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Examining Labor Market Recovery During the COVID-19 Pandemic Using Occupational Lousiness Indicators

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Abstract

The COVID-19 pandemic has dramatically disrupted the United States labor market, and many commentators have interpreted the ongoing labor dynamics as evidence of a "Great Resignation", emphasizing workers' dissatisfaction with their employment situation as a significant instigator of labor market uncertainty. In this paper, I develop an indexed "lousiness" score for a given occupation based on occupational survey data. I then track the rebound in employment and labor force participation in the wake of the COVID-19 pandemic for workers within "lousy" and "non-lousy" occupations, revealing a sizable gap between their respective rates of return throughout 2020 and 2021. I then use industry-level data from the Job Openings and Labor Turnover Survey to calculate aggregated hiring and quit rates over time, revealing a larger increase in employee-initiated churn rates for industries with a high concentration of "lousy" occupations since the summer of 2020. This supports the perception that employee concerns about flexibility, safe working conditions, and emotional stress are affecting their employment choices and labor force participation rates to a greater degree than before COVID-19.

Contents

1 Introduction

The effects of the COVID-19 pandemic in the United States are clearly numerous and widespread, and one of the most severe upheavals, especially at the onset of the pandemic, occurred in the labor market. The severity and ramifications of the initial layoffs in the spring of 2020 have been widely analyzed and studied over the past two years (Bartik et al, 2020; Dalton, 2020; Bernstein et al, 2020; Marinescu et al, 2021), but the effects of these massive layoffs gradually weakened as the United States reopened and employees began returning to work. The labor market remained relatively unstable, however, and in 2021 researchers began noticing a dramatic increase in voluntary resignations among employees within the United States. This has been referred to by several economists and policymakers as the "Great Resignation", a term coined by Professor Anthony Klotz in early 2021 (Cohen, 2021; Kellett, 2022). The overall impact of the Great Resignation remains uncertain, but it is worth examining the occupations and industries that remain most affected by the pandemic shock and the ensuing employee uncertainty. If this post-pandemic behavior constitutes a deviation from previous sectoral trends in the labor market (Foerster et al, 2022) or from past responses to economic shocks (Fernald et al, 2017; Gordon, 2014; Cerra and Saxena, 2008), then a renewed analysis of worker behavior in the wake of a recession may help understand future labor market trends.

In this paper, I develop an indexed indicator of an occupation's "lousiness" based on typical work characteristics reported by employees in the Occupational Information Network (O*NET) survey. I then develop and use the categorizations of "lousy" and "non-lousy" occupations to chronicle the decline and subsequent rebound in employment and labor force participation that occurred in March 2020 and beyond. Lastly, I use data from the Job Openings and Labor Turnover Survey (JOLTS) to analyze the difference in labor turnover rates within these types of occupations during the year 2021.

Throughout this paper, the word “lousy” is not intended as a critical or dismissive label applied to the people who work within those occupations. It is merely a description of an abundance of occupational characteristics that may frustrate or dishearten current or prospective laborers which can be found in certain types of work. This description has previously been used regarding wages by Howell, 2019; and regarding both wages and perceived job security by Wick, 2020. This paper uses the term “lousiness” in regard to characteristics of a given occupation and the daily routine of its workers, thus expanding the collective knowledge of what workers look for when choosing an occupation.

2 Background and Data Description

The COVID-19 pandemic refers to the ongoing global health emergency caused by the transmission of SARS-CoV-2, a severely contagious respiratory disease. It originated in Wuhan, China in November 2019 and began widely spreading in the United States in March of 2020. To limit the spread of the disease among the American population, several state and local governments imposed “stay at home” orders on their residents. Additionally, as individuals became more wary of large crowds or public spaces due to the risk of COVID-19 transmission, consumer demand plummeted. Many businesses responded by having their employees work from home or laying them off altogether. In May of 2020, the Bureau of Labor Statistics estimated that 20.5 million total non-farm jobs had been lost and the national unemployment rate was 14.7 percent. Between March 21 and May 9, a total of 36.5 million people filed for unemployment insurance, with the Coronavirus Aid, Relief, and Economic Security (CARES) Act expanding states' ability to provide benefits to individuals who had lost their jobs. As time passed, the economic situation became more stable, and government restrictions were lifted (Moreland et al, 2020), businesses started the process of re-hiring workers. This accelerated even further when several COVID-19 vaccines became widely available to the public in the spring of 2021. However, the pandemic's effects have remained at the forefront of American life, including several extremely contagious new variants of the virus, several spikes in the number of newly observed cases, and wide uncertainty about future public health conditions and the merits of continued restrictions.

The Job Openings and Labor Turnover Survey (JOLTS) catalogs the number of hirings, job openings, layoffs, separations, and quits in the employment market within a given month. The data are separated by both state and industry, and both seasonally adjusted and non-seasonally adjusted data is available. All levels are in thousands. The data is published monthly on the Bureau of Labor Statistics website. It is important for a number of calculations and interpretations of labor market development, including net labor turnover, unfilled labor demand, and the relative churn rate of different industries.

The Current Population Survey (CPS), a joint effort by the United States Census Bureau and the Bureau of Labor Statistics, is a monthly survey of approximately 60,000 American households which provides a large amount of employment statistics and labor force data. This data is used to estimate the monthly unemployment rate, labor force participation rate, the amount of discouraged workers, and earnings information. The classification of employed persons into specific industries and occupational categories allows for a comparison of labor trends over time within various employee groups of a similar background. Supplemental data is also collected on a monthly basis in an effort to understand how the labor force is responding to economic trends.

The Occupational Information Network (O*NET) is a free online database containing standardized occupational characteristics. It is developed under the sponsorship of the U.S. Department of Labor/Employment and Training Administration through a grant to the North Carolina Department of Commerce. Topics reported by the O*NET survey data include the level of education or experience required for certain jobs, the typical activities performed, the skills and knowledge required, and the occupational outlook/pay scale for the type of work. Workers within a certain occupation respond to the survey based on the importance and volume of each attribute within their occupation, and each occupation is then assigned a score (usually from 0 to 100) for each attribute based on the average answer. Nearly 1,000 occupations covering all sectors of the United States economy are catalogued by the database.

For this analysis, I combine responses from the CPS survey into ten major occupational categories according to the 2018 Standard Occupational Classification codes associated with each response. This is done to ensure occupations of roughly equivalent training, skills, and benefits are classified together while allowing broad classifications of employees from different industries in a similar manner. These ten categories are:

- Management, business, and financial occupations, including managers, analysts, and financial specialists
- Professional occupations, including computer and mathematical occupations,

engineers, scientists, lawyers, educators, and health practitioners

- Service occupation, including healthcare support, protective service, food preparation and service jobs, grounds cleaning and maintenance, and personal care and service occupations
- Sales and related occupations, such as cashiers, sales agents, and telemarketers
- Office and administrative support occupations, such as clerks and secretaries
- Farming, fishing, and forestry occupations, including many agricultural, fishing, conservation, and logging workers
- Construction and extraction jobs
- Installation, maintenance, and repair occupations
- Production occupations, including machine operators, assemblers, upholsterers, food production workers, etc.
- Transportation and material moving occupations, including drivers, machine operators, packers, etc.

Most of my categorical analysis of lousiness will exclude agricultural workers. Additionally, industry groups are classified according to the 2017 North American Industry Classification System (NAICS) within both the CPS and JOLTS data. The distribution of the different occupational categories within each industry can be found in Appendix A.

3 Employment Analysis

3.1 Lousiness Score

Achieving an understanding of which occupations can be classified as lousy or not requires the development of some sort of indexed assessment of the lousiness of a given occupation. To do this, I selected certain occupational attributes from the Occupational Information Network's publicly available database. When selecting these standardized description variables, I consider four major factors: 1) the freedom of an employee to control their own schedule, routine, and work environment (Golden et al, 2013), 2) the amount of stress, boredom, pressure, and other emotional discomfort the employee might face on a regular basis (Bhui et al, 2016), 3) the amount of exposure to an unsafe work environment the employee is subjected to; an especially important factor in pandemic times, as many jobs were not able to be done while socially distanced (Mongey et al, 2020), and 4) whether the nature of the occupation allowed the employee to showcase leadership, organizational skills, initiative, time management, and other positive workplace traits (Bhui et al, 2016). It is reasonable to assume that a heavy combination of these factors would likely contribute to an individual being dissatisfied with their employment situation.

Once these 20 variables are selected, I follow a process similar to Dingel and Neiman, 2020; Mongey and Weinberg, 2020; and Mongey et al, 2020 in order to develop a simple measure for a given occupation's lousiness based on its attributes. First, I index these variables by k=*1...K*. The O*NET database reports the employment-weighted average of the respondent's answers, resulting in the indexed measure $\overline{m_{jk}}$ for each industry j in the SOC classification. To map these occupations to specific OCC codes in the CPS data, I use a crosswalk obtained from the Census Bureau, which I check against the occupational names in the CPS database and modify accordingly.

I then convert these measurements to a binary {0,1} value m^*_{jk} based on whether $\overline{m_{jk}}$ exceeds a specific measurement threshold, which is different for each variable based on how the O*NET database categorizes the responses for each occupation. While this process contained a certain inevitable degree of subjectivity (as is inherent in any description of lousy aspects of an occupation), I felt that in general, m^*_{jk} provides a Yes/No answer to the question *"Is the value of this variable significant enough that it accurately characterizes the experience of workers in this occupation to the point where it may have an effect on its workers' satisfaction?"*

I then combine these categorized measures into a single measure for each occupation, $\overline{Lousiness_j}$, by taking the unweighted mean of m^*_{jk}. That is, $\overline{Lousiness_j} = (\sum_{k=1}^{K} m^*_{jk})K^{-1}$. This returns a decimal value between 0 and 1, which will be referred to as an occupation's "lousiness score" during this analysis.

The O*NET attributes that contribute to the final lousiness score are listed in Table 1. The second column indicates whether a value greater than or lesser than the cutoff point resulted in a value of 1 for m^*_{jk}. Note that a value equal to the cutoff point resulted in a value of 1 in both circumstances. The third column indicates the cutoff point (from the aggregate score of the variable in a given occupation, which is between 0 and 100). A full breakdown of these variables and the survey questions used to calculate them can be found in Appendix B.

The lousiness scores for the 538 occupations included in this SOC categorization range from .1 to .7. The mean occupational score is approximately .376, the median is .35, and the standard deviation is .105. The occupations with the lowest

Variable Name	>/<?	Cutoff Value
Time Management Level	<	40
Judgment and Making Decisions Level	<	50
Organizing, Planning, and Prioritizing Work Level	<	50
Deal with Customers	>	60
Face to Face Discussions	>	85
Frequency of Conflict	>	60
Exposure to Disease	>	50
Exposure to Hazardous Conditions	>	60
Degree of Automation	>	50
Duration of Typical Work Week	>	60
Freedom to Make Decisions	<	60
Structured versus Unstructured Work	<	60
Importance of Repeating Same Tasks	>	60
Time Pressure	>	70
Work Schedule	<	30
Physical Proximity	>	60
Stress Tolerance	>	70
Independence	<	70
Initiative	<	40
Leadership	<	60

Table 1: O*NET indicators used for calculation of $\overline{Lousiness_j}$

and highest lousiness scores are displayed in Table 2.

When this data is weighted by the number of employees in each occupation, I obtain a number of related lousiness statistics about the U.S. employment population (using the WTFINL values in the CPS as frequency weights). The population-weighted average lousiness score was .3955 in February 2020, and the population median was .4 in the same month. This warrants the generation of a binary variable L_j^*, which takes a value of 1 if $\overline{Lousiness_j}$ for occupation j is greater than the population-weighted median value of $\overline{Lousiness}$. That is, a lousy occupation is one with an occupational lousiness score of .45 or higher. Once this binary value is introduced, I determine the percent of workers in "lousy"

Lousiest Occupations	Score	Least Lousy Occupations	Score
Roustabouts, Oil and Gas	.7	Farmers, Ranchers, and Other Agricultural Managers	.1
Transportation Security Screeners	.65	Remote Sensing Scientists and Technologists	.1
Mail Clerks and Mail Machine Operators (Except Postal Service)	.65	Agricultural Technicians	.15
Postal Service Mail Sorters and Processors	.65	Database Administrators	.15
Gambling Cage Workers	.65	Business Continuity Planners	.15
Subway and Streetcar Operators	.65	Teaching Assistants, Post-secondary	.15
Orderlies	.65	Environmental Scientists and Specialists	.15
Chemical Plant and System Operators	.65	Geographers	.15
Graders and Sorters, Agricultural Products	.6	First-Line Supervisors of Farming, Fishing, and Forestry Workers	.15
Embalmers	.6	Computer and Information Research Scientists	.2
15 more	.6	*25 more*	.2

Table 2: Lowest and highest values of $\overline{Lousiness_j}$

occupations by various demographic and education indicators during the month of February 2020. This is shown in Table 3 on the next page.

Table 3 makes it apparent that different demographic groups work "lousy" jobs in different proportions, which is then confirmed by a *probit* regression for which the baseline category is a white man with a bachelor's degree over the age of 55. As shown in the regression output in Appendix C, younger workers (age 35 and below), women, minorities (especially Blacks, Asians, and Hispanic women), and individuals without advanced degrees are much more likely to be working in a "lousy" occupation.

Additionally, while an occupation's lousiness is developed without considering its wage level, there may be some correlation between the two. Figure 1 compares the median annual wage (as of May 2021) of a given occupation to that occupation's lousiness score. While the statistically significant negative correlation between the two could be a possible caveat in the subsequent analysis (on average, the lousiness score decreases by .0009 when median wage increases by $1,000), the R-squared of .06 is very low, many high-wage jobs have high lousiness scores, and many

Group	Average Lousiness Score	% of Labor Force in "Lousy" Jobs
All	.3913	22.77%
Age		
Age 18-24	.4209	39.41%
Age 25-34	.3936	22.58%
Age 35-44	.3855	18.89%
Age 45-54	.3849	18.76%
Age 55-64	.3855	19.91%
Age 65+	.3754	18.69%
Gender		
Male	.3883	21.97%
Female	.3947	23.66%
Race		
White	.3853	19.79%
Black	.4061	29.69%
Asian	.3774	21.25%
Hispanic	.4063	28.32%
Other/Mixed Race	.4018	27.85%
Education Level		
No High School Diploma	.4210	38.81%
High School Diploma	.4097	30.39%
Some College	.4085	29.10%
Associate's/Vocational Degree	.3957	19.04%
Bachelor's Degree	.3743	14.41%
Post-graduate/Professional Degree	.3472	9.65%
Worker Type		
Full-Time Workers	.3873	19.25%
Part-Time Workers	.4116	35.27%

Table 3: Lousiness Demographics

low-wage jobs have low lousiness scores. Furthermore, this correlation is no longer significant when an occupation's O*NET "Job Zone" (representing the required education or training level) is controlled for. As a result, occupational lousiness cannot be considered synonymous with low wages, an important distinction when discussing the rate of return to work during the pandemic. This also allows for increased applications of compensating wage differentials within "lousy" jobs.

In total, out of approximately 165 million members of the labor force in February 2020, approximately 37.5 million individuals reported a "lousy" occupation as their primary occupation.

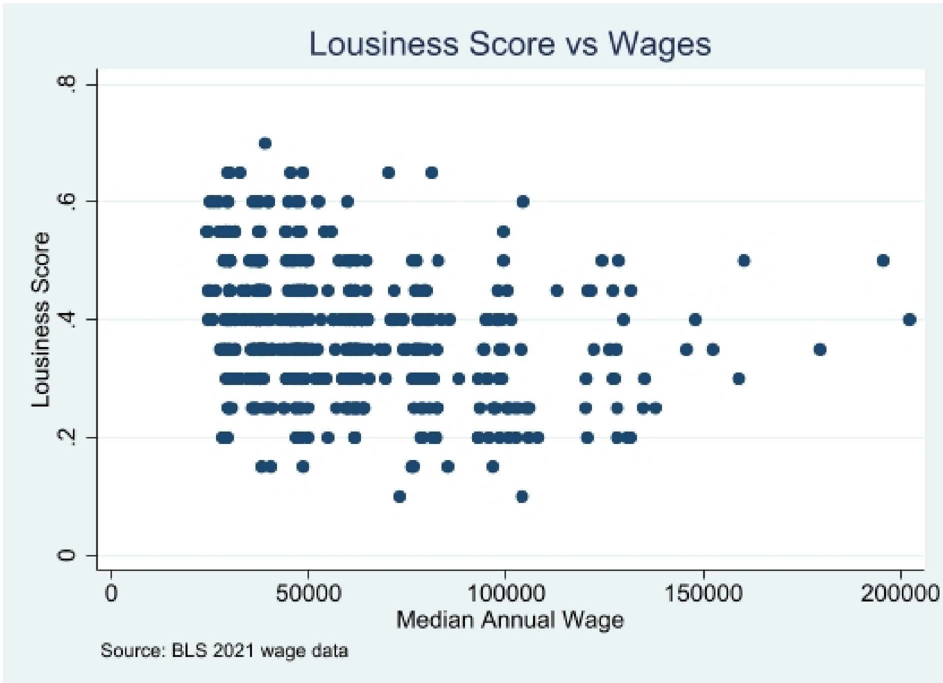

Figure 1: Occupational lousiness score compared to its median annual wage

3.2 Labor Force Participation Rate By Demographics

While the CPS data does not allow for the direct calculation of labor force participation rates for workers in lousy and non-lousy jobs, I use this demographic information to develop a portrait of the labor force participation of these groups before and during the COVID-19 pandemic. Faberman et al, 2022, found evidence that the pandemic led to an overall lower willingness to work, leading to a contraction in labor supply and a tightening of the labor market. Additionally, Hobijn and Șahin, 2021, discovered that the labor force participation cycle depends primarily on fluctuations in job loss and job finding rates, making it a somewhat illuminating metric for measuring the employment trajectory of the post-COVID workforce. According to the Bureau of Labor Statistics, the seasonally-adjusted civilian labor force participation rate remained relatively consistent between February 2014 and February 2020, ranging from 62.5 to 63.4 percent during that timespan. In the wake of the initial economic downturn, this decreased to 60.2 percent in April 2020, rose back up to 61.7 percent in July 2020, and then remained around that mark through the end of 2021. In order to account for this gap, it makes sense to note which demographic groups experienced the sharpest decline in labor force participation. Figures 2-5 below show the indexed labor force participation rates among various demographic groups; that is, the LFP for a given month divided by the LFP in February 2020.

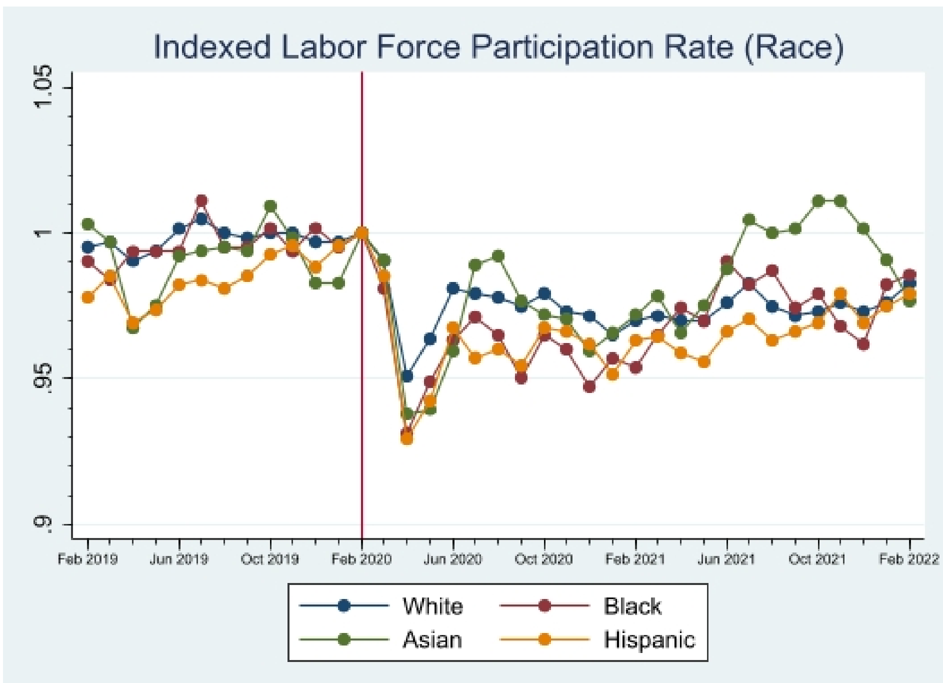

Figure 2: Indexed LFP rate among racial groups

This allows us to compare the downswing and eventual rebound in LFP between these demographic groups. Labor force participation data was obtained from the Federal Reserve Bank of St. Louis' database (calculated and adjusted using the CPS data), and all of the data is seasonally adjusted except for the racial groups' participation rates, for which complete seasonally-adjusted data is not available.

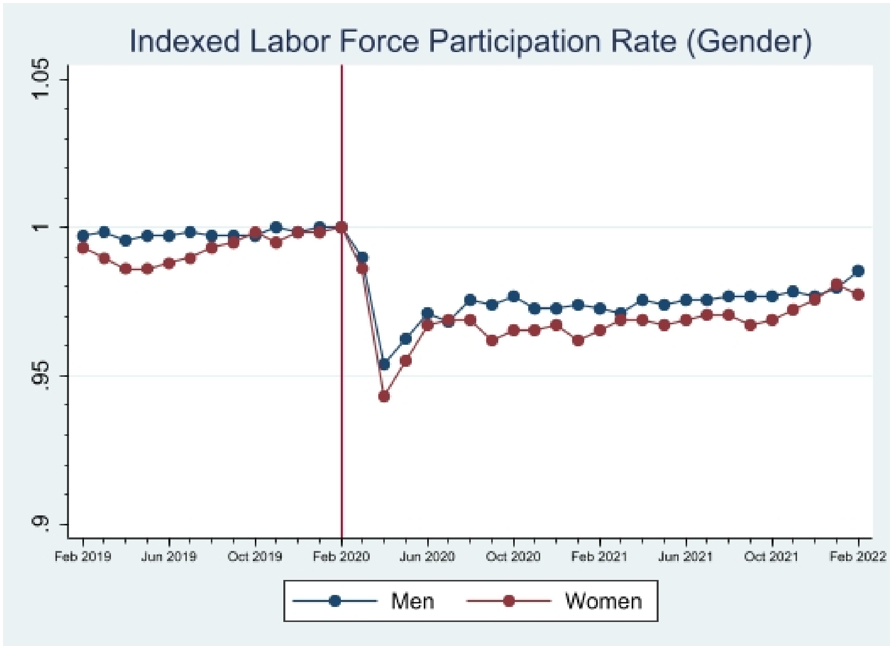

Figure 3: Indexed LFP rate among men and women

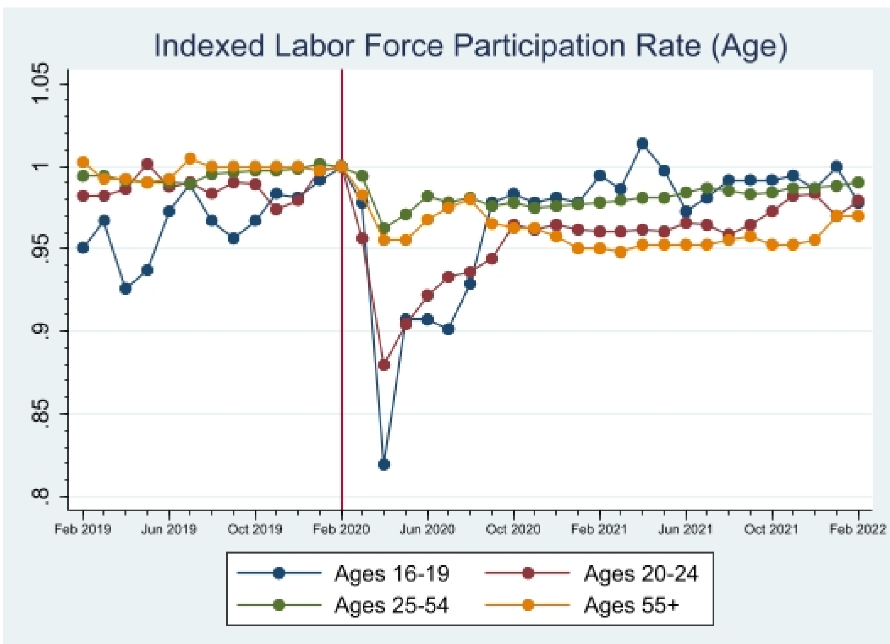

Figure 4: Indexed LFP rate by age group

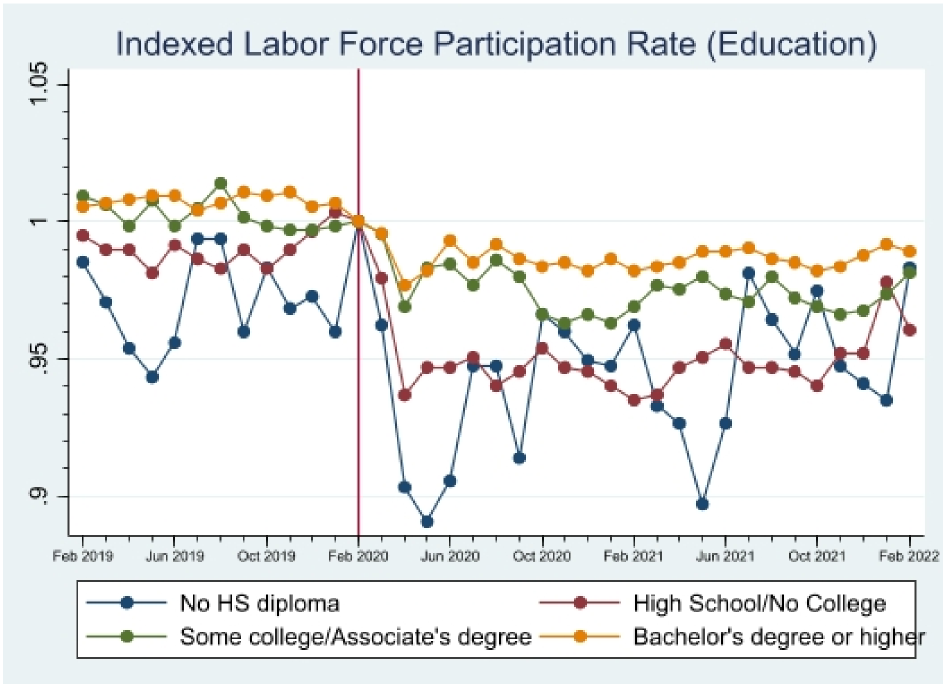

Figure 5: Indexed LFP rate by educational level

These findings help understand the trend even more clearly for several reasons. First, the labor force participation rate of demographic groups more associated with "lousy" occupations consistently had their labor force participation rate decrease by a greater proportional amount in the initial period of the pandemic (March-May 2020). This suggests the initial labor market contraction affected these groups most severely, consistent with Lee et al, 2021, and other demographic analyses of the pandemic's effects. Second, the labor participation rate of minorities, younger workers, and less educated workers varied wildly during the months following the pandemic, with a much greater range of data points than the pre-pandemic years or the other categories. Other noteworthy aspects of this data include the consistent yet decreased labor force participation rate among workers aged 55 and older, possibly due to an increase in early retirements (as suggested by Coibion et al, 2020; and Faria e Castro, 2021), and the persistent gap between men's and women's indexed labor force participation for the duration of the pandemic, as explored by Albanesi and Kim, 2021. In Section 3.4, this will be expanded upon in determining aggregate labor force participation levels among workers in "lousy" and "non-lousy" occupations during COVID-19.

3.3 Employment Trends

It is reasonable to suggest that this sharp decline in labor force participation is generating friction within the labor market. And while much of this drop can be attributed to early retirements, many of those departing the labor force are prime-age workers. This may be due to increased childcare or other domestic responsibilities brought about by the pandemic (Montes et al, 2021; Widra and Schweitzer, 2021), or unease about returning to a potentially dangerous work environment (Widra and Schweitzer, 2021). Thus, despite the fact that unemployment has returned to pre-pandemic lows (as detailed in Section 4.5), many businesses continue to report that they are struggling to meet staffing needs, and an enormous number of workers are leaving or planning to leave their current jobs (Hope, 2022). Using the occupational lousiness score developed earlier, one can attempt to quantify whether this labor market friction is disproportionately affecting "lousy" occupations. If this disproportionality is confirmed, then these job characteristics may be seen as undesirable by the post-pandemic workforce, requiring managers to adapt the occupational responsibilities away from these characteristics if at all possible.

To do this, I develop the variables L_k and N_k, which represent the number of workers in "lousy" and "non-lousy" jobs in month k. I assign an initial value of $k = 0$ to February 2020, the last month before the COVID-19 lockdowns began, and then index $k = 1, 2, 3...23$ through January 2022, the most recent month that CPS data was available. I then develop the indices L_k^* and N_k^* as a measurement of how close the level of employment in lousy and non-lousy jobs in month k were to their February 2020 level. That is, $L_k^* = (L_k/L_0)$ and $N_k^* = (N_k/N_0)$. The non-seasonally adjusted graphs of L_k and N_k are shown in Figure 6.

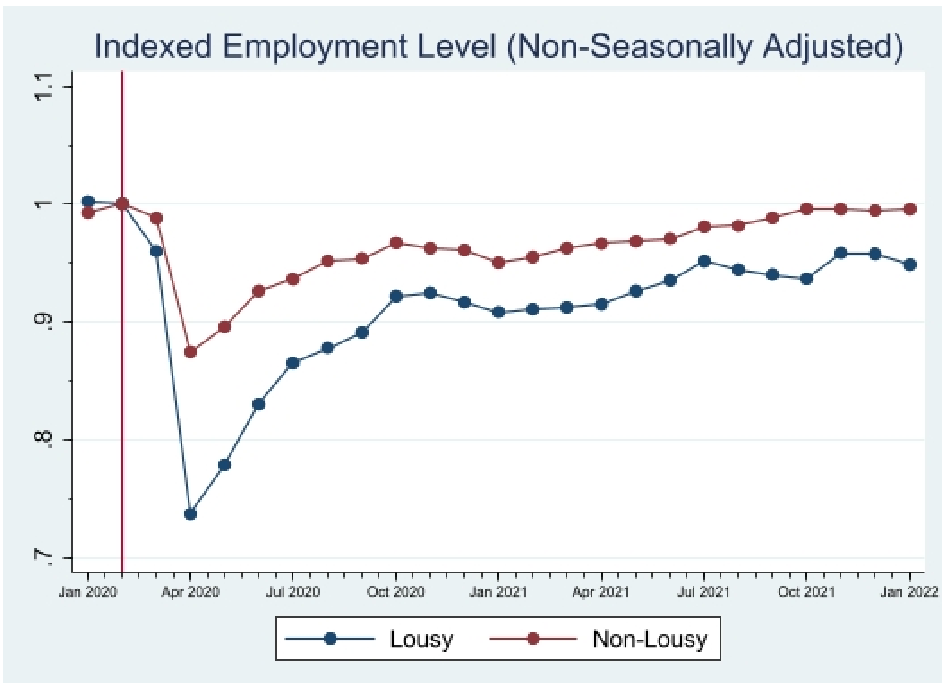

Figure 6: Indexed employment level for lousy and non-lousy jobs

Right away, one can observe that the initial stay-at-home orders and decreased consumer demand affected lousy employment much more than non-lousy employment. The number of workers in lousy jobs experienced a 26.33% decrease from February 2020 to April 2020, compared to a 12.5% decrease for non-lousy jobs. Additionally, non-lousy employment remained at a very solid level from August 2020 onward, remaining above 95% of the February 2020 total in every month since. By the fall of 2021, the number of employed workers in non-lousy jobs in the economy was within 1 percent of the February 2020 total. Conversely, the number of workers in lousy occupations experienced a much greater variation, rising in the summer months and falling again in the winter, yet never coming close to reaching the February 2020 number (peaking at approximately 95.9% in November 2020).

Given the observable increased seasonal variance in "lousy" jobs, I correct for this by calculating the expected score of L_k^* and N_k^* for January 2017-December 2019, deriving the average level of employment in both types of jobs for each month of the year based on those three years of data (creating the seasonality statistics $\frac{L_k^{'}}{E}$ and $\frac{N_k^{'}}{E}$ for each of the $k = 1, 2...12$ months of the year, where $E = \overline{L_k^{'}}$ or $\overline{N_k^{'}}$), and dividing each value of L_k^* and N_k^* by that month's score. While by no means perfect, Figure 7 helps visualize the post-lockdown trend in returning to work while minimizing interference from seasonal cycles.

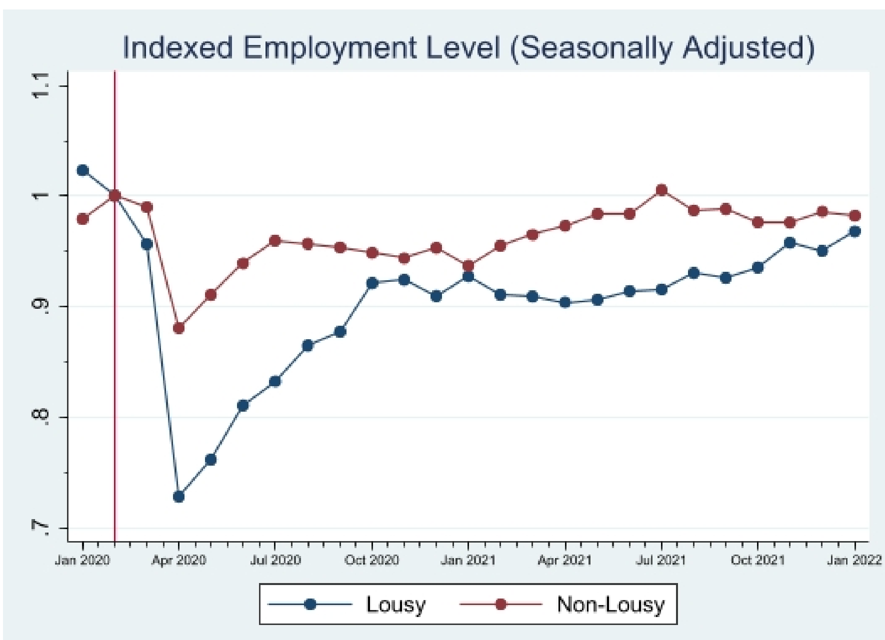

Figure 7: Seasonally-adjusted indexed employment levels

Even after seasonal trends are corrected, there is still an observable gap of roughly 1.15 million workers in these "lousy" occupations. Furthermore, while the indexed number of workers in "lousy" occupations did recover dramatically in the initial months following the easing of pandemic restrictions, a more sustained gap between the indexed employment levels emerged in the following months. This gap did not narrow until the winter of 2021-22, and it remains to be seen whether the Great Resignation will widen the gap even further during 2022.

To demonstrate the origin and extent of this disparity, I develop and run the following quadratic regression models of the seasonally-adjusted employment totals for a given month, starting from October 2020, when L_t^* and N_t^* first reached a similar indexed value (within 5 percent of each other). Doing this highlights the different acceleration rates of both types of employment throughout 2021, such that the rate of change of L_t^* was initially negative during the winter of 2020-21 and increased afterwards, while the rate of change of N_t^*, initially very large, decreased over time but maintained a positive value.

$$L_t^* = -270.9t + 21.8t^2 + 33152.4 + \epsilon_t,$$
$$N_t^* = 1150.9t - 45.7t^2 + 112243.4 + \epsilon_t$$

Note that the value of t is indexed to 1 in October of 2020, and that L_t^* and N_t^* are both measured in thousands.

The full regression results can be found in Appendix C, and these results confirm that the majority of employment growth in non-lousy industries occurred in the first half of 2021 (perhaps as firms developed plans to transition back to in-person work), and has tapered off relatively recently, while the bulk of the increase in lousy industries occurred during the summer and fall of 2021, once vaccines had been fully rolled out and consumers resumed relatively normal behavior. The increase in “lousy” employment eclipsed the increase in “non-lousy” employment for the first time in September 2021. The coefficients of both regressions are significant at the 95% confidence level.

3.4 Labor Force Participation Levels During COVID-19

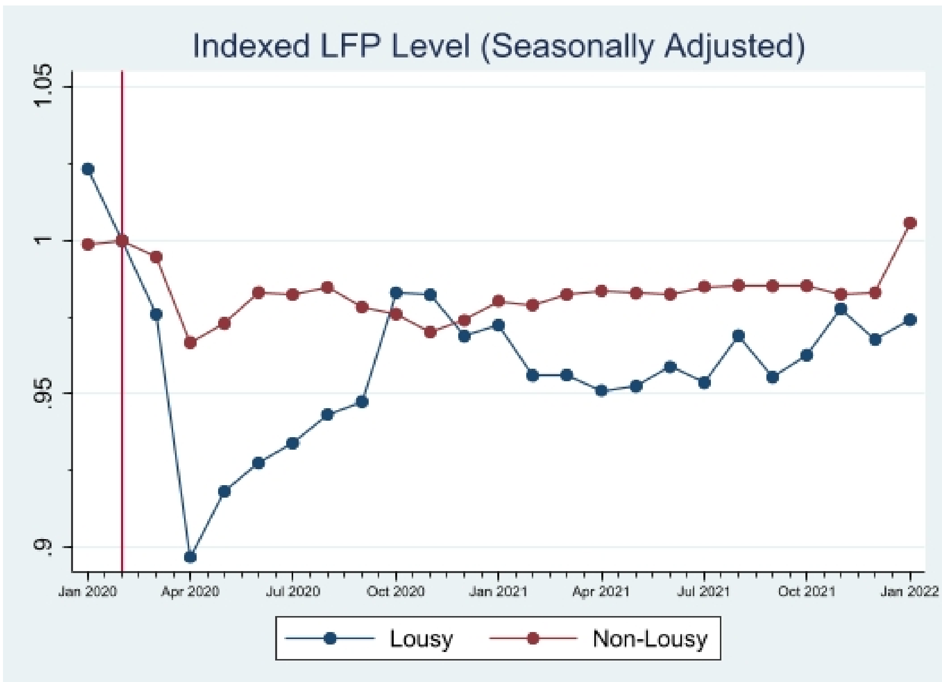

Figure 8: Seasonally-adjusted indexed LFP level

Ideally, this trend of increased job growth would continue into 2022 despite the Great Resignation. However, this is largely dependent on the aggregated labor force participation level among available workers in lousy and non-lousy jobs (based on the individual’s most recent occupation, as reported in the CPS data), a key determinant in the available supply of workers within their respective occupational markets. This is depicted in Figure 8.

As expected, the labor force participation level of workers in lousy occupations (denoted $LFP^*_{L_k}$) dropped by a much larger margin (a 10.3% decrease from February 2020 to April 2020, compared to a 3.3% decrease for workers in non-lousy jobs). The labor force participation level of workers in non-lousy occupations ($LFP^*_{N_k}$) remained relatively constant throughout the recovery, while workers in lousy jobs experienced a dramatic increase in the latter half of 2021 before falling off again and remaining relatively low, albeit volatile, during the majority of 2021.

The seasonally-adjusted level of workers of non-lousy jobs who participated in the labor force remained relatively unchanged after the initial easing of COVID-related restrictions, and did not reach pre-pandemic levels until January 2022. This may be due to retirements, childcare responsibilities, or unease about returning to work, as discussed in Section 2. The linear regression of $LFP^*_{N_k}$ from June 2020 through the end of 2021 returns a coefficient value that is not significant at the 95% confidence level. This, combined with the declining increase in employment among workers in non-lousy jobs found earlier, suggests that the labor market for these jobs has remained relatively stable since restrictions were lifted. For workers of lousy occupations, however, the rate of return to the labor force drastically changed during 2020 and is best modeled by a log-linear regression over the same timespan. This suggests that the "re-opening" effect on the availability of workers in jobs that may have been cut wore off after the initial easing of COVID-related restrictions, and workers in lousy occupations were relatively slow to return in the second half of 2021. Both of these regressions can be found in Appendix C.

Furthermore, workers of lousy occupations exhibited a much greater degree of volatility in their labor force participation rates even after correction for seasonal trends, with the standard error for the expected value of $LFP^*_{L_k}$ roughly 6.8 times that of $LFP^*_{N_k}$. This level of uncertainty among employees within lousy occupations suggests that the economic impact of COVID uncertainty (Baker et al, 2020) may disproportionately affect these workers and occupations.

To see if this discrepancy persists among various occupational and demographic groups, I use this same analysis to measure the difference in employment levels between lousy and non-lousy jobs among those groups using the CPS demographic and occupational data. That is, $D^*_k = LFP^*_{L_k} - LFP^*_{N_k}$. These values can be found in Figure 9. Note that all values are indexed to February 2020 and are not seasonally-adjusted.

Using the demographic data found in Figure 9, it is clear that the gap between the

Figure 9: Difference in indexed workforce totals based on lousiness indicator among various demographic groups

rebound of workers within lousy and non-lousy occupations persists across demographic groups. The notable exception is individuals aged 65 and older, which suggests that the majority of early retirees come from non-lousy occupations, perhaps because they are more likely to be able to afford an early retirement. Several lower educational levels have a less dramatic gap, meaning the distinction between the two groups may not be as stark as the gap observed in higher educational levels. However, many of these groups have seen a rapid decline in LFP rates among workers within lousy occupations in recent months. This suggests that occupational lousiness remains a significant obstacle in the labor supply of many job types.

Table 4 contains the same analysis, but workers are now sorted by the occupational categories that were defined in Section 2, excluding agriculture. Note that the percentages below each occupational category name are the percent of workers within that occupation that can be classified as lousy. Once again, there is a clear gap between the rebound of non-lousy jobs and lousy jobs in many occupational categories. The exceptions are Administration, Management, and Professional jobs, perhaps due to the increased demand for workers in those occupations to manage firms' virtual work environments. The gap in Service occupations dissipated by the end of 2021, mainly due to a sharp drop in non-lousy employment. This may be related to decreased consumer demand due to the transmission of the Omicron variant or increased frustrations among service workers that the lousiness index does not account for. However, a clear disparity remains among Transportation and Sales workers (the two groups with the highest proportion of workers concentrated in lousy jobs). This suggests that the characteristics of a work environment or job duties remain a significant factor in employee decisions.

Group		May 2020	Aug 2020	Nov 2020	Feb 2021	May 2021	Aug 2021	Nov 2021	Jan 2022
Administration (26.88%)	Lousy	1.034	1.066	1.024	1.027	1.041	1.051	1.045	1.055
	Non-Lousy	.978	1.016	1.025	1.018	1.018	.959	1.018	1.037
Construction (2.77%)	Lousy	.654	.806	.923	.901	.852	.855	.956	.883
	Non-Lousy	.933	1.003	1.001	.972	.981	1.012	1.000	1.007
Maintenance (3.31%)	Lousy	.796	.646	.766	.741	.857	.916	.485	.543
	Non-Lousy	.978	.993	.983	.994	1.045	1.055	.982	1.004
Management (5.18%)	Lousy	.933	1.008	1.070	.995	1.064	1.051	1.010	1.012
	Non-Lousy	.991	1.003	.998	.998	1.006	1.021	1.022	1.026
Production (9.00%)	Lousy	.954	.775	1.040	.986	.905	.936	.840	.916
	Non-Lousy	.914	.952	.950	.946	.942	.994	.955	.964
Professional (9.82%)	Lousy	.997	.976	1.000	.998	.971	.935	1.000	.994
	Non-Lousy	.997	.989	.960	.979	.960	.961	.987	1.006
Sales (45.02%)	Lousy	.930	.971	1.015	.978	.935	.948	.925	.914
	Non-Lousy	.950	1.029	.985	1.008	.993	.982	.996	1.008
Service (36.41%)	Lousy	.845	.913	.934	.897	.931	.949	.958	.942
	Non-Lousy	.942	.978	.980	.926	.954	1.008	.985	.945
Transportation (75.90%)	Lousy	.933	.890	.899	.933	.962	.988	.963	.948
	Non-Lousy	.978	.946	1.043	.992	1.006	1.076	1.057	1.083

Table 4: Indexed rate of change by occupational category based on lousiness (1=February 2020 levels)

This shows the rate of return to work across these occupational categories was slow and uneven, and this is likely to significantly affect employment growth in 2022 and beyond. This could be due to a variety of factors- such as the relative capability for remote work in some occupations, the lack of demand for many customer-oriented occupations in response to the change in consumer behavior, or the increased demand for automated work as a safeguard against infection (McKinsey Global Institute, 2021a; McKinsey Global Institute, 2021b; Chernoff and Warman, 2020; Autor and Reynolds, 2020; Leduc and Liu, 2020). However, Table 4 shows that this most severely impacted the rate of return of employees to lousy occupations, and that the majority of the downturn since August 2021 (when vaccines were widely available and most lockdown orders had been lifted, despite a still alarming level of cases) was among workers within these lousy occupations.

4 Labor Turnover Analysis

These findings warrant a detailed examination of the different dynamics that occurred within the labor market that may have contributed to this difference in return-to-work rates, and one can use the Job Openings and Labor Turnover Survey data to do exactly that. Expanding on the work done by Hall, 2005 and Elsby et al, 2010, I use the JOLTS data to create a portrait of labor market behavior in the wake of the COVID-19 pandemic and observe any differences between the way industries predominantly consisting of lousy occupations and the way industries with few lousy occupations responded. Calculating the industry-wide response also helps to understand how much of the difference observed in the previous section is due to shifts in labor demand, rather than my hypothesis of a noticeable labor supply shift. If layoffs remained high and job openings stayed low, weakened labor demand may be partially responsible for the observed gap. However, if job openings increased and layoffs tapered off quickly, labor demand is likely not responsible for the decreased employment totals.

4.1 Lousy and Non-Lousy Industry Categories

The JOLTS data is gathered and reported at the industry level. While this means no direct comparison of the groups of employees in certain occupations can be made, such a comparison can be simulated using the percents of employees in lousy occupations using the Current Population Survey data. I do this by calculating the population-weighted mean binary value of L_j^* for each industry and comparing this to the mean value of the total labor force in February 2020 (.2277). If the industry mean exceeds the population mean by at least 10 percent, I classify the industry as "lousy". If the industry mean is lower than the population mean by at least 10 percent, the industry can be classified as "non-lousy". To sort industries into these

Industry	% of Workers in Lousy Jobs
Accommodation and food services	67.14%
Transportation and utilities	56.43%
Retail trade	49.53%
All industries	22.21%
Wholesale trade	21.68%
Management, administrative, and support	17.70%
Arts, entertainment, and recreation	16.83%
Non-durable goods manufacturing	16.71%
Healthcare and social assistance	14.79%
Finance and insurance	14.73%
Information	12.31%
Durable goods manufacturing	9.35%
Educational services	8.00%
Real estate	7.49%
Professional and business services	5.26%
Construction	4.83%

Table 5: Breakdown of the percentage of workers in lousy jobs in each industry

broad categories, I use a crosswalk between the 2017 NAICS industry classification codes and the IND variable in the CPS data. For the purposes of this analysis, I exclude mining, agriculture, and public administration.

Based on these totals, there are three "lousy" industries (Accommodation and food services, Transportation and utilities, Retail trade) and eleven "non-lousy" industries. The JOLTS data combines "Management, administrative and support" with "Professional and business services". Additionally, the JOLTS data publishes both combined and separate totals for three groups of non-lousy industries: "Manufacturing", representing both durable and non-durable goods manufacturing, "Financial activities", which combines finance and insurance with real estate, and "Education and health services", combining educational services with healthcare and social assistance. Though I would obtain the same end result either way, I use the combined totals for these industry groups. This results in seven data reference points for the "non-lousy" group of industries.

Once these groups of industries are selected, I use the JOLTS data to calculate a composite index for the hiring, job opening, layoff, and quit rates of these industries. Let H_{Li} be the adjusted hiring level for industry i in a given month and H_{Ri} be the adjusted hiring rate for industry i in the same month, as reported by the publicly available JOLTS data. The composite hiring rate for "lousy" industries is then calculated by:

$$\frac{\sum_{i=1}^{N} H_{Li}}{\sum_{i=1}^{N} \frac{H_{Li}}{H_{Ri}}} * 100$$

The composite rates for job openings, layoffs, and quits are calculated in the same fashion, with the industries containing a plethora of "lousy" occupations being indexed $1...N$. Non-lousy industry scores are calculated in the same manner. This has the same effect as taking an employment-weighted average of the industry rates, while also ensuring little to no discongruity between the final values and the JOLTS sample data. The resulting scores are then compared for a given month in the subsequent analysis.

4.2 JOLTS Results and Analysis

The first graph (Figure 10), representing seasonally adjusted hiring rates for both lousy and non-lousy industries, shows a drastic increase in hiring rates for lousy industries after COVID-19, as opposed to the previous three years. The average adjusted monthly hiring rate for lousy industries was 6.42 in 2021, as opposed to 5.45 in 2019 and 5.24 in 2018. The average monthly hiring rate for non-lousy

Figure 10: Aggregate hiring rate for lousy and non-lousy industries

industries in 2021 was 4.23, a tad higher than the 3.90 average in 2019, but not nearly as dramatic of an increase as the one observed within lousy industries. There was a sustained drop in hiring rates during the initial months of the pandemic (as documented by Campello et al, 2020) affecting both types of industries, but this quickly dissipated as stay-at-home orders lifted and much of the country reopened. While much of this increase was due to the re-hiring of workers that had been previously laid off and the lifting of hiring freezes, this trend of higher hiring rates in lousy industries suggests that the gap in the rebound rates of lousy and non-lousy occupations is not due to different hiring behaviors.

The second graph (Figure 11) represents the job openings rate, which JOLTS defines as the number of positions that are open on the last day of a given month. Both figures had remained relatively steady before the pandemic, with the 2019

Figure 11: Aggregate job opening rate for lousy and non-lousy industries

seasonally adjusted monthly average being 5.20 for lousy industries and 4.75 for non-lousy industries. However, contractions in job postings were abundant in the initial stage of the COVID-19 pandemic, both because of the government-imposed stay at home orders and because of the decreased consumer demand due to concerns about being infected. Forsythe et al, 2020a collected data on the drop in available jobs in April and concluded that the disruption was predominantly caused by the virus and customers' reactions to it, rather than stay at home restrictions, and it was likely due to this fear that job openings remained relatively low throughout 2020. However, as the vaccine was distributed and the economy began reopening, job opening rates dramatically increased, as shown in the graph. From January through December 2021, the job openings rate within lousy industries increased by an average of .268 percent per month, while the rate within non-lousy industries increased by .19 percent per month. The adjusted job opening rate in December of 2021 for lousy industries was a whopping 68.9 percent higher than the average of the four previous Decembers. While this data offers some explanation for the slow recovery during the remainder of 2020, the lack of available job openings is clearly not an explanation for sustained employment levels below the pre-pandemic benchmark, nor can it explain the gap between the rate at which workers returned to lousy and non-lousy occupations.

The third rate catalogued by JOLTS is layoffs and discharges, which were at historic highs during the beginning of the pandemic. Nearly a fifth of the workforce was laid off by the end of April (Cajner et al, 2020; Belsie, 2020), which was anticipated to have a disastrous and sustained effect on the labor force, including reduced earnings and higher reallocation rates (von Wachter, 2020; Montenovo et al, 2021; Barrero et al, 2020).

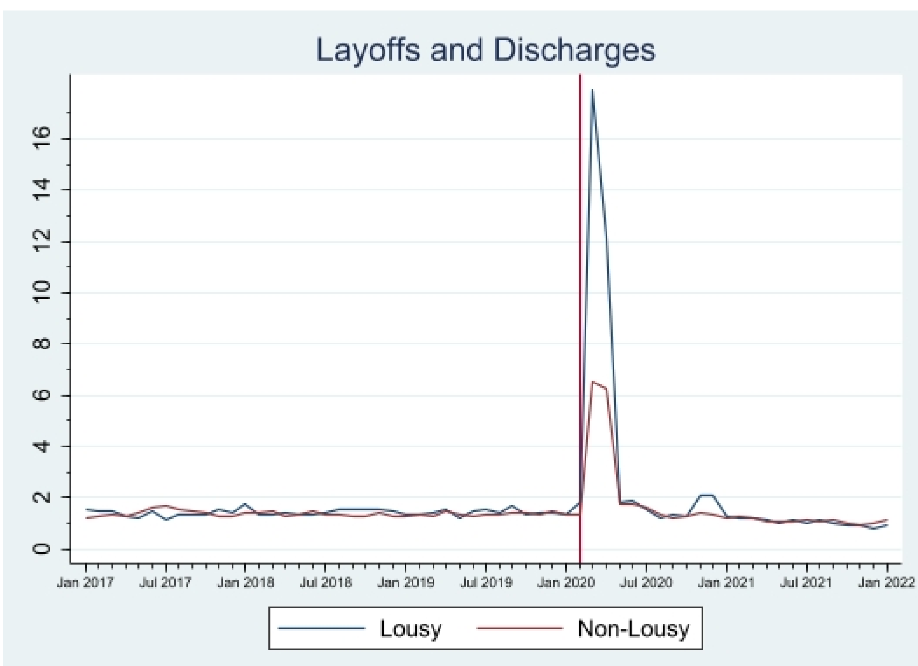

Figure 12: Layoff and discharge rates for both lousy and non-lousy industries

Figure 12 suggests that the number of layoffs and discharges decreased very quickly once most stay-at-home orders were lifted and firms began reopening. Furthermore, other than a relatively small COVID-related shock in the winter (reaching a high of 2.1 in November 2020), there was virtually no difference between the layoff and discharge rates of lousy and non-lousy industry groups. In fact, the average monthly layoff rates in 2021 (1.052 for lousy industries and 1.097 for non-lousy industries) were significantly lower than in 2019 (1.410 and 1.357, respectively). This suggests that firm layoffs and discharges are not a primary cause of either the sustained lower employment levels or the previously observed disparity between workers in lousy and non-lousy occupations.

The final statistic that I use the JOLTS data to calculate is the quit rates of both lousy and non-lousy industries. Much of the current labor market tightness has been blamed on vacancies arising due to quits (Domash and Summers, 2022; Cohen, 2021; Mitchell, 2021), leading to the "Great Resignation" moniker. The quit rates of both industry groups are shown in Figure 13.

Right away, one can observe an initial decline in the quit rate of both lousy and non-lousy industries before steadily increasing, with an even more dramatic increase after the vaccine became widely available and many industries began hiring again, with every month since March 2021 returning a larger quit rate than any month of 2017-2020. On average, the quit rates for lousy industries in the year 2021 was 29.8 percent higher than the average of the previous four years. Non-lousy industries also saw higher quit rates, with the average month seeing a 21.3 percent increase when compared to the previous average.

Figure 13: Quit rates for both lousy and non-lousy industries

4.3 Relative Turnover Ratios

To determine whether these statistics led to disproportionately high worker movement in lousy industries, it makes sense to graph the ratio between the values of each statistic for lousy and non-lousy industries. These are depicted in Figures 14 and 15.

These variables together allow for a comparison of the relative turnover rates of both groups of industries. To determine whether an increase had occurred, I use a two-sample t-test and assume unequal variances. The baseline group (Group 1) is January 2017-December 2019, and the treatment group (Group 2) is August 2020-January 2022. This allows for a suitable comparison of the relative churn rates before and after the lockdowns.

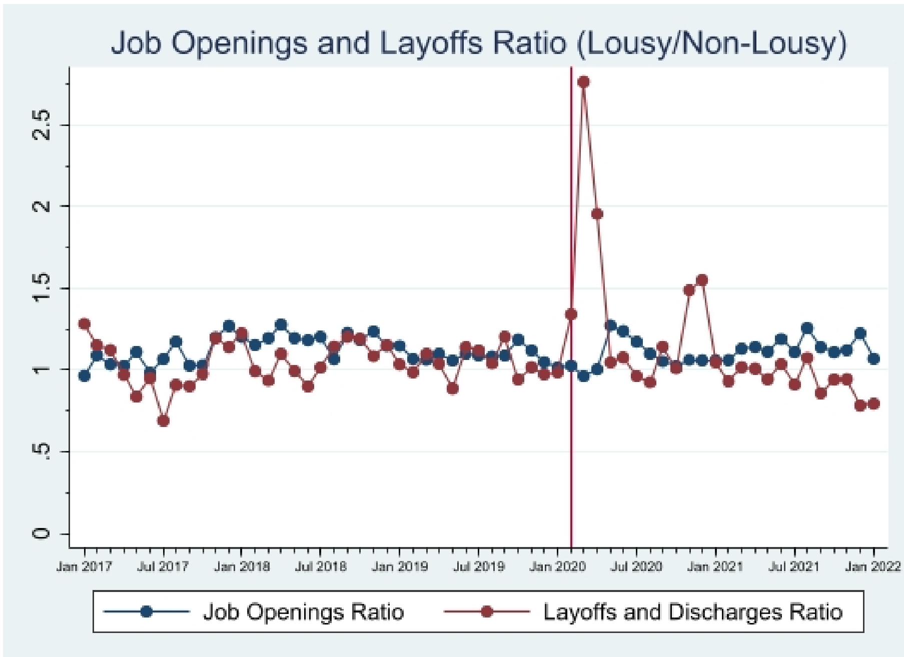

Figure 14: Ratio of layoffs and job openings in lousy and non-lousy industries

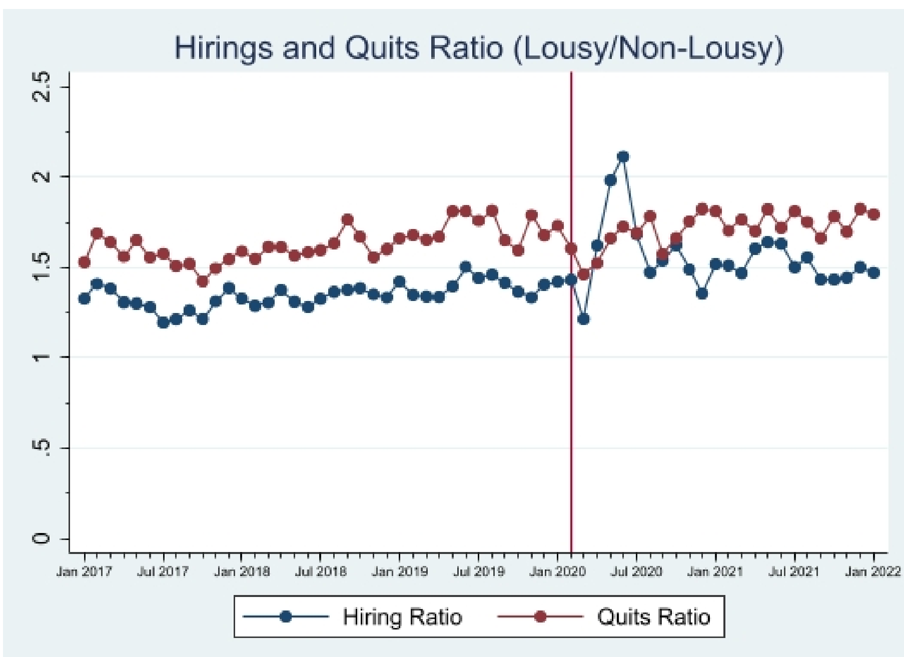

Figure 15: Ratio of hiring and quit rates in lousy and non-lousy industries

The full results of the t-test can be found in Appendix C. The mean ratio of both hirings and quits increased in a significant way during 2021, suggesting an increased labor market churn rate disproportionately affecting lousy industries. The average monthly ratio for hirings in lousy industries to non-lousy industries increased from 1.34 to 1.51, while the average monthly ratio for quit rates increased from 1.63 to 1.75. Both of these tests returned results significant at the 95% confidence level, while the t-test for job openings did not. This presumably led to increased uncertainty among employers trying to fill these openings and a slew of vacant job positions. From August 2021 to January 2022, the total number of employees of lousy occupations who reported as being employed in or seeking work within these industries decreased by considerable margins (approximately 280,000 retail workers, 100,000 transportation workers, and 300,000 food services employees).

4.4 Churn

Quit-initiated churn is well-documented as being pro-cyclical (Lazear and Spletzer, 2012; Macaluso, 2021; Davis et al, 2012). Previous work (Burgess et al, 2000; Weingarden, 2020) defines churn for a given establishment i in month t as:

$$GC_{i,t} = \frac{2 \ \min\{H_{i,t}, S_{i,t}\}}{E_{i,t}}$$

where H is defined as the number of hirings, E is the average of the current and previous monthly employment totals for the given establishment, and S is the total number of separations (quits, layoffs, retirements, etc.). This can then be separated into firm-initiated churn and employee-initiated churn rates:

$$FC = \frac{L}{S}GC, \ EC = \frac{Q+O}{S}GC$$

where L represents layoffs, Q represents quits, and O represents other separations. If the previous groups of industries are considered establishments, the aggregated firm-initiated and employee-initiated churn rates can then be calculated over time for both using the JOLTS data. These are depicted in Figures 16 and 17.

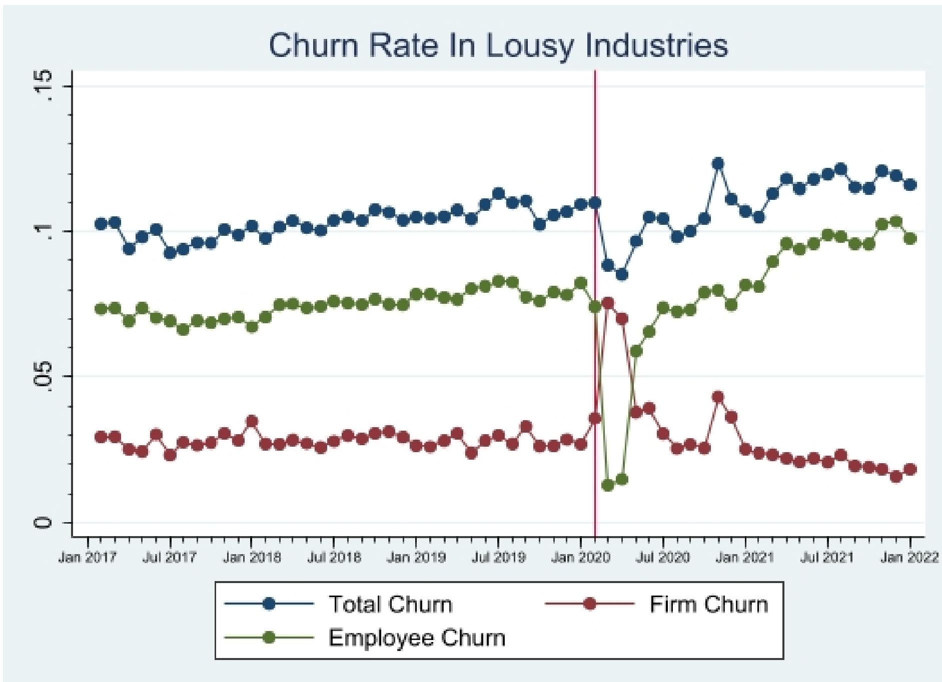

Figure 16: Churn measurements in lousy industries

During the pandemic, employee-initiated churn rates plummeted as firm-initiated churn skyrocketed, which is understandable given the vast number of layoffs that occurred. But since July 2020, churn rates have risen dramatically, particularly employee-initiated churn and particularly within lousy industries. These rates are shown in Table 6.

Furthermore, employee-initiated churn accounted for approximately 73.9 percent of total monthly churn, on average, for lousy industries during the calendar year

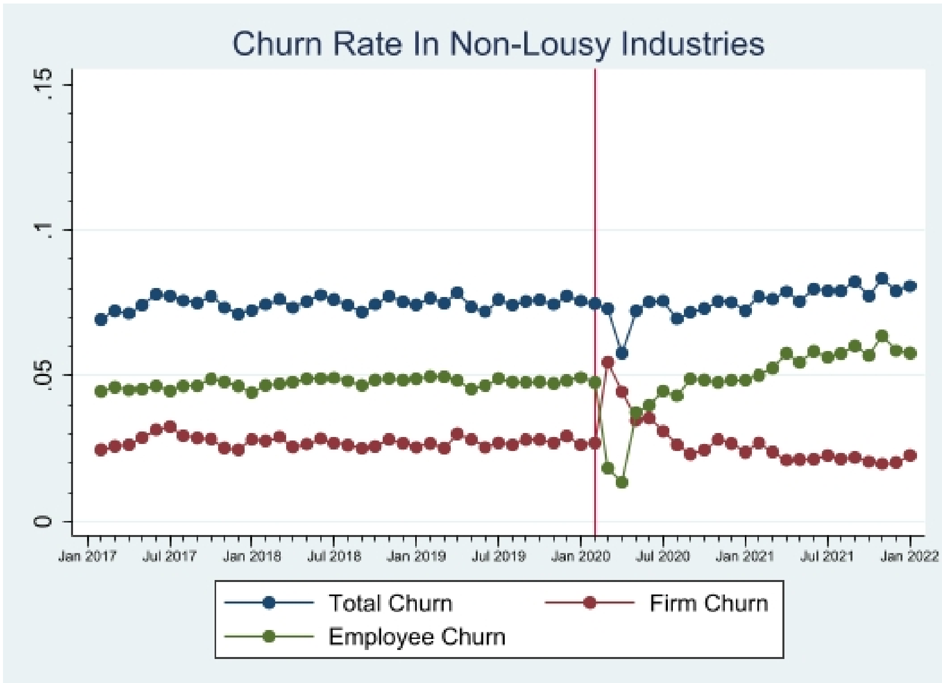

Figure 17: Churn measurements in non-lousy industries

Rate Type	% Growth
GC (Lousy)	21.6%
EC (Lousy)	42.6%
GC (Non-Lousy)	13.4%
EC (Non-Lousy)	35.6%

Table 6: Total percent change in churn rates between July 2020 and December 2021

2019, but 79.5 percent of total monthly churn from January-June 2021 and 83.6 percent of total monthly churn from July-December 2021. In non-lousy industries, employee-initiated churn went from 63.9 percent of average monthly churn in 2019 to 69.9 percent in the first half of 2021 and 73.6 percent in the second half of 2021.

Figure 18 shows the relative ratio of churn rates before and after the pandemic. Though churn rates were already higher in lousy industries before the pandemic, I

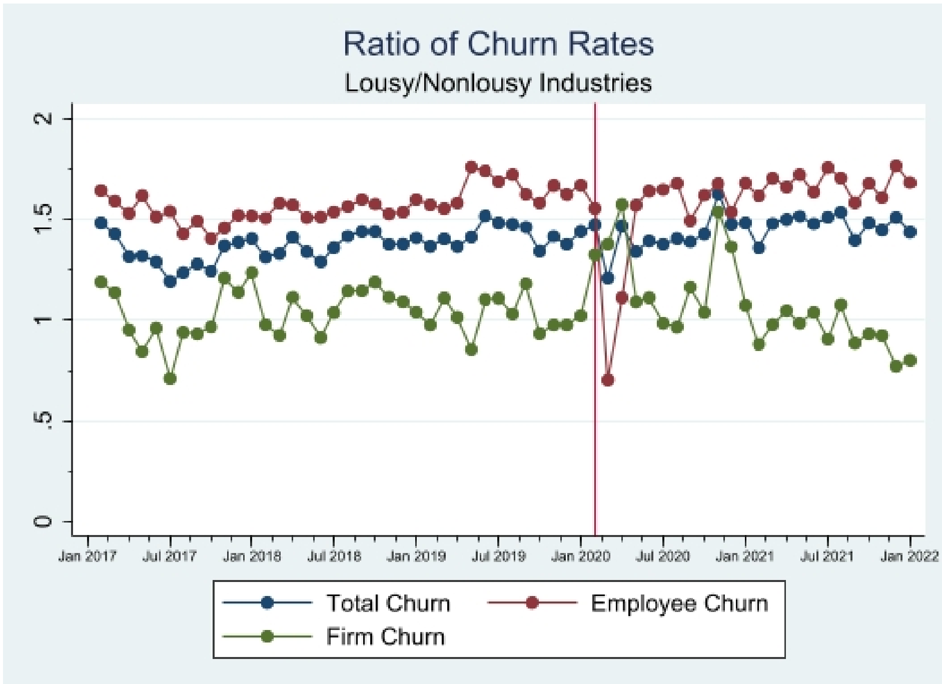

Figure 18: Ratio of hiring and quit rates in lousy and non-lousy industries

use the same t-test as in Section 4.3 to show that there is significant evidence that employee-initiated churn has become more significantly concentrated within lousy industries (retail, transportation, and food services). This also leads to increased total churn relative to non-lousy industries. While the ratio of firm-initiated churn rates skyrocketed in the wake of COVID-19 lockdowns and the explosion of cases at the end of 2020, there is not sufficient evidence to say that the distribution of firm-initiated turnover has changed after COVID-19.

Not only does this confirm that the majority of labor market churn is being initiated by employees rather than by layoffs and discharges, it underscores the dramatic re-calibration that occurred within the labor market, with the post-COVID workforce perhaps sparking a trend of an individual exhibiting more control over their own work situation. This could lead to increased union membership, greater access to remote work, increased employee flexibility, or even a rise in self-employment. Regardless, these increased churn rates confirm that firms will need to adapt their occupational characteristics in order to thrive in the post-pandemic work environment. This also may lead to greater compensating wage differentials being offered within these industries in order to account for workers' shifting attitudes towards working in lousy occupations.

4.5 Unemployment

One last variable to note in this employment analysis is the U-3 unemployment rate, which, since the easing of COVID restrictions, has decreased at a greater rate than previous recessions (Hall and Kudlyak, 2021). While the unemployment rate is notoriously misunderstood by much of the media and the public, a large rate of unemployment, especially in industries previously found to have a high concentration of lousy occupations, may represent a large number of workers who are still looking for work, rather than a departure from those types of occupations or the labor force altogether. After peaking at 14.7 percent in April of 2020, the seasonally-adjusted unemployment rate across all industries was below 7 percent by October of 2020 and reached 3.6 percent as of March 2022, virtually identical to the 3.5 percent unemployment rate in February of 2020. Given that much of the gap in employment has persisted when compared to February 2020 employment figures, this suggests that many workers had left the labor force altogether. The U-4 unemployment rate (only marginally higher at 3.8 percent, virtually identical to previous economic trends) suggests that very little of this gap can be explained by discouraged workers who have been unable to find work.

Figure 19 shows the estimated, non-adjusted unemployment rate for each "lousy" occupational category (Bureau of Labor Statistics). This measures the number of currently unemployed individuals whose last occupation was in one of these four categories. These four groups (service occupations, office and administrative support, transportation, and sales) have at least 10 percent more workers within "lousy" occupations than the population as a whole. The total unadjusted unemployment rate is also included as a reference.

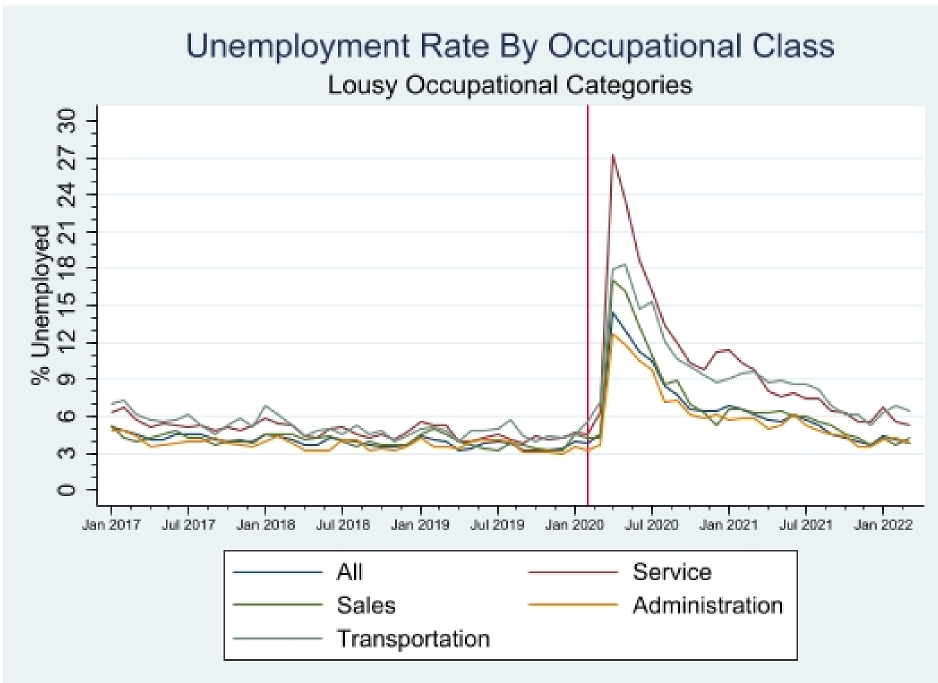

Figure 19: Unemployment rate of various occupational categories

While the degree of difference between the unemployment rates of service and transportation workers and the rest of the labor market is greater than it was before the pandemic, the unemployment rates themselves are not staggeringly high (5.3 percent for service workers and 6 percent for transportation workers in March of 2022). This is roughly similar to their unemployment rates in early 2017, albeit with a higher total unemployment rate. The increased churn observed within these occupations suggests that much of this unemployment could be frictional, or these workers may simply be in search of a new occupation that caters more to their work environment needs. Sales workers remain at roughly the same level of employment as the rest of the country despite the slow recovery in “lousy” sales occupations, which could be due to persistent external factors or declining rates of labor force participation.

These industry and occupational-level turnover statistics help define the context and significance of the gap in the indexed employment levels I found in Section 3. The industries and occupations that have felt the strongest effects of the “Great Resignation” have been those with large concentrations of workers whose occupational environment and characteristics do not allow them the freedom to control their own schedule and responsibilities, minimize their own discomfort, protect themselves from unsafe working conditions, and exhibit positive work qualities that allow for personal and professional growth.

5 Conclusion

The COVID-19 pandemic has undoubtedly transformed both individual workers’ priorities and employees’ daily routines, and these transformations should be accompanied by a thorough examination of how this may affect the employment choices that individuals make. Through the development of an occupation’s lousiness score and the examination of dynamic labor market trends based on these scores, economists and business owners can gain an understanding of which jobs employees gravitate towards or away from. In the wake of COVID-19, workers were much slower to return to jobs and industries that did not allow them freedom and flexibility within their work environment, subjected them to large amounts of stress or pressure, exposed them to unsafe working conditions, and did not encourage them to display personal growth or virtues. They were also much more likely to leave these jobs during the “Great Resignation”, contributing to greater churn rates and more vacancies in sectors such as retail trade, transportation, and food services.

In the post-COVID work environment, as workers have demonstrated that the characteristics of their work matter much more than they did in the past, understanding an occupation’s lousiness score can inform firms about the relative supply that may be available and how the characteristics of a work environment can be modified to mitigate these lousiness concerns. This index can obviously be modified and applied to various types of work during previous years as a way to inform researchers’ understanding of the attributes employees typically search for when selecting an occupation, and how the labor market has changed over time to accommodate for this.

This understanding of lousiness also has useful applications within existing economic theory. For example, compensating wage differentials may have changed for lousy occupations during COVID-19, and perhaps can more closely be calculated through an occupation’s lousiness score. There are also implications in industrial organization regarding the rate at which lousy occupations emerge or disappear within a certain firm or market structure. Public policy can also use occupational lousiness indicators to determine the work environment that best suits the labor force’s needs and attempt to remove lousy characteristics from the daily routine of many occupations as much as possible, in order to maintain a happy and productive post-pandemic workforce.

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Appendix A Occupational worker concentration within each industry

Industry	Administration	Construction	Maintenance	Management	Production	Professional	Sales	Service	Transportation
[HTML]9B9B9B All industries	11.2%	5.1%	3.1%	17.6%	5.3%	24.2%	9.6%	16.7%	6.5%
Accommodation and food services	4.4%	0.2%	0.2%	15.3%	0.9%	1.1%	8.3%	67.3%	2.3%
Arts, entertainment, and recreation	7.7%	0.8%	2.4%	17.4%	0.3%	28.3%	4.4%	36.0%	2.3%
Construction	4.7%	60.2%	5.4%	19.9%	1.9%	2.8%	1.8%	0.7%	2.7%
Educational services	6.3%	0.2%	1.0%	11.7%	0.4%	69.0%	0.2%	9.3%	1.8%
Finance and insurance	22.6%	0.0%	0.1%	46.3%	0.3%	13.5%	15.8%	1.2%	0.2%
Healthcare and social assistance	11.3%	0.1%	0.5%	9.5%	0.5%	49.1%	0.3%	28.1%	0.6%
Information	13.2%	0.7%	8.5%	20.2%	1.1%	43.4%	8.9%	3.1%	0.9%
Management, administrative, and support	13.4%	1.3%	2.9%	15.3%	2.3%	6.1%	3.2%	47.9%	7.6%
Manufacturing, durable goods	9.1%	3.0%	4.6%	18.5%	36.8%	16.7%	3.3%	0.8%	7.1%
Manufacturing, nondurable goods	8.4%	1.5%	4.4%	19.4%	37.5%	11.1%	4.8%	2.6%	10.2%
Mining	7.7%	32.9%	7.7%	13.8%	8.9%	16.0%	1.1%	0.1%	11.9%
Professional services	10.0%	0.7%	0.9%	34.3%	1.2%	47.4%	3.2%	1.4%	0.7%
Public administration	17.4%	1.3%	2.6%	19.5%	1.2%	25.4%	0.4%	30.3%	1.5%
Real estate	9.7%	1.4%	4.3%	33.5%	1.4%	1.9%	38.3%	6.6%	3.2%
Retail trade	16.6%	0.5%	3.2%	6.6%	2.8%	6.6%	49.5%	4.3%	9.7%
Transportation and warehousing	21.2%	0.7%	4.2%	9.8%	1.8%	2.3%	1.6%	1.7%	56.5%
Utilities	11.4%	10.6%	11.6%	23.9%	18.0%	18.2%	1.7%	1.8%	2.7%
Wholesale trade	15.8%	0.5%	4.0%	14.4%	5.1%	6.1%	34.3%	1.2%	17.8%

Table 7: Percentage of each occupational category within each industry's employment total in February 2020. Excludes agriculture.
Source: Current Population Survey

Appendix B O*NET survey questions

The Occupational Network calculates the variables for each occupation that I use in determining the lousiness score by aggregating workers' responses to the surveys below and indexing the average response as a number from 0 to 100.

Time Management Level	"What level of time management is needed to perform your current job?"
	7
"Allocate the time of scientists to multiple research projects"	6
	5
"Allocate the time of subordinates to projects for the upcoming week"	4
	3
"Keep a monthly calendar of appointments"	2
	1

Judgment and Making Decisions Level	"What level of judgment and decision making is needed to perform your current job?"
	7
"Decide whether a manufacturing company should invest in new robotics technology"	6
	5
"Evaluate a loan application for degree of risk"	4
	3
"Decide how scheduling a break will affect work flow"	2
	1

Organizing, Planning, and Prioritizing Work Level	"What level of organizing, planning, and prioritizing work is needed to perform your current job?"
	7
"Prioritize and plan multiple tasks several months ahead"	6
	5
"Plan and adjust a personal to-do list according to changing demands"	4
	3
"Organize a work schedule that is repetitive and easy to plan"	2
	1

Deal With External Customers	"How important is it to work with external customers or the public in this job?"
Extremely important	5
Very important	4
Important	3
Fairly important	2
Not important at all	1

Face To Face Discussions	"How often does your current job require face-to-face discussions with individuals and within teams?"
Every day	5
Once a week or more but not every day	4
Once a month or more but not every week	3
Once a year or more but not every month	2
Never	1

Frequency of Conflict	"How often are conflict situations a part of your current job?"
Every day	5
Once a week or more but not every day	4
Once a month or more but not every week	3
Once a year or more but not every month	2
Never	1

Exposure to Disease	"How often does your current job require that you be exposed to diseases or infection?"
Every day	5
Once a week or more but not every day	4
Once a month or more but not every week	3
Once a year or more but not every month	2
Never	1

Exposure to Hazardous Conditions	"How often does your current job require that you be exposed to hazardous conditions?"
Every day	5
Once a week or more but not every day	4
Once a month or more but not every week	3
Once a year or more but not every month	2
Never	1

Degree of Automation	"How automated is your current job?"
Completely automated	5
Highly automated	4
Moderately automated	3
Slightly automated	2
Not at all automated	1

Duration of Typical Work Week	"How many hours do you work in a typical week on your current job?"
More than 40 hours	3
40 hours	2
Less than 40 hours	1

Freedom to Make Decisions	"In your current job, how much freedom do you have to make decisions without supervision?"
A lot of freedom	5
Some freedom	4
Limited freedom	3
Very little freedom	2
No freedom	1

Structured versus Unstructured Work	"How much freedom do you have to determine the tasks, priorities, or goals of your current job?"
A lot of freedom	5
Some freedom	4
Limited freedom	3
Very little freedom	2
No freedom	1

Importance of Repeating Same Tasks	"How important to your current job are continuous, repetitious physical activities (like key entry) or mental activities (like checking entries in a ledger)?"
Extremely important	5
Very important	4
Important	3
Fairly important	2
Not important at all	1

Time Pressure	"How often does your current job require you to meet strict deadlines?"
Every day	5
Once a week or more but not every day	4
Once a month or more but not every week	3
Once a year or more but not every month	2
Never	1

Work Schedule	"How regular is your work schedule on your current job?"
Seasonal (only during certain times of the year)	3
Irregular (changes with weather conditions, production demand, or contract duration)	2
Regular (established routine, set schedule)	1

Physical Proximity	"How physically close to other people are you when you perform your current job?"
Very close (near touching)	5
Moderately close (at arm's length)	4
Slightly close (e.g. shared office)	3
I work with others but not closely (e.g. private office)	2
I don't work near other people (beyond 100 feet)	1

Stress Tolerance	Job requires accepting criticism and dealing calmly and effectively with high-stress situations.
"How important is stress tolerance to the performance of your current job?"	
Extremely important	5
Very important	4
Important	3
Somewhat important	2
Not important	1

Independence	Job requires developing one's own ways of doing things, guiding oneself with little or no supervision, and depending on oneself to get things done.
"How important is independence to the performance of your current job?"	
Extremely important	5
Very important	4
Important	3
Somewhat important	2
Not important	1

Initiative	Job requires a willingness to take on responsibilities and challenges.
"How important is initiative to the performance of your current job?"	
Extremely important	5
Very important	4
Important	3
Somewhat important	2
Not important	1

Leadership	Job requires a willingness to lead, take charge, and offer opinions and direction.
"How important is leadership to the performance of your current job?"	
Extremely important	5
Very important	4
Important	3
Somewhat important	2
Not important	1

Appendix C Regression Results

Table 8: Probit regression of employment within a lousy occupation based on demographic information. Baseline category is a white man over the age of 55 with a bachelor's degree.

Probability of Working Within "Lousy" Occupation VARIABLES	(1) Probability
Age$\leq$ 25	0.363***
	(0.0221)
Age$\leq$ 35	0.110***
	(0.0212)
Age$\leq$ 45	-0.0116
	(0.0215)
Age$\leq$ 55	-0.00922
	(0.0207)
Sex	0.0732***
(0=Male, 1=Female)	(0.0158)
Black	0.326***
	(0.0324)
Asian	0.175***
	(0.0285)
Hispanic	0.00429
	(0.0256)
Black Woman	-0.158***
(1 if Black woman, 0 otherwise)	(0.0443)
Hispanic Woman	0.192***
(1 if Hispanic woman, 0 otherwise)	(0.0355)
Other/Mixed race	0.121***
	(0.0433)
No HS diploma	0.690***
	(0.0273)
HS diploma, no college	0.524***
	(0.0196)
Some college, no degree	0.445***
	(0.0216)
Associate's/Vocational degree	0.185***
	(0.0256)
Post-graduate degree	-0.193***
	(0.0262)
Constant	-1.304***
	(0.0314)
Observations	59,077

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Employment Trend Post-October 2020 (1000s)	(1)	(2)
VARIABLES	Employment in Lousy Occupations	Employment in Non-Lousy Occupations
Month	-270.9***	1150.913***
	(55.4)	(295.7)
$Month^2$	21.79***	-45.683***
	(3.17)	(16.91)
Constant	33,152***	112243.4***
	(204.6)	(1092.17)
Observations	16	16
R-squared	0.891	0.737

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Growth in employment within lousy and non-lousy occupations since October 2020. All numbers are in thousands.

Labor Force Size Among Non-Lousy Occupations (1000s)	(1)
VARIABLES	Labor Force
Month	41.49*
	(20.57)
Constant	125,147.3***
	(234.52)
Observations	19
R-squared	0.193

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Labor Force Size Among Lousy Occupations (1000s)	(1)
VARIABLES	Labor Force
ln(month)	397.2**
	(140.0)
Constant	35,199***
	(310.0)
Observations	19
R-squared	0.321

Table 10: Growth in labor force participation level among both groups since June 2020

Two-sample t test with unequal variances	**Group**	**Obs**	**Mean**	**Std. error**	**Std. deviation**	**95% CI**		**Ha: diff > 0**
Hirings Ratio (Lousy/Non-Lousy)	1	36	1.343259	.0113126	.0678754	1.320294	1.366225	Pr(T > t) : 1.0000
	2	18	1.510613	.0181832	.0771449	1.47225	1.47225	
	Combined	54	1.399044	.0144611	.1062666	1.370039	1.428049	
	diff		-.1673537	.021415		-.2110597	-.1236477	
						t =	-7.8148	
Job Openings Ratio (Lousy/Non-Lousy)	1	36	1.122216	.0133184	.0799106	1.095178	1.149254	
	2	18	1.112107	.0144286	.0612155	1.081665	1.142549	Pr(T>t):
	Combined	54	1.118847	.0100389	.0737705	1.098711	1.138982	
	diff		.0101091	.0196358		-.0294874	.0497057	.3047
						t =	0.5148	
Quits Ratio (Lousy/Non-Lousy)	1	36	1.627199	.0158291	.0949747	1.595064	1.659334	
	2	18	1.746516	.0164261	.0696901	1.71186	1.781172	Pr(T>t):
	Combined	54	1.666971	.0141014	.1036239	1.638687	1.695255	
	diff		-.1193171	.0228118		-.1652747	-.0733594	1.000
						t =	-5.2305	

Table 11: Two sample t-tests (assuming unequal variance) for the ratios of hirings, job openings, and quits between lousy and non-lousy industries. The baseline group (Group 1) is January 2017-December 2019, and the treatment group (Group 2) is August 2020-January 2022.

Two-sample t test with unequal variances	**Group**	**Obs**	**Mean**	**Std. error**	**Std. deviation**	**95% CI**		**Ha: diff > 0**
General Churn Ratio (Lousy/Non-Lousy)	1	35	1.374306	.0126263	.074698	1.348647	1.399966	Pr(T > t) : 1.0000
	2	18	1.469994	.0147535	.0625939	1.438867	1.501121	
	Combined	53	1.406804	.0115106	.0837987	1.383706	1.429902	
	diff		-.0956876	.0194188		-.1349274	-.0564478	
						t =	-4.9276	
Employee Churn Ratio (Lousy/Non-Lousy)	1	35	1.571766	.0135975	.0804441	1.544133	1.5994	Pr(T>t):
	2	18	1.656344	.0165689	.0702957	1.621387	1.691301	
	Combined	53	1.600491	.0118814	.0864979	1.576649	1.624332	
	diff		-.0845776	.0214341		-.1279389	-.0412162	.9998
						t =	-3.9459	
Firm Churn Ratio (Lousy/Non-Lousy)	1	35	1.034382	.0200526	.118633	.9936304	1.075134	Pr(T>t):
	2	18	1.020733	.0442348	.1876724	.9274053	1.11406	
	Combined	53	1.029747	.019791	.1440806	.990033	1.06946	
	diff		.0136497	.0485677		-.0865467	.113846	.3905
						t =	.2810	

Table 12: Two sample t-tests (assuming unequal variance) for the ratios of general churn, employee churn, and firm churn between lousy and non-lousy industries. The baseline group (Group 1) is February 2017-December 2019, and the treatment group (Group 2) is August 2020-January 2022.