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*IZA*

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**IZA – Institute of Labor Economics**

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

# ABSTRACT

# Job Search during a Pandemic Recession: Survey Evidence from the Netherlands*

This paper studies job search behavior in the midst of a pandemic recession. We use long-running panel data from the Netherlands (LISS) and complement the core survey with our own COVID-specific module, conducted in June 2020, surveying job search effort of employed as well as unemployed respondents. We estimate an empirical model of job search over the business cycle over the period 2008-2019 to explore the gap between predicted and actual job search behavior in 2020. We find that job search during the pandemic recession differs strongly from previous downturns. The unemployed search significantly less than what we would normally observe during a recession of this size, while the employed search mildly more. Expectations about the duration of the pandemic seem to play a key role in explaining job search effort for the unemployed in 2020. Furthermore, employed subjects affected by changes in employment status due to COVID-19 are more likely to search for a job. Conversely, beliefs about infection risk do not seem to be related to job search in a systematic way.

**JEL Classification:** J21, J64, J68

**Keywords:** COVID-19, job search, labor supply, survey

**Corresponding author:**
Maria Balgova
IZA
Schaumburg-Lippe-Straße 5-9
53113 Bonn
Germany

E-mail: balgova@iza.org

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# 1 Introduction

Do individuals still look for jobs during a pandemic? On the face of it, doing so seems futile. In virtually all countries, the COVID-19 pandemic triggered one of the most severe economic downturns in modern history: lockdowns and government restrictions sharply curtailed economic activity, consumers were held back by fears of infection (Goolsbee and Syverson, 2021), and missing childcare and health concerns weakened labor supply (Alon et al., 2020). Given the recession and the degree of unprecedentedness which makes forming expectations particularly difficult, individuals may believe there is no point to search. However, the pandemic also changed the structure of the economy and caused substantial employment losses. As a result, individuals may search more: to take advantage of the increased ability to work from home or to pivot into a less-affected industry. Understanding job search during this time matters for several reasons. It is crucial to form a complete picture of this extraordinary economic event, but it is also necessary to gauging the path to a fast recovery, and it may provide valuable insights for economic policy-making in case of potential future pandemic-induced recessions.

In this paper, we study job search behavior in a pandemic recession. Specifically, we ask whether employed and unemployed workers search more or less than during a normal recession. We then examine potential drivers: Are concerns over health and safety an obstacle to job search? Do employment shocks on an individual level increase job search effort? What is the role of beliefs about the duration of economic restrictions? To answer these questions, we use data from a long-running panel survey in the Netherlands (LISS), complemented by a specific survey on job search behavior during the pandemic. We find that job search during the pandemic recession differs strongly from previous downturns. The unemployed search significantly less than what we would normally observe during a recession of this size, while the employed search mildly more. This seems to be driven predominantly by individuals' expectations about the duration of the pandemic, rather than childcare availability, concerns over health, or the desire to switch occupations.

The Dutch labor market was strongly hit by the pandemic: the number of vacancies decreased by 30% and the Dutch economy contracted by 8.5% in Q2/2020. However, due to strong labor protection laws and extensive support programs, the effects of the pandemic turned out to be milder than in some other developed countries (such as the UK and the U.S., see von Gaudecker, Holler, et al., 2020): households didn't experience a significant shock to their income, and the unemployment rate increased by only 1.5 percentage points. The initial lockdown in spring 2020, while restrictive, was to some extent more lenient than the measures imposed by other European countries. By summer 2020, when our job search data was collected, social and economic life was largely back to what it used to be. Nevertheless, the uncertainty about a possible second wave of the pandemic persisted and it was unclear for how long the labor market would be affected.[1]

Our data are based on a probability sample of the Dutch population and provide annual information on about 5,000 individuals from the year 2008 onward. We complement the core LISS survey with a COVID-specific module (conducted in June 2020) surveying the panel respondents about their job search effort, including the number of applications sent over the past two months. Importantly, we collect the data on both the employed and the unemployed. We also ask about the respondents' expectations about the economy and changes in their preferences over work arrangements. Other modules from earlier months of 2020 allow us to merge in data on childcare provision, individual beliefs about the health risks, and other information related to the pandemic.

The analysis proceeds in two steps. We start by looking at the 2020 recession through the lens of traditional business cycle fluctuations. We estimate a reduced-form model of job search over the most recent business cycle (2008–2019), and use these results to predict job search behavior in 2020 given the state of the economy and the composition of the employed and unemployed in 2020. In the second step, we recognize that 2020 is a *pandemic* recession: we explore the gap between the predicted and actual job search behavior in 2020. We regress the model prediction error on a broad set of variables capturing the situation in 2020, including expectations about the labor market and the pandemic, individual health risk, and changes in preferences over job characteristics. This allows us to explore which of the many pandemic-related shocks are driving job search behavior.

Our main finding is that the usually strong counter-cyclical pattern of job search effort in the Netherlands no longer holds during the pandemic. The unemployed search significantly less than what we would normally observe during a recession of this size. In fact, the unemployed search less (both along the extensive and intensive margin) in 2020 than they did on average in the five years before the pandemic. The opposite holds for the employed: their job search effort increases in line with a counter-cyclical relationship, and if anything they search slightly more than we would expect given the state of the economy.

Second, our analysis suggests that the main factors behind this divergence stem from particularities of the economic downturn that was caused by the pandemic: unemployed individuals from sectors most affected by economic restrictions search significantly less compared to normal times; employed subjects facing pandemic-related work changes tend to search more. In addition, uncertainty about the duration and severity of the economic downturn seems key to explaining the observed divergence in job search. Consistent with an intertemporal substitution mechanism, we find that individuals who expect a short and temporary impact of the coronavirus pandemic on the labor market search relatively little compared to individuals that expect this impact to be long and severe. On the other hand, health concerns, a pervasive feature of the pandemic, are not related to search effort despite individuals assert on average a

[1] We describe the institutional context and the development of the labor market during our observation period in more detail in Appendix A.

high probability of getting infected. Similarly, apart from a higher job search for the female unemployed, we find little systematic differences in job search by demographics during the pandemic over and above their pre-pandemic pattern.

This paper contributes to the quickly expanding literature on the impact of the COVID-19 pandemic on labor market outcomes of households (e.g. Adams-Prassl et al., 2020; Crossley, Fisher, and Low, 2020; Meekes, Hassink, and Kalb, 2020; von Gaudecker, Holler, et al., 2020). The existing studies focus on changes in working hours, furlough schemes, and job separations; there has been relatively less focus on job search and labor supply decisions in general.

Most of the existing literature on job search during the pandemic (Bauer et al., 2020; Marinescu, Skandalis, and Zhao, 2020; Hensvik, Le Barbanchon, and Rathelot, 2021) focuses on data from online job platforms. They find that both labor demand (vacancies) and labor supply as measured by job applications dropped strongly. The advantage of our paper lies in making use of representative and rich panel survey data, which allows us to go beyond measurement to analyze *what* drives the drop in search during the pandemic.[2] Another advantage is the ability to distinguish between job search of the employed and the unemployed. In line with Faberman et al. (2020) we find that search on the job differs substantially from job search during unemployment. Given the widespread use of labor hoarding policies, search on the job becomes particularly important to understand aggregate job search activity.

In this respect, we also contribute to the literature analyzing the determinants of job search. We show that job finding expectations (Mueller, Spinnewijn, and Topa, 2018) and the duration of unemployment (DellaVigna et al., 2020; Lichter and Schiprowski, 2021) matter during the pandemic, but we also provide evidence of additional pandemic-specific factors which drive job seekers' behavior.

Our final contribution is to the macro-labor literature on job search over the business cycle. The existing studies overwhelmingly make use of data on the unemployed in the U.S., and their findings are mixed.[3] We show that in the Netherlands, patterns of job search effort are counter-cyclical for both the employed and unemployed. During a pandemic recession, however, the unemployed deviate from this pattern.

[2] Bauer et al. (2020) find evidence of a reallocation of the unemployed: job seekers in sectors that were particularly hit hard by the crisis have shifted their search towards less hit sectors. Coibion, Gorodnichenko, and Weber (2020) also makes use of survey data and document, consistent with our findings, a lower share of search for the unemployed which they mainly attribute to early retirement. Our work involves in contrast an examination of different factors directly related to the pandemic.

[3] DeLoach and Kurt (2013) and Gomme and Lkhagvasuren (2015) find that job search is pro-cyclical; Shimer (2004) and Mukoyama, Patterson, and Şahin (2018) find it to be counter-cyclical, and Leyva (2018) find no relationship.

## 2 Data and descriptives

To analyze job search during a pandemic recession, we make use of two data sets. The first is a yearly longitudinal dataset on job search behavior going back to 2008. The second is a dataset comprising several pandemic-related variables that were collected in 2020. Both datasets are based on the Longitudinal Internet Studies for the Social Sciences (LISS) panel which is administered by CentERdata at Tilburg University. We describe each dataset in turn.

### 2.1 Longitudinal data of job search

The LISS panel is based on a probability sample of individuals registered by Statistics Netherlands which ensures representativeness not only on observed but also unobserved characteristics. The core questionnaire includes several questions about job search. Panel members answer these recurring questions every year in spring which allows us to build a time series going back until 2008 for roughly 5,000 individuals each year.

Our measure of job search is the self-reported number of applications sent over the past two months preceding the LISS survey (always in April), setting it to zero for those individuals who stated they were not searching. The number of applications thus reflects both the extensive and the intensive margin of search. An alternative measure, a binary indicator of whether an individual is seriously searching for a job or not, is used for robustness checks.

Respondents are asked for their current labor market status. Importantly, questions about job search are addressed to both employed (or self-employed) and unemployed respondents. Since we expect different determinants of job search for the unemployed, we analyze this group separately. The self-employed are analyzed together with the employed by including a dummy variable for self-employment.

The LISS panel contains a rich set of background characteristics for all respondents including demographic information, household income, the urbanity of the place of residence, civil status, and the sector the individual is working in or has worked in before becoming unemployed. Throughout this paper, we restrict the sample to respondents aged 18 to 65 years.

### 2.2 Pandemic-specific questionnaires

To understand how and why job search changed in 2020, we make use of an additional job search module addressed to all panel members aged at least 16 years in June 2020 (the response rate was above 80%). The full list of survey questions is documented in von Gaudecker, Zimpelmann, et al. (2021). Importantly, the questions on job search in the 2020 module are consistent with the longitudinal questionnaire, allowing comparison over time.[4]

[4] We note that there is a small change in the way labor market states are recorded in 2020 compared to earlier years. The resulting categorization of states before and after 2020 is conceptually comparable and empirically very similar.

Table 1 presents summary statistics of our sample in June 2020. It consists of 2,753 employed (or self-employed) individuals and 151 unemployed individuals. While the number of unemployed is low in absolute terms, making it harder to do inference for this group alone (an additional argument for including the employed in the analysis), they can be considered as representative due to the random sampling structure of the survey.

The demographics of the two groups differ in expected ways: the unemployed are on average less educated than the employed, with only about 34% holding a tertiary degree compared to 48% among the employed. They have a lower household income, with only 25% in the highest employment tercile compared with 46% for the employed. The unemployed are also less likely to be female, married, have children living in their household, or live in an urban location. One in ten individuals in the employed category is self-employed.

Turning to search outcomes, about 60% of the unemployed report seriously searching for a job and the average unemployed has applied for almost five jobs within the last two months. With about 0.2 applications, job search is considerably lower among the employed; however, given the large number of employed in the economy, their search makes up a significant part of the aggregate behavior.

Next, we consider three groups of variables that might drive job search behavior during a pandemic recession. Most of these variables were collected in June, but a few were elicited in the COVID questionnaires in May. First, we ask respondents for their perceived likelihood of getting infected with the virus within the next two months and for the likelihood of becoming hospitalized if infected. The employed report a slightly higher infection probability of 31% compared with 23%, possibly reflecting the risk of becoming infected at the workplace or while commuting. On average, both groups expect a one in four chance hospitalization if infected.

Second, we collect a set of variables that reflect changes in employment. We ask respondents if their work situation changed because of the pandemic: a change in employment status, a change in contractual working hours, or a change in earnings (for the self-employed). This is the case for 10% of the employed and 17% of the unemployed. Additionally, 10% of employed individuals report that they are affected by NOW, the Dutch short-time work policy.[5]

The third group of variables summarizes the expectations of respondents with respect to the future development of the labor market. While about 40% of both groups expect the economic restrictions to end in 2021, 26% expect the restrictions to last until at least 2022. Further, 27% of the employed and 34% of the unemployed expect an unemployment rate of at least 9% in 2021 or 2022. We also ask subjects if they think the pandemic made it harder to find a job in their line of work: 40% of the employed and 35% of the unemployed agree.

[5] This rate is notably lower than what is reported in official statistics (24%) for two reasons: First, 24% of respondents state they do not know whether they fall under this program which is expected since there is no requirement to reduce working hours. Second, this question was asked in an earlier wave such that this observation is missing for about 35% of the observations.

Table 1: Summary table — main variables

| | (1) Employed | (2) Unemployed |
|---|---|---|
| **Search outcomes** | | |
| no. of applications last two months | 0.21 | 4.78 |
| | [1.24] | [6.59] |
| seriously searching for a (new) job | 0.036 | 0.58 |
| **Demographics** | | |
| age in years | 44.1 | 44.2 |
| | [12.4] | [16.5] |
| lower secondary education | 0.15 | 0.23 |
| upper secondary education | 0.37 | 0.41 |
| tertiary education | 0.48 | 0.34 |
| female | 0.53 | 0.44 |
| children | 0.51 | 0.38 |
| married | 0.51 | 0.31 |
| household income: middle | 0.42 | 0.33 |
| household income: high | 0.46 | 0.25 |
| urban location | 0.43 | 0.38 |
| self-employed | 0.10 | - |
| **Health concerns** | | |
| probability of infection | 0.31 | 0.23 |
| | [0.23] | [0.20] |
| probability of hospitalization if infected | 0.24 | 0.25 |
| | [0.24] | [0.28] |
| **Work changes** | | |
| work change due to corona | 0.096 | 0.17 |
| unemployment duration in years | - | 0.23 |
| | - | [0.88] |
| applied for short-time work | 0.10 | - |
| **Expectations** | | |
| expect restrictions until 2021 | 0.41 | 0.39 |
| expect restrictions until 2022 | 0.26 | 0.26 |
| expect high future unemployment | 0.27 | 0.34 |
| finding same/old job harder | 0.40 | 0.35 |
| number of observations | 2753 | 151 |

This table summarizes the variables of the job search module asked in the LISS panel in June 2020 (or for some variables in earlier waves) separately for the employed and the unemployed. All results restrict to individuals aged between 16 and 65. SDs are in brackets (omitted for binary variables).

# 3 Results

## 3.1 Job search over the business cycle

To understand the features of job search during a pandemic recession, we start by establishing the characteristics of job search in the Netherlands during a normal recession. Our time series starts in 2008. At this point, the Dutch economy was in a boom which was to be swiftly followed by a double-dip recession caused first by the credit crunch and then by the European sovereign debt crisis. The unemployment rate returned to its pre-recession state just before the pandemic (more details in Section A.3 in the Appendix).

The average number of job applications, together with the aggregate unemployment rate, are plotted in Figure 1. The figure shows that job search of both the employed and the unemployed is counter-cyclical: individuals search more when the unemployment rate is high. In the years of the tightest labor market (2008 and 2019), the employed made on average 0.1 applications over the past two months, while this number almost tripled in 2014 at the height of unemployment. The unemployed, who search more overall, display the same counter-cyclical behavior: they made on average about five applications in 2008 and 2019, but almost eleven in 2015.

This positive relationship between the unemployment rate and job search may arise because of two different effects. It may be due to the changes in the composition of the employed and unemployed, or due to an actual behavioral response to the business cycle. To distinguish between them, and to explore the drivers of job search behavior formally, we estimate the following empirical model of job search:

$$J_{it} = \alpha + \beta_1^L X_{it} + \gamma^L R_t + \epsilon_{it} \tag{1}$$

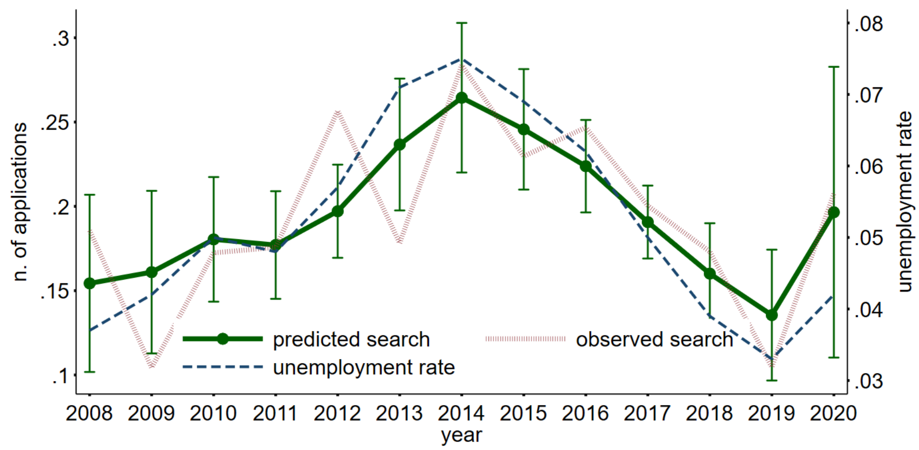
where $J_{it}$ is the measure of job search of individual $i$ in year $t$, and $X_{it}$ captures individual characteristics (age, gender, education, marital status, a parent dummy, normalized household income, a dummy for urban location, and the length of unemployment spell for the unemployed), including sector dummies. We allow for endogenous response to business cycle fluctuations by including the aggregate unemployment rate $R_t$. The regression is fitted separately for the employed ($L = E$) and unemployed ($L = U$). This regression effectively decomposes the variation in job search over time and across individuals into changes in individual characteristics, and the changes in search behavior over the business cycle. It is estimated by pooled OLS.[6]

The results of the model are summarized in Table B.1 in the Appendix. The coefficients on the unemployment rate are positive, confirming the counter-cyclical pattern of job search seen in Figure 1. A one percentage point increase in the unemployment rate leads to 0.8 additional job applications by the unemployed, and 0.03 more applications by the employed, suggesting a strong behavioral response. Individual characteristics matter too, especially for on-the-job-search: the lower educated, married individuals, and individuals in higher-

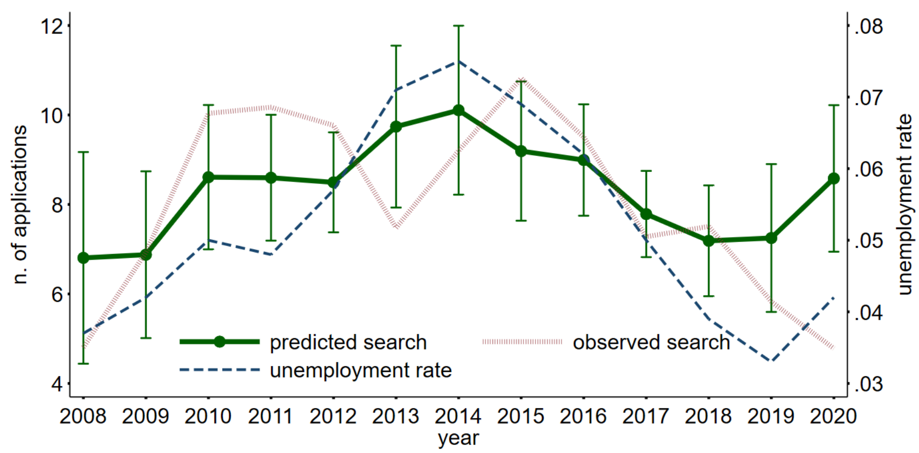
[6]We keep missing values for all variables as separate categories to maximize sample size.

Figure 1: Unemployment rate and observed and predicted job search (number of applications) over the business cycle

(a) Employed




(b) Unemployed




*Notes:* This figure plots observed and predicted job search as well as the unemployment rate over the business cycle. The dashed line represents aggregate unemployment rate at the time of the LISS survey (April for 2008-2019, June for 2020). The thick fuzzy line plots the observed average number of job applications sent over the 2 months prior to the survey. The solid line with dots represents the number of job applications as predicted by our pooled OLS model of job search as a function of individual characteristics and the unemployed rate (Table B.1 in the Appendix). The value for 2020 is an out-of-sample prediction based on this model.

income households search less. Because the characteristics of the employed and unemployed are different in a recession compared to a boom (see Table B.2 in the Appendix), the impact of demographics further contributes to the increase in job search when the unemployment rate is high.

### 3.2 Job search during a pandemic recession

The business cycle patterns described in the previous section suggest that job search should increase in a pandemic recession. Figure 1 shows that the search of the employed follows the expected pattern: the number of applications in 2020 almost doubled compared to the previous year, rising from 0.1 to little over 0.2. The unemployed, on the other hand, searched less: in the midst of the pandemic recession, the unemployed sent on average the same number of applications as during the height of the boom in 2008.

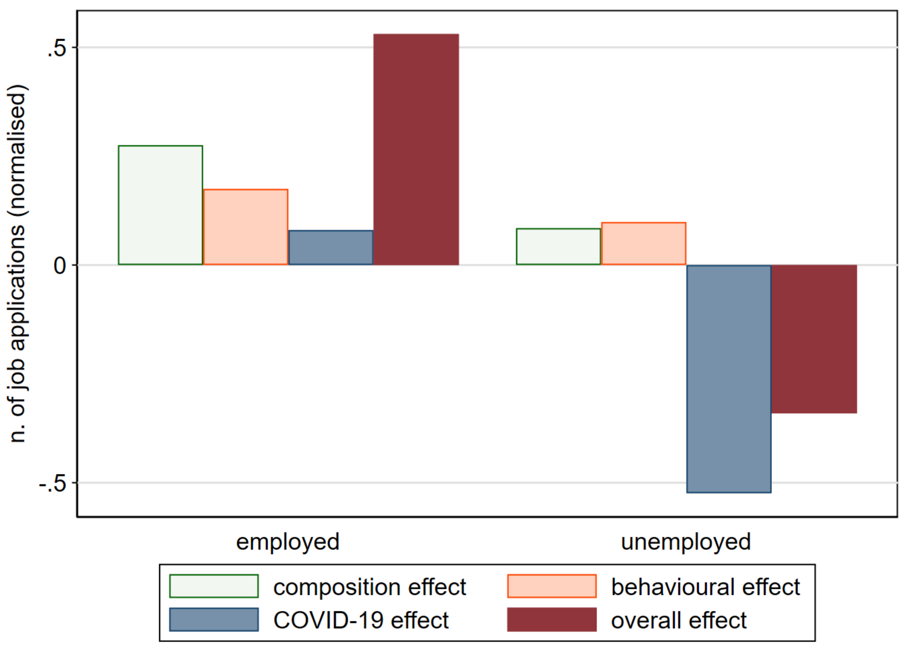
While our model predicts that job search should increase in response to a higher unemployment rate (the behavioral channel), it may be the case that the composition of the unemployed changed in a pandemic-specific way which reduced their overall job search. To test this, we use the estimated model to make an out-of-sample prediction for the number of applications in 2020. This estimate (together with the in-sample predictions for the years 2008–2019) is plotted in Figure 1. The plot shows that the model fits the cyclicality of job search well in 2008–2019. For 2020, however, it predicts a sharp uptick in the number of job applications sent by the unemployed. This means that neither the behavioral response, nor the composition effect, can account for the large drop in the observed search in 2020. In fact, this "missing search" of the unemployed is even larger compared to the out-of-sample prediction than compared to the pre-pandemic behavior. In contrast, the model predicts job applications by the employed during the pandemic very well. If anything, the employed search even more than predicted.

We interpret the gap between the predicted and actual search in 2020 as the COVID-19 effect. To understand its size compared to the other drivers of job search, we decompose the overall change in 2020 (relative to 2019) into the composition, behavioral, and COVID-19 effects. They are plotted in Figure 2. Starting with the last bar, the graph confirms that in 2020, the employed search more than in 2019, and the unemployed search less. The contribution of the behavioral effect is positive (i.e. increases job search) for both groups. The composition effect increases job search too. Table B.2 in the Appendix shows that in terms of changing demographic characteristics of the employed and unemployed, the pandemic recession looks similar to a strong recession: the employed become older and better educated just like in a usual recession, but the magnitude of this change is significantly larger, and the selection on marital status and children in the household intensifies. The only difference between the pandemic recession and a normal recession, in terms of the composition of the employed and unemployed, is the importance of household income. While in a normal recession the employed are drawn from relatively poorer households (the income of the household of the unemployed doesn't change significantly), the opposite was true in 2020: household income was relatively higher for both the employed and the unemployed. Because household income is a significant and positive predictor of job search for the employed, this goes some way to explain the large increase in the number of applications sent by the employed.

Figure 2 confirms that the pandemic impacts the employed and the unemployed differently. For the employed, the small positive COVID-19 effect reinforces the positive impacts of the behavioural and the composition effect on the job search. For the unemployed, the COVID-19 effect is large and negative, outweighing the relatively small positive behavioural and composition effects, and driving the missing search of this group.

We run three robustness checks. We re-estimate the model using an alternative measure of job search (a binary indicator), adding GDP growth to capture business cycle fluctuations not covered by the unemployment rate, and as a fixed effects model exploiting the panel structure of the LISS. These specifications show that our results replicate for alternative definitions of search, hold alongside more traditional measures of the business cycle, and are robust to controlling for unobservable individual heterogeneity (all results can be found in Appendix C).

Figure 2: Decomposing job search in 2020 into behavioural, composition, and COVID-19 effects




*Notes:* This figure plots the decomposition of the overall difference between the observed job search in 2020 and the predicted job search in 2019. The composition effect is calculated as the difference between the predicted job search in 2019 and the predicted job search in 2020, tracing the changes in individual characteristics but holding the unemployment rate at its 2019 level. The behavioural effect is calculated by comparing the predicted 2020 job search with the 2019 and 2020 unemployment rate (keeping worker characteristics at their 2020 levels). The COVID-19 effect is the difference between the model prediction for 2020 (based on 2020 worker characteristics and unemployment rate) and the observed number of job applications. A negative value means that the effect lowers search activity. The values are normalized by the average levels of search in 2019.

## 3.3 Explaining job search during a pandemic recession

In this section, we build upon the COVID-19 effect in job search, i.e. the 2020 prediction error $J_{2020} - \hat{J}_{2020}$, and ask which variables are related to it. By better understanding individual heterogeneity of job search during the pandemic, we might be able to understand why the employed search slightly more and the unemployed search significantly less relative to what would be expected based on previous years.

We take variables that capture different aspects of the pandemic: Besides of demographic characteristics and sector fixed effects ($X_i$), both already used in model (1) —and as main focus of this regression specification— we make use of a broad range of variables ($\boldsymbol{P_i}$) that are specifically related to a pandemic recession and were, hence, not included in model (1). Table 2 reports results for different sets of these variables and with the number of applications as the dependent variable.

$$J_{2020} - \hat{J}_{2020} = \alpha^{2020} + \beta_1^{2020} X_i + \boldsymbol{\eta} \boldsymbol{P_i} + \nu_i \tag{2}$$

To set the stage, we start with a version that includes only demographic and sectoral variables. As we used the same set of variables from previous years to create $J_{2020} - \hat{J}_{2020}$, specification (1) captures a differential 2020 effect of these variables. Column (1) of Table 2 reports the predictive power of these regressions with the full list of coefficients displayed in Tables B.3 and B.4 in the Appendix. We find that for the unemployed job search is significantly lower for individuals that worked during their previous job in the two sectors arguably most affected by pandemic-related restrictions: catering and culture and recreation. Other sectors and the employed do not exhibit any noticeable patterns, strengthening the idea that the drop in search is indeed related to economic restrictions. The results for demographic variables are on the other hand less conclusive. Especially for the employed, none of the demographic variables is consistently related to the prediction error of job search in 2020 (Table B.3). If anything, individuals with children in their household search more than we would expect. For the unemployed, some of the corresponding coefficients displayed in Table B.4 are statistically significant. Most notably, we find a higher job search for females and young individuals relative to pre-pandemic times.

We then turn to variables more directly related to the pandemic. We start by including variables related to health concerns due to COVID-19 like the subjective infection risk and the belief about the likelihood of getting hospitalized conditional on an infection. Health concerns are likely to be important during a pandemic, and we document in Table 1 the relatively large variation in beliefs across groups. Thus, it seems plausible that the low search of the unemployed is driven by a fear of getting infected. However, the coefficients for both the belief of getting infected and the conditional risk of being hospitalized are insignificant and close to zero for the employed as well as the unemployed, suggesting that the role of health concerns in explaining search during a pandemic is limited (see column (2) of Table 2).

As a second set of variables, we examine the role of changes related to work. This includes information on whether individuals are experiencing or expecting changes in their work environment. In addition, it includes information on whether individuals are on short-time work for the employed and the duration in unemployment for the unemployed. It seems plausible that these variables relate to the effort put into finding a new job and that for example, people in short-time work exert a higher search intensity. Column (3) of Table 2 reports the coefficients for these variables. For the employed, we see a significantly higher search effort for individuals that report changed conditions in the work environment due to the pandemic, while short-time work does not exhibit a significant effect. For the unemployed, individuals in longer unemployment are searching significantly less, consistent for example with dynamic selection or discouragement. Overall, these work-related changes go some way toward explaining search behavior in 2020.

Third, we concentrate on the role of beliefs regarding the length and the severity of the pandemic recession. In particular, we include dummies for whether individuals expect lockdown measures to continue until 2021 and 2022 or longer, whether they expect the unemployment rate to increase in the future and whether they think it has become harder to find a job during the pandemic. The last variable is referring to the job they currently work in or worked in before becoming unemployed. We can view these variables as capturing two dimensions of the search process. First, from a static perspective, these variables might capture aspects related to the returns to search, with ambiguous predictions on search effort, as for example the diverging results on search over the business cycle show. Second, these variables, especially the ones on beliefs about the duration, capture a dynamic component and might cause an intertemporal substitution of search effort. If individuals expect the economic restrictions due to corona are short-lived and the economy will recover soon, individuals might reduce their (costly but ineffective) search now and delay it into the near future where they expect search to be effective again. The prediction of such an intertemporal substitution mechanism is that search should contract for individuals that expect the pandemic to last short and increase if individuals' belief the pandemic might go on for a longer period or the unemployment rate to worsen in the future. Column (4) of Table 2 reports resulting coefficients for these beliefs variables. Consistent with the described intertemporal substitution mechanism, we find for the unemployed that search effort is lowest for individuals that expect restrictions to end in 2021, with search increasing the longer individuals expect the restrictions to be in place. In addition, individuals that expect unemployment to be higher in the future show a significantly higher search effort. This pattern is not present for the employed, for which the rationale to search might be different in general.

Column (5) in Table 2 pools the different variable sets and shows coefficients from one joint regression. We again see that beliefs about the direct health effects are not related to job search in a meaningful way, whereas beliefs about the duration of economic restrictions and severity of the economic downturn as well as in part changes in the work environment show a significant association with job search. To examine which variables matter and which don't for predicting search in a more disciplined way, we apply a lasso-selection approach to the pooled specification. Results from these specifications are reported in column (6). This specification picks — especially for the unemployed — again mainly variables related to changed work environments and beliefs about duration restrictions. In addition, it also picks variables from the demographic specification as highlighted in column (5) of Tables B.3 and B.4 in the Appendix. The cross-validated mean prediction error for this specification is the lowest of all the other specifications, confirming that these variables indeed perform well in out-of-sample predictions. A similar picture emerges when using the binary search indicator as dependent variable (Table C.1).

In sum, our results show little evidence that factors directly related to the pandemic such as the risk of getting infected contribute to the decrease in search relative to pre-pandemic times. In contrast, particularities of the economic downturn caused by the pandemic — sector-specific economic restrictions, high uncertainty about the speed of economic recovery, and work-related changes— can potentially explain part of the missing search for the unemployed as well as the diverging search pattern between the employed and the unemployed.

Table 2: Explaining Job-Search 2020. Depvar: Number of Applications

| | Demographics (1) | Health Concerns (2) | Work Changes (3) | Expectations (4) | Pooled (5) | LASSO (6) |
|---|---|---|---|---|---|---|
| **Panel A: Employed** | | | | | | |
| probability of infection | | 0.135 | | | 0.163 | 0.186+ |
| | | [0.098] | | | [0.102] | [0.099] |
| probability of hospitalization if infected | | 0.117 | | | 0.087 | |
| | | [0.149] | | | [0.149] | |
| work change because of corona | | | 0.261* | | 0.214+ | 0.227+ |
| | | | [0.130] | | [0.122] | [0.132] |
| affected by short-time work | | | 0.108 | | 0.085 | |
| | | | [0.091] | | [0.103] | |
| expect restrictions until 2021 | | | | -0.135* | -0.144* | -0.121** |
| | | | | [0.068] | [0.069] | [0.045] |
| expect restrictions until 2022 | | | | 0.011 | -0.010 | |
| | | | | [0.087] | [0.086] | |
| expect high future unemployment | | | | 0.007 | 0.017 | |
| | | | | [0.053] | [0.050] | |
| finding same job harder | | | | 0.045 | 0.009 | |
| | | | | [0.048] | [0.047] | |
| $R^2$ | 0.023 | 0.002 | 0.005 | 0.004 | 0.035 | 0.027 |
| Cross-Validated MPE | 0.40 | 0.40 | 0.40 | 0.40 | 0.42 | 0.41 |
| N | 2753 | 2753 | 2753 | 2753 | 2753 | 2753 |
| Mean no. appl. 2020 | 0.207 | 0.207 | 0.207 | 0.207 | 0.207 | 0.207 |
| **Panel B: Unemployed** | | | | | | |
| probability of infection | | -3.659 | | | -0.456 | |
| | | [3.482] | | | [3.141] | |
| probability of hospitalization if infected | | 2.763 | | | 0.096 | |
| | | [2.903] | | | [2.868] | |
| work change because of corona | | | -0.045 | | 1.905 | |
| | | | [1.560] | | [1.689] | |
| unemployment duration in years | | | -1.068** | | -1.748** | -1.342** |
| | | | [0.339] | | [0.513] | [0.318] |
| expect restrictions until 2021 | | | | 2.012+ | 2.397* | |
| | | | | [1.051] | [1.158] | |
| expect restrictions until 2022 | | | | 3.746* | 3.915* | 1.844 |
| | | | | [1.640] | [1.696] | [1.436] |
| expect high future unemployment | | | | 3.520* | 3.096* | 2.957* |
| | | | | [1.491] | [1.476] | [1.450] |
| finding same job harder | | | | 0.622 | 1.285 | 1.893+ |
| | | | | [1.400] | [1.277] | [1.047] |
| $R^2$ | 0.273 | 0.013 | 0.017 | 0.096 | 0.392 | 0.296 |
| Cross-Validated MPE | 5.44 | 5.14 | 4.97 | 5.24 | 5.88 | 4.36 |
| N | 151 | 151 | 151 | 151 | 151 | 151 |
| Mean no. appl. 2020 | 4.78 | 4.78 | 4.78 | 4.78 | 4.78 | 4.78 |

*Notes:* This table summarizes the regression-coefficients from regressing $\tilde{J}_i$ on different variables using OLS. The regressions are performed separately for the employed (Panel A) and the unemployed (Panel B). The full list of regression-coefficients is shown in Table B.3 and Table B.4. Robust SE are in brackets. +, * and ** indicate significance at the .1, .05 and .01 significance level respectively. The cross-validated MPE reports the mean of the mean prediction errors obtained after performing a five-fold cross-validation. Column (1) includes demographic controls in 2020 (coefficients not shown), column (2) includes characteristics on health concerns namely the subjective probability of getting infected with Covid-19 as well as the probability of being hospitalized conditional on getting infected. Column (3) includes variables on work-related changes including a dummy for whether individuals receive Short time Work due to corona for the employed and the unemployment duration for the unemployed. Column (4) reports coefficients of variables capturing individuals' expectation about the duration of economic restrictions due to corona as well as whether they perceive job-found to be harder. Column (5) presents results from a pooled regression and column (6) reports coefficients from a lasso-selection model applied to the pooled variable set that minimizes the out-of-sample prediction.

# 4 Conclusion

This paper studies job search during the 2020 pandemic recession in the Netherlands using rich survey data about job search behavior. We focus on individuals' self-reported job search as surveyed in June 2020 and compare the extent of job search with the levels we would expect based on the demographic composition of both the employed and unemployed and importantly with the business cycle over the pre-pandemic period 2008–2019.

Our findings indicate that the relationship between aggregate unemployment and job search is different in 2020 compared to pre-pandemic times. The unemployed search significantly less than we would expect, while job search effort of the employed increases, both relative to the pre-pandemic levels and to our prediction. In a second step, we then investigate what drives this COVID-19 effect. Overall, we find little support for the hypothesis that factors directly related to the pandemic such as the risk of getting infected contribute to the decrease in search relative to pre-pandemic times. In contrast, particularities of the economic downturn caused by the pandemic — sector-specific economic restrictions, high uncertainty about the speed of economic recovery and work-related changes — can potentially explain part of the missing search for the unemployed as well as the diverging search pattern between the employed and the unemployed.

Our findings have important policy implications. First, the atypically low search effort of the unemployed during the COVID-19 recession bears the risk of amplifying detachment from the labor market during the pandemic. With the health crisis likely continuing well into 2021 such temporary detachments could lead to long-run scars for the affected workers and dampen the speed of recovery of the labor market. Policy-makers might design policies that counteract such a detachment, for example by providing additional job search assistance, retraining, or other preparatory measures to the currently unemployed in order to facilitate a swift recovery of the labor market once the pandemic barriers are lifted. Second, the slight increase in job search of the employed, particularly by those who experienced pandemic-induced changes to their working conditions, may call for supporting measures facilitating sectoral re-allocation of workers.

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# Appendix A Institutional Context

This section gives an overview over the institutional context in the Netherlands during June 2020. We first sketch social distancing policies and economic support programs taken by the government and then move on to key features of the labor market during that period. A more detailed description for the full year of 2020 is given by von Gaudecker, Holler, et al. (2020).

## A.1 Social distancing policies

To stop the steep rise in infections during March 2020, the Dutch government imposed several restrictions on economic and social life. Most of these policy measures resembled those in other European countries. Schools, restaurants, and several other businesses involving personal contacts were closed. People were advised to stay at home and to avoid social contacts. However, restrictions did not involve a general curfew and some measures were much more lenient. Businesses, such as stores for clothes, utilities, or coffee shops remained open as long as they could guarantee to maintain the social distancing rules.

From the end of April on, infection numbers started falling which allowed the Dutch government to gradually lift economic restrictions. By June, schools were opened again and businesses such as hairdressers, restaurants and cinemas could operate under restricted capacity. With the main exceptions of bans on larger (indoor) gatherings, the requirement to wear masks in public transport, and the mandate to keep a distance of 1.5 meters to other people, social and economic life was largely back to what it was before. Nevertheless, the uncertainty about the possibility of a second wave persisted and it was unclear for how long the labor market would be affected.

## A.2 Economic support measures

In order to reduce the impact of the social distancing policies and of behavioral reactions to the virus spread on the labor market, the Dutch government implemented several measures. The most important one was the short-term allowance (*Noodmaatregel Overbrugging voor Werkgelegenheid*, NOW). In order to prevent job losses the Dutch government supported all businesses that expected a loss in gross revenues of at least 20% by providing an advance for labor costs. The amount of the advancement depended on the expected revenue loss and may be up to 90% of the labor costs. In return, employers on the scheme committed to pay full salaries and not to make any lay-offs. The advancement also covered employees on fixed-term or temporary contracts; in contrast to short term work arrangement in other countries, such as UK and Germany, the employees were not required to reduce working hours and did not experience income deductions. This form of short-time work (see, e.g., Giupponi and Landais, 2020, for a current perspective) has been used previously by the Dutch government.

The short-term allowance scheme was introduced in March and prolonged in May for another four months. While the Dutch could reasonably expect their government to continue supporting affected businesses during the pandemic, is was not clear how long the government is willing to sustain the program under these conditions – especially since generous short-term work might impede necessary structural change on the labor market.

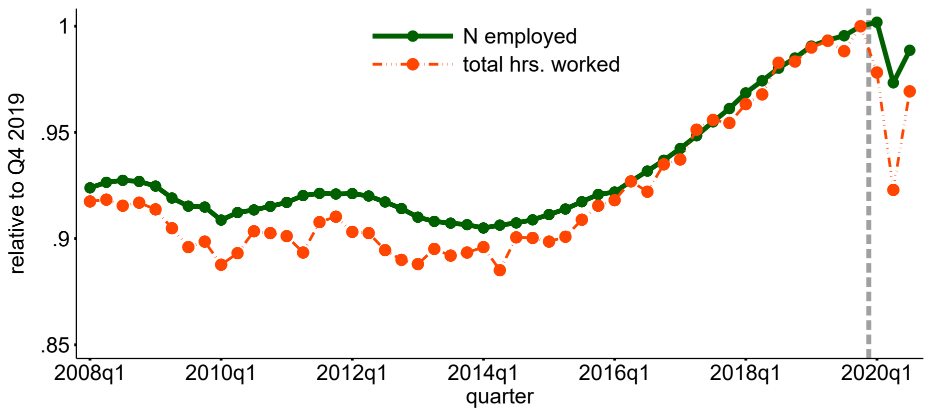
## A.3 The Dutch labor market

Figure A.1a shows quarterly time-series of number of employed individuals and total hours worked, relative to quarter 4 of 2019. Both measures show a similar, positive trend up to the end of 2019 followed by a sharp decline. Total hours exhibit a slight drop already in the first quarter of 2020 and fall by 8% in the second quarter. Despite the fall in productivity induced by the pandemic, the support measures partly shielded the Dutch labor market from job separations: the number of employed fell only by about 2% in the second quarter of 2020. These employment patterns are also present in our panel data (von Gaudecker, Holler, et al., 2020). Working hours on average fell by almost five hours per week in April and stayed roughly at this level until September.

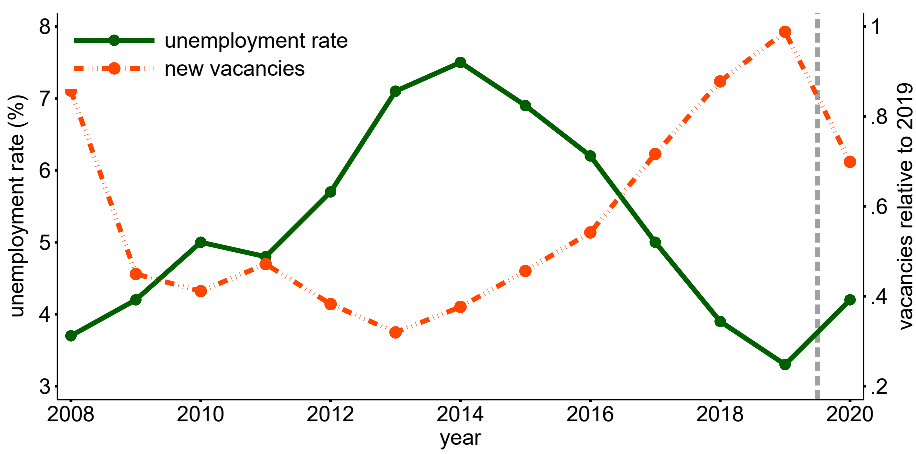
The labor market, however, was mostly affected at the intensive margin. In Figure A.1b we present the trajectory of the unemployment rate and the number of new vacancies over the same period. The unemployment rate rose by 1.3 percentage points and the number of new vacancies dropped by almost 30%. This constitutes a relatively smaller downturn compared to other countries, such the U.S. (Bick and Blandin, 2020), especially in unemployment rates.

Figure A.1: Aggregate labor market statistics in the netherlands (2008–2020)

(a) Employment and hours worked




(b) Unemployment rate and new vaccancies




*Notes:* This graph shows aggregate labor market statistics for the Netherlands. Figure (a) shows quarterly aggregate labor market statistics since 2017, relative to Q4/2019 for hours worked and number of employed. Figure (b) shows the trajectory of aggregate unemployment —measured for the month in which the LISS survey was conducted (April for 2008-2019, June for 2020)— and the number of new vacancies—measured in the second quarter and relative to Q4 2019— between the years 2008–2020. *Source*: Statistics Netherlands.

# Appendix B Additional Figures and Tables

Table B.1: Model of job search behavior as a function of individual characteristics and business cycle fluctuations

| | definitely seeking | | number of applications | |
|---|---|---|---|---|
| | employed | unemployed | employed | unemployed |
| age in years | 0.991 | 1.137** | -0.014 | 0.131 |
| | [0.015] | [0.049] | [0.011] | [0.105] |
| Age sq. | 1.000 | 0.999** | 0.000 | -0.002 |
| | [0.000] | [0.001] | [0.000] | [0.001] |
| upper secondary education | 1.364** | 1.349* | 0.075* | 2.495* |
| | [0.079] | [0.196] | [0.030] | [0.974] |
| tertiary education | 1.734** | 1.245+ | 0.074* | 1.505 |
| | [0.168] | [0.156] | [0.026] | [1.102] |
| self employed | 1.795** | 1.000 | 0.093+ | 0.000 |
| | [0.144] | [.] | [0.050] | [.] |
| unemployment duration in years | 1.000 | 1.043 | 0.000 | 0.453+ |
| | [.] | [0.037] | [.] | [0.219] |
| female | 1.147 | 0.765* | -0.009 | -2.001* |
| | [0.106] | [0.087] | [0.011] | [0.681] |
| children | 0.881** | 0.927 | -0.035 | -0.604 |
| | [0.043] | [0.144] | [0.029] | [0.844] |
| married | 0.652** | 0.814 | -0.121** | -0.279 |
| | [0.041] | [0.143] | [0.030] | [0.798] |
| household income: middle | 0.579** | 0.844 | -0.207** | -0.824 |
| | [0.044] | [0.134] | [0.025] | [0.481] |
| household income: high | 0.453** | 1.378 | -0.281** | 0.507 |
| | [0.050] | [0.298] | [0.026] | [1.025] |
| urban location | 0.722** | 1.134 | -0.086** | 0.195 |
| | [0.056] | [0.135] | [0.019] | [0.623] |
| linear trend | 0.976 | 0.986 | 0.003 | 0.154 |
| | [0.017] | [0.020] | [0.003] | [0.114] |
| unem. rate | 1.075+ | 1.144* | 0.026** | 0.796* |
| | [0.040] | [0.068] | [0.008] | [0.303] |
| Constant | 0.071** | 0.146* | 0.640* | 1.136 |
| | [0.032] | [0.135] | [0.237] | [3.661] |
| Pseudo $R^2/R^2$ | 0.042 | 0.058 | 0.006 | 0.063 |
| N | 37477 | 1431 | 37477 | 1431 |

*Notes:* The dependent variable in first two columns is the binary indicator of whether the individual is searching for a job. The dependent variable in the last two columns is the number of job applications sent over the preceding 2 months (set equal to 0 for those who state they are not searching). Controls in all regressions also include sector. Years 2008-2019. Standard errors in brackets. +, * and ** indicate significance at the .1, .05 and .01 significance level respectively.

Table B.2: Individual characteristics during a recession and during COVID-19, relative to normal times, by labour market status.

| | employed | | | unemployed | | |
|---|---|---|---|---|---|---|
| | normal | high unempl. rate | COVID-19 | normal | high unempl. rate | COVID-19 |
| age in years | 43.014 | 0.741** | 1.054** | 44.250 | -0.223 | -0.058 |
| | [12.106] | [0.127] | [0.245] | [13.940] | [0.726] | [1.302] |
| lower secondary education | 0.222 | -0.021** | -0.076** | 0.314 | -0.044+ | -0.082* |
| | [0.416] | [0.004] | [0.008] | [0.464] | [0.024] | [0.041] |
| upper secondary education | 0.374 | 0.011* | -0.005 | 0.365 | 0.037 | 0.046 |
| | [0.484] | [0.005] | [0.010] | [0.482] | [0.026] | [0.044] |
| tertiary education | 0.402 | 0.009+ | 0.079** | 0.318 | 0.003 | 0.019 |
| | [0.490] | [0.005] | [0.010] | [0.466] | [0.025] | [0.042] |
| missing education | 0.001 | 0.001* | 0.002* | 0.003 | 0.003 | 0.017* |
| | [0.033] | [0.000] | [0.001] | [0.055] | [0.004] | [0.007] |
| unemployment duration in years | 0.000 | 0.000 | 0.000 | 1.543 | -0.176+ | -1.318** |
| | [0.000] | [0.000] | [0.000] | [1.996] | [0.098] | [0.166] |
| female | 0.512 | -0.001 | 0.017+ | 0.526 | -0.017 | -0.083+ |
| | [0.500] | [0.005] | [0.010] | [0.500] | [0.027] | [0.045] |
| children | 0.541 | -0.006 | -0.034** | 0.440 | 0.026 | -0.056 |
| | [0.498] | [0.005] | [0.010] | [0.497] | [0.026] | [0.045] |
| married | 0.551 | -0.008 | -0.044** | 0.416 | -0.005 | -0.105* |
| | [0.497] | [0.005] | [0.010] | [0.493] | [0.026] | [0.044] |
| monthly household income | 1974.398 | -104.242** | 248.731** | 1334.011 | 45.068 | 286.659** |
| | [3267.100] | [28.256] | [64.022] | [853.672] | [47.102] | [78.672] |
| urban location | 0.369 | -0.015** | 0.060** | 0.317 | -0.045+ | 0.067 |
| | [0.483] | [0.005] | [0.010] | [0.466] | [0.024] | [0.042] |
| Observations | 22263 | 37477 | 25016 | 663 | 1431 | 814 |

*Notes:* This table shows differences in normal times The "normal" column contains the mean characteristics for the employed and unemployed. The "high unemployment rate" and "COVID-19" columns contain the difference between the normal mean and mean characteristics during recession and the pandemic, respectively. Normal = years 2008-2011 and 2017-2019. High unemployment rate = years 2012-2016. COVID-19 = year 2020. Standard errors in brackets. +, * and ** indicate significance at the .1, .05 and .01 significance level respectively.

Table B.3: Explaining Job-Search 2020. Depvar: Number of Applications (full regression table for the employed)

| | Demographics (1) | Health Concerns (2) | Work Changes (3) | Expectations (4) | Pooled (5) | LASSO (6) |
|---|---|---|---|---|---|---|
| age in years | -0.005 | | | | 0.002 | |
| | [0.015] | | | | [0.014] | |
| age squared | 0.000 | | | | -0.000 | |
| | [0.000] | | | | [0.000] | |
| upper secondary education | -0.105 | | | | -0.103 | -0.121** |
| | [0.074] | | | | [0.075] | [0.043] |
| tertiary education | 0.021 | | | | 0.040 | |
| | [0.081] | | | | [0.077] | |
| female | 0.107+ | | | | 0.091 | |
| | [0.061] | | | | [0.060] | |
| children | 0.092+ | | | | 0.094+ | 0.100* |
| | [0.048] | | | | [0.049] | [0.047] |
| married | 0.035 | | | | 0.046 | |
| | [0.042] | | | | [0.042] | |
| household income: middle | 0.139+ | | | | 0.164* | |
| | [0.080] | | | | [0.079] | |
| household income: high | 0.106 | | | | 0.138+ | |
| | [0.082] | | | | [0.082] | |
| urban location | 0.027 | | | | 0.019 | |
| | [0.048] | | | | [0.048] | |
| Industrial Production | 0.056 | | | | 0.066 | |
| | [0.126] | | | | [0.120] | |
| Culture, Recreation | 0.074 | | | | 0.061 | |
| | [0.232] | | | | [0.238] | |
| Construction | 0.260 | | | | 0.303 | 0.276 |
| | [0.242] | | | | [0.235] | [0.226] |
| Retail | -0.078 | | | | -0.079 | |
| | [0.085] | | | | [0.086] | |
| Catering | 0.435 | | | | 0.360 | 0.381 |
| | [0.404] | | | | [0.412] | [0.397] |
| Transport, Communication, Utilities | 0.167 | | | | 0.172 | |
| | [0.161] | | | | [0.156] | |
| Financial Sector | -0.086 | | | | -0.063 | |
| | [0.088] | | | | [0.078] | |
| Business Services | 0.219 | | | | 0.240 | 0.251 |
| | [0.183] | | | | [0.179] | [0.164] |
| Public Sector | 0.027 | | | | 0.051 | |
| | [0.091] | | | | [0.080] | |
| Education | -0.129 | | | | -0.115 | |
| | [0.094] | | | | [0.082] | |
| Healthcare and Welfare | -0.097 | | | | -0.072 | |
| | [0.085] | | | | [0.075] | |
| Missing Sectoral Info | -0.289** | | | | -0.364** | -0.375** |
| | [0.086] | | | | [0.102] | [0.082] |
| self employed | 0.038 | | | | -0.019 | |
| | [0.129] | | | | [0.127] | |
| missing education | -0.264** | | | | -0.315** | |
| | [0.083] | | | | [0.097] | |
| missing hh income | -0.038 | | | | -0.058 | |
| | [0.103] | | | | [0.103] | |
| probability of infection | | 0.135 | | | 0.163 | 0.186+ |
| | | [0.098] | | | [0.102] | [0.099] |
| probability of hospitalization if infected | | 0.117 | | | 0.087 | |
| | | [0.149] | | | [0.149] | |
| work change because of corona | | | 0.261* | | 0.214+ | 0.227+ |
| | | | [0.130] | | [0.122] | [0.132] |
| affected by short-time work | | | 0.108 | | 0.085 | |
| | | | [0.091] | | [0.103] | |
| missing short-time work | | | 0.039 | | 0.504+ | 0.184 |
| | | | [0.079] | | [0.304] | [0.113] |
| expect restrictions until 2021 | | | | -0.135* | -0.144* | -0.121** |
| | | | | [0.068] | [0.069] | [0.045] |
| expect restrictions until 2022 | | | | 0.011 | -0.010 | |
| | | | | [0.087] | [0.086] | |
| expect high future unemployment | | | | 0.007 | 0.017 | |
| | | | | [0.053] | [0.050] | |
| finding same job harder | | | | 0.045 | 0.009 | |
| | | | | [0.048] | [0.047] | |
| missing expect restrictions | | | | -0.097 | -0.369 | |
| | | | | [0.105] | [0.315] | |
| missing expect unemployment | | | | -0.085 | -0.005 | |
| | | | | [0.081] | [0.081] | |
| $R^2$ | 0.023 | 0.002 | 0.005 | 0.004 | 0.035 | 0.027 |
| Cross-Validated MPE | 0.40 | 0.40 | 0.40 | 0.40 | 0.42 | 0.41 |
| N | 2753 | 2753 | 2753 | 2753 | 2753 | 2753 |
| Mean no. appl. 2020 | 0.207 | 0.207 | 0.207 | 0.207 | 0.207 | 0.207 |

**Notes:** This contains the full list of regression coefficients for Panel A of Table 2. Standard errors in brackets. +, * and ** indicate significance at the .1, .05 and .01 significance level respectively.

Table B.4: Explaining Job-Search 2020. Depvar: Number of Applications (full regression table for the unemployed)

| | Demographics (1) | Health Concerns (2) | Work Changes (3) | Expectations (4) | Pooled (5) | LASSO (6) |
|---|---|---|---|---|---|---|
| age in years | -0.812** | | | | -0.808** | |
| | [0.280] | | | | [0.262] | |
| age squared | 0.010** | | | | 0.010** | |
| | [0.003] | | | | [0.003] | |
| upper secondary education | -1.820 | | | | -1.720 | -2.524+ |
| | [1.751] | | | | [1.676] | [1.380] |
| tertiary education | 2.278 | | | | 1.656 | 0.679 |
| | [1.966] | | | | [2.000] | [1.605] |
| female | 4.475** | | | | 4.752** | 3.868** |
| | [1.316] | | | | [1.344] | [0.992] |
| children | 0.655 | | | | 0.197 | |
| | [1.506] | | | | [1.528] | |
| married | 1.019 | | | | 1.830 | |
| | [1.411] | | | | [1.433] | |
| household income: middle | -0.561 | | | | -1.258 | |
| | [1.315] | | | | [1.347] | |
| household income: high | -1.355 | | | | -2.158 | |
| | [1.439] | | | | [1.670] | |
| urban location | -1.308 | | | | -0.680 | |
| | [1.399] | | | | [1.300] | |
| Industrial Production | -1.467 | | | | -0.594 | |
| | [3.143] | | | | [2.944] | |
| Culture, Recreation | -7.879* | | | | -8.509* | |
| | [3.880] | | | | [3.589] | |
| Construction | -4.229 | | | | -4.700 | -5.207+ |
| | [3.908] | | | | [4.257] | [2.683] |
| Retail | -2.032 | | | | -1.947 | |
| | [3.362] | | | | [3.289] | |
| Catering | -11.661** | | | | -10.600** | -6.959** |
| | [2.922] | | | | [3.727] | [1.562] |
| Transport, Communication, Utilities | 0.589 | | | | 2.122 | 4.271 |
| | [4.345] | | | | [4.047] | [3.723] |
| Financial Sector | -5.652+ | | | | -5.179 | -3.881* |
| | [3.137] | | | | [3.253] | [1.494] |
| Business Services | -1.957 | | | | -1.490 | |
| | [4.445] | | | | [5.250] | |
| Public Sector | 1.237 | | | | -0.768 | |
| | [6.124] | | | | [6.099] | |
| Education | -4.194 | | | | -2.831 | |
| | [3.320] | | | | [3.174] | |
| Healthcare and Welfare | -3.337 | | | | -2.493 | |
| | [2.755] | | | | [2.562] | |
| Missing Sectoral Info | 0.755 | | | | 1.301 | 3.801** |
| | [2.699] | | | | [2.846] | [1.126] |
| missing education | 0.303 | | | | 2.120 | |
| | [3.071] | | | | [2.996] | |
| missing hh income | -0.138 | | | | 0.595 | |
| | [2.363] | | | | [2.439] | |
| probability of infection | | -3.659 | | | -0.456 | |
| | | [3.482] | | | [3.141] | |
| probability of hospitalization if infected | | 2.763 | | | 0.096 | |
| | | [2.903] | | | [2.868] | |
| work change because of corona | | | -0.045 | | 1.905 | |
| | | | [1.560] | | [1.689] | |
| unemployment duration in years | | | -1.068** | | -1.748** | -1.342** |
| | | | [0.339] | | [0.513] | [0.318] |
| expect restrictions until 2021 | | | | 2.012+ | 2.397* | |
| | | | | [1.051] | [1.158] | |
| expect restrictions until 2022 | | | | 3.746* | 3.915* | 1.844 |
| | | | | [1.640] | [1.696] | [1.436] |
| expect high future unemployment | | | | 3.520* | 3.096* | 2.957* |
| | | | | [1.491] | [1.476] | [1.450] |
| finding same job harder | | | | 0.622 | 1.285 | 1.893+ |
| | | | | [1.400] | [1.277] | [1.047] |
| missing expect restrictions | | | | 4.197+ | 4.538+ | |
| | | | | [2.182] | [2.364] | |
| missing expect unemployment | | | | 3.384* | 2.980 | |
| | | | | [1.647] | [2.003] | |
| missing finding job harder | | | | -0.538 | -1.317 | |
| | | | | [1.319] | [1.215] | |
| $R^2$ | 0.273 | 0.013 | 0.017 | 0.096 | 0.392 | 0.296 |
| Cross-Validated MPE | 5.44 | 5.14 | 4.97 | 5.24 | 5.88 | 4.36 |
| N | 151 | 151 | 151 | 151 | 151 | 151 |
| Mean no. appl. 2020 | 0.207 | 0.207 | 0.207 | 0.207 | 0.207 | 0.207 |

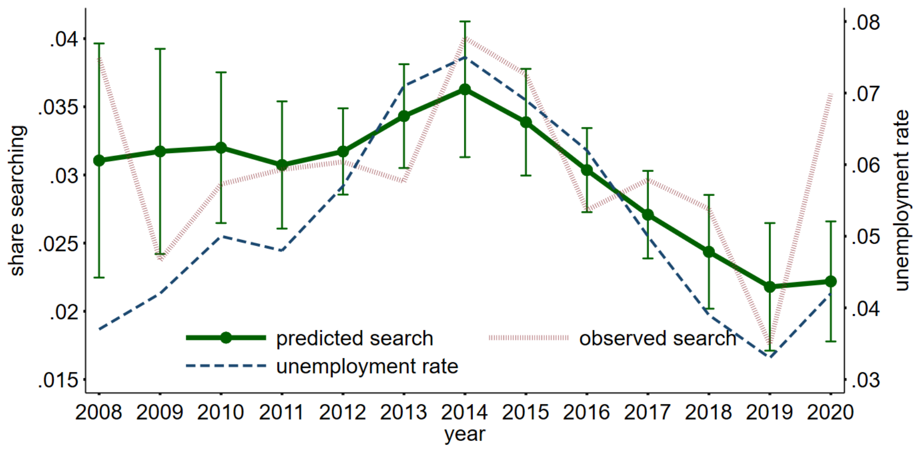
**Notes:** This contains the full list of regression coefficients for Panel B of Table 2. Standard errors in brackets. +, * and ** indicate significance at the .1, .05 and .01 significance level respectively.

# Appendix C Robustness

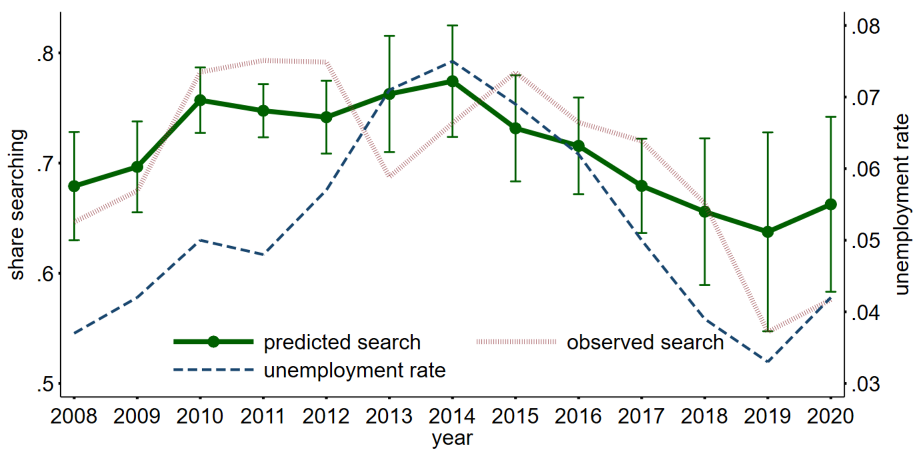
## C.1 Alternative Outcome measure: ‘seriously searching for a job’

Figure C.1: Unemployment rate and observed and predicted job search (binary search indicator) over the business cycle

(a) Employed

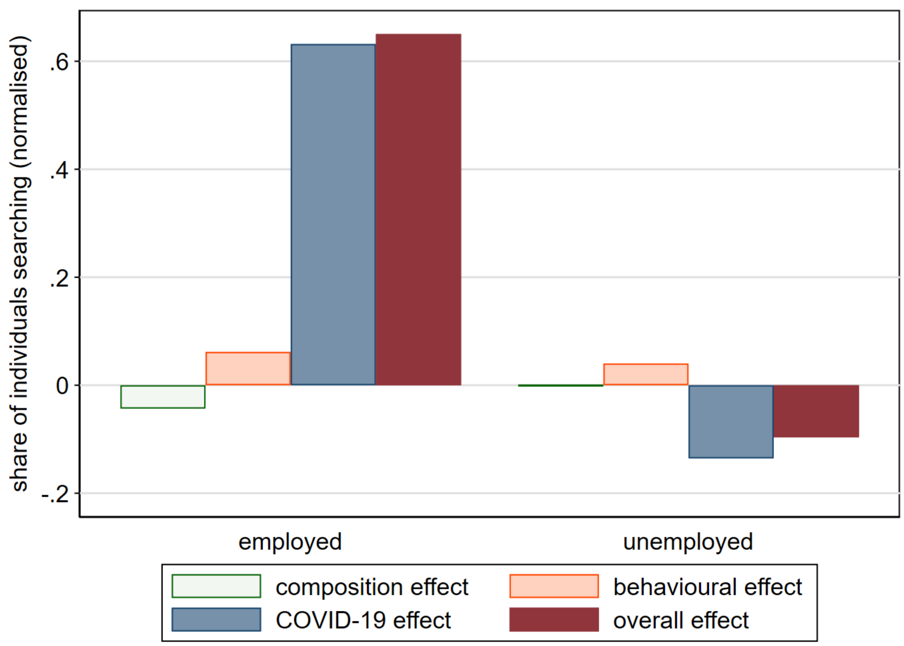



(b) Unemployed




*Notes:* The dashed line represents aggregate unemployment rate at the time of the LISS survey (April for 2008-2019, June for 2020). The thick fuzzy line plots the observed average number of job application sent over the 2 months prior to the survey. The solid line with dots represents the number of job applications as predicted by our pooled OLS model of job search as a function of individual characteristics and the unemployed rate (Table B.1 in the Appendix). The value for 2020 is an out-of-sample prediction based on this model.

Figure C.2: Decomposing job search in 2020 into behavioural, composition, and COVID-19 effects




*Notes:* The figure plots the decomposition of the overall difference between the observed job search in 2020 and the predicted job search in 2019. Composition effect is calculated as the difference between the predicted job search in 2019 and the predicted job search in 2020, tracing the changes in individual characteristics but holding the unemployment rate at its 2019 level. The behavioural effect is calculated comparing the predicted 2020 job search with 2019 and 2020 unemployment rate (keeping worker characteristics at their 2020 levels). The COVID-19 effect is the difference between the model prediction for 2020 (based on 2020 worker characteristics and unemployment rate) and the observed share of individuals searching. A negative value means that the effect lowers search activity. The values are normalized by the average levels of search in 2019.

Table C.1: Explaining Job-Search 2020. Depvar: Search >0 (actual-pred.)

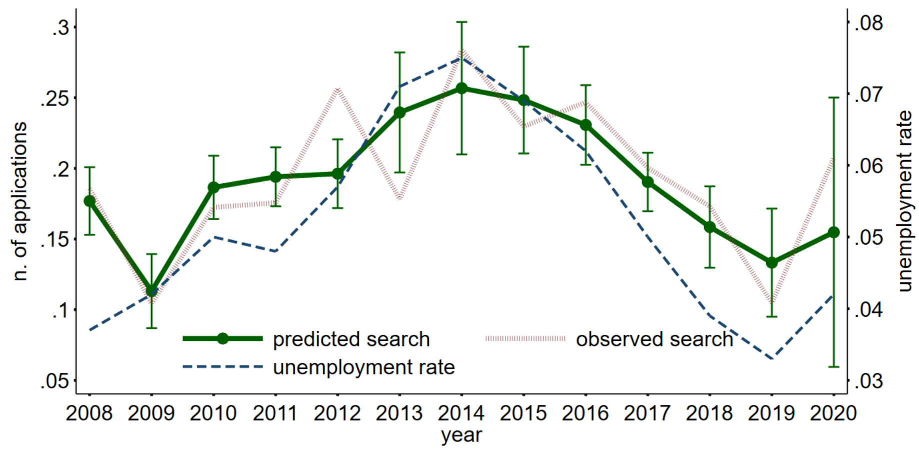
| | Demographics (1) | Health Concerns (2) | Work Changes (3) | Expectations (4) | Pooled (5) | LASSO (6) |
|---|---|---|---|---|---|---|
| **Panel A: Employed** | | | | | | |
| probability of infection | | 0.135 | | | 0.163 | 0.150 |
| | | [0.097] | | | [0.102] | [0.098] |
| probability of hospitalization if infected | | 0.116 | | | 0.087 | 0.101 |
| | | [0.149] | | | [0.149] | [0.131] |
| work change because of corona | | | 0.260* | | 0.214+ | 0.228+ |
| | | | [0.130] | | [0.122] | [0.132] |
| affected by short-time work | | | 0.108 | | 0.085 | |
| | | | [0.091] | | [0.103] | |
| expect restrictions until 2021 | | | | -0.135* | -0.144* | -0.121** |
| | | | | [0.068] | [0.069] | [0.045] |
| expect restrictions until 2022 | | | | 0.011 | -0.010 | |
| | | | | [0.087] | [0.086] | |
| expect high future unemployment | | | | 0.007 | 0.017 | |
| | | | | [0.053] | [0.050] | |
| finding same job harder | | | | 0.045 | 0.009 | |
| | | | | [0.048] | [0.047] | |
| $R^2$ | 0.022 | 0.001 | 0.005 | 0.004 | 0.035 | 0.028 |
| Cross-Validated MPE | 0.40 | 0.40 | 0.40 | 0.40 | 0.42 | 0.41 |
| N | 2753 | 2753 | 2753 | 2753 | 2753 | 2753 |
| **Panel B: Unemployed** | | | | | | |
| probability of infection | | -3.659 | | | -0.456 | |
| | | [3.482] | | | [3.141] | |
| probability of hospitalization if infected | | 2.763 | | | 0.096 | |
| | | [2.903] | | | [2.868] | |
| work change because of corona | | | -0.045 | | 1.905 | |
| | | | [1.560] | | [1.689] | |
| unemployment duration in years | | | -1.068** | | -1.748** | -1.342** |
| | | | [0.339] | | [0.513] | [0.318] |
| expect restrictions until 2021 | | | | 2.012+ | 2.397* | |
| | | | | [1.051] | [1.158] | |
| expect restrictions until 2022 | | | | 3.746* | 3.915* | 1.844 |
| | | | | [1.640] | [1.696] | [1.436] |
| expect high future unemployment | | | | 3.520* | 3.096* | 2.957* |
| | | | | [1.491] | [1.476] | [1.450] |
| finding same job harder | | | | 0.622 | 1.285 | 1.893+ |
| | | | | [1.400] | [1.277] | [1.047] |
| $R^2$ | 0.273 | 0.013 | 0.017 | 0.096 | 0.392 | 0.296 |
| Cross-Validated MPE | 5.40 | 5.29 | 5.09 | 5.43 | 5.71 | 4.37 |
| N | 151 | 151 | 151 | 151 | 151 | 151 |

*Notes:* This table summarizes the regression-coefficients from regressing $\tilde{J}_i$ on different variables using OLS. The regression performs separate regressions for each of the three employment states separately. Robust SE are in brackets. +, * and ** indicate significance at the .1, .05 and .01 significance level respectively. The cross-validated RMSE reports the mean RMSE after performing a five-fold cross-validation.

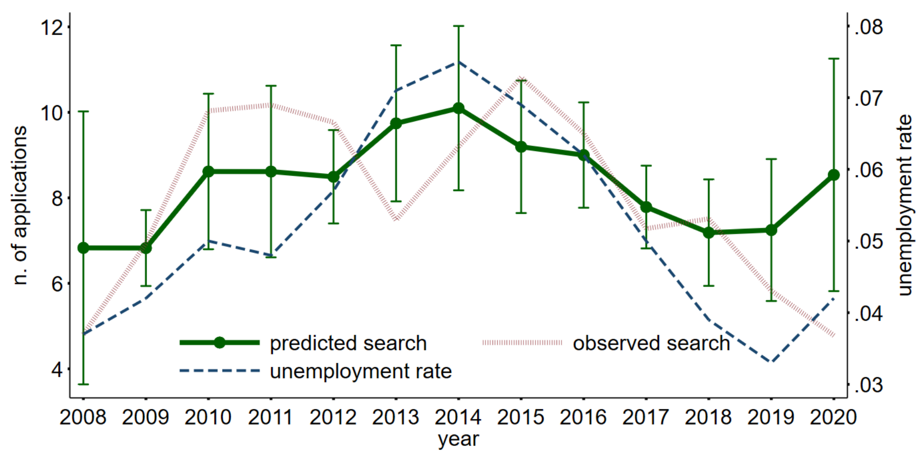
### C.2 Additional business cycle measure: GDP growth

Figure C.3: Unemployment rate and observed and predicted job search (number of applications) over the business cycle

(a) Employed




(b) Unemployed




*Notes:* Version of Figure 1 including GDP growth as a measure of the business cycle in the empirical model of job search. This figure plots observed and predicted job search as well as the unemployment rate over the business cycle. The dashed line represents aggregate unemployment rate at the time of the LISS survey (April for 2008-2019, June for 2020). The thick fuzzy line plots the observed average number of job application sent over the 2 months prior to the survey. The solid line with dots represents the number of job applications as predicted by our pooled OLS model of job search as a function of individual characteristics, the unemployed rate, and lagged rate of nominal GDP growth. The value for 2020 is an out-of-sample prediction based on this model.

Table C.2: Explaining Job-Search 2020. Depvar: Number of Applications (prediction including GDP)

| | Demographics (1) | Health Concerns (2) | Work Changes (3) | Expectations (4) | Pooled (5) | LASSO (6) |
|---|---|---|---|---|---|---|
| **Panel A: Employed** | | | | | | |
| probability of infection | | 0.135 | | | 0.163 | 0.150 |
| | | [0.097] | | | [0.102] | [0.098] |
| probability of hospitalization if infected | | 0.116 | | | 0.087 | 0.101 |
| | | [0.149] | | | [0.149] | [0.131] |
| work change because of corona | | | 0.260* | | 0.214+ | 0.228+ |
| | | | [0.130] | | [0.122] | [0.132] |
| affected by short-time work | | | 0.108 | | 0.085 | |
| | | | [0.091] | | [0.103] | |
| expect restrictions until 2021 | | | | -0.135* | -0.144* | -0.121** |
| | | | | [0.068] | [0.069] | [0.045] |
| expect restrictions until 2022 | | | | 0.011 | -0.010 | |
| | | | | [0.087] | [0.086] | |
| expect high future unemployment | | | | 0.007 | 0.017 | |
| | | | | [0.053] | [0.050] | |
| finding same job harder | | | | 0.045 | 0.009 | |
| | | | | [0.048] | [0.047] | |
| $R^2$ | 0.022 | 0.001 | 0.005 | 0.004 | 0.035 | 0.028 |
| Cross-Validated MPE | 0.40 | 0.40 | 0.40 | 0.40 | 0.42 | 0.41 |
| N | 2753 | 2753 | 2753 | 2753 | 2753 | 2753 |
| **Panel B: Unemployed** | | | | | | |
| probability of infection | | -3.659 | | | -0.456 | |
| | | [3.482] | | | [3.141] | |
| probability of hospitalization if infected | | 2.763 | | | 0.096 | |
| | | [2.903] | | | [2.868] | |
| work change because of corona | | | -0.045 | | 1.905 | |
| | | | [1.560] | | [1.689] | |
| unemployment duration in years | | | -1.068** | | -1.748** | -1.342** |
| | | | [0.339] | | [0.513] | [0.318] |
| expect restrictions until 2021 | | | | 2.012+ | 2.397* | |
| | | | | [1.051] | [1.158] | |
| expect restrictions until 2022 | | | | 3.746* | 3.915* | 1.844 |
| | | | | [1.640] | [1.696] | [1.436] |
| expect high future unemployment | | | | 3.520* | 3.096* | 2.957* |
| | | | | [1.491] | [1.476] | [1.450] |
| finding same job harder | | | | 0.622 | 1.285 | 1.893+ |
| | | | | [1.400] | [1.277] | [1.047] |
| $R^2$ | 0.273 | 0.013 | 0.017 | 0.096 | 0.392 | 0.296 |
| Cross-Validated MPE | 5.40 | 5.29 | 5.09 | 5.43 | 5.71 | 4.37 |
| N | 151 | 151 | 151 | 151 | 151 | 151 |

*Notes:* This table summarizes the regression-coefficients from regressing $\tilde{J}_i$ on different variables using OLS. The regression performs separate regressions for each of the three employment states separately. Robust SE are in brackets. +, * and ** indicate significance at the .1, .05 and .01 significance level respectively. The cross-validated RMSE reports the mean RMSE after performing a five-fold cross-validation. In contrast to Table 2, GDP growth is used in addition to the unemployment rate for the predicition in 2020.

## C.3 Additional analysis: fixed effects

As additional evidence on the differential impact of the pandemic on the employed and the unemployed, we exploit the panel structure of the LISS. We restrict out attention to respondents who are recorded in the survey for at least 3 years, including 2020, and we estimate a model of within-individual changes in job search as a function of the individual's employment status and the business cycle. A dummy for the pandemic allows us to separately identify differences in individual behaviour in 2020. The results of the fixed effects model are presented in Table C.3. As in the pooled OLS model, search is counter-cyclical: individuals search more when the unemployed rate is high. In 2020, however, the number of applications sent by the unemployed drops significantly for the unemployed; the number of applications by the employed increases, but not significantly. The differential effects of the pandemic are thus robust to controlling for unobservable individual heterogeneity.

Table C.3: Within-individual variation in job search behavior over the business cycle and during the pandemic

| | definitely seeking | | number of applications | |
|---|---|---|---|---|
| | (logit) | (logit FE) | (OLS) | (FE) |
| pandemic × employed | 0.325* | 0.229 | 0.043 | 0.018 |
| | [0.138] | [0.148] | [0.060] | [0.056] |
| pandemic × unemployed | -0.667* | -0.397 | -2.044** | -1.412** |
| | [0.271] | [0.354] | [0.324] | [0.313] |
| employed × unem. rate | 0.106** | 0.151** | 0.032* | 0.035** |
| | [0.035] | [0.039] | [0.014] | [0.014] |
| unemployed × unem. rate | 0.201* | 0.153 | 1.481** | 1.442** |
| | [0.083] | [0.119] | [0.085] | [0.085] |
| unemployed | 4.310** | 4.046** | 1.213* | 0.743 |
| | [0.495] | [0.717] | [0.490] | [0.499] |
| Pseudo $R^2/R^2$ | 0.281 | 0.284 | 0.260 | 0.227 |
| N | 18379 | 4484 | 18379 | 18379 |

*Notes:* The dependent variable in first two columns is the binary indicator of whether the individual is searching for a job. The dependent variable in the last two columns is the number of job applications sent over the preceding 2 months (set equal to 0 for those who state they are not searching). The dependent variables in all four regressions are employment status (employed/unemployed), the unemployment rate interacted with the employment status, the pandemic dummy interacted with the employment status, and a constant. The first and third columns use pooled data; the second and last columns include individual fixed effects. The sample contains individuals who appeared in the survey at least three times, including the year 2020. Years 2008-2020.