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

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Abstract

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. The survey provides data on the job search effort in terms of the number of applications 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. For the employed, the propensity to search is even greater than what we would expect, but those who do search make significantly fewer job applications. 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 individuals whose work situation has been affected by COVID-19 are searching more actively for a new job.

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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 the onset of the COVID-19 pandemic is crucial to form a complete picture this extraordinary economic event and may provide valuable insights for economic policy-making in case of similar recessions in the future.

In this paper, we study job search behavior in a pandemic recession. Specifically, we ask whether employed and unemployed individuals search more or less than during a normal recession. We then examine potential drivers of job search during the pandemic: 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.

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 Zimpelmann et al., 2021). Households did not experience a significant shock to their income, and the unemployment rate increased by only 1.5 percentage points. After an initially restrictive lockdown in spring 2020, social and economic life was largely back to what it used to be by summer 2020, when our job search data was collected. Nevertheless, 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-19-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, given the relatively low levels of unemployment, we collect the data

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

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. This allows us to explore the gap between the predicted and actual job search behavior in 2020. In the second step, we focus on individual job search effort in 2020, regressing it on a broad set of variables capturing expectations about the labor market and the pandemic, experienced changes to the work environment, and subjective health risk. This allows us to explore which of the several pandemic-related shocks had the biggest impact on 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. For the employed, a mixed pattern emerges. While their propensity to search is even greater than what we would expect given the state of the economy, those who do search make significantly fewer job applications. Overall, the pandemic led to a significant drop in the number of job applications on the aggregate level.

Second, our analysis suggests that the main drivers behind this divergence are the economic impacts of the pandemic, rather than the direct health-related factors. Workers affected by changes in their hours worked, and those in the hardest-hit sectors, search differently than in a normal recession. Economic expectations about the pandemic – and the uncertainty about the duration and severity of the downturn – also play a significant role. Consistent with an inter-temporal substitution mechanism, we find that unemployed individuals who expect a short and temporary impact of the COVID-19 pandemic on the labor market search relatively little compared to individuals that expect this impact to be long and severe. On the other hand, we do not find evidence that health concerns prevent people from searching: employed women search even more when they believe their infection risk is high.

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; Zimpelmann et al., 2021). The existing studies focus on changes in working hours, furlough schemes, and job separations; there has been relatively less attention given to job search and labor supply decisions in general.

The main source of data on job search during the pandemic are online job platforms. This data indicates that both labor demand (vacancies) and labor supply as measured by job applications dropped strongly (Bauer et al., 2020; Marinescu, Skandalis, and Zhao, 2020; Hensvik, Le Barbanchon, and Rathelot, 2021). 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 understanding 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] In line with Bransch (2021), we show that in the Netherlands job search effort is typically countercyclical for both the employed and unemployed. A pandemic recession disrupts these patterns, contributing further to the increased economic uncertainty.

[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 countercyclical, and Leyva (2018) find no relationship.

2 Data and descriptives

To analyze job search during a pandemic recession, we make use of two datasets. 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 to 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.[4] We use two additional measures, a binary indicator of whether an individual is seriously searching for a job, and the number of job applications conditional on searching, to separately examine the extensive and intensive margins of search.

Respondents are asked to self-assess their current labor market status and our categorization of labor market status builds on that variable (see Appendix B). Our sample excludes individuals who are not in the labor force. 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. While the number of unemployed is low in absolute terms, making it harder to do inference for this group alone, they can be considered as representative due to the random sampling structure of the survey. In general, the main focus of our analysis is on the employed, although we report results for both groups.

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 16 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

[4] The distribution of the number of applications is plotted in Figure B.1.

years in June 2020 (the response rate was above 80%). The full list of survey questions is documented in von Gaudecker et al. (2021). Importantly, the questions on job search in the 2020 module are consistent with the longitudinal questionnaire, allowing comparison over time.[5]

Table 1 presents summary statistics of our sample in June 2020. To maximize sample size, we recode variables that contain missing information to zero and include an additional dummy that equals one if the underlying information was missing. These dummies are summarized in Appendix Table B.1. Our sample consists of 2,753 employed (or self-employed) individuals and 151 unemployed individuals.

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 that they are 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 per worker, 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 number of applications.

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 2020, but a few were elicited in the COVID-19 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% for the unemployed, possibly reflecting the risk of becoming infected at the workplace or while commuting. On average, both groups expect a one in four chance of 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.[6]

The third group of variables summarizes the expectations of respondents

[5] 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.

[6] 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 the payments go to the employer and there is no requirement to reduce working hours. Second, this question was asked in an earlier wave such that this observation is missing for 19% of the employed.

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 that the pandemic made it harder to find a job in their line of work: 40% of the employed and 35% of the unemployed agree.

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
hard-hit sectors	0.16	0.21
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
	[0.29]	[0.38]
unemployment duration in years	-	0.23
	-	[0.88]
applied for short-time work	0.10	-
Expectations		
expect restrictions until 2021	0.41	0.39
	[0.49]	[0.49]
expect restrictions until 2022	0.26	0.26
	[0.44]	[0.44]
expect high future unemployment	0.27	0.34
	[0.44]	[0.47]
finding same/old job harder	0.40	0.35
	[0.49]	[0.48]
number of observations	2753	151

Notes: 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) seperately for the employed and the unemployed. All results restrict to individuals aged between 16 and 65. SD 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 labor market returned to its pre-recession state just before the pandemic (more details in Appendix A.4).

The average number of job applications, together with the aggregate vacancy count, 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 number of job postings is low (and the unemployment rate is high). In the years of the tightest labor market (2008 and 2019), the employed (panel (a)) made on average 0.14 applications over the past two months, while this number doubled in 2014 when the labor market was the weakest. The unemployed (panel (b)), 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 negative relationship between the number of vacancies 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:

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

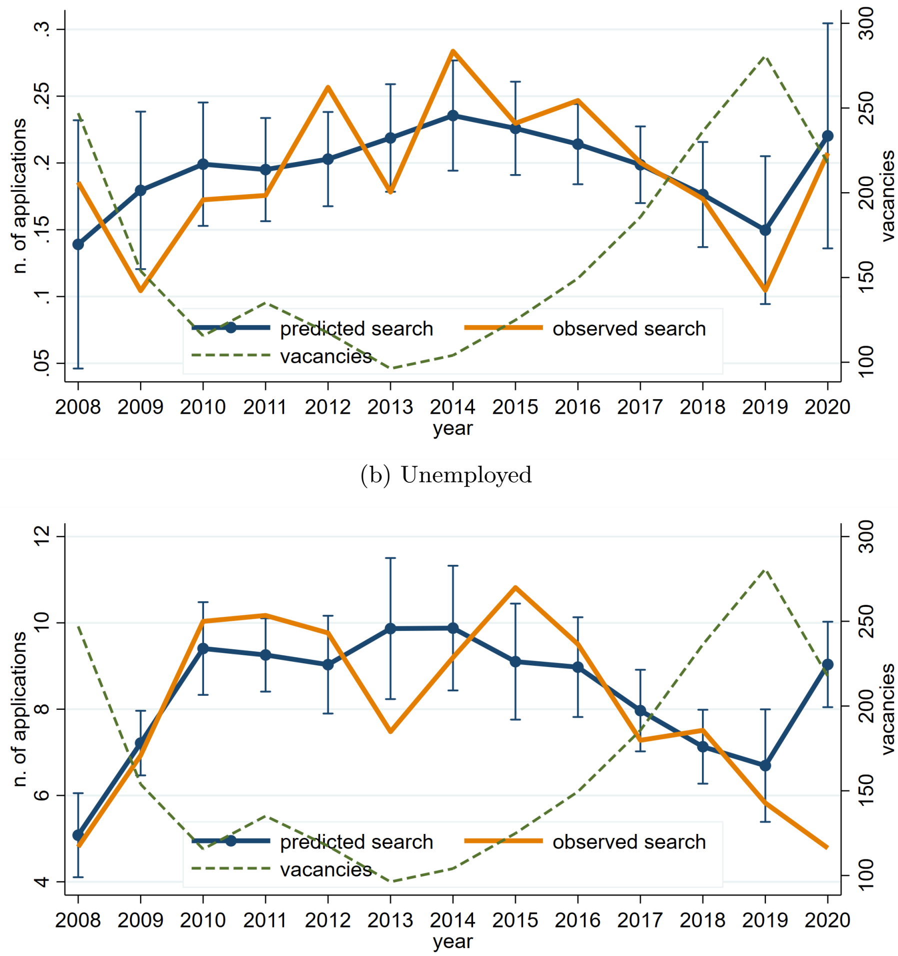
where J_{it} is the measure of job search of individual i in year t (in our main specification it is the number of applications), and X_{it} captures a variety of individual characteristics: age, gender, education, marital status, a parent dummy, equivalized household income in terciles, a dummy for urban location, a dummy for self-employment, the length of unemployment spell and sector dummies (refering to the previous job for the unemployed). We allow for endogenous response to business cycle fluctuations by including the aggregate number of vacancies 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.

The results of the model are summarized in Appendix Table C.1. The coefficients on the number of vacancies are negative, confirming the counter-cyclical pattern of job search seen in Figure 1. The relationship is somewhat stronger for the unemployed than for the unemployed, both in terms of magnitude and statistical significance. We run a series of robustness checks with alternative business cycle measures (aggregate unemployment rate, sector-specific vacancy

Figure 1: 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 aggregate number of vacancies over the business cycle. The dashed line represents aggregate vacancy count in Q1 of each year (the LISS survey is conducted in April). 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 vacancy count (Appendix Table C.1). The value for 2020 is an out-of-sample prediction based on this model.

trends and levels) and functional forms (Poisson regressions to control for the excess number of zeros in job application counts, and a panel regression controlling for individual fixed effects). The results, summarized in Appendix C.1, are in line with our baseline findings of a counter-cyclical job search pattern.

In addition to the behavioral business cycle effect, we find that changes in individual characteristics matter too. This is especially true for the employed: the less educated, married individuals, and individuals in higher-income households search less. Because the characteristics of the employed and unemployed are different in a recession compared to a boom, the composition effect contributes to the increase in job search when the number of vacancies is low. We document these changes in Appendix Table B.2.

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 more than 0.2. The unemployed, on the other hand, searched less. Despite the sharp drop in the number of vacancies, 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 lower number of vacancies (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 to the business cycle nor the composition effect can account for the large drop in the observed search in 2020. In contrast, the model predicts job applications by the employed during the pandemic very well.

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 ($J_{2020} - \hat{J}_{2019}$) into the composition, behavioral, and COVID-19 effects.

$$
\begin{aligned}
J_{2020} - \hat{J}_{2019} &= \hat{J}(X_{2020}, R_{2019}) - \hat{J}(X_{2019}, R_{2019}) && \text{(2a)} \\
&\quad + \hat{J}(X_{2020}, R_{2020}) - \hat{J}(X_{2020}, R_{2019}) && \text{(2b)} \\
&\quad + J_{2020} - \hat{J}(X_{2020}, R_{2020}) && \text{(2c)}
\end{aligned}
$$

The composition effect is the impact of the change in worker characteristics (X) between 2019 and 2020, holding the number of vacancies (R) constant at its 2019 level (expression (2a)). The behavioral effect (expression (2b)) is calculated as the change in the predicted job search when the number of vacancies drops to its

2020 level, given worker characteristics in 2020. Finally, the COVID-19 effect (expression (2c)) is the difference between the full-model prediction for 2020 and the observed levels of search.

We perform this decomposition exercise first for the total number of job applications. The comparison of the observed and predicted search in Figure 1 shows that the employed send more job applications than in 2019, but this is in line with the prediction for 2020. The COVID-19 effect on search overall is thus broadly zero. This is reflected in panel (a) of Figure 2, which shows that, for the employed, both the overall change in the number of applications compared to 2019 and the COVID-19 effect are not statistically significant.

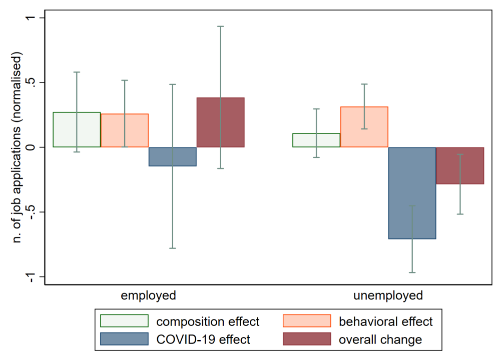
In panels (b) and (c) of Figure 2, we further break down these changes into extensive and intensive margins. Panel (b) shows that the share of the employed who claim they are searching increased significantly between 2019 and 2020, and almost none of this increase can be explained by composition changes or the behavioral response to the business cycle. At the same time, panel (c) shows that these employed submit significantly fewer applications than expected, with the COVID-19 effect more than compensating for the composition and behavioral effects.[7] Overall, the small increase in the total number of job applications between 2019 and 2020 is in fact driven by two large but offsetting COVID-19 effects. More employed workers are searching, but they send fewer job applications.

The patterns look different for (the relatively smaller sample of) the unemployed. Figure 2 shows that the COVID-19 effect on total job applications is negative and significant, driven in equal measure by a decline in the number of job applications, and by a drop in the share of the unemployed searching. This negative COVID-19 effect outweighs the other changes, primarily the behavioral response to the downturn, which would have caused the unemployed to search much more.

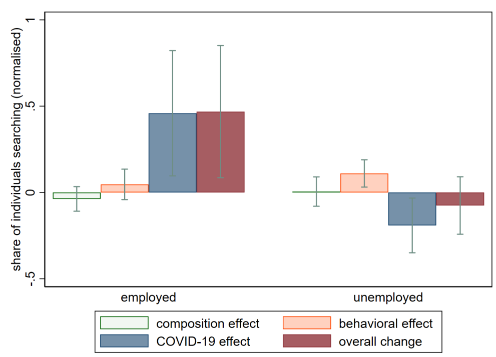
[7] We analyze the changes due to the composition effect in greater detail in Appendix Table B.2. It shows that in terms of changing demographic characteristics of the employed and unemployed, the pandemic recession looks similar to a strong recession: the employed become older and better educated just 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.

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

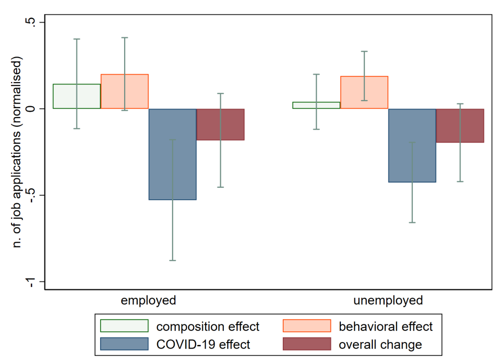
(a) Total number of job applications



(b) Share of individuals who are searching



(c) Number of applications if actively searching



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 behavioral 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. Vertical gray lines indicated bootstrapped confidence intervals (based on 1000 replications) for 5% significance level.

An important caveat is that the results of this decomposition are conditional on unbiased forecasts of cyclical job search. There are several reasons why this might not be the case. First, there are three possible sources of forecast error: mismeasurement, omitted variable bias, and structural breaks. Any bias arising from mismeasurement is probably much smaller in the composition effect (where we have direct measures on worker characteristics) than in the behavioral effect, which depends on accurately capturing labor market conditions. Since we don't observe labor market tightness experienced by each individual in our survey, we proxy for it using aggregate vacancy count. This might lead to attenuation bias and underestimating the behavioral effect of the fall in vacancies in 2020; our robustness checks in Appendix C.1, using alternative labor market indicators and with individual-specific job-finding expectations for a sub-sample of respondents, go some way to addressing this problem. Omitted variable bias, on the other hand, is more likely to matter for the composition effect, since there are some important variables (such as search effort) which are not a part of our survey; the impact of this bias on the composition effect is ambiguous. Finally, as all time-series models, our forecasts may suffer from undetected structural breaks. If the relationship between labor market conditions, worker characteristics, and job search change over time, our forecast for 2020 would be biased.[8] Indeed, the onset of the pandemic might present just such a structural break. This would lead to underestimating the composition and behavioral effects and overestimating the COVID-19 effect. However, this is less of a problem if we interpret the COVID-19 effect as including *any* changes to job search due to the pandemic, those due to one-off shocks as well as those resulting from a structural break in the pattern on job search. The second issue with the estimated COVID-19 effect is that we are unable to separately identify the COVID-19 shock from the white noise prediction error we would expect to see in the absence of a pandemic. This means that the pandemic effect might equally be over- or under-estimated.

Overall, the decomposition suggests that during the pandemic the employed and the unemployed converged in their search behavior. The unemployed, who are more likely to state they are searching, saw a decline in their share of searchers, while the employed, whose baseline share is lower, search more. At the same time, both groups send significantly fewer job applications than in a normal recession. Overall, this paints a picture of a labor market with a relatively high share of workers intending to search, or searching passively, while actual job applications plummet, perhaps as a result of the uncertain economic environment. We explore this question in more depth in the next section.

3.3 Explaining job search during a pandemic recession

In this section, we examine the job search behavior in 2020 in more detail. In particular, we use J_{2020} as the dependent variable outcome and ask which vari-

[8]The possibility that the relationship between labor market conditions, worker characteristics, and job search changes over the business cycle is of similar concern. However, our time series is not long enough to allow for time-varying coefficients.

ables relate to it.[9] By exploiting individual heterogeneity of job search during the pandemic, we aim to better understand the job search patterns observed in the aggregate.

We focus on variables that capture different aspects of the pandemic. Besides demographic characteristics and sector fixed effects (X_i), both already used in model (1) – and as the 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).

$$J_{2020} = \alpha^{2020} + \beta_1^{2020} X_i + \boldsymbol{\eta} \boldsymbol{P_i} + \nu_i \quad (3)$$

Table 2 reports results for the different sets of variables, using the total number of applications as the dependent variable. In all regressions, we control for basic demographic factors and report robust standard errors.[10]

Column (1) of Table 2 shows results for all employed while column (6) does so for the unemployed. Since we have significantly more employed in our sample than unemployed and the employed are composed of a relatively heterogeneous group, we split them along two dimensions. Column (2) considers only individuals in strongly affected sectors, defined as those with the highest relative drop in vacancies between 2019 and 2020 (these sectors were culture and recreation, catering, and transportation, communication and utilities), while column (3) shows results for workers in other sectors. The split in men vs. women is reported in columns (4) and (5). We focus on these two heterogeneities as both the sector-specific nature of the shock (Barrero, Bloom, and Davis, 2020) as well as the potential difference between genders (Alon et al., 2020) have been identified as core differences of the pandemic recession compared to "normal" recessions. We report additional heterogeneities by self-employment vs. dependent employment, whether individuals are on short-time work or not, and by high vs. low formal education in Appendix Table C.6.

We start by reporting results for variables related to health concerns due to COVID-19, such as 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, for example, the low search of the unemployed may be driven by a fear of getting infected in the workplace. However, the coefficients for both the belief of getting infected and the conditional risk of being hospitalized are insignificant and close to zero for both the employed and the unemployed. Zooming into different employment subgroups, we see a difference between women and

[9] An alternative would be to use the prediction error $J_{2020} - \hat{J}_{2020}$ as dependent variable. In Appendix Table C.5 we show that results are identical for raw search effort and prediction error when including the covariates used for the prediction (apart from the coefficients for the covariates themselves).

[10] The list of variables is age and age-squared, two education dummies, a dummy for gender, marital status and whether there are any children in the household, two dummies for household income, a dummy for urban location, and a set of industry dummies. Appendix Table C.5 reports coefficients for these demographics.

men. In particular, for women, there is a modestly sized positive association between health concerns and the number of applications that is significant at the 5% significance level, while for men the coefficient is slightly negative and close to zero.[11] Similarly, more strongly affected sectors exhibit a larger positive coefficient relative to other sectors, though large standard errors hinder interpretation. Other heterogeneities, as documented in the accompanying Appendix Table C.6, do not show any other noteworthy heterogeneity, with all coefficients not distinguishable from zero at any significance level. Overall, these results suggest that the role of health concerns in explaining search during a pandemic is limited, except for a modestly positive association for employed women.

As a second set of variables, we examine the role of changes in respondents' work environment. 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 more search effort. For the employed, we see higher search effort for individuals who report changes in the work environment due to the pandemic that is significantly different from zero at the 10% significance level. Zooming into different employment groups, we see again that this seems to differ by gender, with male employees exhibiting a stronger positive association between experienced work changes and search effort. Other employment groups show no significant differences. Short-time work, on the other hand, does not exhibit a significantly positive association with search effort. For the unemployed, individuals in longer unemployment are searching significantly less, which is consistent with both dynamic selection and 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. Second, these variables, especially the ones on beliefs about the duration, capture a dynamic component and might cause an inter-temporal substitution of search effort. If individuals expect the economic restrictions due to the pandemic to be short-lived and the economy to recover soon, they might reduce their (costly but ineffective) search now and delay it into the near future when they expect job search to be effective again. This inter-temporal substitution mechanism implies that search should contract for

[11] While we can only speculate about the different response to the perceived health concerns between women and men, it seems plausible that women are more concerned about their health in their current job inducing them to search more, potentially for a job with a lower risk of getting infected.

individuals that expect the pandemic not to last long, and increase if individuals believe the pandemic might go on for a longer period or the labor market to deteriorate further in the future. Consistent with this mechanism, we find, for the unemployed, that search effort is lowest for individuals that expect restrictions to end in 2020, 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. For the employed, for whom the rationale to search might be different in general, we find a significantly lower search effort for individuals who expect restrictions to end in 2021, with little heterogeneity between different employment groups.

Note that, since we only observe those pandemic specific variables in 2020, we can only use cross-sectional variation in these variables across subjects to gauge their impact on job search. If e.g., health concerns would increase equally for all individuals during the pandemic, we might not observe any effect for the cross-sectional variation although the aggregate change over time might be relevant. The estimated coefficients might be, hence, downward biased. Reassuringly, we observe a large heterogeneity in these pandemic specific variables (e.g. the belief of getting infected is 10% for the first quartile, but 50% for the third quartile) which leads us to conclude that we are able to proxy at least a substantial part of the effect of the pandemic by variation across individuals.

The demographic controls we are using throughout are interesting in their own right. Appendix Table C.5 reports the full set of demographic variables for the employed and the unemployed separately. It reports the results using the raw number of applications as in the baseline results but complements this with a specification that uses the residuals from the model introduced in the previous section. This residualized measure of job search allows us to interpret the demographic variables as capturing differences in search relative to their effect during normal (pre-pandemic) times, while the demographic coefficients from the regressions with the raw number of applications capture the broader overall differences in search behavior. For the employed, individuals with children in the household and individuals in middle and high-income households appear to search slightly more relative to normal times, but there are few other systematic differences. For the unemployed, we see a clear negative association with age and a significantly higher search for women (both overall and relative to normal times). In addition, individuals previously working in sectors strongly affected by lockdown measures, such as culture and recreation and catering, search significantly less compared to normal times.

To investigate the robustness of our results, we turn to alternative specifications of the dependent variable. As our dependent variable is the number of applications made, one might wonder to what extent the results are driven by extensive margin responses (searching vs. not searching) or by outliers (some individuals searching a lot). Appendix Table C.7 addresses these different points for the employed and unemployment separately. We look at extensive margin responses using three definitions: an indicator for any applications send out (which we construct from our main dependent variable), an indicator variable indicating "searching definitely" (which we construct from a separate, categorical

Table 2: Explaining number of applications in 2020

	Employed					Unemployed
		Sectors		Gender		
	All (1)	Strongly Affected (2)	Other (3)	Female (4)	Male (5)	All (6)
probability of infection	0.162	0.311	0.146	0.347*	-0.014	-0.429
	[0.102]	[0.268]	[0.109]	[0.159]	[0.114]	[3.137]
prob. of hospitalization if infected	0.086	0.600	-0.037	-0.024	0.143	0.369
	[0.149]	[0.624]	[0.103]	[0.143]	[0.247]	[2.656]
work change because of corona	0.215+	0.178	0.234+	0.089	0.428+	1.841
	[0.122]	[0.243]	[0.129]	[0.131]	[0.253]	[1.665]
affected by short-time work	0.085	0.013	0.149	0.088	0.058	
	[0.103]	[0.138]	[0.139]	[0.121]	[0.157]	
expect restrictions until 2021	-0.144*	-0.172	-0.140+	-0.166	-0.125+	2.342*
	[0.069]	[0.121]	[0.079]	[0.115]	[0.069]	[1.169]
expect restrictions until 2022	-0.010	0.165	-0.056	-0.107	0.083	3.816*
	[0.086]	[0.242]	[0.085]	[0.123]	[0.113]	[1.698]
expect high future unemployment	0.016	-0.128	0.052	0.008	0.039	3.049*
	[0.050]	[0.100]	[0.055]	[0.076]	[0.050]	[1.464]
finding same job harder	0.009	-0.146	0.045	0.021	-0.017	1.311
	[0.047]	[0.136]	[0.046]	[0.070]	[0.068]	[1.287]
self employed	0.074	-0.159	0.092	-0.008	0.183	
	[0.127]	[0.163]	[0.141]	[0.202]	[0.169]	
unemployment duration in years						-1.307*
						[0.501]
R^2	0.035	0.094	0.035	0.056	0.049	0.251
N	2753	446	2307	1456	1297	151
Mean no. appl. 2020	0.21	0.24	0.20	0.23	0.18	4.78
Demographic and sector controls	x	x	x	x	x	x

Notes: This table summarizes the regression coefficients from regressing the number of applications in 2020 on different variables using OLS. The regressions are performed separately for the employed (column (1)) and the unemployed (column (6)). All regressions include demographic and sector controls in 2020. The full list of regression-coefficients for these regressions is shown in Table C.5. In column (2) the sample of employed subjects is restricted to those individuals working in sectors that experienced a drop of at least 40% in the number of vacancies between the years 2019 and 2020. These sectors are culture and recreation, catering and transportation, communication and utilities. Column (3) considers all employed from all other, less affected sectors or with missing sectoral information. The sample of employed is restricted to women in column (4) and men in column (5). Robust SE are in squared brackets. +, * and ** indicate significance at the .1, .05 and .01 significance level respectively.

variable on job search) and an indicator for sending out 8 or more applications. For intensive margin responses, we use the number of applications conditional on making at least one application. In Appendix Table C.7, we see that for the employed, all of the extensive margin responses (columns (2)–(4)) are similar to the baseline results in column (1). The response on the intensive margin (column (5)) is very noisy because only a small number of employed fall in that category. In contrast, for the unemployed, we see mostly responses on the intensive margin. The diverging response margins between the employed and unemployed are consistent with the documented response margins for the COVID-19 effect in section 3.2. To test whether our results are driven by outliers, in column (6) we winsorize our baseline dependent variable at 30 applications (as opposed to 100 in our headline regressions); the estimated coefficients don't change. Finally, we estimate our model via poisson and zero inflated poisson regression (column (7) and column (8) respectively) and report average marginal effects from these models. The resulting effect sizes are similar to those of the baseline specification, yet estimated somewhat more precisely.

The lower search effort by the unemployed might be also influenced by a more lenient enforcement of application requirements by the employment agency in 2020. The requirement of at least four applications per month was technically still in place, but caseworkers were asked to account for pandemic related difficulties. We show in Appendix A.3 that the share of applications made via the state employment agency did not substantially decrease in 2020 (Figure A.1 a and b). Under the assumption that 'enforced' job applications are more often done over this channel than over other channels, this would have been expected if the change in requirements had a large impact on job search patterns. Furthermore, we show that there is no statistically significant change in the bunching at the application requirement (Figure A.1 c). Finally, the fact that, based on our main analysis, expectations predict individual job search during the pandemic suggests that the aggregate drop in applications of the unemployed is at least not entirely driven by the change in enforcement regime.

In sum, our results show little evidence that factors directly related to the pandemic, such as the perceived 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 differences in search pattern between the employed and the unemployed.

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 the aggregate number of posted vacancies 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 is subject to offsetting changes along the extensive and intensive margins: A higher share of the employed search for a job, but at a lower intensity than expected. In a second step, we investigate what drives job search during the pandemic. We find that the risk of getting infected predicts job search for employed women. Overall, however, factors directly related to the pandemic contribute little to search effort. 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. Overall, our findings illustrate that job search during the COVID-19 induced pandemic recession differs from normal recessions in a number of ways. This also links to the broader differences of the COVID-19 recession relative to normal times like temporary differences in search requirements for the unemployed and an increased burden of childcare due to school closures.

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 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 larger job search for those subjects who experienced pandemic-induced changes to their working conditions may call for supporting measures facilitating sectoral reallocation 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 Zimpelmann et al. (2021).

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 Search effort requirements for the unemployed

Usually, unemployed individuals in the Netherlands are required to apply for at least four jobs per month. From March 2020 on, while the requirement technically still applied, the Dutch employment agency was more lenient than usual towards the unemployed to account for pandemic related difficulties.[12] Starting at the beginning of 2021, the requirement was again strictly enforced.[13]

Our data provides direct evidence on whether and how job search methods changed during the pandemic. Every year, the survey asks the respondents who claim to be searching for a job to list all the methods they used to look for work in the preceding 2 months (respondents can choose multiple search methods). Figure A.1 shows that only a small fraction of searches happens through the channel "search through the employment agency", and this share was only marginally smaller in 2020 compared to 2019. Moreover, this drop in searching via the employment agency is entirely driven by the other search methods becoming more popular, rather than by a drop in the absolute share of workers searching this way. In fact, both the employed and the unemployed were somewhat more likely to search via the employment agency in 2020 compared to 2019.

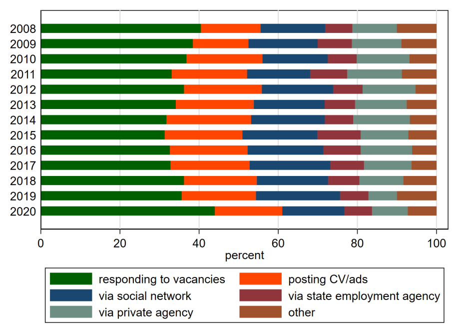
Of course, this evidence is indirect: it might still be the case that a loosening in search requirements led to a drop in search overall, beyond the other impacts of the pandemic. To address this, we compare the probability that an unemployed worker makes 8 or more applications (i.e. the minimum requirement of the Dutch employment agency) before and during the pandemic (conditional on making any applications), controlling for the same set of variables we used in our model of job search over the business cycle (Table C.1). If the reduction of job search activity by the unemployed was driven by more lenient employment agency, we should expect to see a particularly large drop at 8 applications. The relative probability of the unemployed making a given number of job applications (or more) is plotted in panel (c) of Figure A.1. It shows that the probability of making 8 (or more) applications declined in 2020 relative to the "normal" years of 2008-2019, but this decline was not statistically different from the general drop in applications made in 2020. In summary, while we cannot exclude that the change in job search of the unemployed is unrelated to the changes in the strictness of job search effort requirements by the employment office, the exercise also doesn't provide any evidence to the contrary.

[12] See https://www.activasz.nl/werkgevers/nieuws/uwv-coulant-bij-door-coronavirus-verstoorde-re-integratie/ or https://www.rtlnieuws.nl/economie/life/artikel/5062776/uwv-coulant-geen-korting-op-uitkering-bij-als-sollicitatie-niet.

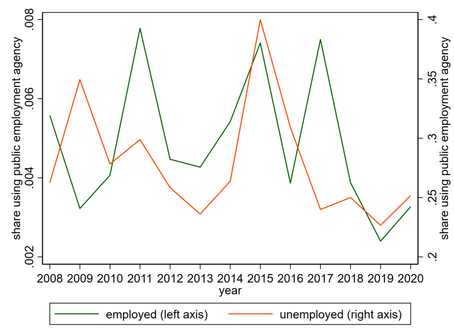
[13] See https://www.uwv.nl/particulieren/actueel/uwv-controleert-weer-op-sollicitatieactiviteiten.aspx

Figure A.1: Search methods and effort over time

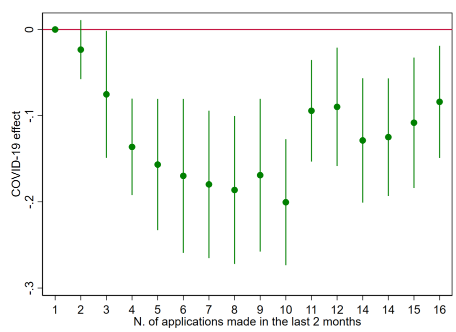
(a) Share of workers searching via different methods, by year



(b) Share of workers searching via the state employment agency



(c) Change in the relative distribution of job applications made by the unemployed



Notes: Panel (a) plots the relative frequency each search method is used by all workers (those searching as well as those who are not). The sum of these frequencies is normalized to 100% every year, so the plotted shares reflect relative popularity of a given search method. Panel (b) shows the share of all employed and unemployed workers who have indicated they are searching via the public employment agency. As in panel (a), the share is calculated from both job seekers and non-seekers. Panel (c) plots the estimated probability of an unemployed worker making a given number of jobs applications (or more) during COVID-19 compared to 2009-2019, controlling for the business cycle indicators and worker characteristics as in our main specification in Table C.1. *Source:* LISS.

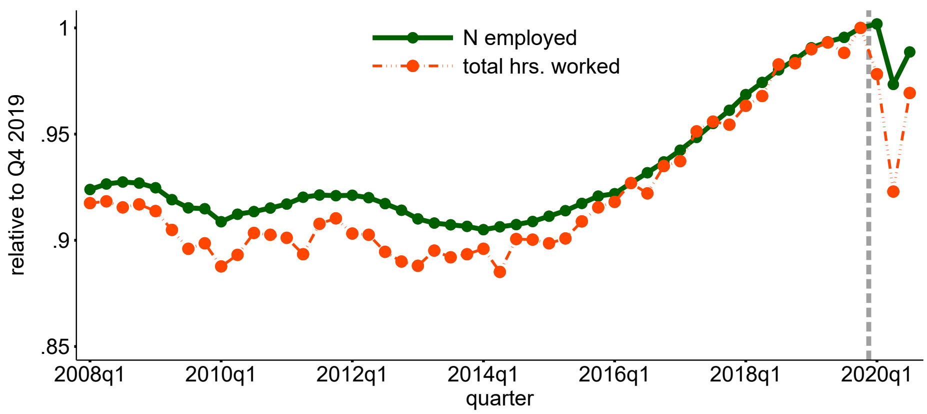
A.4 The Dutch labor market

Figure A.2a 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 (Zimpelmann et al., 2021). Working hours on average fell by almost five hours per week in April and stayed roughly at this level until September.

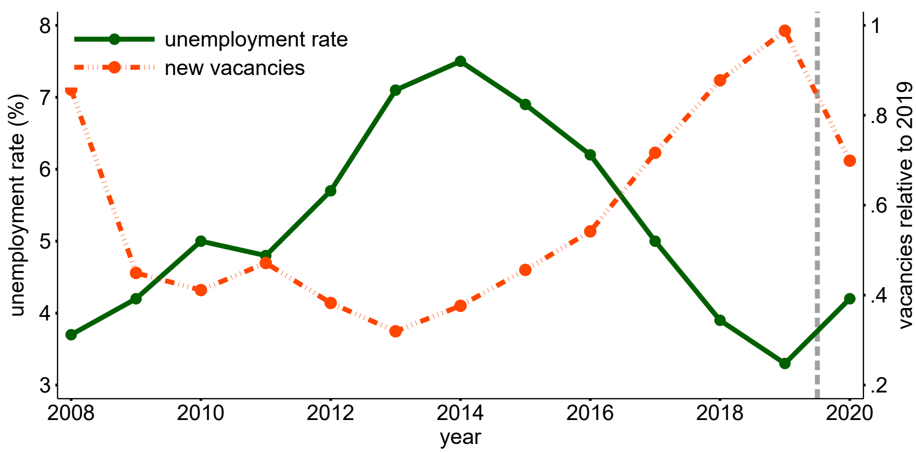
The labor market, however, was mostly affected at the intensive margin. In Figure A.2b we present the trajectory of the unemployment rate and the number of new vacancies over the same period. The unemployment rate rose by 1.3 percentage points and the number of new vacancies dropped by almost 30%. This constitutes a relatively smaller downturn compared to other countries, such the U.S. (Bick and Blandin, 2020), especially in unemployment rates.

Figure A.2: 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 Data and Definition of Main Variables

B.1 Definition of Labor Market States

This section describes the main definition of labor market states.

We classify individuals labor market state as unemployed based on their self assesed labor market state at/around the time of the survey. Individuals where asked in the June 2020 wave —the same wave in which our search module was implemented— to self-assign their labor market state based on the following question. *Which of the following options describes your work situation at the beginning of June 2020 best?*

- employed
- self-emplyed
- unemployed
- retired
- social assistance
- student or trainee
- homemaker

For the years prior to 2020 we use responses to a similar phrased question that differed mainly in that it allowed for more detailed responses in particular, it listed the following response options.

- paid work
- no work
- unpaid work
- seeking
- other work
- not seeking
- first job
- work break
- student
- household

- rentier
- early pension
- disabled
- volunteer

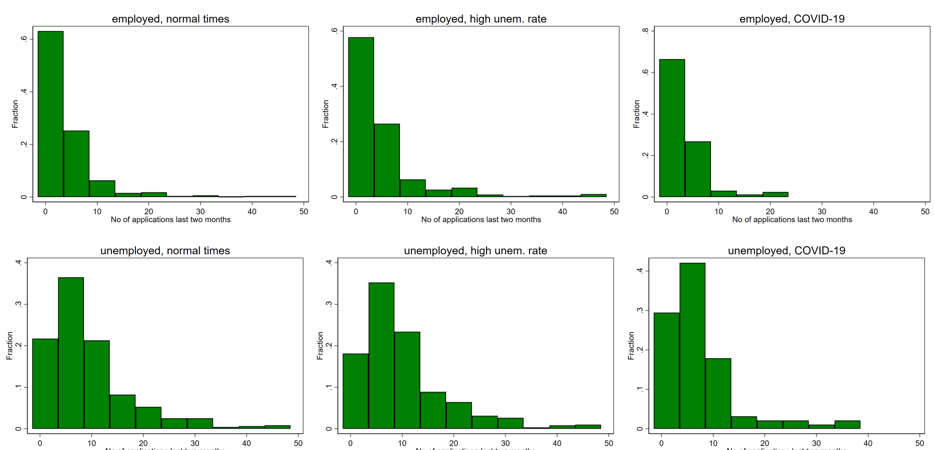
The question was asked in two steps, first individuals where allowed to respond with multiple options, but where asked in a second step to list the best fitting option only.

Unemployment Definition:
We classify individuals as unemployed based on their self assesed labor market state at/around the time of the survey based on the responses above. For the June 2020 wave we classify everyone as unemployed who responds with "unemployed". For the previous years, individuals that respond with "seeking" and "work break" are selected.

Employment Definition:
Our employment definition is built on the same variable as the unemploment definition. In particular, our employment category for 2020 combines the two responses "employed" and "self-employed". For the previous years, we count everyone as employed who selects "paid work" and "other work".

B.2 Summary Statistics of Main Variables

Figure B.1: The distribution of the number of applications made during the previous 2 months, for employed and unemployed, during different phases of the business cycle



Notes: The distribution of the number of applications during normal times (2008-2011 and 2017-2019), high unemployment years (2012-2016) and during the pandemic (2020). The distribution was capped at 50 applications per person per 2 months, and excludes 0.

Table B.1: Summary table — Missing info of main variables

	(1) Empoyed	(2) Unemployed
Missing Info		
any missing info	0.38	0.42
any missing info, excluding sector	0.34	0.28
missing household income	0.094	0.060
missing expected duration lockdown	0.16	0.13
missing expected unemployment	0.16	0.13
missing short time work info	0.19	0*
missing sectoral info	0.16	0.32
number of observations	2753	151

This table provides information on the share of missing information for variables with missing values used in the baseline regressions and as displayed in Table 1. * The share of missing information on short time work for the unemployed is zero by construction. *Any missing info* refers to share of observations where at least one variable has a missing value, *any missing info, excluding sector* refers to the share of observations with at least one variabe has a missing value but ignoring the sectoral information. All other lines represent the shares of missing observations for specific variables. All results restrict to individuals aged between 16 and 65. SD are in brackets.

B.3 Sample Composition over the Business Cycle

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.

Appendix C Additional Figures and Tables

C.1 Job search over the Business Cycle

Table C.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
aggregate vacancies (Q1)	0.994	0.961**	-0.005+	-0.255**
	[0.012]	[0.012]	[0.003]	[0.061]
age in years	0.991	1.133**	-0.014	0.104
	[0.015]	[0.049]	[0.011]	[0.108]
Age sq.	1.000	0.999**	0.000	-0.001
	[0.000]	[0.001]	[0.000]	[0.001]
upper secondary education	1.369**	1.342*	0.076*	2.443*
	[0.079]	[0.199]	[0.031]	[0.968]
tertiary education	1.739**	1.243+	0.074*	1.480
	[0.169]	[0.158]	[0.026]	[1.092]
self employed	1.799**	1.000	0.093+	0.000
	[0.145]	[.]	[0.050]	[.]
unemployment duration in years	1.000	1.048	0.000	0.490*
	[.]	[0.035]	[.]	[0.208]
female	1.146	0.767*	-0.010	-1.977*
	[0.106]	[0.089]	[0.011]	[0.676]
children	0.880**	0.929	-0.035	-0.600
	[0.043]	[0.143]	[0.029]	[0.840]
married	0.652**	0.821	-0.122**	-0.236
	[0.041]	[0.145]	[0.030]	[0.808]
household income: middle	0.578**	0.840	-0.207**	-0.852
	[0.044]	[0.132]	[0.025]	[0.478]
household income: high	0.449**	1.382	-0.283**	0.503
	[0.049]	[0.298]	[0.026]	[1.025]
urban location	0.719**	1.146	-0.087**	0.262
	[0.056]	[0.138]	[0.019]	[0.617]
linear trend	0.984	1.010	0.006	0.314**
	[0.019]	[0.017]	[0.004]	[0.064]
Constant	0.109**	0.526	0.837**	9.064**
	[0.033]	[0.459]	[0.239]	[2.207]
(Pseudo) R^2	0.041	0.059	0.006	0.067
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 estimated regression is logit, and the estimates are displayed as odds ratios. 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 regression is OLS. 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 C.2: Model of job search behavior (n. of applications) as a function of individual characteristics and different business cycle indicators.

	dependent variable: n. of applications								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	OLS	OLS	OLS	Poisson	ZIP	n. apps≤30
employed × unem. rate	0.0263**								
	(0.00757)								
unemployed × unem. rate	0.796*								
	(0.300)								
employed × aggregate vacancies (Q1)		-0.00471+					-0.0256+	-0.0218**	-0.00262
		(0.00256)					(0.0145)	(0.00815)	(0.00149)
unemployed × aggregate vacancies (Q1)		-0.255**					-0.0352**	-0.0220**	-0.159**
		(0.0605)					(0.00800)	(0.00695)	(0.0261)
employed × aggregate vacancies (Q2)			-0.00408						
			(0.00254)						
unemployed × aggregate vacancies (Q2)			-0.242**						
			(0.0645)						
employed × sector vacancies (Q1)				-0.0359					
				(0.0248)					
unemployed × sector vacancies (Q1)				-2.132**					
				(0.502)					
employed × sector vacancies (Q1/Q2 growth)					0.168				
					(0.177)				
unemployed × sector vacancies (Q1/Q2 growth)					11.12+				
					(5.891)				
employed × indiv. expected job loss						0.00723**			
						(0.00138)			
N	38908	38908	38908	37739	37739	14501	38908	38908	38831
R^2	0.235	0.237	0.237	0.239	0.238	0.015	0.448	.	0.373

Notes: OLS, Poisson, and Zero-inflated Poisson regressions of the number of job applications on macroeconomic indicators (shown) and controls (individuals' age, education, employment status, sector, gender, marital status, number of children, self-employed dummy, living in urban area, household income, and unemployment duration if unemployed), plus a linear trend. The coefficients are estimated separately for the employed and the unemployed. Years 2008-2019. Standard errors in brackets, clustered at year level. +, * and ** indicate significance at the .1, .05 and .01 significance level respectively.

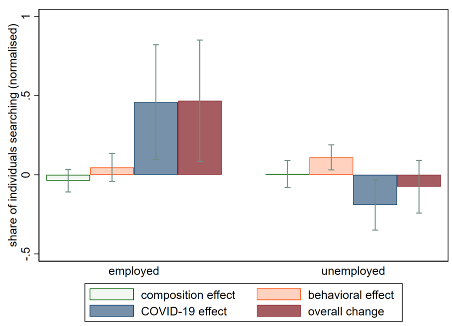
Table C.3: Model of job search behavior (binary search indicator) as a function of individual characteristics and different business cycle indicators. Logit regression.

	dependent variable: searching dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
employed × unem. rate	1.075+					
	(0.0396)					
unemployed × unem. rate	1.144*					
	(0.0684)					
employed × aggregate vacancies (Q1)		0.994				
		(0.0117)				
unemployed × aggregate vacancies (Q1)		0.961**				
		(0.0115)				
employed × aggregate vacancies (Q2)			0.997			
			(0.0108)			
unemployed × aggregate vacancies (Q2)			0.965**			
			(0.0118)			
employed × sector vacancies (Q1)				0.911		
				(0.0966)		
unemployed × sector vacancies (Q1)				0.730**		
				(0.0693)		
employed × sector vacancies (Q1/Q2 growth)					2.184+	
					(0.953)	
unemployed × sector vacancies (Q1/Q2 growth)					2.370	
					(3.058)	
employed × indiv. expected job loss						1.024**
						(0.00199)
Observations	38908	38908	38908	37739	37739	14475
Pseudo R^2	0.320	0.320	0.319	0.268	0.268	0.088

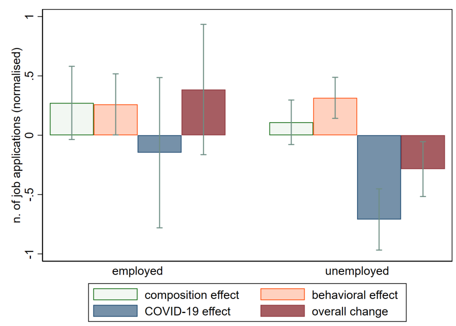
Notes: Logit regressions of a binary search indicator on macroeconomic indicators (shown) and controls (individuals' age, education, employment status, sector, gender, marital status, number of children, self-employed dummy, living in urban area, household income, and unemployment duration if unemployed), plus a linear trend. The coefficients are estimated separately for the employed and the unemployed, are expressed as odds ratios. Years 2008-2019. Standard errors in brackets, clustered at year level. +, * and ** indicate significance at the .1, .05 and .01 significance level respectively.

Figure C.1: Decomposing job search in 2020 into behavioral, composition, and COVID-19 effects. Robustness to different search measures, macroeconomic indicators, and models.

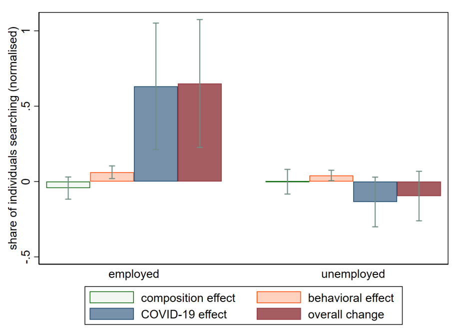
(a) Share searching; vacancies



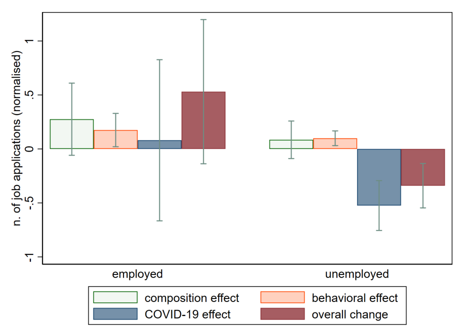
(b) N. of applications; vacancies



(c) Share searching; unem. rate



(d) N. of applications; unem. rate



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 behavioral 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.

C.1.1 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 behavior in 2020. The results of the fixed effects model are presented in Table C.4. 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.4: 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.

C.2 Explaining Job Search in 2020

Table C.5: Explaining Job-Search 2020: Full list of Coefficients

	Employed				Unemployed			
	Baseline: Actual		Predicted − Actual		Baseline: Actual		Predicted − Actual	
	OLS	LASSO	OLS	LASSO	OLS	LASSO	OLS	LASSO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
self employed	0.074		-0.020					
	[0.127]		[0.127]					
age in years	-0.012	-0.003	0.002		-0.657*		-0.762**	
	[0.014]	[0.002]	[0.014]		[0.261]		[0.261]	
age squared	0.000		-0.000		0.008*		0.009**	
	[0.000]		[0.000]		[0.003]		[0.003]	
upper secondary education	-0.024		-0.097	-0.121**	0.566		-1.874	-2.798*
	[0.074]		[0.074]	[0.044]	[1.556]		[1.556]	[1.387]
tertiary education	0.119		0.048		2.971	2.146+	1.493	0.411
	[0.076]		[0.076]		[1.909]	[1.195]	[1.909]	[1.608]
female	0.082		0.092		2.696*		4.673**	4.073**
	[0.060]		[0.060]		[1.336]		[1.336]	[0.998]
children	0.059		0.094+	0.101*	-0.334		0.265	
	[0.048]		[0.048]	[0.047]	[1.532]		[1.532]	
married	-0.076+	-0.082+	0.046		1.595		1.830	
	[0.042]	[0.044]	[0.042]		[1.411]		[1.411]	
household income: middle	-0.044		0.163*		-2.011		-1.160	
	[0.079]		[0.079]		[1.341]		[1.341]	
household income: high	-0.145+		0.136+		-1.634		-2.137	
	[0.081]		[0.081]		[1.662]		[1.662]	
urban location	-0.067		0.020		-0.480		-0.742	
	[0.048]		[0.048]		[1.297]		[1.297]	
industrial production	0.041		0.066		-0.145		-0.692	
	[0.120]		[0.120]		[2.908]		[2.908]	
culture, recreation	0.063		0.063		-5.536		-8.557*	-4.508*
	[0.238]		[0.238]		[3.574]		[3.574]	[2.142]
construction	0.141		0.305	0.278	-2.444		-4.904	-5.632*
	[0.235]		[0.235]	[0.225]	[4.148]		[4.149]	[2.690]
retail	-0.135		-0.077		-0.003		-2.116	
	[0.085]		[0.085]		[3.281]		[3.281]	
catering	0.354	0.445	0.361	0.385	-5.320		-10.737**	-7.430**
	[0.412]	[0.396]	[0.412]	[0.396]	[3.649]		[3.649]	[1.646]
transport, communication, utilities	0.178		0.173		2.233		2.006	4.079
	[0.156]		[0.156]		[4.028]		[4.028]	[3.739]
financial sector	-0.153*		-0.062		-0.192		-5.126	-3.928*
	[0.078]		[0.078]		[3.250]		[3.250]	[1.532]
business services	0.169	0.249	0.241	0.247	-0.897		-1.461	
	[0.179]	[0.167]	[0.179]	[0.165]	[5.224]		[5.224]	
public sector	-0.062		0.050		0.444		-0.591	
	[0.080]		[0.080]		[6.153]		[6.153]	
education	-0.164*		-0.115		-2.974		-2.977	
	[0.082]		[0.082]		[3.159]		[3.159]	
healthcare and welfare	-0.145+		-0.072		-4.033		-2.583	
	[0.075]		[0.075]		[2.553]		[2.553]	
missing sectoral info	-0.185+		-0.365**	-0.291**	-1.660		1.413	3.535**
	[0.102]		[0.102]	[0.048]	[2.800]		[2.800]	[1.151]
missing hh income	0.117		-0.059		-0.019		0.492	
	[0.103]		[0.103]		[2.394]		[2.394]	
probability of infection	0.162		0.162		-0.429		-0.429	
	[0.102]		[0.102]		[3.137]		[3.137]	
probability of hospitalization if infected	0.086		0.086		0.369		0.366	
	[0.149]		[0.149]		[2.656]		[2.656]	
work change because of corona	0.215+	0.306*	0.215+	0.223+	1.841		1.842	
	[0.122]	[0.136]	[0.122]	[0.132]	[1.665]		[1.665]	
affected by short-time work	0.085		0.085					
	[0.103]		[0.103]					
missing short-time work	0.504+	0.118	0.504+					
	[0.304]	[0.084]	[0.304]					
expect restrictions until 2021	-0.144*	-0.117**	-0.144*	-0.154**	2.342*		2.343*	
	[0.069]	[0.044]	[0.069]	[0.045]	[1.169]		[1.169]	
expect restrictions until 2022	-0.010		-0.010		3.816*	1.774	3.817*	1.827
	[0.086]		[0.086]		[1.698]	[1.405]	[1.698]	[1.435]
expect high future unemployment	0.016		0.016		3.049*	2.325+	3.049*	2.969*
	[0.050]		[0.050]		[1.464]	[1.321]	[1.464]	[1.450]
finding same job harder	0.009		0.009		1.311	1.840+	1.311	1.978+
	[0.047]		[0.047]		[1.287]	[1.059]	[1.286]	[1.031]
missing expect restrictions	-0.370		-0.371		4.327+		4.329+	
	[0.315]		[0.315]		[2.316]		[2.316]	
missing expect unemployment	-0.006		-0.007		2.867		2.868	
	[0.081]		[0.081]		[1.939]		[1.939]	
unemployment duration in years					-1.307*		-1.797**	-1.406**
					[0.501]		[0.501]	[0.319]
missing finding job harder					-1.317		-1.317	
					[1.223]		[1.223]	
R^2	0.035	0.019	0.035	0.024	0.251	0.097	0.390	0.307
Cross-Validated MPE	0.42	0.38	0.42	0.40	6.27	4.45	5.40	4.39
N	2753	2753	2753	2753	151	151	151	151
Mean no. appl. 2020	0.21	0.21	0.21	0.21	4.78	4.78	4.78	4.78

Notes: Column (1) and column (5) report the full list of regression coefficients for the main regressions in Table 2. The dependent variable is the number of applications. The left-out sector category is 'Other'. In column (3) and (7), the dependent variable is the difference between the actual number of applications and the predicted number of applications based on demographic and sectoral information and model (1). The even columns report coefficients from a lasso-selection model that minimizes the cross-validated out-of-sample prediction. Standard errors in squared brackets. +, * and ** indicate significance at the .1, .05 and .01 significance level respectively.

Table C.6: Explaining Job-Search 2020: Additonal Sample Splits

	All	Employment Type		Affected by Short-time Work		Education	
	Employed	Self Employed	Dep. Employees	Yes	No	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
probability of infection	0.162	0.079	0.111	0.408	0.150	0.212	0.152
	[0.102]	[0.429]	[0.098]	[0.403]	[0.102]	[0.160]	[0.113]
prob. of hospitalization if infected	0.086	0.560	0.075	-0.254	0.110	-0.025	0.149
	[0.149]	[0.759]	[0.152]	[0.475]	[0.154]	[0.155]	[0.216]
work change because of corona	0.215+	0.156	0.231+	0.426	0.191	0.524*	0.032
	[0.122]	[0.209]	[0.123]	[0.461]	[0.117]	[0.212]	[0.137]
affected by short-time work	0.085	1.197	0.001			0.115	0.087
	[0.103]	[1.136]	[0.077]			[0.220]	[0.095]
expect restrictions until 2021	-0.144*	-0.686	-0.072	0.161	-0.190*	-0.001	-0.252*
	[0.069]	[0.553]	[0.049]	[0.138]	[0.078]	[0.057]	[0.109]
expect restrictions until 2022	-0.010	-0.416	0.039	0.381	-0.075	0.092	-0.084
	[0.086]	[0.562]	[0.070]	[0.256]	[0.091]	[0.098]	[0.124]
expect high future unemployment	0.016	0.082	0.019	-0.199	0.032	0.061	-0.026
	[0.050]	[0.343]	[0.044]	[0.151]	[0.054]	[0.072]	[0.067]
finding same job harder	0.009	0.112	-0.015	0.086	-0.000	0.085	-0.085
	[0.047]	[0.161]	[0.048]	[0.146]	[0.050]	[0.072]	[0.063]
self employed	0.074			0.652	0.029	-0.055	0.120
	[0.127]			[0.795]	[0.127]	[0.161]	[0.189]
R^2	0.035	0.146	0.037	0.135	0.039	0.073	0.038
N	2753	276	2477	284	2469	1326	1427
Mean no. appl. 2020	0.21	0.35	0.19	0.29	0.20	0.24	0.18
Demographic and sector controls	x	x	x	x	x	x	x

Notes: This table presents several additional sample splits for the main regressions on the employed in Table 2. The dependent variable is the number of applications. The sample of employed individuals is restricted to the self-employed in column (2) and to dependent employees in column (3). The regression focusing on subjects that where affected by short-time work is presented in column (4) while column (5) is based on individuals who were not affected or for whom this information is missing. In columns (6) and (7) the sample is split by education level where high education refers to tertiary education. Robust SE are in squared brackets. +, * and ** indicate significance at the .1, .05 and .01 significance level respectively.

Table C.7: Explaining Job-Search 2020: Robustness

	Baseline	Ext. Margin			Int. Margin	Winsorized	Poisson	ZIP
	No. Applications	Seriously Searching	Any Applications	≥ 8 Applications	No. Applications if any	No. Applications	No. Applications	No. Applications
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Employed								
probability of infection	0.162	0.024	0.042+	0.011+	-0.745	0.162	0.169+	0.163+
	[0.102]	[0.017]	[0.022]	[0.006]	[1.540]	[0.102]	[0.087]	[0.098]
probability of hospitalization if infected	0.086	-0.009	0.011	-0.003	1.276	0.086	0.098	0.097
	[0.149]	[0.016]	[0.020]	[0.007]	[2.046]	[0.149]	[0.132]	[0.106]
work change because of corona	0.215+	0.037*	0.047*	0.002	-0.020	0.215+	0.130+	0.130+
	[0.122]	[0.018]	[0.021]	[0.007]	[0.968]	[0.122]	[0.068]	[0.075]
affected by short-time work	0.085	0.001	0.016	0.003	-0.171	0.085	0.106	0.055
	[0.103]	[0.012]	[0.017]	[0.006]	[1.403]	[0.103]	[0.085]	[0.078]
expect restrictions until 2021	-0.144*	-0.014	-0.030*	-0.008*	-0.085	-0.144*	-0.176*	-0.133*
	[0.069]	[0.010]	[0.014]	[0.004]	[0.720]	[0.069]	[0.071]	[0.058]
expect restrictions until 2022	-0.010	-0.003	-0.018	-0.002	1.212	-0.010	-0.029	-0.004
	[0.086]	[0.011]	[0.015]	[0.005]	[1.151]	[0.086]	[0.068]	[0.069]
expect high future unemployment	0.016	0.005	0.015	-0.003	-0.337	0.016	0.023	0.032
	[0.050]	[0.009]	[0.011]	[0.003]	[0.525]	[0.050]	[0.048]	[0.047]
finding same job harder	0.009	0.018*	0.008	0.003	-0.617	0.009	-0.005	-0.015
	[0.047]	[0.008]	[0.009]	[0.003]	[0.613]	[0.047]	[0.049]	[0.045]
R^2	0.035	0.030	0.033	0.028	0.270	0.035	/	/
N	2753	2753	2753	2753	164	2753	2753	2753
Mean dep. var 2020	0.21	0.04	0.06	0.01	3.48	0.21	0.21	0.21
Panel B: Unemployed								
probability of infection	-0.429	0.027	0.228	0.118	-3.377	-0.191	-1.143	-0.575
	[3.137]	[0.266]	[0.238]	[0.218]	[3.685]	[3.061]	[2.638]	[2.552]
probability of hospitalization if infected	0.369	-0.087	-0.220	-0.073	0.665	0.451	0.034	-0.731
	[2.656]	[0.184]	[0.174]	[0.186]	[3.430]	[2.617]	[2.551]	[2.152]
work change because of corona	1.841	-0.013	0.101	0.114	0.979	1.962	2.527*	1.264
	[1.665]	[0.124]	[0.106]	[0.115]	[2.220]	[1.600]	[1.243]	[1.277]
unemployment duration in years	-1.307*	-0.047	-0.167**	-0.107**	-1.079	-1.277**	-3.699*	-3.463*
	[0.501]	[0.057]	[0.049]	[0.035]	[2.673]	[0.470]	[1.538]	[1.518]
expect restrictions until 2021	2.342*	0.412**	0.189	0.210*	3.783+	2.272*	3.729**	3.920**
	[1.169]	[0.116]	[0.118]	[0.103]	[2.203]	[1.122]	[1.332]	[1.419]
expect restrictions until 2022	3.816*	0.238+	0.132	0.132	6.290*	3.430*	4.658**	4.841**
	[1.698]	[0.128]	[0.118]	[0.099]	[2.877]	[1.529]	[1.517]	[1.508]
expect high future unemployment	3.049*	-0.170+	0.021	0.059	5.774**	2.772*	3.189**	3.536**
	[1.464]	[0.100]	[0.093]	[0.087]	[2.171]	[1.367]	[1.106]	[1.127]
finding same job harder	1.311	0.177	0.137	0.067	0.216	1.220	0.593	0.727
	[1.287]	[0.139]	[0.127]	[0.108]	[1.939]	[1.243]	[1.164]	[1.246]
R^2	0.251	0.257	0.311	0.262	0.369	0.250	/	/
N	151	151	151	151	95	151	151	151
Mean dep. var. 2020	4.78	0.58	0.63	0.28	7.60	4.69	4.78	4.78
Demographic and sector controls	x	x	x	x	x	x	x	x

This table presents several robustness analyses for the main regressions in Table 2. It summarizes the coefficients from regressing indicators of job search effort in 2020 on different variables using OLS. The regressions are performed separately for the employed (Panel A) and the unemployed (Panel B). All regressions include demographic and sector controls in 2020. In column (1), our main specification is repeated that uses the number of applications as main outcome variable. Column (2) and column (3) focus on the extensive margin of job search effort and use binary variables as dependent variable which indicate if an individual stated to be 'seriously searching for a job' and if the number of applications is greater than zero respectively. Column (4) uses a dummy variable indicating that individuals applied for at least 8 jobs per two month. In column (5) the sample is restricted to all individuals that have sent a non-zero amount of applications. A robustness check in which we winsorize the number of applications at 30 (instead of 100) is presented in column (6). Column (7) and (8) represents average marginal effects from a poisson regression and a zero-inflated poisson regression respectively. Robust SE are in squared brackets. +, * and ** indicate significance at the .1, .05 and .01 significance level respectively.