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Labour Market Flows and Worker Trajectories in Canada during COVID-19

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Abstract

We use the confidential-use files of the Labour Force Survey (LFS) to study the employment dynamics in Canada from the beginning of the COVID-19 pandemic through to mid-summer. Using the longitudinal dimension of this dataset, we measure the size of worker reallocation, and document the presence of high labour market churning, that persists even after the easing of social-distancing restrictions. As of July, many of the recent job losers – especially those who had been temporarily laid-off between February and April – have regained employment. However, this apparent strong recovery dynamics hides important heterogeneity, and large groups of workers, such as those who were not employed prior to the pandemic, face important difficulties with finding a job. Three factors appear to be key in accounting for the incomplete employment recovery of July: (1) the unusually high separation flows that characterize the labour market in the reopening phase; (2) the low reemployment probability of recent job losers who were classified as out of the labour force during the lockdown; and (3), the low job-finding rate of individuals who were out of work prior to the pandemic. Our results further suggest that gross job losses were higher among women and young workers during the shutdown, and that older workers were more likely to leave the labour force when the economy reopened.

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1 Introduction

The Canadian labour market underwent an unprecedented trajectory since the onset of the COVID-19 pandemic. The massive job losses due to the shutdown of the early phase of the outbreak were followed by a vigorous rebound upon the gradual reopening of the economy, as was the case for many countries. As of July, employment was 1.3 million below its pre-COVID level, despite 3 million jobs lost during the spring (Statistics Canada 2020). This unusual trajectory has been extensively analyzed (e.g. Lemieux et al. (2020), Jones et al. (2020), Statistics Canada (2020)). However, the discussions have largely focused on the behaviour of the economy in *net* terms, and little is known about the employment flow dynamics that have accompanied the virus propagation. Although highly informative about the impact of COVID-19, these net changes are likely to hide sizable worker reallocation flows across labour-market states and jobs, especially given the considerable magnitude of the COVID-19 shock. In particular, the net changes could mask important gross job losses that might be revealing of the depth of the recession. Therefore, a clear understanding of the underlying labour reallocation process is critical to not only assess the severity of the shock, but also to draw implications for the potential recovery of the next months.

This paper uses the confidential-use files of the Labour Force Survey (LFS) to study the dynamics of employment in Canada from the early onset of COVID-19 to mid-summer.[1] This paper is, to our knowledge, the first to analyze the impact of the pandemic using these data.[2] We propose a novel characterization of the trajectory of the Canadian economy in COVID-19 times, based on a detailed analysis of the worker reallocation process of the pandemic months. Our analysis takes advantage of the longitudinal dimension of the confidential version of the LFS.[3] Specifically, this dataset is the only one currently available that allows us to build panels following workers' trajectories for six consecutive months over the COVID period. More precisely, these panels can span the month prior to the start of the outbreak (and the ensuing shutdown) through to mid-summer, after the lifting of most of social-distancing restrictions. Another key advantage of this data is that it allows us to examine the evolution of non-response in the LFS since the beginning of the pandemic.[4] The virus has severely

[1]Specifically, we use Statistics Canada's internal-use files. These restricted-access/confidential-use LFS files are, to the best of our knowledge, very similar (if not identical) to the confidential-use LFS files that are made available to researchers in the Research Data Centres (RDCs). In both cases, one can take advantage of the longitudinal dimension of the LFS data, a key requirement of our analysis.

[2]Exceptions are two short Statistics Canada papers (i.e. Chang, Morissette & Qiu (2020) and Hou, Picot & Zhang (2020)), that are part of the "COVID-19 Data insight for better Canada" series, meant to provide timely insight on the current crisis. Additional details are provided in the literature review below.

[3]The variables needed to construct panels in the LFS are not made available in the public-use files. See the data section for more details.

[4]Specifically the information on when a person enters the LFS and whether her/his labour market infor-

constrained the data collection activities of statistical agencies, resulting in unusually high (survey) non-response rates in many countries. This raises concerns about the reliability of COVID-time statistics.[5] Evaluating the scale of the non-response problem, and most importantly, its implications for labour-force estimates, is critical for assessing the impact of COVID-19. This paper, by documenting the evolution of this phenomenon in Canada using the confidential-use LFS, takes a step in this direction.[6]

In our analysis, we measure the size of gross worker flows in and out of employment since the start of the outbreak. This is necessary for an informed evaluation of the magnitude of the COVID-19 shock: since the gross employment outflows are partially offset by the inflows, the net employment changes, albeit dramatic, can only give a lower bound on the number of jobs lost during the shutdown. Gross flows are also key for assessing the strength of the recovery, as the high net employment gains of the reopening might hide large gross outflows. We find that along the pandemic path, the economy experienced considerable gross job losses: the 20 to 64 year-olds lost 1.3 million jobs between February and March, and a further 2.3 million between March and April. Job losses remained persistently high even after the reopening: between April and May, 1 million workers 20 to 64 years of age lost their jobs. In comparison, we find that the cumulative monthly employment outflows between February and May 2009 (i.e. during the Great Recession) were around 1.6 million for the same population. These figures are indicative of the remarkable severity of the shock and also reveal high excess reallocation flows or high labour market "churn", which suggests unusual worker mobility patterns.[7] Understanding the consequences of these patterns for the upcoming recovery requires further analysis of the COVID-19 employment dynamics.

Thus, our paper examines the composition of the COVID employment flows. Although an unusually large number of early-pandemic job losers were classified as temporary layoffs, around two-thirds of the outflows went towards non-participation and to a lesser extent,

mation was fully imputed is suppressed in the public-use files.

[5]See U.S. Bureau of Labor Statistics (2020*b*) for the U.S. case or https://ilostat.ilo.org/topics/covid-19/covid-19-impact-on-labour-market-statistics for a more general discussion.

[6]Another difference with the public-use files of the LFS is that the confidential files provide 4 digit National Occupation Classification (NOC) codes, versus up to 2 digits for the public version. Given the important focus of the literature on the effect of COVID-19 across occupations (e.g. Béland et al. (2020a), Gallacher & Hossain (2020)), this might be a key advantage. This paper makes relatively limited use of the detailed NOC codes, but further research could take better advantage of this feature of the confidential-use LFS files for a thorough analysis of the distributional impact of the virus, and its implications for labour reallocation across occupations.

[7]In the worker flows literature, excess worker reallocation flows refer to offsetting flows in and out of employment, defined as the sum of reallocation flows (i.e. inflows and outflows), minus net employment changes, i.e. the flows that are "hidden" by the net change (e.g. Davis & Haltiwanger (1992)). Note that certain papers distinguish between *churning* and *excess* worker flows, the former being defined as excess worker reallocation minus excess job reallocation (e.g. Burgess et al. (2000)). In what follows, we will, to avoid excessive jargon, use "churning" instead of "excess reallocation".

search unemployment.[8] This raises important questions regarding the recovery dynamics, as it suggests that many of the job losses were permanent. Moreover, the recovery will also crucially depend on the entry rates of workers that were non-employed *before* the advent of the virus. It is key, therefore, to examine the trajectories of individuals during the pandemic. We do so by using our LFS panel to analyze labour-market transitions. Approximately two-thirds of the workers who were employed in February (i.e. the month just before the propagation of the virus) but non employed in April (when social distancing restrictions were peaking) regained employment in July. As a result, almost nine out of ten workers who were employed in February have a job in the summer.

Given the unprecedented severity of the COVID shock, these numbers can be seen as reassuring regarding the strength of the rebound. But the reemployment dynamics hide significant heterogeneity. The job losers classified as not in the labour force (NILF) in April have low reemployment rates; this, taken with the fact that a large part of employment outflows was towards non-participation, could be taken as a worrying sign. Another concerning aspect is that the job-finding rates of individuals not employed in February were negatively impacted by the pandemic in the reopening months. This indicates that this group has been largely excluded from the sizable employment gains of the rebound.[9] In sum, our flow analysis suggests that the incomplete employment recovery of July can be explained by three important factors: the low reemployment probabilities of the numerous NILF job losers; the depressed hiring dynamics of those who where jobless before the outbreak; and the persistently high job losses of the reopening months.

Due to the high churn observed in COVID times, it is important to assess the distributional impact of the virus. We therefore examine labour-market histories conditional on socio-demographic and job characteristics. Many papers have already addressed this question using Canadian cross-sectional data (e.g. Lemieux et al. (2020), Béland et al. (2020a)). But again, net changes can hide large gross job losses within groups, and therefore, might result in an understating of the distributional consequences of the shock. We find that youths, the low-educated, and workers in low-tenured and non-unionized employment were more likely to lose their jobs during the shutdown. Moreover, our results suggest a higher risk of job

[8]The high share of temporary layoffs in outflows is in line with the surge in the number of unemployed workers classified as on "temporary layoff" (e.g. Jones et al. (2020), Statistics Canada (2020)). As a result, the share of unemployed workers classified as engaged in "job search" shrunk. This increase in temporary unemployment is one of the important features of the COVID-19 slowdown and it is not surprising that this is reflected in the outflows. However, although temporary layoffs represent a higher share than usual of the job losses (about one-third), around two-thirds of the outflows are towards labour-force status with no apparent link with an employer (i.e. job search and non-participation).

[9]For instance, a NILF individual who reported wanting a job in February was two times less likely to be employed in July than a similar worker in 2019 (16% versus 32%).

loss *and* a lower reemployment probability (after the reopening) for women as compare to men. The analysis also indicates an uneven impact across age groups, which is reflected in participation decisions. On the one hand, job losers who are 50 to 64 years of age were more likely to leave the labour force upon the reopening of the economy and on the other, there are signs of lower entry into the labour force for 20 to 29 year-olds. These results call for further analysis of the impact of the virus on retirement and education decisions.

Related literature and contribution. The COVID-19 social-science research has been evolving at an extraordinary pace. Within this already large literature, our work can be related to papers that study the labour-market impact of the pandemic in North America.

Several papers have analyzed the initial impact of COVID-19 in Canada (i.e. over the spring months). Lemieux et al. (2020) document striking declines in employment and especially hours worked (-32% between February and April among the 20-64 year-olds). They also show that the decline in hours disproportionately impacted low-earning workers, which is consistent with the findings of Koebel & Pohler (2020). There is also evidence that COVID has had a significantly negative impact on youths and the low-educated (e.g. Béland et al. (2020a)), the self-employed (e.g. Béland et al. (2020b)), and widened the gender employment differences among parents with young children (e.g. Qian & Fuller (2020)). Finally, Jones et al. (2020) examine the early reopening dynamics, and present contrasting signs about the strength of the rebound: in particular, many of the temporary laid-off went back to work in May, but the number of job searchers increased.[10]

Most of the existing research on the Canadian labour market relies on the public-use files of the LFS.[11] Yet, an important limitation of these data is that one cannot follow individuals over time, resulting in an inability to analyze labour-market flows and trajectories over the pandemic period. As such, little is known so far about the COVID-19 gross employment dynamics in Canada. Our paper intends to fill this gap. In addition, since the confidential LFS provides information regarding data imputation and entry and exit of households into LFS samples, we are able to propose a novel and detailed picture of the evolution and impact of non-response rates during COVID.

The U.S. literature on the labour-market impact of COVID is already substantive. Within this literature, our work primarily relates to papers that analyze labour mobility. Since the

[10] In addition, a substantial literature has been interested in the impact of COVID across occupations, in line with the widespread belief that the task content of jobs is critical when determining the effect of the pandemic. Key dimensions include: the possibility to perform tasks remotely (e.g. Gallacher & Hossain (2020)), the frequency of close contact with coworkers and the public (e.g. Béland et al. (2020a)) and belonging to an essential industry (e.g. Jones et al. (2020)).

[11] As previously discussed, exceptions are two papers from the "COVID-19 Data insight for better Canada". Chang et al. (2020) provide employment separation rate estimates from the start of the outbreak and Hou et al. (2020) examine transition rates in and out of unemployment, with a focus on immigrants.

public-use files of the Current Population Survey (the U.S. counterpart of the LFS) allows for the possibility of following individuals over time, there is already a substantial body of research on this topic, as opposed to Canada.[12] Cowan (2020) analyzes labour market transitions between February and March across subgroups of workers and finds that women, visible minorities and the low-educated had a higher job loss probability. Forsythe (2020) who analyzes labour market flows over the same period finds that the hiring rate remains unaffected by the early phase of the virus — an intriguing result that we also observe in our analysis. Cheng et al. (2020) also study the reopening phase and their results suggest a strong but fading reemployment dynamics upon the easing of COVID-19 restrictions across U.S. states. In addition, Şahin, Tasci & Yan (2020) estimate the historical relationship between unemployment claims and unemployment outflows as to generate unemployment projections for the next months.[13]

While the U.S. Current Population Survey (CPS) allows for the building of panels of up to four months in length,[14] the ability to follow individuals over *six* months is a particular strength of the LFS. Therefore, the Canadian LFS makes it possible to follows trajectories from before the start of the outbreak, through the shutdown, and into the advanced phases of the economy's reopening. Since, in many cases, reopening policies are gradual (or, at least, have gradual effects) it is important to follow individuals long enough to assess the effect of such policies.[15] Moreover, the fact that the LFS is available at a monthly frequency is another key advantage; in many European countries, for instance, labour force survey data are quarterly. These features of the LFS, combined with the fact that governments implemented strict and pervasive constraints on economic activity, makes the Canadian case an informative one for assessing the economic impact of the virus in high-income countries.

Outline. The rest of the paper is divided as follows. Section 2 presents our data. In section 3 we explore how the COVID-19 pandemic impacted the LFS survey. Section 4 provides a discussion of our labour market flows results, whereas section 5 focusses on the worker trajectory findings. Finally, section 6 concludes.

[12]See Madrian & Lefgren (1999) and Rivera Drew, Flood & Warren (2014) for discussions on the longitudinal matching of individual observations in the Current Population Survey.

[13]Moreover, Coibion, Gorodnichenko & Weber (2020) document a stark decline in participation due to the pandemic, which can be accounted for by early retirements.

[14]The CPS is based on a 4-8-4-month rotating sample design: households in a given rotation are interviewed for four consecutive months, and then leave the sample for eight months, before being interviewed four additional consecutive months.

[15]If the LFS had a similar rotating scheme to the CPS, we would only have been able to follow an individual from February to May, when only part of the shutdown restrictions had been eased (or alternatively, from the shutdown to, say, June or July). However, it is possible to use information on unemployment duration to look at longer histories. But this has limitations, as many workers might have transited into non-participation. Moreover, such an approach makes it difficult to consider job characteristics, which are typically available when the worker is employed (or under the form of recall information).

2 Data

For our empirical analysis, we rely on the internal-use files of the Canadian Labour Force Survey (LFS).[16] Although we use LFS data going back to 2018, our main focus is on the February 2020 through July 2020 period.

The LFS is a monthly household survey that collects labour market information of the Canadian population.[17] It is the official source of employment and unemployment data. The LFS is also one of Statistics Canada's larger surveys, as it interviews approximately 54,000 households every month.

The high frequency of the data (i.e. monthly) and its tight production deadline (from enumeration to public release),[18] ensures that the LFS is a timely source of data for examining the impact of COVID-19 on the Canadian labour market. The rotating panel feature of the LFS is key to our analysis. The LFS follows households for six consecutive months, with one-sixth of the households being replaced every month. As such, we can construct mini panels up to six months in length.[19] This allows us to follow individuals through the COVID-19 shutdown and subsequent re-opening of the economy.

We restrict our attention to civilian workers aged 20 to 64, and exclude those living in the territories.[20] We impose the age restrictions so as to compare our findings with existing evidence regarding the COVID-19 shutdown (e.g. Lemieux et al. (2020), Jones et al. (2020)). Finally, we focus our attention on Canada's ten provinces (i.e. exclude the territories) for data-access reasons; the internal-use files that we rely upon do not have information on the territories.[21]

[16] As discussed in the introduction, these restricted-access files are, to the best of our knowledge, very similar (if not identical) to the confidential-use files that are provided in the RDCs.

[17] Specifically, the target population of the LFS consists of the "*...civilian, non-institutionalized population 15 years of age or older. It is conducted nationwide, in both the provinces and the territories. Excluded from the survey's coverage are: persons living on reserves and other Aboriginal settlements in the provinces, full-time members of the Canadian Armed Forces, the institutionalized population, and households in extremely remote areas with very low population density.*" (Statistics Canada 2018).

[18] For example, enumeration for the July 2020 data started July 19, the first day following the July 12 to 18 reference week, and the data was publicly released on August 7, 2020.

[19] This requires the use of the confidential-use files, as the variables needed to construct the mini panels are suppressed in the public-use files. The details regarding the construction of the mini panels are left to the appendix (i.e. Appendix A.1). See Brochu (2020) for more information on the distinction between public-use and confidential-use LFS files.

[20] The LFS asks socio-economic characteristics of all adults (15 years and up) that live in targeted dwellings, including full-time members of the Canadian armed forces. However, no labour market information is gathered for the latter group, as they are not part of the target population.

[21] It should be noted that the public-use files also only cover the ten provinces. The same holds true for the confidential-use files that are typically made available in the RDCs. LFS data for the territories is considered a different product (datatset), and as such, it would require a separate RDC application. Finally, it must be recognized that the official employment and unemployment statistics (which are based on LFS data) only apply to the Canadian provinces.

Given that our focus is on labour market flows and transitions, our analysis relies mainly on mini panels. As such, we must provide additional information regarding the periods covered by our panels and any additional panel-related restrictions that we impose. The monthly span and frequency of the panel vary depending on the flow/transition of interest. For example, when we focus on labour market flows from February 2020 to March 2020, we rely on the two-month balanced panel covering the February 2020 - March 2020 period. Say, instead, we want to look at the probability a worker is employed in June, conditional on her/him being employed in February but out of work in April. In that case, we use a balanced panel that spans the 5-month period, but only includes three months of data (i.e. February 2020, April 2020 and June 2020). We do so for sample size reasons. Using the full 6-month mini panel (February 2020 through July 2020) for all of our analyses, would force us to rely on only one rotation - the rotation that entered the survey as of February. This would dramatically reduce our sample size (i.e. 1/6 of its original size).[22]

Requiring a balanced panel means that we drop observations (individuals) for three reasons: first, we drop individuals whose rotation group rotated-out part-way through the panel; second, we remove individuals that join an existing household part-way through the panel, as identified by the new birth variables; and third, individuals who are absent in the data for some, but not all months, for reasons other than mentioned above are also dropped.

Of the three reasons, the first is the most restrictive. For example, when looking at a panel that spans four months, one must drop three rotations out of six, i.e. we lose half the sample–even before imposing any additional restrictions. The second restriction is the least restrictive; meaning that very few observations are lost. This is due to the short time-span of our panels, and may also be influenced by reduced mobility brought about by COVID-19. The third and final reason encompasses multiple possibilities: an individual moved out before the end of the mini panel (but whose household did not rotate out), perhaps there were "unusual circumstances" that resulted in no information being recorded,[23] or even the matching across months was poor.[24] Although one cannot separate out the importance of each, one can say that as a group they represent a small proportion of the sample.[25]

Given that the LFS is not a panel per se, one must rely on a series of variables to match an individual's information over time (see the appendix for more details). We thus verify that we are indeed following the same person over time. We follow the lead of Rivera Drew

[22]The composition of individuals would change across time for all other rotations. For example, those that are part of the January rotation would rotate out of the survey as of June, and would be replaced by a new set of households as of July.

[23]This could be due to a household changing its mind and not wanting to share information any further, or the LFS not being able to find a "donor" for possible record imputation, to name just a couple of reasons.

[24]This could be due to a problem with the matching variables.

[25]For the two consecutive month panels, for example, it is only a couple of percentage points.

et al. (2014) and drop observations for which there are inconsistencies in age (in years) and gender across time. These variables should not change over time (other than becoming one year older) as the age and gender questions are asked of when an individual first enters the survey.[26] We lose very few observations due to this restriction.

3 Non response and imputation during COVID-19

The COVID-19 pandemic and the ensuing policy restrictions thoroughly disrupted economic activity of many countries. Statistical agencies were not exempted, as their collection activities were severely constrained. This has, to a certain extent, been documented for the U.S., (e.g. CPS: U.S. Bureau of Labor Statistics (2020*b*)), but very little is known for Canada (e.g. LFS), which raises important concerns about our current assessment of the impact of COVID-19 on the Canadian labour market. This section attempts to fill the gap in the literature.

We start by first documenting the LFS non-response problem. Figure 1 shows non-response rates (for the LFS) covering the January 2019 through June 2020 period. One can see a dramatic rise starting in March 2020, with the non-response rate reaching 28.2% by June 2020. To put these recent numbers into perspective, the monthly non-response rate had only exceeded 13% twice (14% in July 2018; 13.4% in August 2018) since the start of the modern day LFS, i.e. since 1976.[27]

To understand the implications of such a rise, we take advantage of information on when respondents entered the survey, and whether their labour market information was imputed, information that is suppressed in the public-use files.[28] If one looks at figure 2, one can see that prior to the COVID-19 shock, approximately 11,000 individuals per month entered the survey as part of the incoming rotation group, i.e. people in the first month of their six-month window.[29] By March 2020, however, this number had dropped by about a third as compared to the previous month. The number did start to recover as the country started to re-open, but it has never returned to its pre-COVID levels.

At first glance, it would appear that non response is mainly an incoming rotation issue, since the number of observations in the March sample fell by a similar amount (see figure 3), i.e. it was just hard to get a hold of "new" respondents. In fact, the story is more nuanced.

[26] The LFS records the exact date of birth (i.e. day, month and year). As such, a person's age could change from one month to the next, i.e. increase by one year.

[27] See Brochu (2020) for a detailed discussion of LFS non-response rates.

[28] The conclusions that we draw below are not sensitive to these sample restrictions.

[29] This number does not measure all new participants to the survey. Some individuals enter part-way through the six-month window, but this is a relatively small fraction of new entrants.

The suspension of all field collection activities resulting from the COVID-19 shutdown not only made it much more difficult to initially contact new LFS units (households), it also made it difficult to follow up with units that were hard to reach by telephone.[30] This is confirmed in the data. If a household does not respond in the current month, but had responded in a previous one (and there is no indication that the residents of the households had moved out), the LFS will carry forward their socio-demographic information, but impute their *current* labour market information. The LFS follows a hot-deck procedure, where it uses previously collected information (socio-demographic and also some labour-market related) to find a current "donor".[31] As such, the drop in the overall sample size does not give justice to the true extent of the non-response problem experienced during these COVID times. Fortunately, the confidential-use LFS files can identify individuals for which all labour market information was imputed (which Statistics Canada refers to as whole record imputation (WRI)).

From figure 3, one can see that WRI (the gap between the two curves) has increased since February, which is indicative that non response is not just an incoming rotation issue.[32] If one looks at March, for example, one sees that the drop in the sample that excludes WRI (which accounts for both non response of new households, and of those households that had answered in the past), is in absolute terms, two-thirds larger than the drop in the incoming rotation as shown in figure 1 (which only accounts for non response of new households).

An important question to address is whether the increase in non response, as measured by the rise in WRI, impacts the data. To look at this issue, we present in table 1 five labour-market summary statistics which have been extensively analyzed in the COVID literature (i.e. employment rate, unemployment rate, participation rate, temporary layoffs as a share of the labour force, and employed but absent from work as a share of total employment) for samples with and without WRI. We show numbers for February, April and June, and also for the different panels that we rely upon in various parts of our analysis.[33] For comparison sake, we also show numbers using cross-sectional data. Focussing on the first column of results, the pre-COVID period, one can see that the February numbers (e.g. February employment rate) are similar from one panel to the next, and also with the ones that rely on cross-sectional data. The same holds true when we look at the April and June rates. This is not surprising

[30]This information is based on email conversations with a Statistics Canada methodologist during the late July / early August 2020 period.

[31]It uses the same WRI approach for the case where it cannot reach some, but not all household members. Given the option of proxy response, this is of second order importance. See Statistics Canada (2017) for a more detailed description of the hot-deck procedure, and the exact list of variables used to find a donor.

[32]It is important to recognize that the LFS cannot carry out WRI for non-respondents that are part of the incoming rotation group, as there is no prior information that can be used to find a donor.

[33]For example, the February employment rate when using our balanced two-month panel spanning the months of February and March is 76.6%. When using a three-month panel spanning a five-month period (i.e. February, April and June data), the February rate stands at 77.4%.

given that dropping individuals when they rotate out of the LFS is the single most important reason for why our sample shrinks when the length of the panel increases.

What is of particular interest, however, is that dropping individuals whose labour-market information was fully imputed has very little effect on our findings (see table 1). A similarity between the two sets of numbers does not necessarily mean that the imputation procedure got it right, but it is reassuring nevertheless.[34] There are institutional and historical considerations that would lend credibility to this interpretation: first, labour force status and occupation (in addition to socio-economic characteristics) are used to find a donor for imputation. That occupations be relied upon is critical in the present context given that COVID-19 affected occupations very differently (Lemieux et al. 2020). Second, although historically high by LFS standards, a non-response rate in the mid- to late-20s is not unchartered territory for statistical agencies. More precisely, Statistics Canada (and other statistical agencies around the world) have faced rising non-response rates over the last 20-30 years and they have experienced rates in this ballpark (and higher) for other surveys (e.g. Canadian General Social Survey).[35] Finally, the LFS is a long-running survey which means they have had experience with disruptions to field operations, at least at the regional level, whether they be weather related (e.g. Quebec ice storm (1998); Hurricane Juan hiting Atlantic Canada (2003)) or labour strife (e.g. interviewer strike (2003)).

In sum, this section attempts to provide a better understanding of the impact of COVID-19 on the LFS, and in the process, explore whether the substantive rise in full-record imputation that arose affected the data as measured by some important summary statistics for the current crisis. Further work is needed to fully address this issue, including documenting the characteristics of those whose labour market information was fully-imputed during COVID-19.

4 Labour market flows

4.1 Worker flows in and out of employment

The Canadian labour market underwent dramatic changes since the beginning of the pandemic. Severe employment losses that occurred between February and April, were followed by a strong rebound between April and July. Yet, employment is still significantly below its

[34] It is similar to the case when carrying out regression analysis with and without weights. It is comforting when the results are similar, in that the findings are not dependent on whether the statistical agency calculated the weights correctly.

[35] See Barrett et al. (2014) and Green & Milligan (2010) for a discussion of this worldwide phenomena, and its implication for researchers.

pre-COVID level. While most of the discussion has focused on employment changes in net terms, little is known thus far about gross worker flows that underlie these changes. We use the longitudinal dimension of our LFS data to analyze monthly worker flows in and out of employment over the February to July period. This allows us to draw a picture of worker movements from the month just before the propagation of the virus, up to the late reopening stages of the economy.

Using our two-month mini panels, we estimate the total number of workers that flow between employment and non-employment from period $t-1$ to period t, and the employment stock in period $t-1$. Our flow rate for period t is the ratio of these two estimates. Expressing total flows between month $t-1$ and t, in terms of employment as of period $t-1$, is done to remain consistent with the existing studies that have analyzed the impact of the pandemic on employment changes (e.g. Lemieux et al. (2020)). For instance, the separation rate for April would be the number of workers flowing out of employment between March and April expressed in terms of total employment in March. More details are provided in appendix A.2.

The upper panel of table 2 reports gross monthly flows in and out of employment for 2020 (and 2019 for comparison). Unsurprisingly, there were unusually high separation flows over the February to April 2020 period. The February-March and March-April gross outflows are 7.5% and 13.9%, respectively. In comparison, the outflow rates for the same periods in 2019 (and for 2018, as found in appendix table A1) are much lower, falling in the 2-3% range. Interestingly, inflow rates (i.e. hiring) during these months are similar to those of 2019 (and 2018), which is perhaps unexpected given the strictness of the restrictions imposed on the economy at this time. This evidence suggests that the dramatic COVID-led job losses are not due to a decline in hirings, but solely driven by massive flows out of employment. As such, the impact of the COVID-19 shutdown is likely much larger than previously believed. In absolute terms, the cumulative outflows between February and April represent 3.6 million job losses (versus 2.5 million for the net job losses).

A second takeaway of this table is that the reopening months are also characterized by high outflows: for May-June, the separation rate stood at 6.5%, and around 5% for June-July. Therefore, the rebound observed over the months of May and June masks substantial "churning", as measured by the very high worker reallocation rates observed in these months, as compared to the previous years (see tables 2 and A1). In effect, it hides job losses that are remarkably important. Moreover, there is a discernible asymmetry between the size of the outflows of the early pandemic phases, and that of the inflows seen during the reopening. This asymmetry, combined with the persistently high outflow rates, both contribute in explaining why employment has yet to recover to its pre-COVID level.[36]

We complement this analysis by examining the movements due to absence from work. It has been argued that these absences have surged during the shutdown, partly due to the misclassification of temporarily laid-off workers as being employed but absent from work (e.g. U.S. Bureau of Labor Statistics (2020*a*), Jones et al. (2020)). Our estimates of employment flows could be contaminated by this misclassification issue as well, which may understate the size of the labour movements due to COVID. To address this concern, we report in the bottom panel of table 2 estimates of flows in and out of the LFS category "employed, at work". However, we enlarge this grouping to include employment absences that are least likely to be related to the outbreak (i.e. vacation, parental leave and labour conflicts). As such, our "employment, at work" outflows focus on transitions to non-employment, and to employment absences due to illness, caring for relatives and no availability of work. Inflows are similarly defined. As expected, this approach tends to produce larger flow estimates. The broad picture, however, is similar to that of the employment-flow dynamics. In particular, the at-work dynamics features high separation rates starting in February and persisting in the late spring and early summer (as compared to 2019).

4.2 Composition of worker flows

Further analysis of these unusual dynamics is key to understanding the employment recovery. In particular, assessing the degree of persistence in the massive COVID-related job losses is critical in evaluating the strength of the rebound. A first step of this analysis is to look at the composition of the employment flows using more detailed labour force status information. It has been documented that the recent downturn was characterized by a dramatic increase in the stock of workers classified as "unemployed, on temporary layoffs", as compared to previous recessions (e.g. Jones et al. (2020), Statistics Canada (2020)). This suggests that many of the job losses were only temporary in nature, and have been or will be recovered. To some extent, this seems to be confirmed in the data by a decline in the number of temporary unemployed workers since the beginning of the reopening. However, by looking only at the stocks, it is difficult to tell whether such decline is indeed due to reemployment of these workers, or instead due to flows into search unemployment and inactivity.

Table 3 shows the share of the total employment flows (i.e. flows in and out of employment) for individuals transitioning to and from temporary unemployment, search unemploy-

[36] See tables A4 and A5 for estimates of employment flows by occupation groups. The tables show high employment outflows and churning in all the occupation categories considered (as compares to 2019). It also reveals significant heterogeneity across occupations, with the highest job losses experienced in the 'sales and services', 'arts, culture and recreation', and 'manufacturing' sectors.

ment, and out of the labour force (NILF). Clearly, the temporary-unemployment share is remarkably important as compared to previous years: it represents about one-third of outflows, while it is typically around or below 5% in 2018 and 2019 (see appendix tables A2 and A3). This simple fact, which is in line with the surge in the temporary unemployment stock, is a good illustration of the very unusual nature of the employment inflows and outflows in recent months. The reopening stages are also characterized by a large share of employment inflows from temporary unemployment, as suggested by the May to July numbers. This indicates that a large reemployment movement took place with the progressive easing of the COVID-19 restrictions, which is consistent with the decline in temporary unemployment over this same period. However, it appears (again) that there is an asymmetry between inflows and outflows, suggesting that a substantial fraction of the COVID-related job losses have not been recovered. Another noticeable feature of the composition of flows is the high share represented by outflows to non-participation (NILF) between February and April (hovering around 50% of the outflows). One must be careful however when interpreting this number given the fine line between labour market statuses in COVID times.[37] Although this suggests that the pandemic shock induced numerous permanent job losses and transitions out of the labour force, it is difficult to gauge the size of these flows given the lack of clear distinction between labour-market states. Our worker transition analysis of the next section will help shed more light on the nature of these movements.[38]

All in all, this analysis allows us to characterize the COVID-time dynamics of the labour market as follows: first, the net job losses of the early stages of the pandemic can be accounted for entirely by massive employment outflows; second, these outflows are persistently high, even during the reopening stages of the economy, which is indicative of significant labour market "churning"; and finally, there is an asymmetry between the size and nature of the separation flows for February to April and the hiring flows for April to July. The size of the outflows is higher, and the temporary layoffs take up a larger share of outflows than inflows. This asymmetry, taken with the persistently high separation flows, accounts for the partial employment recovery observed in July. Additionally, one can observe that the flows out of employment to non participation seem to represent an important fraction of the jobs lost between February and April. However, the murky line between non-employment states in

[37]See Lemieux et al. (2020) who emphasize the grey zone between unemployment and non participation given the fall in job search and hiring activities, and Jones et al. (2020) who stress the fine line between employment and non-employment given the surge in the number of employed but absent from work.

[38]The bottom panel of table 3 shows the composition of flows in and out of the "employed, at work" category, but like the bottom panel of 2, excludes movements due to vacation, parental leave, and labour conflicts. The table indicates that, since the start of the outbreak, the majority of the outflows from this stock has been towards absence from work, but that a substantial fraction (around one quarter) has been towards non-participation.

COVID times prevents us from drawing strong conclusions about the implications of this fact for employment dynamics, at least at this stage of the analysis.

5 Worker transition analysis

5.1 Trajectories of early-pandemic job losers

Our worker-flow analysis of the previous section suggests large employment inflows for COVID job losers as social-distancing restrictions eased. However, these inflows do not offset the large employment outflows of the early pandemic stages (February to April), given that employment is still significantly below its pre-COVID level. Moreover, as we move beyond the reopening, it appears that the share of employment inflows from temporary unemployment is on the decline. The employment dynamics of the upcoming months will critically depend on the nature of worker trajectories associated with these flows. What explains the asymmetry between the outflows of the early stages and the inflows of the reopening phase? This asymmetry and the partial employment recovery are consistent with two opposite interpretations, with completely different implications for the employment dynamics in the ensuing months. First, this could be due to a staggered but steady return to work of COVID job losers as a result of the gradual easing of social-distancing restrictions, and the adaptation of businesses to the new environment. Alternatively, this could be attributable to permanent job losses, which would cause workers to slowly reallocate across jobs, occupations, and industries, or even lose their attachment to the labour market.

Analyzing the trajectories of workers since the beginning of the pandemic could be informative for the relative importance of the two possible interpretations discussed above. Specifically, looking at the transition patterns for workers who have lost their job due to COVID factors can help us better understand the labour-market dynamics of the reopening phase. As such, accurately identifying these workers is key. To do so, we once again make use of the detailed labour market status information regarding unemployment and absence from work. Given the dramatic rise in the number of temporary layoffs and absences from work (other than vacation) during the lockdown months, we can use this labour market information to create a sample that is, arguably, a reasonable representation of the COVID job losers. Moreover, and perhaps more importantly, we can take full advantage of the longitudinal dimension of our panel to analyze four- to six-month worker histories spanning the economy's trajectory over the February to July period. The analysis below is based on these approaches

Table 4 reports, for April to July, the monthly transition probabilities of workers from temporary unemployment (i.e. unemployed, on temporary layoff), and those classified as employed but absent from work (excluding, again, absences due to vacation, parental leave, and labour conflict). The temporary unemployed have high monthly transitions to employment, standing at around 50% from April to July. This is consistent with our worker-flow analysis, which suggests large reemployment flows after April. However, it seems that the fraction of workers flowing to states with presumably low job attachment has been increasing over time since the start of the reopening: between June and July, almost 40% of the temporary unemployed have transited to search unemployment and non-participation. The trajectories of those absent from work also display increasing flows to low job-attachment states, but to a lesser extent: the transition rate of this group to search unemployment and non-participation is around 18% over June and July.

However, this analysis provides an imperfect picture of the trajectories of COVID-19 job losers, as temporary unemployment and absence from work might be subject to seasonal variations not related to the pandemic, especially when looking at summer months. Table 5 analyzes trajectories of the workers employed in February (i.e. the month just before the beginning of the propagation of the virus in Canada) *and* non-employed in April, when social distancing restrictions were peaking. The transitions suggest again important reemployment flows upon reopening: the share of these workers flowing back to employment after April is increasing over time, and as of July, approximately two-thirds of this group are employed again. However, with these numbers alone, it is difficult to gauge the size of these reemployment flows, given that the composition of workers with similar histories in previous years is probably very different due to the pervasiveness of the COVID shock. Hence, to get an additional sense of the magnitude of these flows, we compare the trajectories of workers employed in February 2020 (i.e. before the pandemic) with those employed in the same month in 2019 (see table 7). The probability of being employed in July (conditional on employment in February) is 88.4% for the 2020 group, versus 94% for 2019; the 2020 group is also slightly more likely to be non participating in July (6.2% versus 3.8%). When put in perspective — accounting for the severity of the COVID shock — these numbers can be seen as reassuring regarding the strength of the reemployment dynamics of the reopening phase.[39]

These numbers, however, might hide important heterogeneity. To address this issue, we conduct the transition analysis of table 5 by looking at trajectories of workers conditional

[39]We find, moreover, that the majority of these reemployed workers went back to their previous industry and occupation. Table 6, reports the probability of remaining in the same industry/occupation between February and the months of May, June, and July, conditional on being non-employed in April. The table shows that the majority of these workers did not experience an industry or occupation switch, even when considering the most detailed classifications (5-digit NAICS industries and 4-digit NOC occupations), which suggests that many of them went back to their previous employer. It appears, moreover, that the probability of no switch is especially high for the temporarily unemployed in April.

on the detailed out-of-work status in April. This reveals important differences in trajectories of workers who were out of work but presumably kept a link with their former employer (i.e. those in temporary unemployment and absent from work), and the group of workers who were classified as out of the labour force. It appears that a large majority of those with an employer attachment have been reemployed, but the picture looks very different for those who were NILF in April. As of July, only 58.4% of the NILF group was reemployed, versus 75.9% for the temporary laid-off group. Given that, as emphasized in the worker-flow analysis, a large share of the employment outflows of the early pandemic stages was towards non-participation (see table 3), the staggered return to work of this group is presumably key in accounting for the incomplete employment recovery of July. Importantly, this also indicates that the behaviour of these workers in the next months might be an important determinant of the pace at which the labour market recovers.

All in all, the transition analysis suggests important heterogeneity in the trajectories of the COVID job losers, which is in line with the now well-established idea that the shock is being felt very differently across occupations and industries. Many appear to have regained employment, especially among those who were classified as temporarily out of work (temporary laid-off and absent from work). But even among this group, there are some signs of a fading link with pre-COVID employers, as suggested by increasing transitions to search unemployment and non-participation since the start of the reopening. In addition, and perhaps most concerning, the numerous workers who have transited from employment to non-participation between February and April seem to be having a hard time regaining employment. Understanding the sources of this heterogeneity might be key for drawing implications about the nature of the recovery. Moreover, this will be crucial for understanding the distributional impact of the pandemic.

5.2 Trajectories of non-employed individuals

Our discussion of the labour market trajectories during COVID-19 has focused on the experience of recent job losers at the expense of individuals who had been out of work before the pandemic. Table 2 indicates that, upon the reopening, temporary unemployment represents a higher than usual share of employment inflows. In addition, the large employment probabilities of workers temporarily out of work in April (and employed before the pandemic, see table 5) suggest that reemployment flows account for a large share of the reopening employment gains. On still needs to evaluate the trajectories of individuals out of work at the time of the initial COVID shock if on is to better understand the employment dynamics during the pandemic. Assessing how the sizeable employment inflows have benefited individuals without a prior job is important for drawing distributional implications of the outbreak. Moreover, in a typical year, non-employed individuals classified in search unemployment or in non-participation — i.e. without any obvious attachment to a given employer, as opposed to workers classified as temporarily laid-off — represent the lion's share of employment inflows (see appendix tables A2 and A3). Therefore, although the current discussions have been mainly focused on labour market outcomes of the COVID-19 job losers, the fact remains that the trajectories of individuals out of work prior to the pandemic are likely to matter a great deal for employment dynamics.

Table 7 reports employment and unemployment probabilities for May to July, of individuals not employed in February (for 2019 and 2020). The table indicates that the employment probability of the 2020 group is quite low when compared to similar workers in 2019, and when contrasted with the reemployment dynamics of the reopening. This is true for both unemployed and non-participating individuals who report wanting a job in the LFS, i.e. for workers who can be considered as attached to the labour market. In 2020, a worker who was unemployed in February had a 42.8% probability of being employed in July; in 2019, the same employment probability was 55.8%. Strikingly, an individual not in the labour force but wanting a job in February was two times more likely to be employed in July in 2019 than 2020 (32% versus 16%).

5.3 Trajectories conditional on individual and job characteristics

We complement our analysis by looking at individuals' trajectories, conditioning on socio-demographic and job characteristics. The severity of the shock and the high churn experienced by the labour market suggest that the pandemic has important distributional consequences. This is in line with what has been documented in the existing literature (e.g. Lemieux et al. (2020), Béland et al. (2020a)). We address the three following questions: 1) how has the initial impact of the COVID shock been distributed across workers and jobs? 2) What characteristics are correlated with reemployment in the case of the pandemic job losers? And 3) how has the trajectories of the different subgroups of the pre-COVID non-employed been affected? Given that the focus of the paper is on job mobility, our outcomes of interest are individuals' transitions across labour force states. Specifically, we look at transitions from February to July in order to follow workers along the different phases of the pandemic.

The initial impact of COVID-19 on job losses. We examine the impact of COVID-19 on gross job losses across groups of workers, by relying on mini panels for 2019 and 2020 (covering the months of February and April).[40] The econometric model takes the following form

$$y_{i,m,s} = \alpha_0 + \alpha_1 d_s + X'_{i,s}\beta + \left(d_s \times X'_{i,s}\right)\gamma + \varepsilon_{i,m,s}, \tag{1}$$

where $y_{i,m,s}$ is a labour-force-status dummy for individual i as of m = April in year $s \in \{2019, 2020\}$,[41] and d_s is a dummy variable taking the value one if the individual is observed in 2020. $X_{i,s}$ is a vector of indicator variables for socio-demographic and job characteristics for individual i as of February in year s. The socio-demographic variables consist of female and aboriginal indicator variables, dummy variables for age,[42] highest educational attainment,[43] young-child parenting interacted with the female indicator,[44] and province of residence. For the job characteristics variables, we have dummy variables for union status (i.e. member or covered by a union), job-tenure situation,[45] and one-digit occupation groups.[46]

The sample consists of individuals employed in February (in 2019 and 2020) and observed in the data two months later (i.e. April).[47] We consider two sets of regressions. First, we analyze transitions to non-employment (i.e. $y_{i,m,s} = 1$ if individual i is not employed in month m (i.e. April) of year s, 0 otherwise), to better understand the composition of the high job loss flows of the shutdown (see table 2). Second, we analyze transitions to non participation (i.e. $y_{i,m,s} = 1$ if individual i transits to non-participation in month m (i.e. April) of year s, 0 otherwise). Given the large share of employment outflows to non-participation (see table 3) and the low reemployment probability of the NILF in April (table 5), we deem important

[40] More precisely, we rely on two panels: the two-month panel spanning the February 2019 to April 2019 period, and the two-month panel spanning the February 2020 to April 2020 period.

[41] We present the equation in a general form by using an m subscript for the month as to be consistent with the notation used in the subsequent analysis, where the month of observation is allowed to vary.

[42] Age dummies: 20 to 29, 40 to 49, and 50 to 64. Those that are 30 to 39 years of age are the reference group.

[43] Highest educational attainment dummies: dropout, college (post-secondary/trades certificate, community college, CEGEP and university certificate below bachelor's), and bachelor's degree and up. The reference group consists of those that have no more than a high school degree (and also includes those that have some post-secondary education but no certificate, diploma or degree).

[44] More precisely, a binary variable that equals one if the person is female and has a child under the age of six.

[45] Job tenure dummies: 1 to 11 months, and 12 to 35 months. Workers with 36 months or more of job tenure with the same employer are the reference group.

[46] We use the NOC's ten larger categories (i.e. one-digit groups). Health is the reference group. Including broad occupation groups instead of exploiting more detailed NOC information has the advantage of allowing us to analyze heterogeneity across occupations based on the coefficients of the associated dummies. An alternative approach, that could be followed in further research using the LFS, is to analyze transitions conditional on task-content index values (e.g. potential for remote work, public facing), as in Cheng et al. (2020).

[47] The unit of observation is a person (with data for February and April) in a given year: each person is only observed once in the sample, i.e. in 2019 or 2020. For each person one has their labour force status in April and their socio-demographic and job characteristics as of February (i.e. two months earlier).

to examine the characteristics of the NILF job losers. For each regression set, we add the covariates sequentially.

The results are reported in table 8. Column (1) focusses on the probability that an individual employed in February will be non-employed in April (of that same year), whereas Column (4) focusses on whether the individual employed in February will be in the non-participation state in April (again of the same year). In both cases, the only explanatory variable is the year dummy. These estimates, which complement the flow analysis of section 4 give a good illustration of the severity of the initial shock. For instance, the coefficient estimate (of the year dummy) suggests an increase in the job loss likelihood of 14 percentage points in 2020, as compared to 2019. Given the considerable magnitude of the shock, it might be reasonable to attribute such a change to the virus. The probability of transition to non-participation is also very large compared to 2019 (i.e. an additional 7 percentage points), reflecting the important share of employment outflows towards non-participation highlighted in our flow analysis (table 3).

Columns (2) and (4) analyze transitions to non-employment and non-participation, but where we now add demographic covariates, on their own and interacted with the year dummy. Our estimates suggest a higher probability of job loss for women than men, as well as higher transitions to non-participation. The differential effect seems of substantial magnitude and is highly significant. This is in line with the literature documenting a more severe impact on women in the U.S. But this contrasts with the existing evidence for Canada that is mixed: for instance, Béland et al. (2020a), looking at net changes, find no distinguishable difference across genders. Looking at gross job losses offers a different picture revealing a clear negative effect for women relative to men. The estimates also reveal higher transitions to non-employment for youths (20 to 29 year olds) as compared to those 30 to 39 year of age, and to a lesser extent, for lower level of educations (as compared to college and up).

Columns (3) and (6) add job-characteristics covariates. The estimated impact is substantially higher for low-tenure jobs. Tenure below one year was associated with an additional 5 percentage points job-loss probability, as compared to workers that had been with their employer three or more years. This is consistent with the literature arguing that low-tenure jobs are the most fragile due to heterogeneity in match quality (e.g. Jung & Kuhn (2019)) and information frictions (e.g. Jovanovic (1979), Pries & Rogerson (2005)). Obviously, industry and occupation might also play a role. Unsurprisingly, there are important differences across occupations, which tend to be amplified when looking at flows. For instance, being employed in sales and services (as compared to health) was associated with an additional 10 percentage point job-loss probability. Note that controlling for job characteristics attenuates the coefficient for the youth age group; this suggests that occupations and especially tenure might play a key role in accounting for the high impacts for youths.

Reemployment probability. We examine reemployment patterns of the early-pandemic job losers, using mini panels for 2020 only.[48] Our econometric model is as follows

$$y_{i,m} = \phi_0 + X_i' \psi + \nu_{i,m}, \tag{2}$$

where $y_{i,m}$ is a labour force status dummy for individual i in month $m \in \{\text{May, June, July}\}$. X_i are individual socio-demographic and job characteristics as of February. We estimate equation (2) for each m separately, and as such, the sample varies with m. More precisely, for each month m, the sample consists of workers employed in February but not in April, and for whom we observe their labour force status in month m.[49]

We explore the reemployment transitions, and to further understand the trajectories of job losers we also look at the transitions out of the labour force. As previously done, we add the covariates sequentially: we first only include the socio-demographic variables, and then add the job characteristics.

The results for reemployment transitions are reported in table 9, whereas those for transitions out of the labour force are presented in table 10. The estimates indicate lower reemployment probabilities for women than men for May and June, which suggests that women have more difficulties regaining employment upon the reopening (columns (1), (3), (5)). Controlling for job characteristics attenuates the gender differential, suggesting that part of the difference could be due to occupation composition (columns (2), (4), (6)). Indeed, we observe large differences across occupations in terms of reemployment, with low reemployment probabilities for education and social services or arts and culture (as compared to health).

The results also suggest a distinct reemployment patterns for individuals 50 to 64 years of age. These individuals have remarkably low reemployment probability in July relative to other groups (column (6) of table 9). At the same time, they were significantly more likely to exit the labour force in June, and especially in July (column (6) of table 10). These results align with Coibion et al. (2020), which would suggest that a large numbers of older workers are retiring early due to the virus. This possibility, combined with the typically low job-finding probabilities of these older workers, raises concerns about the pace at which employment will recover.[50] Further research should analyze the mechanisms behind these

[48]More precisely, we rely on three panels: the three-month panel covering February, April and May; the three-month panel covering February, April and June; the three-month panel covering February, April and July.

[49]The unit of observation is a person. For each person i one has their labour force status in month m and their socio-demographic and job characteristics as of February.

[50]As explained by Coibion et al. (2020), retired individuals typically have very low rates of entry into the labour market.

labour-market outflows.[51]

The effect of COVID-19 on the trajectory of the non-employed. We now analyze the impact of COVID-19 on the trajectories of individual who were non-employed before the pandemic. We consider again model (1), but focusing now on those who were non-employed (and also the sub-group of non-participants) in February and who we observe in month m of the same year, for $m \in \{\text{May, June, July}\}$. We again use data for 2019 and 2020. We analyze transitions to employment, i.e. our dependent variable, $y_{i,m,s}$ is a dummy taking the value of one if individual i (who was not employed in February) is employed in month m of the same year. Table 11 shows regression results for the sample of workers who were unemployed in February, and table 12 for non-participating individuals. Again, we present separately results for the unconditional-mean 2020 effect and for after adding individual characteristics.

Columns (1), (3), and (5) of table 11 show the impact of the economy's reopening on the employment probabilities of those who were unemployed in February. The virus seems to have had a strong and significant negative impact on these workers, which confirms the results of table 7. The effect is quite persistent as it lasts even during the late phase of the reopening. This is in stark contrast with the strong (but partial) rebound of the reopening, and the large reemployment flows for certain groups of workers (table 5). Table 12, which focusses on those out of the labour force in February, suggests a lower average impact for this group as compared to the unemployed. However, there is heterogeneity within this population. Moreover, the result suggest a relatively high negative effect on the non-participating youths, at least for June (see column (5)). This, taken with the high job loss rates for youths (and discussed above) can be seen as a sign of relative vulnerability.

6 Conclusion

This paper analyzes the dynamics of the Canadian labour market from the beginning of the propagation of COVID-19, and the ensuing lockdown, to the reopening of the economy. We take advantage of the longitudinal dimension of the confidential-use files of the Labour Force Survey to analyze the size and composition of employment inflows and outflows, and to examine worker trajectories over the course of the pandemic. Our analysis shows that the Canadian labour market has experienced high "churning", which has persisted even after the easing of social distancing restrictions. We find evidence suggesting large reemployment flows of recent job losers, especially among workers who have been temporarily laid-off during the lockdown. There is, however, important heterogeneity in worker trajectories in

[51] Moreover, it is important to understand the motive for leaving the labour force and the profile of the leavers for assessing the implications of the crisis for the evolution of wealth and consumption distributions.

recent months. Even for those who seemed to have temporarily lost their jobs, we observe increasing transitions to job-search unemployment and non-participation, which suggests an erosion of the link with previous employers. Even more concerning, is the evidence suggesting reemployment difficulties of COVID job losers who are classified out of the labour force in April, and the unusually low job-finding rate of workers not employed prior to the pandemic. Examining more closely the outcomes and behaviour of these groups might be key to drawing implications about the labour market recovery moving forwards, and for distributional consequences of COVID-19.

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A Appendix

A.1 Creation of mini panels

In this appendix we provide information on how we construct our LFS mini panels.

The LFS follows a rotating panel design where households stay in the sample for six consecutive months. Every month one-sixth of the sample (i.e. households) is replaced by households in a similar area. The LFS is officially designed to generate cross-sectional samples; it follows dwellings and not individuals. If, for example, an individual leaves the dwelling part way through the six-month window, he/she is beyond the scope of the survey. Similarly, an individual that joins a household late will only be asked labour market information as of the time he/she started living in the targeted dwelling/household.

The LFS does not have a single person identifier variable. For our period of interest, one can nonetheless uniquely identify individuals across monthly files using the following two variables: the LFS household identifier (HHLDID), and the LINE variable that (uniquely) identifies a person within the household. The HHLDID variable (also called DWELID) is in fact made up of 10 variables (PROV, PROV1, PSEUDOUI, FRAME, STRAFRAM, TYPE, CLUST, ROTATION, LISTLINE and MULT). Once combined, they generate the unique 18-digit household/dwelling identifier.

It should be noted that for earlier periods (i.e. prior to 1996), the creation of mini panels requires the use of different sets of variables. See Brochu and Green (2013) and Brochu (2020) for details.

A.2 Worker-flow computation

Labour-market flows are computed using two-month panels. We compute the separation rate as:

$$\text{outflows}_t = \frac{\sum_i \omega_{i,t-1}\mathcal{I}(E_{i,t-1}=1, E_{i,t}=0)}{\sum_i \omega_{i,t-1}\mathcal{I}(E_{i,t-1}=1)},$$

for all period t in the sample of interest, and where $E_{i,t}$ is a dummy taking value of one when individual i is employed in t, $\mathcal{I}$ is the indicator function, which takes the value of one when the expression in parenthesis is true and zero otherwise, and where $\omega_{i,t} \geq 0$ represents the LFS weights of individual i in period t. Similarly, we compute hiring flows as:

$$\text{inflows}_t = \frac{\sum_i \omega_{i,t-1}\mathcal{I}(E_{i,t-1}=0, E_{i,t}=1)}{\sum_i \omega_{i,t-1}\mathcal{I}(E_{i,t-1}=1)},$$

for all t in the sample. Using these outflow and inflow measures, excess reallocation flows are computed following:

$$\text{excessflows}_t = \text{inflows}_t + \text{outflows}_t - |\text{inflows}_t - \text{outflows}_t|,$$

for all t in th sample. Resulting measures of flows are reported in tables 2 and A1. We compute flows in and out of the LFS category "at work" (excluding workers on vacation, parental leave, and absent due to labour conflicts), as in table 2, and by occupations, as in tables A4 and A5, following the same approach (considering flows in and out of employment, and in and out of given occupation groups).

B Figures and tables

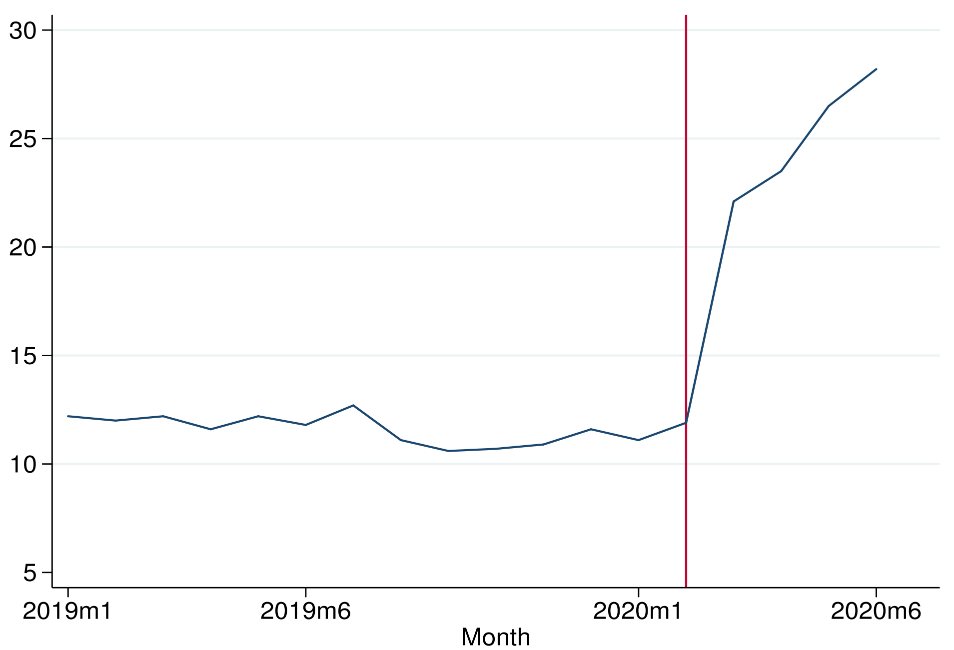

Figure 1: Monthly household non-response rates (%). Data provided to the authors by Statistics Canada. Share of households in the monthly LFS with no available information. The red vertical line indicates February 2020. The data includes all LFS households in the ten Canadian provinces.

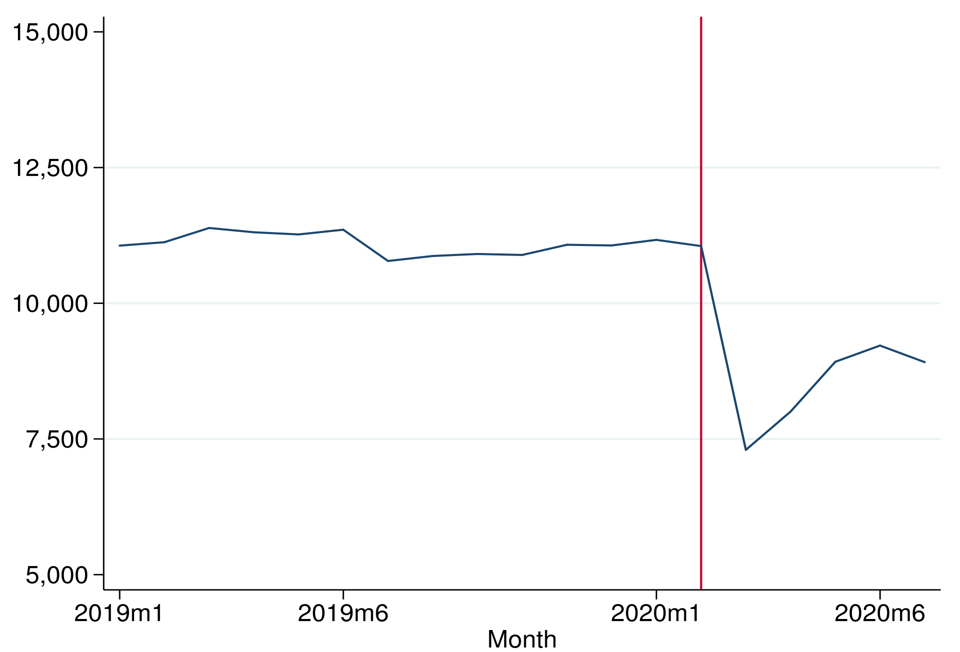

Figure 2: Sample size of incoming rotations. Source: Authors' calculations. Number of individuals in the incoming rotation group in each month of the LFS. The red vertical line indicates February 2020. Monthly cross-sectional samples of individuals aged 20 to 64, from all ten Canadian Provinces, excluding full-time members of the armed forces. See sections 2 and 3 for further information about samples used in the analysis.

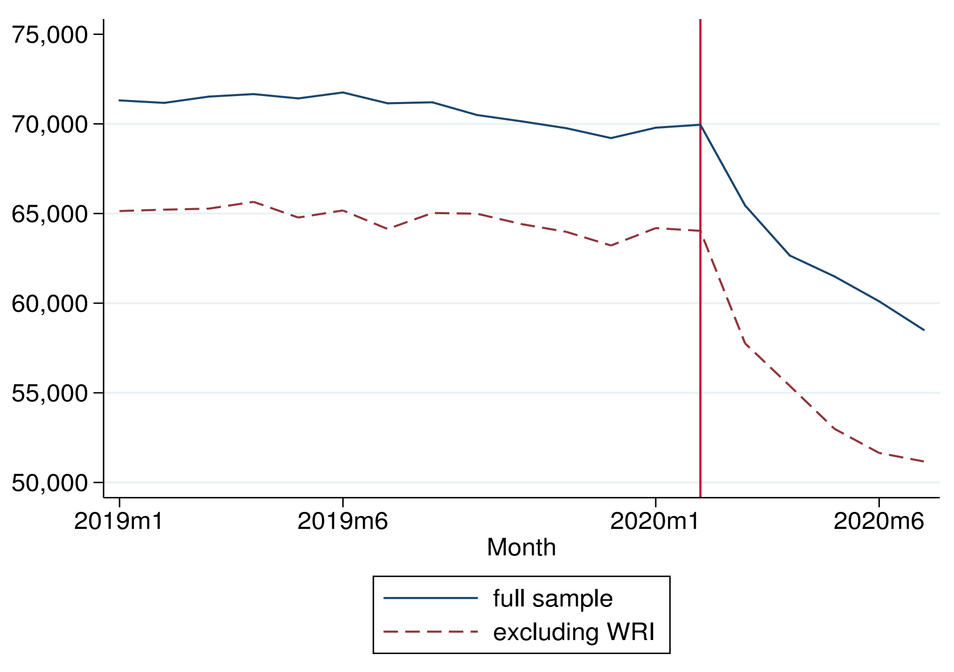

Figure 3: Sample size with and without whole record imputation (WRI). Source: LFS and authors' calculations. The blue plain line shows the total number of individuals in the sample and the red dotted line shows the number of individuals after excluding those for whom LFS information has been fully imputed. The red vertical line indicates February 2020. Monthly cross-sectional sample of individuals of individuals aged 20 to 64, from all ten Canadian Provinces, excluding full-time members of the armed forces. See section 2 and 3 for further information about WRI issues in the LFS.

Table 1: Labour-force estimates for select samples, 2020

	February		April		June	
	all	no WRI	all	no WRI	all	no WRI
Employment rate (%)						
Cross-section	76.5	76.7	65.5	65.6	71.8	72.1
Consecutive-month panel	76.6	77.2	65.9	66.0	72.1	72.1
Three-month-span	76.8	77.2	66.5	66.4	–	–
Five-month-span	77.4	77.9	–	–	–	–
Unemployment rate						
Cross-section	5.5	5.4	12.9	13.0	11.0	10.7
Consecutive-month panel	5.5	5.3	12.7	12.5	10.9	10.7
Three-month-span	5.6	5.2	12.5	12.6	–	–
Five-month-span	5.2	4.9	–	–	–	–
Absent from work (employment share)						
Cross-section	7.3	7.4	20.9	20.7	11.8	11.9
Consecutive-month panel	7.3	7.4	20.7	20.4	11.8	11.8
Three-month-span	7.3	7.3	21.0	20.3	–	–
Five-month span	7.5	7.3	–	–	–	–
Temporary unemployment (labour-force share)						
Cross-section	0.3	0.3	6.9	7.1	3.2	3.1
Consecutive-month panel	0.3	0.3	6.9	6.8	3.1	2.9
Three-month-span	0.3	0.3	6.9	7.0	–	–
Five-month span	0.3	0.2	–	–	–	–
Participation rate						
Cross-section	81.0	81.0	75.2	75.4	80.7	80.7
Consecutive-month panel	81.1	81.5	75.5	75.5	80.9	80.7
Three-month span	81.3	81.5	75.9	75.6	–	–
Five-month span	81.6	81.9	–	–	–	–

Notes: select labour-force estimates, for a subset of the samples that are used in the analysis. "Cross-section" refers to the cross-sectional LFS monthly samples. "Consecutive-month" panel refers to the samples of individuals observed for two consecutive months; "three-month-span" panel refers to (1) the sample of individual observed in February and April (i.e. spanning three months from February) and (2) the sample of individuals observed in April and June; "five-month span" refers to the sample of individuals observed in February, April, and June. All samples are for individuals aged 20 to 64, excluding full-time members of the armed forces. In the case of the panel samples, the summary statistics are for the first month in which individuals are observed. "Temporary unemployment" refers to estimates of unemployed workers counted as being on temporary layoff, expressed in terms of the labour force. "Employed, at work" is for the share of employed workers who did not declare being absent from work. In all cases, we show the statistics for the entire sample (under column "all"), and after excluding individuals whose labour force information was fully imputed, i.e. with no whole record imputation (no WRI). All estimations are weighted.

Table 2: Worker flows in and out of employment

	In and out of employment (%)									
	2020					2019				
	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul
Outflows	7.5	13.9	6.7	4.6	5.0	2.3	2.4	2.1	2.0	3.8
Inflows	2.5	3.8	9.8	10.2	5.5	2.3	3.2	3.8	2.5	2.4
Net change	-5.0	-10.1	3.2	5.6	0.5	0.4	0.8	1.7	0.6	-1.4
Excess flows	4.9	7.5	13.3	9.1	9.9	4.6	4.9	4.2	4.0	4.8
	In and out of employment, at work (including vacation, etc.) (%)									
	2020					2019				
	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul
Outflows	17.3	21.9	5.9	4.5	5.6	3.6	4.1	3.4	3.4	5.2
Inflows	3.2	6.5	15.6	15.8	8.2	3.9	4.8	5.5	3.9	3.8
Net change	-14.0	-15.4	9.8	11.3	2.6	0.3	0.8	2.1	0.5	-1.4
Excess flows	6.5	13.0	11.7	8.9	11.2	7.2	8.1	6.9	6.9	7.7

Notes: estimations of monthly employment inflows and outflows, based on two-consecutive-month LFS panels for individuals aged 20 to 64, excluding full-time members of the armed forces. Outflows for period $t-1$ and t is an estimation of the total number of workers employed in $t-1$ and non-employed in t, in terms of total employment in $t-1$. Inflows are computed similarly but are based on estimates of workers transiting from non-employment to employment. Excess flows are defined as total reallocation (i.e hiring + separation) from period $t-1$ to period t, minus the absolute value of the net change (i.e. |hiring - separation|). Flows in and out of the "employment, at work" category are estimated following the same approach. Note, however, that we include workers in the stock of reference who are absent due to vacation, parental leave, and labour conflicts, i.e. we do not consider flows associated with these motives. See appendix A.2 for details. All totals are estimated using samples of individuals observed for two consecutive months. All estimations are weighted.

Table 3: Composition of flows in and out of employment, 2020

In and out of employment (%)	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul
Outflows					
Temporary unemployment	32.5	37.8	32.8	24.5	12.8
Search unemployment	15.9	11.5	16.9	24.9	30.7
NILF	50.0	49.2	48.3	48.7	55.0
Inflows					
Temporary unemployment	4.2	26.8	40.2	35.7	29.7
Search unemployment	36.9	17.6	11.0	17.5	28.3
NILF	56.2	53.7	45.6	42.4	38.9

In and out of employment, at work (incl. vacation) (%)	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul
Outflows					
Absent from work (excl. vac.)	58.2	43.8	45.0	47.0	39.9
Unemployment	21.5	29.8	30.5	25.1	25.7
NILF	20.3	26.4	24.5	27.9	34.4
Inflows					
Absent from work (excl. vac.)	39.1	66.1	47.1	41.2	43.9
Unemployment	30.4	15.7	30.9	36.3	36.1
NILF	30.5	18.3	22.0	22.5	20.0

Notes: analysis of the compositions of employment inflows and outflows. Two-consecutive-month samples for individuals aged 20 to 64, excluding full-time members of the armed forces. Total flows are computed as in tables 2. Share of flows that are towards/from temporary unemployment (i.e. unemployment, on temporary layoff), search unemployment (i.e. unemployed workers declaring searching for a job), and non-participation. The bottom panel analysis the composition of flows in and out of the LFS category "employment, at work", but including workers on vacation, on parental leave, or absent due to labour conflicts. Similarly, the category "absent from work" exclude workers absent due to these motives. See notes in table 2 and appendix A.2 for more details. All estimations are weighted.

Table 4: Monthly transition probabilities of the out of work (%), 2020

	Apr-May	May-Jun	Jun-Jul
From temporary unemployment			
Employment	49.8	57.0	47.4
Employment, at work (incl. vac.)	35.4	46.8	34.7
Search unemployment	5.5	8.5	15.3
NILF	15.9	11.1	18.2
From absent from work (excl. vac.)			
Employment, at work (incl. vac.)	33.8	43.0	37.8
Search unemployment	2.6	3.9	6.5
NILF	11.4	8.7	11.3

Notes: estimation of monthly transition probabilities of workers who are either on temporary layoff or who are absent from work, except due to vacation, parental leave, or labour-conflict motives. Two-consecutive-month LFS panels for individuals aged 20 to 64, excluding full-time members of the armed forces. The category "employment, at work", includes workers absent due to vacation, parental leave, or labour conflicts. All estimations are weighted.

Table 5: Monthly transition probabilities of the early-outbreak job losers (%)

	May	June	July
From non-employment in April			
Employment	37.0	58.0	64.1
Employment, at work (incl. vac.)	24.8	48.4	57.6
Search unemployment	14.1	12.7	12.5
NILF	31.3	17.5	17.9
From temporary unemployment in April			
Employment	52.5	71.4	75.9
Employment, at work (incl. vac.)	37.1	62.9	68.1
Search unemployment	4.6	6.5	7.5
NILF	12.0	7.2	9.0
From absent from work in April (excl. vac.)			
Employment	80.6	85.3	83.9
At work (incl. vac.)	33.1	57.1	66.9
Search unemployment	2.3	2.6	3.9
NILF	9.5	7.8	10.4
From NILF in April			
Employment	29.6	51.6	58.4
Unemployment	8.9	21.7	26.2

Notes: estimation of monthly transition probabilities of workers who lost their job between February and April, conditional on their detailed labour-force status in April. Sample for individuals aged 20 to 64, excluding full-time members of the armed forces. Individuals employed in February, non-employed in April, and observed in May, June, or July. Transitions to "employment, at work" include transitions to absence due to vacation, parental leave, and labour conflicts. Transitions conditional on being absent from work exclude these motives. All estimations are weighted.

Table 6: Probability of no occupation (NOC) or industry (NAICS) switch of the reemployed spring-2020 job losers (%)

	May	June	July
From non-employment in April			
Occupation, 2 digits	76.5	72.5	69.9
Occupation, 4 digits	71.5	66.7	62.5
Industry, 2 digits	88.0	84.6	83.2
Industry, 5 digits	77.1	73.1	71.0
From temporary unemployment in April			
Occupation, 2 digits	78.5	78.1	79.1
Occupation, 4 digits	73.6	74.1	73.0
Industry, 2 digits	89.5	90.6	91.2
Industry, 5 digits	77.5	80.8	76.3
From absent from work in April (excl. vac.)			
Occupation, 2 digits	78.4	75.6	76.6
Occupation, 4 digits	73.4	72.4	74.1
Industry, 2 digits	92.0	90.7	89.5
Industry, 5 digits	78.2	76.9	77.0

Notes: estimation of the probability of no occupation/industry switch conditional on reemployment after a job loss in the spring. Sample for individuals aged 20 to 64, excluding full-time members of the armed forces. Individuals employed in February, non-employed in April, and employed again in May, June, or July. We consider the National Occupational Classification (NOC) and the North-American Industry Classification System (NAICS). "Absent from work" excludes absences due to vacation, parental leave, and labour conflicts. All estimations are weighted.

Table 7: Transition probabilities conditional on LFS status in February (%)

	2020			2019		
	May	June	July	May	June	July
From employment						
Employment	84.2	88.4	88.4	96.5	96.2	94.0
Unemployment	8.1	6.4	5.4	1.6	1.6	2.2
Employment, absent from work	10.6	7.6	5.5	2.8	2.9	2.5
Temporary unemployment	4.6	3.0	1.6	0.1	0.1	0.3
From unemployment						
Employment	29.0	36.8	42.8	46.6	51.5	55.8
Unemployment	40.8	40.0	37.5	38.4	33.0	26.4
From NILF, wants a job						
Employment	15.0	18.5	16.2	25.9	25.9	31.5
Unemployment	17.6	21.8	18.8	14.4	14.3	16.3
From NILF						
Employment	10.9	13.1	14.4	13.7	16.3	17.0
Unemployment	7.9	8.9	9.0	5.4	5.1	4.8

Notes: estimation of transition probabilities of individuals in various labour force states as of February, over the May-to-June period. Sample for individuals aged 20 to 64, excluding full-time members of the armed forces. Individuals non-employed in February and observed in May, June, or July, for 2019 and 2020. The category “NILF, wants a job” refer to individuals classified as not in the labour force in the LFS, but who declare wanting a job (either full-time or part-time). All estimations are weighted.

Table 8: Employment-separation probability in the early phase of the outbreak

	To non-employment			To non-participation		
	(1)	(2)	(3)	(4)	(5)	(6)
Post COVID-19	0.142***	0.150***	0.111***	0.073***	0.085***	0.066***
	(0.003)	(0.010)	(0.016)	(0.002)	(0.008)	(0.013)
Select interaction terms with post COVID-19 indicator:						
Female		0.035***	0.036***		0.027***	0.023***
		(0.007)	(0.007)		(0.005)	(0.006)
20 to 29		0.080***	0.047***		0.054***	0.036***
		(0.010)	(0.010)		(0.008)	(0.008)
40 to 49		-0.024***	-0.007		-0.003	0.005
		(0.008)	(0.008)		(0.006)	(0.006)
50 to 64		-0.017**	0.006		-0.006	0.005
		(0.008)	(0.008)		(0.006)	(0.006)
Dropout		0.023	0.013		-0.003	-0.006
		(0.016)	(0.016)		(0.011)	(0.011)
College		-0.025***	-0.001		-0.017**	-0.003
		(0.009)	(0.009)		(0.007)	(0.007)
Bachelor degree +		-0.088***	-0.041***		-0.050***	-0.025***
		(0.016)	(0.016)		(0.010)	(0.011)
Female × Young child		-0.025**	-0.009		-0.015	-0.006
		(0.012)	(0.012)		(0.010)	(0.010)
Tenure: 0-11 months			0.053***			0.029***
			(0.010)			(0.008)
Tenure: 12-35 months			0.037***			0.016**
			(0.009)			(0.007)
Self-employed			-0.098***			-0.040***
			(0.008)			(0.007)
Union			-0.078***			-0.047***
			(0.007)			(0.005)
Constant	0.032***	0.042***	0.021***	0.018***	0.022***	0.013**
	(0.001)	(0.005)	(0.007)	(0.001)	(0.004)	(0.005)
adj. R^2	0.055	0.082	0.119	0.026	0.045	0.066
N	67,846	67,846	67,846	67,846	67,846	67,846

Notes: estimation of the effect of COVID-19 on job separations between February and April. Sample for individuals aged 20 to 64, excluding full-time members of the armed forces, who are employed in February and observed in April, for 2019 and 2020. In columns (1)-(3), the dependent variable is an indicator for non-employment in April. In columns (4)-(6), it is an indicator for non-participation in April. Columns (1) and (4) show the result of regressions with only a dummy for 2020. Columns (2) and (5) are for regressions with socio-demographic variables (as of February) and their interactions with the 2020 indicator variable. Columns (3) and (6) also include job characteristics (as of February) and their interaction with the year-2020 indicator. Only select interacted variable coefficients point estimate and standard errors are shown in the table. Tables for the full set of coefficients are available upon request. All regressions are weighted. Huber-White robust standard errors shown in parentheses. * denotes statistical significance at 10%; ** significance at 5%; *** significance at 1%.

Table 9: Reemployment probability of the early-outbreak job losers

	May		June		July	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.051**	-0.018	-0.072***	-0.032	0.004	0.029
	(0.021)	(0.024)	(0.028)	(0.032)	(0.039)	(0.047)
20 to 29	-0.048*	-0.015	-0.061	-0.026	-0.037	-0.030
	(0.028)	(0.029)	(0.038)	(0.038)	(0.053)	(0.054)
40 to 49	-0.009	-0.025	-0.060	-0.077*	-0.073	-0.083
	(0.032)	(0.031)	(0.040)	(0.040)	(0.058)	(0.059)
50 to 64	0.033	0.008	-0.051	-0.069*	-0.134**	-0.141***
	(0.029)	(0.029)	(0.036)	(0.037)	(0.053)	(0.054)
Dropout	0.017	0.011	0.021	0.017	-0.050	-0.051
	(0.040)	(0.039)	(0.048)	(0.047)	(0.085)	(0.085)
College	0.005	-0.002	0.031	0.025	0.069	0.067
	(0.024)	(0.024)	(0.031)	(0.031)	(0.044)	(0.045)
Bachelor degree +	-0.009	-0.011	0.002	0.012	-0.025	0.004
	(0.028)	(0.029)	(0.038)	(0.040)	(0.055)	(0.058)
Female × Young child	0.009	-0.001	-0.020	-0.029	-0.057	-0.047
	(0.041)	(0.041)	(0.054)	(0.052)	(0.072)	(0.072)
Tenure: 0-11 months		-0.078***		-0.110***		-0.016
		(0.026)		(0.034)		(0.049)
Tenure: 12-35 months		-0.067***		-0.029		0.028
		(0.025)		(0.033)		(0.047)
Self-employed		0.087**		0.085*		0.010
		(0.040)		(0.052)		(0.076)
Union		0.041		-0.024		0.009
		(0.027)		(0.034)		(0.047)
Constant	0.346***	0.399***	0.582***	0.689***	0.610***	0.742***
	(0.033)	(0.064)	(0.042)	(0.077)	(0.062)	(0.102)
adj. R^2	0.049	0.063	0.041	0.059	0.033	0.050
N	4,077	4,077	2,549	2,549	1,202	1,202

Notes: reemployment probability of spring-job-losers conditional on individual and job characteristics. Sample for individuals aged 20 to 64, excluding full-time members of the armed forces, who are employed in February and non-employed in April, and observed in May, June, or July 2020. The dependent variable is an indicator for employment in May, June, or July. Columns (1), (3), (5) shows results of regressions with socio-demographic variables in February, and (2), (4), and (6) also include job characteristics in February. The table shows select coefficients point estimates and standard errors. Tables for the full set of coefficients are available upon request. All regressions are weighted. Huber-White robust standard errors are shown in parentheses. * denotes statistical significance at 10%; ** significance at 5%; *** significance at 1%.

Table 10: Transitions out of the labour force of the early-outbreak job losers

	May		June		July	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.030	0.001	0.013	-0.021	0.023	0.000
	(0.021)	(0.024)	(0.020)	(0.024)	(0.033)	(0.039)
20 to 29	0.003	-0.012	-0.028	-0.036	0.022	0.018
	(0.028)	(0.028)	(0.026)	(0.026)	(0.038)	(0.038)
40 to 49	0.048	0.047	0.053*	0.050	0.079*	0.068
	(0.031)	(0.031)	(0.031)	(0.031)	(0.045)	(0.046)
50 to 64	0.023	0.027	0.096***	0.090***	0.127***	0.125***
	(0.027)	(0.028)	(0.028)	(0.029)	(0.041)	(0.042)
Dropout	-0.026	-0.014	-0.009	-0.003	0.064	0.054
	(0.034)	(0.034)	(0.037)	(0.037)	(0.062)	(0.061)
College	0.020	0.022	-0.031	-0.032	-0.039	-0.046
	(0.023)	(0.024)	(0.023)	(0.023)	(0.033)	(0.034)
Bachelor degree +	0.024	0.022	-0.021	-0.036	0.048	0.005
	(0.029)	(0.030)	(0.029)	(0.031)	(0.046)	(0.049)
Female $\times$ Young child	0.031	0.033	0.097**	0.089*	0.105*	0.089
	(0.041)	(0.040)	(0.046)	(0.046)	(0.064)	(0.063)
Tenure: 0-11 months		0.032		0.013		0.007
		(0.025)		(0.024)		(0.036)
Tenure: 12-35 months		0.007		-0.027		-0.003
		(0.024)		(0.024)		(0.034)
Self-employed		0.053		0.027		0.126*
		(0.040)		(0.043)		(0.070)
Constant	0.312***	0.262***	0.191***	0.177***	0.159***	0.102
	(0.032)	(0.058)	(0.032)	(0.058)	(0.049)	(0.088)
adj. R^2	0.038	0.047	0.043	0.053	0.048	0.071
N	4,077	4,077	2,549	2,549	1,202	1,202

Notes: probability of transition out of the labour force of spring-job-losers, conditional on individual and job characteristics. Sample for individuals aged 20 to 64, excluding full-time members of the armed forces, who are employed in February and non-employed in April, and observed in May, June, or July 2020. The dependent variable is an indicator for non-participation in May, June, or July. Columns (1), (3), (5) shows results of regressions with socio-demographic variables in February, and (2), (4), and (6) also include job characteristics in February. The table shows select coefficients point estimates and standard errors. Tables for the full set of coefficients are available upon request. All regressions are weighted. Huber-White robust standard errors are shown in parentheses. * denotes statistical significance at 10%; ** significance at 5%; *** significance at 1%.

Table 11: Employment probability of individuals unemployed before COVID-19

	May		June		July	
	(1)	(2)	(3)	(4)	(5)	(6)
Post COVID-19	-0.177***	-0.225***	-0.147***	-0.268***	-0.130***	-0.340**
	(0.024)	(0.077)	(0.032)	(0.099)	(0.047)	(0.148)
Select interaction terms with post COVID-19 indicator:						
Female		0.023		-0.003		-0.026
		(0.052)		(0.069)		(0.108)
20 to 29		0.003		-0.004		0.265*
		(0.071)		(0.094)		(0.150)
40 to 49		0.062		0.073		0.080
		(0.076)		(0.103)		(0.149)
50 to 64		0.070		0.133		0.030
		(0.070)		(0.091)		(0.134)
Dropout		0.093		0.140		0.076
		(0.079)		(0.102)		(0.168)
College		-0.006		0.075		0.100
		(0.061)		(0.078)		(0.116)
Bachelor degree +		0.030		0.072		0.053
		(0.068)		(0.089)		(0.133)
Female × Young child		0.169*		0.096		0.152
		(0.097)		(0.133)		(0.211)
Unemp.: 6-11 months		-0.122		-0.041		-0.003
		(0.087)		(0.120)		(0.179)
Unemp. : 12 months +		0.087		0.024		0.068
		(0.069)		(0.084)		(0.143)
Constant	0.466***	0.539***	0.515***	0.575***	0.558***	0.725***
	(0.018)	(0.056)	(0.023)	(0.074)	(0.034)	(0.108)
adj. R^2	0.033	0.080	0.021	0.095	0.016	0.078
N	3,005	2,899	1,886	1,813	853	818

Notes: estimation of the effect of COVID-19 on the employment probability of individuals unemployed before COVID-19. Sample for individuals aged 20 to 64, excluding full-time members of the armed forces, who are unemployed in February and observed in May, June, or July, for 2019 and 2020. The dependent variable is an indicator for employment in May, June, or July. Column (1), (3), and (5) show results of regressions with an indicator for the year 2020 only. Columns (2), (4), and (6) are for regressions with socio-demographic variables in February, alone and in interaction with the year-2020 indicator. Only select interacted-variable coefficient point estimates and standard errors are shown in the table. Tables for the full set of coefficients are available upon request. All regressions are weighted. Huber-White standard errors are shown in parentheses. * denotes statistical significance at 10%; ** significance at 5%; *** significance at 1%.

Table 12: Employment probability of NILF individuals before COVID-19

	May		June		July	
	(1)	(2)	(3)	(4)	(5)	(6)
Post COVID-19	-0.029***	-0.073**	-0.032***	-0.031	-0.025	-0.037
	(0.008)	(0.032)	(0.011)	(0.042)	(0.017)	(0.067)
Select interaction terms with post COVID-19 indicator:						
Female		0.024		-0.008		-0.015
		(0.018)		(0.023)		(0.035)
20 to 29		-0.036		-0.097**		-0.011
		(0.033)		(0.044)		(0.067)
40 to 49		-0.001		-0.035		0.060
		(0.033)		(0.046)		(0.066)
50 to 64		0.023		-0.015		0.026
		(0.028)		(0.037)		(0.057)
Dropout		0.034*		0.048*		-0.000
		(0.020)		(0.027)		(0.038)
College		0.013		0.041		0.064
		(0.021)		(0.028)		(0.041)
Bachelor degree +		0.039		0.057*		0.084*
		(0.024)		(0.032)		(0.048)
Female × Young child		0.014		0.024		-0.061
		(0.029)		(0.041)		(0.058)
Constant	0.137***	0.212***	0.163***	0.230***	0.170***	0.301***
	(0.006)	(0.024)	(0.008)	(0.030)	(0.012)	(0.049)
adj. R^2	0.002	0.063	0.002	0.097	0.001	0.115
N	12,722	12,722	8,237	8,237	3,879	3,879

Notes: estimation of the effect of COVID-19 on the employment probability of individuals out of the labour force before COVID-19. Sample for individuals aged 20 to 64, excluding full-time members of the armed forces, who are NILF in February and observed in May, June, or July, for 2019 and 2020. The dependent variable is an indicator for employment in May, June, or July. Column (1), (3), and (5) show results of regressions with an indicator for the year 2020 only. Columns (2), (4), and (6) are for regressions with socio-demographic variables in February, alone and in interaction with the year-2020 indicator. Only select interacted-variable coefficient point estimates and standard errors are shown in the table. Tables for the full set of coefficients are available upon request. All regressions are weighted. Huber-White standard errors are shown in parentheses. * denotes statistical significance at 10%; ** significance at 5%; *** significance at 1%.

Table A1: Worker flows in and out of employment, 2018

In and out of employment (%)					
	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul
Outflows	2.2	2.6	2.2	1.9	3.6
Inflows	2.4	3.0	3.5	2.6	2.6
Net change	0.2	0.3	1.4	0.7	-1.0
Excess flows	4.4	5.3	4.3	3.8	5.1

In and out of employment, at work (incl. vac.) (%)					
	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul
Outflows	3.7	4.0	3.2	3.1	4.9
Inflows	3.9	4.7	5.1	3.8	3.9
Net change	0.2	0.7	1.9	0.7	-1.1
Excess flows	7.3	8.0	6.5	6.1	7.7

Notes: estimations of monthly employment inflows and outflows, based on two-consecutive-month LFS panels for individuals aged 20 to 64, excluding full-time members of the armed forces. Outflows for period $t-1$ and t is an estimation of the total number of workers employed in $t-1$ and non-employed in t, in terms of total employment in $t-1$. Inflows are computed similarly but are based on estimates of workers transiting from non-employment to employment. Excess flows are defined as total reallocation (i.e hiring + separation) from period $t-1$ to period t, minus the absolute value of the net change (i.e. |hiring - separation|). Flows in and out of the "employment, at work" category are estimated following the same approach. Note, however, that we include workers in the stock of reference who are absent due to vacation, parental leave, and labour conflicts, i.e. we do not consider flows associated with these motives. See appendix A.2 for details. All totals are estimated using samples of individuals observed for two consecutive months. All estimations are weighted.

Table A2: Composition of flows in and out of employment, 2018

	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul
In and out of employment (%)					
Outflows					
Temporary unemployment	11.9	3.5	3.4	1.7	6.4
Search unemployment	26.3	31.3	29.8	38.3	32.4
NILF	57.4	61.9	62.3	55.5	58.9
Inflows					
Temporary unemployment	5.4	8.2	2.7	4.4	1.4
Search unemployment	36.0	39.4	31.4	42.4	42.0
NILF	55.0	46.2	55.5	44.0	49.3

	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul
In and out of employment, at work (incl. vac.) (%)					
Outflows					
Absent from work	47.6	42.7	41.5	44.2	32.3
Unemployment	24.9	23.5	22.8	26.6	28.9
NILF	27.5	33.8	35.7	29.2	38.8
Inflows					
Absent from work	44.1	38.8	32.6	35.6	36.6
Unemployment	27.2	34.0	31.1	38.6	34.4
NILF	28.8	27.2	36.3	25.8	29.1

Notes. Analysis of the composition of employment inflows and outflows. Two-consecutive-month samples, for individuals aged 20 to 64, excluding full-time members of the armed forces. Total flows are computed as in tables 2. Share of flows that are towards/from temporary unemployment (i.e. unemployment, on temporary layoff), search unemployment (i.e. unemployed workers declaring searching for a job), and non-participation. The bottom panel analysis the composition of flows in and out of the LFS category "employment, at work", but including workers on vacation, on parental leave, or absent due to labour conflicts. Similarly, the category "absent from work" exclude workers absent due to these motives. See notes in table 2 and appendix A.2 for more details. All estimations are weighted.

Table A3: Composition of flows in and out of employment, 2019

In and out of employment (%)					
	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul
Outflows					
Temporary unemployment	5.9	3.6	3.1	3.8	6.5
Search unemployment	30.4	33.3	40.5	31.2	32.2
NILF	58.3	57.5	53.7	61.8	59.2
Inflows					
Temporary unemployment	4.5	4.8	3.4	3.6	2.7
Search unemployment	36.0	38.3	35.9	40.2	39.6
NILF	54.2	48.6	50.8	47.3	52.2

In and out of employment, at work (incl. vac.) (%)					
	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul
Outflows					
Absent from work	46.1	46.2	46.1	47.2	30.9
Unemployment	25.0	24.9	26.4	21.6	29.8
NILF	28.9	28.9	27.5	31.1	39.3
Inflows					
Absent from work	44.0	37.4	31.9	38.5	40.7
Unemployment	27.2	34.5	34.8	34.2	30.7
NILF	28.8	28.1	33.4	27.2	28.6

Notes. Analysis of the compositions of employment inflows and outflows. See notes of table A2 for details.

Table A4: Employment inflows and outflows, one-digit NOC occupation groups

	2020					2019				
	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul
Management										
Separation	3.6	7.3	3.6	3.4	3.3	1.6	2.3	1.1	1.4	1.5
Hiring	2.0	2.2	4.4	4.6	2.4	1.1	1.3	1.9	1.0	1.0
Net change	-1.6	-5.1	0.8	1.3	-0.9	-0.5	-1.0	0.8	-0.4	-0.5
Excess flows	4.1	4.3	7.2	6.8	4.7	2.2	2.5	2.2	0.2	2.1
Business, finance and administration										
Separation	4.7	10.6	5.1	4.3	3.2	2.0	1.6	2.0	1.6	2.7
Hiring	2.2	2.4	7.0	6.4	4.0	1.8	2.6	2.8	2.3	1.4
Net change	-2.6	-8.2	1.9	2.1	0.8	-0.3	1.0	0.8	0.8	-1.2
Excess flows	4.3	4.8	10.2	8.5	6.4	3.6	3.2	3.9	3.2	2.9
Natural and applied sciences										
Separation	2.4	8.0	3.8	2.1	1.7	1.1	1.8	1.8	1.2	1.3
Hiring	1.9	1.2	5.8	3.0	2.1	1.4	1.6	3.5	1.9	1.9
Net change	-0.5	-6.9	2.1	0.9	0.4	0.3	-0.2	1.7	0.8	0.6
Excess flows	3.8	2.4	7.6	4.3	3.5	2.2	3.3	3.6	2.3	2.6
Health										
Separation	5.1	6.6	4.3	3.4	2.2	1.5	1.6	1.5	1.2	2.1
Hiring	1.5	2.5	4.4	7.5	3.7	1.6	2.0	2.2	2.5	1.9
Net change	-3.6	-4.1	0.1	4.1	1.4	0.5	0.4	0.7	1.3	-0.2
Excess flows	3.1	5.0	8.6	6.8	4.4	3.1	3.2	3.0	2.4	3.7
Education, law and social, community and government services										
Separation	9.5	8.8	6.4	4.6	12.7	2.2	2.2	2.8	1.8	12.1
Hiring	1.5	5.6	6.2	7.3	3.4	1.7	2.6	2.7	2.1	2.1
Net change	-7.9	-3.2	-0.2	2.7	-9.3	-0.5	0.4	-0.7	0.3	-10.0
Excess flows	3.0	11.1	12.4	9.1	6.8	3.5	4.3	5.5	3.6	4.3

Notes: estimations of monthly employment inflows and outflows by one-digit National Occupational Classification (NOC) occupation groups. Two-consecutive-month LFS panels of non-military, of age 20 to 64. Outflows for period $t-1$ and t is an estimation of the total number of workers employed in $t-1$ and non-employed in t, in terms of total employment in $t-1$. Inflows are computed similarly but are based on estimates of workers transiting from non-employment to employment. Excess flows are defined as total reallocation (i.e hiring + separation) from period $t-1$ to period t, minus the absolute value of the net change (i.e. |hiring - separation|). See appendix A.2 for details. All totals are estimated using samples of individuals observed for two consecutive months. All estimations are weighted.

Table A5: Employment inflows and outflows, one-digit NOC occupation groups (continued)

	2020					2019				
	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul	Feb-Mar	Mar-Apr	Apr-May	May-Jun	Jun-Jul
Arts, culture, recreation and sports										
Separation	10.7	15.9	10.1	8.6	6.7	2.7	3.7	2.7	2.2	4.8
Hiring	2.2	5.7	7.1	14.0	8.9	3.2	4.2	5.2	5.1	5.2
Net change	-8.6	-10.2	-3.0	5.3	2.2	0.6	0.5	2.4	2.9	0.4
Excess flows	4.3	11.3	14.2	17.3	13.3	5.3	7.4	5.5	4.4	9.6
Sales and services										
Separation	13.1	22.4	11.1	6.7	6.0	2.4	2.9	2.1	2.6	3.2
Hiring	2.5	5.6	14.5	19.0	11.2	3.0	3.7	4.0	2.7	3.4
Net change	-10.6	-16.8	3.4	12.3	5.2	0.5	0.8	1.9	0.1	0.2
Excess flows	5.0	11.1	22.2	13.5	12.0	4.9	5.7	4.2	5.2	6.3
Trades, transport and equipment										
Separation	7.1	20.0	8.4	4.7	4.0	3.3	3.3	2.6	2.5	3.3
Hiring	4.5	4.1	17.2	14.4	6.1	4.0	5.6	6.4	3.2	3.1
Net change	-2.6	-15.7	8.8	9.8	2.1	0.7	2.3	3.8	0.7	-0.3
Excess flows	8.9	8.3	16.8	9.3	8.0	6.6	6.5	5.3	4.9	6.1
Natural resources and agriculture										
Separation	8.8	16.1	5.3	6.6	7.9	6.6	6.5	2.8	4.9	6.9
Hiring	7.2	7.1	25.5	20.6	8.6	5.1	11.1	17.0	8.3	4.4
Net change	-1.5	-9.0	20.2	14.1	0.7	-1.6	4.6	14.2	3.4	-2.5
Excess flows	14.5	14.1	10.5	13.1	15.9	10.1	13.1	5.5	9.8	8.7
Manufacturing										
Separation	6.5	20.3	7.3	4.2	3.3	3.0	2.3	1.9	2.2	2.6
Hiring	1.9	3.9	19.4	12.5	5.5	1.9	3.0	3.7	1.8	2.3
Net change	-4.6	-16.4	12.0	8.2	2.2	-1.0	0.7	1.8	-0.4	-0.3
Excess flows	3.7	7.9	14.6	8.5	6.5	3.8	4.6	3.9	3.6	4.6

Notes: estimations of monthly employment inflows and outflows by one-digit NOC occupation groups. See notes of table A4 for details.