Big Moves: Tactics for early career success

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Extended Abstract

In this paper, we study how individuals can use relocation as a tactic to progress in their careers and improve their financial outcomes. In a new world of work where hybrid, and remote models of work, coupled with increased flexibility in career trajectories, and growing automation finding tactics that help workers advance in their careers and have access to better wages is an important endeavor (Brynjolfsson, Mitchell, & Rock, 2018; Grey & Suri, 2019; Teevan, J., Baym, N., Butler, J., Hecht, B. et al, 2020).

In our study, we employ two large-scale resume datasets from two different companies - Burning Glass and FutureFitAI. Together, these datasets compile information from personal resumes for over 10 million unique workers across the US for the last three decades. In these data, we can observe workers' detailed occupations (identified by 6-digit codes from the Bureau of Labor Statistics Standard Classification Code (SOC Codes)), the places where the occupations were held, the dates for each occupation, and workers' educational backgrounds. Coupled with US census data, we inferred individual wages based on occupation, location, year, and workers' experience (years since entering the labor market). We also computed disposable incomes by subtracting city-level living costs from individual wages.

To disentangle the effect of relocation from occupational change, we devised an experiment with three different treatment conditions using propensity score matching. The three treatment conditions were then compared against a control group. The treatment conditions and the baseline are as follows:

Treatment 1: Effect of changing occupations but not cities.
Treatment 2: Effect of changing cities but not occupations.
Treatment 3: Compound effect of changing occupations and cities in the same move.
Control: Worker who did not change cities or occupations in the specified time window.

To create treatment and control groups, we used logistic regression to compute a propensity score based on workers' starting city and occupation, destination city and occupation, date of entry into the labor market, and educational quality. This educational quality was approximated by using the Carnegie Index, which places all higher education institutions in the US into different tiers based on criteria like research output, teaching, and type of programs offered. After computing the propensity scores, we perform one-to-one matching capping the distance between propensity scores to keep only close matches in our dataset. Then, we check for differences in the propensity score distributions between treatment and control groups using a KS test to guard against potential biases. Finally, we compute average treatment effects and standard errors and check for statistical significance.

Our results suggest that while changing occupations and cities separately positively affects disposable income on average, changing both cities and occupations (Treatment 3) has a larger effect on disposable income. This effect is larger than the sum of previous effects and increases with work experience, as shown in Figure 1B. We observe the same effect across both datasets. We split our dataset based on workers' origins and destinations to ensure that the effects we observe are not solely due to rural-to-urban migrations. The first group exclusively contained workers whose origin and destination cities were among the top ten most populous Metropolitan Statistical Areas in the US, shown in blue in Figure 1C. The second group contained workers whose origin cities were outside the top ten most populous areas in the US, shown in red in Figure 1C. When we compared the difference in disposable income for our groups, we saw that both have a positive difference, with the first group having a smaller, yet still positive, difference on average. When looking at particular cities, we see that while both groups get an average in LA, Boston, Atlanta, and Dallas, both groups see a positive increase in their disposable incomes after the move. In contrast, both groups perceive a negative effect on their disposable income when moving to New York City.

To explain the positive difference in disposable income after changing cities and occupations, we develop a linear model to understand which occupation and urban variable are associated with a higher increase in disposable income. We find that occupational variables are more important, followed by urban variables, and career stage variables are least important. In particular, we find that moving to more cognitive occupations, with a lower probability of automation, has the largest impact on disposable income. How unique a worker's occupation is in the local labor market is slightly more important than the diversity of the market, but they both contribute to an increase in disposable income. Finally, this work suggests there is path dependency in traditional careers because uncommon job transitions in early career years have a low economic cost, but common transitions are highly rewarded in mid or late career.

In the next stages of this project, we hope to dive deeper into the effect of relocation beyond immediate moves and analyse their impact on the overall career trajectory. We will inquire about frequent career paths correlated to positive outcomes after relocation to provide general recommendations for potential movers. We hope to use this model as part of a broader family of models to power an open-source tool to help workers make better career decisions.

References

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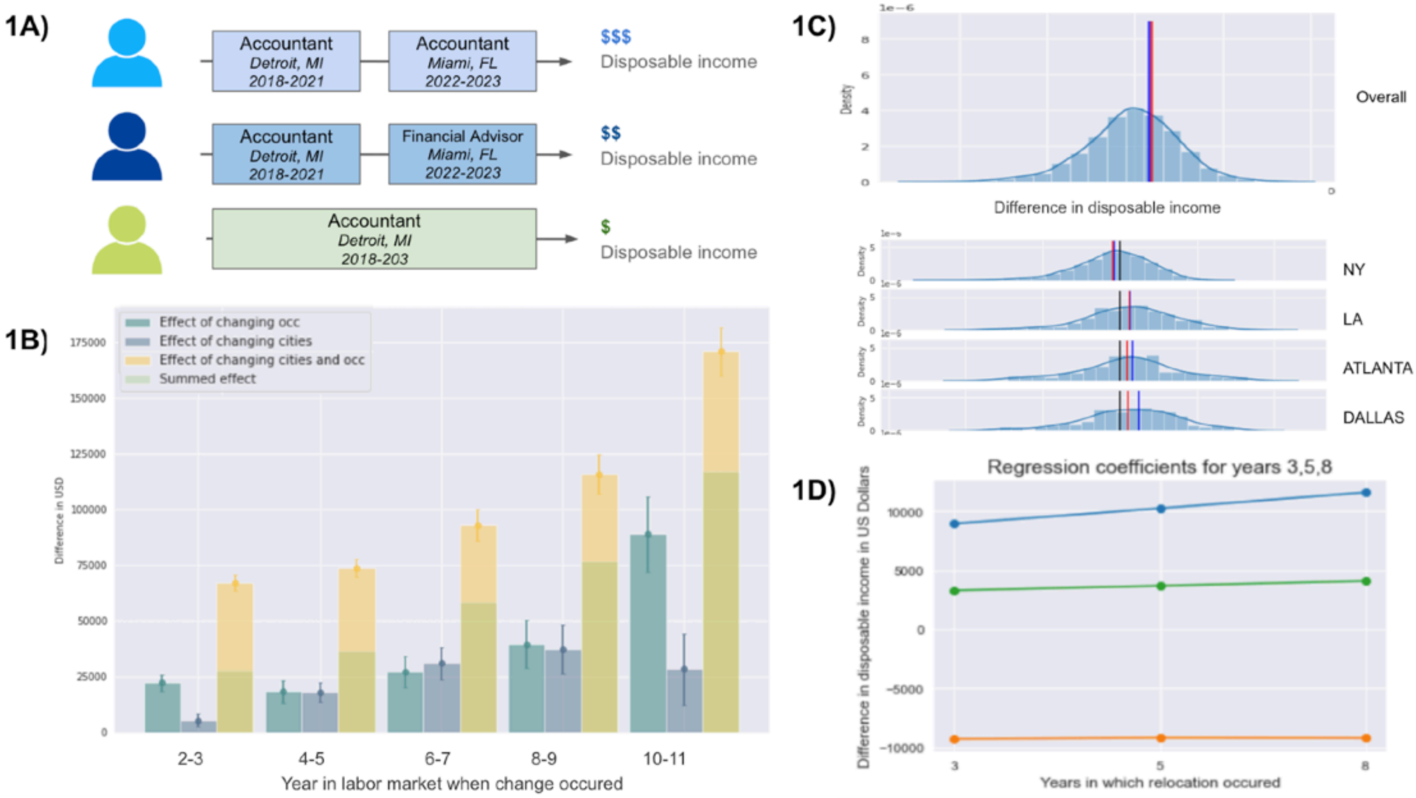

Figure 1. 1A) shows typical career trajectories for workers in our data. 1B) Shows average treatment effect for Treatment 1, 2, and 3 in different years for the careers of workers in our sample. The green bar shows the effect for an occupation change, the blue car shows the effect of city change, and the yellow bar shows the effect of occupation and city change. The yellow bar shows an effect that is larger than the sum of the previous two bars. 1C) Shows the difference between the disposable income gained by movers coming from the top ten MSAs versus movers from non-top ten MSAs overall and for specific cities. 1D) Shows the most important coefficients from our model that explain the increment in disposable income.