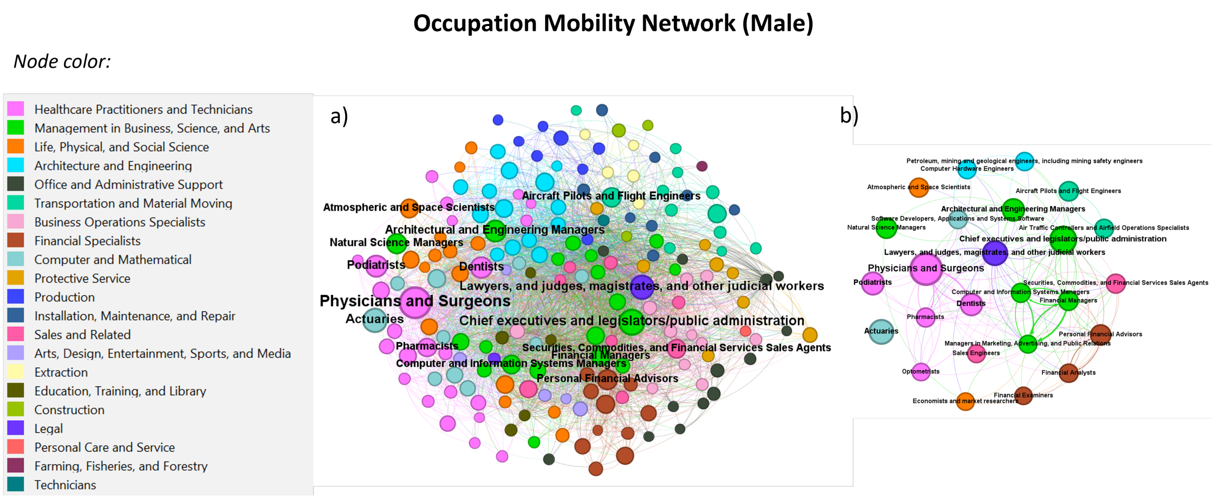


Figure 20: Male occupational mobility network. Network mappings: node size - weighted average income; filter – a) weighted average income $\geq$ 50000, b) weighted average income $\geq$ 100000; node color - occupational field; edge color - target node

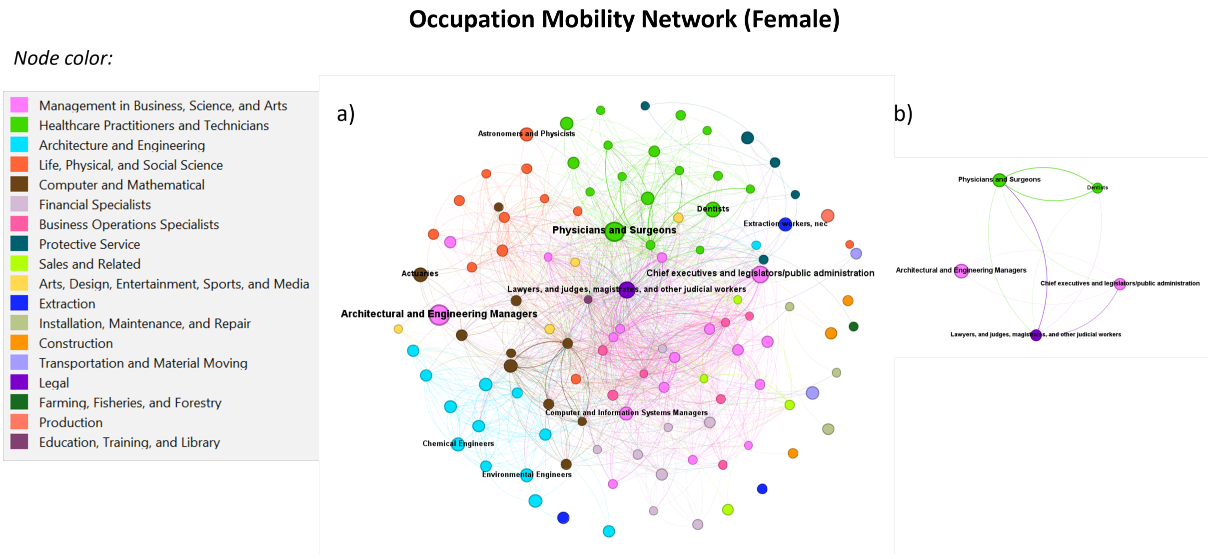


Figure 19: Female occupational mobility network. Network mappings: node size - weighted average income; filter – a) weighted average income $\geq$ 50000, b) weighted average income $\geq$ 100000; node color - occupational field; edge color - target node

Moreover, our analysis reveals that most high-paying jobs for both men and women are concentrated in male-dominated fields. This finding aligns with England's [9] study, which highlights the phenomenon of women gravitating towards traditionally female-dominated fields, while some pursue opportunities in male-dominated sectors for upward mobility. Conversely, men exhibit less inclination to transition into traditionally female domains due to a lack of economic incentives. These mobility patterns, in turn, reinforce the existing gender segregation in the workforce and contribute to income disparities.

4 Conclusion

Our study delves into the dynamics of gender disparities, income inequalities, and occupational mobility within the US labor market from 2000 to 2023. Through a comprehensive analysis of various socio-demographic and socio-economic factors, including race, marital status, educational attainment, and income, we uncover significant patterns and trends that highlight the persistent challenges of achieving gender equality in the workforce.

Firstly, our analysis underscores the persistent nature of occupational gender segregation, with certain fields remaining predominantly male or female-dominated despite societal and economic shifts. Additionally, marital status and race intersect with gender dynamics, influencing occupational choices and representation within specific fields.

Concerning income disparities, our findings highlight significant gaps between male and female earnings, with men consistently earning higher average incomes. These disparities remain significant even after accounting for factors such as marital status, race, education and occupational fields.

Regarding occupational mobility, women exhibit a higher rate of mobility compared to men, with various socio-economic factors such as marital status, education, and race influencing job transitions. Furthermore, individuals with lower incomes are more likely to change their occupation, suggesting a potential link between income instability and career transitions.

Moreover, our analysis of the occupational mobility network sheds light on the concentration of high-paying jobs in male-dominated fields and the limited upward mobility options for women in traditionally female-dominated sectors. While certain fields, such as Sales and Related, emerge as prominent in career trajectories for both genders, disparities in income and mobility patterns persist. These mobility patterns reinforce existing gender disparities and hinder efforts towards achieving gender equality in the labor force.

Overall, our study underscores the multifaceted nature of gender dynamics within the US labor market and the complex interplay between socio-economic factors, income differentials, and occupational mobility. For future research, delving deeper into the underlying causes of gender disparities in different socio-demographic groups within the labor force would be valuable. Additionally, tracking the career trajectories of men and women over time could provide deeper insights into how opportunities for upward mobility are distributed between genders.

5 Domain-Specific Lectures

194.136 Computational Social Science - completed
CHSS292 Gender and Social Change - completed

References

[1] M. Charles and D. B. Grusky. *Occupational ghettos: The worldwide segregation of women and men.* Stanford University Press, 2004.

[2] Thomas Breda, Elyès Jouini, Clotilde Napp, and Georgia Thebault. "Gender stereotypes can explain the gender-equality paradox". In: *Proceedings of the National Academy of Sciences* 117.49 (2020), pages 31063–31069.

[3] F. D. Blau and L. M. Kahn. "Understanding international differences in gender differences in the labor market". In: *Journal of Labor Economics* 11.1 (1993), pages 1–106.

[4] F. D. Blau and L. M. Kahn. "Gender differences in pay". In: *Journal of Economic Perspectives* 14.4 (2000), pages 75–99.

[5] Francine D Blau and Lawrence M Kahn. "The gender wage gap: Extent, trends, and explanations". In: *Journal of economic literature* 55.3 (2017), pages 789–865.

[6] Nikolay Angelov, Per Johansson, and Erica Lindahl. "Parenthood and the gender gap in pay". In: *Journal of labor economics* 34.3 (2016), pages 545–579.

[7] Henrik Kleven, Camille Landais, and Jakob Egholt Søgaard. "Children and gender inequality: Evidence from Denmark". In: *American Economic Journal: Applied Economics* 11.4 (2019), pages 181–209.

[8] C. Goldin. "A grand gender convergence: Its last chapter". In: *American Economic Review* 104.4 (2014), pages 1091–1119.

[9] P. England. "The gender revolution: Uneven and stalled". In: *Gender & Society* 24.2 (2010), pages 149–166.

[10] Penny Mealy, R Maria del Rio-Chanona, and J Doyne Farmer. "What you do at work matters: new lenses on labour". In: *What You Do at Work Matters: New Lenses on Labour (March 18, 2018)* (2018).

[11] Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, Daniel Backman, Annie Chen, Grace Cooper, Stephanie Richards, Megan Schouweiler, and Michael Westberry. *IPUMS CPS: Version 11.0 [dataset].* Minneapolis, MN: IPUMS. 2023.

[12] Mathieu Bastian, Sebastien Heymann, and Mathieu Jacomy. *Gephi: An Open Source Software for Exploring and Manipulating Networks.* 2009.

[13] Stanley Wasserman and Katherine Faust. *Social Network Analysis: Methods and Applications.* Cambridge University Press, 1994.

[14] Phillip Bonacich. "Power and centrality: A family of measures". In: *American journal of sociology* 92.5 (1987), pages 1170–1182.

[15] Sergey Brin and Lawrence Page. "Anatomy of a Large-Scale Hypertextual Web Search Engine". In: *Computer Networks and ISDN Systems* 30.1-7 (1998), pages 107–117.

[16] Harry J Holzer, Paul Offner, and Elaine Sorensen. "Declining employment among young black less-educated men: The role of incarceration and child support". In: *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management* 24.2 (2005), pages 329–350.

[17] Harry J Holzer, Steven Raphael, and Michael A Stoll. "Perceived criminality, criminal background checks, and the racial hiring practices of employers". In: *The Journal of Law and Economics* 49.2 (2006), pages 451–480.

[18] Devah Pager and Hana Shepherd. "The sociology of discrimination: Racial discrimination in employment, housing, credit, and consumer markets". In: *Annu. Rev. Sociol* 34 (2008), pages 181–209.

A Appendix

A.1 Additional Visualizations and Tables

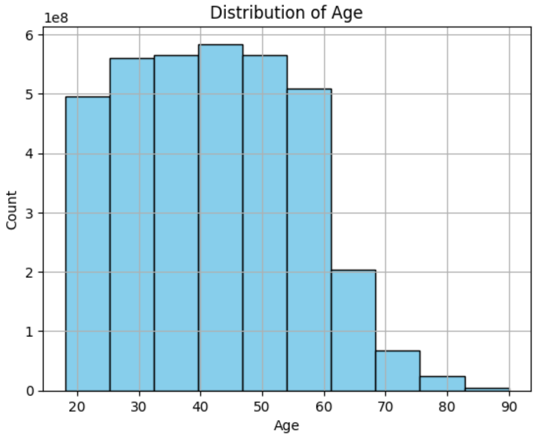


Figure 21: Distribution of Age

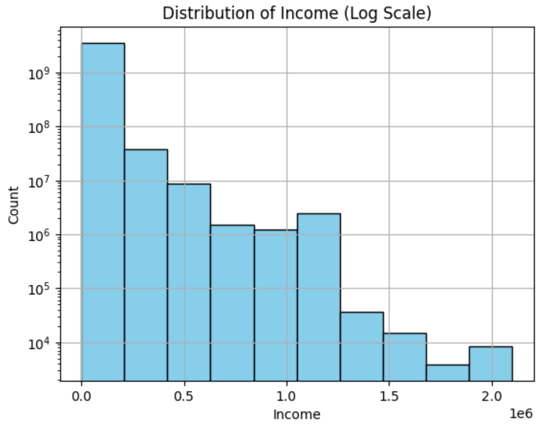


Figure 22: Distribution of Income

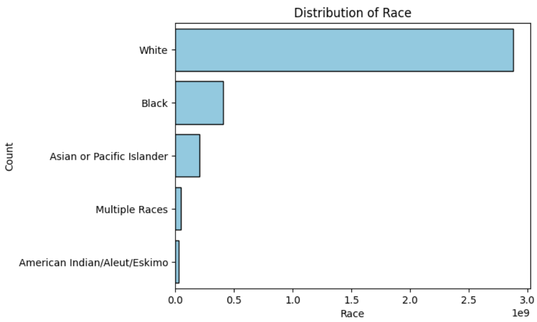


Figure 23: Distribution of Race

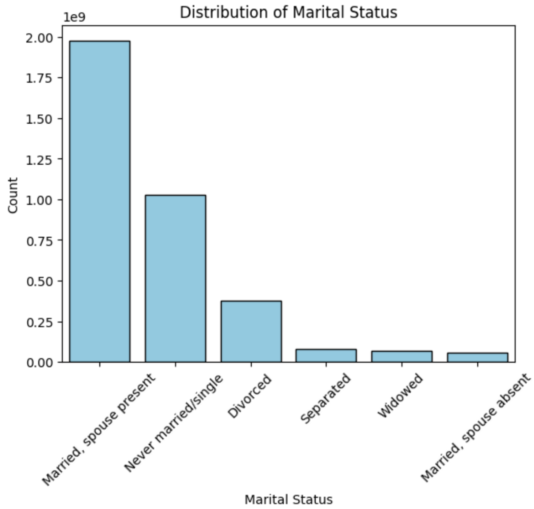


Figure 24: Distribution of Marital Status

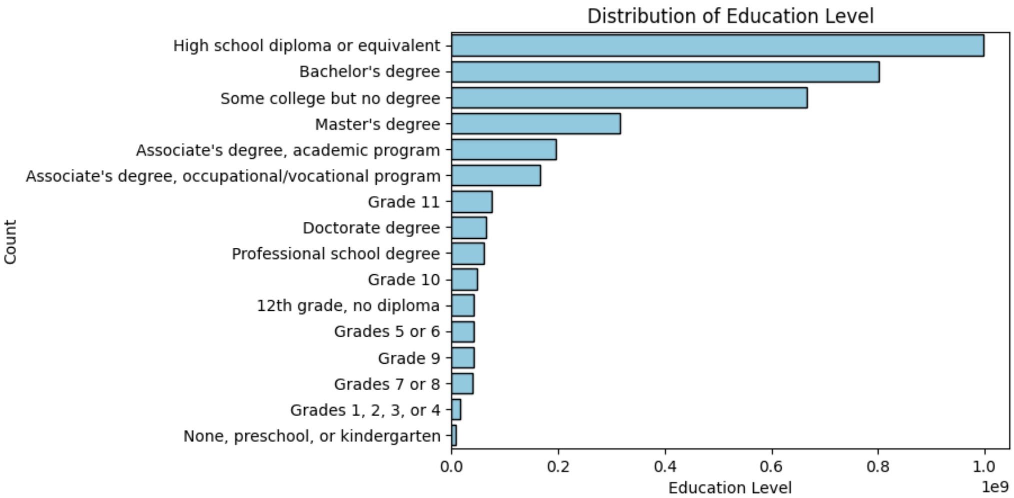


Figure 25: Distribution of Education

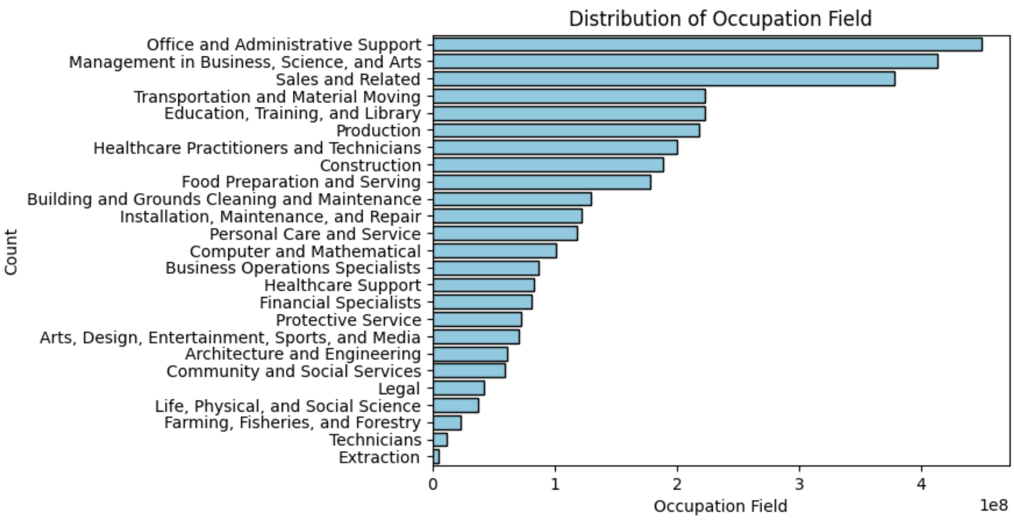


Figure 26: Distribution of Occupational Field

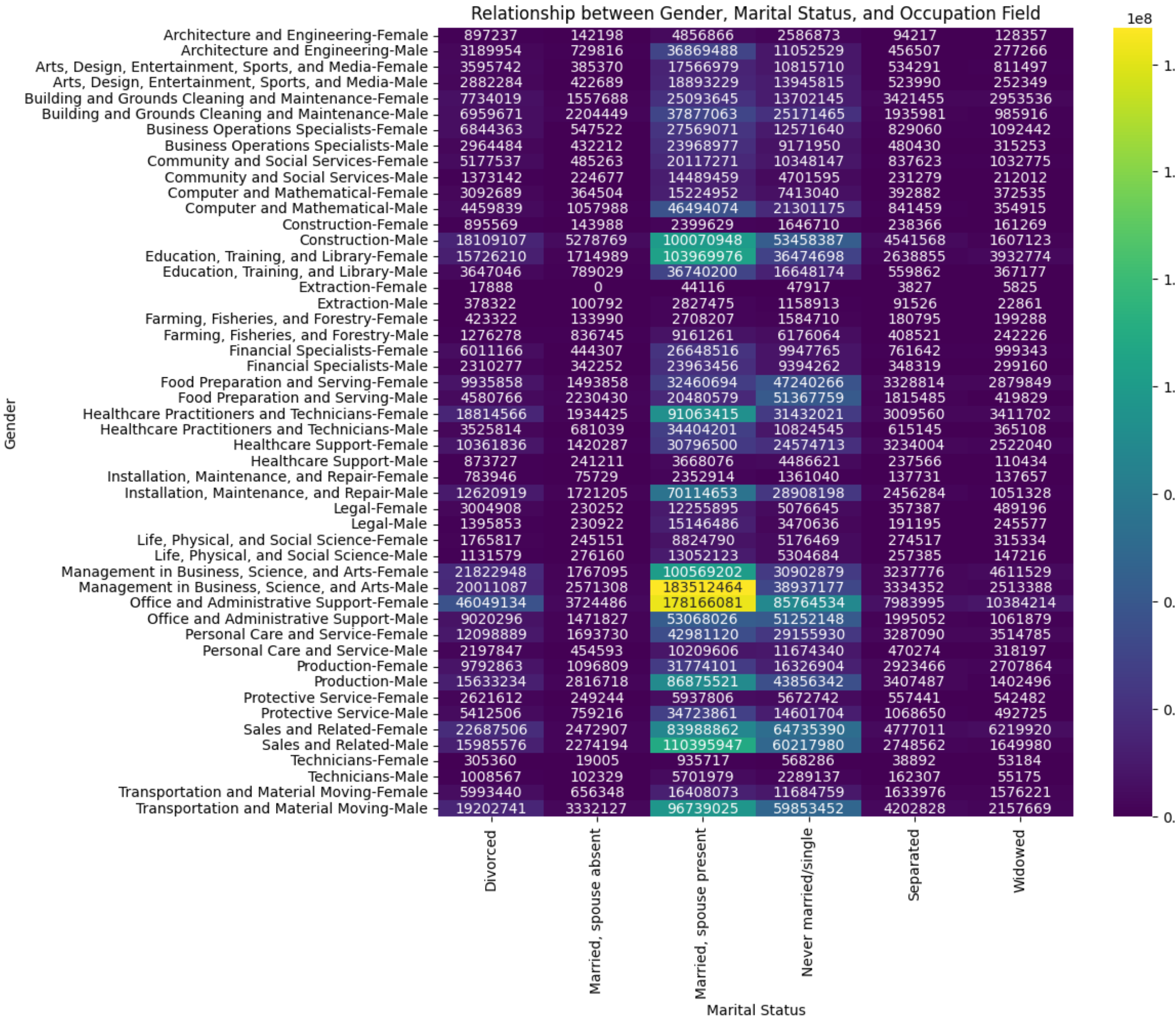


Figure 27: Distribution of gender by marital status in each occupational field

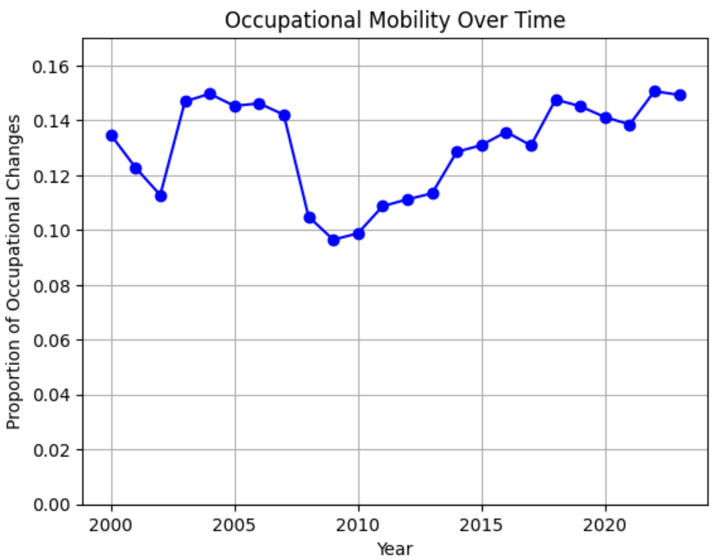


Figure 28: Occupational mobility rate over the years

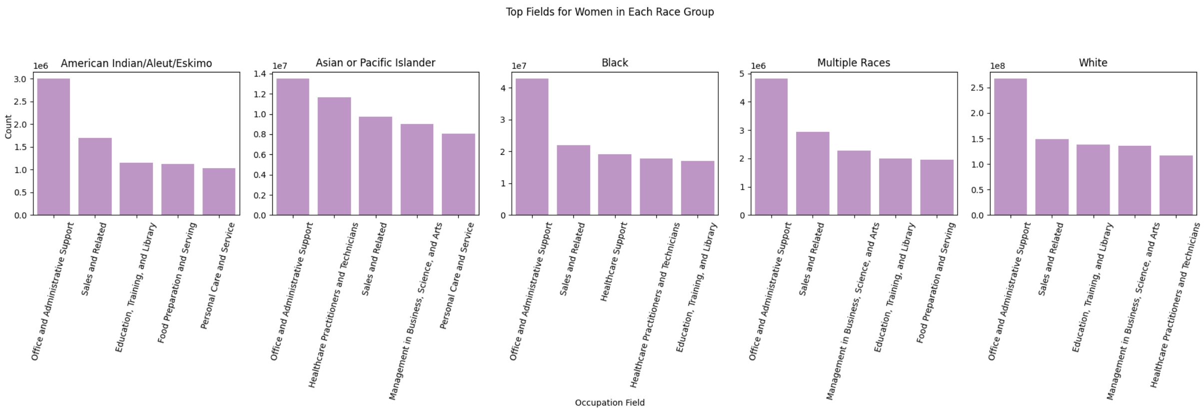


Figure 29: Top 5 fields for women in each racial group

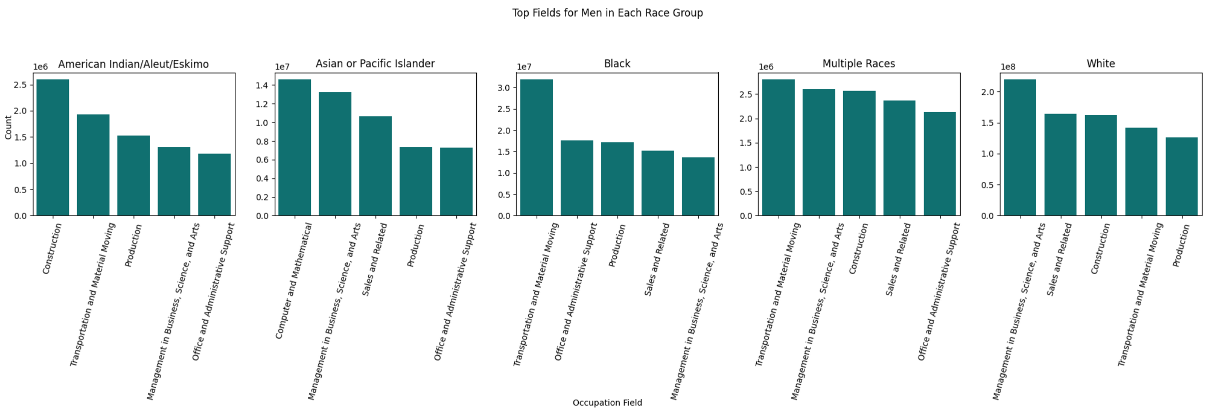


Figure 30: Top 5 fields for men in each racial group

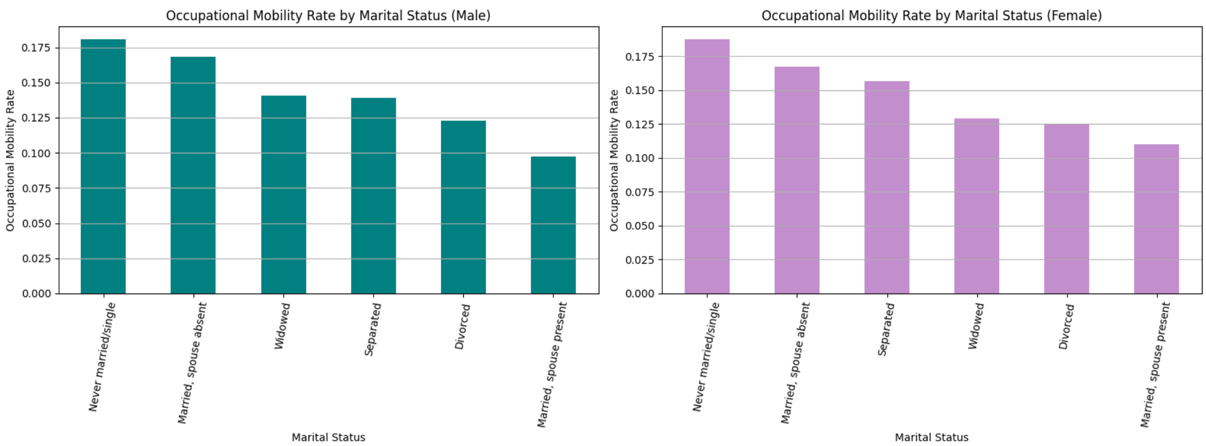


Figure 31: Distribution occupational mobility rate by marital status

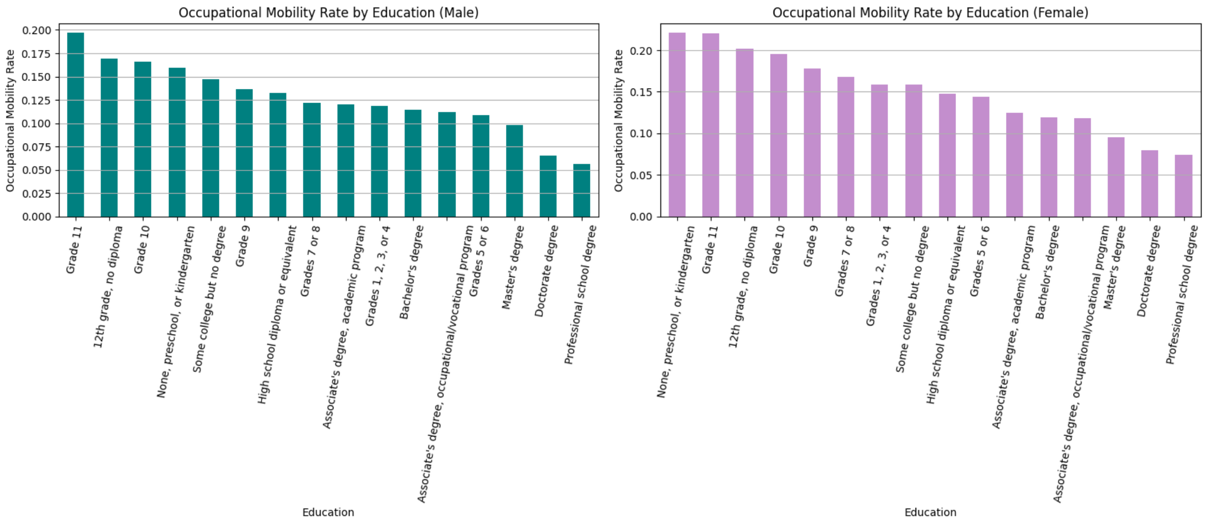


Figure 32: Distribution occupational mobility rate by educational level

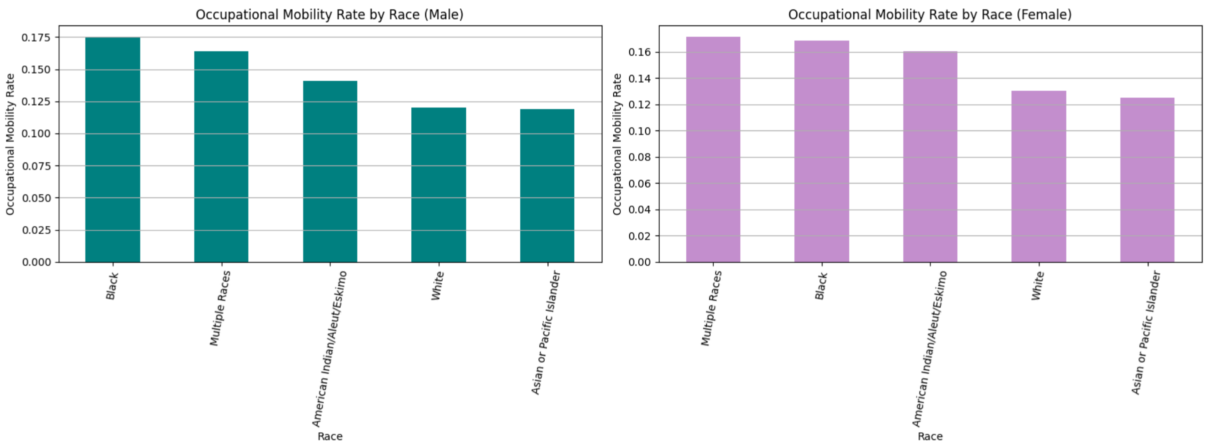


Figure 33: Distribution occupational mobility rate by race

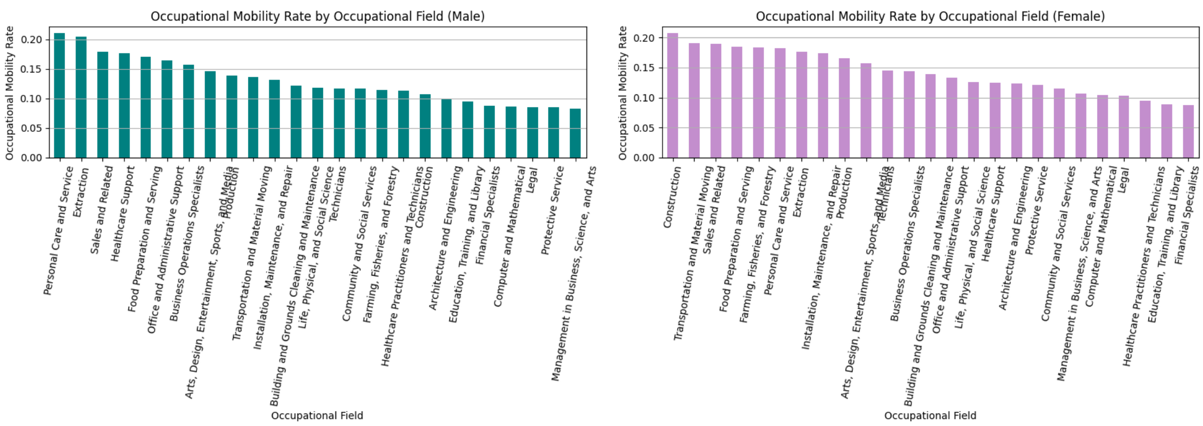


Figure 34: Distribution occupational mobility rate by occupational field

Figure 35: Distribution of occupational fields among races and genders

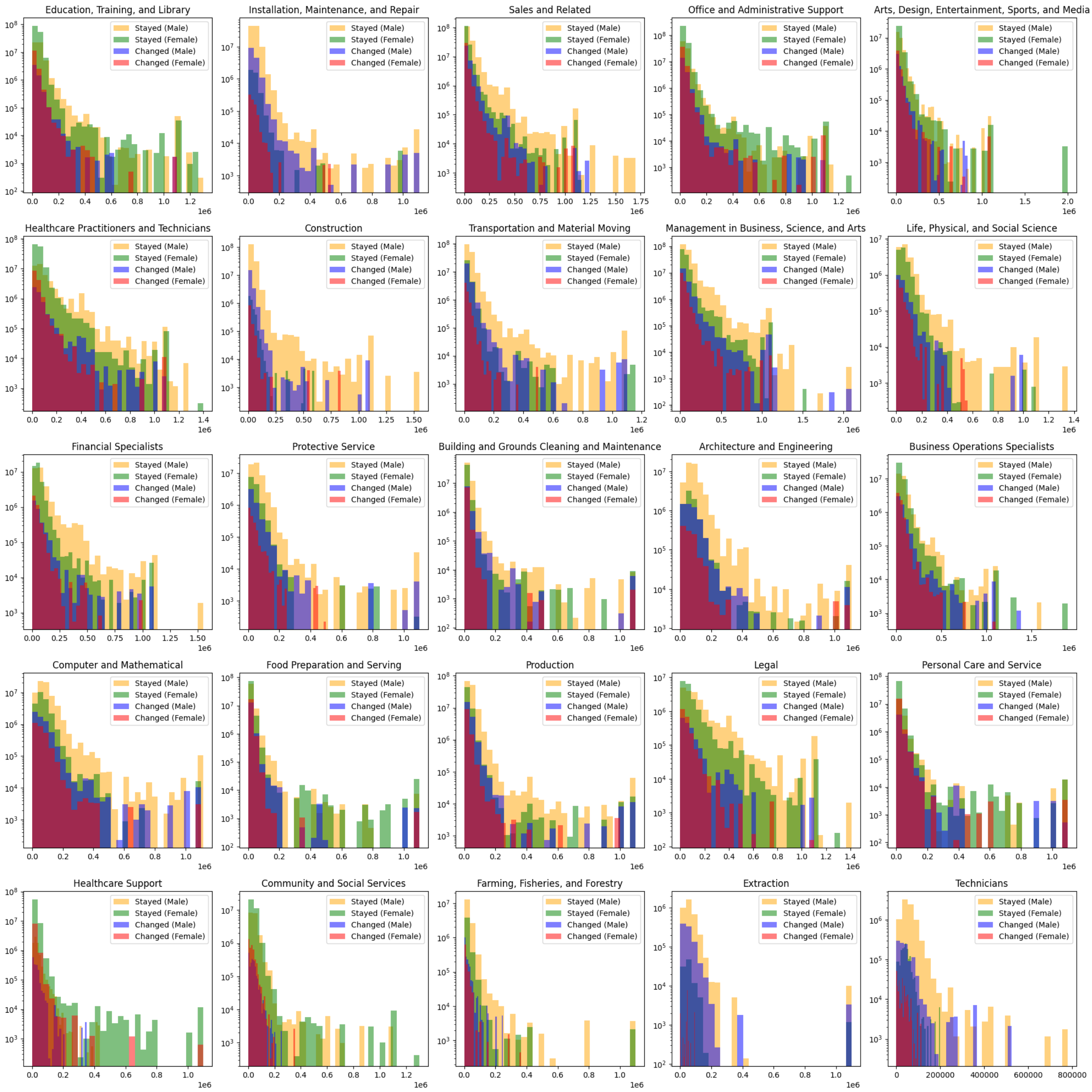


Figure 36: Distribution of income by occupational change and gender across occupational fields

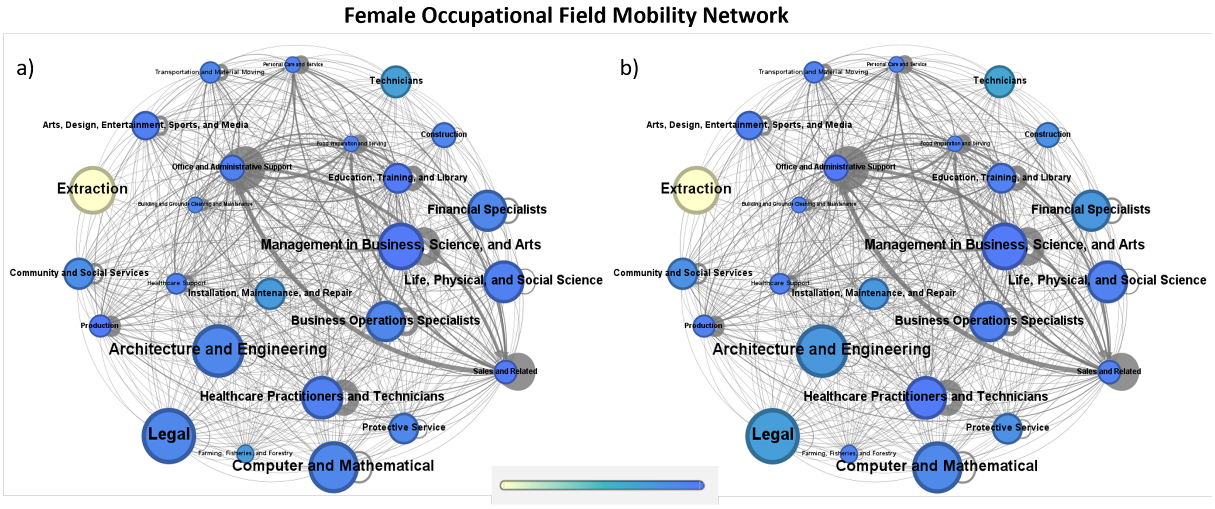


Figure 37: Female occupational field mobility network. Network mappings: node size - weighted average income; color - a) in-degree, b) out-degree

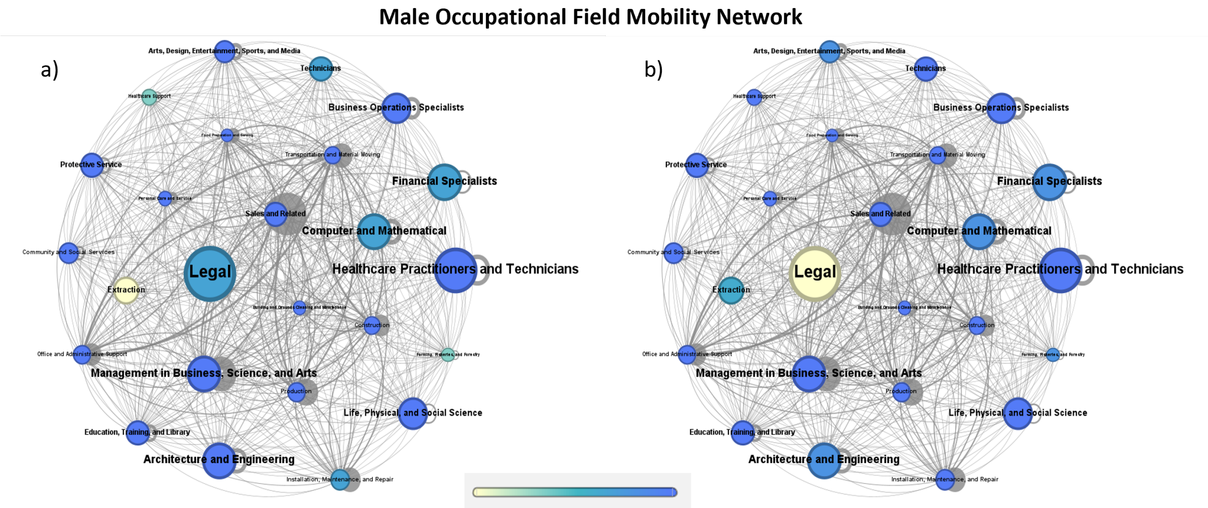


Figure 38: Male occupational field mobility network. Network mappings: node size - weighted average income; color - a) in-degree, b) out-degree

Table 1: Variables in the dataset

Variable	**Description**
YEAR	Survey year
SERIAL	Household serial number
MONTH	Month
CPSID	CPSID, household record
ASECFLAG	Flag for ASEC
HFLAG	Flag for the 3/8 file 2014
ASECWTH	Annual Social and Economic Supplement Household weight
PERNUM	Person number in sample unit
CPSIDV	Validated Longitudinal Identifier
CPSIDP	CPSID, person record
ASECWT	Annual Social and Economic Supplement Weight
ASECWTCVD	ASEC weight adjusted for pandemic-related nonresponse
AGE	Age
SEX	Sex
RACE	Race
MARST	Marital status
EMPSTAT	Employment status
OCC2010	Occupation, 2010 basis
EDUC	Educational attainment recode
ASECOVERP	Identifier for ASEC oversample - Person
OCC10LY	Occupation last year, 2010 basis
INCWAGE	Wage and salary income

Table 2: Gender and income statistics

Gender \ **Income**	**Weighted Mean**	**Weighted Median**
Male	\$53,200	\$38,000
Female	\$36,500	\$28,000

Table 3: Occupational fields by gender dominance

Group	**Occupational Field**
Male-dominated	Extraction
	Construction
	Installation, Maintenance, and Repair
	Architecture and Engineering
	Transportation and Material Moving
	Technicians
	Protective Service
	Farming, Fisheries, and Forestry
	Computer and Mathematical
	Production
	Management in Business, Science, and Arts
	Building and Grounds Cleaning and Maintenance
	Life, Physical, and Social Science
Female-dominated	Business Operations Specialists
	Community and Social Services
	Education, Training, and Library
	Office and Administrative Support
	Healthcare Practitioners and Technicians
	Personal Care and Service
	Healthcare Support
Balanced	Arts, Design, Entertainment, Sports, and Media
	Sales and Related
	Legal
	Food Preparation and Serving
	Financial Specialists

Table 4: Top 5 most central occupational fields for women

Degree	Weighted Degree	Closeness	Betweenness	PageRank	Eigenvector
Management in Business, Science and Arts	Office and Administrative Support	Office and Administrative Support	Management in Business, Science and Arts	Management in Business, Science and Arts	Management in Business, Science and Arts
Office and Administrative Support	Sales and Related	Management in Business, Science and Arts	Office and Administrative Support	Education, Training and Library	Education, Training and Library
Production	Management in Business, Science and Arts	Healthcare Practitioners and Technicians	Healthcare Practitioners and Technicians	Production	Production
Sales and Related	Food Preparation and Serving	Sales and Related	Building and Grounds Cleaning and Maintenance	Sales and Related	Sales and Related
Healthcare Practitioners and Technicians	Personal Care and Service	Food Preparation and Serving	Business Operations Specialist	Healthcare Practitioners and Technicians	Healthcare Practitioners and Technicians

Table 5: The 5 most central occupational fields for men

Degree	Weighted Degree	Closeness	Betweenness	PageRank	Eigenvector
Sales and Related	Sales and Related	Sales and Related	Sales and Related	Building and Grounds Cleaning and Maintenance	Building and Grounds Cleaning and Maintenance
Transportation and Material Moving	Transportation and Material Moving	Transportation and Material Moving	Transportation and Material Moving	Business Operations Specialist	Business Operations Specialist
Production	Production	Production	Production	Community and Social Services	Community and Social Services
Management in Business, Science and Arts	Management in Business, Science and Arts	Management in Business, Science and Arts	Management in Business, Science and Arts	Construction	Construction
Office and Administrative Support	Office and Administrative Support	Office and Administrative Support	Office and Administrative Support	Education, Training and Library	Education, Training and Library

Table 6: Top 5 most central occupations for women

Degree	**Weighted Degree**	**Closeness**	**Betweenness**	**PageRank**	**Eigenvector**
Cashiers	Retail Salespersons	Cashiers	Cashiers	Managers, nec (including Postmasters)	Secretaries and Administrative Assistants
Secretaries and Administrative Assistants	Cashiers	Waiters and Waitresses	Managers, nec (including Postmasters)	Secretaries and Administrative Assistants	Receptionists and Information Clerks
Waiters and Waitresses	Sales Representatives, Wholesale and Manufacturing	Customer Service Representatives	Secretaries and Administrative Assistants	Cashiers	Managers, nec (including Postmasters)
Managers, nec (including Postmasters)	Waiters and Waitresses	Secretaries and Administrative Assistants	First Line Supervisors of Sales Workers	Receptionists and Information Clerks	Cashiers
First Line Supervisors of Sales Workers	Secretaries and Administrative Assistants	First Line Supervisors of Sales Workers	Waiters and Waitresses	First Line Supervisors of Sales Workers	Retail Salespersons

Table 7: Top 5 most central occupations for men

Degree	**Weighted Degree**	**Closeness**	**Betweenness**	**PageRank**	**Eigenvector**
Drivers/Sales Workers and Truck Drivers	Sales Representatives, Wholesale and Manufacturing	Drivers/Sales Workers and Truck Drivers	Managers, nec (including Postmasters)	Managers, nec (including Postmasters)	Retail Salespersons
Laborers and Freight, Stock and Material Movers, Hand	Retail Salespersons	Laborers and Freight, Stock and Material Movers, Hand	Drivers/Sales Workers and Truck Drivers	Laborers and Freight, Stock and Material Movers, Hand	Drivers/Sales Workers and Truck Drivers
Managers, nec (including Postmasters)	Drivers/Sales Workers and Truck Drivers	First Line Supervisors of Sales Workers	Laborers and Freight, Stock and Material Movers, Hand	Drivers/Sales Workers and Truck Drivers	Managers, nec (including Postmasters)
First Line Supervisors of Sales Workers	Laborers and Freight, Stock and Material Movers, Hand	Managers, nec (including Postmasters)	First Line Supervisors of Sales Workers	Retail Salespersons	Laborers and Freight, Stock and Material Movers, Hand
Retail Salespersons	Managers, nec (including Postmasters)	Grounds Maintenance Workers	Retail Salespersons	First Line Supervisors of Sales Workers	First Line Supervisors of Sales Workers