Occupation Ladders over the Business Cycle*

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Abstract

This paper studies occupational mobility over the business cycle. We divide occupations into two broad groups, "attractive" and "nonattractive," where we label an occupation attractive if the total net inflow into this occupation through job-to-job transition is positive or its median annual wage is above the median of the population. We measure total net inflows into both occupation groups. We measure these inflows separately for job-to-job (EE) transitions and transitions from unemployment to employment (UE). We find net inflow from nonattractive to attractive occupations through EE transitions slows during recessions. The relative net inflow through UE transitions has a similar cyclicality. This finding suggests a novel cost of recession: during recessions, workers have fewer opportunities to move to a better occupation.

Keywords: occupational mobility, business cycles, worker flows

JEL Classification: E24, E32, J24, J62

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1 Introduction

Measuring the cost of business cycles has been an important research topic in macroeconomics. The cost of business cycles has been studied in various contexts. The original Lucas (1987) calculation analyzed the cost of consumption variation. Since then, different researchers have considered different aspects of recessions. Examples include the increase in unemployment,[1] which can also lead to a loss of human capital,[2] a decline in firm entry,[3] which can harm future employment growth and also innovation,[4] and a decline in job-to-job transition, which creates misallocation of talents across jobs.[5]

Occupations are viewed as one of the most important attributes when we analyze an individual's labor market situation. An earlier work of Kambourov and Manovskii (2009) emphasizes the occupation specificity of human capital, which determines the wages and workers' career paths. Studies utilizing "task approach" (e.g., Acemoglu and Autor, 2011) characterize an occupation as the combination of various tasks and analyzes how changes in economic environment affect each occupation. Recent applied micro studies, such as Yamaguchi (2012), Guvenen et al. (2020), and Lise and Postel-Vinay (2020), reveal rich interactions between workers' skills and heterogeneous occupations.

This paper provides a novel perspective on the cost of recessions through the lens of occupations. We show the workers continuously switch to different occupations, and the movement to "better" occupations, which we call the *occupation ladder*, slows during recessions. This result indicates the recession reduces the opportunities for workers to climb the occupation ladder. This paper is the first that empirically formalizes the concept of the occupation ladder and examines its relationship to the business cycle.

Applying the insight of Sorkin (2018) to the context of occupation switch, we divide the occupations into two groups: "attractive" occupations and "nonattractive" occupations. The division is based on the net flows of workers across occupations when

[1]See, for example, Mukoyama and Şahin (2006) and Krusell et al. (2009).

[2]See Krebs (2007).

[3]See Lee and Mukoyama (2015).

[4]See Barlevy (2007) and Sedláček and Sterk (2017).

[5]See Baydur and Mukoyama (2020).

they make a job-to-job transition and wage levels.

Based on this division of occupations into two groups, we analyze the cyclicality of the net flows across occupation groups. We focus on the occupation switch upon job-to-job transitions and when a worker finds a new job from unemployment. We find that, during recessions, the net flow of climbing the occupation ladder declines. The cyclical movement of separation and vacancies for these occupation groups are consistent with the interpretation that the value of attractive occupations declines relatively more than that of nonattractive occupations during recessions. These facts points to the view that, during recessions, workers have less access to the opportunities to move up the occupation ladder.

To measure the cost of the slower climb of the occupation ladder during recessions, we construct a simple model where workers face stochastic shocks of job finding, job separation, job-to-job transitions, and occupation switching. The calibrated model shows about one-fifth of the total cost of recessions is due to the slowdown of the occupation switching. Therefore, this novel cost constitutes an economically significant part of the cost of recessions.

This paper is related to several strands of literature. The first is the "cost of business cycles" literature listed above, starting from Lucas (1987). Various studies in this literature argue recessions impose various economic costs to the consumers. Our work suggests a novel source of the cost of recessions to the economy: slowing down the occupation ladder.

Another related literature is the recent analysis of job-to-job flows. Workers are known to on average move to higher-paying jobs when they experience job-to-job transitions, and this movement is an important component of wage growth over the life cycle (see, e.g., Topel and Ward, 1992). The movement of workers toward the better jobs over time is often referred to as the "job ladder." The job-to-job transition rate is highly cyclical (see, for example, Fallick and Fleischman, 2004; Hyatt and McEntarfer, 2012; Haltiwanger et al., 2018; Moscarini and Postel-Vinay, 2018), and the cyclical nature of the job-to-job transition affects how microeconomic match characteristics are distributed in the economy (Gertler et al., 2020; Baydur and Mukoyama, 2020). Studies such as Barlevy (2002) and Mukoyama (2014) show fluctuations in job-to-job flows associated with business cycles can have a macroeconomic impact. Our paper can be viewed as an occupation analog of the job-ladder analysis in this literature. Moreover, because an occupational switch often occurs together with job-to-job transition, the cyclical movement of the job-to-job transition rate interacts nontrivially with the occupation ladder.

Some earlier works have analyzed the patterns of occupational mobility. Moscarini and Thomsson (2007) document the occupational mobility in the US. Moscarini and Vella (2008) analyze the mobility pattern over the business cycle. Neither paper considers the "ladder" aspect of the mobility—they do not take a stand on which occupation is better or worse. Naturally, their interest is gross flow—how often people move occupations and why. Our primary focus is the net flow on the ladder—how the tendency to move up to a better occupation interacts with the business cycle. Another difference is that we focus on the occupational switch upon job-to-job transition and unemployment-to-employment transition. These earlier papers consider all gross movements, including the occupational switch within the same employer.

Finally, recent papers by Carrillo-Tudela and Visschers (2023) and Carrillo-Tudela et al. (2022) are closely related. Carrillo-Tudela and Visschers (2023) also emphasize the cyclicality of occupational switching upon unemployment-to-employment transitions as a factor that influences unemployment dynamics. They do not explicitly consider the occupation ladder, and their focus is on positive analysis, rather than normative analysis (cost of recessions). Carrillo-Tudela et al. (2022) analyze occupation switching through job-to-job transitions. Their main focus is earnings dynamics, but they also the conduct "cost of business cycles" calculation and emphasize the role of cyclical occupational switch. Their analysis hinges on task-based categorization (and earnings change upon switching), whereas our occupation ladder is defined through revealed preferences (worker flows) and median wage information. In this sense, their paper and the current paper are complementary.

This paper is organized as follows. In Section 2, we set up the data and define two categories of occupation: "attractive" and "nonattractive." In Section 3, we examine the patterns of net flows across occupations. In Section 4, we look at other statistics that help us understand the mechanism of the cyclical patterns of net flows. In Section 5, we look at another dataset. Section 6 builds a model to investigate the implications of the cyclical patterns of occupational flows on the cost of recessions.

Section 7 concludes.

2 Baseline data and definitions

We use micro-level data from the Current Population Survey (CPS) to quantify occupational mobility. We obtained monthly CPS data from the Integrated Public Use Microdata Series (IPUMS-CPS) database (Flood et al., 2020). CPS uses rotation groups in which each individual is interviewed for four consecutive months, not interviewed for eight months, and then re-interviewed for another four months before leaving the sample. The rotating panel design of CPS allows us to observe the employment status of each individual next month. In every round, unemployed individuals report their occupation at their latest employer, and employed individuals report their occupation in their current job. After the redesign in 1994, employed individuals also report whether they work for the same employer they reported in the previous month. Using this information, we construct occupational mobility measures separately for those who make a job-to-job transition, EE, and a transition to a new employer with an intervening unemployment spell, UE. Our final sample covers the period from September 1995 to December 2018.

A challenging issue with measuring occupational mobility is the changes in the coding scheme used to record individuals' occupations in the original CPS data. CPS uses the Census classification system for occupations. For the period we cover, one major change occurred to the occupational coding scheme starting in 2003 and a minor change occurred starting in 2011. To alleviate possible measurement errors, we use the IPUMS-CPS variable "OCC2010," which provides a harmonized occupation variable for all the survey months mapped to the Census 2010 occupational classification. We note the 2010 Census classification scheme and the corresponding IPUMS-CPS variable are based on the 2010 Standard Occupation Classification (SOC) scheme. The major occupation categories in the Census classification correspond to two-digit occupations in the SOC scheme.

We further divide the two-digit occupations into two broader categories, *attractive* (denoted by A for "attractive") and *nonattractive* (denoted by N for "nonattractive"). We define an occupation i as attractive if it satisfies either of the following criteria:

(i) The total net inflow into i through an EE transition is positive (the occupation "attracts" workers), or (ii) the median annual wage of population i is above the median annual wage of the entire population.[6]

The first condition is in the spirit of Sorkin (2018): by the revealed-preference argument, a large outflow and a small inflow through EE transition imply people prefer to be in another occupation than in occupation i. This requirement, however, is not perfect. For example, the legal occupation has a small inflow not because it does not attract people, but because the inflow is artificially limited by qualifications.

Thus, we supplement the information with the second condition, using the median wages within the occupation—an objective measure of a "good" occupation.[7] The information on wages comes from the 2006 Occupational Employment and Wage Statistics at the US Bureau of Labor Statistics (BLS). The second possibility of an attractive job is that the median annual wage within that occupation group is above the median annual wage of the entire population.

Table 1 describes our division of attractive (A) and nonattractive (N) occupations. The major occupational categories are listed in the order of median annual wages. Although the median wages of "Transportation and material moving occupations" and "Healthcare support occupations" are below the overall median, the net inflow through EE transitions is positive and thus categorized as attractive.

To compare our categorization with the ones that are often used in the literature, Table 1 also lists a categorization based on task contents. Here, RC represents "routine cognitive," NRC represents "non-routine cognitive," RM represents "routine manual," and NRM represents "non-routine manual." This type of categorization has been employed in the literature on labor market polarization, such as Acemoglu and Autor (2011). In this Table, we follow Carrillo-Tudela and Visschers's (2023) categorization. We can see all NRC occupations, which are typically considered high-skill occupations, are all categorized as attractive. All RM occupations are also in the attractive-occupation group. However, some RC and NRM occupations are categorized as nonattractive. Thus, our categorization, which is based on the worker

[6] To avoid classification error due to the changes in the coding schemes, we restrict our sample to observations after the 2002 changes were implemented when we determine whether an inflow occurs into an occupation group.

[7] We use the annual wage, but the result would be identical if we were to use the hourly wage.

Occupation title	A/N	Carrillo-Tudela and Visschers (2023)
Management occupations	A	NRC
Legal occupations	A	NRC
Computer and mathematical occupations	A	NRC
Architecture and engineering occupations	A	NRC
Business and financial operations occupations	A	NRC
Life, physical, and social science occupations	A	NRC
Healthcare practitioners and technical occupations	A	NRC
Education, training, and library occupations	A	NRC
Arts, design, entertainment, sports, and media occupations	A	NRC
Installation, maintenance, and repair occupations	A	RM
Community and social services occupations	A	NRC
Construction and extraction occupations	A	RM
Protective service occupations	A	NRM
Office and administrative support occupations	A	RC
Production occupations	A	RM
Transportation and material moving occupations	A	NRM
Sales and related occupations	N	RC
Healthcare support occupations	A	NRM
Building and grounds cleaning and maintenance occupations	N	NRM
Personal care and service occupations	N	NRM
Farming, fishing, and forestry occupations	N	N/A
Food preparation and serving related occupations	N	NRM

Table 1: Two-digit occupational categories

flows and wages, are related to the task-based categorization, although nonnegligible distinctions exist.

3 Occupational flows over the business cycle

In this section, we observe how business cycles affect the mobility of workers across occupations. First, consider workers who experience EE transitions. Let the total number of workers who experience the i-to-j occupational switch when they switch jobs to be EE_{ij}, where $i, j = A, N$. Note we have these measures for every month in our sample. We suppress the time subscript to simplify our notation. We first compute the net inflow to A occupations:

$$F_{EE,A} \equiv \frac{EE_{NA} - EE_{AN}}{E_A}, \tag{1}$$

where the denominator E_A is the size of employment in A occupations. Similarly, for the net inflow to N, we compute

$$F_{EE,N} \equiv \frac{EE_{AN} - EE_{NA}}{E_N}, \tag{2}$$

where the denominator E_N is the size of employment in N occupations. Because we have only two categories, $F_{EE,A}$ and $F_{EE,N}$ have the opposite signs, although the magnitude can be different due to different denominators.[8]

Figure 1 plots the time series of $F_{EE,A}$. The red vertical lines correspond to the two SOC changes that occurred in 2002 and 2010. These changes divide our series into three subperiods. The monthly series is smoothed with a 12-month moving average within each of these subperiods. To highlight cyclical movements, we plot the changes in the national unemployment rate (measured on the right axis) and shaded the NBER recession periods on the same figure. The graph shows two facts: (i) $F_{EE,A}$ is positive everywhere, and its average is 0.07%; and (ii) $F_{EE,A}$ declines during both recessions. The first fact implies, on average, workers climb the *occupation ladder*: they tend to move from nonattractive to attractive occupations. This fact is not surprising (although not guaranteed, because of the wage requirement) given how we constructed attractive versus nonattractive occupations. The second fact, which

[8]Further details on the construction of the occupational flows is explained in Appendix A.

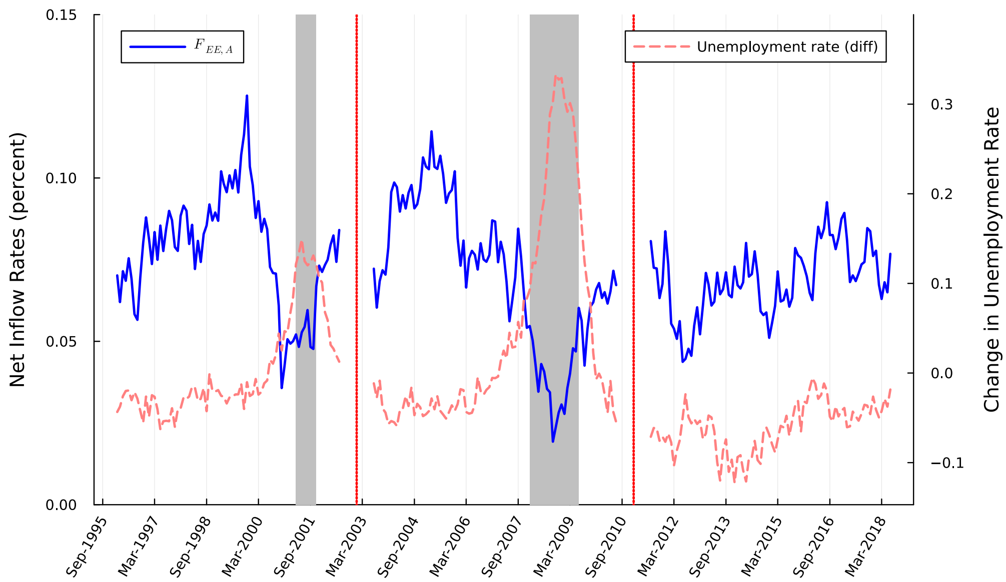

Figure 1: Net inflow rates into attractive occupations via EE transitions. Gray areas correspond to NBER recessions and vertical red-dotted lines correspond to changes in SOC. The changes in the national unemployment rate is measured on the right axis. The monthly series is smoothed with a 12-month moving average.

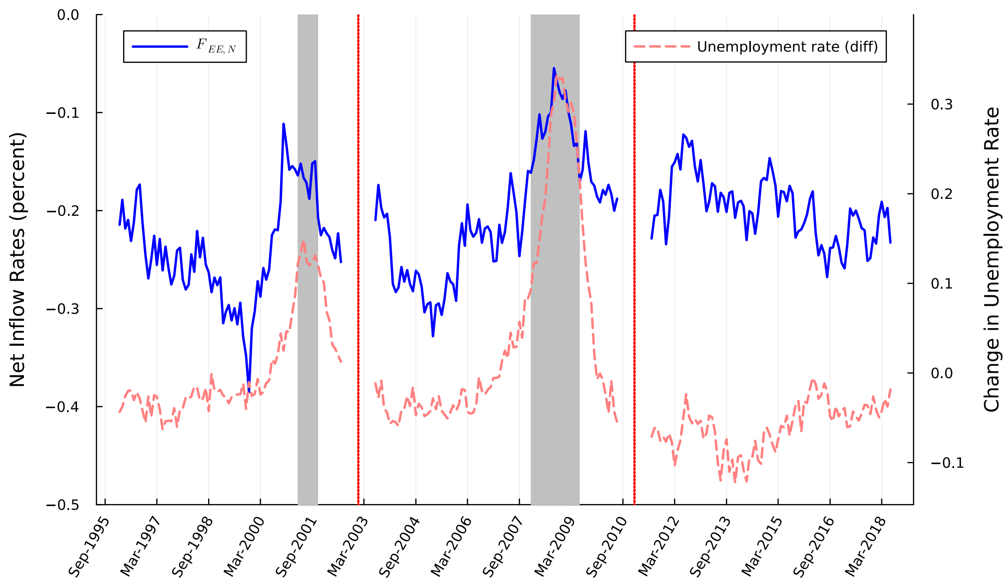

Figure 2: Net inflow rates into nonattractive occupations via EE transitions. Gray areas correspond to NBER recessions and vertical red-dotted lines correspond to changes in SOC. The changes in national unemployment rate is measured on the right axis. The monthly series is smoothed with a 12-month moving average.

is our main finding, is less obvious and more important: the occupation ladder is cyclical. In recessions, the net movement from N to A slows down.[9] As we elaborate on below, this fact suggests a novel cost of recession: a recession impedes workers from moving to a better occupation.

Figure 2 plots $F_{EE,N}$. As discussed above, by construction, $F_{EE,N}$ has an opposite sign of $F_{EE,A}$. However, it has a larger magnitude in percentage terms, averaging at -0.20%, because the size of employment in N occupations is smaller. The figure shows the cyclicality is similar (with the opposite sign) to $F_{EE,A}$. The interpretation is similar to the above: during a recession, the net movement from attractive occupations to nonattractive occupations goes up; that is, the ascent of the occupation ladder slows down.

Figures 3 and 4 plot the same objects as Figures 1 and 2 but with the UE flows.

[9]Appendix B demonstrates our finding is robust to looking at the share of the flows instead of the share of stocks. Appendix C constructs similar plots for different gender, age, and education groups.

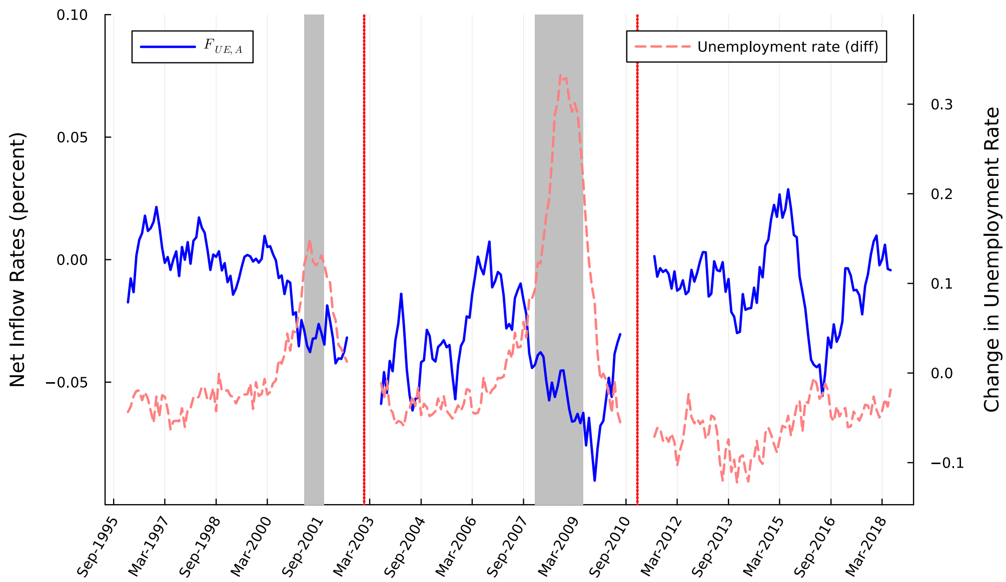

Figure 3: Net inflow rates into attractive occupations via UE transitions. Gray areas correspond to NBER recessions and vertical red-dotted lines correspond to changes in SOC. The changes in the national unemployment rate is measured on the right axis. The monthly series is smoothed with a 12-month moving average.

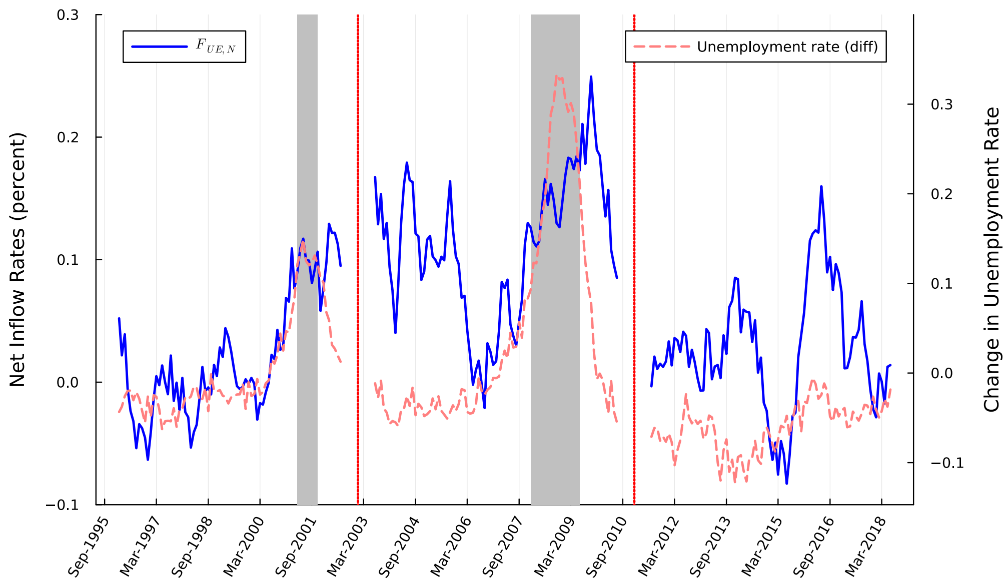

Figure 4: Net inflow rates into nonattractive occupations via UE transitions. Gray areas correspond to NBER recessions and vertical red-dotted lines correspond to changes in SOC. The changes in the national unemployment rate is measured on the right axis. The monthly series is smoothed with a 12-month moving average.

That is, they measure the occupational switch upon job finding from unemployment. Let the total number of unemployed workers who find a job and change occupations be UE_{ij} for $i, j = A, N$. Then, the net inflow rate from nonattractive to attractive occupations via UE transitions is given by

$$F_{UE,A} \equiv \frac{UE_{NA} - UE_{AN}}{E_A}. \tag{3}$$

For the net inflow to N via UE transitions, we compute

$$F_{UE,N} \equiv \frac{UE_{AN} - UE_{NA}}{E_N}. \tag{4}$$

The average values of $F_{UE,A}$ and $F_{UE,N}$ are -0.02% and 0.06%, respectively. Note the signs are different from the corresponding net inflow rates via EE transitions. This finding implies unemployed workers on average move down the occupation ladder.

The cyclicality in Figure 3 is similar to Figure 1, and the cyclicality of Figure 4 is similar to Figure 2, but the cyclical patterns are weaker with UE than EE. A UE-related occupational switch is less related to the cycle: similarly to Carrillo-Tudela and Visschers (2023), two forces are at work here. On the one hand, fewer openings exist in recessions, and thus fewer opportunities are available to move to a more attractive occupation. On the other hand, during recessions, workers tend to be unemployed longer, and when the duration is longer, the worker is more likely to take a job with any occupation, including the possibility of moving down the occupation ladder.

4 Separation, vacancy, and other statistics

In this section, we explore additional data features for attractive and nonattractive occupation groups to understand the cyclicality of occupation ladder.

4.1 Separations by occupation group

First, we construct measures of job separations to unemployment (EU transitions) by occupation category using the monthly CPS data. Specifically, we calculate the fraction of employed individuals in a given occupation category who lose their job in the next month and become unemployed.

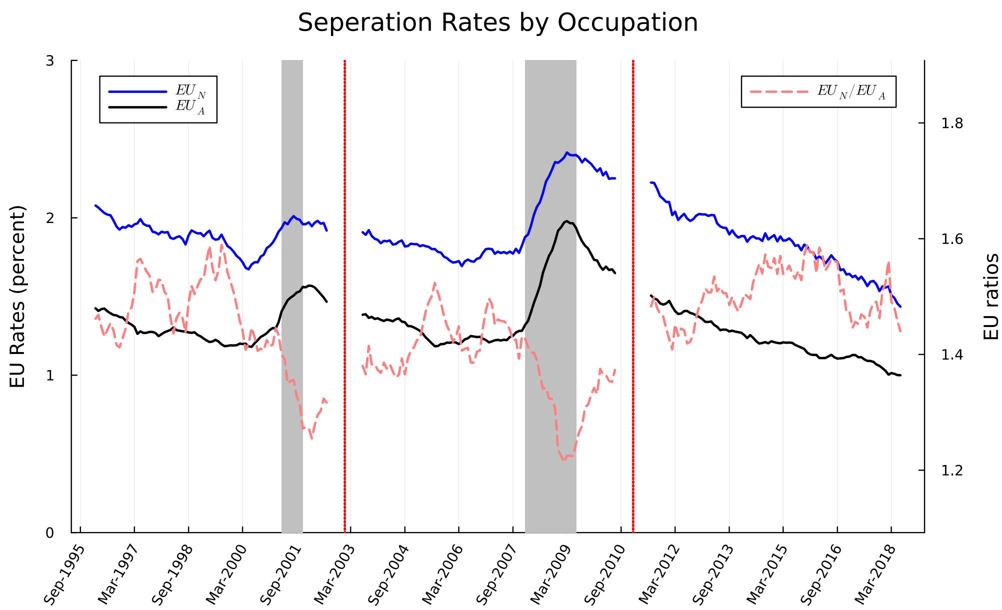

Figure 5: Separation rates into unemployment by attractive and nonattractive occupations. The separation-rate ratio (nonattractive to attractive) is shown on the right scale. Gray areas correspond to NBER recessions and the vertical red-dotted lines correspond to the changes in SOC. The monthly series is smoothed with a 12-month moving average.

Figure 5 shows the monthly plot of these series for attractive and nonattractive occupations. Employed individuals in attractive occupations are, on average, less likely to lose their job and become unemployed. The average monthly separation rate for attractive occupations is about 1.2%, whereas an average of about 1.8% of the employed individuals in nonattractive occupations lose their job every month and become unemployed. These numbers indicate that the attractive-occupation jobs are more stable than those for the nonattractive occupations. The mobility pattern indicates the stability can be one of the benefits of being in an attractive occupation. This result is consistent with Jarosch (2023): workers go through EE transitions to move to more stable jobs.

Transition rates to unemployment are countercyclical for each occupation group. However, the increase in EU rates is larger for attractive occupations. To highlight this fact, we plot the ratio of separation rates for nonattractive occupations to that of attractive occupations on the right scale in Figure 5. The average value of the ratio is around 1.5, indicating the separation rates to unemployment for nonattractive occupations are 50% more than that of attractive occupations. The ratio falls to about 1.25 during both recessions, which is a significant drop relative to normal times.

In sum, Figure 5 suggests attractive occupations are more stable but also more sensitive to business cycles. This pattern indicates that although attractive occupations can generate more surplus from the job-worker match, the surplus is more cyclical than nonattractive occupations. This mechanism is also consistent with the net flow pattern we observed in Section 3.

4.2 Vacancies, unemployment, and market tightness by occupation group

Here, we examine the same mechanism through the lens of vacancies. If the relative match surplus of attractive occupations are smaller during recessions, this movement should also be reflected in labor demand. One popular indicator of labor demand is vacancies.

To explore the behavior of vacancies, we use occupation-level vacancy data from the Conference Board's Help Wanted Online (HWOL) database. The HWOL database provides total vacancies for each of the two-digit occupation categories in the SOC

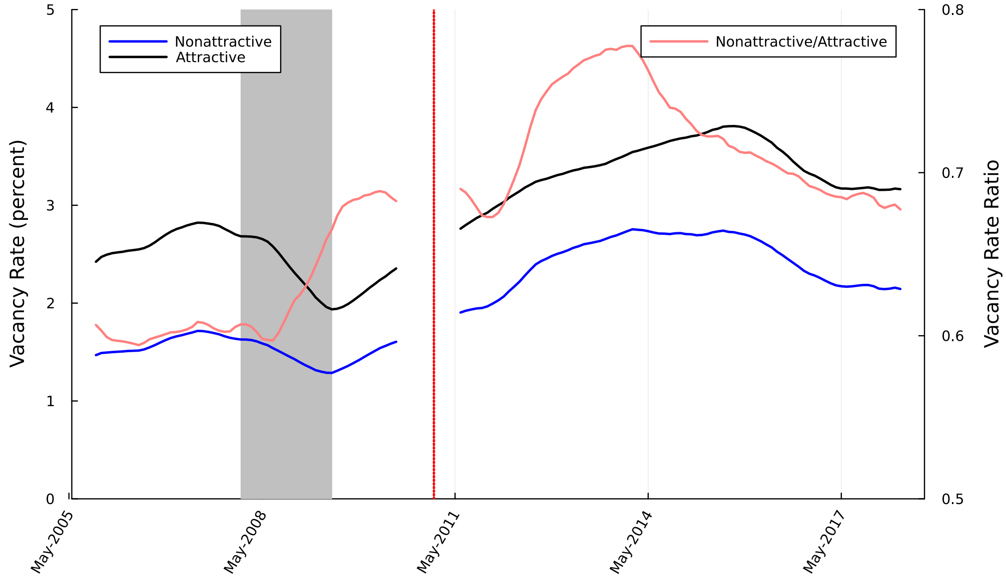

Figure 6: Vacancy rates for attractive and nonattractive occupations. The vacancy-rate ratio (nonattractive to attractive) is shown on the right scale. Gray areas correspond to NBER recessions and the vertical red-dotted line corresponds to the change in SOC. The monthly series is smoothed with a 12-month moving average.

2010 classification system, which correspond to major occupation groups in Census classification. The data span a period from May 2004 to October 2018 covering the Great Recession. We supplement this data with the number of employed and unemployed persons in the US by occupation obtained from the BLS database.[10]

In Figure 6, we plot vacancy rates calculated as the ratio of total vacancies in a given occupation group to the labor force size in that occupation group. On average, vacancy rates are higher for attractive occupations, implying higher demand. For both occupation groups, the vacancy rates sharply decline during the Great Recession and then slowly recover. The series also show a mild upward trend.

Although vacancy rates decline during the Great Recession for both occupation groups, the decline is higher for attractive occupations. In Figure 6, the solid red line, measured on the right scale, shows the ratio of vacancy rates for nonattractive occupations to that of attractive occupations. The ratio moves from 0.6 to about

[10]The original series on the BLS database are not seasonally adjusted. We adjust them using Census X-11 suite, which the BLS also uses for other time series.

0.7 during the Great Recession, implying the negative impact of the Great Recession on labor demand is larger for attractive occupations. This movement is consistent with the surplus from attractive occupations being more sensitive to business-cycle conditions. The movement of labor demand, in turn, affects the job- and occupation-switching behavior highlighted in Section 3.

The chances of finding a job depends not only on the number of available vacancies, but also on the number of job seekers. In Figure 7, we plot the unemployment rate for each occupation group calculated using the BLS series. The unemployment rate is countercyclical and is higher among the nonattractive occupations. The unemployment rate increases faster for attractive occupations during the Great Recession. To show this fact more clearly, we plot the ratio of the unemployment rate of the nonattractive occupations to attractive occupations in Figure 7. This ratio, measured on the right scale, shows the share of unemployed who had an attractive occupation in their previous jobs increased more than nonattractive occupations during the Great Recession. Once again, this result is consistent with the relative decline in match surplus for attractive occupations during recessions.

In a standard matching model, the frictions in the labor market are summarized by an aggregate matching function. Standard assumptions on the matching function imply a worker's job-finding rate depends positively on the market tightness defined as the ratio of vacancies to the unemployment rate. Our analysis with vacancy and unemployment rates both imply that finding an attractive-occupation job becomes relatively more difficult during recessions. Combining our data on vacancies and unemployment, we construct a measure of market tightness separately for attractive and nonattractive occupations. We plot these time series in Figure 8 together with their ratio measured on the right scale. The figure shows market tightness is procyclical for both occupation groups, but it is cyclically more sensitive for attractive occupations.

5 Another dataset: NLSY97

In Section 3, we found the net flow into attractive occupations declines in recessions. In Section 4, other labor market statistics, such as separations and vacancies, point

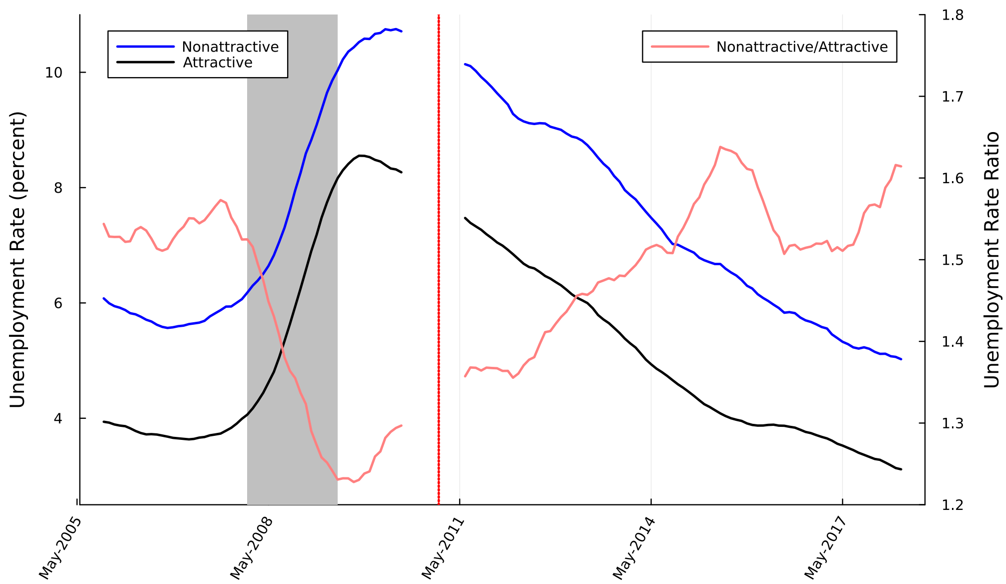

Figure 7: Unemployment rates for attractive and nonattractive occupations. The vacancy-rate ratio (nonattractive to attractive) is shown on the right scale. Gray areas correspond to NBER recessions and vertical red-dotted line corresponds to changes in SOC. The monthly series is smoothed with a 12-month moving average.

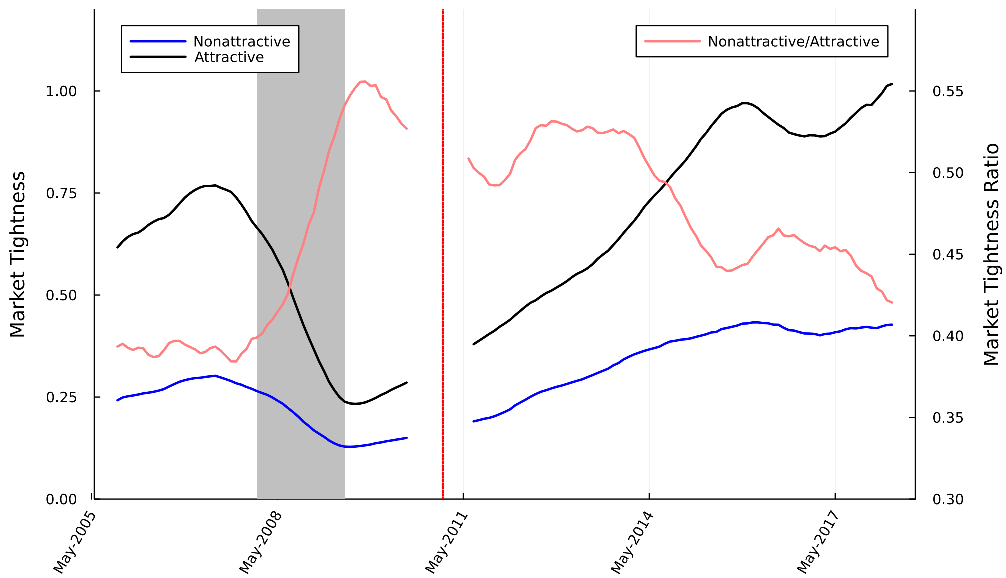

Figure 8: Market tightness for attractive and nonattractive occupations. The market-tightness ratio (nonattractive to attractive) is shown on the right scale. Gray areas correspond to NBER recessions and vertical red-dotted line corresponds to changes in SOC. The monthly series is smoothed with a 12-month moving average.

to more cyclical surplus for jobs in attractive occupations. To further supplement our findings with the CPS data, we use data from the National Longitudinal Survey of the Youth (NLSY).

We use the recent 1997 cohort, which is a representative sample of about 9,000 American youth born between 1980 and 1984. This dataset provides detailed employment information for these individuals since the first interview in 1997 until to this day. Despite its small sample size and limited age variation, this dataset has at least three advantages that can complement the CPS data for our purposes. First, we note relatively big jumps in the share of some occupation groups in the CPS data after the major change implemented in 2003, even in the harmonized IPUMS-CPS occupation variable. NLSY uses the 2002 Census occupational coding scheme for all the survey years and is not subject to such occupational classification errors. Second, the data contain information about wages, which allows us to relate wage gains upon EE transitions to occupational switch.[11] Finally, the ability to follow an individual's employment history for a long time enables us to explore occupational ladder over the life cycle of an individual.

In constructing our sample, we drop the job spells that started before the individual turned 18 years old. As the individuals in our sample age over time, their educational attainment increases too. To account for the potential effects of education, we perform our analysis in this section also with a subset of individuals who have never obtained a degree beyond high school in any survey year. This low-education group is particularly helpful, because most of these individuals are done with schooling when they turn 18.

5.1 Results on worker stocks and flows

In Figure 9, the blue curve shows the share of attractive occupations in total employment over time. The series start in January 1999 when these individuals are between

[11] Another alternative we considered is the Survey of Income and Program Participation (SIPP). Although SIPP panels have much larger sample sizes, they unfortunately do not provide a good coverage for recession years. Most importantly, the 2004 SIPP panel ends in January 2008 and the next SIPP panel (2008) starts in September 2008, which excludes the first three quarters of the Great Recession.

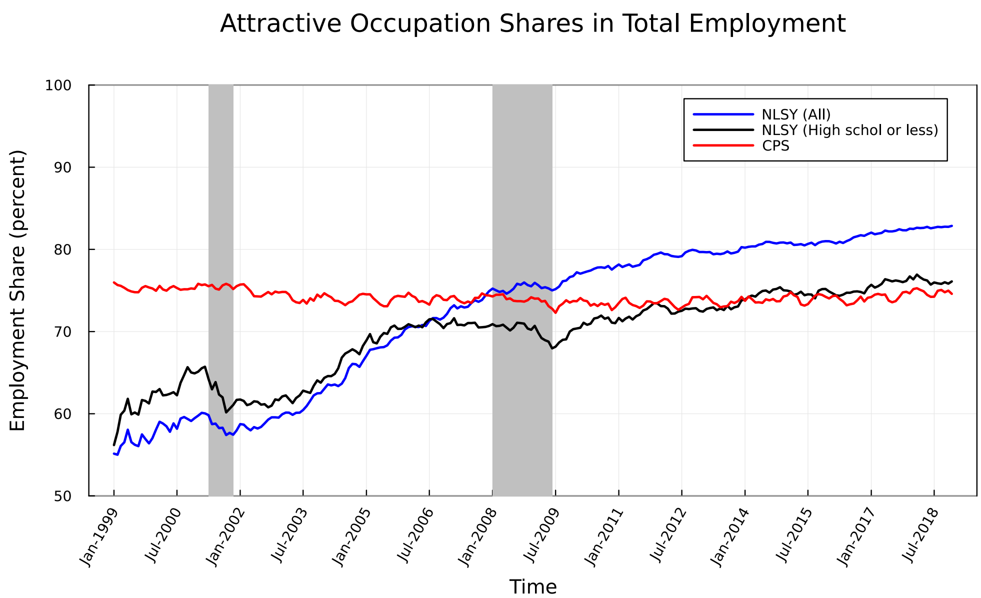

Figure 9: Shares of attractive occupations in NLSY97. Gray areas correspond to NBER recessions. The monthly series is smoothed with a 12-month moving average.

ages 15 and 19 and a good number of them are still attending school.[12] The series end in December 2018 when these individuals reach their prime ages. To compare our calculations with the entire population, we plot the share of attractive occupations in total employment from our CPS sample for the corresponding month. Note the NLSY time series tracks the life cycle and the calendar time simultaneously, because it tracks a single cohort.

Two patterns emerge from Figure 9. First, individuals climb the occupation ladder over the life cycle, with improvements concentrated early in their careers. Second, although the proportion of attractive occupations are eventually higher in the entire population, the progress among the low-education group is also large and significant. The employment share of attractive occupations in this group increases from 55% at the start of their careers to 75% when they reach prime ages.

Next, we plot net inflows to attractive occupations via EE transitions in Figure 10. As in the CPS data, the net inflow rates via EE transitions are mostly positive and relatively higher when they are younger. The second observation partly reflects the fact that most of these individuals are employed in a job with an attractive

[12] Sample sizes significantly drop if we start the series one year earlier.

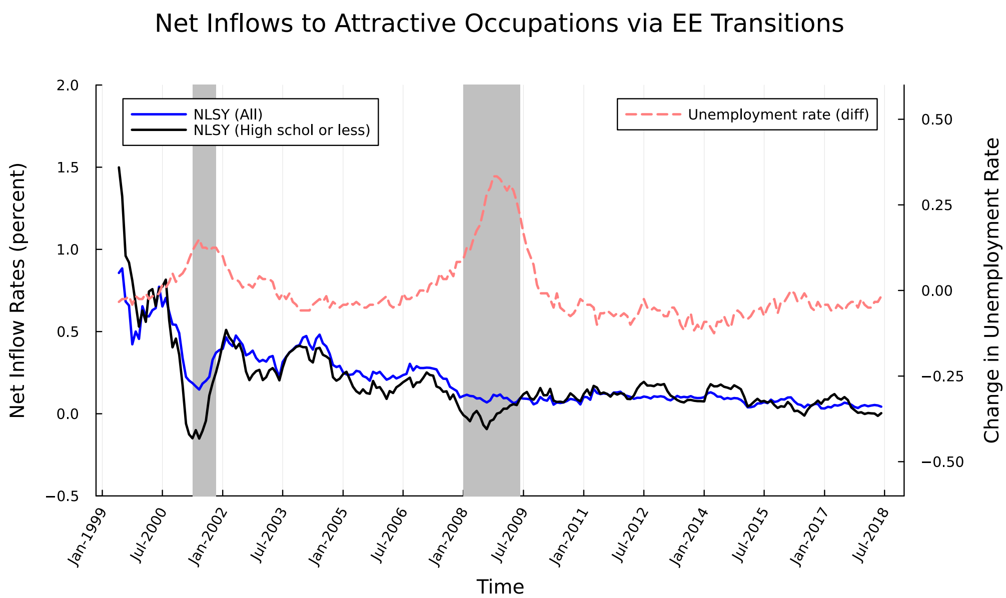

Figure 10: Net inflow rates into attractive occupations via EE transitions in NLSY97. Gray areas correspond to NBER recessions. The monthly series is smoothed with a 12-month moving average.

occupation at older ages. More importantly, the net inflow rates drop sharply during both of the recessions. Therefore, the observations in Section 3 are robust. This pattern is more pronounced for those with a high school degree or less.

5.2 Hourly wages

Another advantage of the NLSY data is that the hourly wage rate is available and we are able to calculate wage gains upon an EE transition. We calculate real hourly wages by dividing the reported nominal hourly wages by the Consumer Price Index. The calculation process for hourly wages produces extremely low and extremely high wage-rate values. Therefore, we drop observations with very high (more than \$400) and very low wage rates (less than \$1). Table 2 provides a cross tabulation of the log difference between the real hourly wage in the old and new job following an EE transition. In the second column, we calculate these wage gains for individuals with

	All	High school or less
Overall	0.105	0.090
AA	0.117	0.093
NN	0.046	0.068
NA	0.312	0.251
AN	-0.162	-0.125

Table 2: Wage gains at EE transitions: Cross tabulation of the log real hourly wage difference between the old and the new job after an EE transition.

a high school degree or less.[13] Overall, wage gains are sizable in our sample and average 10.5%. Our calculations are larger than some of the previous studies using other data sources. Tjaden and Wellschmied (2014) report that wage gains from EE transitions are on average 3.3% in SIPP data. Using data on earnings and hours from Longitudinal Employer-Household Dynamics (LEHD) data, Hahn et al. (2021) report that wage gains from EE transitions averaged 6.2%. These differences partly reflect how we construct our sample. For example, Hahn et al. (2021) also analyze a sample of individuals who entered the labor market in 2010 and track their labor market experience for the next seven years. For this entry cohort, they calculate that the average wage gains upon an EE transition is on average 9.1%.[14] In our sample, the average wage gains via EE transitions in the first seven years (from 1999 and 2005) is 8.9%, which is close to the number calculated in Hahn et al. (2021) for the 2010 entry cohort.

A more striking feature of Table 2 is that these wage gains are much larger when the individuals move from nonattractive to attractive occupation, but it is *negative* when they move from attractive to nonattractive occupations via EE transitions. To further explore whether these wage gains are driven by individual characteristics, we

[13] In Appendix D, we compute the statistics in this Section for higher educational attainment levels.

[14] See their Appendix D for a detailed discussion.

estimate the following regression equation:

$$\Delta w_{it} = \tau_{it}\beta + X_{it}\gamma + \varepsilon_{it}, \tag{5}$$

where Δw_{it} is the log difference between the real hourly wage rate in the new and the old job when individual i changes employers in month t. τ_{it} is a set of indicators for occupational switch and β is the associated vector of coefficients. The set of controls, X_{it}, include job-specific characteristics in the old and in the new job such as an indicator for part-time and government jobs. We also included quadratic terms for the completed tenure in the old job, quadratic terms for the actual experience of the worker at the time of the EE transition, and the log difference in the national unemployment rate in month $t-1$ and t.

The regression results are presented in Table 3. The first column uses all the EE transitions in our sample, and the second column uses only the individuals with a high school degree or less. In both columns, these results confirm our findings in Table 2, even after including controls. We conclude wage gains and losses associated with occupational switch are not driven by individual and job characteristics.[15] Rather, the wage changes are driven by the nature of occupational characteristics.

6 Implications for the cost of recessions

In Section 5.2, we showed the occupational switching can have a large effect on individual wages. The results there potentially underestimates the gains from climbing the occupational ladder, given that nonpecuniary gains can also exist. Such gains have been emphasized in the literature in the context of job ladders—see, for example, Sorkin (2018).

At the macro level, we have already seen the occupation ladder climbing slows during recessions. The natural question is: How much do we lose in recessions due to the aggregate slowdown of climbing up the occupation ladder? In this section, we calibrate a simple model to quantitatively evaluate the importance of the cyclical occupational mobility.

[15] In Appendix, we include interaction of τ_{it} with the highest educational attainment of individual i. The results remain qualitatively unchanged and we estimate larger gains and losses for higher-education groups.

Dependent Variable:	Log Hourly Wage Difference	
Sample:	All	High School or Less
NN	0.0320***	0.0703***
	(0.0111)	(0.0168)
AA	0.0859***	0.0891***
	(0.0095)	(0.0136)
AN	−0.2076***	−0.1932***
	(0.0173)	(0.0287)
NA	0.2516***	0.1788***
	(0.0147)	(0.0222)
Fit statistics		
Observations	19,992	6,952
R^2	0.07166	0.05064
Adjusted R^2	0.07111	0.04900

Clustered (caseid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: Wage gains from EE transitions: The dependent variable is the log real hourly wage difference between the new and the old job. Other controls include indicators for part-time and government job in the old and the new job, quadratic terms for actual experience and tenure in the previous job, and the log difference in the national unemployment rate.

6.1 Model

We model the business cycle as a two-point process of a random variable z_t. We construct the boom (g for "good") and the recession (b for "bad") symmetrically below. The transition probabilities $\pi_{zz'} = \Pr[z_{t+1} = z'|z_t = z]$ for $z, z' = g, b$. Here, prime ($'$) represents the next-period variable.

Occupations $o_t \in \{a, n\}$ is modeled as idiosyncratic state. The occupation $o_t = a$ represents the "attractive" occupation and $o_t = n$ represents the "nonattractive" occupation. The employment state $\epsilon_t \in \{e, u\}$ is also idiosyncratic. The probability of an employed worker becoming unemployed $\sigma_{oz'}$ depends on z' and the occupation o. The probability of an unemployed worker finding a job $\lambda_{oz'}$ and the probability of EE transition $\gamma_{oz'}$ also depend on z' and o. To map the model to our empirical measurement, we assume that an occupational switch occurs upon either EE or UE transition. $p^{UE}_{oo',z'}$ and $p^{EE}_{oo',z'}$ are the conditional switching probabilities of moving from o to o' when the aggregate state is z'.

The expected lifetime wage is defined as

$$V(\epsilon, o, z) = E\left[\sum_{t=0}^{\infty} \beta^t w(\epsilon_t, o_t, z_t)\right], \tag{6}$$

where $E_0[\cdot]$ is the expectation at time 0, $\beta \in (0, 1)$ is the discount factor, and $w(\epsilon_t, o_t, z_t)$ is the income (wage) of a consumer whose occupation is o_t and the employment state is ϵ_t when the aggregate state is z_t.

The lifetime wage can be written recursively as

$$\begin{aligned} V(u, o, z) = {} & w(u, o, z) \\ & + \beta \sum_{z'} \pi_{zz'} \Bigg(\lambda_{o,z'} \left(\sum_{o' \neq o} p^{UE}_{oo',z'} V(e, o', z') + \left(1 - \sum_{o' \neq o} p^{UE}_{oo',z'}\right) V(e, o, z') \right) \\ & \qquad + (1 - \lambda_{o,z'}) V(u, o, z') \Bigg) \end{aligned}$$

for unemployed workers and

$$\begin{aligned} V(e, o, z) = {} & w(e, o, z) \\ & + \beta \sum_{z'} \pi_{zz'} \Bigg(\gamma_{o,z'} \left(\sum_{o' \neq o} p^{EE}_{oo',z'} V(e, o', z') + \left(1 - \sum_{o' \neq o} p^{EE}_{oo',z'}\right) V(e, o, z') \right) \\ & \qquad + \sigma_{o,z'} V(u, o, z') + (1 - \gamma_{o,z'} - \sigma_{o,z'}) V(e, o, z') \Bigg) \end{aligned}$$

for employed workers. The future values for unemployed workers reflect (i) finding a job and moving to another occupation, (ii) finding a job and staying in the same occupation, and (iii) staying unemployed. The future values for employed workers reflect (i) switching to a new job and changing occupations, (ii) switching to a new job and staying in the same occupation, (iii) losing the job, and (iv) staying in the same job.[16]

6.2 Calibration

One period is one month. The transition probabilities for the aggregate state, $\pi_{zz'}$, is set as

$$\begin{bmatrix} \pi_{gg} & \pi_{gb} \\ \pi_{bg} & \pi_{bb} \end{bmatrix} = \begin{bmatrix} 59/60 & 1/60 \\ 1/60 & 59/60 \end{bmatrix},$$

which approximately reflects the length of one cycle according to the NBER dating. In recent years, we experience one cycle every 10 years, and (with the symmetry assumption) the average duration of each state is set at 60 months.

The job-finding probability for the workers in attractive occupation, $\lambda_{az'}$, is computed as follows. First, we define the boom following the NBER dating. Then, we compute the job-finding probability for f_t^a from the data and decompose f_t^a into the HP trend and its deviation:

$$f_t^a = \tilde{f}_t^a + \hat{f}_t^a,$$

where $\tilde{f}_t^a$ is the HP trend and $\hat{f}_t^a$ is the deviation. Let the sample mean

$$\bar{f}_t^a \equiv \frac{1}{T} \sum_{t=1}^{T} f_t^a.$$

Then, compute λ_{ag} by

$$\lambda_{ag} = \bar{f}_t^a + \frac{1}{N_g} \sum_{t \in G} \hat{f}_t^a,$$

[16] We do not take a stand on why workers decide to change occupations, in particular when they move to n occupation jobs knowing they pay low. One interpretation is that employed workers face relocation shocks, as emphasized in Jolivet et al. (2006), and these shocks entail moving down the occupation ladder. Carrillo-Tudela et al. (2022) emphasize the role of idiosyncratic shocks to occupational productivity to understand occupational switch.

	$z' = g$	$z' = b$
$\lambda_{az'}$	0.2725	0.2667
$\lambda_{nz'}$	0.2842	0.2817
$\gamma_{az'}$	0.0179	0.0173
$\gamma_{nz'}$	0.0261	0.0258
$\sigma_{az'}$	0.0138	0.0159
$\sigma_{nz'}$	0.0197	0.0205
$p^{EE}_{an,z'}$	0.1412	0.1423
$p^{EE}_{na,z'}$	0.3769	0.3551
$p^{UE}_{an,z'}$	0.1996	0.1977
$p^{UE}_{na,z'}$	0.3719	0.3407

Table 4: Transition probabilities

$w(e,a,g)$	1.2
$w(e,a,b)$	1.2
$w(e,n,g)$	1.0
$w(e,n,b)$	1.0
$w(u,a,g)$	0.4
$w(u,a,b)$	0.4
$w(u,n,g)$	0.4
$w(u,n,b)$	0.4

Table 5: Wages

where N_g is the number of periods of NBER booms and G is the set of boom years. Similarly, λ_{ab} can be computed as

$$\lambda_{ab} = \bar{f}_t^a + \frac{1}{N_b}\sum_{t \in B} \hat{f}_t^a,$$

where N_b is the number of periods of NBER recessions and B is the set of recession years. Other probabilities, $\gamma_{oz'}$, $\sigma_{oz'}$, and $p^{EE}_{oo',z'}$ are computed analogously. The results are in Table 4.

Table 4 has some notable outcomes. First, as is well known, the job-finding probabilities for unemployed workers are procyclical and the separation probability is countercyclical. The EE transition rate is procyclical. Second, as we emphasized in Section 4, attractive occupations are more sensitive to business cycles in that their transition rates change more over the business cycle. Third, note the probability of an occupational switch is the combination of the job switching (or job finding) and the conditional probability. Both are cyclical. One notable feature of the conditional probabilities is that $p^{EE}_{na,z'}$ and $p^{UE}_{na,z'}$ are strongly procylical. This feature drives the strong cyclicality of the net occupational flow, which we observed in Section 3.

Table 5 summarizes our assumption on wages. In the baseline case, we assume an attractive occupation provides 20% better wages than a nonattractive occupation. In Table (2), the wage gain from NA transition is about 31%, and the overall wage gain is 11%. Thus, we estimate the pure effect of moving from N occupation to A occupation as $31 - 11 = 20\%$. The value of unemployment is 40% of the nonattractive occupation wage. The 40% replacement ratio is standard in the literature (Shimer, 2005).

6.3 Results

Let the lifetime wages $V(\epsilon, o, z)$ be computed as in (6). We first consider the counterfactual experiment where all recessions are eliminated by setting all transition probabilities of the idiosyncratic shock to the values during booms. That is, the new probabilities are $\hat{\lambda}_{ab} = \lambda_{ag}$, $\hat{\lambda}_{nb} = \lambda_{ng}$, $\hat{\gamma}_{ab} = \gamma_{ag}$, $\hat{\gamma}_{nb} = \gamma_{ng}$, $\hat{\sigma}_{ab} = \sigma_{ag}$, $\hat{\sigma}_{nb} = \sigma_{ng}$, $\hat{p}^{EE}_{an,b} = p^{EE}_{an,g}$, $\hat{p}^{EE}_{na,b} = p^{EE}_{na,g}$, $\hat{p}^{UE}_{an,b} = p^{UE}_{an,g}$, and $\hat{p}^{UE}_{na,b} = p^{UE}_{na,g}$. Note that our exercise is different from Lucas (1987), where the world without business cycles is imagined as the situation where all macroeconomic variables are replaced by the mean value. Rather, our measurement is the cost of recession—we replace all "recessions" by "booms." In this sense, our calculation follows the tradition of the "plucking view" of Friedman (1964) (also see Dupraz et al., 2024).

Let the counterfactual lifetime wage be $\hat{V}(\epsilon, o, z)$ and define the cost of recession for an individual with state (ϵ, o, z), $\hat{\Delta}(\epsilon, o, z)$, as

$$\hat{\Delta}(\epsilon, o, z) \equiv \frac{\hat{V}(\epsilon, o, z) - V(\epsilon, o, z)}{\hat{V}(\epsilon, o, z)}.$$

This cost of recession includes various reasons that makes recessions worse than booms. The cost here includes a greater loss of income due to more frequent and prolonged unemployment.

To isolate the effect of the change in the movement along the occupation ladder during the recessions, let us run another counterfactual experiment. Here, we maintain the assumption of the first counterfactual experiment for most of the probabilities; that is, the values are set at the boom value. The only exceptions are the conditional occupation switching probabilities $p^{EE}_{oo',z'}$ and $p^{UE}_{oo',z'}$. For $p^{EE}_{oo',z'}$ and $p^{UE}_{oo',z'}$, instead of setting them at the boom value (i.e., the value with $z' = g$), we maintain the probabilistic structure of the original baseline.

Specifically, we set these conditional probabilities so that the unconditional probability of "moving up" or "moving down" the occupation ladder becomes the same as the baseline. Thus, the new conditional probabilities $\tilde{p}^{EE}_{na,b}$ $\tilde{p}^{UE}_{na,b}$, $\tilde{p}^{EE}_{an,b}$, and $\tilde{p}^{UE}_{an,b}$ now satisfy

$$\begin{aligned} \gamma_{ng}\tilde{p}^{EE}_{na,b} &= \gamma_{nb}p^{EE}_{na,b}, \\ \lambda_{ng}\tilde{p}^{UE}_{na,b} &= \lambda_{nb}p^{UE}_{na,b}, \\ \gamma_{ng}\tilde{p}^{EE}_{an,b} &= \gamma_{nb}p^{EE}_{an,b}, \end{aligned} \tag{7}$$

and

$$\lambda_{ng}\tilde{p}^{UE}_{an,b} = \lambda_{nb}p^{UE}_{an,b}.$$

In the first equation above, the right-hand side, $\gamma_{nb}p^{EE}_{na,b}$, is the baseline unconditional probability of an occupational switch from the nonattractive occupation to the attractive occupation when the economy is in recession. We set the new conditional probability $\tilde{p}^{EE}_{na,b}$ in the new counterfactual so that the unconditional probability of an

	$\hat{\Delta}(\epsilon, o, z)$	$\tilde{\Delta}(\epsilon, o, z)$	$R(\epsilon, o, z)$
(e, a, g)	0.0033	0.0029	13.8
(e, n, g)	0.0035	0.0024	30.4
(u, a, g)	0.0034	0.0028	16.7
(u, n, g)	0.0035	0.0026	26.1
aggregate g	0.0034	0.0028	17.9
(e, a, b)	0.0043	0.0038	10.0
(e, n, b)	0.0046	0.0027	41.2
(u, a, b)	0.0044	0.0039	11.0
(u, n, b)	0.0055	0.0030	45.3
aggregate b	0.0044	0.0035	18.7

Table 6: Welfare costs

occupational switch is the same as in the baseline. Because the EE transition probability in this counterfactual is set at the boom level γ_{ng}, the unconditional probability is as in the left-hand side of (7): $\gamma_{ng}\tilde{p}^{EE}_{na,b}$. Thus, we use the formula in equation (7) for setting the new conditional probability $\tilde{p}^{EE}_{na,b}$. The other three equations are analogous.

The other probabilities are the same as the first counterfactual experiment. We define the new welfare cost as

$$\tilde{\Delta}(\epsilon, o, z) \equiv \frac{\tilde{V}(\epsilon, o, z) - V(\epsilon, o, z)}{\tilde{V}(\epsilon, o, z)}.$$

This value measures the cost of recessions *except for* the effect of the occupational ladder. Therefore, the gap between $\hat{\Delta}(\epsilon, o, z)$ and $\tilde{\Delta}(\epsilon, o, z)$ measures the cost of the changed mobility of the occupation ladder during the recessions. We compute the relative contribution of the occupation ladder (in %) as

$$R(\epsilon, o, z) \equiv \left(1 - \frac{\tilde{\Delta}(\epsilon, o, z)}{\hat{\Delta}(\epsilon, o, z)}\right) \times 100.$$

Table 6 exhibits $\hat{\Delta}(\epsilon, o, z)$, $\tilde{\Delta}(\epsilon, o, z)$, and $R(\epsilon, o, z)$ for the consumer with the individual state (ϵ, o) when the welfare is compared at the aggregate state z. The lifetime wage loss from recessions $\hat{\Delta}(\epsilon, o, z)$ is about 0.3% to 0.6% of income. A significant part of it, about 10% to 45%, is due to the changed speed of movement along the occupation ladder.

The rows with "aggregate" are the average welfare change weighted by the steady-state population in each aggregate state. On average, about 18% to 19% of the cost of recession is due to the occupation ladder. Note, again, our estimate here is a conservative one, because the benefit of moving to a better occupation is likely to be larger than the measured wage gains. Therefore, our experiment here demonstrates the effect of slowing down the occupation ladder is during recession is a nonnegligible part of the aggregate cost of recessions.

7 Conclusion

We introduced a new concept, "occupation ladder," in this paper. As in the case of the job ladder, workers tend to move to a better occupation over time. To examine the worker movement along the ladder, we first empirically identified "attractive" occupations and "nonattractive" occupations using the flow movements of workers and wage information.

Then, we examined the cyclical behavior of worker flows along the occupational ladder. We found the net flow into attractive occupations is procyclical. That is, workers move up the occupation ladder faster during booms. This fact provides a novel perspective on the cost of recessions.

Other facts on separation and vacancies corroborate the view that the value of an attractive-occupation job is more cyclical than that of a nonattractive-occupation job. For the workers, therefore, the opportunity for a good occupation is hindered by the lack of opportunities during recessions.

Finally, we constructed a simple accounting model to measure the cost of recessions on the workers' lifetime earnings. The overall cost of recessions is about 0.3% to 0.6% of income. In aggregate, the lack of opportunities for climbing the occupation ladder accounts for about 18% to 19% of the overall cost. Our results from NLSY97 indicates the occupation ladder matters more for young workers. It is an important future research topic to further investigate the scarring effect of recessions through the occupation ladder for young workers.

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Online Appendix for “Occupation Ladders over the Business Cycle”

A Constructing the net inflow rate

When constructing attractive- and nonattractive-occupation groups, we use the information on the net inflow rates via EE transitions in the cross section. In this Appendix, we provide details about how we construct these measures and describe their relationship before classifying them as attractive or nonattractive.

The current occupation classification system, SOC 2010, was adopted in 2010 and is based mainly on the 2002 classification system, SOC 2002. The changes in the new classification system are minor, and we do not observe any large difference between the employment shares in December 2009 and January 2010 for a given occupation. However, major changes were implemented in 2002 in the occupation classification relative to the previous one adopted in 1990. Although the IPUMS-CPS database provides a crosswalk for the occupations reported based on the previous classification system, we observe big jumps in employment shares for certain occupations going from December 2002 to January 2003. To avoid potential measurement issues related to changes in the occupations classification system in 2002, we restrict our sample from the basic CPS monthly files that span the period from January 2003 to December 2018. Then, we pool all the observations and calculate the net inflows for all possible combinations of occupation pairs i and j. We perform these calculations separately for UE and EE transitions. Similar to equations 1 and 2, we calculate the net inflow rate into occupation i from equation j as follows:

$$F_{EE,ij} \equiv \frac{EE_{ji} - EE_{ij}}{E_i} \qquad \text{and} \qquad F_{UE,ij} \equiv \frac{UE_{ji} - UE_{ij}}{E_i}.$$

These calculations provide a matrix of net inflow rates for each occupation pair i and j. We represent these rates for EE and UE transitions as a heatmap in Figure A.11. The rows correspond to the occupation in the current job for EE transitions, and to the occupation in the previous job for UE transitions. The columns correspond to the occupation in the next job. Positive and negative numbers are represented by the tones of colors red and blue, respectively. As the number gets small in absolute value, its color becomes lighter in color. The diagonal elements are equal to zero by

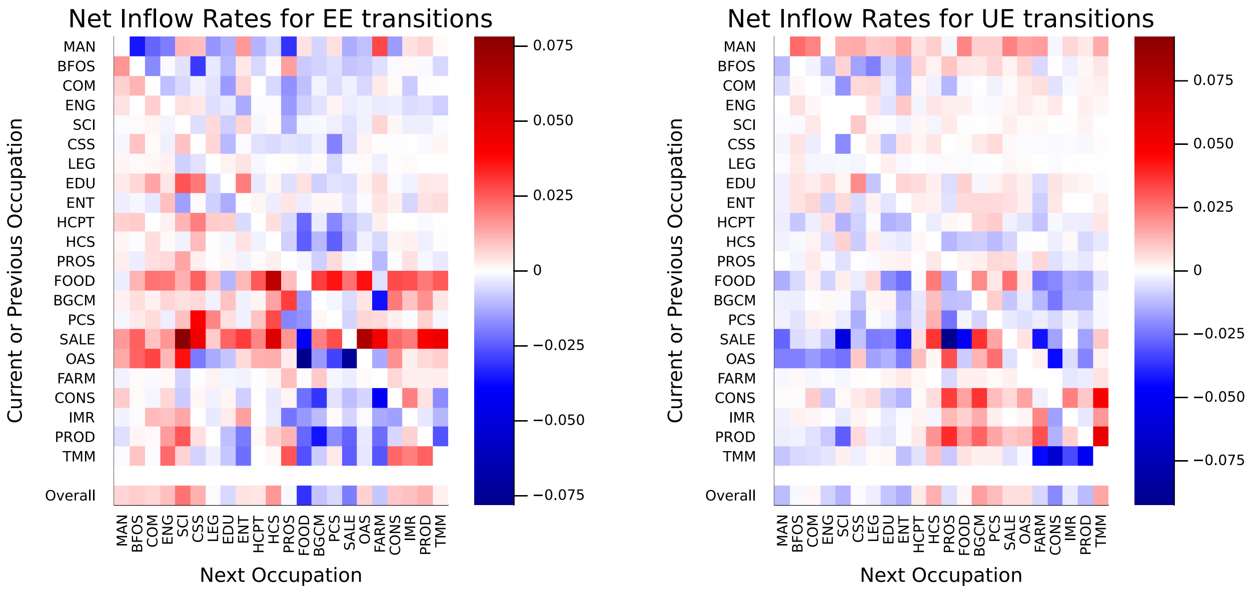

Figure A.11: Net inflow rates via EE and UE transitions by occupation. The occupation categories are based on SOC 2010. The calculations use CPS data from January 2003 to December 2018.

construction and their colors are white. The last row shows the overall inflow rate into the occupations in the columns.[17]

Inspection of Figure A.11 for EE transitions reveals food preparation and serving ("FOOD") and sales related ("SALE") occupations lose on net to most of the other occupation categories, because most of the cells in their columns are blue. However, when one looks at the net inflow rates via UE transitions, these occupation categories gain from many other occupation groups. An opposite pattern is present in Figure A.11 for managerial occupations ("MAN"), shown in the first column. The majority of the cells are red in the first column for EE transitions, but all of the cells are blue for UE transitions, implying people move out of managerial occupations when they become unemployed. These opposite patterns for EE and UE transitions in Figure A.11 illustrate the importance of studying occupation switches by transition type.

[17] We divide the overall inflow rate by 10 to avoid having a dominant color in the last row.

B Flows as a share of total EE transitions

Here, we calculate net inflows into attractive occupations as a share of total EE transitions. That is, we divide the difference between EE_{NA} and EE_{AN} by total EE transitions:

$$\tilde{F}_{EE,A} = \frac{EE_{NA} - EE_{AN}}{EE}. \tag{8}$$

By construction, $\tilde{F}_{EE,N} = -\tilde{F}_{EE,A}$. Figure B.12 shows net inflows into A occupations as a share of total EE transitions also markedly drop during both recessions. Note that the overall EE rate slows down during recessions. Figure B.12 further shows that among the individuals who make an EE transition during a recession, a smaller fraction is able to climb the occupation ladder.

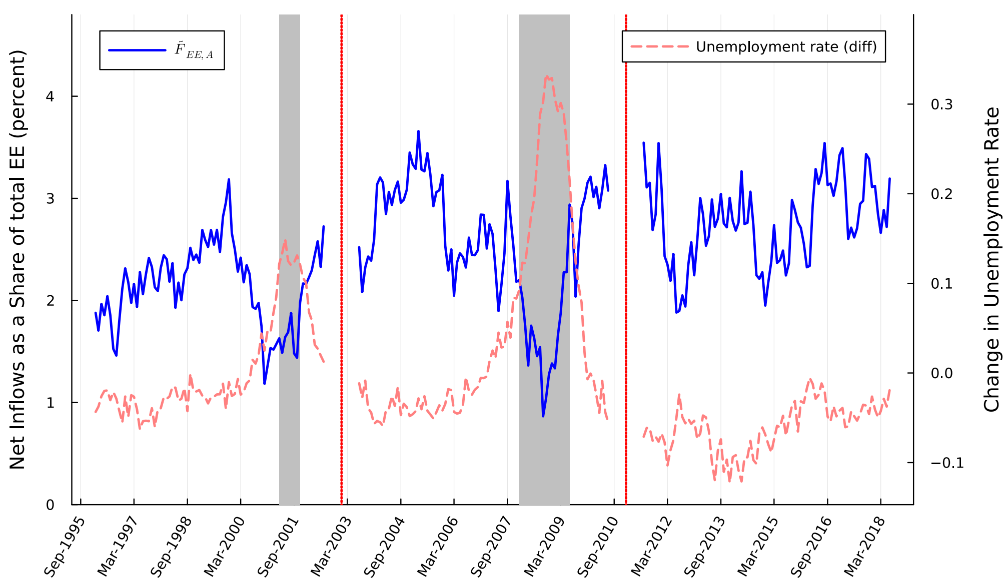

Figure B.12: Net inflows to attractive occupations as a share of total EE transitions. Gray areas correspond to NBER recessions and vertical red-dotted lines correspond to changes in SOC. The changes in the national unemployment rate are measured on the right axis. The monthly series is smoothed with a 12-month moving average.

In Figure B.13, we plot the net inflow rates into attractive occupations as a share of total UE transitions. The cyclicality of this series is similar to the series in Figure 3 in that unemployed individuals tend to move down the occupation ladder. Noting that job-finding rates are lower during recessions, Figure B.13 further implies that,

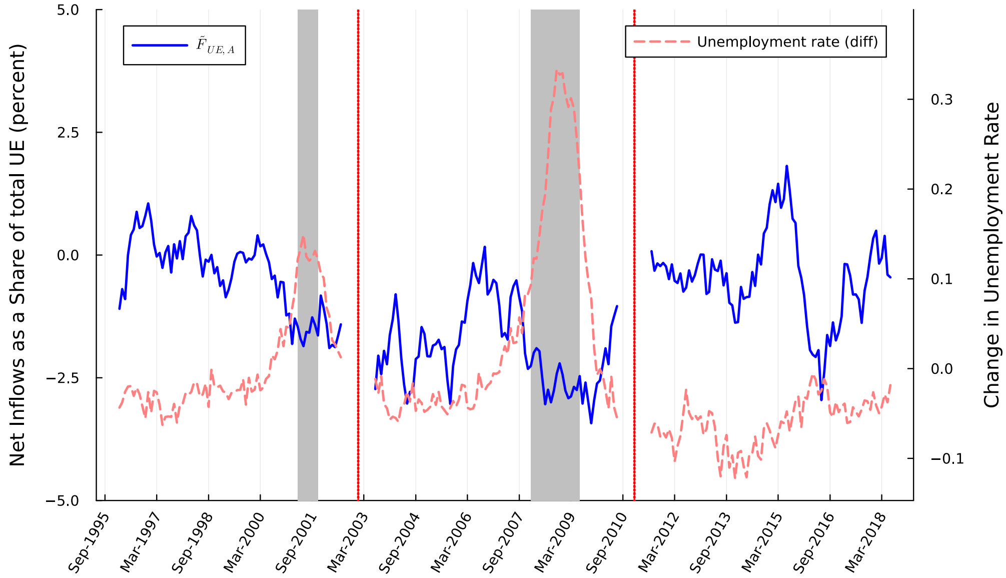

Figure B.13: Net inflows to attractive occupations as a share of total UE transitions. Gray areas correspond to NBER recessions and vertical red-dotted lines correspond to changes in SOC. The changes in the national unemployment rate are measured on the right axis. The monthly series is smoothed with a 12-month moving average.

among the unemployed who were able to find a job, proportionally more people are moving down the occupation ladder.

C Flows by demographics

In this section, we plot the net inflow rates from nonattractive to attractive occupations by individual characteristics. We focus on EE transitions. In each figure, all the series correspond to the simple moving average of the original series over a 12-month period.

Figure C.14 shows the breakdown of net inflow rates into attractive occupations via EE transitions by gender. The general pattern in net inflow rates is present for both men and women, although women are more likely to move to an attractive occupation when they switch jobs and their career progress along the occupation ladder is more sensitive to business cycles.

Figure C.15 shows the breakdown of net inflow rates into attractive occupations

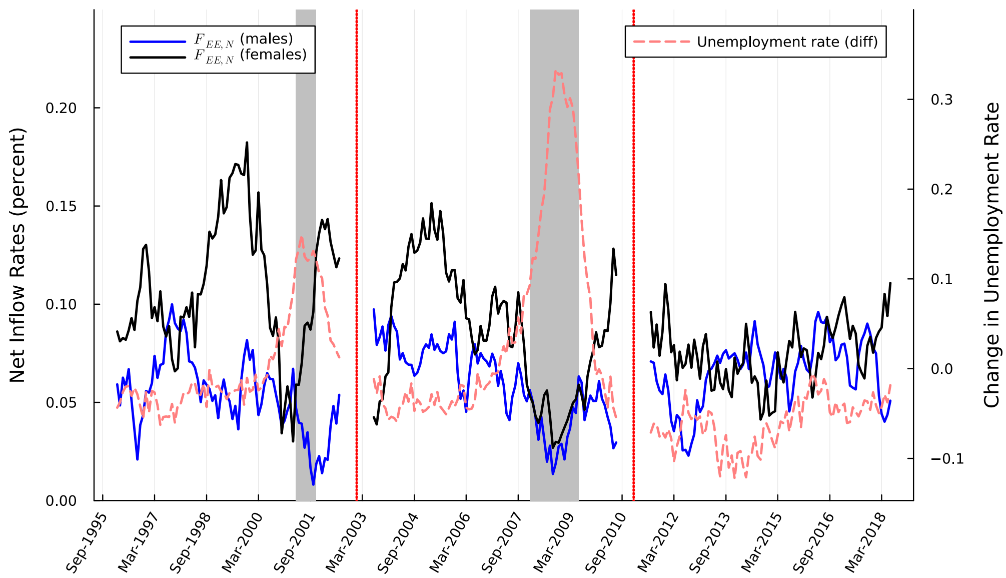

Figure C.14: Net inflow rate into attractive occupations via EE transitions by gender. Gray areas correspond to NBER recessions and vertical red-dotted lines correspond to changes in SOC. The changes in the national unemployment rate are measured on the right axis. The monthly series is smoothed with a 12-month moving average.

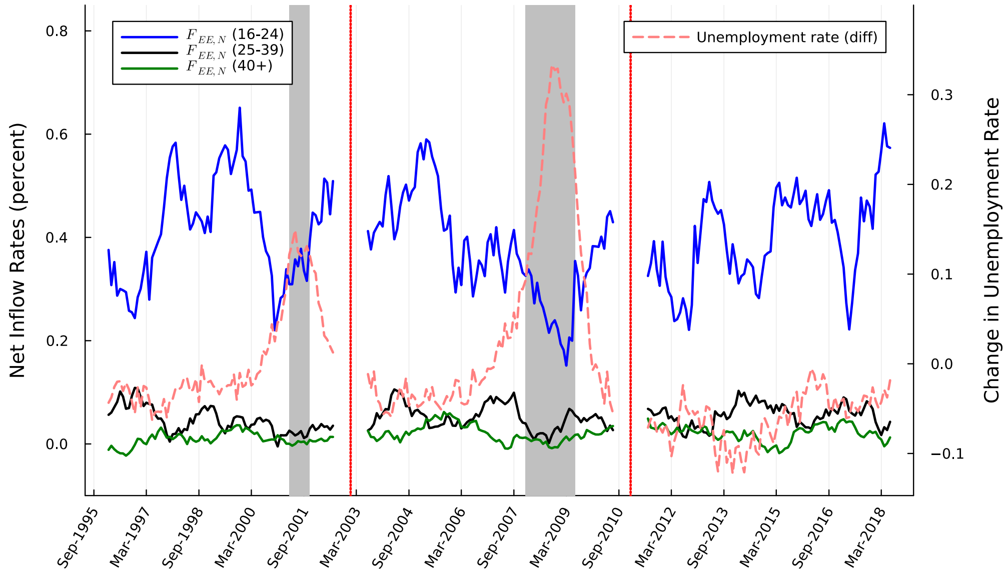

Figure C.15: Net inflow rate into attractive occupations via EE transitions by age groups. Gray areas correspond to NBER recessions and vertical red-dotted lines correspond to changes in SOC. The changes in the national unemployment rate are measured on the right axis. The monthly series is smoothed with a 12-month moving average.

via EE transitions by different age groups. Young individuals (aged between 16 and 24) are a lot more likely than older individuals to move from a nonattractive occupation to an attractive one. This finding accords with our analysis with NLSY data displayed in Figure (10). The net inflow rate is on average about 0.4%, which is roughly eight times larger than that of an individual aged between 25 and 39. The net inflow rates for young individuals are also more sensitive to the business cycles. For example, at the peak of the Great Recession, the inflow rate from nonattractive occupations to attractive occupations is slightly below 0.2% for young individuals, compared with about 0.4% at the start of the recession. Given that the early career prospects play an important role in one's future labor market experience, Figure C.15 highlights the importance of a cyclical occupation ladder.

Figure C.16 shows the net inflow rates into attractive occupations via EE transitions for different education groups. We define three education groups: (i) high school or less, (ii) some college education, and (iii) college and above. On average, people

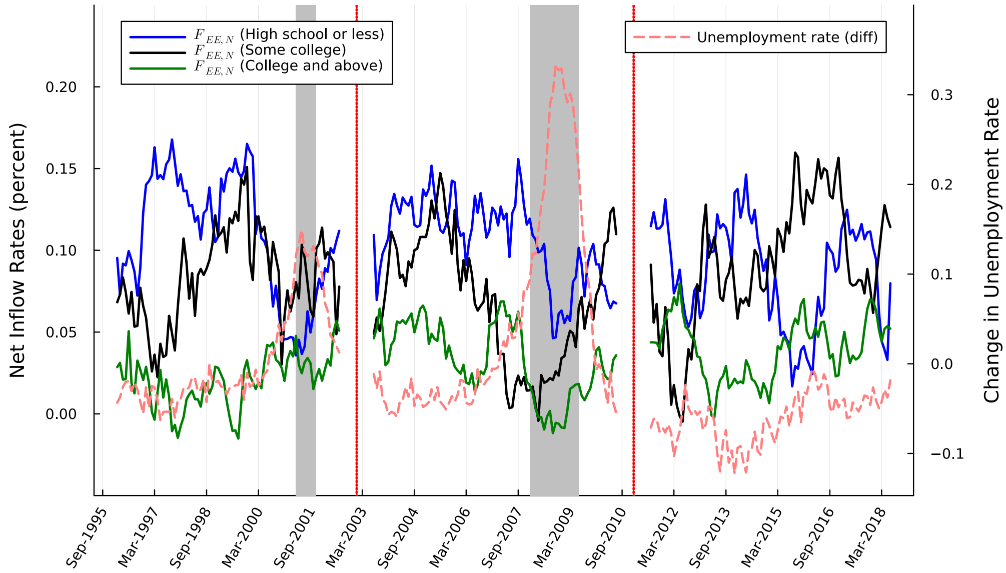

Figure C.16: Net inflow rate into attractive occupations via EE transitions by education: less than high school (HS), high school, some college (COL) education, and college degree and above. Gray areas correspond to NBER recessions and vertical red-dotted lines correspond to changes in SOC. The changes in the national unemployment rate are measured on the right axis. The monthly series is smoothed with a 12-month moving average.

at every education level tend to move from nonattractive to attractive occupations, and an inverse relationship exists between the education levels and the inflow rates to attractive occupations. This inverse relationship is possibly due to the fact that highly educated individuals are already in attractive occupations. Nonetheless, all education categories are negatively affected by the business cycles in that net inflow rates from nonattractive to attractive occupations decline during recessions.

D Wage gains by educational attainment

In this section, we divide our NLSY sample by different education groups defined as in the previous section. As before, we drop the job spells that start before the individual turns 18 years old. In addition, we drop the job spells when he/she completes his/her highest degree to mitigate the effects associated with schooling decisions.

In Table 7, we report the sample averages of wage gains by each education group.[18] The qualitative results remain unchanged, and we observe larger gains and losses for higher education groups.

	High school or less	Some college	College and above
Overall	0.089	0.106	0.157
AA	0.092	0.112	0.153
NN	0.067	0.057	0.057
NA	0.251	0.313	0.450
AN	−0.128	−0.138	−0.214

Table 7: Wage gains at EE transitions by education: Cross tabulation of the log real hourly wage difference between the old and the new job after an EE transition.

To further explore wage gains by education, we estimate the following regression equation:

$$\Delta w_{it} = \sum_{educ} educ_i \tau_{it} \beta^{educ} + X_{it}\gamma + \varepsilon_{it}, \tag{9}$$

where $educ$ denotes the three education categories defined above. $educ_i$ is a dummy variable that is equal to 1 if the highest educational attainment of individual i is equal to the given education education category, and β^{educ} is the associated vector of education-specific coefficients. The set of controls are as in Table 3.

The regression results are presented in Table 8. The results are similar to our findings in Table 3. In particular, individuals experience wage losses when they move from an attractive occupation to a nonattractive occupation in every education category, whereas they gain when they move in the opposite direction or remain in the same occupation. Moreover, these gains and losses increase with educational attainment with the exception of NN transitions.

[18] Note that a small number of individuals graduated from high school and achieved their highest degree ever after reaching age 18. By construction, the job spells after age 18 but before graduating from high school are excluded from our sample. Therefore, the wage gains for the education group with a high school degree or less are slightly different than those reported in Table 2.

Dependent Variable:	Log Hourly Wage Difference
NN transitions:	
High school or less	0.0872***
	(0.0165)
Some college	0.0782***
	(0.0254)
College and above	0.1127***
	(0.0418)
DD transitions:	
High school or less	0.1034***
	(0.0115)
Some college	0.1244***
	(0.0150)
College and above	0.1654***
	(0.0153)
DN transitions:	
High school or less	−0.1947***
	(0.0290)
Some college	−0.1985***
	(0.0457)
College and above	−0.3000***
	(0.0598)
ND transitions:	
High school or less	0.1744***
	(0.0228)
Some college	0.2456***
	(0.0490)
College and above	0.3472***
	(0.0526)
Observations	13,321
R^2	0.07041
Adjusted R^2	0.06901

Clustered (individual) standard-errors in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8: Wage gains from EE transitions by education: The dependent variable is the log real hourly wage difference between the old and the new job. Other controls include indicators for part-time and government job, in the old and the new job, quadratic terms for actual experience and tenure in the previous job, and log difference in national unemployment rate.