Human Capital Heterogeneity of the Unemployed and Jobless Recoveries

Nic Pusateri
Sacred Heart University

February 2023

The jobless recovery enigma remains largely unsolved. As a special case of broader unemployment, the term "jobless recovery" describes an economic recovery where output recovers—and even expands—yet employment growth remains anemic. While the effects of these prolonged recoveries are significant—from increased crime to a lifetime reduction in wages—they are not well understood. Building on the insights of labor market matching models that incorporate heterogeneity among workers, this paper sheds light on jobless recoveries, developing a first-of-its-kind index of human capital heterogeneity for the unemployed, and testing that index using of a Structural Vector Autoregression. I demonstrate that the extent to which unemployed human capital is heterogeneous and specific, rather than homogeneous and general, plays a key and under-appreciated role in the labor market; increases in human capital heterogeneity can account for between one-quarter to three-quarters of the joblessness of the past three recoveries in the pre-COVID era.

Email: pusaterin@sacredheart.edu. I am grateful to Carlos Ramirez, Garrett Jones, and Lawrence White for their helpful comments on many drafts. I also appreciate the very helpful comments from editors William Lastrapesas and Loukas Karabarbounis.

Published in *Journal of Macroeconomics* • Available at https://doi.org/10.1016/j.jmacro.2023.103505

1. Introduction

The jobless recovery enigma remains largely unsolved. As a special case of broader unemployment, jobless recoveries are fairly new. Coined in 1991 by Nicholas Perna, the term “jobless recovery” has been used to describe each of the last three traditional recoveries (1991, 2001, and 2009), where output recovered—and even expanded—yet employment growth remained anemic (Nasar 1991; Groshen and Potter 2003; Schmitt-Grohé and Uribe 2012).[1] While the effects of these prolonged recoveries are large, they are not well understood.

One effect of these prolonged recoveries is increased crime; Andresen (2013) finds a robust relationship between unemployment and criminal activity. Another detrimental effect of jobless recoveries is a significant reduction in lifetime earnings for labor market entrants; as potential entrants seek jobs during a jobless era, their reservation wages drop, and they are placed on a lower lifetime wage path (Kahn 2010). Additionally, prolonged jobless eras have significant policy implications for a wide range of policy issues—from unemployment benefits and retraining programs to fiscal and monetary stimulus.

What has caused these labor market changes? Why have recent employment recoveries lagged behind output? Proposed explanations for these slow, or jobless, recoveries include the increase in modern technology (Goos, Manning, and Salomons 2014; Michaels, Natraj, and Van Reenen 2014; Graetz and Michaels 2017), sectoral labor reallocation (Groshen and Potter 2003; Stock and Watson 2003; Chen et al. 2011; Burger and Schwartz 2015; Panovska 2017), an increase in just-in-time employment (Aaronson et al. 2004), a decrease in labor mobility (Frey 2009), an increase in globalization and offshoring (Waddle 2019), and even changes in educational job requirements (Carnevale, Smith, and Strohl 2013). Although each of these varied explanations offers a partial answer, they remain incomplete and contested.

To address this puzzle, I employ the literature on labor market frictions. Frictions in the matching market for labor have long been incorporated into standard models (Hosios 1990; Hall 1999; Mortensen and Pissarides 1999). Categorizing frictions as either amplifying or contributing to the persistence of shocks, Hall (1999) concludes that labor market frictions can help to explain how seemingly “small impulses” generate signif-

[1] This paper is explicitly focused on recoveries rather than recessions. As such, the 2021 COVID-19 recovery that is still underway is currently beyond the scope of this work and will not be addressed. Additionally, Lenza and Primiceri (2022) warn of using COVID-19 data in parameter estimation and suggest, at this point, dropping such data is appropriate.

icant contractions (Hall 1999, p. 41). While much work improved our understanding of the effects of these frictions, the extent to which worker heterogeneity interacts with and magnifies them is less well understood. Pries (2008), Bils, Chang, and Kim (2011), Epstein (2012), Ravenna and Walsh (2012, 2014), Chassamboulli (2013), Mueller (2017), and Gregory, Menzio, and Wiczer (2020) have all demonstrated the importance of worker heterogeneity in labor market models. While conclusions have differed (from Pries (2008) suggesting that worker heterogeneity is critical to explaining slow recoveries to Bils, Chang, and Kim (2011) suggesting that heterogeneity reduces separations and unemployment), a strong consensus has emerged that worker heterogeneity is important to the understanding of labor market frictions.

In addition to labor market frictions, the literature on "capital-based macroeconomics" offers valuable insight into the jobless recovery enigma. Those who work within capital-based macro have long held that physical capital is heterogeneous and multi-specific. They contend that capital should not be considered as a homogeneous "K"—as is often the case in macroeconomic modeling (Solow 1957)—but rather as a structure of production where the reallocation of capital is costly due to its specificity and heterogeneity (Böhm-Bawerk 1890, 1891; Hayek 1950; Garrison 2002). This insight has only recently been applied to human (rather than physical) capital and has yet to be empirically examined (Boettke and Luther 2012; Burns 2018).

Building on the insights of labor market frictions and capital-based macroeconomics, I investigate the question of jobless recoveries and suggest that the extent to which unemployed human capital is heterogeneous and specific, rather than homogeneous and general, plays a key, and underappreciated, role in the labor market frictions that drive jobless recoveries. My suggestion is not entirely unique. Using a basic labor-market matching model to analyze productivity heterogeneity among the unemployed, Pries (2008, p. 675) finds that, "relatively small cyclical changes in the composition of unemployment can have a significant effect on firms' vacancy creation decisions, and thus on job-finding rates and the unemployment rate." Similarly, Ravenna and Walsh (2012) report that increases in worker heterogeneity significantly contribute to the slow pace of recoveries. Further, Grigsby (2022) finds that the employment dynamics of the Great Recession can be explained by skill heterogeneity in the absence of frictions, highlighting the importance of skill heterogeneity. While not based on human capital heterogeneity specifically, the current labor market matching literature provides a strong theoretical basis for my empirical analysis.

To empirically demonstrate the importance of human capital heterogeneity in the US, I develop a first-of-its-kind index of human capital heterogeneity. Using monthly Current Population Survey (CPS) micro-data, I capture the diversity of skills among the unemployed to build an index of human capital heterogeneity, a valuable addition to the literature, for it is the only empirical measurement of aggregate skill heterogeneity for the unemployed over time. This measure quantifies the diversity of skills among those searching for jobs and allows me to examine the impact of both trends and fluctuations in the diversity of skills on various labor market outcomes. While applied to the question of jobless recoveries herein, this index has many other useful applications.

Using the Unemployed Human Capital Heterogeneity Index ($\mathrm{HCHI_U}$), I test the importance of human capital heterogeneity on labor market outcomes using a structural vector autoregression (SVAR), which provides the first empirical analysis of the how human capital heterogeneity has contributed to recent jobless recoveries. While many labor market models recognize worker heterogeneity (Bingley and Westergaard-Nielsen 2003; Pries 2008; Macaluso 2017; Hall and Schulhofer-Wohl 2018; Mueller et al. 2018; Grigsby 2022, to name a few), none has explicitly considered the aggregate level of human capital heterogeneity of the unemployed as an important labor market variable. The recent works of Boettke and Luther (2012) and Burns (2018) indicate an important role for human capital heterogeneity, but they perform no empirical test. Macaluso (2017) provides both a theoretical and an empirical investigation into the importance of skill remoteness (a concept that implicitly relies on human capital heterogeneity), however, Macaluso focuses on occupational mismatch rather than heterogeneity and does not link the analysis to jobless recoveries. By testing the theoretical insights of Pries (2008) Boettke and Luther (2012), and Burns (2018), I provide a valuable contribution to the extant literature.

My results show that the movements in human capital heterogeneity for the unemployed are strongly pro-cyclical and that increases in unemployed human capital heterogeneity cause significant decreases in both employment and vacancies. Using counter-factual analysis, I estimate that increases in human capital heterogeneity can account for one-third of the joblessness of the 1991 recovery, one-quarter of the joblessness in the 2001 recovery, three-quarters of the joblessness in the 2009 recovery, suggesting a significant role for Unemployed Human Capital Heterogeneity Index ($\mathrm{HCHI_U}$) as a labor market friction.

With high levels of occupational dispersion and increased $\mathrm{HCHI_U}$ volatility, labor market policy may help mitigate the effects of these increased frictions. Beyond the direct effect, these frictions have also been found to contribute to increased monoposony power (Dube, Lester, and Reich 2011; Dube 2019) and decreased wages (Papageorgiou 2022). Removing policies that generate artificial frictions—e.g., occupational licensing,—adopting new policies that reduce frictions—e.g., hiring subsidies and unemployment benefits, which both been shown to have some small, positive effects (Yashiv 2004),—or implementing policies that work with the realities of the market—e.g., well-designed minimum wage policies—provide potentially beneficial avenues to explore.

2. Jobless Recoveries

While the term "jobless recovery" is widely used in popular media, policy, and academic literature, the term's validity is still debated. Galí, Smets, and Wouters (2012) examine the relationship between employment and output, finding no change in the relationship between unemployment and gross domestic product (GDP) after 1990, suggesting the term "slow recoveries" is more appropriate than "jobless recoveries." Moreover, Lazear and Spletzer (2012) find no evidence structural unemployment changed over the last few recoveries. While debated, most of the literature supports the suggestion that the past three recoveries—1991, 2001, and 2009—were indeed jobless. However, before investigating how human capital heterogeneity is tied to jobless recoveries, I first demonstrate that this issue is critical.

Following Galí, Smets, and Wouters (2012), I test for a divergence in the relationship between unemployment and GDP in the jobless recovery era using an "Okun's law regression" for US data between 1948Q1 and 2019Q4 (Okun 1962).[2] In Equation (1) I test the same specification proposed by Galí, Smets, and Wouters with the updated sample; in Equation (2) I test for a divergence using 1984Q4 rather than 1990Q1 as suggested by DeNicco and Laincz (2018).[3] Equations (1) and (2) are estimated using ordinary least squares (OLS), viz,

$$\Delta u_t = \underset{(0.029)}{0.23}^{***} - \underset{(0.023)}{0.27}^{***}\Delta y_t - \underset{(0.032)}{0.06}^{**} dum90_t * \Delta y_t \tag{1}$$

[2] Galí, Smets, and Wouters (2012) estimated Equation (1) for the sample 1948Q1 to 2011Q4; here, I extend the sample to 2019Q4.

[3] Equations (1) and (2) robust standard errors in parentheses; * $p < .1$, ** $p < .05$, *** $p < .01$.

$$\Delta u_t = \underset{(0.030)}{0.24}^{***} - \underset{(0.022)}{0.27}^{***}\Delta y_t - \underset{(0.031)}{0.07}^{***} dum84_t * \Delta y_t \tag{2}$$

where Δu_t is the change in the civilian unemployment rate; Δy_t is the seasonally adjusted percentage change in real GDP from the preceding period; $dum90$ is an indicator variable equaling 1 for quarters 1990Q1–2017Q4, 0 otherwise; and, $dum84$ is an indicator variable equaling 1 for quarters 1984Q4–2017Q4, 0 otherwise.

Contrary to Galí, Smets, and Wouters (2012), I find robust evidence of a change in the relationship between unemployment and GDP, suggesting "jobless", rather than simply "slow" recoveries.[4] While not definitive, the significant negative coefficient on $dum90_t * \Delta y_t$ and $dum84_t * \Delta y_t$ suggest that the relationship between unemployment and GDP after 1990 (1984) has changed.

Having established that the relationship between unemployment and GDP growth changed in the in jobless recovery era, I next examine the behavior of employment during recoveries. Updating Groshen and Potter (2003), Schreft and Singh (2003), and Semmler, Madrick, and Khemraj (2006) I calculate the percentage change from the trough of the recovery in total nonfarm payroll. Figure 1 displays the trend of each recovery before and after the jobless era.[5]

Figure 1 clearly demonstrates the post-1984 divergence of recovery payroll. Each shaded line on the graph shows the percentage change in employment from the trough of the recession for a given recovery. The shaded, orange lines display this statistic for recoveries before 1984, whereas the shaded, dashed, blue lines show this statistic for recoveries after 1984, the structural breakpoint proposed by DeNicco and Laincz (2018). Averages for the two periods are shown with the bold, orange and bold, dashed, blue lines, respectively. The clustering of employment data for recoveries before and after 1984 suggest a structural change in the behavior of employment. Furthermore, the vertical distance between the average recoveries pre-1984 and post-1984 indicates the jobless nature of recent recoveries.

Contrary to Galí, Smets, and Wouters (2012) and Lazear and Spletzer (2012), Figure 1 suggests that the recoveries after 1984 have indeed been "jobless." While Equations (1) and (2) and Figure 1 do not provide insight as to the cause of the recent jobless recoveries, they do establish that the phenomenon needs further investigation.

[4]These results differ from Galí, Smets, and Wouters (2012) due to the extended sample and revised GDP numbers.

[5]The recovery of 1980 is excluded, see Figure 1 notes.

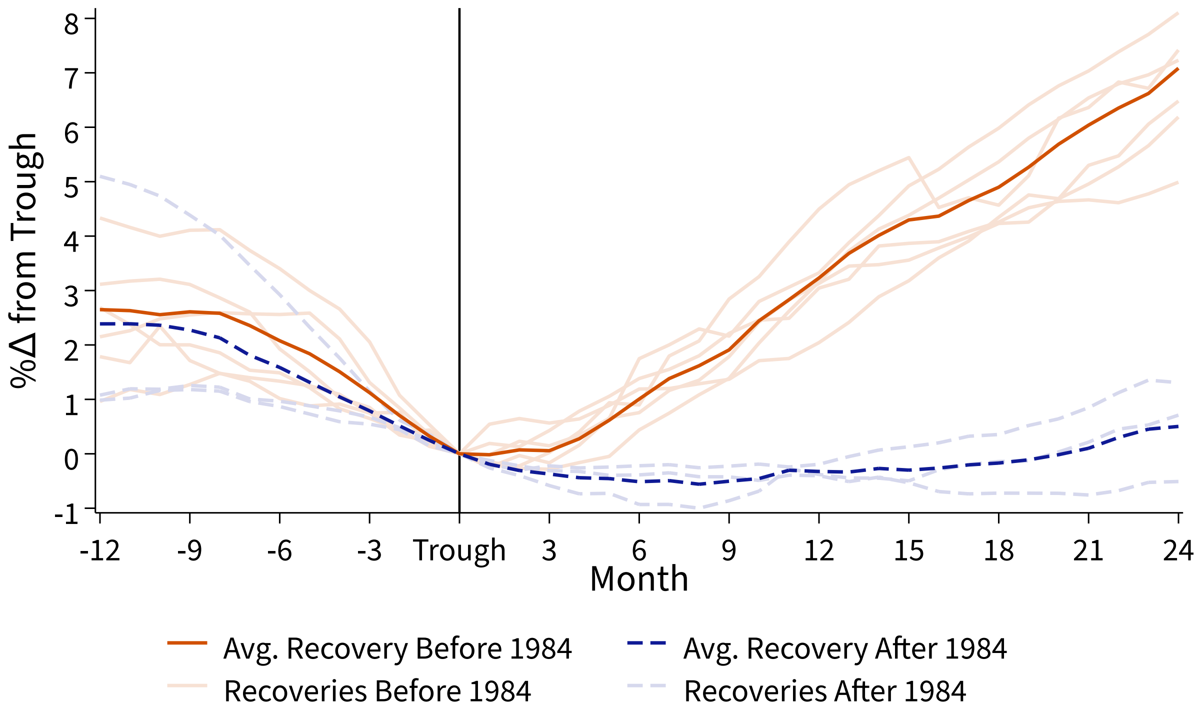

FIGURE 1. Total Nonfarm Payroll during Recovery

Source: US Bureau of Labor Statistics; NBER; author's calculation. *Data*: Total nonfarm payroll, thousands of persons, seasonally adjusted. *Notes*: Included recoveries (individual statistics plotted in shaded color): 1954, 1958, 1961, 1970, 1975, 1982, 1991, 2001, and 2009; the recovery of 1980 was excluded due to the double dip nature of the 1982 recession. "Trough" is defined as the final month of the recession.

3. Human Capital Heterogeneity and Specificity

Different jobs require different skills. Just as physical capital differs in form and function, e.g., "a tractor is not a hammer" as Powell (2010, p. 124) entertainingly states, human capital also differs in form and function, e.g., an economist is not a registered nurse. The knowledge and skills required for the two occupations of registered nurse and economist are specific and distinct. The Occupational Information Network (O*NET) lists the top five skills for registered nurses as: (1) active listening, (2) social perceptiveness, (3) service orientation, (4) speaking, and (5) coordination. O*NET lists the top five skills for economist as: (1) active listening, (2) critical thinking, (3) mathematics, (4) speaking, and (5) writing. Although these occupations overlap in active listening[6] and speaking,

[6]Anyone who has recently attended an economics seminar may debate "active listening" as the top skill for economist.

clearly the skills required differ.[7] The knowledge requirements listed by O*NET further demonstrate the occupational distance. The top five O*NET knowledge requirements for registered nurses are: (1) medicine and dentistry, (2) customer and personal service, (3) psychology, (4) English language, and (5) education and training; whereas for economist the top five are: (1) economics and accounting, (2) mathematics, (3) English language, (4) computers and electronics, and (5) education and training (O*NET 2018). Again, these knowledge requirements have some overlap (English language and education and training), however, like skills, the differences capture the heterogeneity of human capital between registered nurses and economists. These skill differences are the focus of this section.

Such differences in skill sets are an important factor in the labor market. From the firm's perspective, hiring a registered nurse to produce an economic study would not be prudent; the potential employee's skills must match the skills required in the vacant position. Similarly, for an unemployed economist, a job opening for a registered nurse is not a promising employment opportunity. This simple logic implies, *ceteris paribus*, that an increase in skill diversity and specificity (what I have termed *human capital heterogeneity*) among job seekers reduces the probability of a successful labor market match.[8] In this way, human capital heterogeneity is itself a labor market friction, operating through increasing signaling, search, and hiring costs.

To illustrate, consider two simple economies. The first economy has one good (good "A") and one production process so every worker in this economy only needs one set of skills to produce the single good. The second is an economy with two goods (goods "A" and "B") with different production processes. Workers who produce good "A" must learn different skills than workers who produce good "B." Learning the required skills is costly, thus switching between producing "A" and "B" is costly.[9] The first economy can be considered a "one island" economy whereas the second is a classic "two island" economy. Pilossoph (2013) and Garin, Pries, and Sims (2018) both develop such a "two

[7] Although the top required skills differ between registered nurses and economists, this does not mean that registered nurses do not benefit from being skilled in mathmatics or economists do not benefit from being skilled in social perceptiveness.

[8] Pries (2008) and Ravenna and Walsh (2012, 2014) demonstrate a such a matching friction with diversity in productivity and skills; however, these models can conceptually be extended to apply to human capital. Rather than duplicate such a model here, I point the reader to Pries (2008).

[9] These cost capture both pecuniary and non-pecuniary cost of switching occupations. Empirically, switching occupations carries a large wage cut from loss of tenure (Hersch and Reagan 1990; Topel 1991). Additionally, there is significant psychological evidence of strong identification with occupation, especially when comparing current identification with alternative occupational identifications, that increases the non-pecuniary cost of changing occupations (Miller and Wager 1971; Greene 1978; Van Dick et al. 2005).

island" model, based on the model of Lucas and Prescott (1978), to demonstrate the importance of sectoral shocks in the labor market. In the first, one island economy, the stock of human capital is perfectly homogeneous. If you were to lose your job producing good "A" and seek another job, you have the requisite skills and knowledge, as all jobs have the same skill and knowledge requirements. In the second, two island economy, if workers were to lose their jobs producing "A", they must search for other "A" producing jobs or acquire the skills and knowledge to produce "B"; assuming a 50/50 split between the share of the two occupations, there are, by construction, only half as many "A" producing jobs as there would be if all jobs were "A" producing, reducing the match probability for those in this model.[10] This two island economy demonstrates how of the level of human capital heterogeneity introduces a friction for job seekers; the probability of being matched with a job has decreased in the two island economy due to the increased heterogeneity of human capital. In this example, the extent to which the human capital stock is more heterogeneous can be measured as some function of the share of those in occupations producing "A" or "B."

In a far more elegant model, Pries (2008) incorporates productivity heterogeneity into the standard Mortensen and Pissarides (1994) model of labor markets. Solving Shimer's 2005 puzzle, Pries (2008) can account for the observed volatility in the job-finding rate, the vacancy unemployment ratio, and the unemployment rate by incorporating worker heterogeneity. He concludes that incorporating heterogeneity in labor market models better explains the data of slow, or jobless, recoveries.

Accounting for horizontal worker-side heterogeneity in production capacity, Epstein (2012) demonstrates that such heterogeneity "can potentially help explain both the majority of the V/U ratios slow-moving adjustment properties and the majority of its elasticity with respect to output per worker" (Epstein 2012, p. 2). With heterogeneity in match quality and the ability of workers to search for jobs in which they are less than ideally matched, Epstein accounts for the empirical observance of sluggish V/U movement.

In an important and related paper, Ravenna and Walsh (2012) incorporate heterogeneity among workers labor market models and can account for the slow recovery of the Great Recession. In a follow-up paper, they conclude that allowing for heterogeneity in the pool of unemployed mimics "the effects of a decline in the efficiency of the

[10] The mechanism for this reduction in match probability is increased signaling, search, and hiring cost given the increased heterogeneity.

matching function" (Ravenna and Walsh 2014, p. 38). These studies demonstrate the potential importance of human capital heterogeneity's effect on the matching function.

Combining these insights with the simple two island model above, heterogeneity in the human capital of the unemployed can potentially to play an important role in the labor market. As heterogeneity increases, frictions rise and the amplitude and persistence of unemployment shocks is extended.

Building on this literature, I construct an empirical measure of the aggregate level of US human capital heterogeneity. Although the worker heterogeneity in the theoretical literature above is largely based on unobserved characteristics, observable heterogeneity also contributes to labor market frictions (Mueller 2017).

3.1. Empirically Measuring Unemployed Human Capital Heterogeneity

To measure human capital heterogeneity of the unemployed, the question of what is to be measured must first be addressed. Following the literature, I consider the unemployed, rather than the employed, when examining labor market frictions driven by heterogeneity (Pries 2008; Epstein 2012; Ravenna and Walsh 2012, 2014). Although measuring the level of human capital heterogeneity of the entire labor force is also of interest, it is beyond the scope of the present paper. Motivated by the two-island example above, and following the literature on specific human capital, I measure skills at the occupational level (Kambourov and Manovskii 2009a,b; Gathmann and Schönberg 2010). In the two island economy, the heterogeneity and specificity of skill is revealed by the occupation of the workers who produce either good "A" or "B." Although occupation is not a direct measure of human capital, fine-grained occupational data do capture the diversity of skills and knowledge (e.g., the skill and knowledge differences between an economist and a registered nurse). While human capital is traditionally measured by education, occupational data provide a more accurate picture of the skills and knowledge of individuals as there data capture the skills and knowledge used rather than the educational signal obtained (Caplan 2018). Robst (2007) reports that almost half of students work in an occupation that is unrelated to their college major, suggesting that measuring occupation, rather than education, is preferred. Additionally, occupational data have the advantage of frequent measurement, allowing for higher-frequency analysis than do educational data.

To index the occupational data, I use the inverse of a Herfindahl-Hirschman Index (HHI) (Hirschman 1945; Herfindahl 1950). While the HHI is most often used to measure firm concentration or competition within an industry (Gutiérrez and Philippon 2017), an HHI simply measures concentration. Consequently, the inverse of an HHI measures dispersion or heterogeneity.[11]

Applying this measure of dispersion to the occupations of the unemployed, I generate a measure of their skill dispersion—the Unemployed Human Capital Heterogeneity Index ($\mathrm{HCHI_U}$), viz,

$$\mathrm{HCHI}_{\mathrm{U},t} = \left(\sum_{i=1}^{N} s_{i,t}^{2} \right)^{-1} \tag{3}$$

where s is the share of individuals in i occupation at time t from 1 to N occupations.

Shares of occupations provide a fine-grained picture of economic activity. Higher concentrations of a given occupational share correspond to more homogeneous human capital, whereas more dispersed employment by occupation corresponds to greater human capital heterogeneity. Thus, low values of the $\mathrm{HCHI_U}$ reveal a relatively homogeneous stock of unemployed human capital and high values of the $\mathrm{HCHI_U}$ indicate a relatively heterogeneous stock of unemployed human capital. Conceptually, $\mathrm{HCHI_U} \in \{1, N\}$, where 1 represents perfect homogeneity (all unemployed labor belong to a single occupation) and N represents perfect heterogeneity throughout N occupations (all unemployed labor perfectly equally dispersed among N occupations).

Consider the following scenarios. If all unemployed workers were of the same occupation, the $\mathrm{HCHI_U}$ would be 1, i.e., perfect homogeneity exist in the unemployed stock of human capital. If the unemployed pool of workers were evenly split between two occupations, the $\mathrm{HCHI_U}$ would be 2; if the unemployed pool of workers were evenly split between five occupations, the $\mathrm{HCHI_U}$ would be 5. Thus, the maximum of $\mathrm{HCHI_U} = N$, where N is the total number of occupations.

Empirically, the $\mathrm{HCHI_U}$ is calculated using US Current Population Survey (CPS) microdata from 1976M1 to 2018M12, which uses observations where the respondent was currently unemployed and reported an occupation.[12,13] Although occupational coding has changed over time, this measure uses the occupation coding variable available

[11] This measure of heterogeneity is well known in ecology as an Inverse Simpson's Index (Simpson 1949).

[12] Table A1, shown in the Appendix, lists the top and bottom five occupations by share over time. This table demonstrates the key contributors to the movement of the index over time.

[13] While the respondents are unemployed, they are able to report an occupation. For those that do not report a current occupation but had reported an occupation prior to unemployment, I assume that a worker's skills are equal to their prior job's skills, following Gathmann and Schönberg (2010); Pavan (2011).

at the time of the survey (e.g., occ1970 for a survey conducted in 1976M1, occ1990 for a survey conducted in 1992m1, and occ2010 for a survey conducted in 2015m1), and the codes are consistent within a month across respondents, permitting intra-month aggregation. This method allows for the growing number of occupations, a significant contributor to the heterogeneity over time, to factor into the analysis.[14,15,16] To control for seasonal effects, I seasonally adjusted the HCHI_U using X-13ARIMA-SEATS. Finally, this measure is adjusted for a change in coding procedure that occurred in 1994.[17]

3.2. Exploring the Human Capital Heterogeneity Index

Figure 2 displays the HCHI_U for 1976M1–2018M12. The index contains interesting low- and high-frequency features. One low-frequency feature is the small, positive trend over time which indicates that the heterogeneity of the unemployed has slowly increased from the mid-1970s to the late 2010s. Examining the construction of the index (Equation (3)) this increase may be the result of two potential factors: first, a realized increase in the number of occupations among the unemployed (ΔN), and second, a more even distribution of unemployed in each occupation (Δs). To better understand the movements of HCHI_U I explore these two factors in turn.

If the number of new job types exceeds the number of job types that are disappearing, potential heterogeneity increases. While the number of potential occupation codes in the CPS data has increased over time (from 444 in 1976M1 to 569 in 2011M1, the latest update in the relevant sample), this does not imply, by construction, a higher HCHI_U for two reasons. First, zero shares are not counted in an HHI, thus an increase in the potential occupations must be realized in actual occupational responses for the increase to alter the HCHI_U. Second, the HCHI_U is an index of the unemployed, not the employed. The increase in potential occupations for the employed would have to be realized in the unemployed sample to affect the index. While the US is gaining more occupations, such as software developers or biomedical engineers (2010 occupational codes 1020 and 1340 respectively), than it is losing, e.g., occupations such as telegraph

[14]The index is qualitatively similar when using the occ2010 codes for all respondents from 1976 through 2018.

[15]If standard, 2-digit SOC codes were used, they would mask important changes in the underlying occupational structure that contribute to heterogeneity over time.

[16]Specifically, the number of occupations listed within the data rises from 444 (occ1970) to 569 (occ2010) over the course of the sample, a 28% increase.

[17]Kambourov and Manovskii (2013) demonstrate the issues associated with the pre-dependent coding procedure used before 1994 for monthly CPS data. The index was adjusted to remove the discontinuous jump associated with this procedural change that occurred at the time of the change.

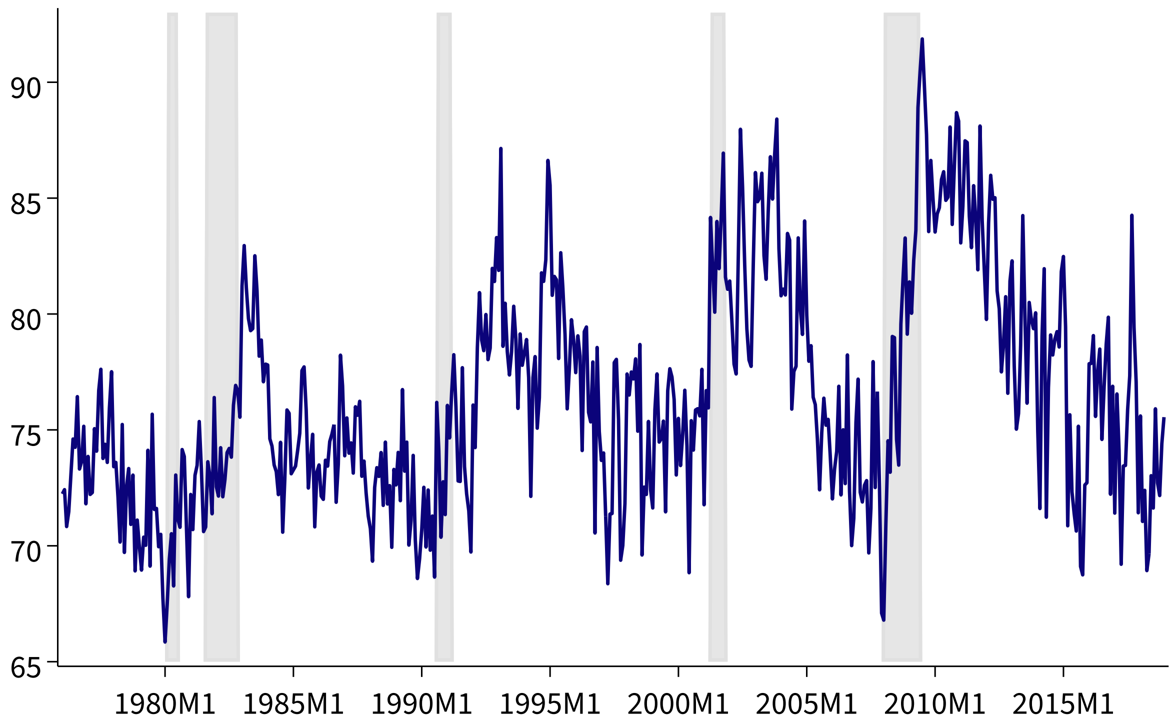

FIGURE 2. Human Capital Heterogeneity Index

Source: Current Population Survey; author's calculation. *Note*: Human Capital Heterogeneity Index of the Unemployed for 1976M1–2018M12 seasonally adjusted, viz, Equation (3); $HCHI_U \in \{1, N\}$, where 1 represents perfect homogeneity and N represents perfect heterogeneity among N occupations; grey shaded area represents NBER recession dates. Over this sample, the mean is 76.4, the standard deviation is 4.9, the minimum is 65.8, and the maximum is 91.9.

operators or newsboys (1970 occupational codes 384 and 266 respectively), this increase in occupational diversity must realized among the unemployed for the index to increase.

To evaluate this first, potential driver of the increase in the $\mathrm{HCHI_U}$, Figure 3 plots the fraction of potential occupation present among the unemployed. Specifically, it shows the unique occupation among the unemployed at time t divided by the total number of potential occupations at time t (as measured by the contemporaneous occupational codes from CPS). Figure 3 reveals that the increase in the $\mathrm{HCHI_U}$ is not being driven by increases in N, but rather must be being driven by a more even distribution of the unemployed within a given set of occupations. In fact, the decadal average of the unique number of occupations among the unemployed is remarkably stable from the 1980s through the 2010s, with each decadal mean falling within a range of 10 occupations.

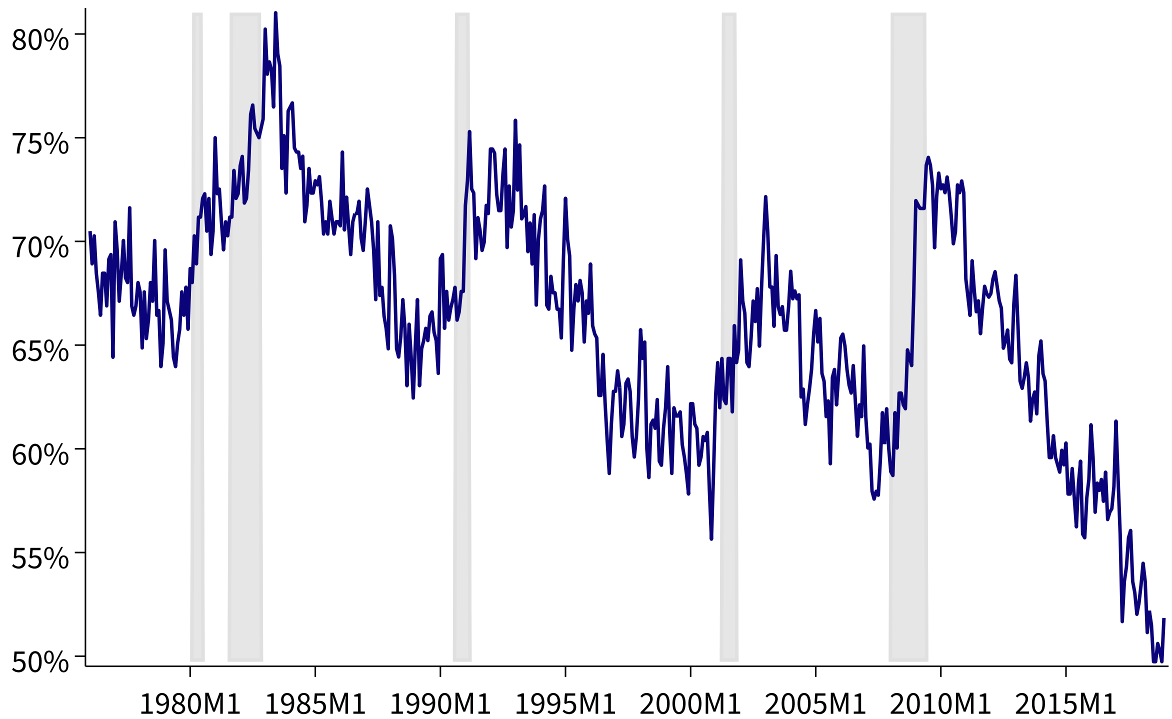

FIGURE 3. Fraction of Potential Occupations Present Among Unemployed

Source: Current Population Survey; author's calculation. *Note*: Data for 1976M1–2018M12. Series represents unique observed occupation among the unemployed divided by the potential occupations from the CPS *occ* variable in a given month.

Together, Equation (3) and Figure 3 suggest that the increase in the HCHI_U is being driven by a an increasingly even distribution of the unemployed among a fairly stable number of occupations.

Another low-frequency feature is the increase in volatility over time. The recessions, and subsequent recoveries, of 2001 and 2007 demonstrate far greater volatility than those of 1900, 1982, or 1991. This increased volatility is likely a consequence of the general positive trend: as more general human capital diversity exists, the potential swings in the HCHI_U are greater.

Figure 4 displays the HCHI_U by decade, revealing these low-frequency features. The positive trend of the HCHI_U as well as its increased volatility are readily apparent. Additionally, the similarity of the 1970s and 1980s, and the subsequent difference of the later years—the 1990s, 2000s, and 2010s—stand out; the upper quartile of the distribution in the 1970s and 1980s is well below the mean of the 1990s, 2000s and 2010s. Furthermore, the distribution of the 1990s, 2000s and 2010s is far wider than than of the earlier decades.

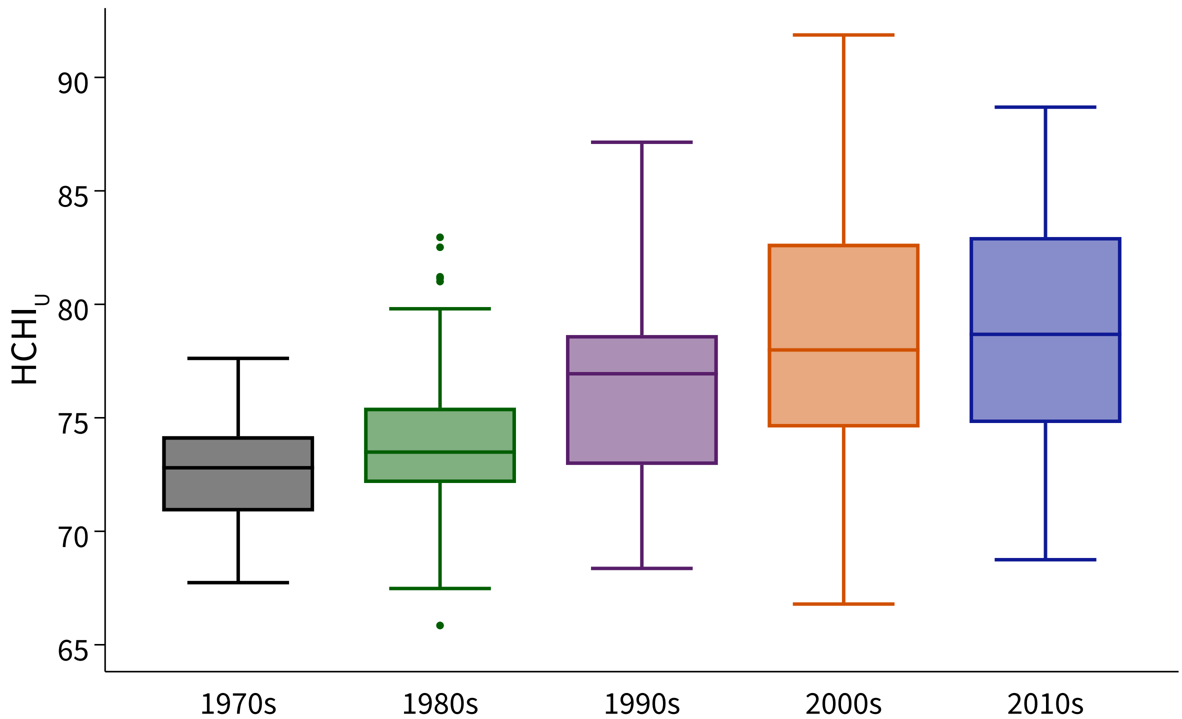

FIGURE 4. Human Capital Heterogeneity Index by Decade

Source: Current Population Survey; author's calculation. *Note*: Human Capital Heterogeneity Index of the Unemployed for 1976M1–2018M12 seasonally adjusted, viz, Equation (3); $HCHI_U \in \{1, N\}$, where 1 represents perfect homogeneity and ∞ represents perfect heterogeneity.

Tables 1 and 2 formalize the extent to which the volatility of the HCHI_U has increased over time. Specifically, Table 1 displays the ratio of the standard deviation of the HCHI_U before and after 1984M9, the break-point suggested by DeNicco and Laincz (2018).[18] Ratios near one represent no change in volatility whereas ratios below one suggest the pre-jobless era was less volatile than the post-jobless era. With a ratio of 0.68, the HCHI_U demonstrates a noted increase in volatility after 1984M9.

Table 2 formalizes the simple measure of Table 1 with a standard volatility regression. Table 2 displays ordinary least squares (OLS) regressions of the absolute value of the deviation of the index from its period mean (pre or post 1984M9), on a constant and a dummy for the jobless era (1984M9–2018M12), with and without a control dummy for NBER recessions. The results from Table 2 confirm those from Table 1; the HCHI_U displays deferentially volatile behavior in the jobless era as seen by a significant coefficient

[18] Specifically, DeNicco and Laincz (2018) suggest that the break-point is 1984Q4, which I translate into monthly data as 1984M9.

Table 1. Relative Volatility

	$\text{std}(x)^{pre-84} / \text{std}(x)^{post-84}$
HCHI_U	0.68

Source: See Table A2. *Notes*: Standard deviations are computed relative to the jobless era given by 1984M9–2018M12. The pre-84 period is 1976M1–1984M8.

on the variable "post84." This finding is robust to the inclusion of a recession indicator variable. Equations (1) and (2) and Tables 1 and 2 tell a story of increased volatility in the jobless era for the HCHI_U.

Table 2. Volatility Regression

	post84	nber	_cons
HCHI_U	1.49***		2.51***
	(.25)		(.21)
HCHI_U	1.54***	0.38	2.43***
	(.27)	(.39)	(.27)

Source: See Table A2. *Notes*: The regression run is $|x - \bar{x}| = \alpha + \beta_1 Post84 + \beta_2 NBER + \epsilon$; robust standard errors in parentheses; * $p < .1$, ** $p < .05$, *** $p < .01$; the full sample period is 1976M1–2018M12, the two subsample periods are 1976M1-1984M8 and 1984M9–2018M12.

In addition to the interesting low-frequency features above, one high-frequency feature of interest is the index's strong counter-cyclical behavior. The HCHI_U generally increases during recessions and falls throughout recoveries, a behavior that aligns with both intuition and the theoretical models of Pries (2008), Epstein (2012), and Ravenna and Walsh (2012, 2014). As workers are separated from jobs, the pool of unemployed grows, causing an increase in the heterogeneity of workers as workers from various occupations are separated. Intuitively, separations that occur throughout a recession are not confined to a single occupation; many occupations experience separations during a recession. Figure 3 demonstrates that during recession the number of occupations present among the unemployed increases. This increase in the number of realized occupations increases heterogeneity and drives the index up.

The low- and high-frequency features of the human capital heterogeneity index provide insights into movements in the broader labor market that suggest an important role for human capital heterogeneity.

4. Empirical Approach

4.1. Sectoral Shocks

When constructing an empirical model for labor market movements, sectoral shocks must be incorporated, as their importance has been well established (Stock and Watson 2003; Burger and Schwartz 2015; Panovska 2017). My analysis of the impact of human capital heterogeneity (HCH) on the labor market controls for sectoral shocks following Mehrotra and Sergeyev (2013). To do this, I first estimate an approximate factor model using sector employment data from the BLS Current Employment Statistics survey. With share of employment by sector for logging; mining; construction; durable goods; non-durable goods; wholesale trade; retail trade; rail transportation; utilities; information; financial activities; professional and business services; education and health services; leisure and hospitality; and other services, I estimate Equation (4) for 1976M1–2018M12, viz,

$$\eta_t = \boldsymbol{\lambda}_t F_t + \epsilon_t \tag{4}$$

where η_t is a $N \times 1$ vector of share of employment by sector; $\boldsymbol{\lambda}_t$ is a $N \times K$ matrix of factor loadings; F is a $K \times 1$ vector of factors; and, ϵ_t is a $N \times 1$ vector of shocks. The residual, ϵ_t, captures the sector-specific shocks of interest.

Using, ϵ_t, I create an index of sectoral shocks overtime, viz,

$$S_t^{sector} = \frac{1}{K}\left(\sum_{i=1}^{K} \epsilon_{i,t}^2\right)^{\frac{1}{2}} \tag{5}$$

where S_t^{sector} is measured as sectoral shocks in standard deviation units. This variable captures the sector-specific movements in employment rather than part of larger, multi-sector movements.

4.2. SVAR Model

The key structural model of interest for this paper is displayed in Equation (6), viz,

$$\boldsymbol{A}\mathrm{Y}_t = \boldsymbol{B}(L)\,\mathrm{Y}_{t-1} + \gamma S_t^{sector} + e_t \tag{6}$$

where $\boldsymbol{A}$ is a 7×7 matrix of the contemporaneous effects; $\mathrm{Y}_t \equiv \left[y_t, p_t, i_t, v_t, w_t, h_t, l_t\right]'$ is a seven-dimensional vector of Output (y_t), Prices (p_t), Interest Rates (i_t), Vacancies (v_t), Hours (w_t), $\mathrm{HCHI_U}$ (h_t), and Employment (l_t); $\boldsymbol{B}$ is 7×7 matrix of polynomials in the lag operator, L; S_t^{sector} is an exogenous index of sectoral shocks calculated according to Equation (5); and finally, e_t is a vector of structural shocks.

Following Bernanke (1986, p. 52), I treat the structural shocks, e_t, "as 'primitive' exogenous forces, not directly observed by the econometrician, which buffet the system and cause oscillations. Because these shocks are primitive, i.e., they do not have common causes, it is natural to treat them as approximately uncorrelated." This allows the structural model in Equation (6) to be rewritten as a reduced form vector autoregression (VAR), viz,

$$\mathrm{Y}_t = \boldsymbol{C}(L)\,\mathrm{Y}_{t-1} + \gamma S_t^{sector} + u_t \tag{7}$$

where $\boldsymbol{C}(L) = \boldsymbol{A}^{-1}\boldsymbol{B}(L)$ and $u_t = \boldsymbol{A}^{-1}e_t$.

4.3. Identification

In order to fully identify the model, restrictions must be placed on the contemporaneous effects of the unexpected shocks. Monthly data enable more restrictions than do lower-frequency data such as quarterly or yearly data. To identify the model, I make three key assumptions and one assertion that generate the needed restrictions. First, prices are sticky. Second, there is a policy lag. And third, there is a bureaucratic lag. Finally, I assert that by construction the Unemployed Human Capital Heterogeneity Index ($\mathrm{HCHI_U}$) does not respond to concurrent macroeconomic shocks within a month.

The assumption of price stickiness is common and well rooted in the macroeconomic literature (Gordon 1990; Ball and Mankiw 1994; Klenow and Malin 2010). The use of monthly data further supports this assumption, as the price level is unable to respond to concurrent events within a month. This assumption is bolstered by the use of core personal consumption expenditure (PCE)—a deflator for the price of consumer goods and services—where changes to overall macroeconomic conditions would take more time to manifest themselves.

The second assumption of a policy lag was first proposed by Bernanke and Blinder (1992). Since, it has been used extensively in the VAR literature. The assumption is that policy-makers do not know the values of contemporaneous non-policy variables, so current policy is not responsive to contemporaneous changes in non-policy variables. This assumption is reinforced by the use of monthly data.

The third assumption is based on labor market realities. Because firms take time to adapt to changing conditions, it is reasonable to assume that firms do not respond to a concurrent event by gaining approval for a new hire and then posting the vacancy, all within the month of the motivating event. Due to bureaucratic hierarchies, firms take time to respond to contemporaneous changes in the general economy; a labor demand lag exist (Pigou 1905). Such a delay does not impact employment as employment can be altered from the supply side as well as the demand side.

My final assertion is grounded in the composition of the HCHI_{U} itself. The interviews for the responses reference the beginning of each month (the 12th of the month for January–November and the 5th of the month in December). Because the interviews reference the beginning of the month, the index is not responsive to events that happen in the remainder of the month. This suggests that human capital heterogeneity cannot change in response to events within the same month.

Without any contemporaneous restrictions based on the assumptions and assertion above, $\boldsymbol{A}$, the matrix of contemporaneous effects, is displayed in Equation (8), viz,

$$\boldsymbol{A}Y = \begin{bmatrix} 1 & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} & a_{17} \\ a_{21} & 1 & a_{23} & a_{24} & a_{25} & a_{26} & a_{27} \\ a_{31} & a_{32} & 1 & a_{34} & a_{35} & a_{36} & a_{37} \\ a_{41} & a_{42} & a_{43} & 1 & a_{45} & a_{46} & a_{47} \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 & a_{56} & a_{57} \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & 1 & a_{67} \\ a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & 1 \end{bmatrix} \begin{bmatrix} y_t \\ p_t \\ i_t \\ v_t \\ w_t \\ h_t \\ l_t \end{bmatrix} \tag{8}$$

The assumption of price stickiness implies $a_{21} = a_{23} = a_{24} = a_{25} = a_{26} = a_{27} = 0$. The assumption of a policy lag implies $a_{31} = a_{32} = a_{34} = a_{35} = a_{36} = a_{37} = 0$. The assumption of a bureaucratic lag implies $a_{41} = a_{42} = a_{43} = a_{45} = a_{46} = a_{47} = 0$. Finally, the construction of the HCHI_{U} implies $a_{61} = a_{62} = a_{63} = a_{64} = a_{65} = a_{67} = 0$. Together, these three assumptions and one assertion enable the identification of a non-recursive structural VAR where the dynamics of the system can be captured. Equation (9) displays Equation (8) with these restrictions, viz,

$$\boldsymbol{A}Y = \begin{bmatrix} 1 & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} & a_{17} \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 & a_{56} & a_{57} \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & 1 \end{bmatrix} \begin{bmatrix} y_t \\ p_t \\ i_t \\ v_t \\ w_t \\ h_t \\ l_t \end{bmatrix} \tag{9}$$

Together, Equation (9) and the definition of u_t from Equation (6), state that unexpected movements in output, within month t, are a function of unexpected movements in prices, interest rates, vacancies, hours, human capital heterogeneity, employment, and structural shocks in output, within month t. Unexpected movements in prices, within month t, are only a function of structural changes in prices, within month t. Unexpected movements in the interest rate, within month t, are only a function of structural changes in the interest rate, within month t. Unexpected movements in vacancies, within month t, are only a function of structural changes in vacancies, within month t. Unexpected movements in hours, within month t, are a function of unexpected movements in output, prices, interest rates, vacancies, human capital heterogeneity, employment, and structural shocks in hours, within month t. Unexpected movements in human capital heterogeneity of the unemployed, within month t, are only a function of structural changes in human capital heterogeneity of the unemployed, within month t. And finally, unexpected movements in employment, within month t, are a function of unexpected movements in output, prices, interest rates, vacancies, hours, human capital heterogeneity, and structural shocks in employment, within month t. These assumptions allow for a fully (over)identified model where the dynamics of the system can be obtained.[19]

[19]Although this system is over-identified, the results are robust to a just-identified Cholesky approximation of Equation (9).

4.4. Data

All data are monthly and related to the US economy for the years 1976 to 2018. The heterogeneity of human capital for the unemployed, displayed in Figure 2, is measured according to the HCHI_{U} discussion presented in Section 3. Figure A1 displays the time series for output, interest rates, prices, vacancies, hours, and employment. Output is measured using the natural logarithm of interpolated real gross domestic product (RGDP).[20] The interest rate is the effective federal funds rate. Prices are measured using core PCE.[21] Vacancies are the level of vacancies, using data from Barnichon (2010) for the dates before Job Openings and Labor Turnover Survey (JOLTS) data are available and using the JOLTS data once available, as suggested by Barnichon (2010). Hours are the average weekly hours of production and non-supervisory employees in manufacturing.[22] Employment is measured as total non-farm payroll. And, S_t^{sector} is measured according to Section 4.1. Output, Prices, Vacancies, Hours, HCHI_{U}, and Employment are all seasonally adjusted. The summary statistics for all of the variables in the model are displayed in Table A3. The full list of data sources and units are displayed in Table A2.

5. Results

To analyze the dynamics of the system and the impact of human capital heterogeneity on the labor market, I report the impulse response functions (IRFs).[23] Figure 5 displays the IRFs of the full, seven-variable SVAR model. The dynamics of interest are captured in the IRFs of the labor market variables—employment, vacancies, and hours. Additionally, I report the IRFs for output, price level, and interest rate for completeness.

A one-period, one-standard-deviation shock to Unemployed Human Capital Heterogeneity Index (HCHI_{U}) causes employment to fall by roughly 8% of a standard deviation through the first 12 months then fade to zero over the next 12 months. This –8% impact

[20] I use real GDP that is interpolated from quarterly to monthly data following the broad literature (see Bernanke and Mihov (1998); Gambacorta, Hofmann, and Peersman (2014); Boeckx, Dossche, and Peersman (2017) for example). Results are robust to a monthly measure of industrial production.

[21] Results are robust to Consumer Price Index (CPI).

[22] While a more general measure of hours would be ideal, data for average weekly hours of all employees does not date back to 1976. Following standard convention, I use manufacturing hours as representative of all hours.

[23] The point estimates from the structural vector autoregression (SVAR) of Equation (7) are not of interest and are not reported.

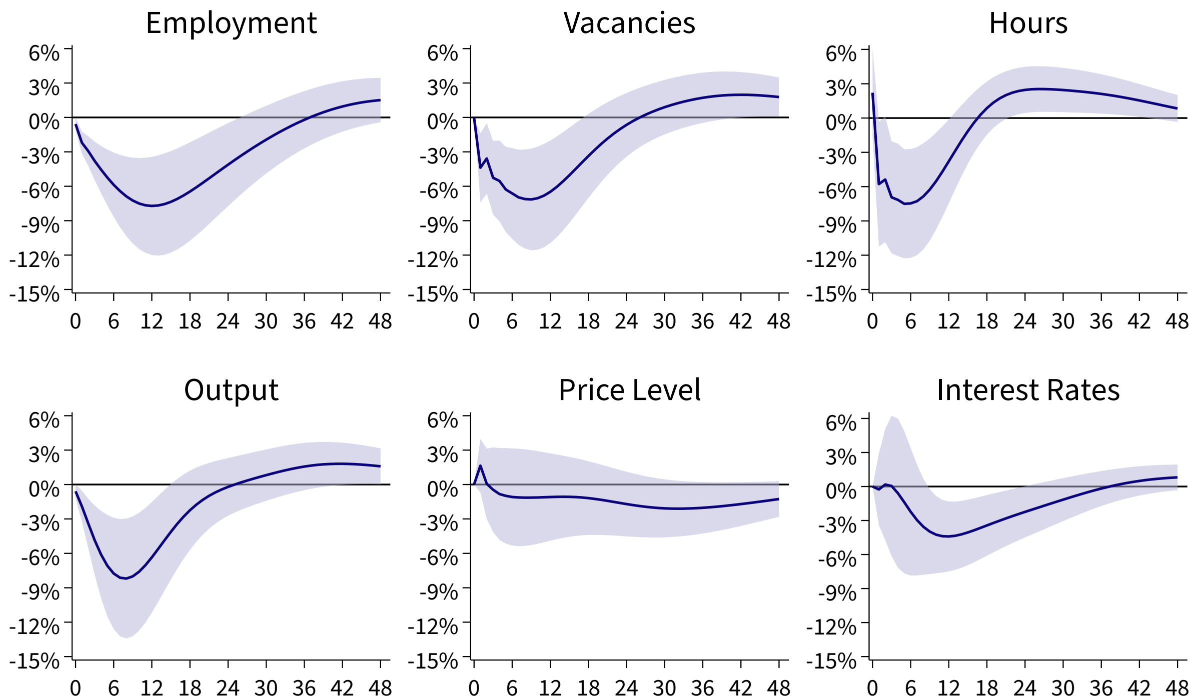

FIGURE 5. Multi-Variate IRF, Standard Deviation $HCHI_U$ Shock

Source: See Table A2. *Note*: One Standard deviation $HCHI_U$ Shock; Shaded area represent 90% confidence intervals; The vertical axis is measured in percent of a standard deviation; Lag-length selected by Schwarz's Bayesian information criterion (SBIC) criteria.

is equivalent to a reduction in employment of just over 1.5 million workers, or roughly 21% of the jobs lost during the Great Recession.

In response to a one-period, one-standard-deviation shock to $HCHI_U$, vacancies fall by roughly 7% of a standard deviation through the first 9 months and then approach zero over the next year. The initial negative impact on vacancies is a loss of just under 70,000 vacancies posted or roughly 3.5% of the loss in vacancies during the Great Recession. The results depicted for vacancies and employment align with the theoretical predictions of Pries (2008), Epstein (2012), and Ravenna and Walsh (2012, 2014) who show that an increase in heterogeneity of the unemployed causes a reduction in vacancies and employment.

Following a one-period, one-standard-deviation shock to $HCHI_U$, hours fall by roughly 7.5% of a standard deviation through the first 5 months and fade to zero over the next 12 months before turning positive for months 24 through 39. This initial reduction in hours is equivalent to a reduction of above 3 minutes, or 4% of the hours lost during the great recession. The dynamics of hours and employment support the conclusion of Panovska (2017) that hours and employment have become substitutes rather than complements. This can be seen as hours rebound quickly and increase as employment continues to fall. Firms substitute into increased hours from the reduction in employment.

As the IRFs of Figure 5 show, human capital heterogeneity has an economically meaningful and statistically significant impact on the labor market. The impact of the $\mathrm{HCHI_U}$ on employment takes 12 months to fully realize and another 12 months to fully dissipate. Given the strong pro-cyclicality of the $\mathrm{HCHI_U}$, these results suggest that human capital heterogeneity may account for a large share of the delayed employment growth of the past few recoveries. As the skill sets of the unemployed grow increasingly diverse, the probability that potential employees find a job with their given skill is reduced; similarly, the probability that an employer is able to find an employee with the required skills is also reduced. As Figure 5 displays, this simple change in the probability of a match has meaningful employment effects. Another important mechanism is the decline in vacancies. As fewer vacancies are posted, the probability of transitioning from unemployed to employed is reduced.

To quantify the effect of $\mathrm{HCHI_U}$ on the recent jobless recoveries, I engage in simple counter-factual analysis. What if employment after 1984 behaved as if it were before 1984, as if there were no jobless recoveries? Figure 1 displays the average employment growth for recoveries before the jobless recovery era. Using this growth path, I construct counter-factual employment paths for the 1991, 2001, and 2009 recoveries. Next, using the net change of the $\mathrm{HCHI_U}$ from its trough to its peak surrounding the recent jobless recoveries, I calculate the relevant $\mathrm{HCHI_U}$ "shock." Next, I calculate the average effect of human capital heterogeneity on employment from the IRFs over the relevant period. Finally, I compare actual employment with the pre-jobless era counter-factual employment to quantify what percent of the difference can be explained by effects of the increases in human capital heterogeneity. This exercise allows captures the dynamics of employment and the $\mathrm{HCHI_U}$ over the relativent time period.[24]

At the trough of the 1991 recovery (1991M3), US employment was 109 million. Twenty-four months after the start of the recovery, employment was 110 million. The counter-

[24]The results of this exercise are intended to provide a general estimate of the effects of human capital heterogeneity on the labor market; they are not precise point estimates the effect as the true counter-factual employment path cannot be known. Additionally, the changes in the $\mathrm{HCHI_U}$ preceding the recoveries of 1991, 2001, and 2009, while drastic, are not proper exogenous "shocks." I suggest viewing the results from this counter-factual analysis as suggestive rather than definitive.

factual employment at twenty-four months after the trough would have been 116 million. The difference between the counter-factual employment and actual employment is 32% of a standard deviation in employment. Surrounding the 1991 recession, the HCHI_U increased, from trough to peak, by 1.97 standard deviations. From the IRFs depicted in Figure 5, the average effect of a standard deviation shock in HCHI_U on employment over twenty-four months is a reduction of 5.69% of a standard deviation. Using these statistics, the increase in HCHI_U surrounding the recession of 1991 is able to explain roughly one third (35%) of the "joblessness" of the 1991 recovery.

At the trough of the 2001 recovery (2001M11), US employment was 131 million. Twenty-four months after the start of the recovery, employment was 130 million. The counter-factual employment at twenty-four months after the trough would have been 140 million. The difference between the counter-factual employment and actual employment is 50% of a standard deviation in employment. Surrounding the 2001 recession, the HCHI_U increased, from trough to peak, by 2.26 standard deviations. From the IRFs depicted in Figure 5, the average effect of a standard deviation shock in HCHI_U on employment over twenty-four months is a reduction of 5.69% of a standard deviation. Using these statistics, the increase in HCHI_U surrounding the recession of 2001 is able to explain roughly one-quarter (26%) of the "joblessness" of the 2001 recovery.

Performing the same analysis for the 2009 recovery yields even more impressive results. At the trough of the 2009 recovery (2009M6), US employment was 131 million. Twenty-four months after the start of the recovery, employment was 132 million. The counter-factual employment at twenty-four months after the trough would have been 140 million. The difference between the counter-factual employment and actual employment is 42% of a standard deviation in employment. Surrounding the 2007 recession, the HCHI_U increased, from trough to peak, by 5.1 standard deviations. From the IRFs depicted in Figure 5, the average effect of a standard deviation shock in HCHI_U on employment over twenty-four months is a reduction of 5.69% of a standard deviation. Using these statistics, the increase in HCHI_U surrounding the recession of 2007 is able to explain near three-quarters (69%) of the "joblessness" of the 2009 recovery.

The counter-factual analysis suggests that human capital heterogeneity for the unemployed played a significant role in the joblessness of the past three recoveries. As the unemployed stock of human capital grows in diversity, the probability of matching potential employees with employers decreases for the unemployed. Additionally, as the heterogeneity of the unemployed increased, firms open fewer vacancies, reducing employment opportunities. The trend in HCHI_U and the results above suggest that labor market frictions, and subsequently matching probability, have worsened in recent years. Both the direct and indirect mechanisms worked together to create the recent jobless recoveries. Additionally, while the current levels of $HCHI_U$ are well below their highs in the mid 2010's, the general, positive trend in the data suggests that future recoveries will remain anemic and that jobless recoveries are the new norm. These results complement those of Şahin et al. (2014), suggesting that heterogeneity induced labor market frictions are a significant cause of unemployment in the modern era.

6. Conclusion

I empirically demonstrate the importance of unemployed human capital heterogeneity in labor market dynamics. First, I develop a unique index of human capital heterogeneity for the unemployed, which reveals that the unemployed stock of human capital has become more heterogeneous and more volatile over time. Additionally, the heterogeneity of the unemployed stock of human capital is strongly pro-cyclical. Next, I test the importance of the human capital heterogeneity index on the labor marking by estimating a structural vector autoregression. Finding that increases in human capital heterogeneity lead to significant decreases in employment and vacancies, I perform counter-factual analysis to show that movements in the unemployed human capital heterogeneity index can account for one third of the joblessness during the 1991 recovery, one-quarter of the joblessness during the 2001 recovery, and nearly three-quarters of the joblessness during the 2009 recovery.

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Appendix A. Components of the Human Capital Heterogeneity Index

The Unemployed Human Capital Heterogeneity Index ($HCHI_U$) is composed of many specific occupations. Table A1 displays the top and bottom five occupations by share of the unemployed for 1950, 1960, 1970, 1980, 1990, 2000, 2010, and 2017. This table demonstrates the change over time of the occupational composition of the unemployed.

Table A1. Top & Bottom Five Occupations of Unemployed

Year	Occupation (2010)	Share (%)
1950	Dentists	0.002
	First-line supervisors of sales workers	0.002
	Astronomers and physicists	0.003
	Health diagnosing and treating practitioners, nec	0.003
	Crushing, grinding, polishing, mixing, and blending workers	0.003
	Office clerks, general	3.761
	Sales and related workers, all other	4.787
	Agricultural workers, nec	5.130
	Material moving workers, nec	13.413
	Other production workers including semiconductor processors and cooling and freezing equipment operators	14.706
1960	Physical scientists, nec	0.001
	Chiropractors	0.001
	Agricultural and food scientists	0.003
	Astronomers and physicists	0.003
	Subway, streetcar, and other rail transportation workers	0.003
	Carpenters	3.301
	Driver/sales workers and truck drivers	3.707
	Sales and related workers, all other	4.190
	Material moving workers, nec	9.957
	Other production workers including semiconductor processors and cooling and freezing equipment operators	11.073
1970	Mathematical science occupations, nec	0.001
	Health diagnosing and treating practitioners, nec	0.001
	Chiropractors	0.001

Continued on next page

Table A1: Top & Bottom Five Occupations of Unemployed, *continued*

Year	Occupation (2010)	Share (%)
	Construction and building inspectors	0.003
	Law enforcement workers, nec	0.003
	Driver/sales workers and truck drivers	2.803
	Assemblers and fabricators, nec	2.821
	Material moving workers, nec	2.967
	Retail salespersons	3.140
	Other production workers including semiconductor processors and cooling and freezing equipment operators	6.012
1980	Construction and building inspectors	0.001
	Law enforcement workers, nec	0.004
	Computer control programmers and operators	0.005
	Atmospheric and space scientists	0.006
	Buyers and purchasing agents, farm products	0.009
	Construction laborers	2.700
	Laborers and freight, stock, and material movers, hand	2.948
	Driver/sales workers and truck drivers	3.065
	Assemblers and fabricators, nec	3.239
	Other production workers including semiconductor processors and cooling and freezing equipment operators	4.572
1990	Air traffic controllers and airfield operations specialists	0.003
	Physical scientists, nec	0.004
	Marine engineers and naval architects	0.004
	Archivists, curators, and museum technicians	0.009
	Meter readers, utilities	0.012
	Janitors and building cleaners	2.539
	Managers, nec (including postmasters)	2.725
	Driver/sales workers and truck drivers	2.742
	Cashiers	3.823
	Laborers and freight, stock, and material movers, hand	4.537
2000	Statisticians	0.007
	Archivists, curators, and museum technicians	0.007
	Plant and system operators, nec	0.012
	Air traffic controllers and airfield operations specialists	0.013

Continued on next page

Table A1: Top & Bottom Five Occupations of Unemployed, *continued*

Year	Occupation (2010)	Share (%)
	Earth drillers, except oil and gas	0.013
	Janitors and building cleaners	2.430
	Managers, nec (including postmasters)	2.679
	Chefs and cooks	2.679
	Laborers and freight, stock, and material movers, hand	4.971
	Cashiers	5.108
2010	First-line supervisors of fire fighting and prevention workers	0.003
	Statisticians	0.003
	Riggers	0.007
	First-line supervisors of police and detectives	0.008
	Geological and petroleum technicians, and nuclear technicians	0.008
	Carpenters	2.351
	Driver/sales workers and truck drivers	2.406
	Retail salespersons	2.700
	Construction laborers	2.822
	Cashiers	3.407
2017	statistical assistants	0.004
	manufactured building and mobile home installers	0.005
	gaming managers	0.006
	power plant operators, distributors, and dispatchers	0.010
	avionics technicians	0.010
	chefs and cooks	2.274
	retail salespersons	2.687
	laborers and freight, stock, and material movers, hand	2.739
	construction laborers	2.979
	cashiers	3.821

Source: CPS and US Census; author's calculations. *Note*: Occupational share and description from the CPS occ2010 variable.

Appendix B. Data

The definitions, units, and sources for the variables used in this paper are displayed in Table A2. Summary Statistics for these variables are displayed in Table A3. Time series of variables not shown in main text are displayed in Figure A1.

TABLE A2. Variable Definitions, Units, and Sources

Variable	Definition	Unit	Source
$HCHI_U$	Human Capital Heterogeneity Index for the Unemployed	A one value for the index indicates perfect homogeneity; an ∞ value represents perfect heterogeneity; Seasonally Adjusted	Author's calculation
Output	Real Gross Domestic Product	Natural Logarithm of Billions of Chained 2012 Dollars, Seasonally Adjusted Annual Rate, interpolated to monthly data	BEA
Interest	Effective Federal Funds Rate	Percent; not Seasonally Adjusted	Fed
Prices	Personal Consumption Expenditures Excluding Food and Energy	Index 2012=100, Seasonally Adjusted	BEA
Vacancies	Total Non-farm Job Openings	Level in Thousands; Seasonally Adjusted	Barnichon 2010
Hours	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing	Hours; Seasonally Adjusted	BLS
Employment	All Employees: Total Non-farm Payrolls	Thousands of Persons; Seasonally Adjusted	BLS

Notes: All variables are detrended using the Hodrick-Prescott time-series filter and converted into standard deviations from trend for analysis in Equation (7); λ is set using the Ravn-Uhlig rule, viz, $\lambda = 1600\,p4$ where p is the number of periods per quarter, e.g. for monthly data $p = 3$.

TABLE A3. Summary Statistics

	Mean	SD	Min	Max
Output	9.32	0.35	8.68	9.84
Price Level	74.36	22.51	29.98	111.01
Interest Rates	4.98	4.04	0.07	19.10
Vacancies	4,176.12	975.42	2232.00	7,558.00
Hours	40.89	0.74	37.30	42.30
HCHI_{U}	76.44	4.86	65.85	91.87
Employment	117,732	19,760.86	78,503.00	149,821
Standardized HP Filtered Output	0	1	-3.62	2.49
Standardized HP Filtered Price Level	0	1	-2.88	3.00
Standardized HP Filtered Interest Rates	0	1	-2.26	4.54
Standardized HP Filtered Vacancies	0	1	-2.64	2.26
Standardized HP Filtered Hours	0	1	-6.64	2.50
Standardized HP Filtered HCHI_{U}	0	1	-3.37	3.12
Standardized HP Filtered Employment	0	1	-2.38	2.57
S_t^{sector}	0.12	0.04	0.03	0.51
N	516			

Source: See Table A2. *Notes*: Both an augmented Dickey-Fuller and a Phillips-Perron test revealed stationarity for all filtered variables.

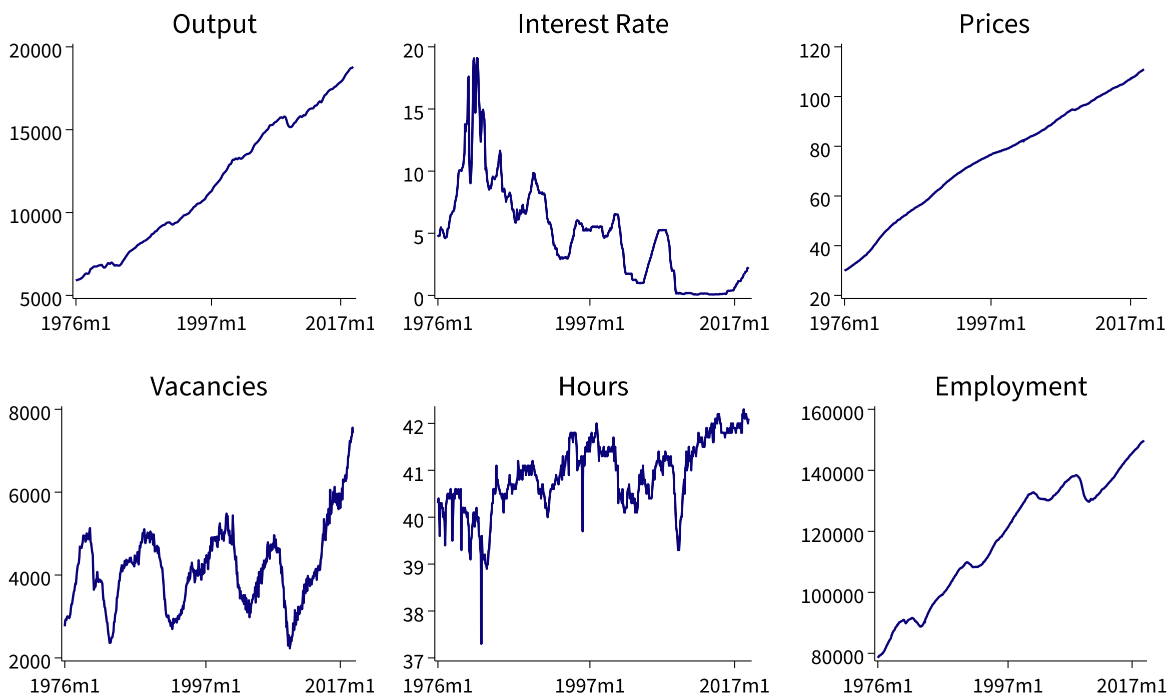

FIGURE A1. Data Frames

Source: See Table A2. *Note*: Units presented in Table A2.