Skill Mismatch One Year Into the COVID19 Pandemic

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November 1, 2021

Abstract

In this paper, we examine whether the economic recovery from the COVID19 pandemic has been accompanied by abnormal rates mismatch between an individual's pre-pandemic occupation and their occupation in the first five months of 2021. We consider an individual to be mismatched if they are employed in a new occupation that is not higher paying than their pre-pandemic occupation, is not contained within the same 2 digit occupation code as their new occupation, and has dissimilar skills requirements from their pre-pandemic occupation as measured by the Euclidean distance between the O*NET skills of the two occupations. We find evidence of an increase in the prevalence of mismatch for women, Hispanics, married individuals,individuals with a high school level education, and workers at the beginning of their careers. With the exception of married individuals, these demographic groups largely correspond to the demographic groups for which non-employment rates increased the most in spring 2020. We find that this rise in mismatch is entirely driven by individuals who were out of work in spring 2020, indicating that this mismatch is a result of individuals who are returning to work being unable to find work in occupations that are well matched.

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†We would like to thank Guido Matias Cortes, Ye Jia, Justin Kakeu, Fabian Lange, Huju Liu, and Wimal Rankaduwa for their helpful comments. We would also like to thank participants at the 55th Annual Canadian Economics Association Meetings, and seminar participants at the University of Prince Edward Island.

1 Introduction

The COVID19 pandemic has undoubtedly marked the most sudden disruption to labor markets in modern history. Between February and April 2020, the U.S. unemployment rate skyrocketed from 3.5% to a record 14.8%, the largest 2 month increase in the recorded history of U.S. unemployment.[1] Although this shock's impact was felt by a broad range of the population, it has become well established that its impact differed across demographic groups and occupations.

Physical distancing measures that were implemented in the early weeks of the pandemic resulted in a large number of layoffs as many businesses were required to operate at a reduced capacity, or in some cases to stop operating altogether (Besley and Stern 2020, Brodeur et al. 2020). Relatively insulated from these layoffs were workers in predominantly white collar jobs that allowed workers to telecommute (Boeri et al. 2020, Bick et al. 2020, Dingel and Neiman 2020, Montenovo et al. 2020, Papanikolaou and Schmidt 2020). The demand side effects of the pandemic were less concentrated, and were similar to the anticipated effects of a "normal recession". Job vacancies declined in nearly all occupations, with the notable exception of essential occupations such as nurses, grocery store workers, etc. (Forsythe et al. 2020a, Kahn et al. 2020b). Beyond layoffs, there were additional pandemic induced job separations initiated by employees, the most notable reason for this being childcare requirements at home following closures of schools and daycares (Albanesi and Kim 2021, Kahn et al. 2020a). While the employment impacts of the pandemic differed across occupations, it has also been documented that all demographic groups were not equally impacted. Job separations were more common among women than men (Cortes and Forsythe 2020,Albanesi and Kim 2021,Alon et al. 2020,Mongey et al. 2020), giving rise to the popular term "she-cession" to describe the current economic downturn. Furthermore, Hispanic workers (Fairlie et al. 2020,Cortes and Forsythe 2020), younger workers (Montenovo et al. 2020,Cortes and Forsythe 2020), immigrants (Borjas and Cassidy 2020), and workers without a college education (Mongey et al. 2020) were also among the most likely to experience a job separation.

We now know that a large number of those individuals who were initially impacted by the pandemic have since returned to work (Cheng et al. 2020). Oftentimes, these individuals returned to work for a pre-pandemic employer (Brochu et al. 2020, Cheng et al. 2020, Hall and Kudlyak 2020,Forsythe et al. 2020b). However, as of mid-2021, little is known about whether those who began new employment relationships tend to be working in jobs that are good matches for their skills. Earlier work in the skill

[1] See https://data.bls.gov/timeseries/LNS14000000. The previous record was an increase of 1.5 percentage points from November 1974 to January 1975, when the unemployment rate rose from 6.6% to 8.1%, and in levels the previous record was an unemployment rate of 10.8% in both November and December of 1982.

mismatch literature leaves reason to believe that skill mismatch may have increased since the onset of the pandemic. Historically, workers have been more likely to become mismatched during economic downturns (Moscarini 2001, Moscarini and Vella 2008, Zago 2020). However, in addition to the rise in mismatch that would be expected of a "normal recession", there are further reasons to believe that skill mismatch may be exacerbated during the COVID19 pandemic. The sudden shift in consumption patterns of households is expected to decrease the demand for goods that are provided by workers in a face-to-face environment (Autor and Reynolds 2020), potentially increasing the likelihood that workers with such skills will become mismatched. Furthermore, the pandemic has provided firms with an incentive to automate their operations in order to mitigate the risk that physical requirements poses to their operations (Blit 2020, Chernoff and Warman 2020). This is expected to exacerbate already present declines in demand for workers in routine task oriented occupations. Our lack of understanding of whether workers have found employment in occupations that are good matches for their skills forms a significant gap in the literature on the economic impact of the COVID19 pandemic. Skill mismatch is known to have negative impacts on the earnings of individual workers who become mismatched (Poletaev and Robinson 2008, Gathmann and Schönberg 2010, Yamaguchi 2012, Robinson 2018). Furthermore, increases in skill mismatch at the macro level tend to result in reductions of an economy's aggregate output (Garibaldi et al. 2020, Odio Zúñiga and Yuen 2020).

In this paper, we contribute to the literature on the labor market impact of the COVID19 pandemic by documenting the prevalence of skill mismatch in the first five months of 2021, relative to the same months in recent pre-pandemic years. We consider an individual to be mismatched if each of the following 3 criteria are satisfied: (i) there needs to be an occupation switch at the 2-digit level (ii) into an occupation that pays no more than the previous occupation, and (iii) which is sufficiently distant in terms of skill content.By using this measure of mismatch, we are focusing on individuals who have switched into jobs that are both of a lower quality in a normative sense, and requiring a very different type of human capital.

We do not consider an individual who has moved into a higher paying occupation as mismatched since movements into occupations that are higher skilled are rarely associated with earnings penalties, even if the types of skills that are required of the new occupation are significantly different from those that were required of the old occupation (Robinson 2018). This primarily prevents individuals who have moved into managerial roles from being classified as mismatched. We furthermore consider an individual to be mismatched if and only if the Euclidean distance between the normalized skills of

these two occupations (as measured using occupation Skills, Abilities, and Knowledge requirements from O*NET) is at least 1. This indicates that the value of the average skill in one's new occupation is at least one standard deviation away from the value of that skill in their pre-pandemic occupation.This last distance requirement ensures that we do not consider an individual to be mismatched if they have found employment in an occupation that requires similar skills as their pre-pandemic occupation. An example of such a pair of occupations would be "Financial Examiners" and "Actuaries", which are contained within different 2-digit SOC occupation groups but are both analytical in nature.

We use a difference-in-difference approach in order to determine whether mismatch, as defined above, has increased during the pandemic relative to the recent pre-pandemic years 2018 and 2019. We find that in the first five months of 2021, individuals are more likely to have moved into mismatched occupations than otherwise similar individuals in the first 5 months of 2018 or 2019. However, we find that this rise in skill mismatch has not occurred for all demographic groups. Increases in skill mismatch are found among married individuals, women, Hispanics, individuals with a high school level education, and, most notably, early career workers.Although the rise in skill mismatch has been concentrated among groups that are traditionally economically disadvantaged, we find no evidence of an increase in skill mismatch among African-Americans or immigrants. We do find that, with few exceptions, the demographic groups experiencing increased mismatch mirror the demographic groups that were the most likely to experience job separations in the early weeks of the pandemic. Specifications in which we control for whether an individual was observed to be out of work in any of March, April, or May of 2020 account for nearly the entirety of the rise in skill mismatch among all demographic groups, except for workers at the beginning of their career for whom this explains only about one-third of the rise in mismatch.

In addition to an increase in the incidence of mismatch for certain demographic groups, we present evidence that indicates that these workers are moving into more distant occupations conditional on moving into a lower paying occupation in a different 2-digit occupation group. This evidence suggest that those individuals who are moving into lower paying occupations have a greater intensity of mismatch than individuals who moved into lower paying occupations pre-COVID. We further examine the earnings implications of skill mismatch and find that an individual who becomes mismatched is expected to earn on average 15% less than a non-mismatched individual who initially worked in the same two digit occupation group. This highlights the individual level consequences that are associated with the increased prevalence of skill mismatch that is documented in this paper. Since the increase

in mismatch has predominantly been concentrated among demographic groups that are traditionally economically disadvantaged, it is expected the presence of a corresponding earnings penalty will increase between group income inequality.

The remainder of this paper is organized as follows. Section 2 describes the methodology, Section 3 describes the results, Section 4 examines the earnings implications of mismatch, Section 5 covers robustness checks, and Section 6 concludes.

2 Data and Methodology

This project uses Current Population Survey (CPS) data from January 2017 to May 2021. The CPS is a monthly survey administered to a sample of approximately 60,000 Americans every month. Once a household is surveyed, it remains in the sample for a period of four consecutive months. Exactly one year after the household's first appearance in the sample, it is observed again for another four consecutive months. We link individuals across months by creating a unique identifier for each individual.[2]

Although the CPS records an individual's occupation in any given month, occupational coding errors are unfortunately common in the CPS data. These occupational coding errors are a significant hindrance to examining research questions related to occupational mobility (Neal 1999, Moscarini and Thomsson 2007, Kambourov and Manovskii 2008). Consider, for example, an individual who is Professor of Economics. Without any change in occupation, it's plausible that this individual may be classified as an "Economist" in one month and a "Post-Secondary Teacher" in a subsequent month, despite no change in occupation having occurred.

In order to address this issue, we use a procedure that is similar to Moscarini and Thomsson (2007). If an individual's occupation in month t differs from their occupation in month $t-1$, we replace the individual's time t occupation with their occupation at time $t-1$ if each of the following 3 conditions are satisfied; they have not reported a change in industry, they have not reported a change

[2]This unique identifier is constructed by combining the household identifiers (HRHHID and HRHHID2) that are present in the CPS, with the "person line number" (PULINENO). Since the CPS surveys households rather than individuals, additional demographic characteristics are used in the construction of person identifiers in order to avoid linking members of different families that have occupied the same address during the survey period. These additional characteristics are; sex, race, age during first month surveyed, country of birth, mother's country of birth, and father's country of birth. Age during first month in the survey is constructed by subtracting one from age during the second 4 month period in the survey, followed by subtracting one from age if age increases by one during the 4 month survey period.

in their class of worker[3], and they have not reported any job search activity in the previous 4 weeks. Similarly, we also replace their time t occupation with their time $t-1$ occupation if they report that their job duties and activities have not changed from the previous month. Finally, in the event that an individual's occupation at times $t-1$ and $t+1$ are identical but differ from the occupation at time t, we replace the time t occupation with the time $t-1/t+1$ occupation. These reclassifications inevitably eliminate some valid occupational changes. However, we believe that the value of reducing spurious occupation changes outweighs the loss of such valid changes.

A further complication with the data arises due to changes in the CPS occupation codes that were introduced in January 2020. The Standard Occupation Classification (SOC) codes were updated from the 2010 codes to a new set of 2020 codes. Furthermore, analysts began verifying whether an individual's occupation is plausible given their level of education. In the event that one's education is deemed insufficient for their occupation, their occupation codes are revised accordingly. We address these concerns by first examining whether the changes introduced in 2020 produce higher rates of mismatch by estimating the rate of mismatch that arose between January 2020 and February 2020, the only months after the change that are unlikely to be impacted by COVID19, and comparing this to the rates of mismatch that arose between January 2017 or 2018 and February 2017 or 2018. We find that the prevalence of mismatch at the beginning of 2020 was significantly lower than that of early 2017 or 2018, suggested that the changes introduced in early 2020 are less likely to produce spurious cases of mismatch than the benchmark era data.

We restrict our analysis to those individuals whose first appearance in the CPS data occurs in either the month of January or February, and in one of the years 2017, 2018, or 2020. The individuals who first appear in 2017 or 2018 collectively serve as a pre-pandemic benchmark group to which we compare individuals who first appear immediately before the onset of the pandemic. We exclude anyone who was not employed in their first February in the survey, and furthermore we exclude individuals who do not re-appear in the sample one year after their initial appearance. For the pandemic era subsample, these restrictions allow us to examine the skills of one's occupation immediately before the pandemic, and to compare these skills to those of their occupation in early 2021.

We are left with a total of 114,591 usable observations, 76,205 of which are from our pre-pandemic benchmark era, while the remaining 38,386 observations are from the pandemic era. We report the

[3]Classes of workers include, "Government-Federal", "Government-State", "Government-Local", "Private, for Profit", "Private- Nonprofit","Self-Employed, Incorporated", "Self-Employed, Unincorporated", and "Without Pay".

means of our demographic characteristics of interest in Table 1 separately for the benchmark and pandemic time periods. "Married" consists of all individuals whose reported marital status is either married or common-law. "White","African American","Hispanic", and "Asian American" are dummy variables indicating the race of the individual. "Less Than High School", "High School", "Post-Secondary < Bachelor's", "Bachelor's", and "Post-Secondary > Bachelor's" are dummy variables indicating the individual's highest level of education. We find no noteworthy differences between the demographic characteristics of the benchmark and pandemic era subgroups.

Similarly, we report the proportion of individuals who were initially employed in each of the two digit Standard Occupational Classification (SOC) occupations in columns (1) and (2) of Table 2. The initial occupation distributions in the two subgroups are similar, with the only notable difference being a higher proportion of individuals employed in "Business Operations" occupation in February 2020 relative to February 2017/2018. In column (3) we report the occupation distribution in early 2021. We observe surprisingly little change in the overall occupation distribution since the onset of the pandemic.

2.1 Non-Employment

While we are primarily interested in examining skill mismatch, we also examine non-employment rates of individuals during Spring 2020, and again in the first five months of 2021. Similarly, we report the equivalent non-employment rates for our benchmark time period. We classify an individual as being not employed if their reported labor force status is anything other than "Employed-Present" or "Employed-Absent", where the latter must be in combination with a reason for absence other than sick/vacation days. We classify individuals who are absent from work for other reasons as not employed since they were unlikely to have been generating an income at that point in time, and in many cases these individuals are more accurately categorized as being on temporary layoff. Unsurprisingly, in the row entitled "Not Employed First Year" in Table 3, we find that non-employment rates in spring 2020 − the months of March, April, and May − were significantly higher than the equivalent rates from springs 2017/2018. Note that, since we exclude individuals who were not working in the first February in which they appear, these are non-employment rates conditional on having worked a few months earlier. By the first five months of 2021, the non-employment rates of individuals who were working in February 2020 have declined dramatically (as shown in the row "Not Employed Second Year" in Table 3), however it remains well above the equivalent benchmark value.

2.2 Mismatch

The observation that non-employment rates have declined substantially since spring 2020 indicates that a sizeable number of individuals were out of work and have since found employment. While approximately 60% of those who were out of work returned to work in their last pre-pandemic occupation by early 2021, we know very little about the degree to which those who have found employment in other occupations are working in occupations that are good matches for their skills.

As shown in the row "Mismatch" of Table 3, approximately 8.9% of individuals in the benchmark era are estimated as having become mismatched between February 2017 or 2018 and early the following year. This has risen to approximately 9.4% during the COVID19 pandemic. The figures use our main measure of mismatch computed in the following way. We consider an individual to be mismatched if each of the following three conditions are satisfied: The mean annual log earnings of their new occupation are not statistically higher (at the 5% significance level) than the mean log annual earnings of their old occupation; their new occupation is contained within a different two-digit SOC occupation category than their old occupation; and the skill distance as shown in Equation 1 is at least 1.

O*NET contains the degree to which 118 different skills are required for an occupation. Using data from O*NET, we calculate the skill distance between two occupations by first matching each occupation to its Skills, Abilities, and Knowledge requirements (hereafter collectively referred to as "skills" for simplicity). We use principal component analysis in order to aggregate these 118 different skills into 10 principal components, $Comp^1, Comp^2, ..., Comp^{10}$. For each individual in the data, skill distance is calculated using the formula in Equation 1:

$$Distance_i = \sqrt{\sum_{j=1}^{10} Eigenvalue^j (Comp^j_{i,t} - Comp^j_{i,t-k})^2} \tag{1}$$

where $Comp^j_{i,t}$ represents the value of the jth principal component that is associated with individual i's job at time t, and $Comp^j_{i,t-k}$ represents the value of the jth principal component that is associated with individual i's job at time $t-k$. For most of our subsequent analysis, time t is Spring (2021 or an earlier benchmark year), while time $t-k$ is the preceding February. $Eigenvalue^j$ is the eigenvalue that is associated with the jth principal component, and is used to place a larger weight on components that explain more of the variation in the overall skill space.

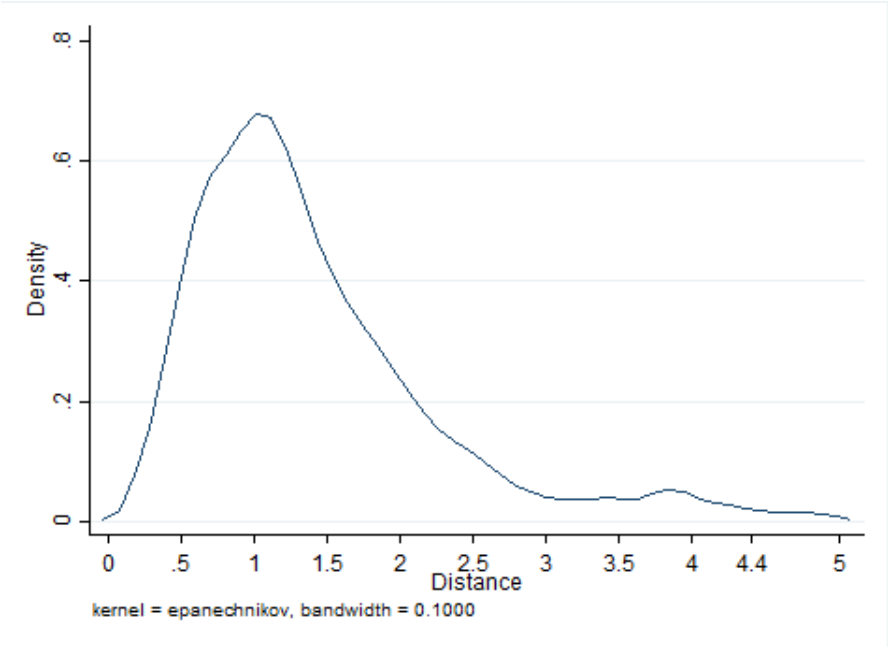

Figure 1: Kernel Density of Distance Conditional on Change in Occupation

Individuals who remain in the same 6-digit occupation have a skill distance of 0 by definition. A 1 unit value of distance indicates that an individual has moved to an occupation in which the average principal component skill measure at time t is 1 standard deviation away from its value at time $t-k$. Those individuals who have found employment in an occupation that requires similar skills as their old occupation will have small distance values. Those who have found employment in an occupation that has very different skill requirements will have large distance values. For illustration purposes, we report in Table 4 examples of the median skill distance for some occupation transitions aggregated at the two digit level. In this example, moves within similar 2-digit occupations have distances smaller than one, as for instance moves from Construction and Extraction occupation groups into Construction and Extraction groups (0.685) or from business operations into business operations (0.687). While a majority of distances in this example are between 1 and 2, some outliers with larger skill distances can be noted: from Transportation into Computer and Mathematical (4.117) or from Business Operations into Healthcare practitioners (3.268).

Figure 1 shows the kernel density plot of distance conditional on a change in occupation. This density peaks near a distance of 1, which we consider to the minimum distance at which one may be considered as mismatched.

2.3 Alternative Measures of Mismatch

We test the robustness of our results by using four similar alternative measures of mismatch. The first one,"Mismatch Alternative 1", lowers the skill distance between occupations that is required in order to classify an individual as mismatched to 0.8. By definition, this measure produces a higher rate of mismatch. As shown in Table 3, the proportion of individuals who are classified as mismatched is estimated as nearly two percentage points higher than the equivalent value using our preferred measure of mismatch. However, we continue to observe an increase in mismatch between the benchmark era and the pandemic.

Our second alternative measure of mismatch, "Mismatch Alternative 2", is similarly constructed except for an increase in the minimum distance threshold that is required for classification as mismatched to 1.2. Statistics from Table 3 indicate that this measure generates a lower rate of mismatch than our preferred measure; however, we continue to observe an increase in mismatch between the benchmark era and the pandemic.

Our third alternative measure of mismatch, "Mismatch Alternative 3", is constructed by first using an alternative method of correcting for spurious occupation changes. With this measure, we consider an occupation change to be spurious if it is not accompanied by a simultaneous change in industry. This eliminates any cases where one is considered to be mismatched after changing to another occupation within the same industry. Otherwise, the criteria for considering an individual to be mismatched are the same as outlined in the previous subsection. As shown in Table 3, this produces rates of mismatch that are only slightly below those using our preferred measure. This small decrease is attributable to the fact that our preferred measure rarely classifies an individual who changes occupations but remains within the same industry as being mismatched.

Our fourth alternative measure of mismatch, "Mismatch Alternative 4", is constructed by making no changes to the raw data in order to correct for spurious occupation changes. Otherwise, the criteria for considering an individual to be mismatched are the same as those outlined in the previous subsection. This inevitably produces more frequent occupation changes and therefore more frequent mismatch, as shown in Table 3. Although rates of mismatch are significantly higher using this measure of mismatch than our preferred measure, we continue to observe higher rates of mismatch during the pandemic era than during the pre-pandemic benchmark era.

2.4 Demographic Differences

We analyze the impact of the pandemic on the each of the dependent variables outlined above by estimating a series of probit models of the general form shown in equation 2.

$$\begin{aligned}\Phi = \beta_0 + \beta_1 Pandemic + \beta_2 Demographics + \beta_3 Pandemic * Demographics + \\ \beta_4 Occupation + \beta_5 Pandemic * Occupation + \\ \beta_6 WasOutofWork + \beta_7 Pandemic * WasOutofWork + \epsilon\end{aligned} \tag{2}$$

Φ, the dependent variable, is a 0/1 indicator for the main measure of mismatch. In other specifications, Φ can also represent sensitivity values of mismatch, as well as indicators for out of work. *Pandemic* is a dummy variable that takes on the value of 1 if the data is from the pandemic era, and 0 if it is from the benchmark era.

We start with a basic specification including *Demographics* as a vector of dummy variables containing each of the demographic characteristics of interest listed in Table 1, with the addition of a quadratic term for age.To the basic model controlling for demographic characteristics we add controls for two-digit SOC occupations(including interactions with the pandemic variable). Furthermore, in the final specification we also include a control for whether an individual was observed to be non-employed in the previous spring (and its interaction with the pandemic variable).

Because the mismatch measure Φ is computed as a change from previous occupation to current one, it mitigates issues of individual selection into occupations due to unobserved fixed effects, which get differenced out. Moreover, COVID has resulted in bad shocks for certain occupations; for instance, we find the rise in mismatch has been concentrated among workers who worked in the "Arts, Design, Entertainment, Sports, and Media" and "Personal Care and Services" occupation groups in February 2020. Accounting for one's starting occupation (e.g. February 2020 for the Pandemic group) addresses this issue. In our results, we report only the marginal effect of the pandemic on the probability of being mismatched after estimating equation 2.

3 Results

In Table 6, we report the estimated marginal effects of the pandemic on the main probability of mismatch as defined in Section 2.2, from three model specifications as described in equation 2. The explanatory variables of interest are: demographics in column (1) (age, marital status, education, ethnicity), to which we add initial occupation in column (2) and an indicator for non-employed in the previous spring in column (3). We only report here the coefficients from the interaction terms between *pandemic* and all the X characteristics, and therefore the marginal effects in this table can be interpreted as the increase in the probability of mismatch between the pandemic and benchmark eras. The marginal effects on the probabilities for all of the other dependent variables outlined in the previous section: out of work in previous spring, not employed, and sensitivity measures of mismatch, are reported in Appendix Tables A1, A2 and A3.

3.1 Mismatch

With regards to our preferred measure of mismatch, column (1) of Table 6 shows notable increases in the probability of being mismatched (conditional on being employed) for members of several demographic groups. We find small (less than one percentage point) but statistically significant increases in the probability of being mismatched among married individuals, women, and individuals around the age of 30. More notably, we find larger increases in mismatch among individuals with a high school level education, Hispanics, and especially individuals around the age of 20. These results indicate that relative to the benchmark era, members of these demographic groups are in early 2021 more likely to be working in occupations that are no higher paying and require a very different skill set from their occupation approximately one year earlier. With the exception of married individuals, the demographic groups that have seen increases in the probability of being mismatched are similar to the demographic groups that saw the largest increases in non-employment rates in spring 2020. Although with predominantly minor differences in magnitude and significance, the alternative measure of mismatch shown in columns (4)-(6) are similar to the results in column (3). When no corrections are made to the occupation changes that are recorded in the raw data, we find larger increases in the probability of being mismatched for members of most demographic groups, as shown in column (7). The most notable difference between the results in column (7) and columns (3)-(6) is that the raw data implies larger increases in mismatch for individuals with higher levels of education.

After accounting for one's initial two digit occupation in column (2) of Table 6, we find the increase in mismatch has been predominantly concentrated among individuals who worked in the occupation

groups "Arts, Design, Entertainment, Sports, and Media" or "Personal Care and Service" prior to the pandemic. We also find weaker evidence of increases in mismatch among individuals who worked in the "Healthcare Support" or "Transportation and Material Moving" groups. Accounting for initial occupation group, however, does little to explain demographic differences in the increase in mismatch. An exception to this is women, for whom we no longer find an increase in the probability of being mismatched after accounting for initial occupation group. However, when we account for whether an individual was observed to be non-employed in the previous spring in column (3) of Table 6, we find that this accounts for the entire increase in mismatch for all demographic groups except for workers around the age of 20.

After accounting for whether an individual was observed as being non-employed in the previous year, we no longer observe any increase in the probability of becoming mismatched for members of most demographic groups, with workers around the age of 20 being the lone exception. This is attributable to a higher probability of becoming mismatched among individuals who experienced a job separation, in combination with the more frequent separations in spring 2020 compared to spring 2017 or spring 2018. Further bolstering the claim that going through a spell of non-employment leads to a higher probability of mismatch, we find similar results using data from the Great Recession era. Although job separations during the Great Recession were not as concentrated in a narrow time period as they were at the onset of the COVID19 pandemic, we find a larger increase in mismatch between fall 2008 and fall 2009 than between fall 2007 and fall 2008.

Table A4 shows that during the Great Recession, there was an increase in mismatch among younger workers, married individuals, men, individuals with less than a high school level education, and white individuals. While these demographic groups do not correspond with the groups for whom mismatch has increased during the COVID19 crisis, this is attributable to the different natures of the two recessions. For example, the impacts of the Great Recession were borne predominantly by men, while the impacts of the COVID19 crisis have been borne primarily by women. This is reflected in the increases in mismatch.

While our main results document the increase in mismatch measured as a dichotomous variable 0/1, we perform a similar marginal effects analysis on the actual log skill distance associated with the mismatch. These results reported in Table A5 show that, conditional on a change to an occupation that is not higher paying and in a different 2-digit group, it is people at the two extremes of the age

distribution that are encountering the largest distance gaps: an 8% larger distance change for the pandemic era compared to non-pandemic times. In line with our previous results, the distance is also larger for women and Hispanics. As a consequence of the focus on essential services during the covid pandemic, workers with less than high-school education experienced a smaller distance in the skill change in the covid era compared to benchmark mismatch episodes, while workers with bachelor's degrees experience a larger distance change.

A further exercise computes the probabilities of mismatch for the benchmark and pandemic groups based on the three specifications: only with demographic characteristics, adding starting occupations, and further adding the non-employment indicator. These results are reported in Table A6 and show conditional mismatch probabilities for various demographics. Besides confirming previous results showing that mismatch rose in the pandemic era, this table also shows differences in mismatch by demographics within the same groups: baseline or pandemic. Comparing baseline with pandemic mismatch probabilites, we recover the same results as those reported in Table 6. From this table we can also see how baseline mismatch varies across groups: women, those with education above Bachelor's, and workers in Healthcare Support or Protective services have smaller incidence of mismatch, while youth, men, those with non-university tertiary education, and workers who go through non-employment have a larger mismatch incidence.

3.2 Non-Employment

On the dimension of employment, we demonstrate in the first column in Table A1 that non-employment rates in spring 2020 were significantly higher for all demographic groups than the equivalent estimates from the benchmark era. However, consistent with earlier literature, we find notable differences across demographic groups. The increases in non-employment were disproportionately large among the youngest workers around the age of 20, women, individuals without post-secondary education, and ethnic minorities.

After controlling for one's two digit occupation in February 2020 (or February 2017/2018 for the benchmark era) in Table A2, we find the increases in non-employment occurred in every single occupation group, albeit with notable differences in magnitude. The most substantial increases in non-employment rates were in the "Arts, Design, Entertainment, Sports, and Media", "Food Preparation and Serving", and "Personal Care and Service" occupation groups. Occupations in these groups tend to involve close in person contact with other individuals or working in settings that typically have

large gatherings of people. Controlling for two-digit occupation group fails to completely account for the differences in the increase in non-employment across demographic groups, although we do observe smaller differences in the marginal effect across age and education groups.

As of early 2021, non-employment rates remain statistically above our benchmark estimates, however the magnitude has declined dramatically since spring 2020, with non-employment being approximately 2-3 percentage points above the benchmark estimates for most demographic groups. A notable exception to this is African-Americans, for whom non-employment rates are nearly 4 percentage points above our benchmark estimates. This has occurred despite the initial non-employment rates for African-Americans not being unusually high relative to members of other ethnic groups. With regards to gender, we no longer observe any notable differences in non-employment rates between men and women. On the dimension of education, we continue to observe relatively larger increases in non-employment among individuals with lower levels of formal education. Interestingly, although the magnitude of the differences is not large, the increase in non-employment rates in early 2021 is smallest for younger workers, who also saw the largest increase in non-employment rates in spring 2020.

When accounting for one's initial two digit occupation, we find that individuals who initially worked in a broad cross-section of occupations remain more likely to be non-employment in early 2020 than similar individuals in the benchmark era. Those who worked in the "Food Preparation and Serving" and "Personal Care and Service" occupation groups saw the largest increase in the probability of being non-employed after approximately one year, with increases in non-employment rates of over 4 percentage points in both cases. Interestingly, we observe no increase in non-employment as of early 2021 for individuals who worked in "Arts, Design, Entertainment, Sports and Media" occupations, despite the initially large increase in non-employment among these workers.

4 Earnings

It has become well established in the literature that individuals who become employed in mismatched occupations earn less on average than their well matched counterparts. In this section, we examine whether similar earnings implications are found among individuals who become mismatched using the definition of mismatch that we develop in this paper. We examine this in order to determine whether the increase in the prevalence of mismatch that we document in this paper has negative earnings implications for those individuals who become mismatched.

We estimate the linear model outlined in equation 3 in which the dependent variable is the natural log of average hourly earnings. $Demographics_i$ is a vector of demographic characteristics listed in Table 1. Average weekly earnings are reported for individuals who are appearing in the CPS for the 4th or 8th time. We divide these average weekly earnings by average weekly hours worked. The smaller sample size for this analysis is attributable primarily to the limited frequency of earnings data. We exclude individuals whose average hourly earnings are less than the U.S. federal minimum wage of $7.25 per hour. We also exclude individuals whose weekly hours worked is not reported or reported as "hours vary". We include a control for whether an individual was observed to be out of work in the previous spring so as to avoid conflating the effect of mismatch on earnings with the effect of an unemployment spell on earnings. We further include controls for the month in which an individual is observed, a dummy for the pandemic era, and an interaction between mismatch and the pandemic dummy to allow the returns to mismatch to differ between the pandemic and pre-pandemic benchmark era.

$$\begin{aligned} Log(Wage)_i = \beta_0 + \beta_1 * Demographics_i + \beta_2 * Mismatch_i + \beta_3 Pandemic_i + \beta_4 Mismatch_i * Pandemic_i \\ \beta_5 Occupation + \beta_6 Pandemic * Occupation + \\ + \beta_7 * OutofWorkLastSpring_i + \beta_8 * Month_i + \epsilon_i \end{aligned} \tag{3}$$

We report the coefficients β_2 and β_4 from this estimation in column (1) of Table 5, with the full results available in Table A7. We find clear evidence that individuals who become mismatched tend to earn approximately 8% less per hour than individuals who have not become mismatched. We fail to find strong evidence that this earnings penalty is different during the pandemic relative to the pre-pandemic benchmark era, although we find weak evidence using 2 of our alternative measure of mismatch that the mismatch earnings penalty may be smaller during the pandemic.

In column (2) of Table 5 (full results in Table A8), we include covariates for an individual's initial two digit occupation. After adding these controls, we find the wage penalty associated with being mismatched has increased to approximately 15%. This indicates that individuals who become mismatched earn, on average, approximately 15% less than well matched individuals who initially worked in the same two digit occupation. This larger penalty is attributable to the fact that individuals who

become mismatched tended to be initially employed in higher paying two digit occupation groups. Given how we have constructed mismatch with a requirement that an individual does not move into a statistically higher paying (6 digit) occupation, this tendency for mismatched individuals to come from higher paying occupations is unsurprising.

5 Robustness Checks

5.1 2020 Occupation Code Changes

Beginning in January 2020, an updated set of occupation and industry codes were introduced to the CPS data[4]. We use the following procedure in order to verify whether these changes could result in more spurious cases of mismatch during the pandemic era relative to the benchmark era. We restrict our subsample to individuals whose first appearance in the data occurs in the month of January in 2017, 2018, and 2020. We further restrict the subsample to individuals who are employed in that particular January, and remain employed in the following month. We compare an individual's occupation in February to their occupation in January, and determine whether an individual has become mismatched in that one month period using each of the definitions of mismatch outlined in subsections 2.2 and 2.3. We restrict our analysis to mismatch that arises between January and February since this is the only transition that occurs following the introduction of the new coding procedures that could not be driven by the COVID19 pandemic.

Since we are only looking at transitions that occur over a one month period, the estimated rates of mismatch are very low, with a mean of 1.1% during the benchmark era and 2.1% during the pandemic era. Table A9 shows the marginal effect of the 2020 data on the probability of being mismatched, as estimated using a simple probit model that contains simply a binary indicator for whether the data is from 2020. It is clear that mismatch is lower in the pre-pandemic portion of 2020, compared to equivalent time periods from the benchmark era. This is most likely due to a change in occupation coding procedures in which analysts began verifying whether an individual's occupation is plausible given their level of education, and if this is not the case recoding their occupation to be one that is appropriate given their level of education. Should this change in procedure reduce spurious occupation changes, it is should also reduce spurious cases of mismatch.Based on this fall in mismatch after the change in occupation coding procedures, we believe that our main results in this paper are lower

[4]See the following User Note in the CPS documentation for more information on these changes https://www.census.gov/programs-surveys/cps/technical-documentation/user-notes/cpsbasic_2020_01.html.

bounds of the true increase in skill mismatch since the onset of the COVID19 pandemic.

5.2 Mismatch Using Job Zones

Using our primary measure of mismatch, we consider only those individuals who have not moved into statistically higher paying occupations as being mismatched. However, in this subsection, we use a different measure of the "overall quality" of an occupation. We use O*NET Job Zones classification, which places each occupation into one of 5 different categories based on the amount of preparation that is required for that occupation. Using this measure of the overall quality of an occupation, we consider an individual to be mismatched only if their new occupation is not contained within a higher job zone (indicating more required preparation) than their previous occupation. We also use the requirements outlined in section 2.2 that their new occupation is at least one distance unit away from their old occupation, and contained within a different two digit occupation group.

We estimate the probit model from Equation 2 using this different measure of mismatch. The results are reported in Table A10. This method of measuring mismatch does not result in increases in mismatch that are as large as those that are generated by our preferred measure using earnings level as a measure of the overall quality of an occupation. However, we continue to find statistically significant increases in mismatch for women and Hispanics with this measure of mismatch. We also continue to find an increase in mismatch, albeit marginally insignificant, among individuals around the age of 20. We no longer find any notable changes in mismatch among married individuals or individuals with a high school level education.

5.3 Linear Probability Model

We re-estimate equation 2 for each of our dependent variables of interest using a linear probability model as opposed to a probit model. The estimated marginal effects using the linear probability model are found in Table A11. We find no notable differences between the Linear Probability Model results in Table A11 and the main analysis using probit model marginal effects (for instance in Table A1).

5.4 Functional Form of Age

The models that we have estimated thus far in this paper have included a quadratic term for age. We therefore test the robustness of our results to estimating the model with the addition of a cubic term

for age. The results from this estimation are found in Table A12. In this table, we report the marginal effects at five year increments of age as opposed to the 10 year increments that have been used thus far in the paper. For comparison purposes, we report in column (2) results that are analogous to the results from column (3) in Table A1 with marginal effects estimated in 5 year increments.We continue to find that that the increase in the probability of being mismatched is concentrated among the youngest workers at the outset of their careers.

6 Conclusion

More than one year into the COVID19 pandemic, there has been a significant recovery in employment numbers relative to the early weeks of the pandemic. However, this recovery has been accompanied by an increased prevalence of skill mismatch. In comparison to the years immediately preceding the pandemic, workers have been more likely to find employment in occupations that require significantly different skill sets from those that were required of their previous job. This rise in skill mismatch has not been uniform across the entire workforce, but has primarily been concentrated among, women, Hispanics, individuals with a high school level education and most notably younger workers at the beginning of their careers. This increase in skill mismatch is accompanied by a decrease in earnings for mismatched individuals, which is expected to increase income inequality since mismatch has increased for traditionally economically disadvantaged groups. Furthermore, the expected consequences of skill mismatch to the macroeconomy are also significant, with an anticipated decline in aggregate output.

Although we can surmise that skill mismatch will come with negative consequences for the economy in the short run, the long term consequences of this rise in skill mismatch are unknown, and should be explored in future research. Pandemic induced skill mismatch may be temporary in nature if labour demand in hard hit occupations returns to pre-pandemic levels, and workers who have been temporarily mismatched begin to return to their pre-pandemic occupations. However, if the skills of workers who were mismatched have atrophied during the pandemic, the consequences of mismatch may extend well into the economic recovery. If patterns of labour demand remain permanently altered due to the pandemic, then skill mismatch is expected to extend well into the future, with long term consequences to the broader economy and to the workers have ended up being mismatched.

Table 1: Sample Means of Demographic Characteristics

	(1) Benchmark Mean	(2) Pandemic Mean
Married	0.630	0.611
Female	0.478	0.475
White	0.854	0.847
African American	0.090	0.093
Hispanic	0.134	0.139
Asian American	0.062	0.066
Age	44.132	43.806
Immigrant	0.074	0.077
Less Than High School	0.059	0.057
High School	0.249	0.235
Post-Secondary < Bachelor's	0.287	0.278
Bachelor's	0.252	0.266
Post-Secondary > Bachelor's	0.153	0.163
N	76,205	38,386

This table consists of the mean of each independent variable of interest during the benchmark time period (column (1)) and the pandemic (column (2)). With the exception of Age, all variables are binary indicators. For the benchmark time period, the subpopulation consists of all individuals who were employed in either February 2017, February 2018, and subsequently reappear in the sample at least once during the months of January-May in the following year. Similarly, for the pandemic time period, the subpopulation consists of all individuals who were employed in February 2020, and subsequently reappear in the sample at least once during the months of January-May in 2021.

Table 2: Proportion of Individuals Employed in Occupation in Feburary 2020 (Pandemic) or February 2017/2018 (Benchmark)

	(1) February 2017 or 2018 Mean	(2) February 2020 Mean	(3) February 2021 Mean
Management	0.129	0.133	0.133
Business Operations	0.053	0.063	0.061
Computer and Mathematical	0.036	0.040	0.039
Architecture and Engineering	0.024	0.022	0.022
Physical and Social Science	0.012	0.012	0.013
Community and Social Service	0.019	0.019	0.019
Legal	0.013	0.011	0.012
Education and Library	0.071	0.064	0.064
Arts Design and Entertainment	0.019	0.018	0.018
Healthcare Practitioners	0.066	0.064	0.065
Healthcare Support	0.021	0.025	0.028
Protective Service	0.019	0.020	0.019
Food Preparation and Serving	0.043	0.042	0.037
Building and Grounds Maintenance	0.030	0.031	0.033
Personal Care and Service	0.032	0.025	0.022
Sales and Related	0.097	0.095	0.094
Office and Administrative	0.112	0.104	0.106
Farming Fishing and Forestry	0.008	0.008	0.007
Construction and Extraction	0.049	0.052	0.054
Maintenance Repair	0.035	0.034	0.034
Production	0.057	0.052	0.054
Transportation and Moving	0.056	0.067	0.065
N	76,205	38,386	38,386

This table consists of the proportion of individuals who worked in each of 22 two digit occupations during February 2017, February 2018 (column (1)), February 2020 (column (2)), and January-May 2021 (column (3)). For the benchmark time period, the subpopulation consists of all individuals who were employed in either February 2017, February 2018, and subsequently reappear in the sample at least once during the months of January-May in the following year. Similarly, for the pandemic time period, the subpopulation consists of all individuals who were employed in February 2020, and subsequently reappear in the sample at least once during the months of January-May in 2021. It is worthwhile noting that the proportions that are shown in the first two columns of this table are the proportion of individuals in the subsample who were initially observed in the occupation in question, even if they changed occupations by the following year. The third column captures the occupation distribution in early 2021.

Table 3: Sample Means of Dependent Variables of Interest

	(1) Benchmark Mean	(2) Pandemic Mean
Not Employed First Year	0.033	0.148
Not Employed Second Year	0.035	0.057
Mismatch	0.089	0.094
Alternative Mismatch 1	0.103	0.109
Alternative Mismatch 2	0.088	0.093
Alternative Mismatch 3	0.134	0.146
Alternative Mismatch 4	0.075	0.078
N	76,205	38,386

This table consists of the mean of each dependent variable of interest (as outlined in subsections 2.1 and 2.2) during the benchmark time period (column (1)) and the pandemic (column (2)). For the benchmark time period, the subpopulation consists of all individuals who were employed in either February 2017, February 2018, and subsequently reappear in the sample at least once during the months of January-May in the following year. Similarly, for the pandemic time period, the subpopulation consists of all individuals who were employed in February 2020, and subsequently reappear in the sample at least once during the months of January-May in 2021.

Table 4: Median Distance Among Job Changers Moving From Initial Occupation Group (Column) to New Occupation Group (Row)

	Business Operations	Education and Instruction	Construction and Extraction	Transportation and Moving
Management	0.981	1.187	2.044	2.309
Business Operations	0.687	1.067	2.479	2.066
Computer and Mathematical	1.276	1.508	1.957	4.117
Architecture and Engineering	2.086	1.527	1.080	2.241
Physical and Social Science	1.923	1.316	2.400	2.162
Community and Social Service	1.072	0.910	2.403	2.631
Legal	1.014	1.542	2.009	2.771
Education and Library	1.093	0.585	2.352	2.113
Arts Design and Entertainment	1.512	1.091	1.714	2.029
Healthcare Practitioners	3.268	1.303	3.442	1.706
Healthcare Support	1.916	1.125	1.563	1.372
Protective Service	3.000	1.554	1.706	1.422
Food Preparation and Serving	1.587	1.517	1.579	1.272
Building and Grounds Maintenance	2.208	1.857	1.213	0.807
Personal Care and Service	1.137	1.005	1.880	1.372
Sales and Related	1.020	1.298	2.020	1.669
Office and Administrative	1.190	1.236	1.990	1.839
Farming Fishing and Forestry	2.197	1.541	0.900	0.700
Construction and Extraction	2.479	2.229	0.685	0.913
Maintenance Repair	2.646	2.424	0.817	1.275
Production	2.399	1.784	0.867	0.994
Transportation and Moving	2.432	2.472	1.025	0.772
N	6,448	7,907	5,737	6,852

This table contains, for all real job changes in the data from an occupation in an initial occupation group (listed in the 4 columns), the median moved among all job changes to an occupation in a new occupation group (listed in the 22 rows). For cases in which these occupation groups are the same, the value corresponds to the median distance moved conditional on a change in 6-digit occupations within the same 2-digit occupation group.

Table 5: Effect of Mismatch on Log Earnings

	(1) Demographic Controls	(2) Initial Occupation Controls
Mismatch	-0.085***	-0.17***
	(0.014)	(0.014)
Pandemic × Mismatch	0.030	0.040*
	(0.024)	(0.023)
N	26,037	26,037

Standard errors in parentheses

This table contains OLS regression results in which the depedent variable is the natural log of weekly earnings as recorded in the CPS. The subsample consists of all individuals who were employed in February 2017, 2018, or 2020 and are subsequently observed as employed in following year. Furthermore, since weekly earnings are recorded only for individuals who are appearing in the CPS for the 4th or 8th time, these are the only individuals in our subsample. We further exclude any individuals whose reported weekly earnings are less than $290 (the amount that one would earn at 40 hours per week at the federal minimum wage)..

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Marginal Effects (On Mismatch)

	(1) Mismatch only Demographics	(2) Mismatch adding Two Digit Occs.	(3) Mismatch adding Out of Work
20 Years Old	0.027***	0.030***	0.019**
	(0.0084)	(0.0097)	(0.0094)
30 Years Old	0.0073**	0.0054	-0.00090
	(0.0033)	(0.0034)	(0.0034)
40 Years Old	-0.0016	-0.0034	-0.0078***
	(0.0029)	(0.0027)	(0.0027)
50 Years Old	-0.0023	-0.0028	-0.0069***
	(0.0027)	(0.0025)	(0.0025)
60 Years Old	0.0042	0.0057	0.00070
	(0.0037)	(0.0036)	(0.0036)
Single	-0.0033	-0.0052	-0.011***
	(0.0034)	(0.0034)	(0.0034)
Married	0.0080***	0.0074***	0.0021
	(0.0028)	(0.0027)	(0.0027)
Men	0.0014	0.0026	-0.0024
	(0.0030)	(0.0029)	(0.0029)
Women	0.0057**	0.0026	-0.0032
	(0.0029)	(0.0032)	(0.0032)
Less Than High	-0.0080	-0.010	-0.019
School	(0.0085)	(0.012)	(0.012)
High School	0.013***	0.016***	0.0071
	(0.0044)	(0.0056)	(0.0055)
Post-Secondary <	-0.0061	-0.0067	-0.013***
Bachelor's	(0.0040)	(0.0043)	(0.0043)
Bachelor's Degree	0.0045	0.0035	0.00035
	(0.0041)	(0.0035)	(0.0035)
Post-Secondary >	0.0089*	0.0020	-0.00032
Bachelor's	(0.0049)	(0.0040)	(0.0041)

White	0.0032	0.0019	-0.0027
	(0.0025)	(0.0024)	(0.0024)
African-American	-0.0096	-0.011	-0.017**
	(0.0069)	(0.0073)	(0.0071)
Hispanic	0.016***	0.017***	0.010*
	(0.0057)	(0.0059)	(0.0058)
Asian-American	-0.0037	-0.0030	-0.010
	(0.0079)	(0.0079)	(0.0077)
Immigrant	0.0064	-0.0041	-0.0081
	(0.0064)	(0.0071)	(0.0070)
Management		-0.0027	-0.012
		(0.0085)	(0.0084)
Business Operations		-0.00017	-0.0060
		(0.012)	(0.012)
Computer and Mathematical		0.018	0.012
		(0.015)	(0.015)
Architecture and Engineering		-0.0021	-0.0094
		(0.019)	(0.019)
Physical and Social Science		0.028	0.020
		(0.028)	(0.028)
Community \Social Service		0.014	0.0080
		(0.019)	(0.019)
Legal		-0.024	-0.029
		(0.019)	(0.019)
Education and Library		0.012	0.0042
		(0.0091)	(0.0089)
Arts, Sports, and Media		0.045**	0.026
		(0.020)	(0.019)
Healthcare Practitioners		0.0067	0.0016
		(0.0093)	(0.0093)
Healthcare Support		0.0087*	0.0078*
		(0.0047)	(0.0046)

Protective Service		0.0017	-0.0028
		(0.0096)	(0.0094)
Food Preparation and		0.0024	0.00011
Serving		(0.0028)	(0.0026)
Building Maintenance		0.0043	0.0020
		(0.0057)	(0.0055)
Personal Care and		0.028***	0.015*
Service		(0.0093)	(0.0081)
Sales and Related		0.00048	-0.0051
		(0.0055)	(0.0055)
Office and		-0.0054	-0.0089*
Administrative		(0.0048)	(0.0048)
Farming, Fishing,		-0.019	-0.022*
and Forestry		(0.012)	(0.012)
Construction and		-0.012	-0.016**
Extraction		(0.0073)	(0.0071)
Installation and		0.00081	-0.0038
Repair		(0.012)	(0.012)
Production		-0.0077	-0.013
		(0.0077)	(0.0076)
Transportation		0.011*	0.0062
\Material Moving		(0.0064)	(0.0063)
Was Not Out of Work			-0.0022
			(0.0021)
Was Out of Work			-0.011
			(0.010)
N	109,730	109,730	109,730
Standard errors in parentheses			

This table contains, for each demographic group listed, the marginal effect of the pandemic on the the probability of being mismatched using our preferred measure of mismatch outlined in section 2.2. Marginal effects are estimated using the model outlined in Equation 2 with only demographic controls for column (1), adding starting occupation for column (2) and adding out-of-work indicator for column (3). As an example of how to interpret the marginal effects, a value of 0.05 indicates that during the pandemic there has been a 5 percentage point increase in the probability that the dependent variable is equal to 1 for a member of the relevant demographic group, relative to the pre-pandemic benchmark period. The subpopulation of interest consists of all individuals who were employed in one of February 2017, February 2018 (for the benchmark era), or February 2020 (for the pandemic era), and are subsequently observed in the sample at least once during the months of January-May in the following year.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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A Appendix

Table A1: Marginal Effects (No Occupation Controls)

	(1) Out of Work Last Spring	(2) Not Employed	(3) Mismatch	(4) Alternative Mismatch 1	(5) Alternative Mismatch 2	(6) Alternative Mismatch 3	(7) Alternative Mismatch 4
20 Years Old	0.19***	0.017***	0.027***	0.016*	0.015**	0.025***	0.050***
	(0.0090)	(0.0058)	(0.0084)	(0.0087)	(0.0074)	(0.0083)	(0.0093)
30 Years Old	0.13***	0.022***	0.0073**	0.0051	0.0024	0.0068**	0.016***
	(0.0035)	(0.0023)	(0.0033)	(0.0035)	(0.0030)	(0.0033)	(0.0039)
40 Years Old	0.11***	0.024***	-0.0016	0.00073	-0.0027	-0.0018	0.00033
	(0.0031)	(0.0022)	(0.0029)	(0.0032)	(0.0027)	(0.0029)	(0.0035)
50 Years Old	0.11***	0.026***	-0.0023	0.0013	-0.0018	-0.0026	0.00046
	(0.0029)	(0.0021)	(0.0027)	(0.0029)	(0.0025)	(0.0027)	(0.0033)
60 Years Old	0.13***	0.026***	0.0042	0.0063	0.0047	0.0034	0.017***
	(0.0043)	(0.0032)	(0.0037)	(0.0040)	(0.0035)	(0.0037)	(0.0048)
Single	0.14***	0.027***	-0.0033	-0.0037	-0.0047	-0.0034	0.0029
	(0.0038)	(0.0028)	(0.0034)	(0.0037)	(0.0031)	(0.0034)	(0.0043)
Married	0.12***	0.022***	0.0080***	0.0092***	0.0056**	0.0072**	0.016***
	(0.0031)	(0.0021)	(0.0028)	(0.0030)	(0.0026)	(0.0028)	(0.0034)
Men	0.11***	0.025***	0.0014	0.0032	-0.0019	0.0017	0.0086**
	(0.0030)	(0.0022)	(0.0030)	(0.0032)	(0.0028)	(0.0030)	(0.0036)
Women	0.15***	0.022***	0.0057**	0.0048	0.0052**	0.0041	0.014***
	(0.0035)	(0.0024)	(0.0029)	(0.0031)	(0.0026)	(0.0028)	(0.0035)
Less Than High	0.18***	0.032***	-0.0080	-0.0027	-0.015*	-0.011	-0.0098
School	(0.010)	(0.0078)	(0.0085)	(0.0094)	(0.0075)	(0.0085)	(0.0098)
High School	0.17***	0.027***	0.013***	0.013***	0.0091**	0.013***	0.0083
	(0.0052)	(0.0035)	(0.0044)	(0.0047)	(0.0040)	(0.0043)	(0.0052)
Post-Secondary <	0.14***	0.029***	-0.0061	-0.0061	-0.0090**	-0.0064	-0.0010
Bachelor's	(0.0045)	(0.0031)	(0.0040)	(0.0043)	(0.0037)	(0.0040)	(0.0049)
Bachelor's Degree	0.094***	0.017***	0.0045	0.0087**	0.0060	0.0018	0.014***
	(0.0040)	(0.0029)	(0.0041)	(0.0044)	(0.0038)	(0.0041)	(0.0051)
Post-Secondary >	0.064***	0.017***	0.0089*	0.0032	0.0078*	0.012**	0.040***

Bachelor's	(0.0045)	(0.0034)	(0.0049)	(0.0052)	(0.0044)	(0.0049)	(0.0063)
White	0.11***	0.018***	0.0032	0.0036	-0.00034	0.0028	0.014***
	(0.0026)	(0.0019)	(0.0025)	(0.0027)	(0.0023)	(0.0025)	(0.0030)
African-American	0.14***	0.034***	-0.0096	-0.0045	-0.0083	-0.0078	0.0044
	(0.0081)	(0.0060)	(0.0069)	(0.0078)	(0.0064)	(0.0069)	(0.0084)
Hispanic	0.15***	0.035***	0.016***	0.015**	0.018***	0.015**	0.011*
	(0.0060)	(0.0041)	(0.0057)	(0.0060)	(0.0053)	(0.0057)	(0.0069)
Asian-American	0.19***	0.030***	-0.0037	-0.0049	-0.0042	-0.0069	-0.0087
	(0.0097)	(0.0066)	(0.0079)	(0.0083)	(0.0070)	(0.0079)	(0.0095)
Immigrant	0.13***	0.020***	0.0064	0.0087	0.013**	0.0072	0.044***
	(0.0081)	(0.0060)	(0.0064)	(0.0069)	(0.0059)	(0.0064)	(0.0083)
N	114,591	114,591	109,730	109,730	109,730	109,730	109,730

Standard errors in parentheses

This table contains, for each demographic group listed, the marginal effect of the pandemic on the dependent indicator variables listed in the column headers. Marginal effects are estimated using the model outlined in Equation 2 with only demographic controls. As an example of how to interpret the marginal effects, a value of 0.05 indicates that during the pandemic there has been a 5 percentage point increase in the probability that the dependent variable is equal to 1 for a member of the relevant demographic group, relative to the pre-pandemic benchmark period. The subpopulation of interest consists of all individuals who were employed in one of February 2017, February 2018 (for the benchmark era), or February 2020 (for the pandemic era), and are subsequently observed in the sample at least once during the months of January-May in the following year. For columns (3)-(6), the subpopulation consists only of those who are employed in their 2nd year in the CPS. See Sections 2.2 and 2.3 for a description of the measures of mismatch in columns (3)-(6).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Marginal Effects (With Occupation Controls)

	(1) Out of Work Last Spring	(2) Not Employed	(3) Mismatch	(4) Alternative Mismatch 1	(5) Alternative Mismatch 2	(6) Alternative Mismatch 3	(7) Alternative Mismatch 4
20 Years Old	0.16***	0.012**	0.030***	0.020*	0.015*	0.028***	0.057***
	(0.0084)	(0.0057)	(0.0097)	(0.010)	(0.0087)	(0.0096)	(0.010)
30 Years Old	0.13***	0.022***	0.0054	0.0031	0.00023	0.0050	0.015***
	(0.0034)	(0.0023)	(0.0034)	(0.0036)	(0.0031)	(0.0034)	(0.0039)
40 Years Old	0.12***	0.025***	-0.0034	-0.0022	-0.0044*	-0.0035	-0.0024
	(0.0031)	(0.0022)	(0.0027)	(0.0030)	(0.0025)	(0.0027)	(0.0033)

50 Years Old	0.12***	0.027***	-0.0028	-0.00021	-0.0022	-0.0032	-0.0010
	(0.0029)	(0.0021)	(0.0025)	(0.0027)	(0.0023)	(0.0025)	(0.0031)
60 Years Old	0.13***	0.025***	0.0057	0.0082**	0.0064*	0.0048	0.018***
	(0.0043)	(0.0032)	(0.0036)	(0.0039)	(0.0034)	(0.0036)	(0.0045)
Single	0.13***	0.026***	-0.0052	-0.0054	-0.0065**	-0.0052	-0.00023
	(0.0037)	(0.0028)	(0.0034)	(0.0037)	(0.0032)	(0.0035)	(0.0042)
Married	0.12***	0.022***	0.0074***	0.0082***	0.0051**	0.0066**	0.015***
	(0.0031)	(0.0021)	(0.0027)	(0.0029)	(0.0025)	(0.0027)	(0.0032)
Men	0.11***	0.025***	0.0026	0.0037	-0.00069	0.0027	0.0095***
	(0.0031)	(0.0023)	(0.0029)	(0.0031)	(0.0027)	(0.0029)	(0.0035)
Women	0.14***	0.021***	0.0026	0.0019	0.0025	0.0013	0.0099***
	(0.0036)	(0.0026)	(0.0032)	(0.0034)	(0.0029)	(0.0032)	(0.0038)
Less Than High	0.15***	0.025***	-0.010	0.000057	-0.023**	-0.014	-0.016
School	(0.0095)	(0.0071)	(0.012)	(0.013)	(0.011)	(0.012)	(0.013)
High School	0.15***	0.022***	0.016***	0.018***	0.010**	0.016***	0.011*
	(0.0051)	(0.0034)	(0.0056)	(0.0060)	(0.0053)	(0.0056)	(0.0064)
Post-Secondary <	0.14***	0.027***	-0.0067	-0.0056	-0.010***	-0.0071*	-0.00082
Bachelor's	(0.0044)	(0.0031)	(0.0043)	(0.0046)	(0.0040)	(0.0043)	(0.0051)
Bachelor's Degree	0.10***	0.019***	0.0035	0.0061	0.0054*	0.0011	0.012***
	(0.0044)	(0.0032)	(0.0035)	(0.0037)	(0.0032)	(0.0035)	(0.0042)
Post-Secondary >	0.083***	0.024***	0.0020	-0.0042	0.0020	0.0044	0.024***
Bachelor's	(0.0056)	(0.0044)	(0.0040)	(0.0043)	(0.0036)	(0.0040)	(0.0052)
White	0.11***	0.019***	0.0019	0.0018	-0.0013	0.0015	0.012***
	(0.0026)	(0.0019)	(0.0024)	(0.0025)	(0.0022)	(0.0024)	(0.0028)
African-American	0.14***	0.033***	-0.011	-0.0062	-0.011	-0.0091	0.0039
	(0.0080)	(0.0060)	(0.0073)	(0.0081)	(0.0067)	(0.0072)	(0.0086)
Hispanic	0.14***	0.033***	0.017***	0.017***	0.019***	0.016***	0.014**
	(0.0058)	(0.0040)	(0.0059)	(0.0062)	(0.0056)	(0.0059)	(0.0070)
Asian-American	0.19***	0.028***	-0.0030	-0.0031	-0.0029	-0.0066	-0.0078
	(0.0097)	(0.0066)	(0.0079)	(0.0083)	(0.0069)	(0.0078)	(0.0093)
Immigrant	0.12***	0.017***	-0.0041	-0.0058	0.0036	-0.0035	0.031***
	(0.0080)	(0.0059)	(0.0071)	(0.0077)	(0.0065)	(0.0072)	(0.0091)

Management	0.085***	0.022***	-0.0027	0.0045	-0.011	-0.0048	0.031***
	(0.0059)	(0.0044)	(0.0085)	(0.0088)	(0.0081)	(0.0084)	(0.0098)
Business	0.063***	0.025***	-0.00017	0.016	0.0085	0.0029	-0.0021
Operations	(0.0081)	(0.0068)	(0.012)	(0.013)	(0.011)	(0.012)	(0.013)
Computer and	0.046***	0.0048	0.018	0.019	0.0054	0.018	0.042**
Mathematical	(0.0087)	(0.0068)	(0.015)	(0.015)	(0.014)	(0.015)	(0.017)
Architecture and	0.064***	-0.0024	-0.0021	-0.00041	-0.019	0.012	-0.028
Engineering	(0.011)	(0.0070)	(0.019)	(0.019)	(0.018)	(0.019)	(0.021)
Physical and	0.083***	-0.013	0.028	0.035	-0.0030	0.027	-0.0052
Social Science	(0.019)	(0.014)	(0.028)	(0.029)	(0.027)	(0.028)	(0.032)
Community	0.045***	0.037***	0.014	0.012	0.027	-0.000075	0.041*
\Social Service	(0.013)	(0.011)	(0.019)	(0.020)	(0.019)	(0.019)	(0.022)
Legal	0.10***	0.0010	-0.024	-0.030	-0.021	-0.026	0.0070
	(0.020)	(0.013)	(0.019)	(0.021)	(0.019)	(0.019)	(0.023)
Education and	0.16***	0.0092	0.012	0.019*	0.0081	0.011	0.012
Library	(0.011)	(0.0059)	(0.0091)	(0.010)	(0.0081)	(0.0091)	(0.010)
Arts, Sports, and	0.28***	0.020	0.045**	0.058***	0.022	0.041**	0.071***
Media	(0.021)	(0.014)	(0.020)	(0.021)	(0.017)	(0.020)	(0.023)
Healthcare	0.084***	0.011*	0.0067	0.0077	0.0078	0.0077	0.0020
Practitioners	(0.0088)	(0.0060)	(0.0093)	(0.0098)	(0.0088)	(0.0093)	(0.010)
Healthcare Support	0.065***	-0.0021	0.0087*	0.0053	0.0038	0.0087**	0.0057
	(0.011)	(0.0081)	(0.0047)	(0.0056)	(0.0036)	(0.0044)	(0.0062)
Protective Service	0.11***	0.00081	0.0017	0.020*	0.0056	0.0015	0.0030
	(0.014)	(0.010)	(0.0096)	(0.011)	(0.0089)	(0.0096)	(0.013)
Food Preparation	0.29***	0.045***	0.0024	-0.00011	0.0028	0.0025	0.00052
and Serving	(0.014)	(0.0089)	(0.0028)	(0.0030)	(0.0028)	(0.0029)	(0.0040)
Building	0.14***	0.036***	0.0043	0.00080	0.0034	0.0045	0.0000050
Maintenance	(0.013)	(0.011)	(0.0057)	(0.0061)	(0.0048)	(0.0057)	(0.0063)
Personal Care and	0.37***	0.075***	0.028***	0.025**	0.021***	0.027***	0.055***
Service	(0.018)	(0.012)	(0.0093)	(0.0098)	(0.0076)	(0.0093)	(0.012)
Sales and Related	0.14***	0.033***	0.00048	-0.0096	0.0038	-0.0018	0.0074
	(0.0072)	(0.0051)	(0.0055)	(0.0061)	(0.0050)	(0.0056)	(0.0068)

Office and	0.089***	0.022***	-0.0054	-0.013***	-0.011***	-0.0057	-0.010*
Administrative	(0.0060)	(0.0046)	(0.0048)	(0.0051)	(0.0043)	(0.0048)	(0.0060)
Farming, Fishing,	0.11***	-0.0046	-0.019	-0.022	-0.015	-0.021*	0.027
and Forestry	(0.026)	(0.020)	(0.012)	(0.014)	(0.012)	(0.012)	(0.019)
Construction and	0.16***	0.026***	-0.012	-0.0033	-0.0016	-0.010	-0.011
Extraction	(0.013)	(0.0088)	(0.0073)	(0.0084)	(0.0064)	(0.0073)	(0.0082)
Installation and	0.081***	0.016*	0.00081	-0.0084	-0.0099	-0.0027	-0.015
Repair	(0.011)	(0.0088)	(0.012)	(0.013)	(0.011)	(0.012)	(0.014)
Production	0.13***	0.020***	-0.0077	-0.00074	-0.0041	-0.0066	-0.0050
	(0.0095)	(0.0063)	(0.0077)	(0.0086)	(0.0066)	(0.0077)	(0.0089)
Transportation	0.14***	0.037***	0.011*	0.0058	0.0087	0.010	0.015*
\Material Moving	(0.0096)	(0.0076)	(0.0064)	(0.0071)	(0.0057)	(0.0064)	(0.0079)
N	114,591	114,591	109,730	109,730	109,730	109,730	109,730

Standard errors in parentheses

This table contains, for each demographic group listed, the marginal effect of the pandemic on the dependent indicator variables listed in the column headers. Marginal effects are estimated using the model outlined in Equation 2 with demographic controls and pre-pandemic 2 digit occupation controls. The subsample and interpretation of the results is identical to Table A1.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Marginal Effects (With Control for Not Employed in Previous Spring)

	(1) Not Employed	(2) Mismatch	(3) Alternative Mismatch 1	(4) Alternative Mismatch 2	(5) Alternative Mismatch 3	(6) Alternative Mismatch 4
20 Years Old	-0.0032	0.019**	0.0058	0.0095	0.017**	0.046***
	(0.0052)	(0.0081)	(0.0085)	(0.0072)	(0.0081)	(0.0092)
30 Years Old	0.0090***	0.0022	-0.0017	-0.00097	0.0018	0.013***
	(0.0022)	(0.0033)	(0.0035)	(0.0030)	(0.0033)	(0.0039)
40 Years Old	0.014***	-0.0054*	-0.0046	-0.0053**	-0.0054*	-0.0023
	(0.0021)	(0.0029)	(0.0032)	(0.0027)	(0.0029)	(0.0036)
50 Years Old	0.016***	-0.0059**	-0.0037	-0.0044*	-0.0061**	-0.0021
	(0.0020)	(0.0027)	(0.0029)	(0.0025)	(0.0027)	(0.0034)

60 Years Old	0.013***	-0.00019	0.00043	0.0014	-0.00085	0.014***
	(0.0031)	(0.0037)	(0.0040)	(0.0035)	(0.0037)	(0.0048)
Single	0.012***	-0.0078**	-0.0099***	-0.0076**	-0.0078**	-0.000054
	(0.0026)	(0.0034)	(0.0037)	(0.0031)	(0.0034)	(0.0043)
Married	0.011***	0.0035	0.0033	0.0022	0.0029	0.013***
	(0.0020)	(0.0029)	(0.0031)	(0.0026)	(0.0028)	(0.0034)
Men	0.015***	-0.0029	-0.0025	-0.0050*	-0.0024	0.0058
	(0.0021)	(0.0030)	(0.0032)	(0.0028)	(0.0030)	(0.0036)
Women	0.0076***	0.00089	-0.0016	0.0019	-0.00047	0.011***
	(0.0022)	(0.0029)	(0.0031)	(0.0026)	(0.0028)	(0.0036)
Less Than High	0.0095	-0.013	-0.0099	-0.017**	-0.016*	-0.013
School	(0.0070)	(0.0083)	(0.0092)	(0.0073)	(0.0083)	(0.0097)
High School	0.0092***	0.0067	0.0052	0.0051	0.0070	0.0047
	(0.0032)	(0.0043)	(0.0047)	(0.0039)	(0.0043)	(0.0051)
Post-Secondary <	0.015***	-0.011***	-0.013***	-0.013***	-0.011***	-0.0043
Bachelor's	(0.0029)	(0.0040)	(0.0043)	(0.0037)	(0.0040)	(0.0049)
Bachelor's Degree	0.0092***	0.00095	0.0038	0.0030	-0.0017	0.012**
	(0.0028)	(0.0041)	(0.0044)	(0.0038)	(0.0041)	(0.0051)
Post-Secondary >	0.011***	0.0066	-0.00019	0.0063	0.0096*	0.038***
Bachelor's	(0.0034)	(0.0050)	(0.0053)	(0.0045)	(0.0050)	(0.0063)
White	0.0074***	-0.00090	-0.0019	-0.0033	-0.0012	0.011***
	(0.0018)	(0.0025)	(0.0027)	(0.0023)	(0.0025)	(0.0031)
African-American	0.018***	-0.014**	-0.011	-0.011*	-0.012*	0.0019
	(0.0054)	(0.0068)	(0.0077)	(0.0062)	(0.0068)	(0.0084)
Hispanic	0.021***	0.010*	0.0079	0.013**	0.0094*	0.0081
	(0.0039)	(0.0056)	(0.0059)	(0.0053)	(0.0056)	(0.0069)
Asian-American	0.0099*	-0.0098	-0.013	-0.0079	-0.013	-0.013
	(0.0058)	(0.0079)	(0.0082)	(0.0070)	(0.0078)	(0.0095)
Immigrant	0.0045	0.0032	0.0044	0.011*	0.0040	0.042***
	(0.0055)	(0.0063)	(0.0068)	(0.0058)	(0.0063)	(0.0083)
Not Out of Work Last	0.0093***	0.000059	-0.000012	-0.00059	-0.00035	0.0099***
Spring	(0.0015)	(0.0021)	(0.0023)	(0.0020)	(0.0021)	(0.0026)

Out of Work Last Spring	0.036***	-0.015	-0.028**	-0.016*	-0.015	-0.014
	(0.0086)	(0.0099)	(0.011)	(0.0090)	(0.0099)	(0.011)
N	114,591	109,730	109,730	109,730	109,730	109,730

Standard errors in parentheses

This table contains, for each demographic group listed, the marginal effect of the pandemic on the dependent indicator variables listed in the column headers.Marginal effects are estimated using the model outlined in Equation 2 with demographic controls, pre-pandemic 2-digit occupation controls, and an indicator for whether an individual was observed to be not employed for at least one month in the previous spring. The subsample and interpretation of the results is identical to Table A1.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Marginal Effects (On Mismatch: Great Recession Era)

	(1) Mismatch Demographics Only	(2) Mismatch Two Digit Occs.	(3) Mismatch Was Out of Work
20 Years Old	0.032***	0.046***	0.044***
	(0.0081)	(0.0097)	(0.0094)
30 Years Old	0.011***	0.013***	0.012***
	(0.0032)	(0.0033)	(0.0033)
40 Years Old	0.00074	-0.00022	-0.0010
	(0.0028)	(0.0026)	(0.0026)
50 Years Old	-0.0015	-0.0032	-0.0039*
	(0.0024)	(0.0023)	(0.0023)
60 Years Old	0.0026	0.00098	0.00037
	(0.0041)	(0.0039)	(0.0039)
Single	0.00075	0.00012	-0.0014
	(0.0036)	(0.0037)	(0.0036)
Married	0.0071***	0.0065***	0.0061**
	(0.0026)	(0.0025)	(0.0025)
Men	0.0095***	0.0091***	0.0084***
	(0.0028)	(0.0027)	(0.0027)
Women	-0.00030	-0.0020	-0.0028
	(0.0028)	(0.0033)	(0.0033)

Less Than High School	0.014**	0.018**	0.016*
	(0.0067)	(0.0088)	(0.0088)
High School	-0.0015	-0.0018	-0.0032
	(0.0036)	(0.0046)	(0.0045)
Post-Secondary < Bachelor's	0.0061	0.0040	0.0027
	(0.0038)	(0.0040)	(0.0039)
Bachelor's Degree	0.0041	0.0036	0.0037
	(0.0046)	(0.0038)	(0.0038)
Post-Secondary > Bachelor's	0.012**	0.0089**	0.0090**
	(0.0055)	(0.0041)	(0.0041)
White	0.0083***	0.0071***	0.0062***
	(0.0023)	(0.0022)	(0.0022)
African-American	0.0020	0.0084	0.0082
	(0.0078)	(0.0082)	(0.0081)
Hispanic	-0.0040	-0.0063	-0.0067
	(0.0070)	(0.0070)	(0.0070)
Asian-American	-0.024**	-0.021*	-0.021*
	(0.012)	(0.011)	(0.011)
Immigrant	0.0062	0.0094	0.0076
	(0.0063)	(0.0064)	(0.0063)
Management		0.013	0.012
		(0.0086)	(0.0086)
Business Operations		-0.0016	-0.0026
		(0.011)	(0.011)
Computer and Mathematical		-0.027	-0.033
		(0.048)	(0.048)
Architecture and Engineering		-0.047**	-0.047**
		(0.019)	(0.019)
Physical and Social Science		0.059*	0.052
		(0.033)	(0.033)
Community \Social Service		0.00023	0.00048
		(0.021)	(0.021)

Legal	-0.0037	-0.0017
	(0.017)	(0.017)
Education and	-0.0027	-0.0037
Library	(0.0084)	(0.0085)
Arts, Sports, and	0.041**	0.040**
Media	(0.019)	(0.018)
Healthcare	0.023*	0.022*
Practitioners	(0.012)	(0.012)
Healthcare Support	-0.0045	-0.0048
	(0.0070)	(0.0069)
Protective Service	0.0050	0.0042
	(0.0099)	(0.0100)
Food Preparation and	-0.00063	-0.00044
Serving	(0.0023)	(0.0023)
Building Maintenance	0.0024	0.0013
	(0.011)	(0.010)
Personal Care and	0.018**	0.019***
Service	(0.0071)	(0.0070)
Sales and Related	0.0012	0.00064
	(0.0053)	(0.0053)
Office and	0.0060	0.0066*
Administrative	(0.0037)	(0.0037)
Farming, Fishing,	-0.068**	-0.072***
and Forestry	(0.027)	(0.027)
Construction and	0.0058	0.0019
Extraction	(0.0079)	(0.0076)
Installation and	0.018	0.017
Repair	(0.011)	(0.012)
Production	0.010	0.0085
	(0.0075)	(0.0074)
Transportation	-0.014**	-0.015**
\Material Moving	(0.0064)	(0.0062)

Was Not Out of Work			0.0031
			(0.0020)
Was Out of Work			0.014
			(0.013)
N	90,395	90,395	90,395

Standard errors in parentheses

This table contains, for each demographic group listed, the marginal effect of the recession on the the probability of being mismatched using our preferred measure of mismatch outlined in section 2.2. Marginal effects are estimated using the model outlined in Equation 2 with only demographic controls for column (1), adding starting occupation for column (2) and adding out-of-work indicator for column (3). As an example of how to interpret the marginal effects, a value of 0.05 indicates that during the recession there has been a 5 percentage point increase in the probability that the dependent variable is equal to 1 for a member of the relevant demographic group, relative to the pre-recession benchmark period. The subpopulation of interest consists of all individuals who were employed in December 2007 (for the benchmark era), or December 2008 (for the recession era), and are subsequently observed in the sample at least once during the subsequent November-March period.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Log Distance Conditional on Moving Into a Lower Paying Occupation In a Different 2-Digit Group

	(1) Demographic Controls	(2) Initial Occupation Controls	(3) Non-Employment Controls
20 Years Old	0.083**	0.084**	0.084**
	(0.034)	(0.033)	(0.033)
30 Years Old	0.013	-0.0018	-0.0025
	(0.017)	(0.016)	(0.016)
40 Years Old	-0.011	-0.030*	-0.031*
	(0.017)	(0.016)	(0.016)
50 Years Old	0.012	-0.0011	-0.0022
	(0.016)	(0.015)	(0.015)
60 Years Old	0.082***	0.085***	0.084***
	(0.022)	(0.022)	(0.022)
Single	0.0028	-0.0047	-0.0056
	(0.019)	(0.019)	(0.019)

Married	0.044***	0.032**	0.031**
	(0.016)	(0.015)	(0.015)
Men	0.0056	0.0081	0.0073
	(0.016)	(0.016)	(0.016)
Women	0.054***	0.028	0.027
	(0.017)	(0.017)	(0.017)
Less Than High	-0.15***	-0.22***	-0.22***
School	(0.045)	(0.043)	(0.043)
High School	0.012	-0.012	-0.013
	(0.020)	(0.020)	(0.020)
Post-Secondary <	0.049**	0.033	0.032
Bachelor's	(0.022)	(0.020)	(0.021)
Bachelor's Degree	0.057**	0.076***	0.075***
	(0.024)	(0.023)	(0.023)
Post-Secondary >	0.043	0.045	0.043
Bachelor's	(0.035)	(0.037)	(0.037)
White	0.022	0.014	0.013
	(0.014)	(0.014)	(0.014)
African-American	0.019	-0.019	-0.020
	(0.036)	(0.034)	(0.034)
Hispanic	0.064**	0.063**	0.062**
	(0.027)	(0.026)	(0.026)
Asian-American	-0.0066	-0.017	-0.017
	(0.047)	(0.047)	(0.048)
Immigrant	0.077*	0.025	0.025
	(0.043)	(0.045)	(0.046)
Management		-0.050**	-0.051**
		(0.022)	(0.023)
Business		0.091**	0.090**
Operations		(0.041)	(0.041)
Computer and		0.11**	0.11**
Mathematical		(0.046)	(0.046)

Architecture and Engineering	-0.082 (0.056)	-0.083 (0.056)
Physical and Social Science	-0.031 (0.075)	-0.031 (0.075)
Community \Social Service	0.24*** (0.052)	0.24*** (0.053)
Legal	-0.12 (0.13)	-0.12 (0.13)
Education and Library	-0.0014 (0.048)	-0.0023 (0.049)
Arts, Sports, and Media	-0.066 (0.060)	-0.066 (0.061)
Healthcare Practitioners	0.039 (0.055)	0.039 (0.055)
Healthcare Support	0.72*** (0.12)	0.72*** (0.12)
Protective Service	-0.33*** (0.12)	-0.33*** (0.12)
Food Preparation and Serving	0.32*** (0.10)	0.32*** (0.10)
Building Maintenance	-0.072 (0.078)	-0.072 (0.078)
Personal Care and Service	0.13 (0.088)	0.13 (0.090)
Sales and Related	0.025 (0.035)	0.024 (0.035)
Office and Administrative	0.0063 (0.041)	0.0063 (0.041)
Farming, Fishing, and Forestry	0.059 (0.29)	0.057 (0.29)
Construction and Extraction	0.15*** (0.054)	0.15*** (0.054)

Installation and		-0.021	-0.022
Repair		(0.046)	(0.046)
Production		-0.11***	-0.11***
		(0.043)	(0.043)
Transportation		0.071	0.070
\Material Moving		(0.046)	(0.046)
Not Out of Work			0.018
Last Spring			(0.012)
Was Out of Work			-0.0036
Last Spring			(0.034)
N	10,038	10,038	10,038

Standard errors in parentheses

This table contains the marginal effects from estimating an OLS model with skill distance between occupations as the dependent variable, for those individuals who have switched into a lower paying occupation that is not within the same two digit SOC occupation group. For example, a value of 0.1 indicates that members of the relevant demographic group who have moved into lower paying occupations during the pandemic have on average moved into an occupation that is approximately 10% further away in distance than an otherwise similar individual in the benchmark era.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Estimated Margins

	(1) Mismatch (D) Benchmark	(2) Mismatch (D) Pandemic	(3) Mismatch (O) Benchmark	(4) Mismatch (O) Pandemic	(5) Mismatch (N) Benchmark	(6) Mismatch (N) Pandemic
20 Years Old	0.095	0.12	0.12	0.15	0.12	0.14
	(0.0043)	(0.0072)	(0.0051)	(0.0083)	(0.0051)	(0.0079)
30 Years Old	0.091	0.098	0.097	0.10	0.099	0.098
	(0.0019)	(0.0027)	(0.0019)	(0.0028)	(0.0020)	(0.0027)
40 Years Old	0.087	0.085	0.085	0.081	0.087	0.079
	(0.0017)	(0.0024)	(0.0016)	(0.0022)	(0.0017)	(0.0022)
50 Years Old	0.083	0.081	0.079	0.076	0.081	0.074
	(0.0016)	(0.0022)	(0.0015)	(0.0020)	(0.0015)	(0.0020)
60 Years Old	0.080	0.084	0.078	0.084	0.080	0.081
	(0.0021)	(0.0031)	(0.0020)	(0.0030)	(0.0021)	(0.0029)

Single	0.088	0.085	0.093	0.087	0.094	0.084
	(0.0020)	(0.0027)	(0.0021)	(0.0027)	(0.0021)	(0.0027)
Married	0.085	0.092	0.082	0.090	0.084	0.086
	(0.0016)	(0.0024)	(0.0015)	(0.0023)	(0.0015)	(0.0022)
Men	0.095	0.096	0.089	0.091	0.091	0.088
	(0.0017)	(0.0024)	(0.0017)	(0.0024)	(0.0018)	(0.0024)
Women	0.076	0.081	0.083	0.086	0.085	0.082
	(0.0016)	(0.0024)	(0.0019)	(0.0026)	(0.0019)	(0.0025)
Less Than High	0.085	0.077	0.13	0.12	0.13	0.11
School	(0.0051)	(0.0069)	(0.0071)	(0.0098)	(0.0072)	(0.0094)
High School	0.084	0.097	0.11	0.12	0.11	0.12
	(0.0023)	(0.0037)	(0.0031)	(0.0047)	(0.0031)	(0.0045)
Post-Secondary <	0.096	0.090	0.11	0.100	0.11	0.096
Bachelor's	(0.0023)	(0.0033)	(0.0025)	(0.0035)	(0.0025)	(0.0035)
Bachelor's Degree	0.087	0.092	0.069	0.073	0.071	0.071
	(0.0024)	(0.0034)	(0.0020)	(0.0028)	(0.0020)	(0.0028)
Post-Secondary >	0.069	0.078	0.055	0.057	0.057	0.057
Bachelor's	(0.0028)	(0.0041)	(0.0024)	(0.0032)	(0.0025)	(0.0032)
White	0.086	0.089	0.083	0.085	0.085	0.082
	(0.0014)	(0.0021)	(0.0014)	(0.0019)	(0.0014)	(0.0019)
African-American	0.093	0.084	0.10	0.091	0.10	0.087
	(0.0041)	(0.0055)	(0.0044)	(0.0058)	(0.0044)	(0.0056)
Hispanic	0.082	0.097	0.089	0.11	0.091	0.10
	(0.0032)	(0.0047)	(0.0033)	(0.0049)	(0.0034)	(0.0048)
Asian-American	0.088	0.084	0.086	0.083	0.088	0.078
	(0.0048)	(0.0063)	(0.0047)	(0.0063)	(0.0048)	(0.0061)
Immigrant	0.058	0.064	0.072	0.068	0.074	0.066
	(0.0036)	(0.0053)	(0.0045)	(0.0056)	(0.0045)	(0.0054)
Management			0.20	0.20	0.20	0.20
			(0.0050)	(0.0050)	(0.0050)	(0.0050)
Business			0.17	0.17	0.17	0.17
Operations			(0.0073)	(0.0073)	(0.0074)	(0.0074)

Computer and	0.17	0.17	0.17	0.17
Mathematical	(0.0087)	(0.0087)	(0.0089)	(0.0089)
Architecture and	0.18	0.18	0.18	0.18
Engineering	(0.011)	(0.011)	(0.011)	(0.011)
Physical and	0.17	0.17	0.17	0.17
Social Science	(0.017)	(0.017)	(0.017)	(0.017)
Community	0.12	0.12	0.12	0.12
\Social Service	(0.010)	(0.010)	(0.011)	(0.011)
Legal	0.077	0.077	0.080	0.080
	(0.011)	(0.011)	(0.011)	(0.011)
Education and	0.071	0.071	0.073	0.073
Library	(0.0048)	(0.0048)	(0.0049)	(0.0049)
Arts, Sports, and	0.13	0.13	0.14	0.14
Media	(0.011)	(0.011)	(0.011)	(0.011)
Healthcare	0.092	0.092	0.094	0.094
Practitioners	(0.0053)	(0.0053)	(0.0054)	(0.0054)
Healthcare Support	0.0066	0.0066	0.0070	0.0070
	(0.0020)	(0.0020)	(0.0021)	(0.0021)
Protective Service	0.035	0.035	0.038	0.038
	(0.0054)	(0.0054)	(0.0056)	(0.0056)
Food Preparation	0.0080	0.0080	0.0084	0.0084
and Serving	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Building	0.016	0.016	0.017	0.017
Maintenance	(0.0028)	(0.0028)	(0.0029)	(0.0029)
Personal Care and	0.031	0.031	0.032	0.032
Service	(0.0038)	(0.0038)	(0.0039)	(0.0039)
Sales and Related	0.062	0.062	0.064	0.064
	(0.0032)	(0.0032)	(0.0033)	(0.0033)
Office and	0.055	0.055	0.057	0.057
Administrative	(0.0029)	(0.0029)	(0.0030)	(0.0030)
Farming, Fishing,	0.040	0.040	0.042	0.042
and Forestry	(0.0090)	(0.0090)	(0.0093)	(0.0093)

Construction and			0.060	0.060	0.061	0.061
Extraction			(0.0046)	(0.0046)	(0.0046)	(0.0046)
Installation and			0.11	0.11	0.11	0.11
Repair			(0.0070)	(0.0070)	(0.0071)	(0.0071)
Production			0.071	0.071	0.073	0.073
			(0.0044)	(0.0044)	(0.0045)	(0.0045)
Transportation			0.046	0.046	0.048	0.048
\Material Moving			(0.0037)	(0.0037)	(0.0037)	(0.0037)
Not Out of Work					0.085	0.082
Last Spring					(0.0012)	(0.0017)
Was Out of Work					0.14	0.13
Last Spring					(0.0084)	(0.0056)
N	109,730	109,730	109,730	109,730	109,730	109,730

Standard errors in parentheses

This table contains, for each demographic group listed, the estimated probability of mismatch for the demographic group listed in the rows, after controlling for the other characteristics listed. (D) in the column header indicates the presence of controls for demographic characteristics only, (O) indicates the addition of controls for 2-digit occupation, and (N) indicates the addition of controls for non-employed in the previous year.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Effect of Mismatch on Log Earnings

	(1) Mismatch	(2) Alternative Mismatch 1	(3) Alternative Mismatch 2	(4) Alternative Mismatch 3	(5) Alternative Mismatch 4
Mismatch	-0.085***	-0.083***	-0.083***	-0.083***	-0.074***
	(0.014)	(0.013)	(0.015)	(0.014)	(0.012)
Pandemic	0.12***	0.12***	0.12***	0.12***	0.12***
	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)
Pandemic ×	0.030	0.041*	0.024	0.026	0.039*
Mismatch	(0.024)	(0.022)	(0.026)	(0.024)	(0.020)
Apr. 2018	-0.010	-0.0095	-0.010	-0.010	-0.011
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
May 2018	-0.021	-0.020	-0.021	-0.021	-0.022

	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Mar. 2019	-0.0037	-0.0036	-0.0037	-0.0038	-0.0042
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Apr. 2019	0.019	0.019	0.019	0.019	0.018
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
May 2019	0.017	0.018	0.017	0.017	0.017
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Mar. 2021	-0.030**	-0.030**	-0.030**	-0.030**	-0.030**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Apr. 2021	-0.0034	-0.0033	-0.0029	-0.0036	-0.0035
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Married	0.072***	0.072***	0.072***	0.072***	0.072***
	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0071)
Women	-0.20***	-0.20***	-0.20***	-0.20***	-0.20***
	(0.0063)	(0.0063)	(0.0063)	(0.0063)	(0.0063)
African American	-0.13***	-0.13***	-0.13***	-0.13***	-0.13***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Hispanic	-0.084***	-0.084***	-0.084***	-0.084***	-0.084***
	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)
Asian American	0.034**	0.034**	0.034**	0.034**	0.034**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
High School	0.21***	0.21***	0.22***	0.21***	0.21***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Post-Secondary Below	0.34***	0.34***	0.34***	0.34***	0.34***
Bachelor's	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Bachelor's Degree	0.66***	0.66***	0.66***	0.66***	0.66***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Post-Secondary Above	0.82***	0.82***	0.82***	0.82***	0.82***
Bachelor's	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Immigrant	-0.0023	-0.0024	-0.0022	-0.0022	-0.0029
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Age	0.050***	0.050***	0.050***	0.050***	0.050***

	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Age × Age	-0.00051***	-0.00051***	-0.00051***	-0.00051***	-0.00051***
	(0.000021)	(0.000021)	(0.000021)	(0.000021)	(0.000021)
Out of Work Last Spring	-0.087***	-0.087***	-0.088***	-0.087***	-0.089***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Constant	1.63***	1.63***	1.62***	1.63***	1.62***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
N	26,037	26,037	26,037	26,037	26,037

Standard errors in parentheses

This table contains OLS regression results in which the depedent variable is the natural log of weekly earnings as recorded in the CPS. The subsample consists of all individuals who were employed in February 2017, 2018, or 2020 and are subsequently observed as employed in following year. Furthermore, since weekly earnings are recorded only for individuals who are appearing in the CPS for the 4th or 8th time, these are the only individuals in our subsample. We further exclude any individuals whose reported weekly earnings are less than $290 (the amount that one would earn at 40 hours per week at the federal minimum wage). The mismatch variable listed in the first row consists of the mismatch variable that is listed in the column header, as outlined in Sections 2.2 and 2.3.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Effect of Mismatch on Log Earnings (With Controls for Initial Occupation Group)

	(1) Mismatch	(2) Alternative Mismatch 1	(3) Alternative Mismatch 2	(4) Alternative Mismatch 3	(5) Alternative Mismatch 4
Mismatch	-0.17***	-0.16***	-0.17***	-0.16***	-0.16***
	(0.014)	(0.013)	(0.015)	(0.014)	(0.012)
Pandemic	0.10***	0.10***	0.10***	0.10***	0.10***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Pandemic × Mismatch	0.040*	0.045**	0.036	0.033	0.042**
	(0.023)	(0.021)	(0.026)	(0.023)	(0.019)
Apr. 2018	-0.014	-0.013	-0.014	-0.015	-0.015
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
May 2018	-0.028**	-0.027**	-0.028**	-0.028**	-0.029**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Mar. 2019	-0.0079	-0.0076	-0.0077	-0.0081	-0.0089

	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Apr. 2019	0.014	0.014	0.014	0.014	0.012
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
May 2019	0.016	0.017	0.016	0.016	0.014
	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)
Mar. 2021	-0.019	-0.018	-0.018	-0.019	-0.019
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Apr. 2021	-0.0040	-0.0039	-0.0030	-0.0044	-0.0047
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Married	0.058***	0.057***	0.058***	0.058***	0.057***
	(0.0068)	(0.0068)	(0.0068)	(0.0068)	(0.0068)
Women	-0.17***	-0.17***	-0.17***	-0.17***	-0.17***
	(0.0070)	(0.0070)	(0.0070)	(0.0070)	(0.0070)
African American	-0.097***	-0.096***	-0.097***	-0.097***	-0.097***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Hispanic	-0.059***	-0.059***	-0.059***	-0.059***	-0.059***
	(0.0088)	(0.0088)	(0.0088)	(0.0088)	(0.0088)
Asian American	0.015	0.015	0.015	0.015	0.015
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
High School	0.18***	0.18***	0.18***	0.18***	0.18***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Post-Secondary Below	0.26***	0.26***	0.26***	0.26***	0.26***
Bachelor's	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Bachelor's Degree	0.52***	0.52***	0.52***	0.52***	0.51***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Post-Secondary Above	0.67***	0.67***	0.67***	0.67***	0.67***
Bachelor's	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Immigrant	0.023*	0.023*	0.023*	0.023*	0.021*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Age	0.043***	0.043***	0.043***	0.043***	0.043***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Age × Age	-0.00043***	-0.00043***	-0.00043***	-0.00043***	-0.00043***

	(0.000021)	(0.000021)	(0.000021)	(0.000021)	(0.000021)
Out of Work Last	-0.046***	-0.045***	-0.047***	-0.046***	-0.047***
Spring	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Old Business and	-0.036**	-0.034**	-0.039**	-0.037**	-0.043***
Financial Operations	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Old Computer and	0.085***	0.083***	0.085***	0.085***	0.080***
Mathematical	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Old Architecture and	0.0076	0.0070	0.0079	0.0070	0.0028
Engineering	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Old Life, Physical,	-0.074***	-0.074***	-0.075***	-0.074***	-0.073***
and Social Science	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Old Community and	-0.33***	-0.33***	-0.33***	-0.33***	-0.34***
Social Service	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Old Legal	-0.066**	-0.066**	-0.064**	-0.066**	-0.077***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Old Educational	-0.32***	-0.32***	-0.32***	-0.32***	-0.33***
Instruction and Library	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Old Arts, Design,	-0.13***	-0.13***	-0.13***	-0.13***	-0.13***
Entertainment, Sports, and Media	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Old Healthcare	-0.032**	-0.032**	-0.031**	-0.033**	-0.043***
Practitioners	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Old Healthcare	-0.38***	-0.38***	-0.38***	-0.38***	-0.40***
Support	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Old Protective	-0.20***	-0.20***	-0.20***	-0.20***	-0.22***
Service	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Old Food Preparation	-0.45***	-0.45***	-0.44***	-0.45***	-0.46***
and Serving Related	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Old Building and	-0.45***	-0.46***	-0.45***	-0.45***	-0.47***
Grounds Maintenance	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Old Personal Care	-0.42***	-0.42***	-0.42***	-0.42***	-0.43***
and Service	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Old Sales and	-0.24***	-0.23***	-0.24***	-0.24***	-0.25***

Related	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Old Office and	-0.29***	-0.29***	-0.29***	-0.29***	-0.30***
Administrative	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Old Farming,	-0.40***	-0.40***	-0.40***	-0.40***	-0.42***
Fishing, and Forestry	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
Old Construction and	-0.18***	-0.18***	-0.18***	-0.18***	-0.20***
Extraction	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Old Installation,	-0.17***	-0.17***	-0.17***	-0.17***	-0.18***
Maintenance , Repair	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Old Production	-0.27***	-0.27***	-0.27***	-0.27***	-0.28***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Old Transportation	-0.34***	-0.34***	-0.34***	-0.34***	-0.35***
and Material Moving	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Constant	2.06***	2.06***	2.06***	2.06***	2.08***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
N	26,037	26,037	26,037	26,037	26,037

Standard errors in parentheses

This table contains OLS regression results in which the depedent variable is the natural log of weekly earnings as recorded in the CPS. The subsample consists of all individuals who were employed in February 2017, 2018, or 2020 and are subsequently observed as employed in following year. Furthermore, since weekly earnings are recorded only for individuals who are appearing in the CPS for the 4th or 8th time, these are the only individuals in our subsample. We further exclude any individuals whose reported weekly earnings are less than $290 (the amount that one would earn at 40 hours per week at the federal minimum wage). The mismatch variable listed in the first row consists of the mismatch variable that is listed in the column header, as outlined in Sections 2.2 and 2.3. Controls are included for an individual's initial two digit occupation (all occupation groups beginning with Old).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Marginal Effects (2020 Occupation Codes)

	(1) Mismatch	(2) Alternative Mismatch 1	(3) Alternative Mismatch 2	(4) Alternative Mismatch 3	(5) Alternative Mismatch 4
2020 Codes	-0.013***	-0.017***	-0.0095***	-0.013***	-0.016***
	(0.0032)	(0.0035)	(0.0028)	(0.0031)	(0.0038)
N	30,554	30,554	30,554	30,554	30,553

Standard errors in parentheses

This table containts the marginal effect of the changes in occupation codes that were introduced in January 2020 (described in Section 5.1) on the probability that an individual has become mismatched in the one month period from January to February. The subsample is restricted to individuals who first appear in January of 2017, 2018, or 2020, and subsequently re-appear in the following month. Furthermore, the subsample is restricted to individuals who are employed in both months. As an example, a value of -0.01 indicates that the probability that the dependent variable is equal to 1 is approximately one percentage point lower in 2020 than in 2017/2018.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Marginal Effects (Job Zone Mismatch)

	(1) Zone Mismatch
20 Years Old	0.014
	(0.010)
30 Years Old	0.0099***
	(0.0038)
40 Years Old	0.0080**
	(0.0032)
50 Years Old	0.0075***
	(0.0029)
60 Years Old	0.0085**
	(0.0041)
Single	0.012***
	(0.0038)
Married	0.0070**
	(0.0032)
Men	0.0030
	(0.0033)
Women	0.016***
	(0.0032)
Less Than High	0.014
School	(0.0094)
High School	0.019***

	(0.0048)
Post-Secondary < Bachelor's	0.00043
	(0.0045)
Bachelor's Degree	0.0038
	(0.0045)
Post-Secondary > Bachelor's	0.016***
	(0.0056)
White	0.0070**
	(0.0028)
African-American	0.0014
	(0.0081)
Hispanic	0.019***
	(0.0062)
Asian-American	0.015*
	(0.0090)
Immigrant	0.021**
	(0.0084)
N	100,545

Standard errors in parentheses

This table contains, for each demographic group listed, the marginal effect of the pandemic on the the probability of being mismatch with occupation zone as a measure of the overall quality of an occupation.Marginal effects are estimated using the model outlined in Equation 2. Other than the change in definition of mismatch, the subsample and interpretation of the results is identical to Table A1.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A11: Marginal Effects (Linear Probability Model)

	(1) Out of Work Last Spring	(2) Not Employed	(3) Mismatch	(4) Alternative Mismatch 1	(5) Alternative Mismatch 2	(6) Alternative Mismatch 3	(7) Alternative Mismatch 4
20 Years Old	0.19***	0.017***	0.025***	0.014*	0.014*	0.024***	0.049***
	(0.0092)	(0.0063)	(0.0078)	(0.0083)	(0.0070)	(0.0078)	(0.0090)
30 Years Old	0.14***	0.022***	0.0077**	0.0052	0.0025	0.0071**	0.017***
	(0.0037)	(0.0026)	(0.0033)	(0.0036)	(0.0030)	(0.0033)	(0.0039)

40 Years Old	0.11***	0.025***	-0.0017	0.00080	-0.0027	-0.0018	0.00044
	(0.0032)	(0.0023)	(0.0029)	(0.0031)	(0.0027)	(0.0029)	(0.0036)
50 Years Old	0.11***	0.026***	-0.0027	0.0012	-0.0019	-0.0030	0.00053
	(0.0031)	(0.0022)	(0.0028)	(0.0030)	(0.0025)	(0.0028)	(0.0034)
60 Years Old	0.13***	0.026***	0.0045	0.0063	0.0049	0.0036	0.017***
	(0.0043)	(0.0032)	(0.0037)	(0.0040)	(0.0035)	(0.0037)	(0.0048)
Single	0.14***	0.027***	-0.0033	-0.0038	-0.0048	-0.0034	0.0030
	(0.0040)	(0.0029)	(0.0034)	(0.0037)	(0.0032)	(0.0034)	(0.0043)
Married	0.12***	0.022***	0.0078***	0.0091***	0.0056**	0.0070**	0.016***
	(0.0030)	(0.0021)	(0.0028)	(0.0030)	(0.0026)	(0.0028)	(0.0034)
Men	0.11***	0.025***	0.0016	0.0034	-0.0018	0.0020	0.0087**
	(0.0030)	(0.0022)	(0.0030)	(0.0032)	(0.0028)	(0.0030)	(0.0036)
Women	0.14***	0.022***	0.0056**	0.0049	0.0054**	0.0041	0.014***
	(0.0034)	(0.0024)	(0.0029)	(0.0031)	(0.0026)	(0.0029)	(0.0036)
Less Than High	0.18***	0.032***	-0.0082	-0.0025	-0.016**	-0.011	-0.010
School	(0.011)	(0.0082)	(0.0090)	(0.0097)	(0.0080)	(0.0089)	(0.010)
High School	0.17***	0.027***	0.013***	0.013***	0.0092**	0.013***	0.0081
	(0.0053)	(0.0036)	(0.0044)	(0.0047)	(0.0040)	(0.0044)	(0.0052)
Post-Secondary <	0.14***	0.029***	-0.0060	-0.0061	-0.0090**	-0.0064	-0.0010
Bachelor's	(0.0045)	(0.0032)	(0.0040)	(0.0043)	(0.0037)	(0.0040)	(0.0049)
Bachelor's Degree	0.094***	0.018***	0.0045	0.0086**	0.0059	0.0018	0.014***
	(0.0040)	(0.0028)	(0.0041)	(0.0044)	(0.0038)	(0.0041)	(0.0051)
Post-Secondary >	0.066***	0.017***	0.0091*	0.0033	0.0081*	0.012**	0.040***
Bachelor's	(0.0044)	(0.0033)	(0.0049)	(0.0052)	(0.0044)	(0.0048)	(0.0062)
White	0.11***	0.018***	0.0033	0.0038	-0.00038	0.0029	0.014***
	(0.0026)	(0.0018)	(0.0025)	(0.0027)	(0.0023)	(0.0025)	(0.0031)
African-American	0.13***	0.035***	-0.010	-0.0052	-0.0083	-0.0084	0.0046
	(0.0084)	(0.0063)	(0.0069)	(0.0079)	(0.0063)	(0.0069)	(0.0084)
Hispanic	0.15***	0.036***	0.016***	0.015**	0.018***	0.015**	0.012*
	(0.0065)	(0.0045)	(0.0058)	(0.0061)	(0.0054)	(0.0058)	(0.0069)
Asian-American	0.19***	0.030***	-0.0033	-0.0041	-0.0040	-0.0064	-0.0087
	(0.0087)	(0.0059)	(0.0078)	(0.0081)	(0.0069)	(0.0077)	(0.0095)

Immigrant	0.13***	0.019***	0.0065	0.0092	0.014**	0.0074	0.045***
	(0.0085)	(0.0063)	(0.0066)	(0.0071)	(0.0061)	(0.0066)	(0.0084)
N	114,591	114,591	109,730	109,730	109,730	109,730	109,730

Standard errors in parentheses

This table contains, for each demographic group listed, the marginal effect of the pandemic on the dependent indicator variables listed in the column headers. Marginal effects are estimated using a linear probability model, as opposed to a probit model which is used to estimate the marginal effects in other tables of this paper. As an example of the interpretation, a value of 0.05 indicates that during the pandemic there has been a 5 percentage point increase in the probability that the dependent variable is equal to 1 for a member of the relevant demographic group, relative to the pre-pandemic benchmark period. The subpopulation of interest consists of all individuals who were employed in one of February 2017, February 2018 (for the benchmark era), or February 2020 (for the pandemic era), and are subsequently observed in the sample at least once during the months of January-May in the following year. For columns (3)-(6), the subpopulation consists only of those who are employed in their 2nd year in the CPS. See Section 5 for a description of the measures of mismatch in columns (3)-(6).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A12: Marginal Effects (Differential Functional Forms of Age)

	(1) Mismatch Cubic Age	(2) Mismatch Quadratic Age
20 Years Old	0.041***	0.027***
	(0.010)	(0.0084)
25 Years Old	0.013***	0.016***
	(0.0049)	(0.0051)
30 Years Old	0.00097	0.0073**
	(0.0039)	(0.0033)
35 Years Old	-0.0033	0.0017
	(0.0034)	(0.0028)
40 Years Old	-0.0030	-0.0016
	(0.0030)	(0.0029)
45 Years Old	-0.00022	-0.0029
	(0.0030)	(0.0029)
50 Years Old	0.0031	-0.0023
	(0.0034)	(0.0027)

55 Years Old	0.0046	0.000051
	(0.0034)	(0.0027)
60 Years Old	0.0023	0.0042
	(0.0038)	(0.0037)
Single	-0.0037	-0.0033
	(0.0034)	(0.0034)
Married	0.0081***	0.0080***
	(0.0029)	(0.0028)
Men	0.0015	0.0014
	(0.0030)	(0.0030)
Women	0.0053*	0.0057**
	(0.0029)	(0.0029)
Less Than High School	-0.013	-0.0080
	(0.0083)	(0.0085)
High School	0.012***	0.013***
	(0.0043)	(0.0044)
Post-Secondary < Bachelor's	-0.0060	-0.0061
	(0.0040)	(0.0040)
Bachelor's Degree	0.0056	0.0045
	(0.0042)	(0.0041)
Post-Secondary > Bachelor's	0.0094*	0.0089*
	(0.0050)	(0.0049)
White	0.0030	0.0032
	(0.0025)	(0.0025)
African-American	-0.0095	-0.0096
	(0.0069)	(0.0069)
Hispanic	0.016***	0.016***
	(0.0057)	(0.0057)
Asian-American	-0.0042	-0.0037
	(0.0079)	(0.0079)
Immigrant	0.0064	0.0064
	(0.0064)	(0.0064)

N	109,730	109,730

Standard errors in parentheses

This table contains, for each demographic group listed, the marginal effect of the pandemic on the dependent indicator variables listed in the column headers. Column (1) is estimated using the probit model in equation 2 with only demographic controls, with the addition of a cubic term for age. Column (2) is estimated using only a quadratic function of age, and is equivalent to the result in column (3) of Table A1. As an example of the interpretation, a value of 0.05 indicates that during the pandemic there has been a 5 percentage point increase in the probability that the dependent variable is equal to 1 for a member of the relevant demographic group, relative to the pre-pandemic benchmark period. The subpopulation of interest consists of all individuals who were employed in one of February 2017, February 2018 (for the benchmark era), or February 2020 (for the pandemic era), and are subsequently observed in the sample at least once during the months of January-May in the following year.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$