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THE GREAT CANADIAN RECOVERY:
THE IMPACT OF COVID-19 ON CANADA'S LABOUR MARKET

Stephen R.G. Jones
Fabian Lange
W. Craig Riddell
Casey Warman

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ABSTRACT

The Canadian labour market experienced a period of unprecedented turmoil following the onset of the COVID-19 pandemic. We analyze the main changes using standard labour force statistics and new data on job postings. Envisaging a phase of temporary severing of employment relationships followed by a phase of more standard labour market search and matching, we use stock and flow data to understand key developments. We fond dramatic changes in employment, unemployment and labour market attachment in the first few months of the pandemic and a broad though gradual recovery through to the end of 2021.

Stephen R.G. Jones
Department of Economics
McMaster University
Hamilton, Ontario
CANADA L8S 4M4
jonessrg@mcmaster.ca

Fabian Lange
Department of Economics
McGill University
855 Sherbrooke Street West
Montreal, QC H3A, 2T7
and NBER
fabian.lange@mcgill.ca

W. Craig Riddell
Vancouver School of Economics
University of British Columbia
6000 Iona Drive
Vancouver, BC V6T 1L4
Canada
craig.riddell@ubc.ca

Casey Warman
Department of Economics
Dalhousie University
6214 University Avenue, Room A23
Halifax, NS B3H 4R2
and NBER
warmanc@dal.ca

1 Introduction

Canada's economy and labour market experienced a period of unprecedented turmoil following the onset of the COVID-19 pandemic. Dramatic flows out of and back into employment took place, accompanied by wide swings in key labour force statistics. This was also a period during which economists had to question traditional ways of measuring and understanding the health of the labour market.[1]

This paper analyses this unique period using master file data from the monthly Labour Force Survey (LFS) and new data on job postings from Burning Glass Technologies together with data on job vacancies from Statistics Canada's Job Vacancy and Wage Survey. The combination of data on new job postings (a flow) with data on job vacancies (a stock) provides a more complete understanding of changes on the demand side of the labour market. Similarly, our use of both the cross-sectional and longitudinal features of the Labour Force Survey yields deeper insights into the supply side, allowing examination of both stocks and flows in a characterization of labour market dynamics. Our overall objective is to provide a thorough examination and assessment of the key labour market impacts of this unique and dramatic event.

Methodologically, since Canada's labour market exhibits highly seasonal patterns in normal times, we use monthly seasonally unadjusted data and employ a research design that compares key developments to the counterfactual average monthly outcomes over the previous five years. We also apply the conceptual framework originally developed by Flinn and Heckman (1983) to test for the equivalence of various labour force states, employing longitudinally matched LFS data to assess month-to-month flows prior to and during the pandemic. In addition, we employ an "event study"

[1] Jones et al. (2020) address some of these measurement and classification issues using data from the initial phase of the pandemic.

type of framework using the full longitudinal capacity of the LFS, given its 6-month rotation group structure, to examine the subsequent behaviour of those who separated from employment in the initial downturn in March and April 2020.

A key feature of our study involves examining not only movements in labour force stocks but also flows among labour force states. Based on this analysis we conceptually distinguish (i) the process of temporarily severing and then re-forming employment relationships from (ii) the search process of matching workers to new positions in the job market.[2] We believe that this distinction allows us to make sense of the rapidly evolving situation in the labour market and synthesize many of the key developments in a useful way. A striking finding is that it is possible to identify groups within those normally classified as employed, unemployed, or not-in-the labour force that form part of the "temporarily severed from their usual employment" group.

Our key findings are as follows:

1. The rapid decline in employment, increase in unemployment and fall in labour force participation in March and April 2020 were unprecedented. Nonetheless, standard measures of labour force activity that normally perform well were less well suited to the unusual pandemic-related circumstances and arguably understate the size of the changes that occurred. We find that the "Employed-Absent" category exhibit behaviour similar to temporary layoff unemployment; consequently the decline in employment is understated by standard measures. Similarly, the Marginally Attached – those not searching but who report that they want a job – exhibit behaviour very similar to the officially unemployed during the initial COVID-related downturn. The measured rise in unemployment would be much larger if the Employed-Absent

[2] Forsythe (2020) employ a similar conceptual distinction to describe the evolution of the U.S. labour market over the COVID pandemic.

and Marginally Attached were classified as Unemployed rather than (respectively) Employed and Non-Participants. Finally, the decline in labour force participation is arguably over-stated given that the Marginally Attached retained a strong attachment to the workforce.

2. Despite the dramatic changes brought about by the initial public health restrictions, Canada's labour market recovered rapidly compared to previous recessions, a substantial initial recovery occurring in the summer and early fall of 2020 and then more gradually thereafter. We analyse key features of the initial partial recovery by following individuals who were employed in February 2020 over the subsequent 5 months, comparing those who remained employed from February to June 2020 to those who transitioned away from paid employment during that period. Three types of "job leavers" are examined based on our earlier findings about groups exhibiting similar behaviour. Those who remained employed throughout had, in February 2020, much higher earnings and hours worked as well as greater cognitive skills requirements and lower manual skill needs than those who transitioned away from paid employment. However, job leavers who were able to regain paid employment by June 2020 did not experience much change in terms of earnings, hours worked and occupational skill requirements. Since more than one-half of job leavers were still non-employed in June we also examine the extent of selection among those who succeeded in regaining employment.

3. Combining the initial partial recovery and the more bumpy but gradual recovery, we compare the degree of heterogeneity in the labour market impacts experienced both during and after the COVID-19 recession by sub-groups defined by gender, age, and educational attainment. For this purpose we employ broad labour force aggre-

gates: employment, unemployment and labour force participation.[3] This detailed comparison of labour market outcomes does not reveal any noteworthy differences in the response to the pandemic by women relative to men, notwithstanding some popular accounts during the COVID-19 period. By age a greater degree of heterogeneity in response is evident. The young (age 15-24) were affected to a greater extent by the COVID shock than were the prime age (25-54) and older (55+) groups, but they also recover by mid-2021, slightly more quickly and more completely than the prime age group. The story for the older group is the opposite: by the end of 2021, recovery is more or less complete for the prime age category but remains partial for the older group. Some differences are also evident by education, with the university educated group being least affected by the initial downturn owing to the occupational skill mix of their employment and their capacity for working from home. Nonetheless, despite the high school and less than high school categories experiencing sharper responses to the onset of the pandemic, the broad pattern of gradual recovery through most of 2021 is present across the educational spectrum.

4. To assess the enduring effects (to date) of the COVID-19 shock we also examine the two endpoints of 2019q4 and 2021q4, disaggregated by gender and, within gender, by age and education level. The main finding is that most groups and subgroups have relatively similar temporal differences in the proportions of the population in each standard labour force state. Two exceptions are worth noting. By education, those with some post-secondary (but less than a BA) experienced a decline in employment and rise in non-participation, a result that holds for both genders. Also, by age, a decline in the proportion employed and a rise in both unemployment and non-

[3]Our focus on the standard labour force aggregates means that we are not speaking to the financial effects of the pandemic. The rapid and substantial policy responses of the federal government imply that the employment outcomes will differ substantially from the impact on household finances.

participation were experienced by the oldest group.

5. Measures of labour demand—both new job postings and the stock of job vacancies—plummeted by about 50 percent in response to the initial COVID-19 shock. However, like employment, unemployment and participation, these demand measures quickly reversed direction and generally continued to grow, albeit at a slower pace. By May 2021 job postings and vacancies were 30 percent above their February 2020 level, and by January 2022 about 50 percent higher.

6. The recovery in job postings was broadly based, not only across provinces but also across industries and broad occupational groups. Despite differences across jurisdictions in policy responses to the pandemic, our evidence of substantial similarity in both the decline and then subsequent recovery of labour demand by province, industry and occupation is noteworthy.

The paper is organized as follows. As background, we begin with a brief chronology of key events during the COVID period to date. Section 2 uses LFS data to examine monthly movements in key labour force aggregates. It addresses participation, employment and hours changes, the changing composition of unemployment and its effects, and the role of attachment to the labour market by various groups of non-participants. We also use the longitudinal feature of the LFS to examine the dynamics of labour market flows and to probe what happened to workers employed in February 2020 in the turbulence after the onset of the pandemic. Section 3 utilizes job posting and vacancy data to document that, following an initial collapse, the demand for labour in Canada recovered quickly and relatively broadly across provinces, industries and occupations. We address the extent to which responses to the initial turmoil differed by major demographic groups in Section 4, and we also compare the final quarters of 2019 and 2021 to assess which groups have enduring consequences even as the aggregate economy inches toward broad recovery. Section 5 concludes.

A Brief Chronology

In March 2020, the initial wave of COVID-19 infections and associated lockdown measures forced large parts of the economy to shut down. During the first six months of the pandemic, the process of temporarily severing employment relationships dominated the flows observed in the labour market and generated large swings in standard labour market magnitudes. Between February and April 2020, almost 5% of the population were temporarily laid-off from their former jobs while a further 5% were forced to absent themselves from their employment even though they continued to be formally employed by their former employers. In addition, by April 2020 the share of persons marginally attached to the labour force—those not searching but who desire work—tripled to reach 4 percentage points above the level observed during the pre-COVID 2015-19 period, which we use as a counterfactual. For reasons we discuss below, a substantial share of this flow into marginal attachment represents temporary separations. All told, within a very short time-frame, around a quarter of those working in February stopped working by April 2020, but remained tethered in some way to their former workplace.

As early as May 2020, this process of temporarily severing employment relationships began to reverse rapidly and within just a few months the majority of those on temporary layoff and those absent from work rejoined employment. Our analysis indicates they largely returned to their former employment (even if often by working from home). Similarly, the share of discouraged and other marginally attached workers rapidly declined and was only slightly elevated by the end of the summer of 2020.

During the first few months of the crisis, although the unemployment rate rose sharply, the number of those actively searching for work remained low. Likewise, labour demand in the search market as measured by job postings contracted sharply and job finding rates among unemployed job searchers declined during the initial months of the pandemic. By April, flows from temporary forms of separations, including temporary layoff unemployment, started to contribute to a build-up in the stock of search unemployment, and reduced job finding rates further raised this stock. By August 2020, the share of search unemployed in the population almost doubled. However, the increase in search unemployment was smaller than the flows out of temporary unemployment so that unemployment rates overall declined from May 2020 onward.

Two factors limited the increase in search unemployment up to the end of 2020. First, employers posted many more jobs after April. By July, postings had recovered to about 90% of their pre-pandemic level. Consequently, job finding rates among unemployed searchers returned to levels observed in the pre-COVID period. Second, a large majority of those temporarily unemployed were rehired rather than transitioning to search unemployment. By April and May 2020, rates of reemployment among those temporarily unemployed were roughly 50% per month, comparable to levels seen in 2015-19 (when the stock of temporary layoff unemployment was much lower). By the end of the summer of 2020, the phase dominated by temporary separations had passed. At this point, the spikes in temporary layoff unemployment and marginal attachment had abated, as had the increase in the share of those employed but absent from work. Yet, in August 2020, about 6% of the population were unemployed and searching for work, compared to 3.5% in February 2020 and 4% for the pre-COVID monthly average for August. On the other hand, job postings and job finding rates had returned to pre-pandemic levels, leading to a gradual decline in the stock of search unemployment. However, the vestiges of the initial shock lingered for a long time. It is only by the late fall of 2021 that the unemployment rate, and other key labour market magnitudes, fully recovered to pre-pandemic levels.

Our work builds on a large literature on COVID and the labour market - internationally and in Canada. Brochu et al. (2020) provide an early analysis of the events in the Canadian labour market during the spring and summer of 2020 relying, as does much of our analysis, on the confidential version of the LFS. As do we, they found substantial reemployment flows of recent job losers, especially among temporary layoffs. Lemieux et al. (2020) is an important early contribution that uses a similar approach to us comparing differences in employment and aggregate hours between April and February in 2020 with the same monthly difference in 2018 to assess the impact of the pandemic. A touchstone for the heterogeneity analysis is Cortes and Forsythe (2021) who examine heterogeneous impacts of the pandemic in the U.S. Brodeur et al. (2021) provides a survey that can serve as a good starting point for exploring the rapidly evolving literature on the impact of COVID on the economy.

In many ways, the labour market dynamics during the COVID pandemic in Canada mirror those in the U.S. As we show in Section 2, distinguishing between search and recall or temporary unemployment is crucial to understanding the dynamics of the Canadian labour market during 2020 and early 2021. Forsythe et al. (2020), Hall et al. (2021), Blandin and Bick (2020), and Kudlyak and Wolcott (2020) all emphasize this distinction in their analysis of the dynamics during the early parts of the

COVID recession in the U.S. Our work substantially builds on Forsythe et al. (2020) as we adapt the variables in the Labour Force Survey to measuring the population of recall unemployed. As in Canada, labour demand as measured by job postings contracted sharply in the U.S. during the first months of the pandemic (Forsythe, 2020) before recovering during the second half of 2020 and throughout 2021. Gallant et al. (2020) demonstrate that a standard Pissarides-Mortensen type matching model calibrated to account for the distinction between search and recall unemployment matches the dynamics of the U.S. labour market during the COVID recession very well. We do not perform a similar calibration exercise in this paper, but future work may investigate whether the standard matching framework augmented in the manner of Gallant et al. (2020) can match the Canadian labour market dynamics as well.

2 Labour Force Behaviour During COVID-19

This section uses the monthly Labour Force Survey (LFS) to examine in detail how Canada's labour market has evolved since the onset of the pandemic in February 2020. The LFS has several advantages. One is that it provides detailed data for a representative sample of the adult (15+) population and does so in a timely fashion with results released within a few weeks of the survey.[4] Another is that responding households remain in the LFS for 6 consecutive months before exiting. We utilize the longitudinal dimension, available in the confidential use files, to examine not only the cross-sectional dimension that provides a snapshot at a point in time but also the

[4]The reference week for the LFS is usually the week containing the 15^{th} of each month.

longitudinal dimension to investigate transitions from one time period to another.[5,6]

At the outset, we note that an important issue in studying labour market developments during COVID-19 is data quality. At the start of the pandemic, the overall LFS non-response rate rose from 11.9% to 22.1% (Feb-March 2020) peaking at over 30% by late summer 2020 (Brochu and Créchet, 2021). This high rate of non-response has since persisted in the Canadian LFS, while the analogous non-response rate for the U.S. Current Population Survey, which peaked at about 35% in mid-2020, has since fallen to the 20-25% range but still lies above the pre-pandemic level.

In a key contribution, Brochu and Créchet (2021) decompose this non-response into "birth" non-response, a failure to initiate an interview at all, and "subsequent" non-response, a failure to achieve a follow-on interview (i.e., attrition from the birth sample). Since neither birth non-response nor subsequent non-response is directly observed, Brochu and Créchet use the incidence of Whole Record Imputation (WRI), only used for non-initial interviews (and for some specific age ranges), and the relative fall-off of response (i) overall and (ii) excluding records with WRI, to assess the importance of "birth" non-response and "subsequent" non-response.

The bottom line is that the chief problem in the COVID-19 era has been birth non-response. Brochu and Créchet (2021) convincingly relate this pattern to pandemic-induced changes in interview modalities, particularly the suspension of in-person interviews, together with changes in telework and call centre arrangements. Overall,

[5] In addition to calculating the transition rates, the confidential use files are necessary when we examine the pre- and post-Covid outcomes in Section 2.6. As well, the detailed occupational information in the confidential files is required to construct the skill indices we use later in the paper.

[6] Early studies that used the longitudinal feature (Osberg (1993), Jones and Riddell (1999)) required the cooperation of Statistics Canada to create the linked files, linkage that can now be carried out in an RDC. Brochu (2021) is a valuable guide to the evolving LFS and to the use of the master files for longitudinal analysis.

they find that the birth non-response problem was more severe for demographic groups with particular vulnerabilities to the COVID-19 shock. They argue that there may have been some understatement of the employment and participation declines from LFS estimates in the March-July 2020 period, although gauging the size of this bias is difficult. However, their result that sample attrition after an initial response was largely unaffected suggests that the reliability of analysis based on panels constructed from LFS responses is relatively unscathed.

Given the highly seasonal nature of Canada's labour market, we use seasonally unadjusted data and compare each month during the COVID period to average behaviour for that month pre-COVID. Such month-by-month comparison allows us to distinguish between behaviour that can be attributed to the COVID downturn and recovery versus month-to-month changes that reflect usual seasonal patterns. Rather than relying on one or two pre-COVID years as the basis for comparison, we use the average monthly outcomes for the 5-year period 2015-19, a relatively stable period in Canada's economy and labour market (Riddell, 2018).[7] The COVID-19 period runs from March 2020 to the most recently available data for December 2021.

The principal framework within which we will assess recent labour force behaviour contrasts (i) the process of temporarily separating and re-forming employment relationships from (ii) the process of matching workers to new positions in the search market. In the former "tied" or attached phase of adaptation, firms and employees maintain linkages of varying strength by continuing to maintain the formal employment relationship even when the employee is absent (and may even be unpaid) or through the widespread use of temporary layoff unemployment.[8] This phase, char-

[7]Averaging over a longer period of time could include turbulent periods such as the global financial crisis in 2008-9, and the resource boom of 1999-2014 which had a substantial impact on Canada's economy and labour market.

[8]Federal government policies encouraged the maintenance of ties between employers and employ-

acteristic of the initial response to the COVID-19 shock, posed challenges for many conventional measures of economic activity. In the latter, "non-tied" phase, the labour market reverted gradually to an unattached search and matching model more familiar to economists. Nonetheless, throughout our sample period vestiges of the attachment model have persisted in both the labour market and in government policy with respect to the labour market.

2.1 Conceptual framework

Owing to the unusual nature of the labour market changes brought about by COVID-19, we examine a large number of labour force states as well as transitions among these states. As a conceptual framework to synthesize what is otherwise a large number of descriptive facts, we employ the theoretical framework for distinguishing among labour force states first developed by Flinn and Heckman (1983) for a 3-state environment (employment E, unemployment U and out-of-the labour force O) and extended by Jones and Riddell (1999) to a 4-state setting (E, U, M and N where marginal attachment M + non-attached N = O)). Employing a Markov framework, Flinn and Heckman show that in the three-state environment U and O are behaviourally equivalent if and only if pUE = pOE where pXY denotes the transition rate from X to Y. Jones and Riddell (1999) argue that the central measurement and policy issues involve those on the margin between U and O such as the non-employed who are not actively searching but state that they desire work (M) or discouraged workers, a subset of M. In this 4-state environment, necessary and sufficient conditions for M to be behaviourally equivalent to non-attachment N

ees. For example, the Canada Emergency Response Benefit paid EI-type benefits without imposing the usual job search requirement and the Canada Emergency Wage Subsidy program subsidized the wages of workers maintained on the payroll.

(those neither searching for or desiring work) are:

$$\text{pME} = \text{pNE} \textit{ and } \text{pMU} = \text{pNU}. \tag{1}$$

Similarly, U and M are equivalent if and only if:

$$\text{pUE} = \text{pME} \textit{ and } \text{pUN} = \text{pMN}. \tag{2}$$

Subsequent research for Canada, the U.S. and UK (countries that include a question about the desire for work among non-searchers) concludes that U, M and N are distinct states, in particular that:

$$\begin{aligned} \text{pUE} &> \text{pME} > \text{pNE} \\ \text{pUU} &> \text{pMU} > \text{pNU} \\ \text{pUN} &> \text{pMN} > \text{pNN} \end{aligned} \tag{3}$$

so that M is an intermediate state with extent of labour force attachment between U and N.[9]

The above tests and findings relate to continuing differences in labour force activity during various phase of the business cycle. In this paper we employ the same conceptual framework but apply it to temporary phases of the COVID-19 downturn and recovery. Thus we examine whether states that are usually behaviourally equivalent – such as Employed at work and Employed absent from work – differed in their behaviour during the pandemic as well as whether states that are usually distinct – such as M and U – were at times behaviourally indistinguishable during certain

[9] See, e.g., Jones and Riddell (2006) and Jones and Riddell (2019) for Canada and the U.S. and Moffat and Yoo (2015) for discussion of the UK evidence.

phases of the COVID-19 period.

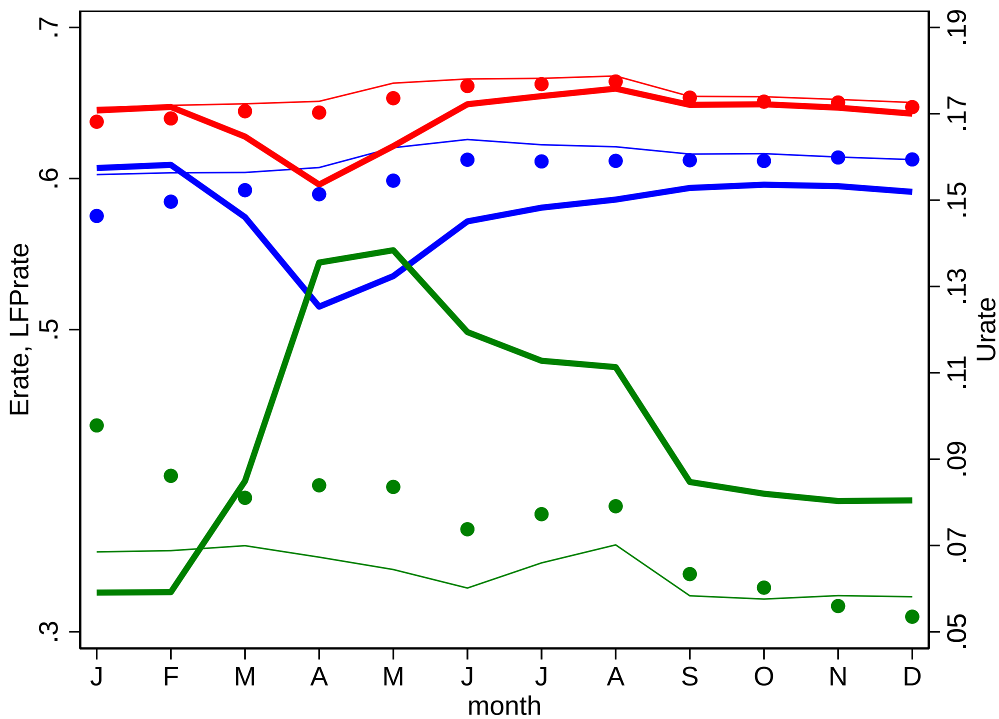
2.2 Movements in Labour Force Aggregates

We illustrate key developments in Canada's labour market during the COVID pandemic in a series of figures, where light lines denote the 2015-19 average rates, by month, heavy lines denote the monthly experience in 2020, and heavy dots denote monthly observations in 2021. The behaviour of the employment rate (or employment/population ratio) Erate, the unemployment rate Urate, and the labour force participation rate LFPrate are shown in Figure 1. In broad terms, we think of the behaviour of these magnitudes until May/June of 2020 in terms of the "tied" model linking individuals and their current/former employers, and we envisage the recovery period since then using a more standard search and matching framework.

The employment/population ratio Erate was slightly higher in January and February 2020 than during those months in 2015-19. It then plummeted by almost 10 percentage points during the initial lockdown in March and April, a decline that is unprecedented in the post-World War Two period. This dramatic decline was followed by a substantial recovery, first rapid during the April to July period and then more gradual until mid-Fall 2020. By October the Erate was approximately two percentage points below its pre-COVID average level for the month. With further restrictions imposed late fall and early winter the gap increased to almost 3 percentage points in early 2021. Subsequently the gap between employment rate and its 2015-19 average level gradually narrowed and was eliminated in November and December 2021.

The behaviour of the unemployment rate Urate is largely a mirror image of that

Figure 1: Employment Rate, Unemployment Rate and Labour Force Participation Rate



Notes: The Employment rate (Employment/Population) is in blue, the Labour Force Participation rate is in red, and both are measured on the left axis. The Unemployment rate is in green and is measured on the right axis. For all series, the light line denotes average values by month for the 2015-19 reference period, the heavy line denotes the values by month for 2020, and the heavy dots denote the monthly values for 2021.

for employment. In the pre-COVID lockdown months of January and February 2020, the Urate was about 0.4 percentage points lower than its 2015-19 average for those months. It rose dramatically in March and April, with a further modest increase in May, reaching the unprecedented level of almost 14% in May. Unemployment rates then declined throughout the remainder of 2020, reaching about 8% in December. Note that some of this fall in the unemployment rate – such as the large declines in May-June and August-September – reflected normal seasonal patterns. Likewise, the more modest decline from June to August in part reflects the normal seasonal pattern of a rise in measured unemployment during that period. With additional restrictions after the Christmas period unemployment rose to almost 10% in January 2021. Since that time the unemployment rate gradually approached its 2015-2019 level, with the gap narrowing substantially during Fall 2021. Indeed, as is evident in Figure 1, in November and December 2021 the national unemployment rate was below its pre-COVID levels for those months.

A striking feature of the first phase of the COVID recession was that many of those who lost or left jobs during the unprecedented deterioration of the labour market in March-April 2020 did not join the ranks of the officially unemployed. This was because they were neither searching for work nor were they classified as being on temporary layoff.[10] In the usual three-state approach to classifying labour force activities, these individuals are treated as having exited the labour force, resulting in a precipitous decline in labour force participation. As shown in the figure, Canada's participation rate LFPrate in early 2020 was slightly lower than the previous five-year average and dropped dramatically from about 65 per cent in February to below 60 per cent in April. By June, only two months later, the decline was reversed and LFPrate again stood at its February 2020 level, about 65%, though still well below its normal level for that month (66.6%). By June 2021, however, the LFPrate was only 0.05 percentage points below its 2015-19 level, and remained only slightly below its pre-COVID level throughout the second half of 2021.

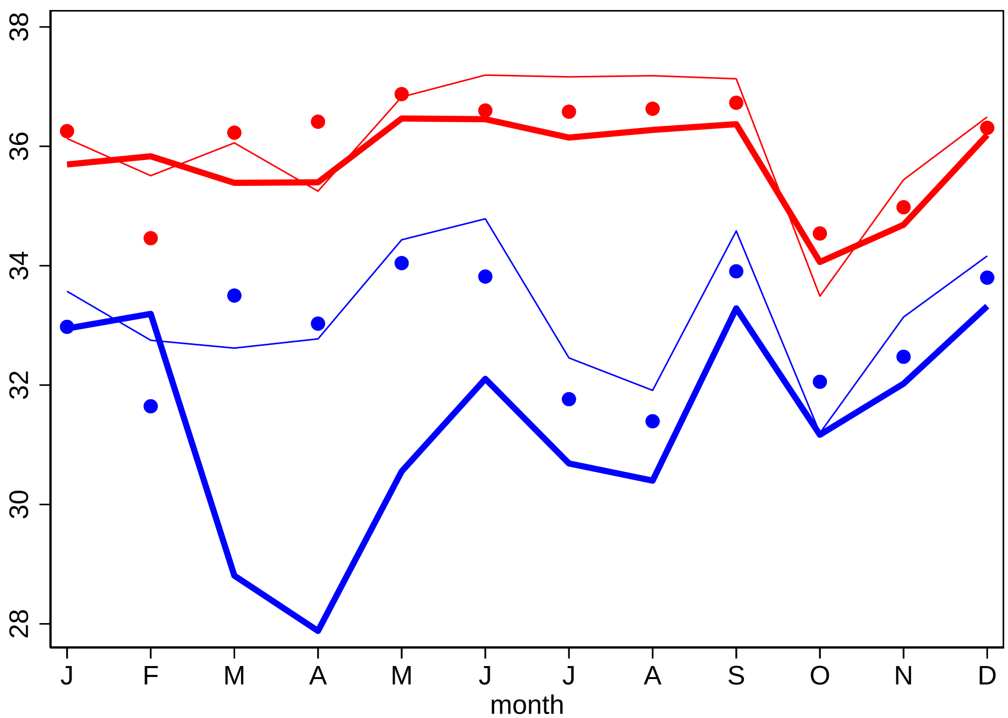
The rapid decline in measured participation early in the COVID-19 downturn together with the equally substantial rise in participation in April and May of 2020

[10]To be classified as a temporary layoff, a person who is laid off must have a definite recall date or an indication from the employer that they will be recalled within the next 12 months. Job search is not required for such persons to be counted as unemployed.

suggests that many of these individuals remained "attached" to the labour force, and perhaps warranted being classified as unemployed rather than non-participants. We explore this issue further below.

2.3 Employment Changes: Hours Worked and Absence from Work

Figure 2: Actual Hours, Employed and Employed-Working



Notes: Actual hours mean values are in blue for the Employed (including those recorded as Employed-Absent) and in red for the Employed-Working subset of the Employed. For both series, the light line denotes average values by month for the 2015-19 reference period, the heavy line denotes the values by month for 2020, and the heavy dots denote the monthly values for 2021.

Erate, Urate and LFPrate are "head count" measures of the extensive margin of labour force activity and do not account for the intensive (hours worked) margin. The LFS asks those classified as employed to report their usual and actual hours of work. The enormous decline in employment in March-April 2020 was accompanied by a large decline in actual hours worked.[11] Figure 2 graphs mean actual hours worked by the Employed (in blue). While there are usually seasonal variations in hours worked, the dramatic decline in average hours by the Employed in 2020 is without precedent in the period under study. The fall from around 33 hours per week at the start of 2020 to around 28 hours by April is dramatic, and is followed by a steady recovery through the summer, converging back to the pre-pandemic levels by early fall. However, it is important to note that this dramatic decline and recovery is almost entirely due to the changing size of the Employed-Absent group, who work zero hours. Figure 2 also shows mean actual hours by month for the Employed-Working sample (in red), all of whom have non-zero hours, and excluding the Employed-Absent group. Once the Employed-Absent are excluded, there is surprisingly little evidence of a COVID-19 effect on hours among the Employed-Working group. During the pre-COVID period as well as in both 2020 and 2021, mean actual hours remain around 36 hours in all months except for the Thanksgiving effect in October.[12,13]

[11]Throughout both 2015-19 and the COVID-19 era, there was comparatively little movement in mean "usual" hours which hovered between 36 and 37 for the whole period. For this reason, we address changes in actual hours, rather than usual hours, in this paper.

[12]The one exception in these hours data is February 2021, when both actual hours measures lie about an hour below the pre-pandemic norm. We suspect this is due to Family Day and related provincial holidays, which affect about two-thirds of the population and fell in the LFS reference week in 2021 but not in earlier years.

[13]In Appendix Figure A1, we compare mean hours worked for the Employed at work based on an occupation's propensity to telework. We classify the occupations into high and low propensity to telework using Dingel and Neiman (2020)'s index. There is surprisingly little relative change in the hours worked for high versus low telework occupations. One exception is during the summer months in which workers in low propensity to telework occupations saw a larger decline in hours worked relative to the 2015-19 period. One additional consideration is the change in composition of Employed workers. The fraction of workers in Employed workers in occupations with a low propensity of telework with positive hours decreases during the COVID recession. Appendix Figure

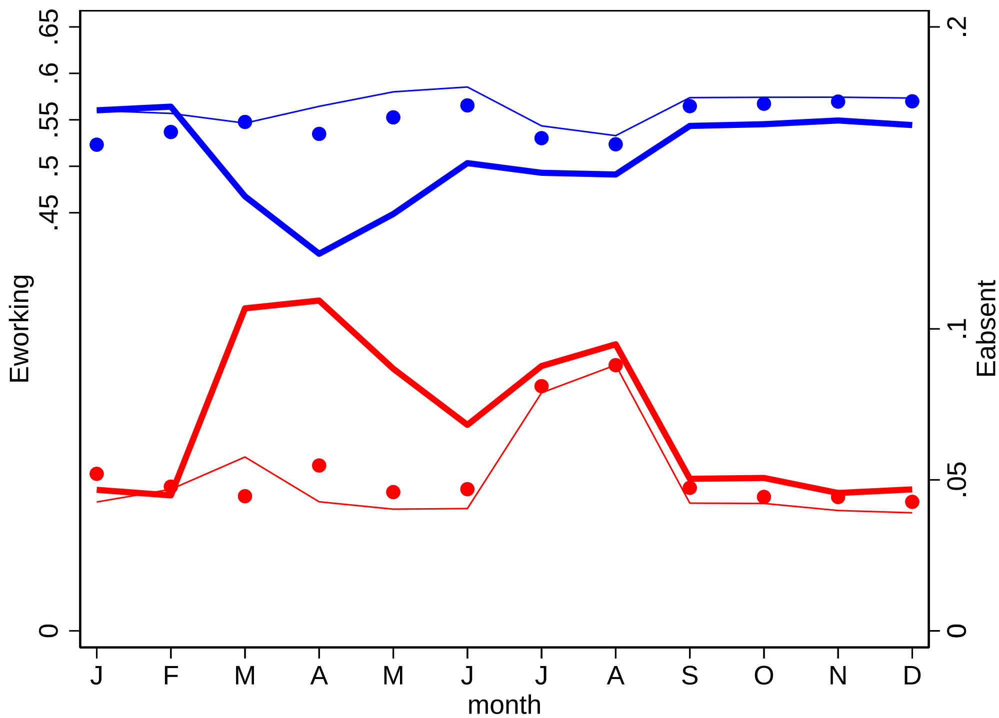
In summary, the dramatic decline in the employment rate early during the pandemic understates the actual decline in work activity because hours worked conditional on employment declined substantially as well. However, this decline in hours is entirely through employment absences without any change along the intensive margin. Figure 3 shows directly how the rate of those employed and at work and those employed but absent from work evolved. Both are expressed as a proportion of the population, so the sum of the two measures equals the employment to population ratio shown in the first figure. In this context it is important to distinguish between those "working from home"—who are employed and at work, albeit perhaps not physically at their usual place of work—and those classified as "Employed but absent from work."

Prior to COVID, the fraction of Employed-Working (relative to the population) fell in the 56-58% range, with seasonal dips to about 55% in March and more substantial temporary declines to around 53-54% during July and August when many workers take vacations. However, after March 2020, the Employed-Working rate fell sharply to just over 40% in April. Since that time the population share of the Employed-Working approached more normal levels, even during July and August when the usual seasonal decline was smaller than normal. By early Fall 2021 the rate had returned to its pre-COVID level by early Fall has remained there since.

As would be expected, the Employed-Absent rate moves inversely to the Employed-Working rate. This Employed-Absent rate usually lies in a narrow range from about 4.0-4.7%, with seasonal increases in March and July-August. However, the rate rose substantially during the initial lockdown during March and April 2020 and remained

A2 shows hours worked for the Employed for the high versus low propensity to telework groupings. The workers in occupations with a low propensity to telework show a larger decline in hours worked during the initial part of the COVID recession.

Figure 3: Employed, Working and Absent



Notes: The Employed-Working rate, relative to the population, is in blue and is measured on the left axis. The Employed-Absent rate is in red and is measured on the right axis. For both series, the light line denotes average values by month for the 2015-19 reference period, the heavy line denotes the values by month for 2020, and the heavy dots denote the monthly values for 2021.

well above normal in May and June 2020. Since the late summer of 2020, however, the gap between the COVID era and normal Employed-Absent rates has generally narrowed.

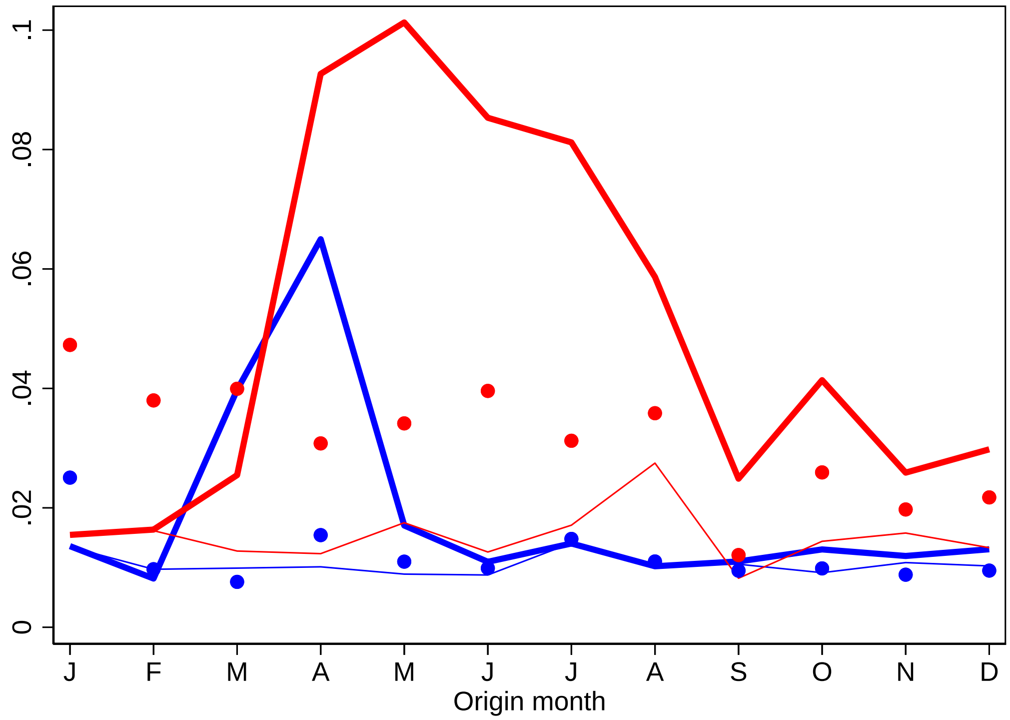
There is an important difference between the usual seasonal pattern of these two employment measures and those observed in response to the COVID shock. In the pre-COVID period the decline in Employed-Working and corresponding rise in Employed-Absent in July and August arises principally from employees on holidays, most of whom continue to be paid by their employer as part of their compensation package. In contrast, the substantial increase in Employed-Absent in March to June 2020 mainly results from individuals working zero hours and not being paid (the majority) or being compensated by their employer under the federal Canadian Emergency Wage Subsidy program. This behaviour—individuals who report that they "have a job" and remain attached to their (former) employer but are furloughed—provides a vivid illustration of the "tied" model of worker-firm relationships during the early COVID period. Such behaviour raises the question of whether we should interpret the Employed-Absent as Employed or some form of non-employment, an issue we return to below. It is also critical to the overall movement of actual hours of work, as in Figure 2 above, where most of the movement in this intensive margin figure is actually driven by the changing importance of those Employed-Absent at an extensive margin.

We next consider transitions between labour force states that underlie the dramatic and unusual changes in the composition of employment. For this we rely on the longitudinal dimension of the LFS and measure the probabilities of monthly transitions; for example, the transition rate from unemployment U to employment E, pUE, is the fraction of those unemployed in month t who are employed in month $t+1$. Transitions are labelled by their destination month.[14]

Figure 4 follows up on the changes in the population Employed-Working and Employed-Absent by examining transitions between these two categories of employment and unemployment. Prior to 2020, the job loss rate from Employed-Working varied around 0.01 with only a small seasonal increase in June to July. This changed during the initial lockdown, when the job loss rate rose to 0.04 in February-March and to over 0.06 in March-April. However, it was a short, sharp shock. The risk

[14]Below, we also address some longer horizon longitudinal behaviour, studying the consequences for those separated from jobs early in the pandemic over the subsequent five months.

Figure 4: Transitions from Employed-Working/Employed-Absent to Unemployment



Notes: The mean transition rate from Employed-Working to Unemployment is in blue and the mean transition rate from Employed-Absent to Unemployment is in red. For both series, the light line denotes average values by month for the 2015-19 reference period, the heavy line denotes the values by month for 2020, and the heavy dots denote the monthly values for 2021.

of further job loss had declined to its 2015-19 average as quickly as May 2020 and remained at normal levels throughout the rest of 2020 and all of 2021.

Transitions from Employed-Absent to unemployment are also typically low, in the range 0.01-0.02, for most of the year, with more pronounced seasonal changes in March and July-August when many families take holidays. During the COVID-19 era, however, enormous increases in the likelihood of moving from Employed-Absent to unemployed are observed, with the probability of LFS respondents reporting job loss rising from below 2% in the first two months of 2020 to 9% and 10% in April and

May. This suggests that as the initial lockdown persisted, many of the furloughed workers (identified in Figure 3) who initially responded that they "have a job" reported in the following month that they were unemployed job seekers or on temporary layoff. Note that the Employed-Absent group is usually small in size, typically 4-5% of the population. As Figure 4 illustrates, this small group was much more likely to transition from being furloughed to unemployed during the initial COVID-related downturn. Furthermore, although their likelihood of transitioning to unemployed has fallen since its peak in April to May 2020, it has remained elevated compared to its 2015-19 average level as well as compared to the risk of job loss among the Employed-Working group.[15] The evolution of the month-to-month transition rates of this group indicates that their initial surge in March and April 2020 (shown in Figure 3) constituted a form of temporary layoff or recall unemployment that was labeled as employment because of the strength of the attachment to the previous employer.

A more formal statement of this point can be made using the conceptual framework outlined previously (Section 2.1). Consider a 4-state environment {Ewk, Eabs, U, O} where Employed-Working Ewk and Employed-Absent Eabs are treated as separate states and O = M+N. Necessary and sufficient conditions for Ewk and Eabs to be equivalent states are:

$$\text{pEwkU} = \text{pEabsU} \textit{ and } \text{pEwkO} = \text{pEabsO}. \tag{4}$$

Alternatively we could begin with a 5-state environment {Ewk, Eabs, U, M, N} and

[15]An implication of these results might be that the Employed-Absent group constitutes a buffer group that is the first to be separated and the last to be recalled.

obtain corresponding conditions for the equivalence of Ewk and Eabs:

$$\text{pEwkU} = \text{pEabsU} \textit{ and } \text{pEwkM} = \text{pEabsM} \textit{ and } \text{pEwkN} = \text{pEabsN}. \tag{5}$$

In normal economic times, these conditions hold (apart from minor seasonal spikes); for example, pEwkU is not significantly different from pEabsU, as shown by the pre-COVID average values in Figure 4. This equivalence also holds in normal times for pEwkM and pEabsM as well as pEwkN and pEabsN although we do not report these results here. Thus, when monitoring or describing labour market behaviour we typically do not distinguish between those employed at work and employed but absent from work. However, the conditions in equations (4) and (5) did not hold during the pandemic—especially during the period from March to August 2020, but continuing throughout most of 2020 and 2021. In particular, the probability of being classified as unemployed, marginally attached or non-attached the following month was substantially higher for the employed absent group than for those employed at work. Thus, treating these as equivalent states, as is done when Ewk and Eabs are combined into Employed, is misleading. Arguably, during the COVID period the Employed-Absent category constitutes a form of "furlough unemployment" in which individuals report that they "have a job" that they hope to return to, similar to temporary layoffs without a definite date of recall.

2.4 Two Phases of Unemployment

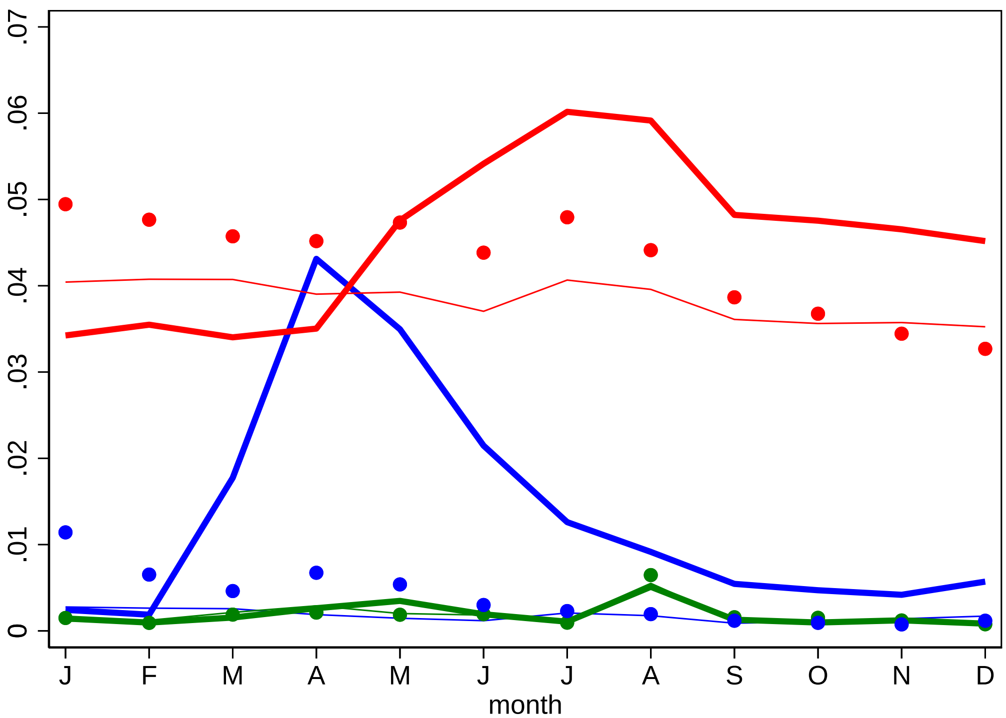
It was particularly noteworthy during the COVID era how dramatically the composition of the unemployed changed, and we illustrate this in Figure 5. In normal times, as indicated by the pre-pandemic averages, those engaged in active job search constitute by far the largest group among the unemployed, usually 3.5-4% of the population. The remaining two groups—those on temporary layoff and future job starts (those with a job to start at a definite date in the next month)—are minor by comparison, usually accounting for 0.1-0.2% of the population. However, during the initial COVID-related downturn, temporary layoff unemployment surged to an unprecedented 4.3% of the population in April 2020, more than the number of unemployed job seekers. Again, this is consistent with a short but important period of "tied" labour market arrangement where many of those without jobs simply waited for recall from the former employer. The importance of recall unemployment has since declined but remained elevated compared to pre-COVID levels until July 2021 and was thus an important vestige of the initial COVID-19 shock for more than a year.

Another noteworthy feature of Figure 5 is that the share of unemployed job searchers started increasing in May 2020, with a delay of about 2 months following the onset of the pandemic. During January to April 2020, unemployed job search was consistently lower than during the same months pre-COVID, but after rising substantially in May and June 2020 it remained above pre-pandemic levels until late Fall 2021. From early summer 2020 on, search unemployment constituted by far the largest component of unemployed followed by those on temporary layoffs.

We next examine the rates of job finding for these different groups within the unemployed. In usual times, those on temporary layoffs and the future starts have higher transition rates back into employment than unemployed job searchers, reflecting their high degree of attachment to an employer. We address how this changed in the COVID-19 era in Figure 6.

Typically about 30-50% of those on temporary layoffs are employed by the fol-

Figure 5: Sizes of Unemployment Categories

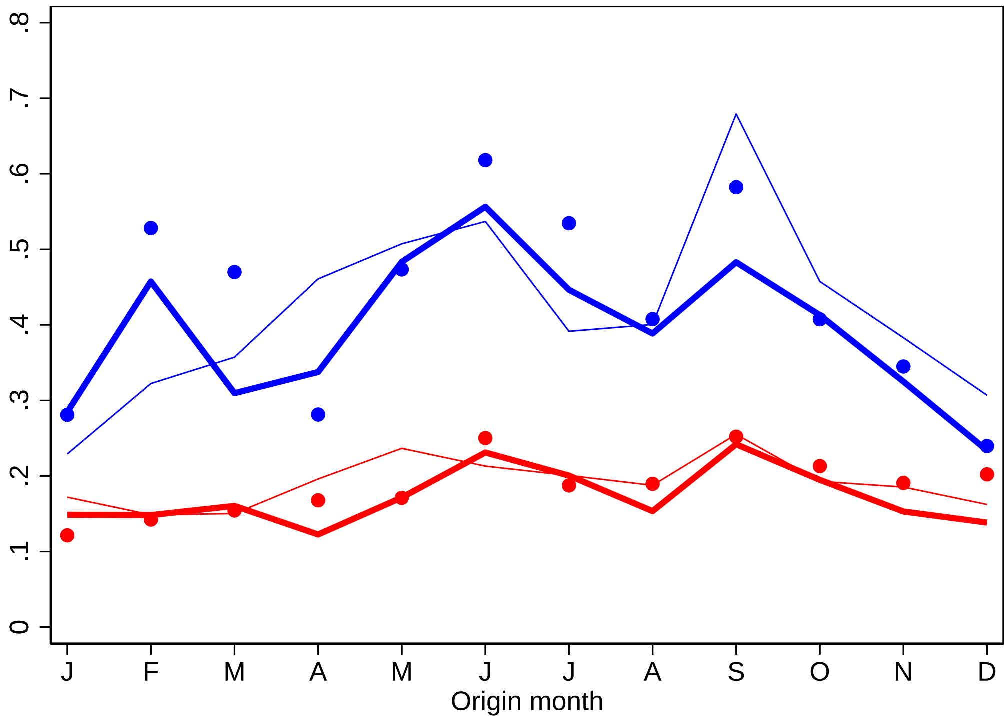


Notes: Job Search Unemployment is in red, Temporary Layoff/Recall Unemployment is in blue, and Future Job Starts are in green. All series are presented as a proportion of the population. For all series, the light line denotes average values by month for the 2015-19 reference period, the heavy line denotes the values by month for 2020, and the heavy dots denote the monthly values for 2021.

lowing month. In a normal year, this rises during the first part of the year, declines during the summer months and then spikes to about 70% during August and September, followed by a steady decline in the remainder of the year. Transition rates during the COVID-19 period follow a broadly similar seasonal pattern, albeit with a much smaller spike in August-September 2020 and with some noteworthy departures from corresponding pre-COVID months, reflecting the tightening and loosening of health restrictions.[16] Overall, we see that quantitatively and qualitatively, transition rates

[16] Since the future job start category of unemployment is so small, we present only the transition rates from job search and temporary layoff unemployment in Figure 6. The job-finding rate from

Figure 6: Transitions from Unemployment Categories to Employment



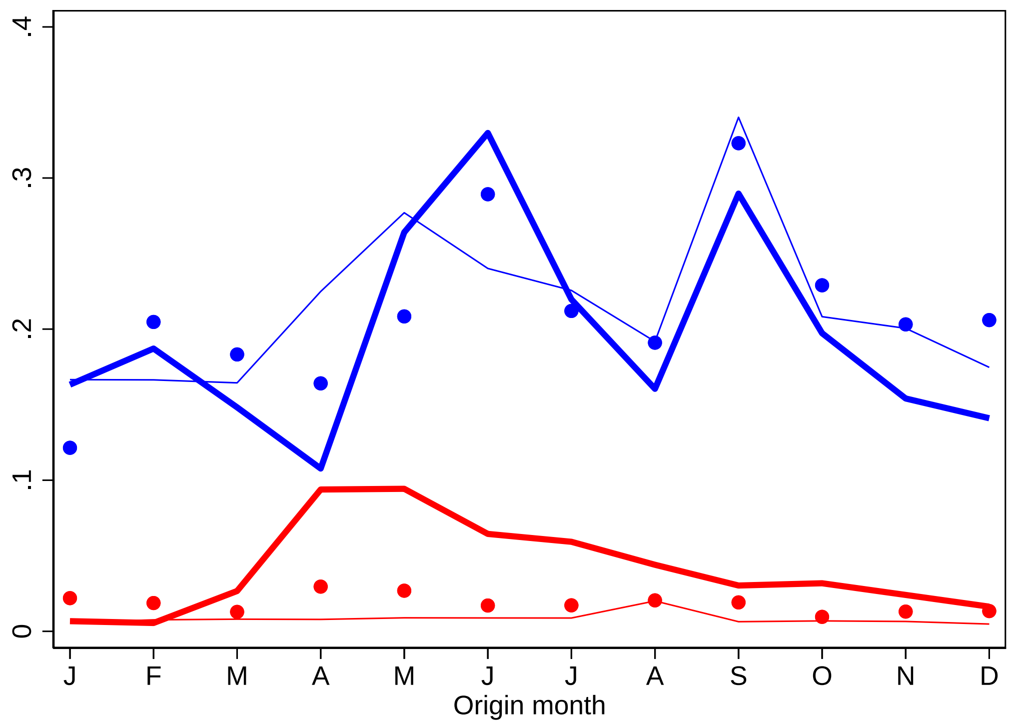
Notes: The mean transition rate from Unemployment-Temporary Layoff to Employment is in blue, the mean transition rate from Unemployment-Job Search to Employment is in red. For both series, the light line denotes average values by month for the 2015-19 reference period, the heavy line denotes the values by month for 2020, and the heavy dots denote the monthly values for 2021. For clarity, we omit the transitions from the Unemployed - Future Job Starts category.

into employment from both groups followed the same pattern we usually observe.

We do, however, observe pandemic-related differences in the rates at which the unemployed move into Employed-Working and Employed-Absent. The transition probability into these two categories of Employment is shown in Figure 7. The probability of moving from Unemployment to Employed-Absent is typically very

future job starts typically lies in the 0.6-0.8 range, with some seasonal variation. In the COVID era, this rate was more volatile and dipped briefly to 0.3 in April 2020 as planned job starts were hit by the pandemic shutdown.

Figure 7: Transitions from Unemployment to Employed-Working/Employed-Absent



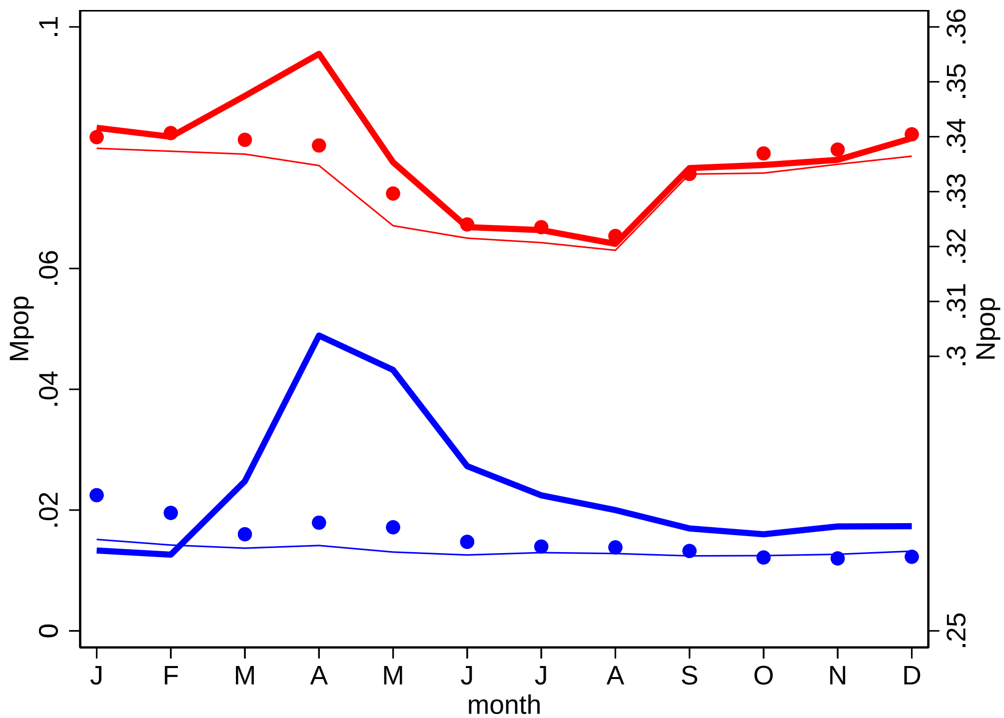
Notes: The mean transition rate from Unemployment to Employed-Working is in blue, the mean transition rate from Unemployment to Employed-Absent is in red. For both series, the light line denotes average values by month for the 2015-19 reference period, the heavy line denotes the values by month for 2020, and the heavy dots denote the monthly values for 2021.

low—close to zero—and stable over the year except for a small seasonal increase in July to August. During the initial months of COVID, however, this likelihood rises substantially to about 0.1 in March-April and April-May 2020. Combining Figures 4 and 7 shows unusually large movements in both directions between furloughed workers (Employed-Absent) and the officially unemployed, further evidence of the fluidity between these two categories. The sharp initial increase in transitions into Employed-Absent is followed by a gradual decline toward average levels, although remaining above those 2015-19 averages in the rest of 2020 and to a lesser extent in most months in 2021. Although modest in size, the continued presence of transitions from Unemployment to Employed-Absent that are higher than their pre-COVID levels suggests that a small amount of this “tied model” type of temporary layoff unemployment remained during the second year of the pandemic. Unemployed to Employed-Working transition rates are much higher throughout the year – typically in the range 0.15 to 0.3 with a pronounced seasonal pattern with spikes in April-May and August-September. A similar seasonal pattern is observed in 2020, with the principal exceptions being the depressed job-finding rate in March-April and the unusually high rate in May-June. After the summer months of 2020, job-finding rates follow a similar seasonal pattern to that observed in 2015-19 but remain somewhat lower than the pre-COVID average. Adherence to normal seasonal patterns is also evident in 2021 but deviations—both above and below—from pre-COVID job-finding rates continued in the first half of 2021. Only in July to December 2021 were transition rates into Employed-Working consistently close to normal levels.

2.5 Adjustment by Attachment of Non-Participants

As noted previously, the massive job losses in March and April 2020 were accompanied not only by a steep rise in unemployment but also by an enormous decline in labour force participation. Figure 8 decomposes non-participants into two main components: the non-employed who are not searching but state that they want work, referred to as the marginally attached, and the non-employed who report that they do not want work, referred to as the non-attached. Both magnitudes are expressed relative to the population. Huge changes in both series, especially in Mpop (the ratio of the Marginally Attached to the Population), are evident during the COVID-19 period. Monthly Mpop levels remained in a narrow range between 0.012 and 0.015

Figure 8: Size of Non-Participant Categories



Notes: The Marginally Attached rate Mpop is in blue and is measured on the left axis. The Non-Attached rate Npop is in red and is measured on the right axis. Both series are presented as a proportion of the population. For both series, the light line denotes average values by month for the 2015-19 reference period, the heavy line denotes the values by month for 2020, and the heavy dots denote the monthly values for 2021.

during 2015-19 and were slightly below their pre-COVID average levels in January and February 2020. In March and April of 2020, though, Mpop rose to unprecedented levels, peaking at almost 0.05 in April, then falling substantially over the next five months to 0.017 in September. After that time, Mpop fluctuated but remained above its 2015-19 average level until June 2021. In the second half of 2021 Mpop levels have been very similar to pre-COVID values. Overall, this pattern in Mpop is consistent with greater attachment to the labour market – especially in the initial months of the pandemic – and suggests that, even in mid-2021, non-participants retained more than usual attachment to the workforce.

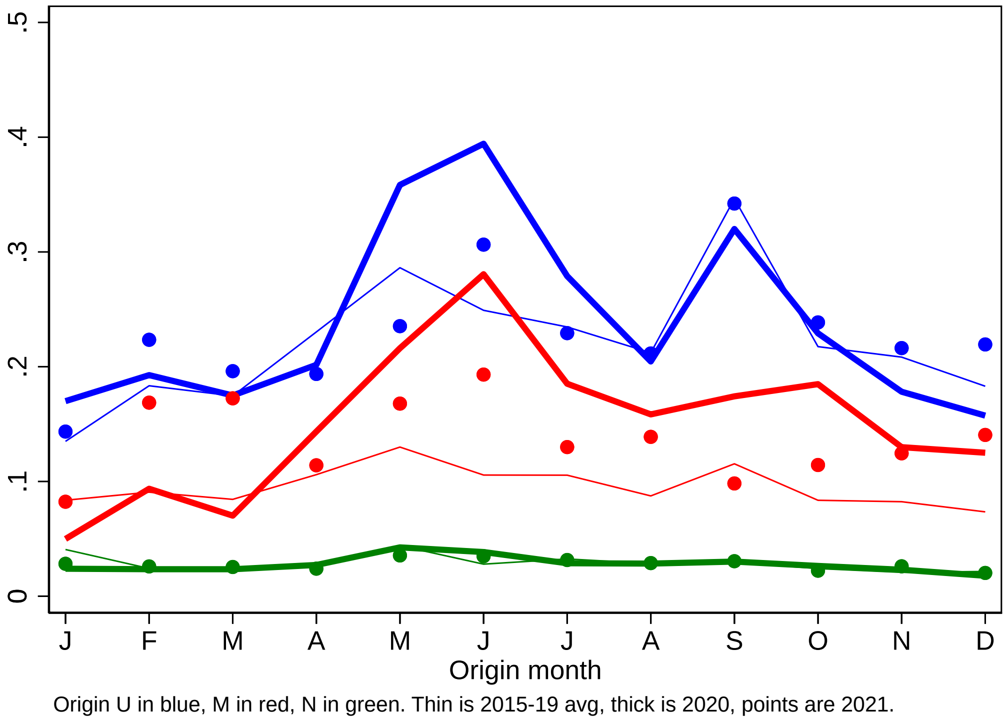
Like Mpop, Npop levels rose steeply in March and April 2020, peaking at 0.36 versus a 2015-19 average value of 0.33 for that month. The fraction of the population that neither searched for nor desired work then declined during May to August, in part reflecting a normal seasonal drop during that period. Since that time Npop has remained slightly higher than average, though at times the gap relative to 2015-19 levels has been small.

As noted earlier, following the steep decline of labour force participation in March and April 2020, the participation rate gradually recovered but nonetheless remained slightly below its pre-pandemic level at the end of our sample period. Figure 8 indicates that this gap can be attributed to a small increase in the fraction of the population neither looking for nor wanting work.

To investigate movements in participation further we next examine job-finding rates from these two non-participation states, relative to the rate from Unemployment. In Figure 9 we show transition rates into Employment from three broad categories of the non-employed – unemployment U, marginal attachment M and non-attachment N. Together M + N sum to those classified as non-participants, or Out of the labour force. Previous research for several countries, including Canada, the U.S. and the UK, has concluded that U, M and N exhibit distinct transition behaviour, with M falling between U and N in terms of the likelihood of being employed in the future (Jones and Riddell, 1999, 2019; Moffat and Yoo, 2015).

The probability of moving from U to E in the following month is very similar in January and February 2020 to its average level in the 2015-19 period. With the introduction of widespread restrictions in March 2020, the March-April 2020 tran-

Figure 9: Transitions from Non-Employment Categories to Employment



Notes: Mean transition rates to Employment from Unemployment (in blue), Marginal Attachment (in red), and Non-Attachment (in green). For all series, the light line denotes average values by month for the 2015-19 reference period, the heavy line denotes the values by month for 2020, and the heavy dots denote the monthly values for 2021.

sition rate is distinctly lower than average (0.20 vs 0.23). However, the job-finding rate jumps substantially in April-May and May-June to levels far above normal and, although it drops substantially in June-July, it nonetheless remains higher than average for those months. Subsequently, job-finding rates of the officially unemployed experience substantial ups and downs reflecting both seasonal fluctuations as well as plausibly the tightening and relaxation of public health restrictions evident in transition rates above and below normal levels. The overall pattern is that job finding rates from unemployment exceed normal levels during the summer of 2020, but fall back to normal levels subsequently with some month-to-month variation around the historical rates observed until the end of 2021.

We noted before (Section 2.1) that a necessary condition for the equivalence of U and M is pUE = pME and for M and N is pME = pNE. Figure (9) reveals that this condition clearly does not hold during 2015-2019: pUE exceeds pME, and pME exceeds pNE throughout, so U, M and N are distinct states. However, we also see that during the COVID period the job finding rates of the marginally attached diverge even more from their pre-pandemic values than is the case for unemployed job searchers. As with pUE, the transition rate pME in January and February 2020 was close to the 2015-19 averages, but it rose dramatically during the next three months, peaking in May-June at 0.28 versus an average level of about 0.1. Job-finding rates of the marginally attached decline in subsequent months, as was the case for the unemployed, but unlike pUE remain much higher than normal throughout the remainder of 2020 and throughout most of 2021. Indeed, even in December 2021, pUE and pME remain much closer to each other (0.22 versus 0.21, a gap of 0.01) than in the pre-pandemic period (0.18 versus 0.07, a gap of 0.11). This suggests that the marginally attached group remained much more attached to the workforce than in previous periods, and closer to the degree of attachment of those searching for work. Thus, in any attempt to construct a more generalized measure of unemployment and/or labour market tightness, the marginal attachment group should receive a higher weight during the COVID period than in earlier time periods.[17]

In contrast, the transition rate pNE, the job-finding rate of the Non-Attached, remained largely unchanged throughout the turbulent COVID-19 period, relative to

[17]See Abraham et al. (2020) and Hornstein et al. (2014) for approaches to construct measures of labour market slack accounting for groups like the marginally attached using relative job finding rates.

transition rates seen in the 2015-19. The sharp rise in non-participation early in the pandemic period, together with its subsequent substantial decline, was driven by the Marginally Attached group. Furthermore, our results suggest that the nature of being marginally attached changed during the COVID pandemic. Relative to historical patterns, being marginally attached during COVID entailed higher relative rates of transitioning to employment.

2.6 Characteristics of Transitions at the Peak of the COVID-19 Turmoil

To conclude this Section, we use the full 6-month panel feature of the LFS to probe more deeply into the period of turmoil at the onset of the pandemic.[18] Above, we have shown that standard measures of activity that perform well in more normal downturns are less well suited to the pandemic recession. For example, the large share of Employed-Absent during the onset of the pandemic suggests that temporary layoffs are in fact undercounted during that period. Also, the marginally attached look more similar to search unemployed than during normal periods. To account for this, we construct novel labour market groupings that depart from the standard LFS classifications but which are, we think, more informative about the processes in operation in the labour market during the initial months of the COVID-19 era.[19]

We use an approach similar to an "event study" to examine workers who were in

[18] The U.S. 4-8-4 rotation group structure in the Current Population Survey has many research-related benefits because households are observed in the same 4 calendar months in contiguous years. However, in the case of analyzing the COVID shock the length of a 6-month panel has important advantages.

[19] These groupings are based on previous findings in this section and are also closely related to those employed by Kahn, Lange and Wiczer (2020) in their analysis of the turbulence of the U.S. labour market.

paid employment in February 2020 and study their initial labour market outcomes in the heart of the recession. In order to have sufficient observations, we use the January and February 2020 in-rotation cohorts and we follow these individuals until June 2020.[20] We identify their first change away from paid employment and then determine who was able to return to paid employment by June, at a point where the labour market had already recovered more than halfway back to the February employment rate. Further, we study the type of job to which these workers returned in terms of earnings, actual hours worked, industry, occupation, and occupational characteristics.

For this analysis our labour market groupings in each subsequent month are as follows: those in paid employment, workers actively searching, workers waiting for some type of recall and those with no observable labour market attachment. The first group contains workers who were "employed and paid" in all five months and make up around 63% of this sample. This group is comprised mainly of workers who were Employed-Working, but also include the Employed-Absent *if they were paid*. With the obvious exception of actual hours worked, workers who were Employed-Absent but paid are on average very similar to the workers who were Employed-Working in terms of their February labour market characteristics.

The remaining three categories contain individuals who experienced a movement away from paid employment. We distinguish between them based on their *first* status other than paid employment between March and June 2020. The Unemployed-Searching group, which makes up 3.6% of the sample, consists of the job search Un-

[20]An implication of the work of Brochu and Créchet (2021) on the problems with *initial* LFS interviews in the pandemic period is that there is merit in using a panel where the initial interview was conducted pre-pandemic. Also, we note that this use of the full length of the panel is rare in empirical work with the LFS and illustrates a benefit of the survey's six-month long rotation group structure.

employed, as conventionally measured. The No Search/Recall group, which makes up almost of a quarter of the sample, includes the Unemployed-Temporary Layoffs, the Unemployed-Future-Starts, the Employed-Absent who were unpaid, and the "awaiting recall" subset of the Marginally Attached.[21] The final grouping (NILF) is the residual and is composed mainly of the the Non-Attached as previously discussed. They make up around 9% of the sample.

Table 1 presents the February 2020 labour market characteristics of these four groups. There are notable differences between workers who were able to maintain paid employment during the peak period of economic turmoil and those that transitioned away from paid employment. Workers who were able to maintain paid employment over the five months covered by the panel had much higher earnings in February, the month prior to the start of the COVID-19 recession. These individuals also worked more hours in the February reference week.[22,23]

Table 1 also reports differences in the occupational skill requirements of the February 2020 occupation for these different groups. To do so, we rely on the task measures by occupation collected by the U.S. Bureau of Labor Statistics and published as the O*NET.[24] We employ factor analysis on the variables from O*NET to construct three skill indices measuring quantitative, interpersonal, and physical strength re-

[21]For brevity we did not examine sub-sets of the Marginal group in this paper. However, previous research concluded that the "waiting" subset of Marginal exhibits very different behaviour from the remainder of the Marginal category, with much higher transition rates into Employment the following month (Jones and Riddell, 2006).

[22]These differences are largely unchanged if workers who are Employed-Absent but paid, a small group, are excluded from the analysis.

[23]Koebel and Pohler (2020) examine the initial downturn period and the variation in government shutdowns. One key finding is that while low-earning workers saw a larger decrease in hours worked, their work highlights that some low-earning workers actually saw an increase in hours worked.

[24]The same data was also used by Dingel and Neiman (2020) to construct an index on work from home suitability.

Table 1: February characteristics by first labour market status change for workers employed in February

	Employed paid	Unemployed search	No search/ recall	NILF
Weekly earnings	1224.0	857.2	781.0	735.9
	(7.13)	(30.08)	(9.13)	(17.33)
Hourly earnings	32.41	24.09	23.17	22.71
	(0.166)	(0.556)	(0.198)	(0.337)
Actual hours worked	36.9	33.62	31.28	29.26
	(0.134)	(0.786)	(0.262)	(0.478)
Occupational skill requirements‡				
Interpersonal skills	0.245	-0.254	-0.391	-0.341
	(0.01)	(0.047)	(0.016)	(0.026)
Quantitative skills	0.262	-0.264	-0.375	-0.407
	(0.01)	(0.048)	(0.015)	(0.026)
Physical strength	-0.190	0.174	0.319	0.197
	(0.01)	(0.048)	(0.016)	(0.026)
Propensity to telework†	0.495	0.321	0.262	0.319
	(0.005)	(0.022)	(0.008)	(0.014)
Percent of sample	63.0	3.6	24.3	9.1

Notes: [1] Sample: workers who were in paid employment in February 2020 and were in the LFS each subsequent cycle until June 2020. [2] Employed paid includes workers who in each of the 5 months of the analysis were either *employed and at work* or *away from work but paid*. [3] The other 3 categories are based on the first non-paid employment status between March and June 2020 for workers who left paid employment. The second group is "unemployed who were actively searching for employment". The third group is "no search/recall" which includes *unemployed waiting for recall* or *future start*, *employed but away from work and not paid*, and *not in the labour force but waiting for recall*. The final group, "not in the labour force", includes those *initially moving out of the labour force (and not waiting for recall)*. [4] Standard errors are in parentheses. [5] ‡ Constructed with variables from the O*NET using factor analysis weighted by the employed population from the 2016 Census. Scores are mean zero and have a unit variance. A unit of a derived factor score is equal to one standard deviation in the skill distribution for the 2016 May Canadian population. [6] † Constructed from Dingel and Neiman (2020) index. 1 = Occupation has high propensity to telework. 0 = Occupation has low propensity to telework.

quirements.[25] The skill indices are mean of zero and one unit corresponds to a standard deviation in the skill distribution for the May 2016 Canadian population based on the employed population from the 2016 Census Masterfile.

Our results on occupational skill requirements also highlight important differences in the labour market characteristics between these four groups. Workers who managed to maintain paid employment during the worst part of the COVID-19 recession tended to work in jobs with higher cognitive skill requirements (both interpersonal and quantitative skills) and lower manual skill requirements (as measured by physical strength requirements[26]). For example, workers in the "Employed paid" group were employed in February in jobs that require around 0.26 standard deviations more quantitative skills than the average of Canadian workers in 2016, and work in jobs requiring more than half a standard deviation greater quantitative skills than workers who end up in unemployed search. This gap is even larger relative to workers in the No Search/Recall and NILF groupings.

The last variable in Table 1 is an indicator variable for whether the February occupation had a high versus low propensity to telework. While almost half of workers who maintained employment during the trough of the COVID recession worked in an occupation with a high propensity for telework, for workers who transitioned away from paid employed, less than a third were in teleworkable occupations.

Potentially, the large differences in February labour market characteristics between workers who maintained paid employment and those that end up displaced in the early part of the recession might be due entirely to differences in the industries and occupations affected by the lockdown in early 2020. To address this, we estimate

[25] We updated the skills constructed in Imai et al. (2019) who used the 2001 Census as weights. See Warman and Worswick (2015) for additional detail on the factor analysis and methods used.

[26] A similar pattern is found for visual and motor skill requirements.

various specifications of the following equation:

$$Y_i = \alpha + \delta_1 Search_i + \delta_2 Recall_i + \delta_3 NILF_i + \beta Age_i \ + \lambda Ind_i \ + \gamma Occ_i \ + \epsilon_i \quad (6)$$

where we include indicators for the first labour force status movement away from paid employment: Search unemployment, Recall unemployment and Not in the labour force. Workers who were in paid employment in each of the five months constitute the default category. The dependent variable Y_i is measured in June 2020.

We present the estimates of equation (6) for February weekly earnings in Table 2. The first column without any controls replicates the weekly earnings results of Table 1. In column 2 we account for age differences using dummies for age groups 15-24, 25-54, 54-70, and 70+. This narrows the earnings gap relative to the always employed group slightly, potentially reflecting that younger or older workers are more susceptible to being laid off during the downturn. From the P-value from a joint F-test, we can see that the differences between the three groups that move away from paid employment is statistically significant. Industry fixed effects are included in column 3,[27] and produce a further reduction in the differences in February weekly earnings. While there is still a sizeable gap relative to the workers who maintained paid employment, the differences between the other three groups are no longer statistically or economically significant. Finally, we add occupational fixed effects in column 4; this produces a further reduction relative to the workers who maintained paid employment.[28]

Overall, the differential impact of the initial turmoil of the COVID-19 recession is important in explaining much of the dramatic change shown in Table 1. Account-

[27]We include 478 industry fixed effects.

[28]We include 281 occupational fixed effects.

Table 2: February weekly earnings by first labour market status change for workers employed in February

	(1)	(2)	(3)	(4)
Search unemployment	-366.7**	-293.0**	-230.1**	-152.7**
	(29.22)	(27.76)	(25.45)	(21.77)
Recall unemployment	-442.9**	-368.6**	-248.4**	-148.5**
	(12.84)	(12.36)	(12.10)	(10.47)
Not in the labour force	-488.0**	-380.7**	-269.5**	-155.7**
	(19.07)	(18.32)	(17.30)	(14.91)
Constant	1,224**	1,293**	1,222**	1,957**
	(6.780)	(7.152)	(6.730)	(362.1)
Age dummies	No	Yes	Yes	Yes
February characteristics				
Industry fixed effects	No	No	Yes	Yes
Occupation fixed effects	No	No	No	Yes
P-values from F-test				
All equal	0.001	0.017	0.326	0.326
Joint zero	0.000	0.000	0.000	0.000
Observations	14,001	14,001	14,001	14,001
R-squared	0.104	0.197	0.377	0.588

Notes: [1] Sample: workers who were in paid employment in February 2020 and were in the LFS each subsequent cycle until June 2020. [2] Default category is workers who in each of the five months were either *employed at work* or *away from work but paid* [3] The other three categories are based on the first non-paid employment status between March and June 2020 for workers who left paid employment. The second group is "unemployed who were actively searching for employment". The third group is "no search/recall" which includes *unemployed waiting for recall* or *future start*, *employed but away from work and not paid*, and *not in the labour force but waiting for recall*. The final group, "not in the labour force", includes those *initially moving out of the labour force (and not waiting for recall)*. [4] Age dummies for 15 to 24 year olds, 55 to 70 year olds and 70 plus, with 25 to 54 year olds as the default category. [5] Standard errors are in parentheses. Statistical significance is denoted by: ** at 1% level, * at 5% level, + at 10% level.

ing for age and the February 2020 industry of employment eliminates the February earning differential among the three groups of workers who moved away from paid employment. Further, while accounting for age, industry and occupational differences reduces the large February earning differential between workers who maintained paid employment and those who had a separation, a sizeable gap still remains.

In Appendix Table A1, we present the results for the February occupational skill requirements. To conserve space, we do not show the columns without controls (these can be calculated from Table 1). In addition to age, we show specifications where we account for whether a job is potentially teleworkable and/or industry. Workers in teleworkable occupations also work in occupations with a little less than a one standard deviation higher interpersonal skill requirements, and one and a half standard deviations lower physical strength requirements. While we still find important differences between workers who maintained paid employment and the other categories, the gap is reduced by around half when teleworkability and industry are conditioned on. As well, the differences between the other categories are eliminated.

In Table 3, we examine the type of employment that workers from our February 2020 sample transition into by June 2020. We exclude cells for which wages may not be replenished for workers that maintain employment with the same employer.[29] Examining changes in compensation, workers who are able to re-enter paid employment do not appear to suffer any loss in compensation in terms of either weekly, hourly earnings or actual hours worked.[30]

We next examine what fraction of workers report being employed in the same in-

[29]See Brochu (2021) for a description of how wages are collected in the LFS.

[30]Changes in hours worked should be interpreted with caution since the measure of actual hours worked may be low in February 2020 due to the LFS reference week in that month including a statutory holiday in many provinces.

Table 3: Paid workers, June relative to February employment related values

	Employed paid	Unemployed searching	No search/ recall	NILF
Weekly earnings		-1.878	20.52	-3.817
		(38.37)	(9.77)	(18.13)
Log weekly earnings		0.027	0.055	0.085
		(0.048)	(0.013)	(0.031)
Hourly earnings		0.972	0.050	0.042
		(0.724)	(0.219)	(0.363)
Log hourly earnings		0.028	0.004	0.014
		(0.023)	(0.007)	(0.014)
Actual hours worked	-0.400	0.094	-1.160	-0.807
	(0.150)	(1.297)	(0.384)	(0.721)
Matching based on:†				
Industry	0.831	0.555	0.762	0.744
	(0.004)	(0.039)	(0.01)	(0.02)
Industry/Occupation	0.752	0.357	0.699	0.613
	(0.005)	(0.038)	(0.011)	(0.023)
Industry/Occupation/Firm size		0.247	0.529	0.444
		(0.034)	(0.012)	(0.023)
Industry/Occupation/Establish. size		0.234	0.540	0.452
		(0.033)	(0.012)	(0.023)
Occupational skill requirements‡				
Interpersonal skills	0.021	-0.032	-0.038	-0.007
	(0.005)	(0.059)	(0.014)	(0.027)
Quantitative skills	0.021	0.038	-0.030	0.011
	(0.005)	(0.065)	(0.013)	(0.028)
Physical strength	-0.005	0.080	0.014	0.080
	(0.005)	(0.052)	(0.014)	(0.027)

Notes: [1] Sample: workers who were in paid employment in February 2020 and June 2020 and were in the LFS in each of the in between cycles. [2] Employed paid includes workers who in each of the 5 months of the analysis were either *employed and at work* or *away from work but paid*. [3] The other 3 categories are based on the first non-paid employment status between March and June 2020 for workers who left paid employment. The second group is "unemployed who were actively searching for employment". The third group is "no search/recall" which includes *unemployed waiting for recall* or *future start*, *employed but away from work and not paid*, and *not in the labour force but waiting for recall*. The final group, "not in the labour force", includes those *initially moving out of the labour force (and not waiting for recall)*. [4] Standard errors are in parentheses. [5] Reported are the fraction of individuals in each cell that report being employed in the same the category of employment as indicated by the row headers. For example, 55.5% of those employed in February who transitioned to unemployed searching in the following months before being reemployed in June, employment in June was in the same industry as in February. [6] ‡ Constructed with variables from the O*NET using factor analysis weighted by the employed population from the 2016 Census. Scores are mean zero and have a unit variance. A unit of a derived factor score is equal to one standard deviation in the skill distribution for the 2016 May Canadian population.

dustry, industry and occupation, and then by industry and occupation and either firm size or establishment size between February and June 2020. Around 83% of workers who maintained paid employment in all five months remain in the same industry but this figure is much lower for other categories, particularly the Unemployed-Searching group. The match rate when industry/occupation and firm size or establishment size is considered is only around 25% for the Unemployed-Searching group, less than half the rate for the no search/recall group.[31]

As is well known, occupation and industry coding is susceptible to measurement error. We therefore examine occupational skill requirements which are less impacted by this measurement error. If an occupation is miscoded, the chosen occupation code is likely to be similar in terms of skill requirements relative to the true occupation, resulting in a small gap due to miscoding. Examining the skill requirements again suggests that workers that are employed in June tend to end up in occupations requiring very similar skills to their February employment.

Together, this evidence suggests that workers who were able to stay in paid employment or had a separation from paid employment at the start of the COVID recession but were able to regain paid employment by June 2020 did not see much change in the quality of their job in terms of measures such as earnings and occupational skill requirements.[32] However, selection issues may influence these results if more capable workers were better able to maintain employment, remain tied to their former workplace, or quickly attain new employment.

[31]The match rate conditional on industry and establishment size might overstate the probability to return to the same employer since individuals might join different employers in the same cell. It might also understate the match rate since establishments might change size and be coded to belong to a different industry.

[32]The indices used to measure skill requirements have a standard deviation of one. Thus, even if some of the changes, such as for quantitative skills among the "employed, paid", are significant, the magnitude of these changes (0.021 in this case) are small.

Additional results in Appendix Table A2 suggest that selection may be an important issue since a large fraction of workers who moved away from paid employment after February 2020 were still unemployed by June.[33] In this Table, we use a linear probability model to assess factors affecting the likelihood that workers who moved away from paid employment at the start of the COVID-19 recession were able to find employment by June 2020. When only labour force status indicators are included (column 1), we find that around 40% of workers that initially moved to unemployment search were able to find work by June 2020. Workers who moved out of the labour force had similar success in securing paid employment by June 2020. For workers with some type of recall or attachment to the employer, their probability of June employment was around 15 percentage points higher. In subsequent columns when we add controls for age, month of first employment status change and finally introduce industry and occupation fixed effects, we find that such controls do not fully account for the reemployment gap.

3 Measuring Labour Demand: Vacancies

We assess the strength of labour demand through the COVID-19 era using counts of jobs posted provided by Burning Glass Technologies (BGT). Burning Glass Technologies is a private company that scrapes the web for all new positions and expends significant effort removing duplicates.[34] We think of job postings as an indicator of

[33] Baylis et al. (2022) examine the probability of employment in June 2020 based on non-work state in April 2020 by different demographic groups.

[34] BGT data has become a fairly standard source of data on hiring intentions in the United States. Kahn et al. (2020) and Forsythe (2020) for example use the BGT for the U.S. in their reports on the state of the U.S. labour market during the COVID recession. Hershbein and Kahn (2018) use BGT data to show that during the Great Recession employers increased skill requirements for new positions and engaged in skill upgrading. Hershbein and Kahn (2018) report that the data

how employers assess the profitability of new employment relationships. As such, this indicator is forward looking as it depends on expectations about future market conditions.[35]

An alternative source on job openings is the Statistics Canada Job Vacancy and Wage Survey (JVWS). These data sources differ in a number of ways. The JVWS is based on a representative survey of all business locations operating in Canada, whereas the BGT data is obtained by scraping the universe of job postings on job boards and company webpages. While JVWS reports open positions, the BGT measures new job postings which can at times refer to multiple positions. The JVWS reports a stock of open positions, whereas BGT data measure a flow.

Unfortunately, the JVWS ceased collecting data in Q2 and Q3 2020 and is thus not suited for examining conditions during crucial months of the COVID-19 pandemic. Another advantage of the BGT data is that is we can use it to measure job postings by province, occupation, industry and day of posting, whereas the JVWS is only available monthly for industry and province, but not for their interaction. We therefore rely primarily on the BGT data because it allows us to examine job postings by occupation-industry-province and because it is timely and available throughout the pandemic.

Figure 10 shows the data from JVWS and BGT on job openings and job postings (normalized to January 2020 levels) to January 2022. With the exception of the Fall

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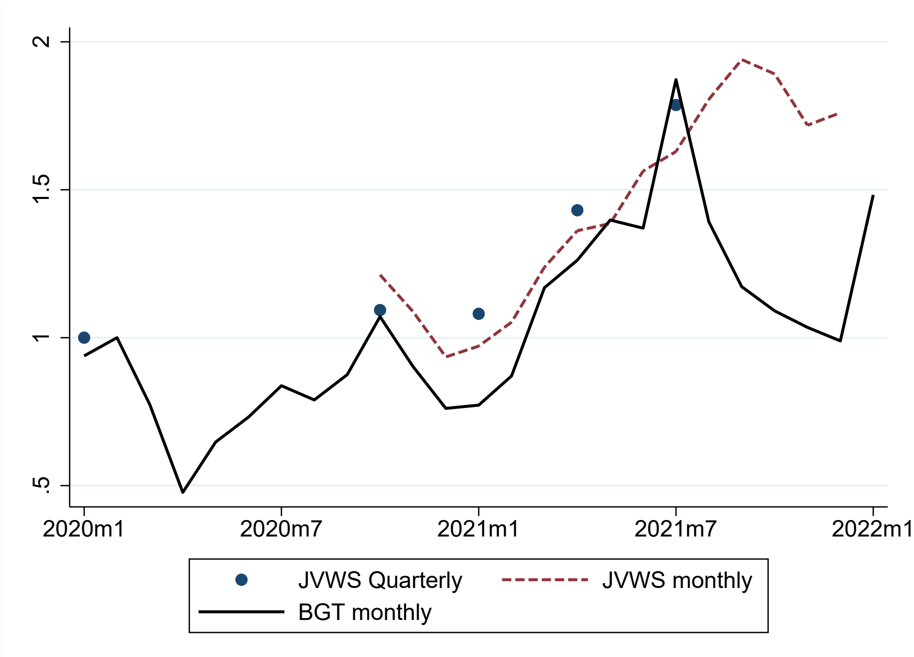
is of high quality, even though it is somewhat biased towards high skill occupations compared to job openings reported in Job Opening and Labor Turnover Survey (JOLTS). In the Appendix, we present evidence that the JVWS and the BGT data in Canada are highly correlated across provinces, industries, occupations, and time (See Figures A3 to A5).

[35] Employers can adjust their workforce through other measures than through posting vacancies, for example through laying off part of their work-force and through measures to reduce turnover. Our measure of job postings does not capture these manifestations of labour demand. We can also not speak to the intensity of employers' recruiting effort.

of 2021, the JVWS series is consistent with the BGT. Unfortunately, we do not know why the series diverged late in 2021.

Figure 10: Job Openings and Job Postings



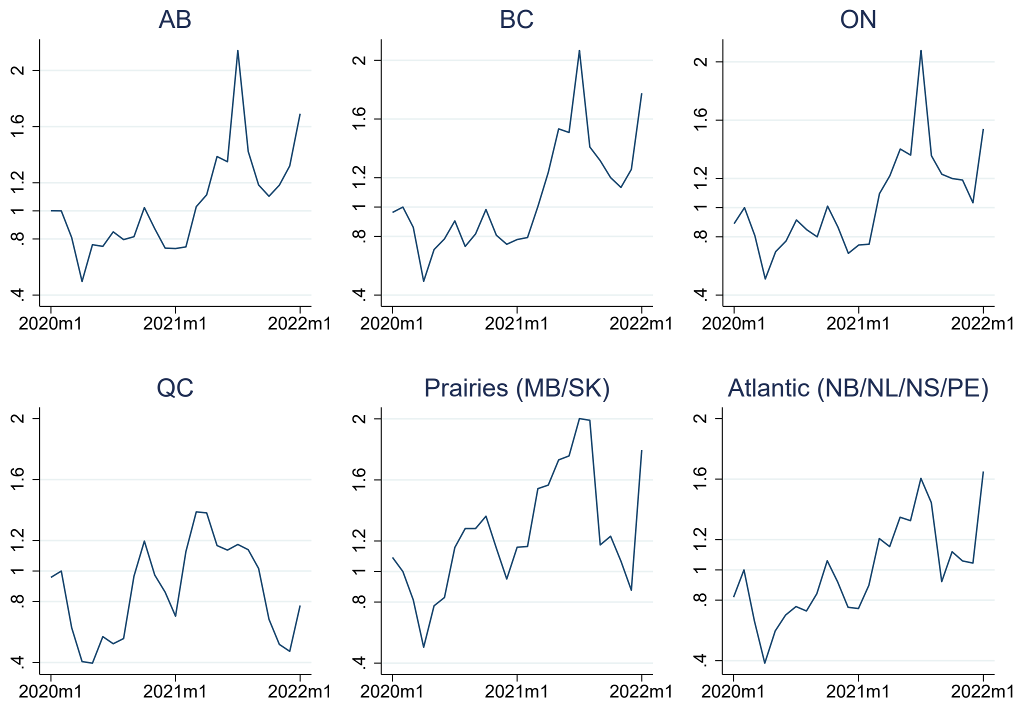
Notes: Job Openings (JVWS) and Job Postings (BGT) are normalized against January 2020 levels. Prior to October 2020, the JVWS only reported quarterly data. Owing to the pandemic, the JVWS ceased collecting data altogether in Q2 and Q3 2020.

The BGT data-series indicates a rapid, precipitous decline late spring of 2020 with job postings bottoming out at about 50% of pre-crisis levels in April 2020. However, at this point job postings started to increase. They attained their pre-crisis levels by October 2020. Both series indicate continued strong labour demand through the end of 2021.

We next address how uniform this pattern in Job Postings was across provinces, industries and occupations. The following figures, constructed using the BGT data, show that this pattern, and notably the recent increase in postings, is broad-based both geographically and across industries and occupations. Figure 11 shows that by May 2021, the rate of postings exceeds that in February 2020 by about 30% across Canada. In the 15 months between February 2020 and May 2021, postings followed the nationwide course of the epidemic fairly closely with relatively little variation depending on the specific course of the pandemic in the different parts of the country. The decline in postings in Québec was not noticeably more pronounced during the first wave when COVID case rates in Québec were significantly higher than in the rest of the country.[36] Likewise, postings in the Atlantic provinces closely followed the national trend despite the fact that these provinces were for a long time spared the worst impact of the pandemic itself.

[36] In late 2021, postings in Québec have fallen behind those in the rest of Canada. Whether this represents a persistent development remains to be seen.

Figure 11: Job Postings across Provinces

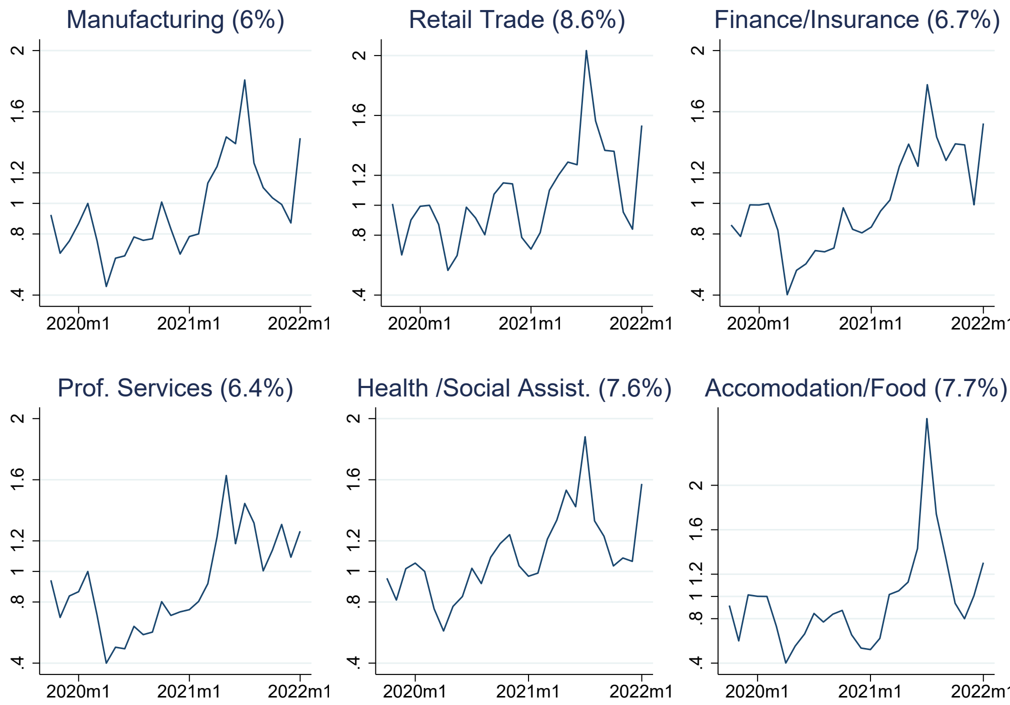


Notes: Data from Burning Glass Technology normalized against 2/2020.

The recovery in postings is broad-based, not only across provinces, but also across industries and broad occupation groups. The following two figures show the time-series of postings for the six two-digit industries as well as the six broad occupation groups (NOC10) that account for the most postings during the period October 2019 to February 2020.[37]

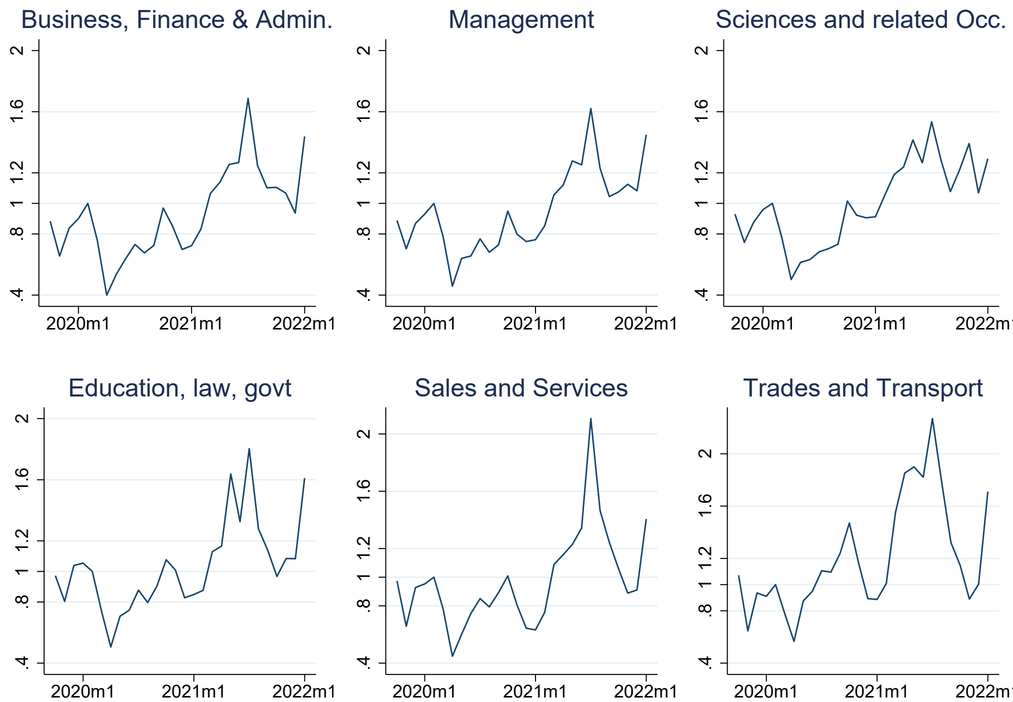
[37] The graphs for all broad industry and occupation groups can be found in the appendix.

Figure 12: Job Postings of Six Largest Industries



Notes: Data from Burning Glass Technology normalized against 2/2020.

Figure 13: Job Postings of Six Largest Occupation Groups



Notes: Data from Burning Glass Technology normalized against 2/2020.

Overall, much has been made in popular accounts of the variety in the experience of COVID-19 across Canada, and in provincial policy responses to the pandemic. Much has also been made of the differential impact of the pandemic recession on different industries and occupations. In light of this, we regard this evidence of substantial comparative similarity in both the decline and then recovery of labour demand by province, industry and occupation as important.

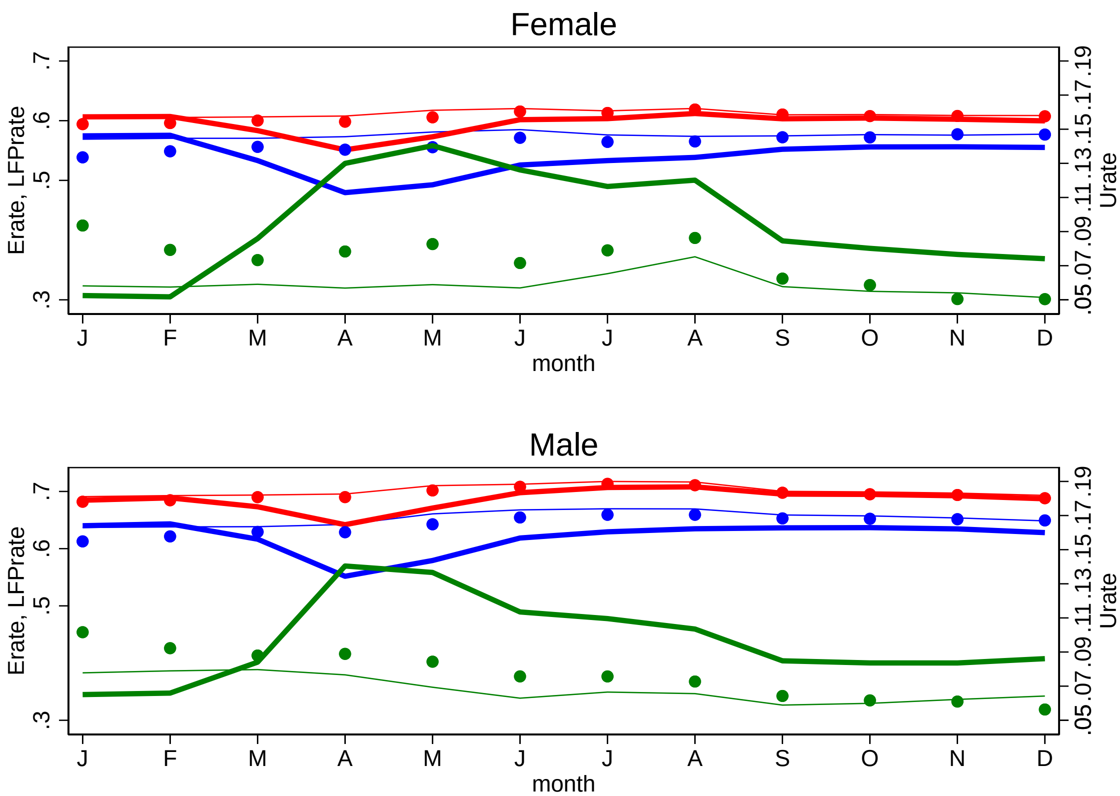
4 Heterogeneity in Responses During and After the COVID-19 Recession

We now examine whether different demographics groups experienced the COVID-19 recession differently. We first address potential differences by gender, age and education during the turmoil of the pandemic and then examine overall changes by demographic group between the final quarters of 2019 and 2021; these serve as "endpoints" for assessment of the enduring effects of the COVID-19 shock. In addition, we assess changes in the occupational skill distribution over the pandemic period. Finally, we summarize the effects of the changing labour market by reporting the evolution of median hourly earnings, including a transparent bound on this series that corrects for selection in which workers were employed during the COVID-19 recession.

We assess heterogeneity of experiences on the basis of key labour market magnitudes: the labour force participation rate, the employment rate and the unemployment rate. We present graphs of these series, analogous to the overall picture in Figure 1 above, here decomposed by gender, age and education level. As before, we compare experience during the pandemic using heavy lines for months in 2020, heavy dots for months in 2021, and light lines for the reference period where monthly averages are computed across 2015-19.

The female and male series in Figure 14 share many common features during both pandemic years. For both, labour force participation and the employment rate dip sharply after February 2020 and reach a low point in April 2020. Thereafter, both time series recover steadily though incompletely through the balance of 2020, undergo a slight dip in the early months of 2021, and recover close to pre-pandemic

Figure 14: Gender Heterogeneity in Labour Market Performance



Notes: Red series are the labour force participation rate, blue series are the employment rate, and green series are the unemployment rate. Light lines denote 2015-19 averages by month, heavy lines denote 2020 monthly observations, and heavy dots denote 2021 monthly observations.

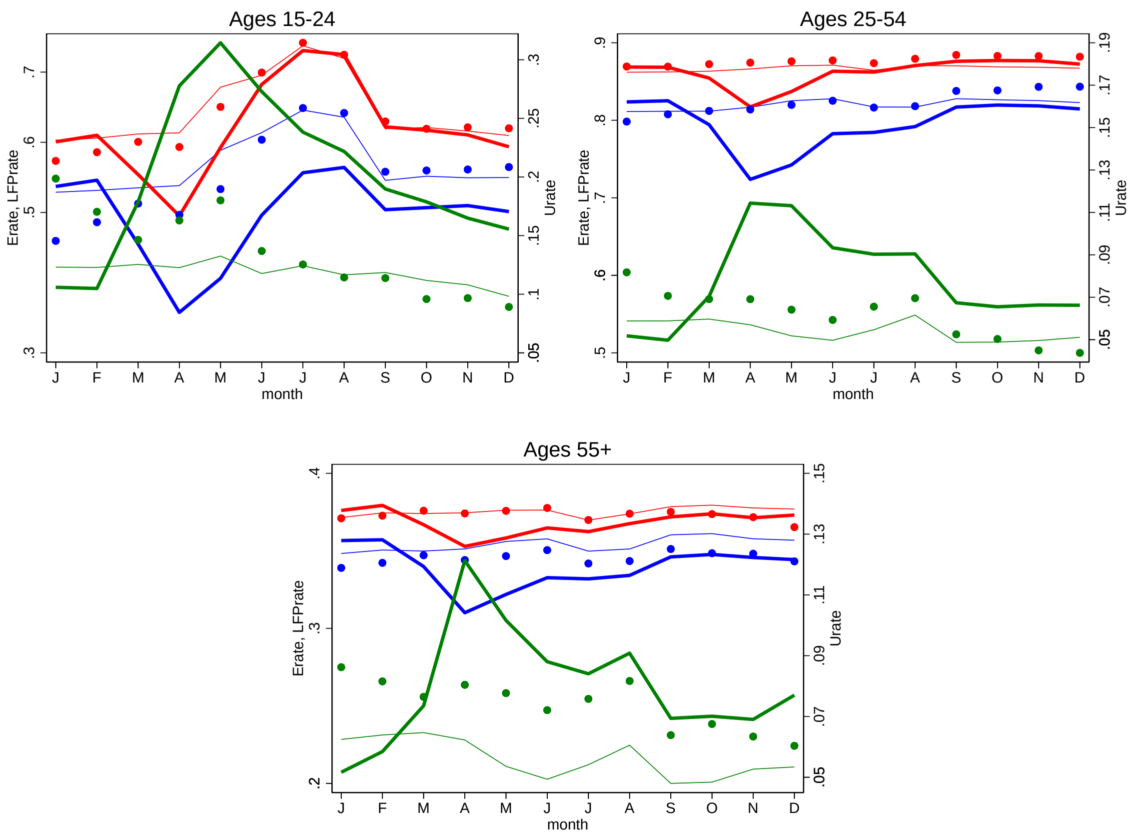
levels by mid-summer 2021. Of course, this pattern of response to the pandemic must be set against ongoing differences in the levels of the two series: it is no surprise that female participation and employment rates lie below those of men. But relative to these level differences, the principal take-away is the similarity of the response by gender to the pandemic.

On first inspection, this similarity by gender is less apparent for the unemployment rate, where the female series peaks in May 2020, has a sluggish recovery in the following two months, and even rises again in August 2020. In contrast, the male unemployment rate peaks earlier, in April 2020, and falls continuously into the Fall of 2020. However, the reference period data for 2015-19 reveals that the female unemployment rate has a strong seasonal component that is not present in the male series. In comparison to the appropriate reference period, there is in fact a striking uniformity of the unemployment rate responses by gender, even in the turmoil period in 2020. In subsequent months, both female and male unemployment rates remain about two percentage points above the usual into the end of 2020, a gap that widens for both series at the start of 2021. Finally, both female and male series slowly converge on the reference period values during 2021, reaching the pre-pandemic levels by late Fall 2021.

In sum, the detailed comparison of labour market performance by gender does not reveal any strong differences in the response to the pandemic by women relative to men, notwithstanding some popular accounts and public debate during the COVID-19 period. There might of course be differences in response among more finely delineated demographic groups. Nonetheless, at the level of the overall labour market, the key finding by gender is one of similarity, not difference.

By age group, there is a greater degree of heterogeneity in response to the pandemic. Figure 15 illustrates the participation, employment and unemployment rates for three age ranges: the young (15-24), the prime aged (25-54), and the older group (55+). While the prime age group naturally displays patterns of behaviour close to those shown earlier in Figure 1, the young display a sharper response to the COVID-19 shock, even allowing for the very different usual levels of these three series among the young. Youth unemployment rates triple after the onset of the pandemic, while both labour force participation and employment rates also react very strongly. That said, it is also striking that these magnitudes manage to recover by mid-2021, slightly earlier and more completely than the prime age group.

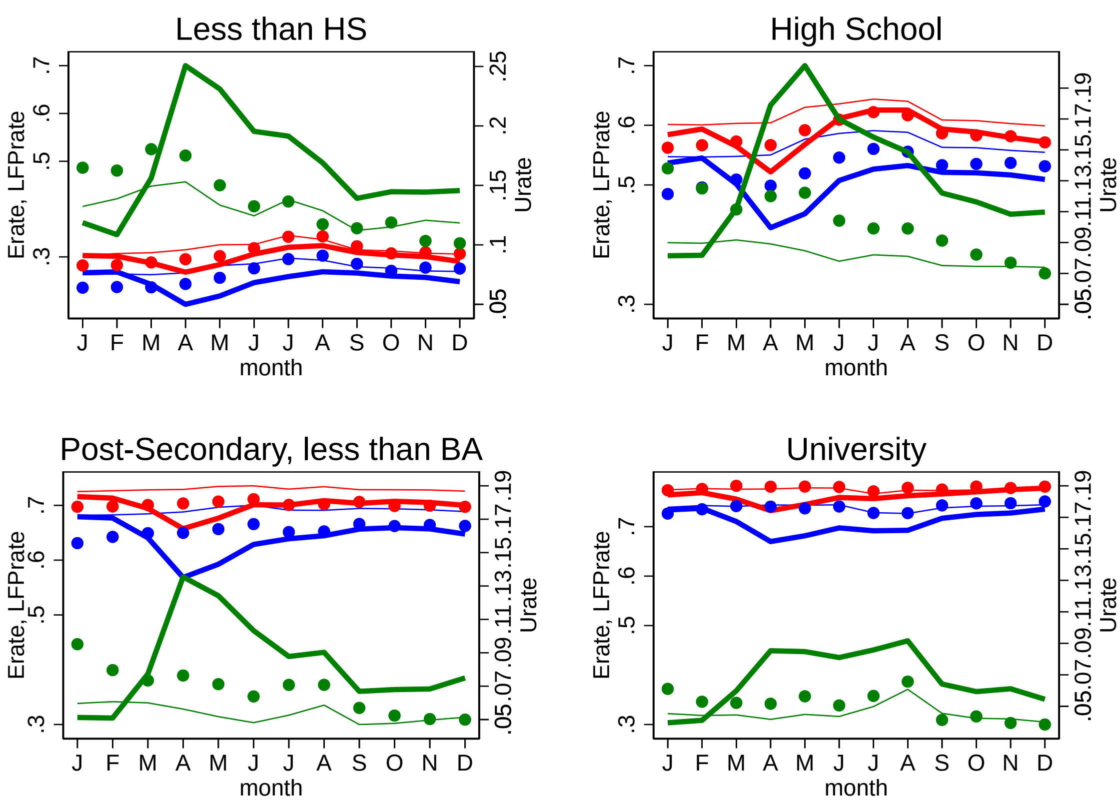
Figure 15: Age Heterogeneity in Labour Market Performance



Notes: Red series are the labour force participation rate, blue series are the employment rate, and green series are the unemployment rate. Light lines denote 2015-19 averages by month, heavy lines denote 2020 monthly observations, and heavy dots denote 2021 monthly observations. Vertical scales differ by age group.

Among the older group, discussion of the response to COVID-19 must be set against the much lower usual rates of participation and employment. Given this, the behaviour of the older group is quite similar to that of the prime aged, including the sharp initial reaction at the onset of the pandemic, the (usual seasonal) uptick in unemployment in late summer, and the slight reversal of recovery at the end of 2021 and the start of 2021. The most notable difference that remains is that the recovery by the end of 2021 is more or less complete for the prime aged but remains partial for the older population.

Figure 16: Education Heterogeneity in Labour Market Performance



Notes: Red series are the labour force participation rate, blue series are the employment rate, and green series are the unemployment rate. Light lines denote 2015-19 averages by month, heavy lines denote 2020 monthly observations, and heavy dots denote 2021 monthly observations. Vertical scales differ by educational group.

Finally with respect to these broad labour market aggregates, we address heterogeneity by educational grouping: less than High School, High School, Post-Secondary but less than a BA, and University.[38] We graph the participation, employment and unemployment rates for each of these groups in Figure 16.

As with the age grouped results, there are natural and persistent differences in levels for these time series by education level. Both the employment rate and the labour force participation rate have a strong gradient in education, being highest for the most educated, while unemployment rates have the opposite gradient in education: these levels differences are clear in the light lines (representing 2015-19 average values by month) in Figure 16. After allowance for these differences, some interesting heterogeneity across educational lines remains in the response to the COVID-19 shock. The University educated are the least affected by the pandemic, probably in part owing to the occupational skill mix of their employment and the capacity for working from home, although the unusual pattern of the University educated unemployment rate in late summer 2020 reflects mainly seasonality (similar that found above for women) rather than a peculiar response to the pandemic. Both the High School and the lowest group had somewhat sharper responses to the onset of the pandemic, compared with the University group, although the broad pattern of gradual recovery through most of 2021 is present across the educational spectrum.

We next consider the overall changes between the fourth quarters of 2019 and 2021. We think this gives a useful assessment of the enduring effects of the COVID-19 shock as the turmoil of 2020 starts to fade in its effects. Table 4 reports proportions of the population in each standard labour market state (Employment, Unemployment, and Not in the Labour Force [NILF]) disaggregated by gender and, within gender,

[38]People with Post-Secondary education who did not complete a degree, certificate, or diploma, are grouped with High School graduates.

by age group and education level. We also report differences in these proportions across this two-year gap.

The main findings in Table 4 are that the differences in labour market proportions between the endpoints are both quite small and fairly similar across most sub-groups. By gender, the endpoint differences are similar for each labour market category, and this pattern also holds for most sub-groups by gender$\times$age or by gender$\times$education. A few particular cases are worthy of mention. By education, those with Post-Secondary (but less than a BA) have taken a clear net drop in employment from 2019 to 2021, by around 3.8 percentage points for females and 2.6 percentage points for males (or 5.7 and 3.6 percent respectively). This is matched by a rise in the proportion of this group who are NILF (with only a modest rise in unemployment). This result holds for both genders. And by age, and also for both genders, the oldest group has also had a drop in the proportion employed accompanied by a rise in both Unemployment and NILF. These are important heterogeneities to watch going forward. But they are also exceptions that confirm the rule: recovery overall has been widespread and is largely complete.

In Appendix Tables A3 and A4, we look at the endpoints by province and industry. Again, the endpoint differences are remarkably similar. There are a few minor exceptions. Employment rates in Alberta and Saskatchewan in 2021 are slightly below the 2019 rates, while the fraction of the population in these provinces that are NILF has increased. While almost all industries are back to pre-COVID levels, accommodation and food services is still down 20 percent.

We now present results on how the occupation skill-mix changed during the COVID era. In particular, Figure 17 depicts a skill-index of the employed population based on the skill requirements constructed from the O*NET described in

Table 4: Change in labour market status between 4^{th} quarter 2021 and 2019, by gender and demographic characteristics

	Females				Males			
	2019q4	2021q4	Difference	s.e.	2019q4	2021q4	Difference	s.e.
Employment								
Overall	0.583	0.575	−0.007	(0.003)	0.656	0.651	−0.005	(0.002)
< HS	0.247	0.263	0.016	(0.006)	0.390	0.384	−0.006	(0.006)
High School	0.504	0.485	−0.019	(0.005)	0.627	0.613	−0.015	(0.005)
Post-Secondary, < BA	0.663	0.625	−0.038	(0.004)	0.727	0.701	−0.026	(0.004)
University	0.731	0.732	0.000	(0.004)	0.756	0.768	0.012	(0.004)
15 to 24	0.576	0.585	0.009	(0.007)	0.540	0.540	0.000	(0.007)
25 to 54	0.801	0.808	0.007	(0.003)	0.870	0.875	0.006	(0.003)
55+	0.315	0.294	−0.021	(0.004)	0.418	0.404	−0.015	(0.004)
Unemployed								
Overall	0.030	0.032	0.003	(0.001)	0.039	0.041	0.003	(0.001)
< HS	0.030	0.033	0.004	(0.002)	0.045	0.043	−0.003	(0.003)
High School	0.035	0.036	0.001	(0.002)	0.048	0.050	0.003	(0.002)
Post-Secondary, < BA	0.026	0.031	0.005	(0.001)	0.037	0.040	0.003	(0.002)
University	0.028	0.030	0.002	(0.002)	0.028	0.034	0.006	(0.002)
15 to 24	0.054	0.048	−0.005	(0.003)	0.071	0.068	−0.003	(0.004)
25 to 54	0.035	0.038	0.002	(0.001)	0.042	0.044	0.002	(0.002)
55+	0.014	0.021	0.007	(0.001)	0.021	0.027	0.006	(0.001)
Not in the labour force								
Overall	0.388	0.392	0.005	(0.002)	0.305	0.308	0.003	(0.002)
< HS	0.724	0.704	−0.020	(0.006)	0.565	0.573	0.009	(0.006)
High School	0.461	0.479	0.017	(0.005)	0.325	0.337	0.012	(0.005)
Post-Secondary, < BA	0.311	0.344	0.033	(0.004)	0.237	0.259	0.022	(0.004)
University	0.240	0.239	−0.002	(0.004)	0.216	0.199	−0.017	(0.004)
15 to 24	0.370	0.367	−0.004	(0.007)	0.389	0.392	0.003	(0.007)
25 to 54	0.164	0.154	−0.009	(0.003)	0.088	0.080	−0.008	(0.002)
55+	0.671	0.685	0.014	(0.004)	0.561	0.570	0.009	(0.004)

Notes: [1] Sample: Aged 15+ from the LFS. [2] Standard errors are in parentheses.

Section 2.6. During COVID-19, Employment shifted towards occupations with high interpersonal and quantitative skills in March and April 2020. Some of this shift was undone once employment recovered in the summer of 2020. However, since Fall 2020, employment trends have started to again favour occupations demanding cognitive skills (measured by the interpersonal and quantitative occupational skill requirements). This shift towards quantitative and interpersonal skills persists even though the employment share in the population has recovered, suggesting that this shift does not just represent selection effects. Rather, it suggests that the COVID-19 pandemic entailed a structural shift towards occupations that require high quantitative and interpersonal skills. Appendix Figure A7 displays the occupational skill requirements by gender. While there are clear differences in the pre-COVID levels in terms of the type of occupations where men and women work, both see a similar increase in terms of cognitive skill requirements and a decrease in terms of manual skills. If we compare changes between the fourth quarters of 2019 and 2021 by gender (similar to what was shown in Table 4), the changes in occupational skill requirements are very similar.[39]

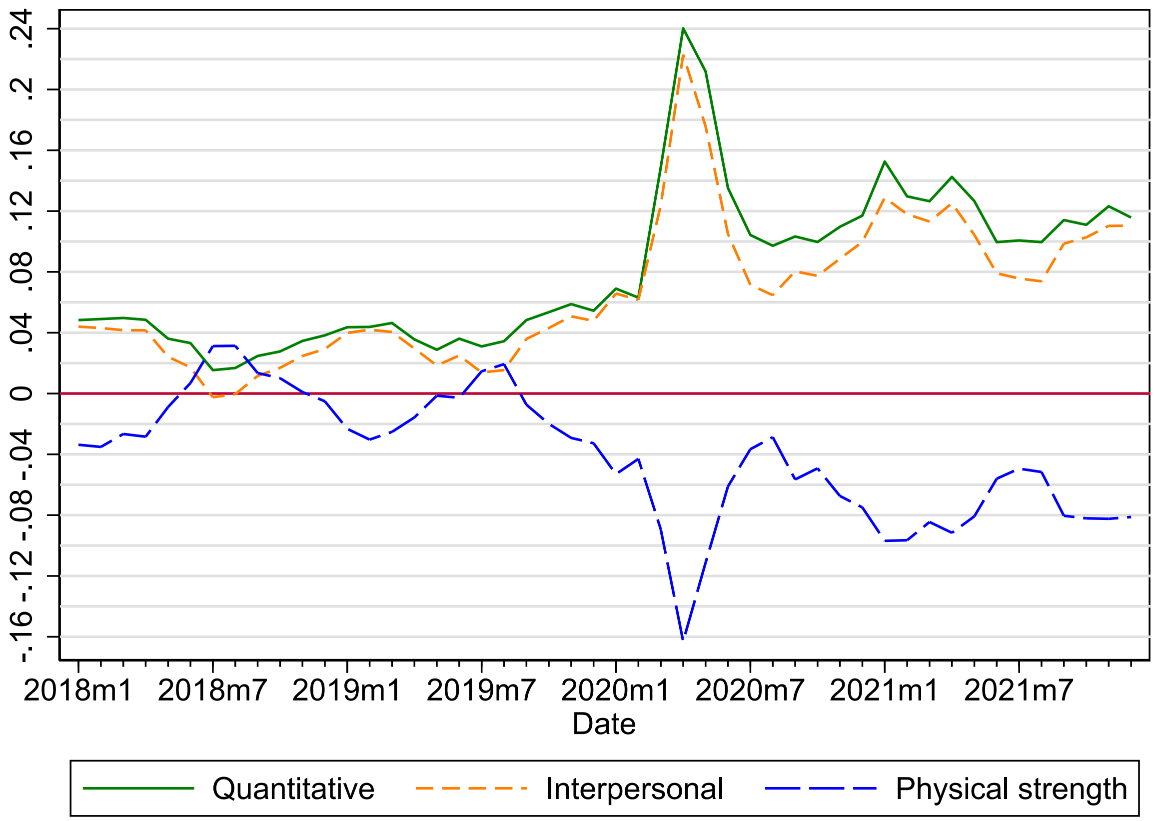
Finally, we turn to COVID-19 era evolution in the price of labour. Figure 18 presents median hourly earnings by month between January 2018 and December 2021.[40] The sharp increase in wages observed during the first few months of the crisis is clearly due to the selectivity of work separations in the initial turmoil of the pandemic. As we have shown in Section 2.6, much of this is due to the occupation-industry distribution of separations.

However, the figure also shows that median wages in April 2021 exceed those in

[39]For females, the 2019 to 2021 last quarter changes are 0.072, 0.067 and -0.044 for quantitative, interpersonal, and physical strength occupational requirements respectively. For males, the comparable changes are 0.052, 0.055 and -0.065.

[40]When we examine the weekly wages, we find similar patterns.

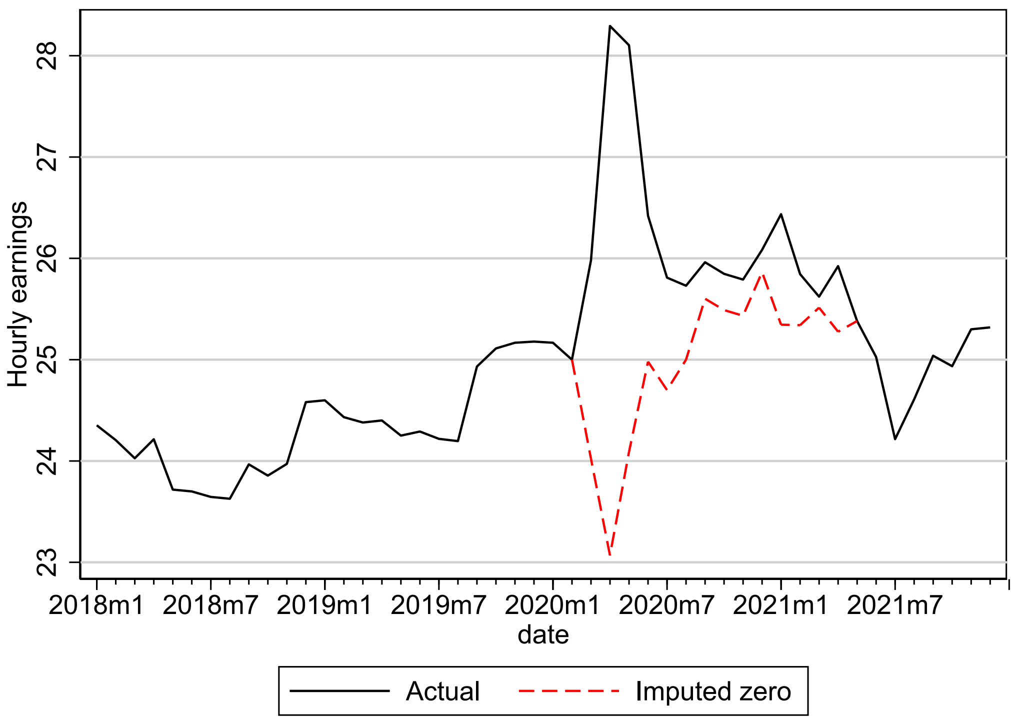
Figure 17: Occupational Skill Requirements



Notes: The quantitative, interpersonal and physical strength requirement of the occupation were constructed from the O*NET using factor analysis. Mean zero and standard deviation of one relative to the 2016 Canadian population.

the period immediately preceding the pandemic. To investigate whether this could plausibly be due to selection, we assumed all employment losses after February 2020 occurred among those with below median earnings. We thus adjusted the median weekly earnings by augmenting the population with a group sufficiently large to keep employment at the February 2020 levels and assigned them weekly earnings of $0. We think this approach provides a lower bound for a selection corrected estimate of median earnings.[41] We show this until May 2021, after which, total employment has surpassed February 2020 levels. It indicates that nominal earnings by August 2021 are at least as high as those observed just prior to the COVID downturn.

Figure 18: Median Hourly Earnings



Notes: Imputed zero line: employment kept at the February 2020 levels and residual are assigned weekly earnings of $0. See text for details.

[41] Conclusions are qualitatively similar if we use a difference base period or adjust to keep the employment rate constant rather than the number of people employed.

5 Conclusion

The COVID-19 era saw the largest shock to Canadian labour markets since the Second World War. The employment rate fell by more than 10 percentage points, labour force participation dropped precipitously, and the unemployment rate rose to nearly 14% in the space of a few months. While these aggregates capture neither the full magnitude nor the multi-faceted scope of the disruption at the onset of the pandemic in early 2020, they do illustrate the unprecedented blow dealt to the Canadian economy by COVID-19. The shock unleashed a short period of turmoil and upheaval that was widely experienced across demographic groups and across many industries, occupations and provinces.

Yet, for all this upending of normal functioning of Canadian labour markets, the ship of the economy began to right itself quickly after the initial COVID-19 shock. Within two months of the pandemic onset, the employment rate had recovered half of its initial losses. The widespread maintenance of worker-firm ties through the use of Employed-Absent and temporary layoff categories began to dissipate by the summer of 2020 and the more standard process of job search and matching in labour markets resumed, accompanied by a strong recovery in measures of labour demand. This process of gradual return to normalcy continued through the end of 2020 and throughout 2021, modified only slightly by the stop-go process of later COVID-19 waves and various provincial economic restrictions. Overall, while the recovery from the initial shock was not V-shaped, it was relatively strong and more rapid than the Canadian experience of recoveries from previous recessions, particularly given the depth to which the economy had dropped in early 2020.

We were also struck by the relative uniformity of responses both to the initial shock and in the path of subsequent economic recovery, across many groups. Even though there were differences across Canada in how provinces responded to the COVID-19 pandemic, for example, with clear associated differences in provincial experiences of the pandemic in terms of case counts, mortality and pressure on the health care system, the same broad patterns of labour market turmoil and recovery are found across the country. Undoubtedly, some changes wreaked by the pandemic onset will endure, and we do not wish to underplay the losses experienced by some specific groups. But in the aggregate it remains notable how little reallocation has been seen by gender, age, education, province and even by industry. Perhaps a main lasting lesson of COVID-19 is the resilience of the Canadian labour market. An important issue for future research is the extent to which the federal government policy response – which, as noted earlier encouraged the maintenance of ties between employers and employees – contributed to this resilience.

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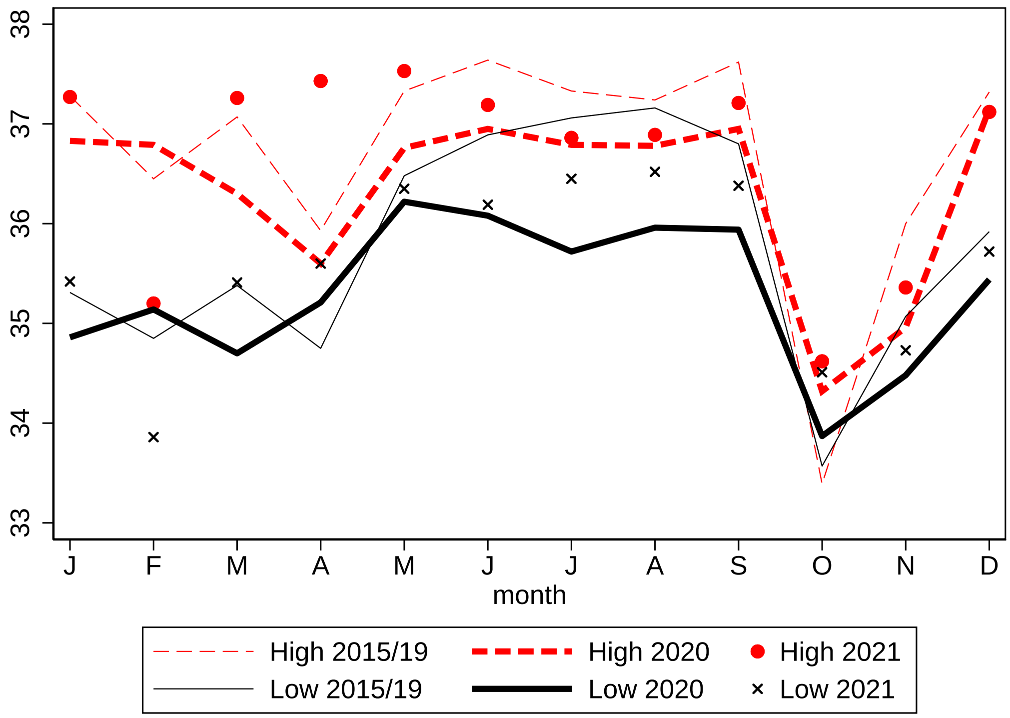
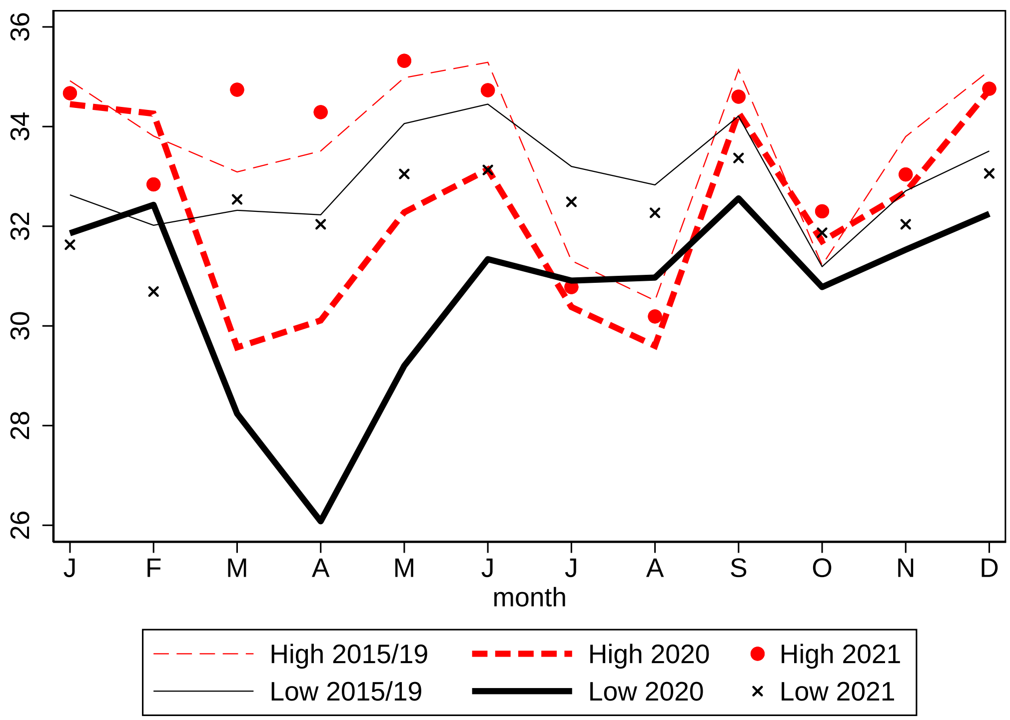
6 Appendix

Figure A1: Actual Hours Employed-Working by Propensity to Telework



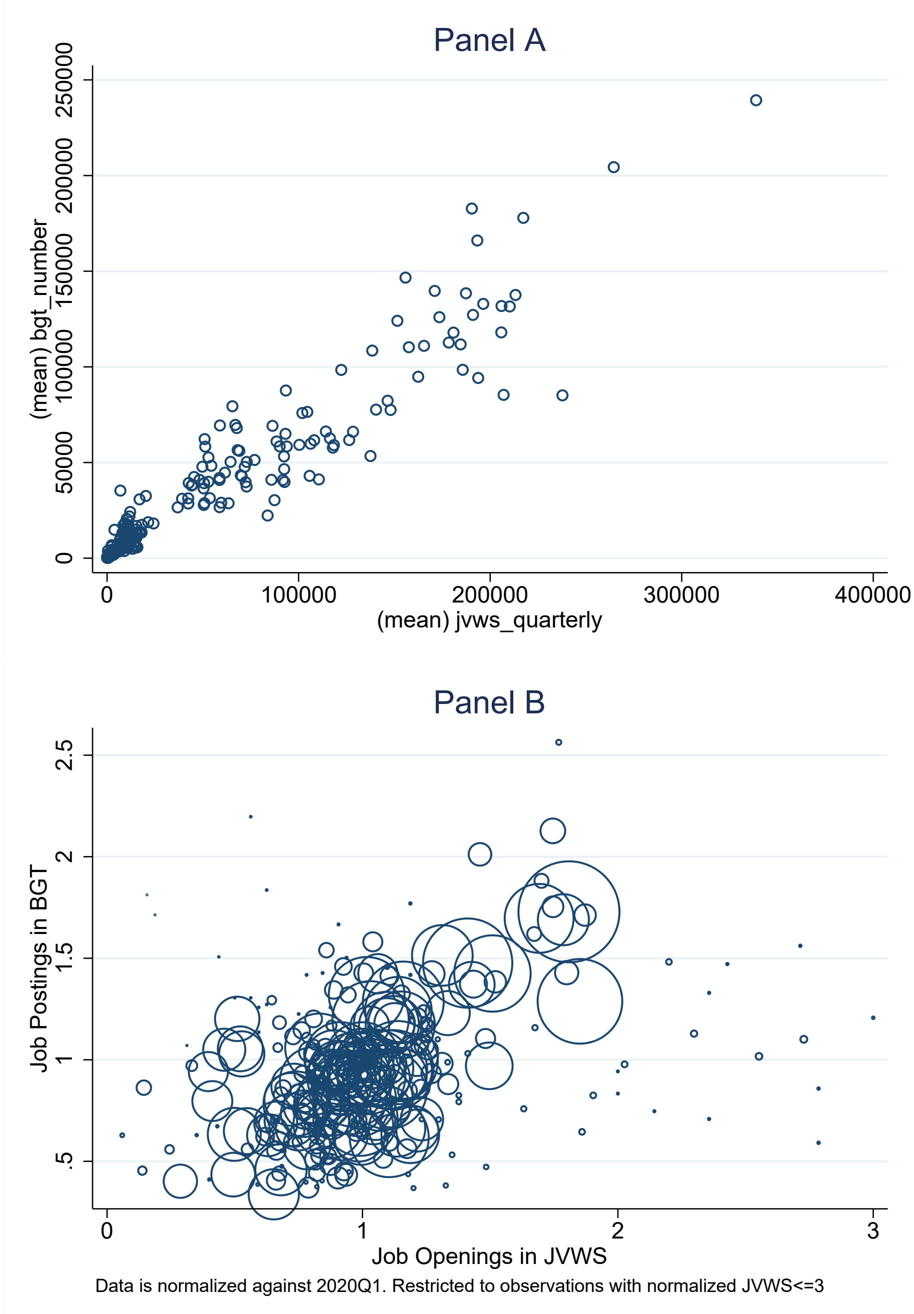
Notes: Each line represents actual hours worked for the employed depending on the reference period and whether the occupation had a "low" or "high" propensity for telework where this classification is based on Dingel and Neiman (2020).

Figure A2: Actual Hours Employed by Propensity to Telework



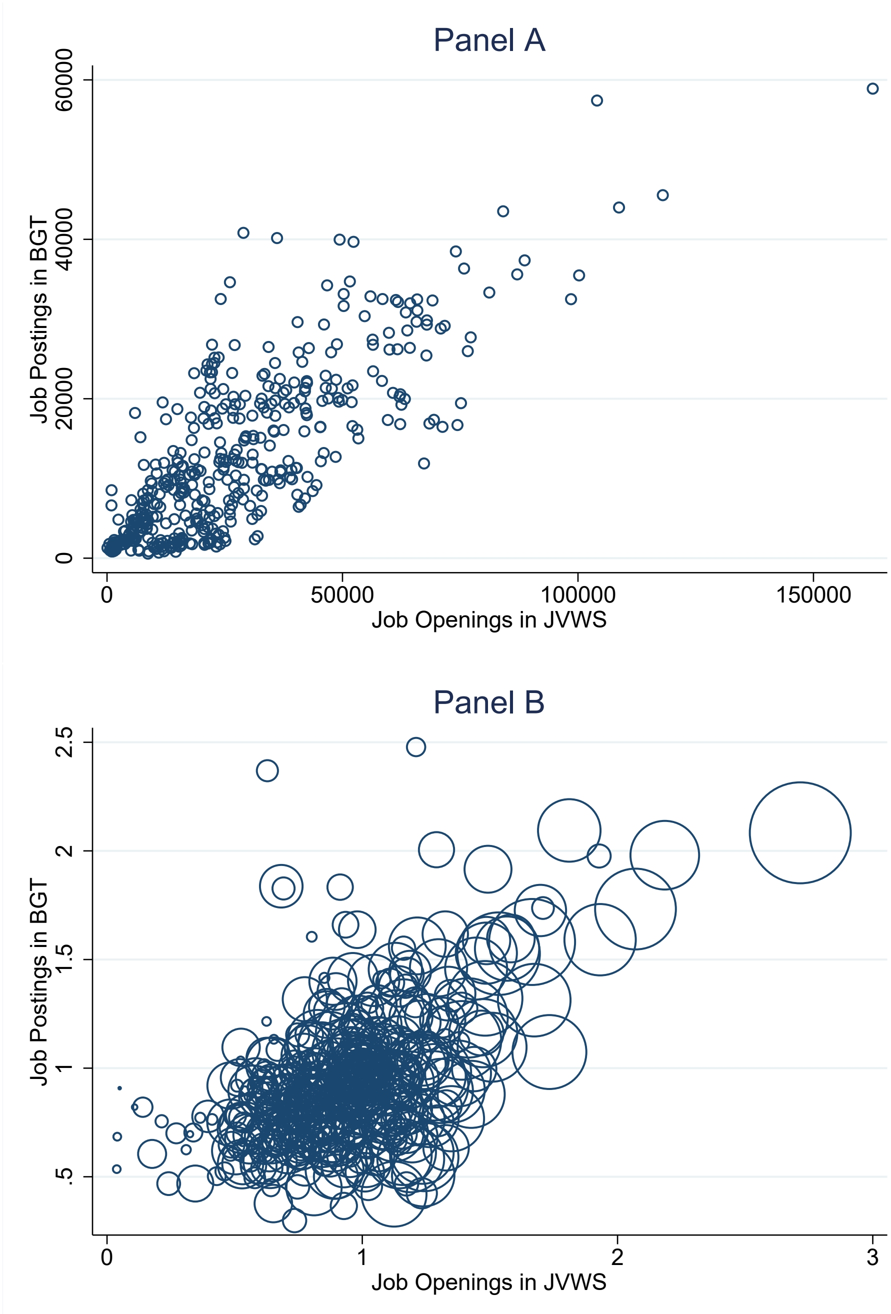
Notes: Each line represents actual hours worked for the employed depending on the reference period and whether the occupation had a "low" or "high" propensity for telework where this classification is based on Dingel and Neiman (2020).

Figure A3: BGT Postings vs JVWS Openings across Provinces and Quarters



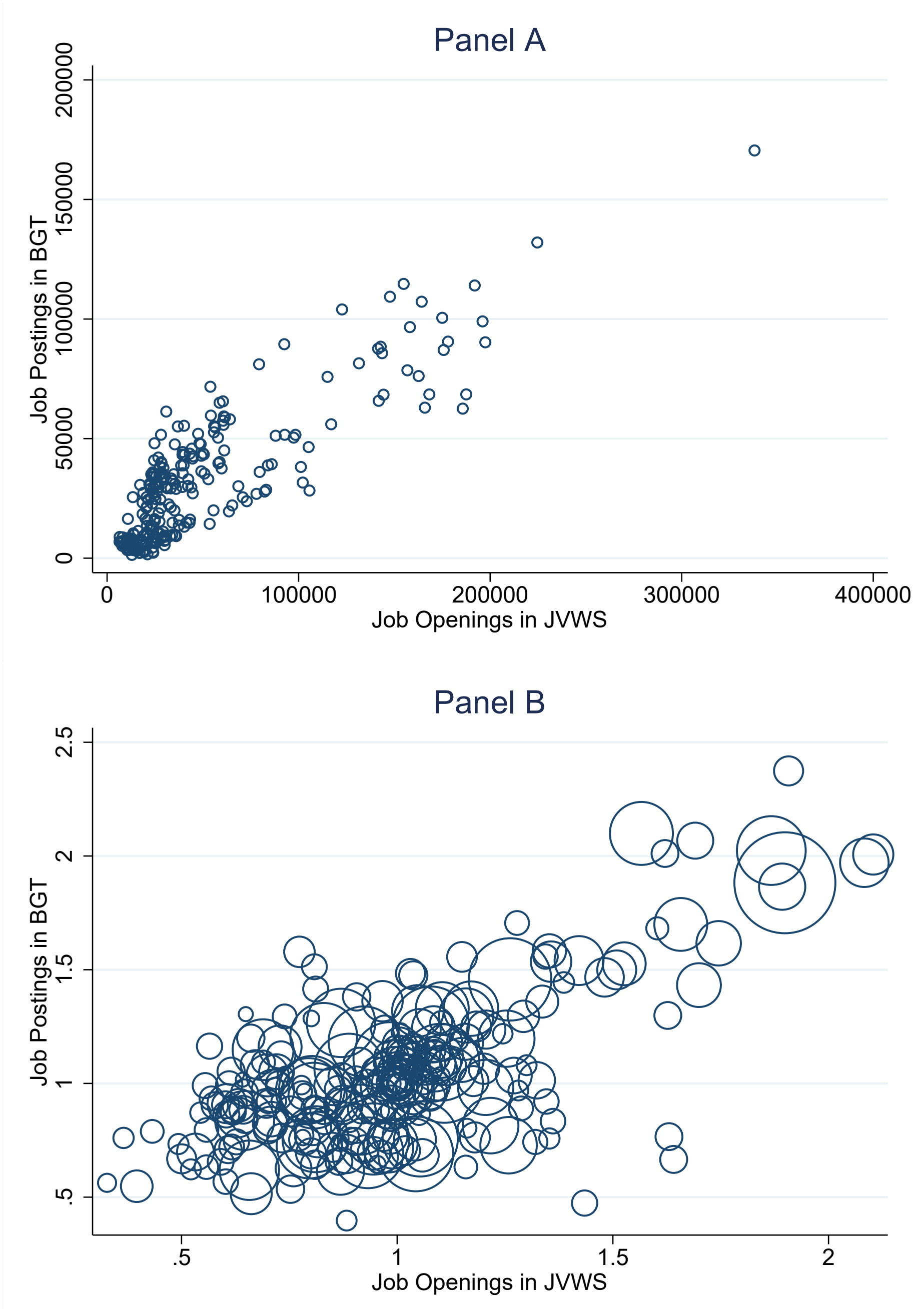
The first figure shows the number of job postings in BGT vs. reported open positions in the JVWS by Province and Quarters since 2015, Q1. The second graph normalize the job openings against 2020Q1 to evaluate how well the data correspond in changes over time. The size of the marker corresponds to the raw number of openings in JVWS. The correlation of postings in Panel A is 0.96 and in Panel B is 0.91.

Figure A4: BGT Postings vs JVWS Openings across Industries and Quarters



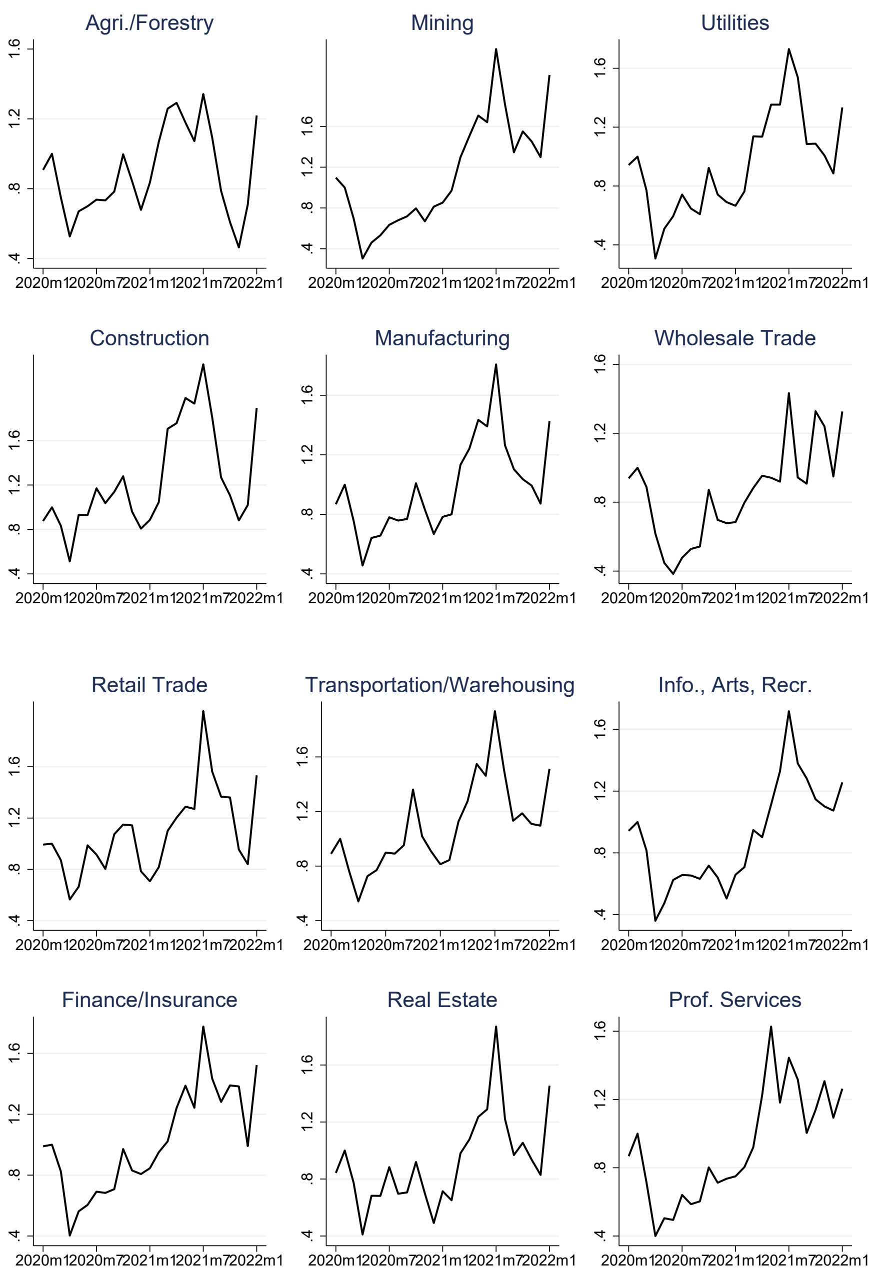
The first figure shows the number of job postings in BGT vs. reported open positions in the JVWS by Industry and Quarters since 2015, Q1. The second graph normalize the job openings against 2020Q1 to evaluate how well the data correspond in changes over time. The size of the marker corresponds to the raw number of openings in JVWS. The correlation of postings in Panel A is 0.80 and in Panel B is 0.67.

Figure A5: BGT Postings vs JVWS Openings across Occupations and Quarters



The first figure shows the number of job postings in BGT vs. reported open positions in the JVWS by Occupations and Quarters since 2015, Q1. The second graph normalize the job openings against 2020Q1 to evaluate how well the data correspond in changes over time. The size of the marker corresponds to the raw number of openings in JVWS. The correlation of postings in Panel A is 0.86 and in Panel B is 0.76.

Figure A6: Vacancy Time series by Industry



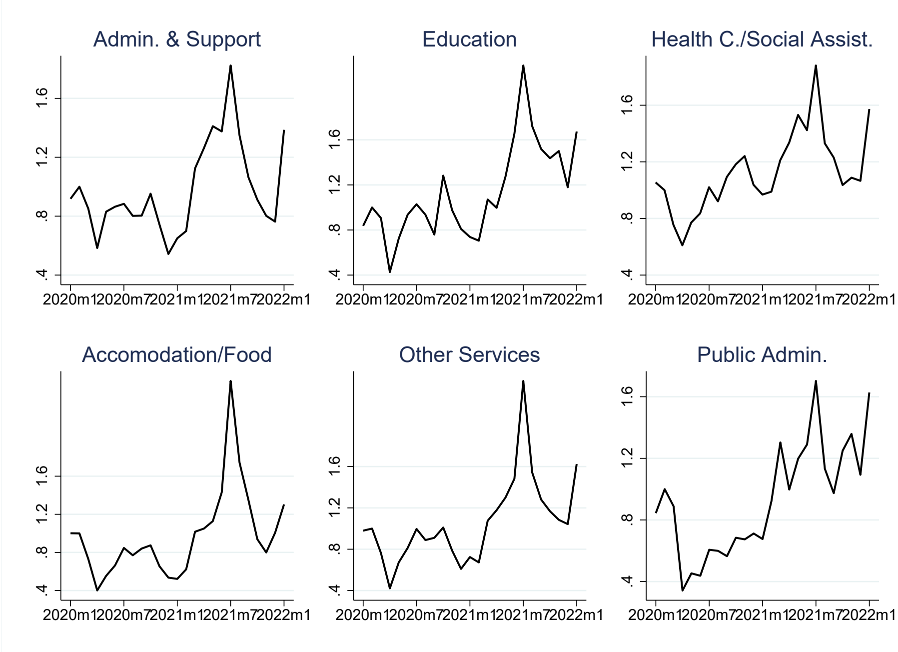
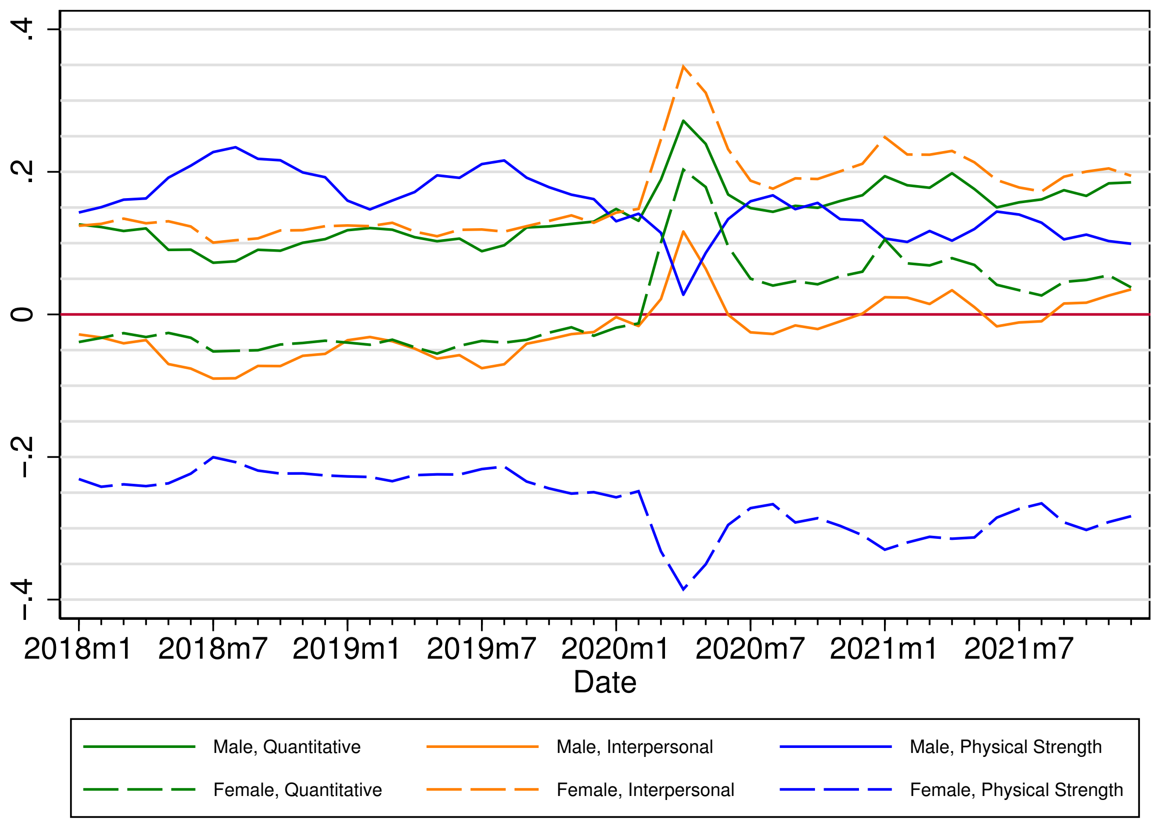

Admin. & Support
Education
Health C./Social Assist.
Accomodation/Food
Other Services
Public Admin.
.4
.8
1.2
1.6
2020m1
2020m7
2021m1
2021m7
2022m1

Figure A7: Occupational Skill Requirements



Notes: The quantitative, interpersonal and physical strength requirement of the occupation were constructed from the O*NET using factor analysis. Mean zero and standard deviation of one relative to the 2016 Canadian population.

Table A1: February occupational skill requirements by first labour market status change for workers employed in February

	Interpersonal skills				Quantitative skills				Physical strength			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Search unemployment	-0.432**	-0.291**	-0.197**	-0.141**	-0.458**	-0.345**	-0.230**	-0.183**	0.321**	0.104**	0.125**	0.0263
	(0.041)	(0.035)	(0.034)	(0.031)	(0.042)	(0.038)	(0.035)	(0.033)	(0.044)	(0.029)	(0.036)	(0.025)
Recall unemployment	-0.566**	-0.367**	-0.259**	-0.190**	-0.562**	-0.403**	-0.261**	-0.202**	0.468**	0.162**	0.193**	0.0708**
	(0.018)	(0.016)	(0.016)	(0.015)	(0.019)	(0.017)	(0.017)	(0.016)	(0.020)	(0.013)	(0.017)	(0.012)
Not in the labour force	-0.482**	-0.349**	-0.256**	-0.195**	-0.553**	-0.446**	-0.289**	-0.238**	0.330**	0.125**	0.160**	0.0539**
	(0.027)	(0.023)	(0.023)	(0.021)	(0.027)	(0.025)	(0.024)	(0.023)	(0.029)	(0.019)	(0.024)	(0.017)
Propensity to telework†		0.974**		0.820**		0.780**		0.699**		-1.499**		-1.441**
		(0.014)		(0.015)		(0.015)		(0.016)		(0.011)		(0.012)
Constant	0.325**	-0.179**	0.188**	-0.190**	0.359**	-0.0439**	0.208**	-0.114**	-0.224**	0.551**	-0.108**	0.555**
	(0.011)	(0.012)	(0.009)	(0.011)	(0.011)	(0.012)	(0.010)	(0.0120)	(0.011)	(0.009)	(0.009)	(0.009)
Age dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
February Industry fixed effects	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
P-values from F-test												
All equal	0.000	0.108	0.214	0.276	0.053	0.053	0.297	0.212	0.000	0.054	0.114	0.188
Joint zero	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	14,001	14,001	14,001	14,001	14,001	14,001	14,001	14,001	14,001	14,001	14,001	14,001
R-squared	0.135	0.368	0.446	0.543	0.149	0.293	0.430	0.499	0.067	0.592	0.428	0.716

Notes: [1] Sample: workers who were in paid employment in February 2020 and were in the LFS each subsequent cycle until June 2020. [2] Default category is workers who in each of the five months were either *employed at work* or *away from work but paid* [3] The other three categories are based on the first non-paid employment status between March and June 2020 for workers who left paid employment. The second group is "unemployed who were actively searching for employment". The third group is "no search/recall" which includes *unemployed waiting for recall* or *future start*, *employed but away from work and not paid*, and *not in the labour force but waiting for recall.* The final group, "not in the labour force", includes those *initially moving out of the labour force (and not waiting for recall)*. [4] Age dummies for 15 to 24 year olds, 55 to 70 year olds and 70 plus, with 25 to 54 year olds as the default category. [5] Standard errors are in parentheses. Statistical significance is denoted by: ** at 1% level, * at 5% level, + at 10% level. [6] † Constructed from Dingel and Neiman (2020) index. 1 = Occupation has high propensity to telework. 0 = Occupation has low propensity to telework.

Table A2: Probability of Paid Employment in June 2020 for workers who were employed in February 2020 but moved to non-paid employment in the early stages of the COVID recession

	(1)	(2)	(3)	(4)
Default (Unemployed search)				
No search/recall	0.155**	0.160**	0.113**	0.113**
	(0.025)	(0.025)	(0.024)	(0.027)
NILF	0.005	0.015	-0.037	0.016
	(0.027)	(0.027)	(0.027)	(0.030)
Constant	0.402**	0.412**	0.442**	0.682
	(0.023)	(0.023)	(0.025)	(0.689)
Additional controls				
Age dummies	No	Yes	Yes	Yes
Month of change	No	No	Yes	Yes
February characteristics				
Industry fixed effects	No	No	No	Yes
Occupation fixed effects	No	No	No	Yes
P-values from F-test				
Recall=NILF	0.000	0.000	0.000	0.000
Joint zero	0.000	0.000	0.000	0.000
Observations	4,825	4,825	4,825	4,652
R-squared	0.021	0.025	0.084	0.308

Notes: [1] Sample: workers who were in paid employment in February 2020 and were in the LFS in each of the in between cycles. [2] 3 categories are based on the first non-paid employment status between March and June 2020 for workers who left paid employment. The default category is "unemployed who were actively searching for employment". The second group is "no search/recall" which includes *unemployed waiting for recall* or *future start*, *employed but away from work and not paid*, and *not in the labour force but waiting for recall*. The final group, "not in the labour force", includes those *initially moving out of the labour force (and not waiting for recall)*. [3] Estimates from linear probability models. [4] Standard errors are in parentheses. Statistical significance is denoted by: ** at 1% level, * at 5% level, + at 10% level.

Table A3: Change in labour market status between 4^{th} quarter 2021 and 2019, by province

	2019q4	2021q4	Difference	s.e.
Employed				
Newfoundland and Labrador	0.508	0.503	−0.005	(0.007)
Prince Edward Island	0.602	0.593	−0.009	(0.009)
Nova Scotia	0.575	0.567	−0.008	(0.006)
New Brunswick	0.560	0.554	−0.006	(0.006)
Quebec	0.615	0.611	−0.005	(0.004)
Ontario	0.616	0.613	−0.003	(0.003)
Manitoba	0.627	0.626	−0.001	(0.005)
Saskatchewan	0.653	0.633	−0.020	(0.005)
Alberta	0.661	0.640	−0.020	(0.005)
British Columbia	0.618	0.615	−0.003	(0.005)
Unemployed				
Newfoundland and Labrador	0.063	0.063	0.000	(0.004)
Prince Edward Island	0.051	0.052	0.001	(0.004)
Nova Scotia	0.048	0.047	−0.000	(0.003)
New Brunswick	0.042	0.046	0.004	(0.003)
Quebec	0.031	0.028	−0.002	(0.001)
Ontario	0.031	0.038	0.007	(0.001)
Manitoba	0.032	0.031	−0.001	(0.002)
Saskatchewan	0.035	0.033	−0.002	(0.002)
Alberta	0.046	0.048	0.001	(0.002)
British Columbia	0.030	0.034	0.004	(0.002)
Not in the labour force				
Newfoundland and Labrador	0.429	0.434	0.005	(0.007)
Prince Edward Island	0.347	0.355	0.008	(0.008)
Nova Scotia	0.378	0.386	0.008	(0.006)
New Brunswick	0.398	0.400	0.002	(0.006)
Quebec	0.354	0.361	0.007	(0.004)
Ontario	0.352	0.349	−0.003	(0.003)
Manitoba	0.341	0.343	0.002	(0.005)
Saskatchewan	0.312	0.334	0.022	(0.005)
Alberta	0.293	0.312	0.019	(0.005)
British Columbia	0.352	0.351	−0.001	(0.005)

Notes: [1] Sample: Aged 15+ from the LFS. [2] Standard errors are in parentheses.

Table A4: Change in proportion of population employed in a given industry between 4^{th} quarter 2021 and 2019

	2019q4	2021q4	Difference	s.e.
Agriculture, forestry, fishing and hunting	0.011	0.009	−0.002	(0.000)
Mining, quarrying, and oil and gas extraction	0.008	0.008	0.000	(0.000)
Utilities	0.004	0.004	0.000	(0.000)
Construction	0.049	0.047	−0.002	(0.001)
Manufacturing	0.055	0.055	0.000	(0.001)
Wholesale trade	0.021	0.021	0.000	(0.001)
Retail trade	0.072	0.073	0.001	(0.001)
Transportation and warehousing	0.034	0.032	−0.001	(0.001)
Information and cultural industries	0.024	0.024	0.000	(0.001)
Finance and insurance	0.028	0.030	0.002	(0.001)
Real estate and rental and leasing	0.012	0.012	0.000	(0.000)
Professional, scientific and technical services	0.050	0.054	0.004	(0.001)
Administrative and support, waste management ...	0.024	0.022	−0.002	(0.001)
Educational services	0.047	0.049	0.002	(0.001)
Health care and social assistance	0.082	0.082	0.001	(0.001)
Accommodation and food services	0.040	0.032	−0.008	(0.001)
Public administration	0.033	0.035	0.002	(0.001)
Other services	0.026	0.023	−0.003	(0.001)
Not Employed	0.381	0.387	0.006	(0.002)

Notes: [1] Sample: Aged 15+ from the LFS. [2] Standard errors are in parentheses.