The Impact of the COVID-19 Pandemic on Gender Inequality in the Canadian Labour Market

by

Fahima Laskar

M.S.S., Shahjalal University of Science and Technology, 2020

B.S.S., Shahjalal University of Science and Technology, 2018

Thesis Submitted in Partial Fulfillment of the
Requirements for the Degree of
Master of Arts

in the
Department of Economics
Faculty of Arts and Social Sciences

SIMON FRASER UNIVERSITY
Summer 2024

Declaration of Committee

Name:	**Fahima Laskar**
Degree:	**Master of Arts**
Title:	**The Impact of the COVID-19 Pandemic on Gender Inequality in the Canadian Labour Market**
Committee:	**Chair:** **Bertille Antoine** Professor, Economics
	Simon Woodcock Supervisor Associate Professor, Economics
	Serena Canaan Committee Member Assistant Professor, Economics
	Jane Friesen Examiner Professor, Economics

Abstract

This thesis investigates the impact of COVID-19 on gender disparities in the Canadian labour market using LFS data from January 2017 to November 2021. The analysis reveals a significant widening of male-female gaps in employment and hours worked, especially for women with school-age children, due to increased childcare responsibilities. Triple-difference estimates confirm that these demands disproportionately reduced women's labour market activity. Although higher education levels, teleworking, and favourable occupational distribution mitigated some negative impacts, the pandemic overall set back gender equality in the labour market. Decomposition analyses highlight the roles of industry composition and health risk exposure in exacerbating these disparities, emphasizing the need for targeted policies to support women's recovery.

Keywords: Gender inequality; COVID-19 pandemic; Labour supply

Dedication

To my wonderful parents, who have given me everything. To my dad, whose love has always been a constant in my life, and to my mom, whose strength and unwavering support, even from across the world, have carried me through this journey. Though you're back home in Bangladesh and I'm so far away from you, your presence is always with me. This thesis is for both of you with all my heart.

Acknowledgements

I am incredibly grateful to everyone who has supported me throughout this journey.

First and foremost, a huge thank you to my supervisor, Dr. Simon D. Woodcock, for your guidance, patience, and encouragement. Your advice and expertise have been invaluable, and I couldn’t have made it through this process without your support.

To my friends and colleagues, thank you for always being there with words of encouragement, especially during the tough times.

To my husband, Imran, thank you for your love, and unwavering support. You’ve been by my side through all the ups and downs, and I couldn’t have done this without you. And to our son, Arfan, you are the light in my life and your presence gives me the strength to keep going.

To my family, thank you for your constant love and support. Even with the distance, you’ve been with me every step of the way.

Thank you to everyone.

Table of Contents

List of Tables

List of Figures

Chapter 1.

Introduction

The COVID-19 pandemic disrupted the global economy in many ways, including government-imposed lockdowns, social distancing measures and unprecedented business closures. The labour market was significantly impacted, albeit the impact was likely different for men and women. January 25th, 2020 marked the first documented COVID-19 case in Canada, though mid-March 2020 was the first substantial surge in the infection (Public Health Agency of Canada, 2020). Between February and April 2020, nearly 5% of the population was temporarily laid off, and another 5% had to be absent from work while still being employed by their previous employers (Statistics Canada, 2022). It is important to identify whether the pandemic impacted women disproportionately. There was a surge in remote work, widespread closure of daycares and schools, and a later transition to online schooling, all of which may have increased the childcare burden for women. The upheaval of the labour market was particularly challenging for women working in front-facing non-essential industries, including retail, accommodation and food services, arts, entertainment and recreation, to name a few. This thesis is an attempt to analyze the impact of the pandemic-induced economic downturn on the labour market outcomes for men and women in the Canadian labour market.

In Canada, women’s participation in the labour force has increased over the last 50 years. The labour force participation rate for women aged 15 and older consequently rose from 58.5% in 1990 to 61.5% in 2022. By September 2023, there were 9.6 million women employed in Canada. This growth highlights the increasing presence of women in the workforce. This represents a 5.1% increase in labour force participation (Statistics Canada, 2023).

Additionally, the gender wage gap has been narrowing, decreasing from 16% in 2007 to 12% in 2022 among paid workers aged 20 to 54. This improvement is largely due to higher educational attainment among women, with a greater proportion of Canadian-born women holding bachelor's degrees than their male counterparts. In 2022, the proportion of Canadian-born women with a bachelor’s degree was 41%, compared to

27% of Canadian-born men (Statistics Canada, 2023). Efforts to address barriers to women’s employment, such as the introduction of affordable universal childcare programs, have further supported women's increased labour market participation. For instance, in Quebec, these programs have resulted in higher female labour force participation rates and greater reliance on paid childcare services (Baker, Gruber and Milligan, 2008). However, disparities in labour market experiences linked to childbearing remain evident in women's labour supply data and contribute significantly to ongoing gender wage inequality. Access to and the affordability of childcare are commonly recognized as major barriers to women's labour market participation and career progression in the United States (Blau and Kahn 2013a; Goldin and Mitchell 2017; Juhn and McCue 2017; Waldfogel 1998). The case for Canada is something similar (Prentice and White, 2019; Schirle, 2015)

The pandemic had wiped out years of women’s economic gains in a couple of months. There was an unexpected increase in childcare responsibilities due to the sudden and remarkable daycare and school closing. The thesis examines the effect of increased childcare burdens across families and how it impacts the labour market outcomes for women during the COVID-19 pandemic. We compare trends between men and women with children and without children, men and women with children from different age groups. We use difference-in-difference estimates to compare the experiences of men and women and use triple-difference estimates to directly examine how the presence of children in the household affects the gender gap.

We analyze how differences in the distribution of men and women across industries contribute to gender disparities in labour market outcomes during the COVID-19 pandemic using the Gelbach (2016) decomposition method. We also use the linear Blinder-Oaxaca decomposition technique to characterize gender disparities in unemployment rates. We strive to understand how gender differences in essential industry employment, remote work capabilities, education level, and occupation contribute to the observed labour market outcomes. By examining these factors, we provide a comprehensive analysis of how structural and occupational differences between men and women influence labour market disparities during the pandemic.

We have examined the Labour Force Survey (LFS) data from 2017 to 2021 and have found there was a significant decline in the probability of employment for women, predominantly for women with school-age children, compared to men in the post-COVID quarters following the introduction of nation-wide social distancing measures in March 2020. Between men and women, we observed a consistent widening of the employment gap in the spring of 2020 (1.6 percentage points), which further widened in the Summer of 2020 (4.9 percentage points) and showed signs of recovery by the Fall of 2020. The recovery continued through Winter 2020-21 and Spring 2021 before widening again in the Summer 2021. The gender gap is more prominent for families with school-aged children. Looking at the triple-difference estimates, it is evident that women with school-age children faced a significant reduction(4.8 percentage points) in employment compared to women without children (1.4 percentage points). These disparities in employment probabilities can be attributed to increased caregiving responsibilities. The impacts on hours worked show a similar pattern, again, mothers of school-going (6-17) children experienced the largest reduction in hours relative to men.

Our linear blinder-Oaxaca decomposition results reveal that while some job and skill characteristics were advantageous for women during the pandemic, other factors exacerbated the unemployment gap between men and women. Notably, women's higher concentration in teleworkable jobs and their representation in occupations like healthcare and education, which were less vulnerable to the initial economic shocks, mitigated some of the negative impacts on employment. However, structural disadvantages, such as a higher prevalence of women in non-essential industries and jobs with greater health risks, contributed to increased unemployment disparities during the COVID-19 pandemic. The Gelbach decomposition estimates highlight that during Spring 2020, controlling for industrial composition—particularly in sectors like retail and hospitality where women were overrepresented—narrowed the gender employment gap by about 1.8% of the total gap, indicating a modest but consistent influence of industry composition on gender disparities during the pandemic.

Chapter 2.

Context and Analytical Approach

Brochu et al. (2020) provide an early analysis of the Canadian labour market during the spring and summer of 2020, utilizing the confidential version of the LFS. They identified significant re-employment flows among recent job losers, particularly those temporarily laid off. Lemieux et al. (2020) compared employment and aggregate hours changes between April and February 2020 with the same period in 2018 to assess the pandemic's impact. Jones et al. (2020) offer valuable insights into re-employment flows and sectoral impacts during the pandemic, which closely align with our examination of gender disparities in the labour market. Their findings on the effectiveness of policy responses and the varied impacts on different demographic groups support our investigation into how COVID-19 worsened gender inequalities in employment and working hours in Canada.

In many respects, labour market dynamics during the COVID-19 pandemic in Canada mirrored those observed in the US. Several studies in the US have shed light on the gender impact of the COVID-19 pandemic. Alon et al. (2020) argued that closures of non-essential businesses and limited telework options would exacerbate gender differences in labour market outcomes, forcing women to choose between work and childcare. Montenovo et al. (2020) found that traditional factors such as occupational distributions and remote work capabilities partly explained gender disparities in employment, with women experiencing slightly higher employment declines. Holder, Jones, and Masterson (2021) noted that job losses disproportionately affected industries where Black women were concentrated. Collins et al. (2020) reported that work hours declined more for women than men, especially those with young children, despite telework capabilities. Heggenes (2020) observed that early school closures negatively impacted women's employment, but did not immediately increase detachment or unemployment. Bartik et al. (2020) noted that women were more likely than men to stop working in April 2020 and less likely than men to resume in May and June. Albanesi and Kim (2021) found that employment reductions through November 2020 were concentrated among women with children, leading to more women leaving the labour force. Surveys also indicated that mothers bore a heavier childcare burden during the early pandemic stages, and in academia, women, particularly those with young children, experienced a greater reduction in research time (Zammaro and Prados 2021; Kapteyn et al. 2020; Deryugina, Shurchkov, and Stearns 2021).

This thesis is most closely related to Couch, Fairlie, and Xu (2022) who estimate early-stage COVID-19 impacts on women's labour market outcomes in the U.S. Couch, Fairlie, and Xu (2022) reveal significant employment declines and exits among mothers due to increased childcare from school closures. Women in impacted sectors faced greater challenges, with remote work offering limited mitigation. They emphasize targeted policy interventions for childcare support and flexible work to address these disparities.

We depart from Couch, Fairlie, and Xu (2022) by focusing on the Canadian labour market and extending the analysis through November 2021, using LFS public-use micro-data. This longer period captures initial disruptions, multiple COVID-19 waves and subsequent adaptations in the labour market. Our study examines how labour market experiences for women and men evolved, providing a comprehensive view of the pandemic's impact on the labour supply.

A key addition to our thesis is assessing how industry composition impacts gender disparities. By controlling for industry, we observe consistent changes in our results, demonstrating the impact of gender differences in industry distribution on these disparities. This approach helps us understand how the pandemic worsened existing gender inequalities in the labour market.

Chapter 3.

Data and Measures

Our estimates are based on the Labour Force Survey (LFS). The LFS is Canada's primary monthly household survey. Conducted during a week that includes the 15th of each month, the survey collects data from about 56,000 households. Once appropriately weighted, the data represents the civilian non-institutional population aged 15 and over across Canada. Our analysis employs the full monthly public-use LFS data files from 2017 through November 2021. We consider March 2020 as a partially COVID-19 pandemic-impacted month and regard April 2020 as the first full COVID-19-impacted month.

We concentrate on employment changes commencing in April 2020, coinciding with the national implementation of social distancing measures. For much of the analysis, we aggregate data across months, referring to post-COVID periods as Spring, Summer, Fall and Winter. February 2020 serves as our baseline pre-pandemic month. We look at the age group variable to identify prime-age adults, and we have decided to restrict our sample to age groups between 25-59. The age of the youngest child variable then helps us determine families with and without children as well as families with different age groups of children.

3.1. Measures Related to COVID-19

The extent to which COVID-19 disrupted an individual's work likely depended on many factors related to COVID-19 closures, including whether they were employed in an essential business, whether their job could be done remotely, and the risks of disease exposure in their workplace.

Our industry classification variable, NAICS_21, is coded at the 2-digit level. To create the essential vs. non-essential categories, we matched these 2-digit industry codes to the more detailed 4-digit codes used by Delaware state standards. This mapping process involved aligning each 2-digit industry code with the corresponding 4-digit codes to determine each industry's essential status accurately.11

The abrupt shift to remote work at the start of the pandemic raised concerns about the number of jobs that can be reasonably performed remotely. To understand telework suitability better, we construct a measure developed by Dingel and Neiman (2020) that reflects a worker's ability to perform tasks remotely. The authors examine the feasibility of remote work by analyzing two surveys, called the Work Context Questionnaire and the Generalized Work Activities Questionnaire from the Occupational Information Network (O*NET). The first survey extracts information related to the physical and social factors affecting the nature of work, and the latter provides information regarding the job behaviours occurring on multiple jobs. We used Dingel and Neiman's (2020) teleworkability scores and tailored them to accurately represent the telework potential within various Canadian industries, considering the unique occupational structures and roles prevalent in these industries. This allowed for a more precise assessment of telework capabilities in Canada.

We have used another COVID-19 measure, which is the health risk Z-score. We follow the approach of Baker et al., 2020. They have developed a measure of exposure to disease or infection, developed from an O*NET question that asks, "How often does your current job require you to be exposed to diseases or infections?"

However, the health risk variables developed by those authors are based on 6-digit SOC codes (Standard Occupational Classification). In our LFS public use dataset we only have NOC (National Occupation Classification) at the 2-digit level. For us to construct the health risk measure, we mapped 6-digit SOC codes to the more detailed 4-digit NOC codes, and then we mapped the 4-digit NOC codes to 2-digit NOC codes. We were able to construct this measure by taking an employment-weighted average of the more detailed occupation codes within the 2-digit NOC codes. We then transformed the health risk measure to a z-score with a mean of 0 and a standard deviation of 1.

[1] Since we matched 2-digit NAICS codes to 4-digit NAICS codes, we derived the 2-digit measures by taking a weighted average of the corresponding 4-digit measures. This approach ensures that the broader industry categories reflect the more detailed industry classifications, though some inaccuracies might remain due to the aggregation process.

3.2. Descriptive Patterns of Male and Female Employment

Figures 1(a) and 1(b) illustrate the employment probability and unconditional2 weekly work hours for men and women aged between 25 to 59 from January 2017 until November 2021.2

Figure 1(a) highlights a persistent employment gap between men and women before COVID-19, with men having a higher employment probability (78.1%) compared to women (68.9%). Among women, those without children had a higher probability of being employed (73.8%) than those with children (66.5%). The pandemic caused a sharp decline in employment probabilities from February to April 2020 for both men and women, with men's employment falling by 16.6 percentage points to 61.5% and women's by 15.8 percentage points to 53.1%. While both men and women eventually saw a recovery, men nearly returned to pre-pandemic levels (76.2%), whereas women's recovery was slower, reaching 66.9% by November 2021. Women without children experienced a smaller drop and a quicker recovery compared to those with children.

In Figure 1(b), which illustrates the average weekly working hours from January 2017 to November 2021, men consistently worked more hours than women across all periods. Before the pandemic, men typically worked about 30-31 hours per week, while women worked between 22-25 hours depending on whether they had children and the age of those children.

The onset of the COVID-19 pandemic in early 2020 led to a sharp decline in working hours for both men and women. Men's hours decreased by about 5-7 hours per week, while women's hours dropped similarly. However, the reduction in working hours was most pronounced for women with children, particularly those with younger children aged 0-5 years. By November 2021, while working hours began to recover, they had not fully returned to pre-pandemic levels. The gender gap in working hours persisted, with

[2] "Unconditional" refers to the average hours worked, calculated across the entire population being studied, regardless of employment status. This includes individuals who were employed (and worked positive hours) as well as those who were not employed (and thus worked zero hours).

women, especially those with younger children, working fewer hours on average compared to men.

In summary, the gender gap in working hours persisted throughout the period, with women consistently working fewer hours on average compared to men. Women with younger children were more affected, experiencing a greater reduction in working hours during the pandemic. Although men's working hours also declined, they recovered more quickly and returned closer to pre-pandemic levels by November 2021. The gap between men's and women's working hours remained significant.

Figure 2(a) shows trends in the probability of being employed for women from January 2017 to November 2021, segmented by the age of their youngest child. When we look at women with school-aged children (6-12 ages and 13-17) ages, they have the highest employment probability compared to mothers with young children (0-5 ages). Looking at the recovery period from May 2020 onwards, employment probabilities began to recover but did not return to pre-pandemic levels. By the end of our sample period, women with children aged 13-17 showed the quickest recovery, nearing pre-pandemic employment levels above 80%, followed by a nuanced recovery for the other two groups of women, the 0-5 age group being the slowest.

Figure 2 (b) shows the trend between women with children for average weekly work hours. Before the pandemic, women with older children worked more hours than those with younger children. From February to April 2020, average unconditional hours of work declined by about 5 to 7 hours for all groups. In the fourth quarter of 2020, as schools reopened in many locations, women with school-age children (6-13 and 14-17) saw their work hours increase more rapidly than those with younger children (aged 0-5). However, the average unconditional hours worked for all groups remained below pre-pandemic levels from January 2017 to February 2020. This reflects that while school reopening facilitated a quicker return to work for women with older children, those with younger children continued to face significant caregiving challenges.

Table 1 further compares the employment and unconditional work hours of men and women. For each group, we report the probability of being employed in each season: Spring, Summer, Fall, and Winter of 2020 and 2021. These periods correspond to distinct phases of disruptions, such as unexpected school closures, interruptions to summer plans, and new COVID-19 variants.

Table 1 shows employment trends for men and women from January 2017 to November 2021. In February 2020, men without children had an employment rate of 73.8%, while women without children had 71.5%, so the male-female gap is 2.3 percentage points. Men with children had an employment rate of 85.8%, and women with children had a lower rate of 70.5%, creating a larger gap of 15.3 percentage points..

The pandemic widened these gaps. During Spring 2020, employment rates plummeted. Men without children saw their rate drop by 14.8 percentage points, while women without children fell by 17.1 points, expanding the gap to 4.6 points. For those with children, the gap widened even more as men’s employment fell by 14.6 points and women’s by 16.9 points, pushing the gap to 17.6 percentage points.

In Summer 2020, men’s employment rebounded more strongly than women’s, further widening the gap. Men without children recovered 9.6 percentage points, while women recovered 7.1 points. For those with children, men recovered 6.7 points, but women only regained 2.7 points, leaving a significant 21.6-point gap.

Examining the employment rates by the age of children, the data shows that women with children aged 0-5 experienced the most significant employment gap relative to men. The gap widened from 27.3 percentage points in February 2020 to 33.5 in Summer 2020. Women with children aged 6-12 saw the gap increase to 17.9 percentage points in Summer 2020. Women with children aged 13-17 initially had the smallest gap and showed a quicker recovery compared to other groups. So, the employment gap did not close significantly by Summer 2020.

Table 2 tells a similar story on unconditional work hours, with pronounced gender disparities. Women, particularly those with children, faced larger reductions in hours worked than men, similar to what we observe in Table 1.

Men without children worked 28.9 hours per week in February 2020, while women worked 25.3 hours, a gap of 3.6 hours. By Spring 2020, this gap narrowed slightly as men's hours fell by 6.4 to 22.5 and women's by 6.1 to 19.2. The summer saw a partial recovery, but the gap widened to 5.2 hours.

Women with children experienced greater declines. For instance, men with children aged 6-12 worked 34.9 hours per week in February 2020, while women worked 25.8 hours, a gap of 9.1 hours. In Spring 2020, the gap increased to 8.5 hours as men's hours dropped by 6.8 to 28.1, and women's by 6.1 to 19.7. By Summer 2020, the gap widened further to 10.6 hours.

This pattern is consistent for women with children aged 13-17. Men worked 36.6 hours per week in February 2020, compared to women's 27.9 hours, an 8.6-hour gap. In Spring 2020, men's hours decreased by 8.0 to 28.6, and women's by 6.2 to 21.7, narrowing the gap to 7.0 hours, which widened again to 8.9 hours by Summer 2020.

In summary, the data from Tables 1 and 2 shows that during the pandemic, women, especially those with children, experienced greater employment and work-hour disruptions than men. This highlights the increased caregiving responsibilities and challenges faced by women, particularly with school closures and remote learning.

Chapter 4. Methodology and Discussion

We use a difference-in-difference estimator to compare the labour market outcomes of men and women before and after the onset of COVID-19. Following (Couch, Fairlie, and Xu, 2022) the estimated equation is:

$$Y_{it} = \alpha + \gamma Female_i + \sum_{q=1}^{7} \pi_q COVID_q + \sum_{q=1}^{7} \delta_q (Female_i \times COVID_q) + \beta' X_{it} + \lambda_t + \theta_t + \epsilon_{it} \quad (1)$$

We consider two dependent variables, Y_{it}. The first is the probability of being employed. This takes the value 1 if labour force status is employed, at work and 0 if otherwise. The second is the log of weekly working hours. We created this variable by scaling the unconditional work hours variable and then applying a log transformation to normalize the distribution, which involved adding 1 to the scaled hours before taking the logarithm. We also top-coded at 60 hours to handle potential outliers, ensuring that extreme values do not disproportionately influence the analysis.

$Female_i$ is a binary indicator that equals one for women. $COVID_q$ are dummy variables for the post-COVID quarters, where $q = 1$ to $q = 7$ correspond to:

- $\mathrm{COVID_1}$: Spring 2020 (April 2020 to May 2020)
- $\mathrm{COVID_2}$: Summer 2020 (June 2020 to August 2020)
- $\mathrm{COVID_3}$: Fall 2020 (September 2020 to November 2020)
- $\mathrm{COVID_4}$: Winter 2020 − 2021 (December 2020 to February 2021)
- $\mathrm{COVID_5}$: Spring 2021 (March 2021 to May 2021)
- $\mathrm{COVID_6}$: Summer 2021 (June 2021 to August 2021)
- $\mathrm{COVID_7}$: Fall 2021 (September 2021 to November 2021)

We have February 2020 as our baseline pre-pandemic month. We consider April 2020 as the first fully COVID-19-impacted month and exclude March 2020 from our sample, since it may give us potentially misleading estimates due to being a partially COVID-19-impacted month.

X_{it} includes personal characteristics (education level, occupation, industry representation, geographical location, age and marital status) for each individual in month t. λ_t are seasonal (monthly) fixed effects, θ_t year fixed effects, and ϵ_{it} is the error term.

We estimate equation (1) separately for men and women and the combination of men and women with young children. We consider three age groups for young children, (ages 0-5, ages 6-12 and ages 13-17)

We consider the parallel trends assumption, which is crucial for validating our DID analysis. This assumption requires that in the absence of the COVID-19 pandemic (our treatment), the change in employment outcomes for women (our treatment group) would have followed the same path as the change observed for men (our control group).

We estimate the triple-difference model to see how the presence of children in the household changes the male-female gap in the post-COVID quarters:

$$Y_{ijt} = \alpha + \gamma Female_i + \sum_{q=1}^{7} \pi_q COVID_q + \phi Child_j + \delta_1 \left(Female_i \times Child_j\right) + \sum_{q=1}^{7} \delta_{2q} \left(Female_i \times COVID_q\right) + \sum_{q=1}^{7} \delta_{3q} \left(COVID_q \times Child_j\right) + \sum_{q=1}^{7} \delta_{4q} \left(Female_i \times COVID_q \times Child_j\right) + \beta' X_{ijt} + \lambda_t + \theta_t + \epsilon_{ijt} \qquad (2)$$

We considered $Child_j$ as the set of dummy variables indicating the presence of children with varying age groups. All the other controls and coefficients are unchanged from equation 1.

4.1. Difference-in-Difference Estimates Relative to Men

Probability of Being Employed

We present our difference-in-difference estimates in Table 1. In panel A, we focus on the probability of being employed for men and women. For all groups, an initial gap opens between men and women in Spring 2020, widens in Summer 2020, then is near zero through Fall and Winter, before widening again in Summer 2021. Gaps are the biggest among groups with the youngest children.

From column 1, the male-female employment gap widened by approximately 1.6 percentage points in Spring 2020 and 4.9 percentage points in Summer 2020, narrowed to near zero in Fall 2020 and increased to 3% in Summer 2021. The presence or absence of children did not change this basic pattern, though the gaps were persistently larger between men & women with children (column 3) than between men & women without children (column 2).

Columns 4,5 and 6 show that the employment impact is similar for women with children of different ages, though gaps were generally larger among women with the youngest children (age 0-5 or age 6-12). This probably reflects the added childcare responsibilities that women faced during periods of remote schooling, which significantly affected their employment opportunities compared to men.

Hours of Work

Panel B of Table 3 reports difference-in-difference estimates of changes in total weekly hours worked during the pandemic. Women, particularly those with children, experienced larger reductions in work hours compared to men.

The overall female-male gap in hours worked increased significantly in the Summer of 2020. This was true for men & women both with and without children. Women with the youngest children (ages 0-5) saw smaller declines in work hours during the spring and summer of 2020 than those with children aged 6-12 and 13-17 presumably due to increased childcare responsibilities during remote schooling. In subsequent quarters, women without children began to recover some of their work hours. However, women with children, particularly school-aged children, continued to struggle, maintaining persistent reductions in work hours compared to men.

In summary, gaps in hours worked widened in the Spring of 2020, widened further in the Summer of 2020, and started to close in the Fall/Winter of 2020/21. However, they widened again in Spring/Summer 2021, especially for families with children. The changes in hours worked align with the patterns observed for the probability of being employed, highlighting significant responses for women in families where children were previously engaged in school during typical weekdays before the pandemic disruptions.

4.2. Triple-Difference Estimates of Changes by the Presence of Children

Probability of Being Employed

We present the triple-difference estimates in Table 4 which compares the gender gaps between parents and non-parents, From panel A, Column (1), we see a decline in employment probability for women with children. The reductions in employment probability were most significant for families with children aged 6-12 (Column 3). Employment probability decreased by 4.8 percentage points in the Spring, 5.1 percentage points in the Summer, and 0.7 percentage points in Winter 2020-2021. Spring 2021 saw a reduction of 1.8 percentage points, while Summer 2021 exhibited no change. However, there was an increase of 0.4 percentage points in Fall 2020 and 1.8 percentage points in Fall 2021. For families with children of other ages, the reductions followed a similar pattern.

Thus, the estimates from our triple-difference model show that women with school-age children experienced substantial employment reductions, particularly during periods of remote schooling and summer breaks. The employment gaps generally opened in Spring 2020, widened in Summer 2020, narrowed in Fall/Winter 2020/21, and then widened again in Spring/Summer 2021. The smaller reductions observed in the Fall align with a reduced impact due to school reopening.

Hours of Work

Panel B of Table 4 provides triple-difference estimates of the female-male gap in average hours of work for women with children in different age groups. Significant reductions in hours worked are primarily observed for women with school-age children.

Similar to panel A, we observe, that women with school-age children faced the most significant reductions in hours worked, particularly during periods of remote schooling and summer breaks. The gaps in hours worked generally widened in Spring 2020, widened further in Summer 2020, narrowed in Fall/Winter 2020/21, and then widened again in Spring/Summer 2021.

The triple-difference estimates of the impact of the pandemic on hours of work allow for comparison between families with school-age children vs. families without children. This methodological approach controls for changes due to the pandemic that are independent of the presence of children. For example, the triple-difference parameters for women in families with school-age children (Columns 3 and 4) show significant reductions in hours worked across most periods relative to women without children.

Our findings emphasize the importance of considering caregiving responsibilities when analyzing gender disparities in employment and work hours, as the demands associated with school-age children likely account for a significant portion of the observed changes.

4.3. Explaining the Male-Female Gap in Unemployment Rates

Now, we turn our focus on investigating the job and skill characteristics of men and women and compare how women are more vulnerable to the pandemic impact relative to men. It can be assumed that differences in occupational and industrial composition between men and women, differences in skill levels, along increased childcare burdens may attributed to the widening of the gender gap between men and women during the post-COVID quarters.

Job Characteristics and Unemployment Risk

We present the pre-pandemic distributions of observable characteristics (skill levels, occupational and industrial distribution, geographical location) in Table 5. We consider the telework suitability and health risk score between men and women and try to understand how the differences in those observed characteristics may contribute to greater gender disparity. We also calculate the national unemployment rate between April 2020 to December 2020.

We built the national unemployment rate from the Labour Force Survey (LFS) data by first categorizing individuals into employed, employed but absent, and unemployed, using the “lfsstat” variable. We then calculated the total unemployed and the total labour force for the specific period. The unemployment rate was calculated by dividing the weighted number of unemployed individuals by the total labour force and converting it into a percentage.

As an example, we applied this same method to analyze unemployment rates in essential versus non-essential industries. We categorized industries into these two groups and calculated the unemployment rates for each, allowing us to assess the impact of economic changes on sectors deemed essential, such as healthcare, compared to non-essential ones such as arts and recreation.

To assign an industry to an unemployed individual, we reference the industry where they were last employed, as recorded in the Labour Force Survey (LFS) data. When calculating unemployment rates by industry for the period from April to December 2020, we aggregate data for individuals who are currently unemployed but were previously employed in specific industries. This method links unemployed individuals to their last industry of employment, helping us analyze unemployment impacts across different sectors during that timeframe.

We can see that women were more likely to have bachelor's degrees (12.6%) and post-graduate degrees (5.6%)compared to men (9.1% and 4.9%). The higher education level likely contributed to having skilled "white collar" jobs and thus likely played a role in narrowing the male-female unemployment gap. Again, we observe women were more concentrated in remote jobs (42.46 percent) compared to men (30.00 percent). However, teleworkable jobs had a higher unemployment rate (7.72 percent) than less teleworkable jobs (6.98 percent).

Traditionally, "male-dominated" industries like construction (14.1% men and 2.2% women) and transportation and warehousing (7.9% men and 2.8% women) contributed to higher unemployment rates for men. On the contrary, education and healthcare occupations had a higher female ratio (11.1% and 23.3%) compared to male (4.3% and 4.7%) likely contributing to a lower unemployment rate for women. However, these sectors are also more at risk of infection exposure, which we considered using our health risk measure. Looking at the health risk z-score, Jobs with higher health risk had an unemployment rate of 6.84 percent, compared to 4.42 percent for lower health risk jobs. Women's greater presence in high-health-risk jobs contributed to higher unemployment rates for them. This is likely because high health risk jobs, such as those in healthcare, hospitality, and retail, were more impacted by the pandemic due to increased exposure to the virus and related lockdown measures. Women tend to take these jobs more because they often align with traditionally female-dominated sectors, which emphasize caregiving, customer service, and interpersonal skills. Additionally, these jobs often offer flexible hours, which can be crucial for balancing work and family responsibilities, making them more attractive to women.

Decomposition of Female-Male Unemployment Gap

We apply the Linear Blinder-Oaxaca decomposition method to analyze the individual contributions of education, industry, occupation, and other characteristics to gender disparities in unemployment rates. This approach allows us to break down the overall differences in a dependent variable into parts attributed to observable characteristics (endowment effect) and parts due to differences in the "prices" or coefficients of these characteristics (Blinder 1973; Oaxaca 1973).

We consider the female-male gap in unemployment, Y[3]. The decomposition can be expressed as:

$$\overline{Y^F} - \overline{Y^M} = \left(\overline{X^F} - \overline{X^M}\right)\beta^* + \left(\overline{X^M}(\beta^F - \beta^M)\right) \qquad (3.1)$$

where $\overline{X^j}$ represents the average individual characteristics for gender j, β^* is a vector of pooled coefficient estimates, and $j = F \; or \; M$ for female or male respectively.

In their 1994 paper, Oaxaca and Ransom developed a method for decomposing differences in outcomes (in our case unemployment gap) between groups into parts that can be explained by differences in characteristics (in our case education, major

[3] We used the linear Blinder-Oaxaca decomposition even though unemployment is a binary outcome because our probability tests showed that the linear model fits the data well. This fit justifies the use of a linear model, making it easier to interpret the results and ensuring that the analysis aligns with the observed data.

occupation, essential industry, telework, health risk and geographical location) and parts that cannot be explained by these differences, which may be attributed to discrimination or differences in the return to those characteristics. The decomposition separates the total difference into the explained (endowment) effect which is the portion of the gap attributable to differences in the observable characteristics of the groups. And unexplained (coefficient or price) effect, the portion of the gap that is due to differences in the coefficients, reflecting differences in how the characteristics are rewarded or valued. We use a pooled sample of all groups to better gauge the full market response. In our estimating equation, the endowment effect is expressed by:

$$\left(\overline{X^F} - \overline{X^M}\right)\beta^* \qquad (3.2)$$

We examine the results from Table 6, the decomposition analysis of the male-female unemployment gap to understand which factors were crucial in explaining this gap. Before the pandemic, the unemployment gap between men and women was shaped by differences in occupation. The major occupation variable accounted for 35.7% of the total endowment effect highlighting how women's representation in specific occupations played a role in reducing their unemployment rates compared to men.

As the pandemic began, the influence of occupation continued to be critical. During the Spring of 2020, occupation and its price effects became even more pronounced, contributing to 28.6% of the overall gap, as the value of different jobs shifted in response to the crisis. The impact of teleworkability and health risk exposure also started to emerge, with telework reducing the gap by 0.5 percentage points, though its significance diminished by the Fall 2021.

Over time, while the importance of teleworkability and health risk exposure decreased, the roles of education and occupation persisted. Women's higher educational attainment consistently contributed to narrowing the unemployment gap throughout the pandemic. These factors emphasize the significance of occupation, education, and how they are valued (price effects), along with their interactions, in shaping gender disparities in unemployment rates during both pre-pandemic and pandemic periods.

Explaining the effect of industrial composition

To gain a deeper understanding of the factors driving gender disparities in labour market outcomes, we utilize the Gelbach decomposition method. We use this technique to isolate the effects of including industry dummies in our estimates, allowing for more precise attribution of observed differences in outcomes to specific explanatory variables. Moreover, the differences in labour market outcomes between men and women, especially those with and without children, are shaped by the industries in which they are employed. By controlling for industry, we can better understand how these differences arise and quantify the extent to which industry contributes to these disparities.

Accounting for industry significantly alters the estimates of our primary variables, which are interactions between post-COVID quarters and gender. This emphasizes the substantial role industry plays in influencing gender disparities. The Gelbach decomposition method helps us to understand these changes.

Following Gelbach (2016), we use a decomposition technique that expresses the change in the coefficient of X_1(primary explanatory variables) due to the inclusion of X_2 (industry dummies) as follows:

$$\beta_1^{\text{base}} = \beta_1 + \Gamma_{X_1 X_2}\beta_2 \qquad (4)$$

where $\Gamma_{X_1 X_2}$ is the matrix of coefficients from projecting the columns of X_2 on the columns of $X_1$and $\Gamma_{X_1 X_2}\beta_2$ captures the bias introduced by omitting X_2 . Here, β_1^{base} is the coefficient of X_1 after including X_2, β_1 is the original coefficient of X_1 and β_2 represents the coefficients associated with X_2. We examine how much of the observed effect in our baseline estimates (captured by β_1^{base}) can be attributed to the inclusion or exclusion of specific explanatory variables, such as industry representation. By quantifying these contributions, we can better analyze the structural factors influencing gender disparities in labour market outcomes due to the COVID-19 pandemic.

The Gelbach decomposition estimates in Table 7 show the modest yet consistent impact of industrial composition on the gender employment gap during the pandemic. For instance, in Spring 2020, controlling for industrial composition slightly reduces the employment gap between men and women by about 1.8% of the total gap (-0.003 out of

-0.164). This small effect is consistent across all periods analyzed, suggesting that while industry plays a role, it does not significantly alter the employment gap.

Similarly, when examining unconditional hours of work, industrial composition accounts for a larger but still moderate portion of the difference. In Spring 2020, industry composition explains about 6.9% of the total difference in hours worked between men and women (-0.047 out of -0.681). This impact remains steady, ranging from 6.6% to 7.9% across other periods, indicating a persistent but not overwhelming influence.

In summary, while industry composition affects gender disparities, its impact is relatively minor. The consistent patterns across all post-COVID quarters highlight the persistent but modest role of industry composition in labour market outcomes for women during the pandemic.

Chapter 5. Conclusion

The COVID-19 pandemic has significantly impacted the Canadian labour market, intensifying existing gender disparities. This thesis explores how the pandemic influenced employment and working hours, highlighting gender differences and the additional childcare burdens that disproportionately affected women.

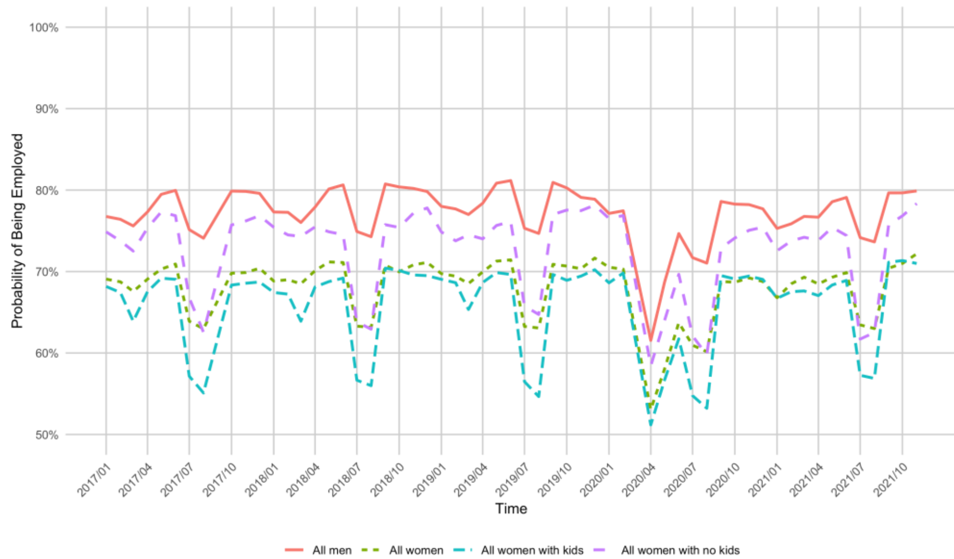
The impacts of the pandemic can be observed from April 2020 onwards using LFS data. Our analysis indicates that employment and hours worked by women decreased more sharply than those of comparable men in the months following the widespread adoption of social distancing measures. The largest relative declines in employment and hours worked were experienced by women with school-age children. Before the pandemic, these women were more actively engaged in the labour market, supported by their children attending school. However, as schools closed and distance learning was implemented, these women's work activities decreased disproportionately compared to men.

Women, who were more likely to hold teleworkable jobs (42.46% for women versus 30.00% for men), experienced some mitigation against the pandemic's impacts, especially during the Spring and Summer of 2020. However, the lower concentration of women in essential industries (40.9% for women versus 41.2% for men) aggravated the unemployment gap initially. During the first three-quarters of the pandemic, the unemployment rates for women in essential industries declined more rapidly than those for men, leading to a gradual reduction in the gender gap. For instance, the national unemployment rate for non-essential industries was 10.7%, whereas for essential industries, it was only 4.7%.

Despite these improvements, the return to pre-pandemic employment levels for both men and women was incomplete by Fall 2021. Women with school-age children were particularly affected, with reductions in hours worked ranging from 8.3% to 26.7% across various post-COVID periods. Employment losses for women with children ranged from 2.3 to 4.3 percentage points. As schools reopened and economic activity picked up, the gender gap continued to decrease, but employment and average unconditional hours for both men and women remained below pre-pandemic levels. These findings highlight the necessity for targeted policies to support women's full recovery and sustained progress in the labour market, considering industry composition, teleworkability, and caregiving duties.

Tables and Figures

a)



b)

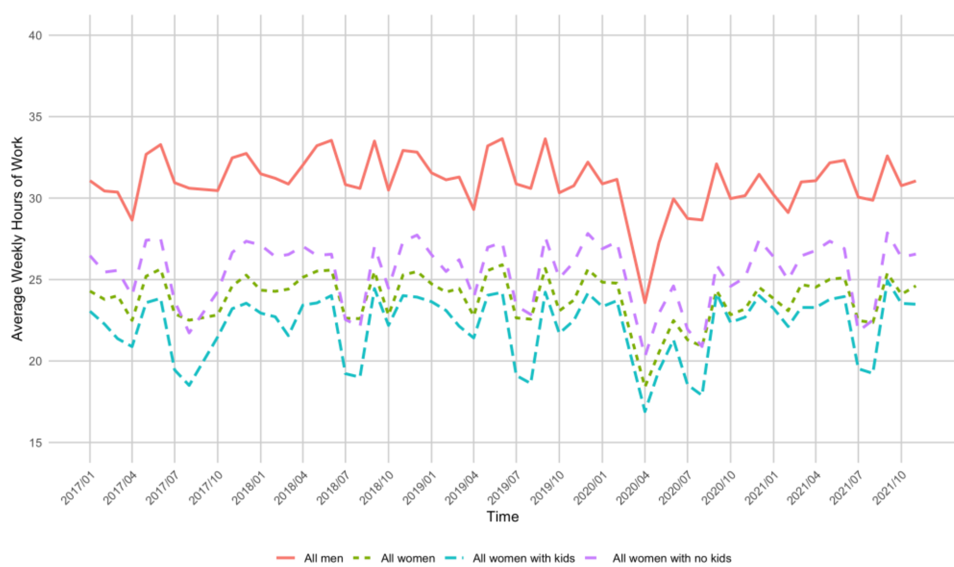
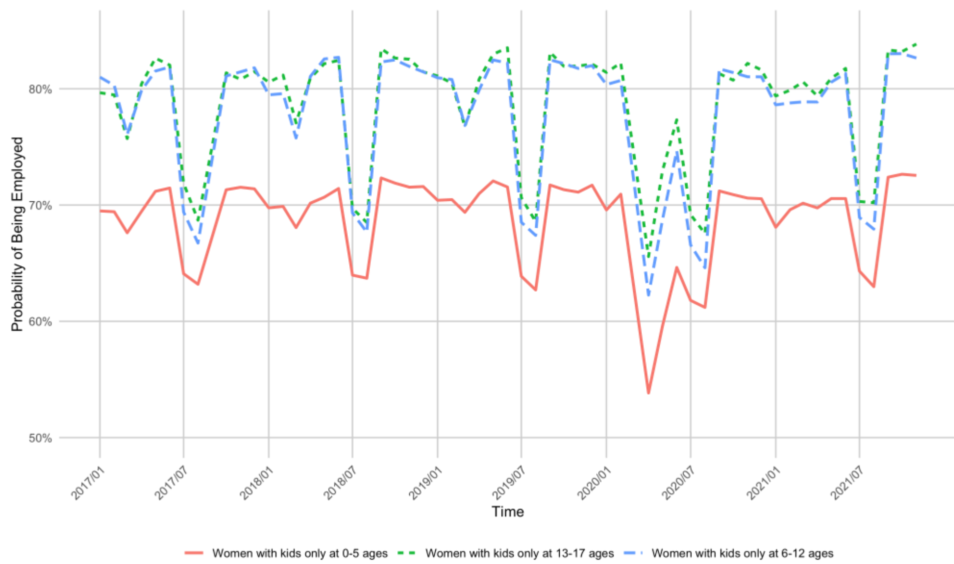


Figure 1. **(a) Probability of Being Employed. Women vs. Men, Janaury 2017 to November 2021. (b): Average Weekly Unconditional Hours of Work, Women vs. Men, January 2017 to November 2021**

Note: Figures 1(a) and 1(b) present detailed monthly trends in employment and work hours for men and women from January 2017 to November 2021. Figure 1(a) displays the probability of being employed, while Figure 1(b) shows the average weekly unconditional hours of work.

a)



b)

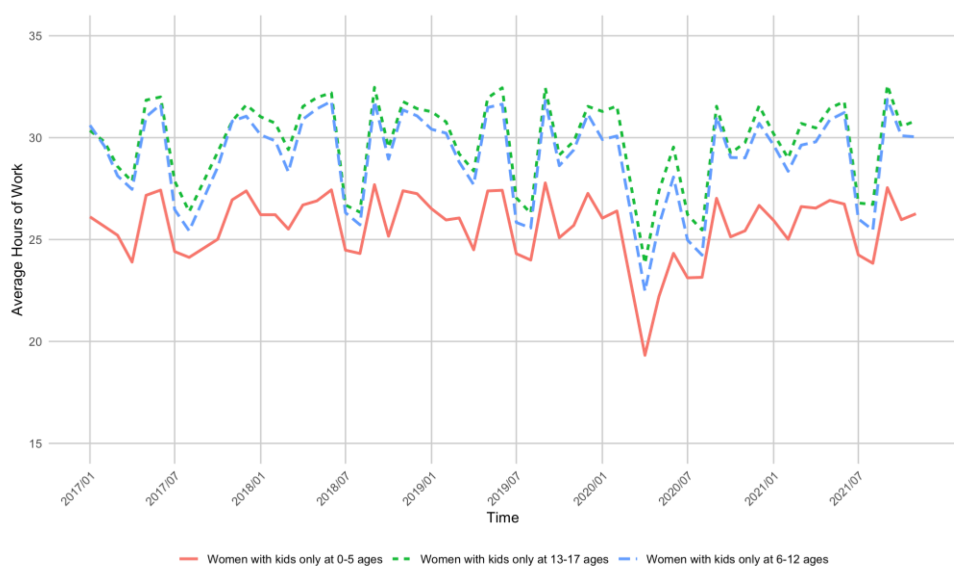


Figure 2. **(a) Probability of being Employed, Women by Children, January 207 to November 2021. (b) Average Hours of Work, Women by Children, January 2017 to November 2021**

Note: Figures 2(a) and 2(b) present monthly trends in employment and work hours for women with children of different age groups from January 2017 to November 2021. Figure 2(a) displays the probability of being employed, while Figure 2(b) shows the average weekly unconditional hours of work.

Table 1. The Probability of Being Employed

	Male	Female	Male-Female Gap
Panel A. All			
Jan 2017 – November 2021	0.781	0.678	0.103
February 2020	0.788	0.710	0.078
Spring 2020	0.642	0.540	0.102
Summer 2020	0.726	0.589	0.137
Fall 2020	0.787	0.692	0.094
Winter 2020_2021	0.771	0.685	0.085
Spring 2021	0.785	0.688	0.096
Summer 2021	0.765	0.639	0.125
Fall 2021	0.810	0.714	0.096
Panel B. With no children			
Jan 2017 - November 2021	0.738	0.693	0.045
February 2020	0.738	0.715	0.023
Spring 2020	0.590	0.544	0.046
Summer 2020	0.686	0.615	0.071
Fall 2020	0.742	0.701	0.041
Winter 2020_2021	0.723	0.696	0.026
Spring 2021	0.739	0.705	0.034
Summer 2021	0.737	0.672	0.065
Fall 2021	0.766	0.723	0.042
Panel C. With children			
Jan 2017 - November 2021	0.838	0.662	0.177
February 2020	0.858	0.705	0.152
Spring 2020	0.712	0.536	0.177
Summer 2020	0.779	0.563	0.217
Fall 2020	0.848	0.685	0.163
Winter 2020_2021	0.835	0.674	0.161
Spring 2021	0.847	0.672	0.175
Summer 2021	0.802	0.606	0.196
Fall 2021	0.869	0.705	0.164
Panel D. With children only at 0-5 ages			
Jan 2017 – Nov 2021	0.845	0.537	0.307
February 2020	0.854	0.582	0.273
Spring 2020	0.697	0.427	0.269
Summer 2020	0.787	0.451	0.335
Fall 2020	0.839	0.547	0.292
Winter 2020_2021	0.829	0.539	0.290
Spring 2021	0.852	0.542	0.310
Summer 2021	0.821	0.488	0.333
Fall 2021	0.876	0.572	0.303

	Male	Female	Male-Female Gap
Panel E. With children only at 6-12 ages			
Jan 2017 - Nov 2021	0.845	0.716	0.129
February 2020	0.864	0.759	0.105
Spring 2020	0.723	0.576	0.147
Summer 2020	0.779	0.600	0.179
Fall 2020	0.866	0.753	0.114
Winter 2020_2021	0.850	0.728	0.122
Spring 2021	0.856	0.716	0.140
Summer 2021	0.798	0.654	0.144
Fall 2021	0.882	0.774	0.108
Panel F. With children only at 13-17 ages			
Jan 2017 - Nov 2021	0.839	0.742	0.097
February 2020	0.873	0.789	0.084
Spring 2020	0.736	0.629	0.107
Summer 2020	0.794	0.647	0.148
Fall 2020	0.860	0.775	0.086
Winter 2020_2021	0.853	0.763	0.089
Spring 2021	0.858	0.769	0.089
Summer 2021	0.803	0.689	0.114
Fall 2021	0.870	0.807	0.063

Notes: The sample consists of all people ages 25 to 59 years. All calculations use LFS sample weights. The sample period covers January 2017 to November 2021. The reference period is February 2020. Post-COVID periods include April to May 2020 for Spring 2020, June to August 2020 for Summer 2020, September to December 2020 for Fall 2020, December 2020 to February 2021 for Winter 2020-2021, March to May 2021 for Spring 2021, June to August 2021 for Summer 2021, and September to November 2021 for Fall 2021. March 2020 is excluded from the analysis due to the transition period before the widespread adoption of social distancing measures.

Table 2. Average Weekly Hours of Work on All Jobs

	Male	Female	Male-Female Gap
Panel A. All			
Jan 2017 – November 2021	31.0	23.5	7.5
February 2020	31.4	24.8	6.6
Spring 2020	24.8	18.6	6.1
Summer 2020	28.7	20.5	8.2
Fall 2020	30.5	23.5	7.0
Winter 2020_2021	30.2	23.9	6.3
Spring 2021	31.5	24.4	7.0
Summer 2021	30.6	22.4	8.2
Fall 2021	31.7	24.7	7.1
Panel B. With no children			
Jan 2017 - November 2021	28.8	24.4	4.4
February 2020	28.9	25.3	3.6
Spring 2020	22.5	19.2	3.5
Summer 2020	26.8	21.6	5.2
Fall 2020	28.3	24.0	4.2
Winter 2020_2021	27.7	24.5	3.2
Spring 2021	29.1	25.4	3.6
Summer 2021	29.1	23.9	5.2
Fall 2021	29.5	25.3	4.2
Panel C. With children			
Jan 2017 - November 2021	33.9	22.5	11.4
February 2020	34.8	24.2	10.6
Spring 2020	27.7	18.2	9.5
Summer 2020	31.2	19.3	11.8
Fall 2020	33.5	22.9	10.6
Winter 2020_2021	33.4	23.3	10.1
Spring 2021	34.7	23.4	11.2
Summer 2021	32.7	20.9	11.7
Fall 2021	34.7	24.1	10.6
Panel D. With children only at 0-5 ages			
Jan 2017 – Nov 2021			
February 2020	34.3	19.3	15.0
Spring 2020	26.9	13.9	13.0
Summer 2020	31.4	14.9	16.5
Fall 2020	32.9	17.8	15.1
Winter 2020_2021	33.4	18.3	15.1
Spring 2021	34.7	18.4	16.3
Summer 2021	33.3	16.2	17.0
Fall 2021	34.5	18.7	15.8

	Male	Female	Male-Female Gap
Panel E. With children only at 6-12 ages			
Jan 2017 - Nov 2021	34.2	24.3	9.9
February 2020	34.9	25.8	9.1
Spring 2020	28.1	19.7	8.5
Summer 2020	31.1	20.5	10.6
Fall 2020	33.9	25.0	9.0
Winter 2020_2021	33.9	24.9	9.0
Spring 2021	34.9	24.7	10.2
Summer 2021	32.6	22.5	10.1
Fall 2021	35.3	26.5	8.9
Panel F. With children only at 13-17 ages			
Jan 2017 - Nov 2021	34.3	25.9	8.4
February 2020	36.6	27.9	8.6
Spring 2020	28.6	21.7	7.0
Summer 2020	31.8	22.9	8.9
Fall 2020	34.3	26.6	7.7
Winter 2020_2021	34.2	26.6	7.6
Spring 2021	35.4	27.3	8.1
Summer 2021	32.8	24.4	8.4
Fall 2021	35.4	28.5	6.9

Notes: The sample consists of all people ages 25 to 59 years. All calculations use LFS sample weights. The sample period covers January 2017 to November 2021. The reference period is February 2020. Post-COVID periods include April to May 2020 for Spring 2020, June to August 2020 for Summer 2020, September to December 2020 for Fall 2020, December 2020 to February 2021 for Winter 2020-2021, March to May 2021 for Spring 2021, June to August 2021 for Summer 2021, and September to November 2021 for Fall 2021. March 2020 is excluded from the analysis due to the transition period before the widespread adoption of social distancing measures.

Table 3. Differene-in-Difference Estimates Relative to Men

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	All	No kid	Any kid	0-5 kid	6-12 kid	13-17 kid
Panel A. The Probability of Being Employed						
Spring2020 * Female	-0.016***	-0.007***	-0.030***	-0.006***	-0.056***	-0.024***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Summer2020 * Female	-0.049***	-0.030***	-0.067***	-0.062***	-0.081***	-0.064***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fall2020 * Female	0.001***	0.002***	0.000***	0.000***	0.006***	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Winter_2020_2021*Female	0.009***	0.013***	0.003	0.006**	0.006***	-0.010***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Spring2021*Female	0.005***	0.010***	-0.001***	-0.008***	-0.008***	-0.010***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Summer2021*Female	-0.030***	-0.028***	-0.028***	-0.034***	-0.028***	-0.039***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	0.006***	-0.001***	0.013***	0.007***	0.017***	0.029***
Fall2021*Female	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

	(1)	(2)	(3)	(4)	**(5)**	(6)

Sample:	All	No kid	Any kid	0-5 kid	6-12 kid	13-17 kid
Panel B. Unconditional Hours of Work						
Spring2020 * Female	-0.007***	0.007***	-0.035***	0.057***	-0.126***	-0.021***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Summer2020 * Female	-0.149***	-0.103***	-0.190***	-0.170***	-0.243***	-0.177***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Fall2020 * Female	0.014***	0.006***	0.020***	0.036***	0.034***	0.013***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Winter_2020_2021*Female	0.058***	0.062***	0.049***	0.069***	0.049***	-0.003***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)
Spring2021*Female	0.032***	0.052***	0.010***	-0.005***	-0.023***	-0.028***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001	(0.001)
Summer2021*Female	-0.096***	-0.103***	-0.073***	-0.097***	-0.083***	-0.114***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fall2021*Female	0.031***	-0.004***	0.068***	0.052***	0.077***	0.116***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Personal	Yes	Yes	Yes	Yes	Yes	Yes
Seasonality	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	863,551,659	456,294,102	407,257,557	141,165,880	116,570,298	74,998,337

Notes: The sample consists of all people ages 25 to 59. The dependent variable is the probability of being employed in Panel A and log weekly unconditional working hours on all jobs in Panel B (including zero hours for those not working and top-coded to 60 hours). Log hours are transformed to approximate logs and include zero hours. The sample period covers January 2017 to November 2021. The reference period is February 2020. Post-COVID periods include April to May 2020 for Spring 2020, June to August 2020 for Summer 2020, September to December 2020 for Fall 2020, December 2020 to February 2021 for Winter 2020-2021, March to May 2021 for Spring 2021, June to August 2021 for Summer 2021, and September to November 2021 for Fall 2021. March 2020 is excluded from the analysis due to the transition period before the widespread adoption of social distancing measures. All specifications include full interaction terms and a constant term. All specifications also control for education level, industrial composition, geographical location, and marital status. Specifications are estimated using LFS sample weights. Robust Standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01

Table 4. Triple-Difference Estimates of Changes by the Presence of Children

	(1)	(2)	(3)	(4)
Sample:	Any kid + no kid	Any 0-5 kid + no kid	Any 6-12 kid + no kid	Any 13-17 kid + no kid
Panel A. The Proabbility of Being Employed				
Spring2020 * Female * Child	-0.014***	0.000**	-0.048***	-0.016***
	(0.000)	(0.000)	(0.001)	(0.001)
Summer2020 * Female * Child	-0.034***	-0.032***	-0.051***	-0.033***
	(0.000)	(0.000)	(0.000)	(0.000)
Fall2020 * Female * Child	0.004***	-0.002	0.004***	-0.001
	(0.000)	(0.000)***	(0.000)	(0.000)
Winter_2020_2021*Female* Child	-0.006***	-0.007***	-0.007***	-0.022***
	(0.000)	(0.000)	(0.001)	(0.000)
Spring2021*Female* Child	-0.018***	-0.019***	-0.018***	-0.020***
	(0.000)	(0.000)	(0.000)	(0.000)
Summer2021*Female* Child	-0.007***	-0.008***	-0.000	-0.010***
	(0.000)	(0.000)	(0.000)	(0.000)
Fall2021*Female* Child	0.016***	0.007***	0.018***	0.030***
	(0.000)	(0.000)	(0.000)	(0.000)

	(1)	(2)	(3)	(4)
Sample:	Any kid + no kid	Any 0-5 kid + no kid	Any 6-12 kid + no kid	Any 13-17 kid + no kid
Panel B. Unconditional Hours of Work				
Spring2020 * Female * Child	-0.014***	0.051***	-0.132***	-0.025***
	(0.001)	(0.001)	(0.002)	(0.002)
Summer2020 * Female * Child	-0.081***	-0.069***	-0.140***	-0.072***
	(0.001)	(0.001)	(0.001)	(0.001)
Fall2020 * Female * Child	0.036***	0.030***	0.028***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Winter_2020_2021*Female* Child	-0.005***	0.007***	-0.011***	-0.063***
	(0.001)	(0.001)	(0.001)	(0.002)
Spring2021*Female* Child	-0.066***	-0.060***	-0.074***	-0.081***
	(0.001)	(0.001)	(0.001)	(0.002)
Summer2021*Female* Child	-0.007***	0.000	0.018***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.002)
Fall2021*Female* Child	0.075***	0.051***	0.081***	0.120***
	(0.001)	(0.001)	(0.001)	(0.002)
Personal	Yes	Yes	Yes	Yes
Seasonality	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Number of Observations	863,551,659	597,459,982	572,864,400	531,292,439

Notes: The sample consists of all people ages 25 to 59. The dependent variable is the probability of being employed in Panel A and log weekly unconditional working hours on all jobs in Panel B (including zero hours for those not working and top-coded to 60 hours). Log hours are transformed to approximate logs and include zero hours. The sample period covers January 2017 to November 2021. The reference period is February 2020. Post-COVID periods include April to May 2020 for Spring 2020, June to August 2020 for Summer 2020, September to December 2020 for Fall 2020, December 2020 to February 2021 for Winter 2020-2021, March to May 2021 for Spring 2021, June to August 2021 for Summer 2021, and September to November 2021 for Fall 2021. March 2020 is excluded from the analysis due to the transition period before the widespread adoption of social distancing measures. All specifications include full triple interaction terms and a constant term. The child indicator equals to 1 for the presence of children of different ages and equals to 0 for no presence of children. All specifications also control for education level, industrial composition, geographical location and marital status. Specifications are estimated using LFS sample weights. Robust standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01

Table 5. Worker and Job Characteristics and Unemployment from COVID-19

	Percentage (Feb. 2017 – Feb. 2020)			April 2020 to December 2020
	Men	Women	Total	National Unemployment Rate
Essential				
Nonessential industry	59.5%	58.8%	59.1%	10.7%
Essential industry	40.6%	41.2%	40.9%	4.7%
Education				
High school dropout	3.5%	2.3%	5.8%	12.3%
High school graduate	9.6%	8.3%	17.9%	10.3%
Some college	2.4%	2.1%	4.5%	11.4%
Diploma	18.4%	18.4%	36.8%	7.6%
Bachelors	9.1%	12.6%	22.6%	6.3%
Above Bachelors	4.9%	5.6%	10.5%	6.0%
Provinces				
Newfoundland and Labrador	1.4%	1.4%	1.4%	12.2%
Prince Edward Island	0.4%	0.4%	0.4%	8.9%
Nova Scotia	2.4%	2.5%	2.5%	8.4%
New Brunswick	1.10%	2.0%	1.10%	8.4%
Quebec	22.9%	22.2%	22.6%	7.4%
Ontario	38.7%	39.3%	39.0%	7.8%
Manitoba	3.4%	3.4%	3.4%	6.7%
Saskatchewan	2.9%	2.9%	2.9%	6.9%
Alberta	12.4%	12.1%	12.2%	9.5%
British Columbia	13.5%	13.8%	13.7%	7.7%
Major industry				
Agriculture	1.6%	0.9%	1.2%	4.8%
Forestry and logging and support activities for forestry	0.5%	0.1%	0.3%	10.3%
Fishing, hunting and trapping	0.2%	0.1%	0.1%	20.2%
Mining, quarrying, and oil and gas extraction	2.6%	0.6%	1.6%	9.6%
Utilities	1.2%	0.4%	0.8%	1.3%
Construction	14.1%	2.2%	8.4%	9.0%
Manufacturing - durable goods	8.1%	2.3%	5.3%	6.9%
Manufacturing - non-durable goods	5.5%	3.8%	4.7%	6.5%
Wholesale trade	4.9%	2.6%	3.8%	5.7%
Retail trade	8.6%	10.6%	9.5%	6.9%
Transportation and warehousing	7.9%	2.8%	5.4%	6.9%
Finance and insurance	4.1%	5.9%	5.0%	2.3%
Real estate and rental and leasing	1.9%	1.8%	1.8%	4.6%
Professional, scientific and technical services	9.1%	7.6%	8.4%	5.0%

Business, building and other support services	4.3%	4.0%	4.1%	9.7%
Educational services	4.3%	11.1%	7.6%	5.6%
Health care and social assistance	4.7%	23.3%	13.6%	3.2%
Information, culture and recreation	3.9%	3.5%	3.7%	9.0%
Accommodation and food services	4.0%	5.7%	4.8%	18.5%
Other services (except public administration)	3.5%	4.8%	4.1%	7.1%
Public administration	5.3%	6.1%	5.7%	1.8%
	Percentage (Feb. 2017 – Feb. 2020)			April 2020 to December 2020
	Men	Women		Men
Major Occupation				
Business, finance and administration occupations, except management	9.0%	23.6%	16.0%	5.3%
Natural and applied sciences and related occupations, except management	12.3%	4.3%	8.5%	4.0%
Health occupations, except management	3.0%	13.5%	8.0%	2.3%
Occupations in education, law and social, community and government services, except management	6.7%	17.7%	12.0%	4.6%
Occupations in art, culture, recreation and sport, except management	2.3%	2.9%	2.6%	7.6%
Sales and service occupations, except management	16.7%	24.2%	20.3%	10.0%
Trades, transport and equipment operators and related occupations, except management	28.4%	2.7%	16.1%	8.6%
Natural resources, agriculture and related production occupations, except management	3.2%	0.8%	2.0%	12.3%
Occupations in manufacturing and utilities, except management	6.7%	3.1%	5.0%	7.9%
Telework				
Share of jobs that can be done at home	30.0%	42.46%	36.16%	
Less than median				6.98%
More than median				7.72%
Health risk				
Exposed to health risk index (Z-score)	-0.23	0.24	0.00	
Less than median				4.16%
More than median				6.84%

Notes: The sample includes all individuals ages 25 to 59 in the labour force. Risk factor calculations use LFS microdata based on February 2017 to February 2020. The last column shows the national unemployment rate from April to December 2020.

Table 5. Oaxaca-Blinder Decomposition of Unemployment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pre-COVID Feb. 2020	Post-COVID Spring 2020	Post-COVID Summer 2020	Post-COVID Fall 2020	Post-COVID Winter 2020-2021	Post-COVID Spring 2021	Post-COVID Summer 2021	Post-COVID Fall 2021
Female Unemployment Rate	0.027	0.092	0.073	0.043	0.048	0.035	0.035	0.022
Male Unemployment Rate	0.039	0.102	0.067	0.052	0.059	0.046	0.033	0.027
Female – Male Gap	-0.012	-0.011	0.006	-0.009	-0.011	-0.011	0.002	-0.005
Endowments	**-0.010*****	**-0.028*****	**-0.013*****	**-0.011*****	**-0.018*****	**-0.011*****	**-0.004*****	**-0.006*****
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Essential/Major Industry	-0.001***	-0.002***	-0.001***	-0.001***	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Major Occupation	-0.005***	-0.013***	-0.006***	-0.003***	-0.007***	-0.004***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.001***	-0.001***	-0.000***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Province	0.000***	0.000***	-0.000***	-0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)
Telework	-0.001***	-0.005***	-0.002***	-0.002***	-0.002***	-0.002***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)
Health Risk (Z-score)	-0.003***	-0.008***	-0.005***	-0.004***	-0.006***	-0.003***	0.000***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pre-COVID Feb. 2020	Post-COVID Spring 2020	Post-COVID Summer 2020	Post-COVID Fall 2020	Post-COVID Winter 2020-2021	Post-COVID Spring 2021	Post-COVID Summer 2021	Post-COVID Fall 2021
Price effects	**-0.005*** (0.000)**	**0.014*** (0.000)**	**0.020*** (0.000)**	**0.004*** (0.000)**	**0.008*** (0.000)**	**0.004*** (0.000)**	**0.003*** (0.000)**	**0.002*** (0.000)**
Essential/Major Industry	0.003*** (0.000)	0.005*** (0.000)	-0.007*** (0.000)	0.002*** (0.000)	-0.002*** (0.000)	0.002*** (0.000)	-0.007*** (0.000)	0.002*** (0.000)
Major Occupation	-0.011*** (0.000)	-0.022*** (0.000)	0.012*** (0.000)	0.004*** (0.000)	0.005*** (0.000)	0.015*** (0.000)	0.007*** (0.000)	0.006*** (0.000)
Education	0.008*** (0.000)	-0.012*** (0.000)	-0.003*** (0.000)	0.010*** (0.000)	-0.002*** (0.000)	-0.000*** (0.000)	-0.013*** (0.000)	0.001*** (0.000)
Province	0.009*** (0.000)	0.011*** (0.000)	-0.003*** (0.000)	-0.002*** (0.000)	0.013*** (0.000)	0.015*** (0.000)	0.011*** (0.000)	-0.001*** (0.000)
Telework	-0.001*** (0.000)	-0.010*** (0.000)	0.006*** (0.000)	-0.001*** (0.000)	-0.008*** (0.000)	-0.001*** (0.000)	0.020*** (0.000)	0.002*** (0.000)
Health Risk (Z-score)	0.000*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	0.000*** (0.000)	-0.001*** (0.000)	0.000*** (0.000)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pre-COVID Feb. 2020	Post-COVID Spring 2020	Post-COVID Summer 2020	Post-COVID Fall 2020	Post-COVID Winter 2020-2021	Post-COVID Spring 2021	Post-COVID Summer 2021	Post-COVID Fall 2021
Interaction	**0.002***** **(0.000)**	**0.003***** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	**-0.002***** **(0.000)**	-0.004*** (0.000)	0.003*** (0.000)	-0.001*** (0.000)
Essential/Major Industry	0.000*** (0.000)	0.000*** (0.000)	-0.001*** (0.000)	0.000*** (0.000)	-0.000*** **(0.000)**	0.000*** (0.000)	-0.001*** (0.000)	0.000*** (0.000)
Major Occupation	0.002*** (0.000)	0.004*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)	-0.001*** **(0.000)**	-0.003*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Education	0.001*** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	0.001*** (0.000)	-0.000*** **(0.000)**	-0.000*** (0.000)	-0.001*** (0.000)	0.000*** (0.000)
Province	-0.000*** (0.000)	-0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	-0.000*** **(0.000)**	-0.000*** (0.000)	-0.000*** (0.000)	0.000*** (0.000)
Telework	-0.000*** (0.000)	-0.001*** (0.000)	0.001*** (0.000)	-0.001*** (0.000)	-0.001*** **(0.000)**	-0.000*** (0.000)	0.003*** (0.000)	0.000*** (0.000)
Health Risk (Z-score)	-0.000*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	-0.001*** (0.000)	0.001*** **(0.000)**	-0.001*** (0.000)	0.004*** (0.000)	-0.000*** (0.000)
Number of Observation	15,253,287	30,682,862	46,269,704	46,504,987	46,154,140	45,466,400	45,231,122	45,891,457

Note: All linear decomposition specifications use pooled coefficient estimates from the full sample of males and females. Sampling weights are used in all specifications. Standard errors are reported in parentheses below contribution estimates. The table presents the endowment and coefficient (price) effects as well as the interaction. It is important to note that the sum of these components accounts for the total observed gap between female and male unemployment rates. Post-COVID periods include April to May 2020 for Spring 2020, June to August 2020 for Summer 2020, September to November 2020 for Fall 2020, December 2020 to February 2021 for Winter 2020-2021, March to May 2021 for Spring 2021, June to August 2021 for Summer 2021, and September to November 2021 for Fall 2021.

Table 6. Gelbach Decomposition

	(1)	(2)	(3)
Sample:	Base	Full	Explained
Panel A: Probability of Being Employed			
Spring2020 * Female	-0.164***	-0.161***	-0.003***
Summer2020 * Female	-0.082***	-0.080***	-0.003***
Fall2020 * Female	-0.026***	-0.023***	-0.003***
Winter_2020_2021*Female	-0.048***	-0.046***	-0.003***
Spring2021*Female	-0.026***	-0.023***	-0.003***
Summer2021*Female	-0.059***	-0.056***	-0.002***
Fall2021*Female	-0.032***	-0.030***	-0.002***
Panel B: Unconditional Hours of Work			
Spring2020 * Female	-0.681***	-0.634***	-0.047***
Summer2020 * Female	-0.419***	-0.373***	-0.046***
Fall2020 * Female	-0.216***	-0.171***	-0.045***
Winter_2020_2021*Female	-0.300***	-0.254***	-0.047***
Spring2021*Female	-0.213***	-0.161***	-0.052***
Summer2021*Female	-0.356***	-0.306***	-0.050***
Fall2021*Female	-0.254***	-0.204***	-0.050***
All controls	Yes	Yes	
Industrial composition	No	Yes	
Number of Observation	2,609,607	2,609,607	

Notes: The sample includes all individuals aged 25 to 59 using LFS microdata with sample weights. Post-COVID periods extend up to November 2021. The asterisks indicate the significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The 'Base' column represents the coefficients from the restricted regression without controlling for industrial composition. The 'Full' column includes the coefficients from the unrestricted regression with all controls. The 'Explained' column shows the difference between the 'Base' and 'Full' coefficients, representing the portion explained by the industrial composition.

References

Albanesi, S. and Kim, J., 2021. Effects of the COVID-19 recession on the US labor market: Occupation, family, and gender. Journal of Economic Perspectives, 35(3), pp.3-24.

Alon, T., Doepke, M., Olmstead-Rumsey, J. and Tertilt, M., 2020. The impact of COVID-19 on gender equality (No. w26947). National Bureau of Economic Research.

Baker, M., Gruber, J. and Milligan, K., 2008. Universal child care, maternal labor supply, and family well-being. Journal of political Economy, 116(4), pp.709-745.

Bartik, A.W., Bertrand, M., Lin, F., Rothstein, J. and Unrath, M., 2020. Measuring the labor market at the onset of the COVID-19 crisis (No. w27613). National Bureau of Economic Research.

Blinder, A.S., 1973. Wage discrimination: Reduced form and structural estimates. Journal of Human Resources, 8(4), pp.436-455.

Blau, F.D. and Kahn, L.M., 2013. Female labor supply: Why is the United States falling behind?. American Economic Review, 103(3), pp.251-256.

Brochu, P., Cr.chet, J. and Deng, Z., 2020. Labour market flows and worker trajectories in Canada during COVID-19. Canadian Labour Economics Forum Working Paper Series, no. 32, University of Waterloo.

Christopherson, K., Yiadom, A., Johnson, J., Fernando, F., Yazid, H. and Thiemann, C., 2022. Tackling legal impediments to women's economic empowerment. International Monetary Fund.

Collins, C., Landivar, L.C., Ruppanner, L. and Scarborough, W.J., 2021. COVID-19 and the gender gap in work hours. Gender, Work & Organization, 28, pp.101-112.

Couch, K.A., Fairlie, R.W. and Xu, H., 2022. The evolving impacts of the COVID-19 pandemic on gender inequality in the US labor market: The COVID motherhood penalty. Economic Inquiry, 60(2), pp.485-507.

Deryugina, T., Shurchkov, O. and Stearns, J., 2021, May. COVID-19 disruptions disproportionately affect female academics. In AEA Papers and Proceedings (Vol. 111, pp. 164-168). American Economic Association.

Dingel, J.I. and Neiman, B., 2020. How many jobs can be done at home? Journal of Public Economics, 189, pp.1-8.

Gelbach, J. B. (2016). When Do Covariates Matter? And Which Ones, and How Much? Journal of Labor Economics, 34(2), pp.509-543.

Goldin, C., 2014. A grand gender convergence: Its last chapter. American Economic Review, 104(4), pp.1091-1119.

Goldin, C. and Mitchell, J., 2017. The new life cycle of women's employment: Disappearing humps, sagging middles, expanding tops. Journal of Economic Perspectives, 31(1), pp.161-182.

Heggeness, M.L., 2020. Estimating the immediate impact of the COVID-19 shock on parental attachment to the labor market and the double bind of mothers. Review of Economics of the Household, 18(4), pp.1053-1078.

Holder, M., Jones, J. and Masterson, T., 2021. The early impact of COVID-19 on job losses among black women in the United States. Feminist Economics, 27(1-2), pp.103-116.

Jones, S.R., Lange, F., Riddell, W.C. and Warman, C., 2020. Waiting for recovery: The Canadian labour market in June 2020. Canadian Public Policy, 46(S2), pp.S102-S118.

Juhn, C. and McCue, K., 2017. Specialization then and now: Marriage, children, and the gender earnings gap across cohorts. Journal of Economic Perspectives, 31(1), pp.183-204.

Kapteyn, A., Angrisani, M., Bennett, D., de Bruin, W.B., Darling, J., Gutsche, T., Liu, Y., Meijer, E., Perez-Arce, F., Schaner, S. and Thomas, K., 2020, June. Tracking the effect of the COVID-19 pandemic on the lives of American households. In Survey Research Methods (Vol. 14, No. 2, pp. 179-186).

Lefebvre, P., Merrigan, P. and Verstraete, M., 2009. Dynamic labour supply effects of childcare subsidies: Evidence from a Canadian natural experiment on low-fee universal child care. Labour Economics, 16(5), pp.490-502.

Lemieux, T., Milligan, K., Schirle, T. and Skuterud, M., 2020. Initial impacts of the COVID-19 pandemic on the Canadian labour market. Canadian Public Policy, 46(S1), pp.S55–S65.

Montenovo, L., Jiang, X., Lozano-Rojas, F., Schmutte, I., Simon, K., Weinberg, B.A. and Wing, C., 2022. Determinants of disparities in early COVID-19 job losses. Demography, 59(3), pp.827-855.

Oaxaca, R., 1973. Male-female wage differentials in urban labor markets. International Economic Review, 14(3), pp.693-709.

Oaxaca, R.L. and Ransom, M.R., 1994. On discrimination and the decomposition of wage differentials. Journal of Econometrics, 61(1), pp.5-21.

Prentice, S. and White, L.A., 2019. Childcare deserts and distributional disadvantages: the legacies of split childcare policies and programmes in Canada. Journal of International and Comparative Social Policy, 35(1), pp.59-74.

Public Health Agency of Canada COVID-19 Surveillance and Epidemiology Team, 2020. A retrospective analysis of the start of the COVID-19 epidemic in Canada. Canada Communicable Disease Report, 46(7/8), pp.236-241.

Statistics Canada. 2022. COVID-19 in Canada: A Two-year Update on Social and Economic Impacts. Available at: https://www150.statcan.gc.ca/n1/pub/11-631-x/11-631-x2022001-eng.htm [Accessed 15 Jul. 2024].

Statistics Canada, 2023. Women in the labour market: Increased potential for pay and participation. StatCan Plus. Available at: https://www.statcan.gc.ca/o1/en/plus/4823-women-labour-market-increased-potential-pay-and-participation [Accessed 31 August 2024].

Schirle, T., 2015. The effect of universal child benefits on labour supply. Canadian Journal of Economics/Revue canadienne d'économique, 48(2), pp.437-463.

Waldfogel, J., 1998. Understanding the ‘family gap’in pay for women with children. Journal of economic Perspectives, 12(1), pp.137-156.

Zamarro, G. and Prados, M.J., 2021. Gender differences in couples’ division of childcare, work and mental health during COVID-19. Review of Economics of the Household, 19(1), pp.11-40.