SEARCH RELATIVITY

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Abstract

Why is the unemployment rate lower at higher educational levels, and simultaneously, the aggregate unemployment rate (AUR) uncorrelated with the distribution of human capital? Why is the unemployment rate of the postgraduates about half the AUR? To answer these questions, we propose a new search-and-matching model in which (i) vacancies have incomplete information about workers' productivities, (ii) unemployed workers submit search qualities to signal their productivities, and (iii) vacancies decide a hiring criteria. This matching procedure generalizes typical all-pay auctions: workers pay their bids (search cost), and the employment opportunity is awarded to the worker according to the optimal auction schemes designed by vacancies. In a Bayesian Nash equilibrium, our model leads to a new class of search-and-matching model, in which a job-finding rate increases with the relative position in the search quality distribution (search relativity). This search relativity answers the two questions and is the key factor explaining almost entirely the heterogeneity in the unemployment rate.

KEYWORDS: Matching Function, All-Pay Auction, Unemployment Distribution.

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1 Introduction

At least since Keynes (1936), economists have been studying the determinants of the average wage rate and the aggregate unemployment rate (AUR). Over the past few decades, the distributions of wages, income, wealth, consumption, health, mortality, etc. have attracted considerable attention from both empirical and theoretical literatures.[1] And yet, perhaps surprisingly, works, especially theoretical ones, on the unemployment distribution and its properties are sparse. This paper purposes to uncover the key factor and mechanism explaining the unemployment distribution.

1.1 Two Seemingly Unrelated Features of Unemployment

Human capital is one of the key determinants of many labor market variables, such as wages and their distribution (Mincer, 1958; Ben-Porath, 1967; Griliches, 1977; Becker, 1994). Inspired by this literature, this section begins with the documentation of *two seemingly unrelated features* of unemployment by educational attainment, namely the statistical puzzle of unemployment and the magic number of "one-half".

The Statistical Puzzle of Unemployment. Figure 1 shows that unemployment rates are lower at higher educational levels in the United States. Each line represents the unemployment rate of each educational level during 1994-2018. The higher the educational level, the lower is the unemployment rate. While these five lines are completely segregated, this negative relationship holds over 25 years. We document in the online Appendix A that the negative association holds controlling individual characteristics and state and *Year*×*Month* fixed effects. Indeed, the documentation of this relationship has a long history (Ashenfelter and Ham, 1979; Mincer, 1991), and we extend the documentation period to 2018.[2]

Statistically, the AUR is likely lower at a higher fraction of high-educated workers in any economy. The AUR is the weighted average of the unemployment rate of each educational category, with the weight equal to the fraction of each category. While high-educated workers have a lower risk of unemployment than their low-educated counterparts, the weighted average of the unemployment rate, the AUR, is expected to decrease with the fraction of high-educated workers.

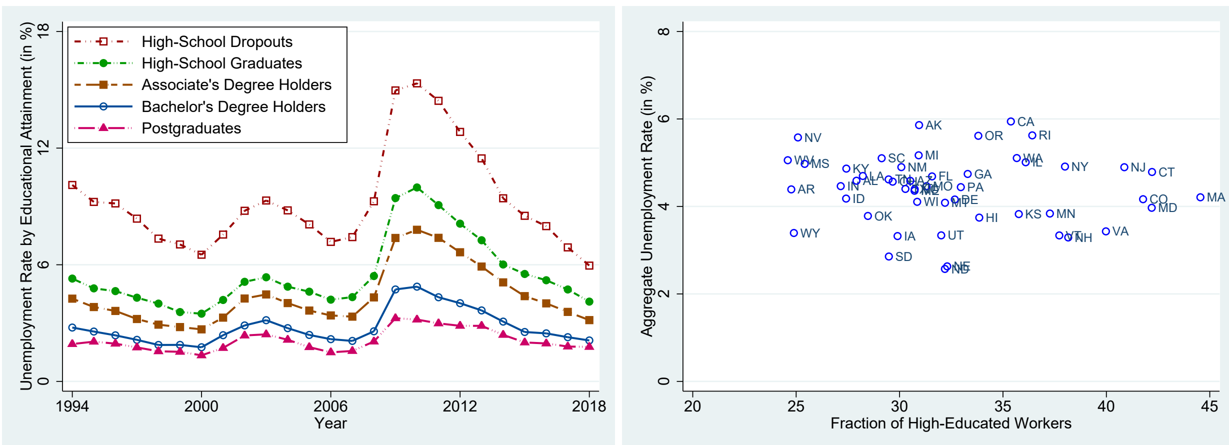
However, Figure 1 illustrates that the AUR and the fraction of high-educated workers are uncorrelated during 1994-2018. Moreover, we illustrate in the online Appendix A that (i) these two variables are uncorrelated in each year between 1994 and 2018, and (ii) their cyclical components are uncorrelated in each year of 1994-2018. Obviously, the increasing fraction of high-educated work-

[1] Readers who are interested in the empirical studies on wage distributions and its dynamics are referred to Juhn et al. (1993), DiNardo et al. (1996), Katz et al. (1999), Lemieux (2006), and Autor et al. (2008). Those who interested in the theoretical works are referred to Galor and Zeira (1993), Burdett and Mortensen (1998), Krusell and Smith (1998), Postel-Vinay and Robin (2002), Shi (2009), Hornstein et al. (2011), Moscarini and Postel-Vinay (2013), Jones and Kim (2014), and Gabaix et al. (2016).

[2] Also, Topel (1993) finds that men of lower wages have a higher risk of unemployment. While men with higher educational levels receive a higher average wage, his finding coheres with our documentation.

ers must have adjusted the unemployment rates of high- and/or low-educated workers to reconcile the two documentations in Figure 1. Interestingly, this adjustment always ceases at the situation, in which the AUR and the fraction of high-educated workers are uncorrelated. A natural question arises: *what economic mechanism makes the AUR and the fraction of high-educated workers always uncorrelated?*

Figure 1: The Statistical Puzzle of Unemployment



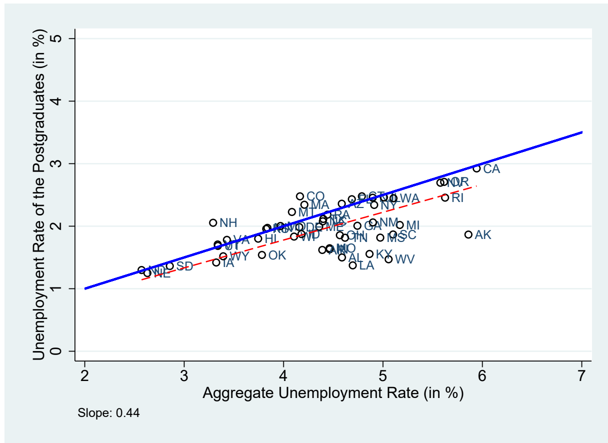
Notes: The left figure displays the unemployment rate by educational attainment in the United States. The right figure displays the correlation between the AUR and the fraction of high-educated workers. The high-educated are defined as those who are bachelor's degree holders and the postgraduates. Each dot illustrates the average aggregate unemployment rate and the average fraction of high-educated in each state during 1994-2018. DC is excluded because it is an outlier. Data are collected from the Current Population Survey. Samples are restricted to labor force participants aged 25-60. Samples below 25 years old are excluded because Ph.D holders are likely graduated and enter the labor market after 25.

The Magic Number of "One-Half". Figure 2 displays the correlation between the AUR and the unemployment rate of the postgraduates in the United States.[3] The dash line is the fitted value, and the solid line represents the mathematical relation in which the unemployment rate of the postgraduates is half the AUR. Clearly, the two lines are close to each other, and the observations lie around these two lines, suggesting that the unemployment rate of the postgraduates is about half the AUR. We document in the online Appendix A that the "one-half" can also be found in each year between 1994 and 2018. A natural question arises: *Why is the unemployment rate of the postgraduates about half the AUR? Can it be other numbers? If not, what economic mechanism creates the number of "one-half"?*

The purpose of this paper is twofold: to explain that the heterogeneity in the unemployment rate emerges mainly via a subtle relation between a job-finding rate and the distribution of productivity, and to show that the *two seemingly unrelated features* of unemployment are mainly attributable to this subtle relation. Despite a voluminous literature on the AUR (Ljungqvist and Sargent, 2008; Elsby

[3]This feature can also be found in Canada and the United Kingdom using the Canadian Labor Force Survey and the United Kingdom Labor Force Survey, respectively.

Figure 2: The Correlation between the AUR and the Unemployment Rate of the Postgraduates, 1994-2018



Notes: This figure displays the relationship between the AUR and the unemployment rate of postgraduates. The horizontal axis measures the average AUR of each state during 1994-2018. The vertical axis measures the average unemployment rate of the postgraduates in the corresponding state during 1994-2018. The dot line is the fitted value, in which the slope is 0.44. The solid line represents the unemployment rate of the postgraduates is half the AUR. Data are collected from the Current Population Survey 1994-2018. Samples are restricted to labor force participants aged 25-60.

et al., 2009; Davis et al., 2010; Shimer, 2012; Sahin et al., 2014), discussions on unemployment distributions are rare partly because the features of an unemployment distribution seem unrelated to each other. If the properties of the unemployment rate by educational attainment are mastered well, the properties of the AUR will be well understood, not vice versa. Therefore, to study the *two seemingly unrelated features* of unemployment not only opens the "black box" of the unemployment distribution, but it also complements the literature on the AUR, enhances our understanding of the functioning of the labor market, and provides insights how labor market policies could affect the unemployment distribution.

1.2 Search Relativity Theory and Related Literature

Ask anyone about the relationship between search effort and a job-finding rate, and what first comes to his or her mind is likely that a job-finding rate increases with search effort. Despite no economy-wide experiment, we may observe that those who search more intensively tend to get rid of unemployment faster. This may formulate our belief that a higher level of one's search effort increases his or her job-finding rate.

While most unemployed workers will accept one job offer only, much of the search effort may not be devoted to contact more jobs. Instead, applicants are dedicated to improve his/her search quality by polishing his/her resume, preparing his/her interview, gathering market information, etc. Since employers are likely uncertain about applicants' productivities, search quality may serve as a signal of their productivities to potential employers. Nevertheless, there is no guarantee that a particular type of signal implies a certain productivity level because less-productive workers may mimic more-productive ones. As a result, employers have to decide a hiring rule, and, simultaneously, unemployed workers choose their own search qualities strategically to employers.

Section 2 provides microfoundations on this search-and-matching process, which is indeed an all-pay auction. While employers are selling job opportunities, unemployed workers are bidders submitting their search qualities and all bidders are required to pay their costs. With more primitive assumptions, we generalize this all-pay auction by considering the optimal auction rules (Myerson, 1981; Riley and Samuelson, 1981; Bulow and Roberts, 1989) detailing resource allocation (i.e., hiring rules) to maximize employers' profits. The standard outcome in this literature is that bidders who place higher valuations of the object win the auction. Without assuming that more-productive workers place higher valuations of being hired, our model shows that their likelihoods of being hired remain higher. Our framework enriches our understanding of typical auction games: those who win auction games do not necessarily like the object the most; instead, their expected valuations of the object may be supermodular in their bid and their type. Hence, our theory is not restricted to risk-neutral bidders (i.e., unemployed workers) or sellers (i.e., employers) and allows for broad wage-setting mechanisms.

We find two interesting Bayesian Nash equilibria. The job-finding rates are identical regardless of workers' productivity in one of the equilibria—our model will reduce to a canonical random search-and-matching model (Pissarides, 2000; Petrongolo and Pissarides, 2001; Pissarides, 2009). In another equilibrium, vacancies will hire the one with the highest search quality. Therefore, the level of search quality does not determine one's job-finding rate because whether one surpasses others in terms of a search quality is the key determinant of who to be hired. As a result, one's job-finding rate increases with his/her percentile rank in the search quality distribution. We call this economic mechanism search relativity, which drives the heterogeneity in the job-finding rate.

Our finding contributes to the literature on the microfoundation of the matching function (Petrongolo and Pissarides, 2001; Stevens, 2007; Mortensen, 2009; Davis et al., 2013). While empirical evidence favors a Cobb-Douglas functional form (Petrongolo and Pissarides, 2001), Stevens (2007) provides microfoundations explaining why the matching function is approximately Cobb-Douglas. The derived matching function in Mortensen (2009), though not a CES matching function, preserves multiple appealing properties. While these two studies focus on the aggregate matching function, Davis et al. (2013) studies the role of vacancies in the hiring process and develops a matching function at the establishment level. Our microfoundation complements the literature by opening the black box of the matching function at the position level. It considers the heterogeneity of workers' productivity to derive the job-finding rate from more primitive assumptions about how hiring processes take place.

Our derived job-finding rate possesses many appealing features. First, it ranges between zero and one, which is not always the case in this literature. Second, it increases with educational level. Third, it increases with market tightness and its responsiveness is smaller at higher education levels. We will show that the heterogeneities in the job-finding rate and its responsiveness capture well the difference in the unemployment and its volatility by educational attainment, which can also be seen in Figure 1. Fourth, the aggregate job-finding rate increases with market tightness and is homogeneous of degree zero, which are implied by many other matching functions in this literature.

Section 3 incorporates this search relativity theory using a search-theoretic framework with heterogeneous workers. In pursuit of a higher job-finding rate, unemployed workers are required to have a slightly better resume, perform slightly better in a job interview, and devote slightly more time to improve their search quality than the candidates ranked slightly higher in the quality ladder. To increase one's search quality without climbing up an quality ladder does not enhance his/her job-finding rate. The determination of the optimal search quality is, therefore, challenging because it requires unemployed workers to consider both marginal search cost and whether an additional search effort allows them to climb up a quality ladder. The application of our generalized all-pay auction solves the problem.

Section 4 characterizes the steady-state equilibrium and explores the properties of the unemployment rate. According to the theory, increasing ones' search intensity level increases their relative positions in a quality ladder and thus their job-finding rates: their unemployment rates decline. Meanwhile, it creates a negative externality on others: there exist workers whose rank declines. Consequently, the rise in their search quality levels has no effect on the AUR; a higher fraction of workers, who put more efforts to improve their search quality, has no effect on the AUR. Analogously, since unemployed workers with a higher educational level tend to put more effort to search, their higher percentile rank in a quality ladder returns them higher job-finding rates—their unemployment rate is lower. Meanwhile, a higher fraction of high-educated workers has no effect on the AUR, explaining *the statistical puzzle of unemployment*.

The magic number of "one-half" is attributed to a statistical property: percentile ranks of any distribution are uniformly distributed between zero and one, with its average one-half. With the highest search benefit, the postgraduates tend to search the most intensively and thus rank top in a quality ladder. Their percentile rank in the distribution of a search quality is always one, twice the average of any economy. Consequently, the postgraduates' job-finding rate is twice the average, and thus they always get a job twice as fast as the average. Therefore, the unemployment rate of the postgraduates is about half the AUR, explaining the puzzling feature of *the magic number of "one-half"*.[4]

Section 5 evaluates the predictive power of our search relativity theory. The success of the theory in explaining the two features suggests that search relativity is one of the key determinants of a job-finding rate. Our model derives a novel formula to disaggregate an AUR into the unemployment rate

[4]We realize that the annual salary of the postgraduates, on average, is not the highest in some European countries: their search benefits are not the highest in the unemployment. In this case, their unemployment rates may not be half the AUR. Our theory may still be applicable in the sense that the unemployment rate of any educational group with the highest search benefits is half the AUR.

by educational attainment. The formula requires only two inputs, the AUR and the distribution of educational levels in the labor force, both of which are easily accessible. Using the United States Current Population Survey (US CPS) 1994-2018, we disaggregate the annual AUR into the unemployment rate by educational attainment in each of the 50 states. The accuracy of the formula is incredible: the null hypotheses, in which the actual and the derived educational unemployment rates are from the same distribution, cannot be rejected at any conventional level of significance in most states. Our model not only explains the *two seemingly unrelated features* of unemployment qualitatively, but also predicts the magnitudes of the unemployment rates well over the past two decades.

To the best of our knowledge, there exists no work that documents or explains the *two seemingly unrelated features* of unemployment. Cairo and Cajner (2016) is the closest work that studies the unemployment rate by educational attainment. Our paper differs from theirs in the objective. Focusing on the relationship between the level and the volatility of the unemployment rate, their paper succeeds in explaining how higher-educated workers experience lower unemployment rates and lower employment volatilities. In contrast, our paper explains the *two seemingly unrelated features* of unemployment and how an unemployment distribution emerges, focusing mainly on the relationship between the AUR and the unemployment rate by educational attainment. While Cairo and Cajner (2016) is an extension of the canonical search-theoretic model with on-the-job training and endogenous separations, our model incorporates search relativity into the canonical model. The derived relation between the AUR and the unemployment rate by educational attainment in our paper does not depend on the separation rate.

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