The Impact of the COVID-19 Pandemic on Employment: Analysis on Different Occupations with Automation and Telework Feasibility

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Table of contents

1. Introduction **1**

2. Literature review **2**

2.1 The elimination of routine jobs during recessions 2

2.2 Recessions as an opportunity to innovate production methods 3

2.3 COVID-19 and incentives for automation 4

2.4 The prevalence of telework 5

2.5 The feasibility of telework across occupations 6

2.6 Covid-19 and telework 7

3. Data **7**

3.1 Labour Force Survey 7

3.2 National Occupational Classification 8

3.3 Matching NOC codes 9

3.4 Automation and telework potential index 9

4. Stylized labour market facts associated with COVID-19 .... **10**

4.1 Employment and unemployment rate 10

4.2 COVID-19 and uncertainty 10

4.3 Automation and telework quartile. 11

5. Methodology **12**

6. Results **14**

6.1 Results for automation 14

6.1.1 Automation: no control variables 14

6.1.2 Automation: controlling demographic 15

6.1.3 Automation: controlling region 16

6.1.4 Automation: controlling industry of the main job 16

6.1.5 Automation: all controls 17

6.2 Results for telework 18

6.2.1 Telework: no control variables 19

6.2.2 Telework: controlling demographic 19

6.2.3 Telework: controlling region 20

6.2.4 Telework: controlling industry of the main job 21

6.2.5 Telework: all controls 22

7. Discussion **23**

8. Conclusion **24**
References.. **26**
Appendix.. **28**

Abstract

This paper uses Labour Force Survey (LFS) data to assess the impact of COVID-19 across occupations depending on their potential for automation and telework. The COVID-19 pandemic resulted in a drastic decrease in the employment rate, the number of hours worked and a surge in the unemployment rate and the absences from work. However, the impact differs substantially across occupations. The findings show that it is not the occupations with the highest automation feasibility that suffers the most significant decrease in employment probability, but rather those with slightly lower automation feasibility. The higher telework feasibility occupations saw a smaller decrease in employment probability than the occupations with low telework feasibility.

1. Introduction

The COVID-19 pandemic has been causing devastating damage to the global and Canadian economy. The pandemic lead to a record high unemployment rate and put an emergency brake on economic activities. Lemieux, Milligan, Schirle and Skuterud (2020) found 6.73 million applications for Canada Emergency Response Benefits that supported workers directly affected by COVID-19; the number of applications represented about one-third of the workforce.

Historical trends show that jobs with higher routine task intensity tend to be eliminated or automated by technologies during recessions through replacement of workers by machines, robots, and computers (Hershbein and Kahn, 2018). The automation process may be accelerated to reduce the spread of COVID-19, encouraging the transition from worker-worker interaction to worker-machine interaction (Blit, 2020). Another way of reducing the spread of COVID-19 is to work from home (i.e. through the adoption of telework). However, not all jobs can be done from home. While occupations such as farming and construction cannot be done from home, occupations like finance and educators can be teleworked (Dingel and Neiman, 2020).

This paper uses Labour Force Survey (LFS) data to observe the impact of COVID-19 on different occupations conditional on their automation and telework potential, controlling for demographic characteristics, industries, and provinces. I analyze if the historical trend of routine jobs being automated during recessions has occurred and if the telework feasibility gave an edge of being employed during COVID-19.

I find that the occupations with the highest automation feasibility do not experience the most significant employment probability decrease. Rather, it is the occupations with slightly lower automation feasibility that saw the most significant decline in employment probability. Telework feasibility findings show that the higher telework feasibility occupations experience a smaller employment probability decrease during COVID-19.

The paper is structured as follows. Section 2 presents a literature review. Section 3 discusses the LFS data and indexes for automation and telework feasibility. Section 4 presents stylized labor market facts related to the impact of COVID-19. In Section 5, I present the methodology. Section 6 reveals the results, and Section 7 provides a discussion on the findings. Finally, Section 8 concludes the paper.

2. Literature review

2.1 The elimination of routine jobs during recessions

Occupations with a higher routine task intensity suffer significantly more loss in employment during recessions than occupations that are less routine task intensive (Hershbein and Kahn, 2018). The activities labelled as "routine tasks" are because their core tasks follow a precise procedure and can be fully codified and thus automatable (Autor, 2015).

According to Cortes, Jaimovich, Nekarda, and Siu (2014), employment in routine jobs decline significantly during recessions and fail to recover during the expansion periods. This holds for recessions of 1980/82, 1991 and 2001, and the Great Recession during 2008-09. The loss in routine jobs failing to recover signifies the permanent replacement and automation of these occupations. The elimination of routine jobs is not a gradual phenomenon; it is an episodic occurrence during recessions. Jaimovich and Siu (2018) look through the past recessions and finds per capita employment in routine jobs fell 3.5% for the 1991 recession and another 1.8% during the jobless recovery. There is a minor rebound, but the employment level does not change until the 2001 recession. During the 2001 recession, it lost another 6.2% of its employment. Routine jobs suffer another decline during the Great Recession of 11.3% with no recovery.

The historical trend suggests the elimination of routine jobs has been occurring with each past recession. These eliminated routine jobs are replaced and automated with machines, computers, and other technologies. Graetz and Michaels (2018) found automation with robots an attractive option since robots' prices have been decreasing. Ignoring the quality change, the price of robots from 1990 to 2005 based on six countries (U.S., France, Germany, Italy, Sweden, and the U.K.) have decreased by half; the quality-adjusted robot prices approximately fell by 80%. Since there is no risk for these technologies to catch and spread COVID-19, it poses as an alternative for human labour during the pandemic.

2.2 Recessions as an opportunity to innovate production methods

Recessions are often described as a "crisis," "downturn," or "slump," and it may seem like nothing positive can be derived from them. However, recessions could provide a silver lining and an incentive for firms to increase their efficiency by automating the tasks through machines and computers; this modernization of the production method is possible because of lower opportunity costs during recessions (Blit, 2020).[1] When the business cycle is going through growth and peak, there are higher opportunity costs. These high opportunity costs inhibit changes, such as technological upgrading, reorganizing, and training. (Hall, 1991; Saint-Paul, 1993; Aghion and Saint-Paul, 1998). These changes will take time and result in a temporary decrease in output, but during recessions, the opportunity cost of decreasing production is lower due to layoffs and a

[1] When the business cycle is going through growth and peak, a firm's best interest is to produce utilizing all their resources—diverting their resources to make changes such as adopting new technology will decrease their earnings as they would be producing less than they can. There is no need to utilize all their resources for production when there is less demand during recessions. This allows for the capacity to make changes to how they produce.

decrease in aggregate demand (Hershbien and Kahn, 2018; Blit, 2020). Hence, the lower opportunity costs during recessions are a chance to transition to automation so the firm can have higher productivity once the recession ends.

The historical trend shows that firms tend to increase automation during recessions. The Great Recession accelerated information and communications technology, adopting emerging robotics and artificial intelligence technology (Blit, 2020). Supporting this idea, Hershbien and Kahn (2018) investigate routine-biased technological change, how machine technologies substitute labour for middle-skill jobs and complement high-skill cognitive jobs. They research on firms' change in production method and the type of workers they hired after the Great Recession. There is a strong positive correlation between capital stock (firm's overall holdings of property, plant, and equipment, including IT investments) and increased hiring standards. Demonstrating that during the recession, the firms substitute middle-skill jobs with machines and look to hire higher-skilled employees so the newly acquired technology complement their tasks. This finding is more prominent in the areas that suffered more significant employment shocks in the Great Recession, showing the relationship between recessions and automation.

2.3 COVID-19 and incentives for automation

The emergence of COVID-19 caused a global pandemic leading to a worldwide recession. This recession provides even more incentive for automation due to health risks and virus transmission. The COVID-19 pandemic changed how people perceive human-to-human interaction. Coombs (2020) states that there was a greater preference for a human element in interactions before the pandemic; however, with COVID-19, consumers prefer automated experience to protect their health and wellbeing as human contacts became risky.

The supplier's side also shows a preference for automation as firms do not want to risk transmission of COVID-19 in the workplace. For firms to protect workers and mitigate risks for their productivity, they would replace worker-worker interactions with worker-machine interactions (Blit, 2020). Both consumers and firms can benefit from automation due to health concerns. As a result, these factors could cause an accelerated technological transformation and automation.

2.4 The prevalence of telework

Working from home or telework has become a widely chosen option for jobs that can be performed at home due to COVID-19. The concept of telework is not entirely new as the share of people who telework has been increasing long before the pandemic. Employees who primarily telework have grown from 0.75% in 1980 to 2.4% in 2010; this may not seem like much, but it has tripled over 30 years (Mateyka, Rapino, and Landivar, 2012).

Dingel and Neiman (2020) find that 37% of jobs in the U.S. can be teleworked, and these jobs tend to pay more, assuming the same number of hours of work; the 37% of the jobs that can be teleworked account for 46% of all U.S. wages. Similarly, four in ten (38.9%) Canadian workers are in jobs that can plausibly be teleworked (Deng, Morissette, and Messacar, 2020).

The share of jobs that can be teleworked varies across different counties. Fewer than 25% of jobs in Mexico and Turkey can be performed at home, while Sweden and U.K. have over 40%. Developing countries with per capita GDP levels below one-third of the U.S. may have half as many jobs that can be teleworked (Dingel and Nieman, 2020). Bloom, Lian, Roberts, and Yang (2015) support this as they found 50% of managers in the U.S., and U.K. and Germany are allowed telework, while in developing countries, it is in the 10 to 20% range.

2.5 The feasibility of telework across occupations

Depending on the job and the worker, telework may not be feasible. Mongey, Pilossoph and Weinberg (2020) find that people who cannot telework tend to be lower-income, lack a college degree, rent a dwelling, be non-white, and lack employer-provided health insurance. Dingel and Neiman (2020) also observes a significant variation across occupations. Occupations such as managers, educators, and those working in computers, finance, and law are more able to work from home, while occupations such as farming, construction, and production cannot.

The pandemic has transferred many jobs from the office setting to home, but some may question if productivity will suffer as a result of telework. Bloom, Liang, Roberts, and Ying (2015) look at China's largest travel agency at the time, Ctrip, to see if telework is ideal for the call centre agents and the firm. Ctrip divided the workers into those who teleworked and those who stayed in the office. Overall, the group that teleworked outperformed the group that worked in the office. Those who teleworked handled 3.3% more phone calls per minute, worked 9.2% more minutes per day. The office workers' usual turnover rate is around 50% a year, but it is only 17% for the telework group. This has been a beneficial experiment for the firm as they gained about $230 per employee per year from an increase in productivity and saved about $1400 on capital cost per employee from lower office rental and IT costs. This research has limitations as it only observes call centre agents whose jobs can easily be done at home, does not require teamwork, and work results are easily quantified. Having said that the idea and the results are still important as it is a good illustration that telework can be a viable option and should be encouraged during the pandemic.

2.6 Covid-19 and telework

Telework is an effective way to keep the workers' health protected while maintaining productivity during the pandemic. Fadinger and Schymik (2020) develop a simple epidemiological model to see how much telework will reduce the infection rate. They found that a one percentage point increase in telework is associated with a 1/3 percentage point drop in the contact rate. This may seem like a slight decrease in contact rate, but it leads to significant quantitative effects on the infection rate. Finally, they also find a strong negative correlation between telework and the infection rate.

Savage and Turcotte (2020) analyze how COVID-19 changes the mode of transportation used by commuters and how it relates to telework. A comparison is made between the mode of transportation prior to the COVID-19 pandemic and the mode of transportation in June 2020 for those who had a job before the pandemic and are still working at the time of the survey. Private vehicle usage decreased from 74.5% to 67.5%, public transit decreased from 12.7% to 3.1%, and most importantly, telework increased from 4.1% to 21.6%. Through teleworking, workers eliminate direct worker-worker interaction to reduce the virus's spread while carrying on their tasks to keep the society functioning.

3. Data

3.1 Labour Force Survey

I use the Canadian LFS data collected by Statistics Canada from January 2000 to December 2020. LFS data are collected nationwide and monthly on labour market activities of Canada's working-age population (15 years of age and over). Containing various information on Canada's labour market indicators such employment, unemployment, labour force participation rate, employment by industry, occupations, hours worked and much more (Statistics Canada, 2020).

3.2 National Occupational Classification

The LFS relies on National Occupational Classification for Statistics (NOC-S) and National Occupational Classification (NOC) code system to classify different occupations. The NOC codes are published by Employment and Social Development Canada and Statistics Canada. They provide a systematic classification structure that categorizes the entire range of occupations in Canada and are arranged in a four-tiered hierarchical structure, where each category and group are designated with a unique set of codes with different number of digits. The description of occupation groups gets more detailed as the number of digits increases. More specifically, the hierarchy of the NOC codes is structured as follows: the most general category of 10 broad occupational categories (one-digit), 40 major groups (two-digit), 140 minor groups (three-digit) and most detailed 500-unit groups (four-digit). I use the 40 major groups, or two-digit NOC codes for my research as more narrowly defined groups are not available through the public use files.

The NOC codes have gone through changes over the years. My data contains NOC-S 2001, NOC-S 2006, and NOC 2011. NOC-S 2001 is used for the year 2000 data, NOC-S 2006 is used from 2001 to 2016, and NOC 2011 is used from 2017 to 2020. The change from NOC-S 2001 to NOC-S 2006 is minor, and this change is not relevant to the major group (two-digit code) that I used. However, from NOC-S 2006 to NOC 2011, a significant change occurs to the major group (two-digit code) as NOC-S 2006 that has 47 major groups are harmonized to the NOC 2011 structure of 40 major groups.

3.3 Matching NOC codes

I create a major group variable that is consistent over the entire sample period, but due to changes in the major group being reduced from 47 to 40 in 2016, several major groups are overlapped. While certain groups have a clear one-to-one match, some do not. This led to identifying which occupations are overlapped then dropping occupations that have lower employment share. This presents inconsistency in employment data which is addressed at the end of this sub-section.

Instead of 40 major groups, I had to proceed with 39 major groups since *Clerical Occupations* of NOC-S 2006 is only suitable for *Office Support Occupations and Distribution* and *Tracking and Scheduling Coordination Occupations* of NOC 2011 and nothing else. To avoid the double counting of the same occupation, *Office Support Occupations and Distribution* is selected since it has a higher employment share and dropped *Tracking and Scheduling Coordination Occupations.*

The dataset is missing certain parts of 2016's data, such as data on the NOC code. Also, dropping certain occupations during the matching process presents inconsistency in employment over the years. To avoid this issue, I only use data from January 2017 to December 2020 if the inconsistency of employment and requiring the missing information from 2016 would be an issue.

3.4 Automation and telework potential index

Each major group occupation is matched with the corresponding automation and telework potential indexes. The indexes range from 0 to 1; an index of 1 indicates that automation or telework for that occupation is fully feasible, and 0 indicates that automation or telework for that occupation is not feasible. Blit created the automation potential index (2020), and the telework potential index was obtained from Statistics Canada.

4. Stylized labour market facts associated with COVID-19

4.1 Employment and unemployment rate

Like for the rest of the world, COVID-19 brought a severely negative impact on the Canadian economy. Throughout the sample period, January 2000 to December 2020, the year-to-year change in the employment rate is lowest in 2020, more than twice as low as the 2008-09 recession (see figure 1). Correspondingly, the year-to-year change in the unemployment rate graph shows the inverse to that of the employment rate, with a record increase in 2020 (see figure 2). The figures show the undoubtable damage that COVID-19 caused to the labour force.

4.2 COVID-19 and uncertainty

Unlike the previous recessions, COVID-19 presents a high level of uncertainty for the future. Correia, Luck, and Verner (2020) state that during a pandemic, businesses reduce investment in response to labour shortages, lower demand, and increased uncertainty. Their research is based on the 1918 Flu Pandemic, so certain aspects may differ from the current pandemic, but the increase in uncertainty is relevant. Leduc and Liu (2020) also note that investment incentives may be partially offset by lower aggregated demand resulting from elevated uncertainty, although their quantitative general equilibrium analysis finds that job uncertainty can still stimulate automation.

The uncertainty of the increase or decrease of COVID-19 cases and frequently changing mandates on lockdowns made businesses hold on to the employees even with less work for them due to a decrease in aggregate demand. To see this, I look at the year-to-year change in the *employed but absent from work* group, and in 2020 it is at its highest compared to the past 20 years (see figure 3). To support this, I look at the *actual hours worked per week at the main job*, this only applies to those who are employed at the time, so I could see how the hours worked changed during COVID-19. The year-to-year change in the *actual hours worked per week at the main job* dropped drastically during 2020 (see figure 4). These figures show the workers may be employed but not working or working reduced hours due to COVID-19.

4.3 Automation and telework quartile.

I divide the major group into quartiles based on the automation and telework index percentile: the first quartile is the 25th percentile, the second quartile is between 26th percentile and 50th percentile, the third quartile is between 51st percentile and 75th percentile, the fourth quartile is 76th percentile. The first quartile is composed of the occupations with the lowest automation or telework indexes, and the fourth quartile is composed of the occupations with the highest automation or telework indexes. Setting February 2020 as the reference month and year (since COVID-19 started to impact Canada in March 2020), I observe the change in employment levels of the automation and telework quartiles (see figures 5 and 6). Since the pandemic caused this recession, the same is done excluding healthcare workers (see figures 7 and 8).

The expected result for the automation quartiles is that the higher automation quartile occupations would suffer more employment loss as the firms could replace workers and automate the occupation. However, the fourth automation suffers less of a decline than other automation quartiles. This does not follow the historical trend of what happens to occupations that can be automated during recessions. However, the recession being caused by the pandemic is also not in line with the historical trend, so the result could be different than expected. The result is similar when healthcare workers are excluded.

Opposite to the automation quartiles, I have expected that the lower telework quartile occupations would suffer more employment loss than those in the higher telework quartile as they would be more likely to telework during the pandemic. Corresponding to the expected results, the occupations in the fourth telework quartile saw less employment loss than the lower telework quartiles.

5. Methodology

The goal is to investigate if the occupation's automation or telework feasibility would worsen or mitigate the negative impact of COVID-19 on employment. I use the following linear probability model:

$$employed_{it} = a_0 + a_1 COVID_t + automation_{it} a_2 + COVID_t \cdot automation_{it} a_3 + X_{it} a_4 + \varphi_t + \varepsilon_{it} \quad (1)$$

$$employed_{it} = \beta_0 + \beta_1 COVID_t + telework_{it} \beta_2 + COVID_t \cdot telework_{it} \beta_3 + X_{it} \beta_4 + \psi_t + \eta_{it} \quad (2)$$

The dependent variable, $employed_{it}$, is a dummy variable taking the value of one if individual *i* is employed in period *t*, and zero otherwise. $COVID_t$ is a dummy variable that takes on the value of one if the individual is observed in the COVID-19 period, i.e., March 2020 onwards. *Automation* and *telework* are vectors of indicator variables for the automation and telework quartiles, respectively. More precisely, the *automation* vector consists of three dummy variables: a dummy variable that equals one if the person's job is in the second quartile of the automation index, and two other dummies for whether the individual's job is in the third and fourth quartile of the automation index, respectively. *Telework* is similarly defined but for the telework index.

X_{it} is a vector of controls for gender, education, age, province of residence, census metropolitan area (CMA), and industry. The control variables are categorical variables that are composed as dummy variables for each category. Gender takes the value of one if the worker is female and zero if male; education, includes six dummy variables;[2] age, includes twelve dummy variables;[3] province, includes ten dummy variables;[4] CMA, includes ten dummy variables;[5] industry of the main job, includes 21 dummy variables.[6] Finally, φ and ψ represent month fixed effects.

With regards to the automation equation, i.e., equation (1), α_1 and α_3 are the parameters of interest. α_1 and α_3 measure how COVID-19 affects the probability of being employed. More specifically, α_3 allows for the effect to vary depending on the level of automation of the occupation. Since the first quartile is the reference group, it measures the additional effect of being in a higher quartile of the automation index - on top of the effect of the first quartile (which is measured by α_1).[7] Similarly, β_1 and β_3 are the parameters of interest for the telework equation.

[2] Education is composed of six categories, 0 to 8 years, some high school, high school graduate, some postsecondary, postsecondary certificate or diploma, bachelor's degree, and above bachelor's degree. Omitted 0 to 8 years of education.

[3] Age is composed of twelve categories, 15 to 19 years, 20 to 24 years, 25 to 29 years, 30 to 34 years, 35 to 39 years, 40 to 44 years, 45 to 49 years, 50 to 54 years, 55 to 59 years, 60 to 64 years, 65 to 69 years, and 70 and over. Omitted 70 and over.

[4] Province is composed of 10 categories, Newfoundland and Labrador, Prince Edward Island, Nova Scotia, New Brunswick, Quebec, Ontario, Manitoba, Saskatchewan, Alberta, and British Columbia. Omitted Newfoundland and Labrador.

[5] CMA is composed of 10 categories, Other CMA or non-CMA, Quebec, Montreal, Ottawa, Toronto, Hamilton, Winnipeg, Calgary, Edmonton, and Vancouver. Omitted Edmonton.

[6] Industry of main job is composed of 21 categories, agriculture, forestry and logging and support activities for forestry, fishing, hunting and trapping, mining, quarrying, and oil and gas extraction, utilities, construction, manufacturing - durable goods, manufacturing - non-durable goods, wholesale trade, retail trade, transportation and warehousing, finance and insurance, real estate and rental and leasing, professional, scientific and technical services, business, building and other support services, educational services, health care and social assistance, information, culture and recreation, accommodation and food services, other services (except public administration), and public administration. Omitted fishing, hunting, and trapping.

[7] For example, if $\alpha_1 < 0$ and all entries of α are also negative, it would mean that COVID-19 had a negative impact for all types of jobs, but the effect was greater for jobs that have a higher level of automation.

6. Results

I first present the results for the automation equation i.e., equation (1) and then show the results for the telework equation i.e., equation (2). In all cases I estimate the regression with and without healthcare workers to see if there is a difference since the goal is observing employment probability during the COVID-19 pandemic.

6.1 Results for automation

The automation quartiles' coefficients before COVID-19 are positive and statistically significant at the 1% level regardless of the healthcare workers' exclusion. The coefficients do not differ too much from each quartile. During COVID-19, the coefficients are statistically significant at the 1% level. These hold except when controlling for either the industry of the main job or all control variables. All estimates are done with month-fixed effects.

6.1.1 Automation: no control variables

Table 1 presents the results from estimating equation (1) without control variables. Estimating the sample with healthcare workers during COVID-19, the employment probability for the second automation quartile, relative to the first automation quartile, decrease by 1.8 percentage points, leading to the employment probability decrease of 5.05%. The third automation quartile's employment probability decrease by 4.35 percentage points relative to the first automation quartile, amounting to a 7.6% employment probability decrease. The fourth automation quartile's employment probability decrease by 1 percentage point relative to the first automation quartile, leading to a 4.25% employment probability decrease.

The sample without healthcare workers during COVID-19; the employment probability for the second, third and fourth automation quartile occupations decrease by 2.2, 4.8, and 1 percentage points relative to the first automation quartile. Leading to 5.4%, 8%, and 4.2% employment probability decrease for the second, third, and fourth automation quartiles.

The important finding is that the third automation quartile has the most significant decrease in employment probability, whether the sample included or excluded the healthcare workers.

6.1.2 Automation: controlling demographic

Table 2 presents the results from estimating equation (1) with demographic control variables: gender, education, and age. Estimating the sample with healthcare workers during COVID-19, employment probability for the second automation quartile, relative to the first automation quartile, decreased by 1.6 percentage points. Amounting to an employment probability decrease of 1%. The third automation quartile's employment probability decreased by 4.25 percentage points compared to the first automation quartile, which leads to a decrease of 3.6% in employment probability. The fourth automation quartile's employment probability decrease by 1.25 percentage points relative to the first automation quartile. This amounts to a 0.56% decrease in employment probability for the fourth automation quartile.

The sample without healthcare workers during COVID-19; the employment probability for the second, third and fourth automation quartile decreased by 1.7, 4.8, and 1.3 percentage points relative to the first automation quartile. This amounts to a 1%, 4%, and 0.6% decrease in employment probability for the second, third, and fourth automation quartiles.

The important finding is that the third automation quartile has the most significant decrease in employment probability when controlling for demographic variables. This result is consistent whether the sample included or excluded the healthcare workers.

6.1.3 Automation: controlling region

Table 3 presents the results from estimating equation (1) with region control variables: province and CMA. Estimating the sample with healthcare workers during COVID-19, the second automation quartile, relative to the first automation quartile, decreased 1.8 percentage points or a 5.6% decrease in employment probability. The third automation quartile's employment probability decreased by 4.2 percentage points relative to the first automation quartile, leading to an 8% decrease in employment probability. The fourth automation quartile's employment probability decreased by 0.9 percentage points relative to the first automation quartile, amounting to a 4.4% decrease in employment probability.

The sample without healthcare workers during COVID-19; employment probability for the second, third and fourth automation quartile decreased by 2.2, 4.6, and 0.9 percentage points relative to the first automation quartile. Amounting to 5.5%, 8.15%, and 4.5% employment probability decrease for the second, third, and fourth automation quartiles.

Controlling for the region shows that occupations in the third automation quartile has the greatest decrease in the employment probability. This is consistent for the sample excluding the healthcare workers.

6.1.4 Automation: controlling industry of the main job

Table 4 presents the results from estimating equation (1), controlling for the industry of the main job. During COVID-19, including healthcare workers, employment probability for the second automation quartile, relative to the first automation quartile, increased by 0.8 percentage points, leading to an employment probability increase of 0.6%. The third automation quartile's employment probability decreased by 0.85 percentage points relative to the first automation quartile. This leads to a 1% decrease in employment probability for the third automation quartile. The fourth automation quartile's employment probability increased by 0.3 percentage points relative to the first automation quartile, leading to a 0.1% increase in employment probability. It should be noted that the fourth automation quartile is not statistically significant. Only the third automation quartile shows a decrease in employment probability.

The sample without healthcare workers during COVID-19, employment probability for the second and fourth automation quartile increased by 0.14 and 0.18 percentage points, but these quartiles are not statistically significant. The third automation quartile, statistically significant at the 1% level, shows employment probability decreases by 1 percentage point relative to the first automation quartile, leading to a 1.2% decrease in employment probability.

Controlling for the industry of the main job shows only the third automation quartile has a decrease in employment probability. This result is consistent when the healthcare workers are excluded.

6.1.5 Automation: all controls

Table 5 presents the results from estimating equation (1), including all control variables: gender, education, age, province, CMA, and industry of the main job. Estimating the sample with healthcare workers during COVID-19, employment probability for the second automation quartile, relative to the first automation quartile, increased by 0.77 percentage points, leading to an increase in employment probability by 1.37%. The third automation quartile's employment probability decreased by 0.75 percentage points relative to the first automation quartile, amounting to a 0.15% decrease in employment probability. The fourth automation quartile's employment probability increase by 0.47 percentage points relative to the first automation quartile, leading to a 1% increase in employment probability. It should be noted that while the second and third automation quartiles are statistically significant at the 1% level, the fourth automation quartile is statistically significant at the 5% level.

The sample without healthcare workers during COVID-19, employment probability for the second and fourth automation quartile increased by 0.34 and 0.39 percentage points, but the second quartile is not statistically significant, and the fourth automation quartile is statistically significant at the 10% level. The third automation quartile, statistically significant at the 1% level, shows employment probability decreases by 0.94 percentage points relative to the first automation quartile, leading to a 0.36% decrease in employment probability.

The result of applying all control variables is consistent with the trend of previous results with different control variables, and that is the third automation quartile experienced the greatest decrease in employment probability. The result is consistent when the healthcare workers are excluded. It is not the occupations with the highest automation feasibility that shows the greatest decrease in employment probability, but the occupations that is one quartile below.

6.2 Results for telework

The telework quartiles' coefficients before COVID-19 are positive and statistically significant at the 1% level regardless of the exclusion of healthcare workers and different control variables. During COVID-19, the coefficients are statistically significant at the 1% level with different control variables regardless of healthcare worker's exclusion. This holds except when controlling for either the industry of the main job or all control variables. All estimates are done with month-fixed effects.

6.2.1 Telework: no control variables

Table 6 presents the results of estimating equation (2) with no control variables. Estimating the sample with healthcare workers during COVID-19, employment probability for the second telework quartile, relative to the first telework quartile, decreased by 6.7 percentage points, showing a 9% decrease in employment probability. The third telework quartile's employment probability decreased by 4.6 percentage points relative to the first telework quartile, amounting to a 7% decrease in employment probability. The fourth telework quartile shows 1.8 percentage points decrease relative to the first telework quartile, leading to a 4.16% decrease in employment probability.

The sample without healthcare workers during COVID-19; the employment probability for the second, third and fourth telework quartile occupations decreased by 9, 2.9, and 1.7 percentage points relative to the first automation quartile. Leading to an 11.5%, 5.4%, and 4.15% employment probability decrease for the second, third, and fourth telework quartiles.

When there are no control variables, the higher telework quartile occupations shows a smaller decrease in employment probability. As the second telework quartile suffers the greatest decline in the employment probability, and the fourth telework quartile suffers the least. This is consistent with the sample excluding healthcare workers.

6.2.2 Telework: controlling demographic

Table 7 presents the results of estimating equation (2) with demographic control variables: gender, education, and age. Estimating the sample with healthcare workers during COVID-19, employment probability for the second telework quartile occupations decreased by 6.7 percentage points, leading to a 6.4% decrease in employment probability. The third telework quartile's employment probability decreased by 5.6 percentage points relative to the first telework quartile amounting to a 5.2% decrease in employment probability. The fourth telework quartile shows a 3.1 percentage points decrease relative to the first telework quartile, showing a 2.8% decrease in employment probability.

The sample without healthcare workers during COVID-19; the employment probability for the second, third and fourth telework quartile occupations decreased by 8.8, 3.7, and 2.7 percentage points relative to the first automation quartile. Leading to an 8.4%, 3.3%, and 2.3% employment probability decrease for the second, third, and fourth telework quartiles.

Controlling for demographic variables, the more telework feasible the occupation is, the less decline in employment probability it experiences. This is consistent with the sample excluding healthcare workers.

6.2.3 Telework: controlling region

Table 8 presents the results of estimating equation (2) with region control variables: provinces and CMAs. Estimating the sample with healthcare workers during COVID-19, employment probability in the second telework quartile decreased by 6.6 percentage points relative to the first telework quartile. This leads to a 10% decrease in employment probability for the second telework quartile. The third telework quartile, relative to the first telework quartile, decreased by 4.8 percentage points. Amounting to 8.15% employment probability decrease to the third telework quartile. The fourth telework quartile's employment probability decreases by 1.6 percentage points relative to the first telework quartile. The fourth telework quartile's employment probability decreases by 4.7%.

The sample without healthcare workers during COVID-19; employment probability for the second, third and fourth telework quartile occupations decreased by 9, 2.7, and 1.5 percentage points relative to the first telework quartile. Leading to a 12.15%, 5.86%, and 4.7% employment probability decrease for the second, third, and fourth telework quartiles.

Controlling for regional factors presented that more telework feasible the occupation, the less decline in the employment probability. This is consistent with the sample excluding healthcare workers.

6.2.4 Telework: controlling industry of the main job

Table 9 presents the results of estimating equation (2) controlling for the industry of the main job. Estimating the sample with healthcare workers during COVID-19, the second and third telework quartiles are statistically significant at the 1% level and saw a 1.8 and 1.1 percentage points decrease relative to the first telework quartile, which amounts to a 2% and 1.35% decrease in employment probability. The fourth telework quartile is statistically significant at the 5% level and saw 0.5 percentage points increase in the employment probability relative to the first telework quartile, showing the fourth telework quartile a 0.27% increase in employment probability.

The sample without healthcare workers during COVID-19, the second telework quartile is statistically significant at the 1% level and saw a 4.2 percentage points decrease in employment probability relative to the first telework quartile. Leading to a 4.4% decrease in employment probability. The third telework quartile is not statistically significant and shows 0.05 percentage points decrease relative to the first telework quartile. The fourth telework quartile is statistically significant at the 1% level and had an increase of 0.6 percentage points in the employment probability relative to the first telework quartile, hence experiences a 0.85% increase in employment probability.

Controlling for the industry of the main job shows if the occupation is more telework feasible, there would be a smaller decrease in employment probability. The fourth telework quartile always has the smallest decrease in the employment probability with previous control variables as well. When controlled for the industry of the main job, it shows a positive correlation between telework and employment. This result is consistent with the sample excluding healthcare workers.

6.2.5 Telework: all controls

Table 10 presents the results of estimating equation (2), including all control variables: gender, education, age, province, CMA, and industry of the main job. Estimating the sample with healthcare workers during COVID-19, the second and third telework quartiles' coefficients are statistically significant at the 1% level; each quartile's employment probability decreased by 1.8 and 1.1 percentage points relative to the first telework quartile, which amounts to a 1.2% and 0.5% decrease in employment probability. The fourth telework shows a 0.3 percentage points increase in employment probability relative to the first telework quartile, amounting to a 0.93% increase in employment probability. It should be noted fourth telework quartile is not statistically significant.

The sample without healthcare workers during COVID-19; employment probability for the second telework quartile decreased by 3.8 percentage points relative to the first telework quartile leading to a 3.1% decrease in employment probability. The third and fourth telework quartile occupations decreased by 0.06 and 0.6 percentage points relative to the first telework quartile.

Leading to a 0.68% and 1.24% employment probability increase. It should be noted that the third telework quartile is not statistically significant and the second and fourth telework quartile are statistically significant at the 1% level.

Overall, the higher telework quartile occupations experience a smaller decrease in employment probability during COVID-19 and show a positive correlation to employment. This result is consistent when healthcare workers are excluded.

7. Discussion

My results pointed to a different direction than what the literature suggested for the occupations with high automation feasibility. It is suggested the routine jobs are automated during recessions, and due to the pandemic nature of the current recession, this effect will be accelerated. This trend is not accurately reflected in my results. My findings for the automation quartiles consistently show that the third automation quartile experiences the greatest decrease in employment probability during COVID-19.

The third automation quartile occupations could explain this inconsistency as it includes 4 out of 6 sales and service occupations from the broad occupational categories, and these occupations are mainly retail jobs. Due to COVID-19, many non-essential retail stores faced storefront closures due to government mandates. While their e-commerce sales are at an all-time high, in-store sales have been decreasing significantly, thus impacting the employees in the sales and service occupations (Aston, Vipond, Virgin, and Youssouf, 2020).[8]

[8] The in-store retail trade saw a 34.5% decline in sales, while E-commerce saw a 94.8 increase. In-store furniture and home furnishing stores saw a 69.6% decline in sales, while E-commerce saw a 191.2% increase. Sporting goods, hobby, book, and music stores saw a 79% decline, while E-commerce saw a 154.9% increase. Clothing and clothing accessories stores saw an 84.2% decline, while E-commerce saw an 83.3% increase.

Frenette and Frank (2020) suggest that automation may not occur immediately even if the technology is available. The price of automation has been declining, as previously mentioned by Graetz and Michaels (2018), but not all firms, especially small businesses, may not have enough resources to invest in automation. There are also legal restrictions to consider, particularly with government-regulated industries, such as public transportation or healthcare. Legal issues with bureaucracy would significantly slow down the transition. Even when the firm acquires the technology, it would require skilled human labour to operate, which may not always be the case.

As for the results of telework quartiles, it is aligned with the literature. The occupations with higher telework feasibility suffered a smaller decrease in employment probability than those with lower telework feasibility.

8. Conclusion

In this paper, I analyze how the COVID-19 pandemic affects the employment of different occupations depending on its automation and telework feasibility. My results show that just because an occupation has high automation feasibility, it does not mean that it will suffer the most significant employment loss during COVID-19. I find a couple of explanations as to why this is the case for my results. I use the automation feasibility as the main determinant of employment probability, but it is also important to consider more detailed occupation characteristics. Such as how non-essential retail workers are being affected by government mandates. Another explanation is that even if COVID-19 is to accelerate automation, it may not be feasible if the firms do not have enough resources to invest in automation. It would be interesting to re-approach this issue in the future to see if the recession caused by the COVID-19 pandemic followed the historical trend of automating routine jobs. The results on telework show that if the occupation has high feasibility of telework, it will suffer a smaller decrease in employment probability. The occupations that could be done remotely from home offer an advantage to be employed when the worker-worker interaction needed to be avoided.

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Appendix

Table 1. Automation: no control variables

	(1) employed (including healthcare workers)	(2) employed (excluding healthcare workers)
COVID	-0.0325***	-0.0320***
	(0.00108)	(0.00107)
2nd automation quartile	0.503***	0.459***
	(0.000855)	(0.000867)
3rd automation quartile	0.509***	0.491***
	(0.000617)	(0.000632)
4th automation quartile	0.503***	0.480***
	(0.000776)	(0.000773)
2nd automation quartile*COVID	-0.0180***	-0.0224***
	(0.00232)	(0.00235)
3rd automation quartile*COVID	-0.0435***	-0.0481***
	(0.00168)	(0.00176)
4th automation quartile*COVID	-0.0101***	-0.0106***
	(0.00206)	(0.00206)
Controls	No	No
Month fixed effects	Yes	Yes
Constant	0.385***	0.408***
	(0.000961)	(0.000973)
Observations	4,736,795	4,736,795
R^2	0.260	0.231

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2. Automation: controlling demographic

	(1) employed (including healthcare workers)	(2) employed (excluding healthcare workers)
COVID	0.00689***	0.00768***
	(0.00236)	(0.00239)
2nd automation quartile	0.372***	0.341***
	(0.000908)	(0.000906)
3rd automation quartile	0.363***	0.347***
	(0.000670)	(0.000680)
4th automation quartile	0.337***	0.317***
	(0.000828)	(0.000817)
2nd automation quartile*COVID	-0.0160***	-0.0172***
	(0.00242)	(0.00243)
3rd automation quartile*COVID	-0.0425***	-0.0484***
	(0.00180)	(0.00186)
4th automation quartile*COVID	-0.0125***	-0.0134***
	(0.00217)	(0.00215)
Gender Control	Yes	Yes
Education Controls	Yes	Yes
Age Controls	Yes	Yes
Month fixed effects	Yes	Yes
Constant	-0.0151***	-0.0225***
	(0.00120)	(0.00121)
Observations	4,736,795	4,736,795
R^2	0.442	0.429

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Automation: controlling region

	(1) employed (including healthcare workers)	(2) employed (excluding healthcare workers)
COVID	-0.0383***	-0.0352***
	(0.00495)	(0.00504)
2nd automation quartile	0.502***	0.458***
	(0.000858)	(0.000868)
3rd automation quartile	0.507***	0.489***
	(0.000626)	(0.000644)
4th automation quartile	0.502***	0.479***
	(0.000783)	(0.000780)
2nd automation quartile*COVID	-0.0177***	-0.0222***
	(0.00233)	(0.00235)
3rd automation quartile*COVID	-0.0418***	-0.0463***
	(0.00170)	(0.00178)
4th automation quartile*COVID	-0.00888***	-0.00945***
	(0.00207)	(0.00207)
Province Controls	Yes	Yes
CMA Controls	Yes	Yes
Month fixed effects	Yes	Yes
Constant	0.333***	0.352***
	(0.00214)	(0.00218)
Observation	4,736,795	4,736,795
R^2	0.262	0.233

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Automation: controlling industry of the main job

	(1) employed (including healthcare workers)	(2) employed (excluding healthcare workers)
COVID	-0.00214***	-0.00214***
	(0.000125)	(0.000125)
2nd automation quartile	0.00343***	-0.0125***
	(0.000862)	(0.000890)
3rd automation quartile	0.0147***	0.0182***
	(0.000651)	(0.000682)
4th automation quartile	-0.0131***	-0.0152***
	(0.000820)	(0.000819)
2nd automation quartile*COVID	0.00801***	0.00135
	(0.00251)	(0.00258)
3rd automation quartile*COVID	-0.00846***	-0.0105***
	(0.00194)	(0.00204)
4th automation quartile*COVID	0.00300	0.00178
	(0.00236)	(0.00235)
Industry Controls	Yes	Yes
Month fixed effects	Yes	Yes
Constant	-0.00720***	-0.00715***
	(0.000518)	(0.000518)
Observations	4,736,795	4,736,795
R^2	0.720	0.720

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Automation: all controls

	(1) employed (including healthcare workers)	(2) employed (excluding healthcare workers)
COVID	0.00597	0.00584
	(0.00375)	(0.00375)
2nd automation quartile	0.0117***	-0.000428
	(0.000850)	(0.000877)
3rd automation quartile	0.0142***	0.0171***
	(0.000639)	(0.000670)
4th automation quartile	-0.00799***	-0.00951***
	(0.000800)	(0.000800)
2nd automation quartile*COVID	0.00772***	0.00344
	(0.00247)	(0.00254)
3rd automation quartile*COVID	-0.00747***	-0.00944***
	(0.00191)	(0.00200)
4th automation quartile*COVID	0.00477**	0.00387*
	(0.00230)	(0.00230)
Gender Controls	Yes	Yes
Education Controls	Yes	Yes
Age Controls	Yes	Yes
Province Controls	Yes	Yes
CMA Controls	Yes	Yes
Industry Controls	Yes	Yes
Month fixed effects	Yes	Yes
Constant	-0.0553***	-0.0554***
	(0.00143)	(0.00143)
Observations	4,736,795	4,736,795
R^2	0.730	0.730

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Telework: no control variables

	(1) employed (including healthcare workers)	(2) employed (excluding healthcare workers)
COVID	-0.0237***	-0.0246***
	(0.00109)	(0.00109)
2nd telework quartile	0.577***	0.518***
	(0.000720)	(0.000722)
3rd telework quartile	0.597***	0.558***
	(0.000651)	(0.000697)
4th telework quartile	0.620***	0.575***
	(0.000655)	(0.000654)
2nd telework quartile*COVID	-0.0670***	-0.0908***
	(0.00203)	(0.00207)
3rd telework quartile*COVID	-0.0498***	-0.0293***
	(0.00178)	(0.00188)
4th telework quartile*COVID	-0.0179***	-0.0169***
	(0.00172)	(0.00172)
Month fixed effects	Yes	Yes
Constant	0.297***	0.343***
	(0.000894)	(0.000925)
Observations	4,736,795	4,736,795
R^2	0.366	0.309

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7. Telework: controlling demographic

	(1) employed (including healthcare workers)	(2) employed (excluding healthcare workers)
COVID	0.00322	0.00360
	(0.00235)	(0.00242)
2nd telework quartile	0.454***	0.417***
	(0.000784)	(0.000767)
3rd telework quartile	0.449***	0.397***
	(0.000750)	(0.000783)
4th telework quartile	0.471***	0.420***
	(0.000812)	(0.000800)
2nd telework quartile*COVID	-0.0677***	-0.0880***
	(0.00216)	(0.00218)
3rd telework quartile*COVID	-0.0562***	-0.0369***
	(0.00201)	(0.00207)
4th telework quartile*COVID	-0.0308***	-0.0268***
	(0.00210)	(0.00207)
Gender Controls	Yes	Yes
Education Controls	Yes	Yes
Age Controls	Yes	Yes
Month fixed effects	Yes	Yes
Constant	0.0236***	0.0253***
	(0.00115)	(0.00119)
Observations	4,736,795	4,736,795
R^2	0.493	0.467

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8. Telework: controlling region

	(1) employed (including healthcare workers)	(2) employed (excluding healthcare workers)
COVID	-0.0337***	-0.0317***
	(0.00463)	(0.00480)
2nd automation quartile	0.576***	0.517***
	(0.000720)	(0.000724)
3rd automation quartile	0.598***	0.559***
	(0.000662)	(0.000713)
4th automation quartile	0.622***	0.576***
	(0.000669)	(0.000671)
2nd automation quartile*COVID	-0.0665***	-0.0898***
	(0.00203)	(0.00207)
3rd automation quartile*COVID	-0.0478***	-0.0269***
	(0.00180)	(0.00191)
4th automation quartile*COVID	-0.0163***	-0.0152***
	(0.00175)	(0.00175)
Province Controls	Yes	Yes
CMA Controls	Yes	Yes
Month fixed effects	Yes	Yes
Constant	0.233***	0.273***
	(0.00195)	(0.00204)
Observations	4,736,795	4,736,795
R^2	0.367	0.310

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9. Telework: controlling industry of the main job

	(1) employed (including healthcare workers)	(2) employed (excluding healthcare workers)
COVID	-0.00212***	-0.00206***
	(0.000124)	(0.000126)
2nd telework quartile	0.0385***	0.0119***
	(0.000803)	(0.000825)
3rd telework quartile	0.0475***	0.0324***
	(0.000812)	(0.000788)
4th telework quartile	0.0566***	0.0406***
	(0.000816)	(0.000753)
2nd telework quartile*COVID	-0.0179***	-0.0421***
	(0.00235)	(0.00245)
3rd telework quartile*COVID	-0.0114***	-0.000515
	(0.00237)	(0.00229)
4th telework quartile*COVID	0.00491**	0.00645***
	(0.00237)	(0.00218)
Industry Controls	Yes	Yes
Month fixed effects	Yes	Yes
Constant	-0.00731***	-0.00722***
	(0.000517)	(0.000518)
Observations	4,736,795	4,736,795
R^2	0.721	0.721

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10. Telework: all controls

	(1) employed (including healthcare workers)	(2) employed (excluding healthcare workers)
COVID	0.00629*	0.00623*
	(0.00375)	(0.00375)
2nd telework quartile	0.0410***	0.0241***
	(0.000789)	(0.000810)
3rd telework quartile	0.0382***	0.0252***
	(0.000800)	(0.000775)
4th telework quartile	0.0437***	0.0308***
	(0.000815)	(0.000752)
2nd telework quartile*COVID	-0.0182***	-0.0376***
	(0.00231)	(0.00240)
3rd telework quartile*COVID	-0.0112***	0.000641
	(0.00234)	(0.00225)
4th telework quartile*COVID	0.00298	0.00617***
	(0.00237)	(0.00218)
Gender Controls	Yes	Yes
Education Controls	Yes	Yes
Age Controls	Yes	Yes
Province Controls	Yes	Yes
CMA Controls	Yes	Yes
Industry Controls	Yes	Yes
Month fixed effects	Yes	Yes
Constant	-0.0535***	-0.0537***
	(0.00143)	(0.00143)
Observations	4,736,795	4,736,795
R^2	0.730	0.730

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

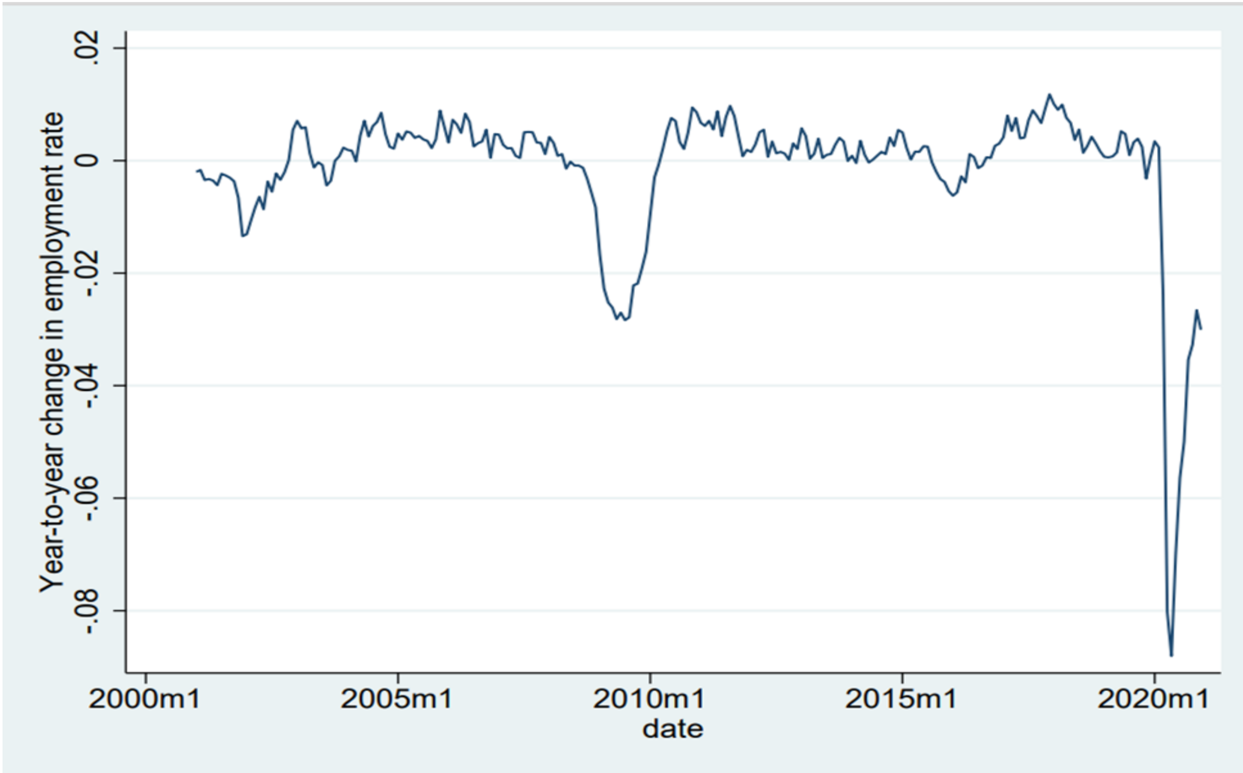

Figure 1. Year-to-year change in employment rate from 2000 to 2020.

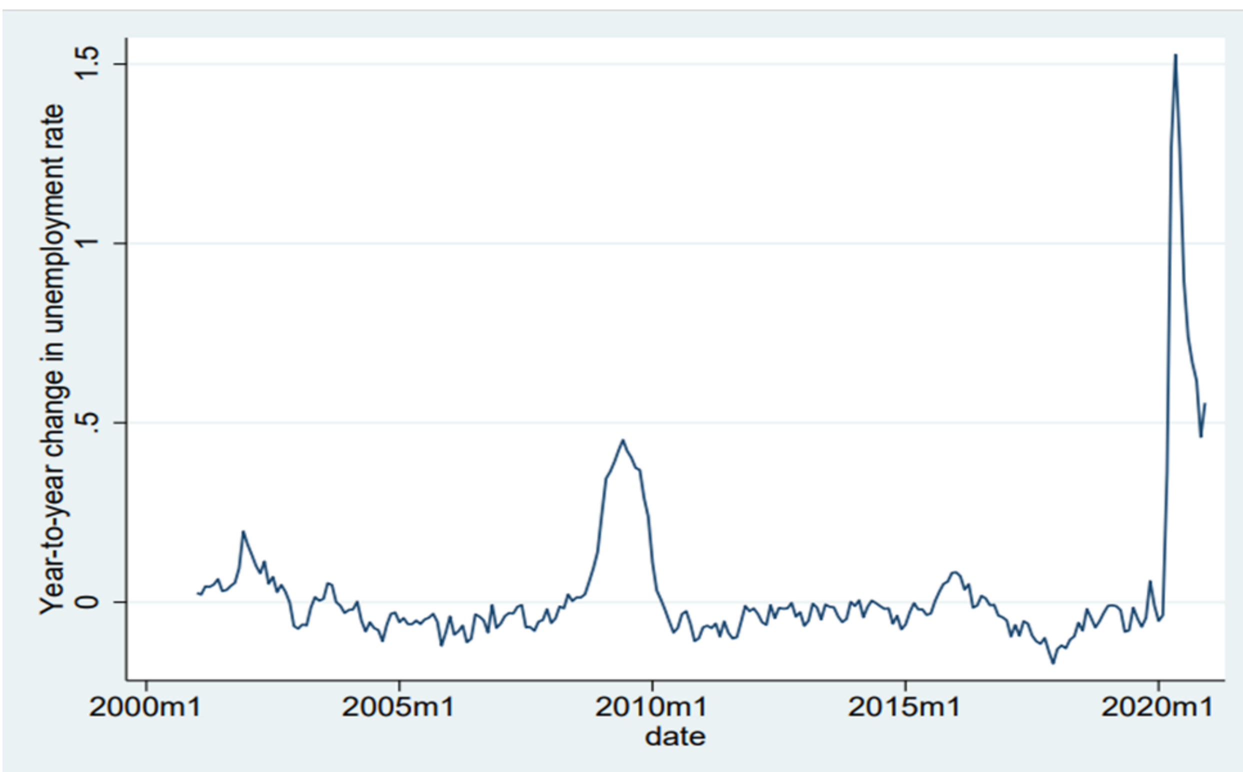

Figure 2. Year-to-year change in unemployment rate from 2000 to 2020.

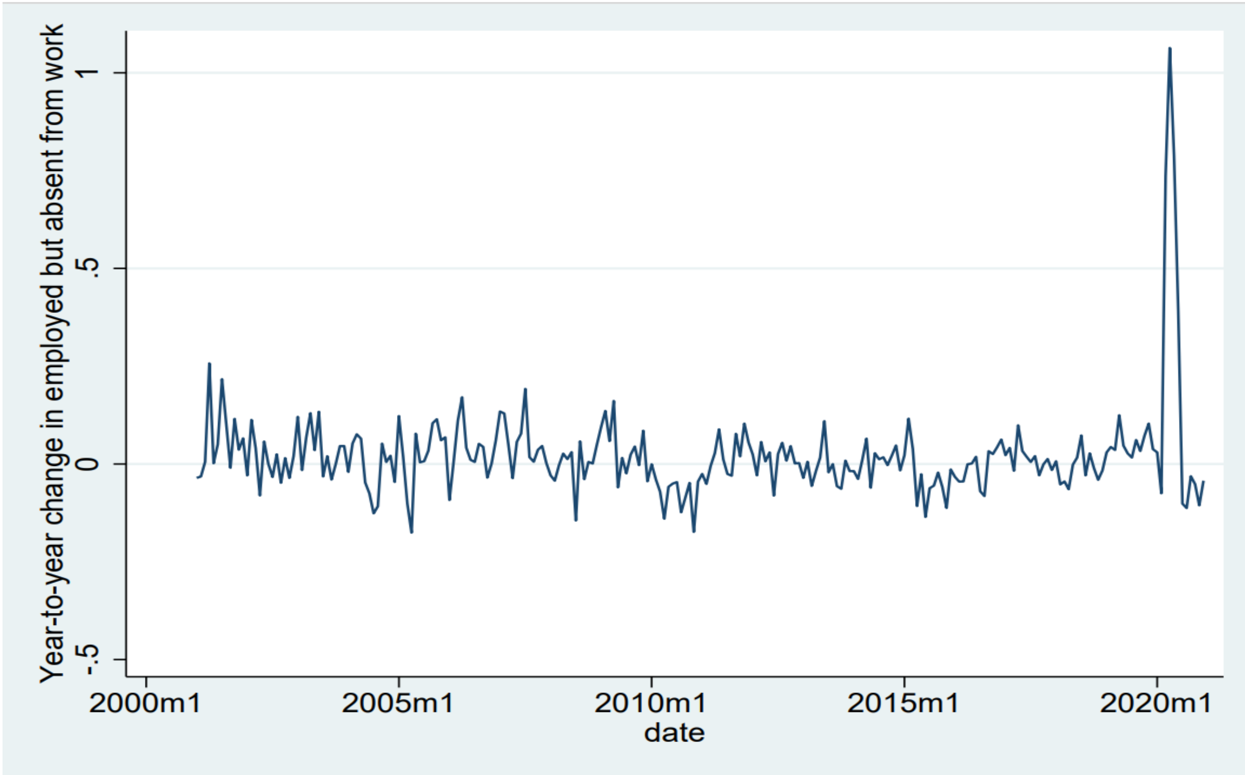

Figure 3. The year-to-year change in employed but absent from work from 2000 to 2020.

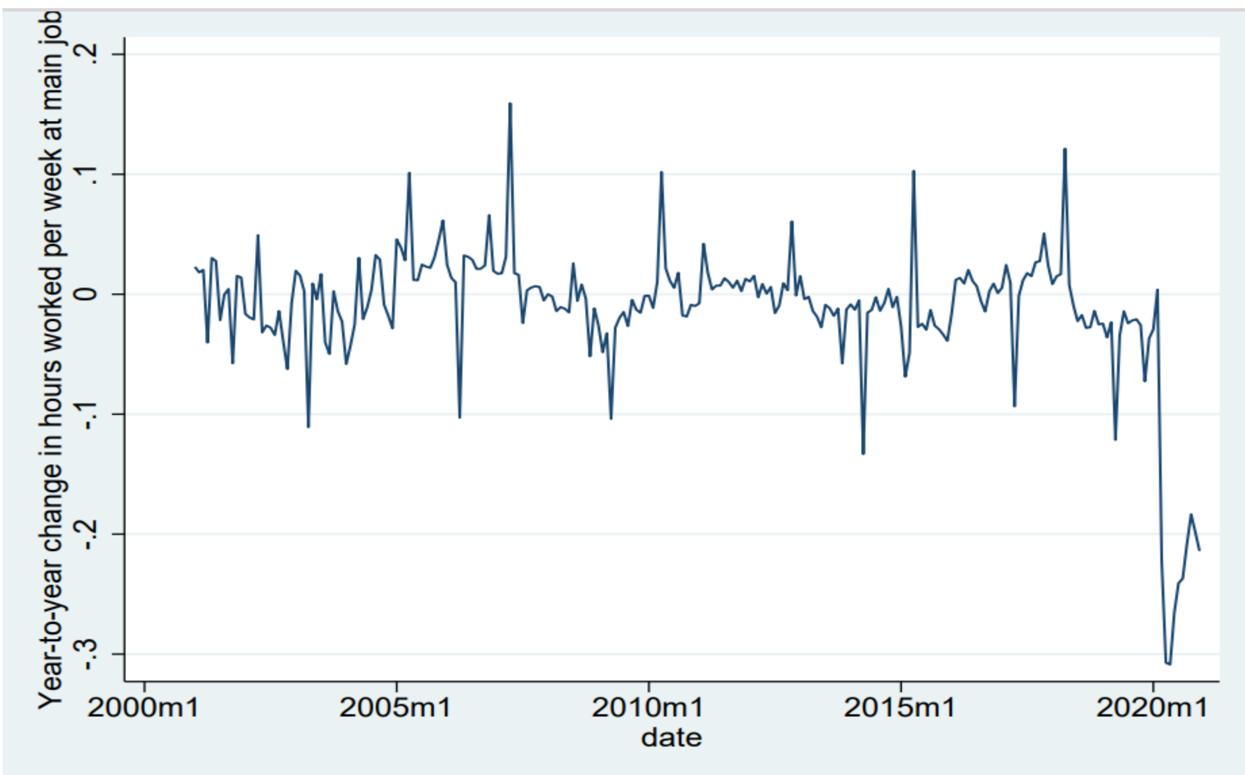

Figure 4. The year-to-year change in the actual hours worked per week at main job from 2000 to 2020.

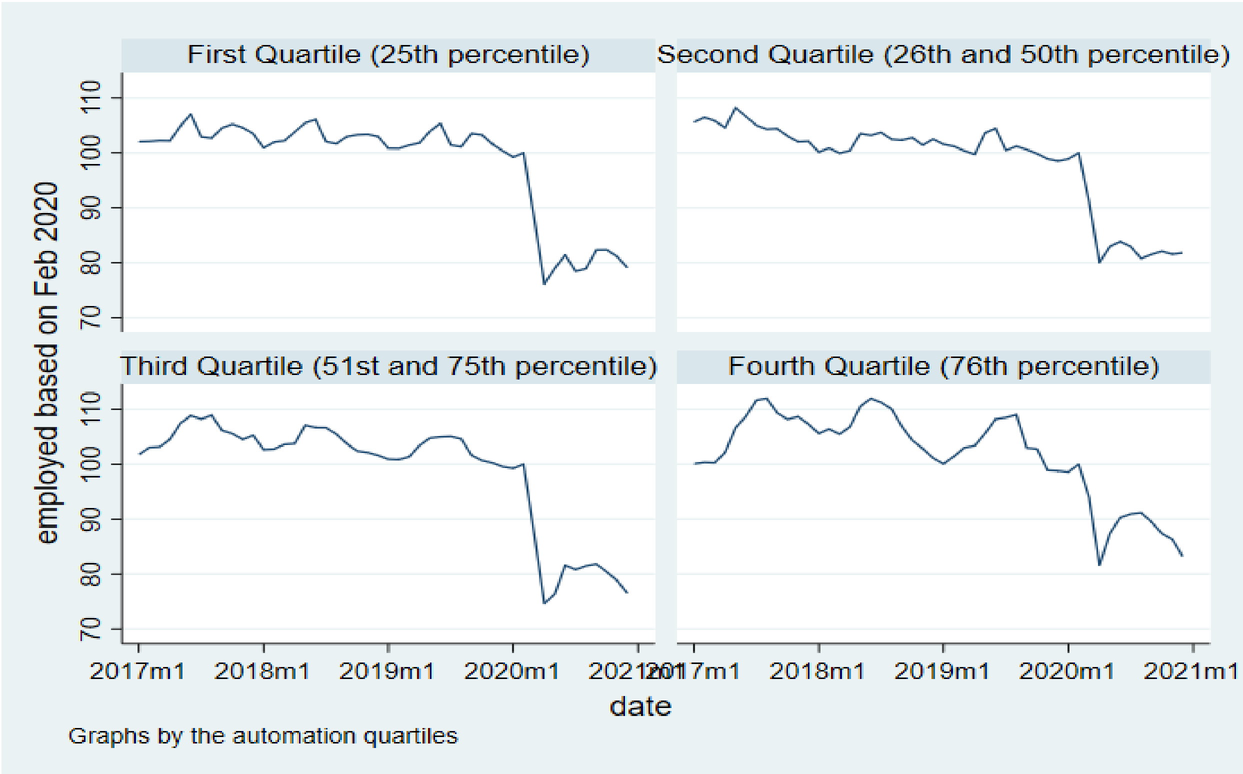

Figure 5. Employment based on the automation quartiles.

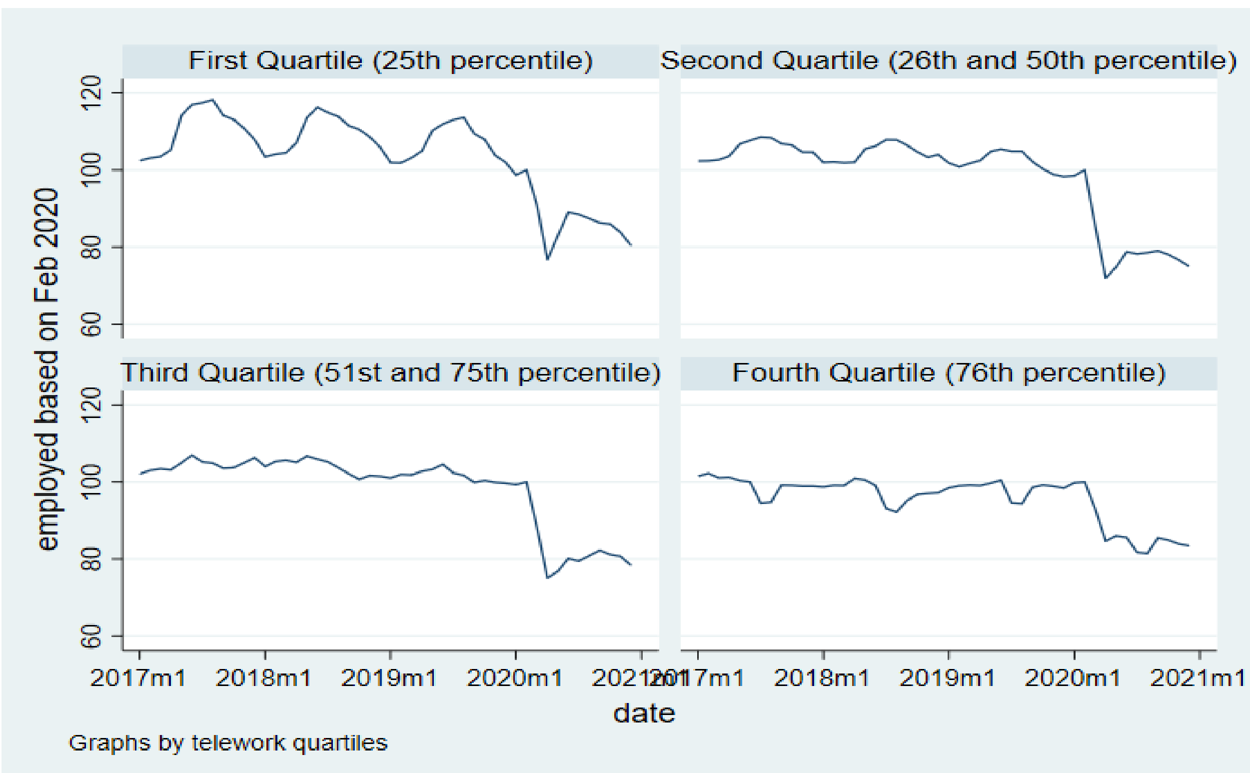

Figure 6. Employment based on the telework quartiles.

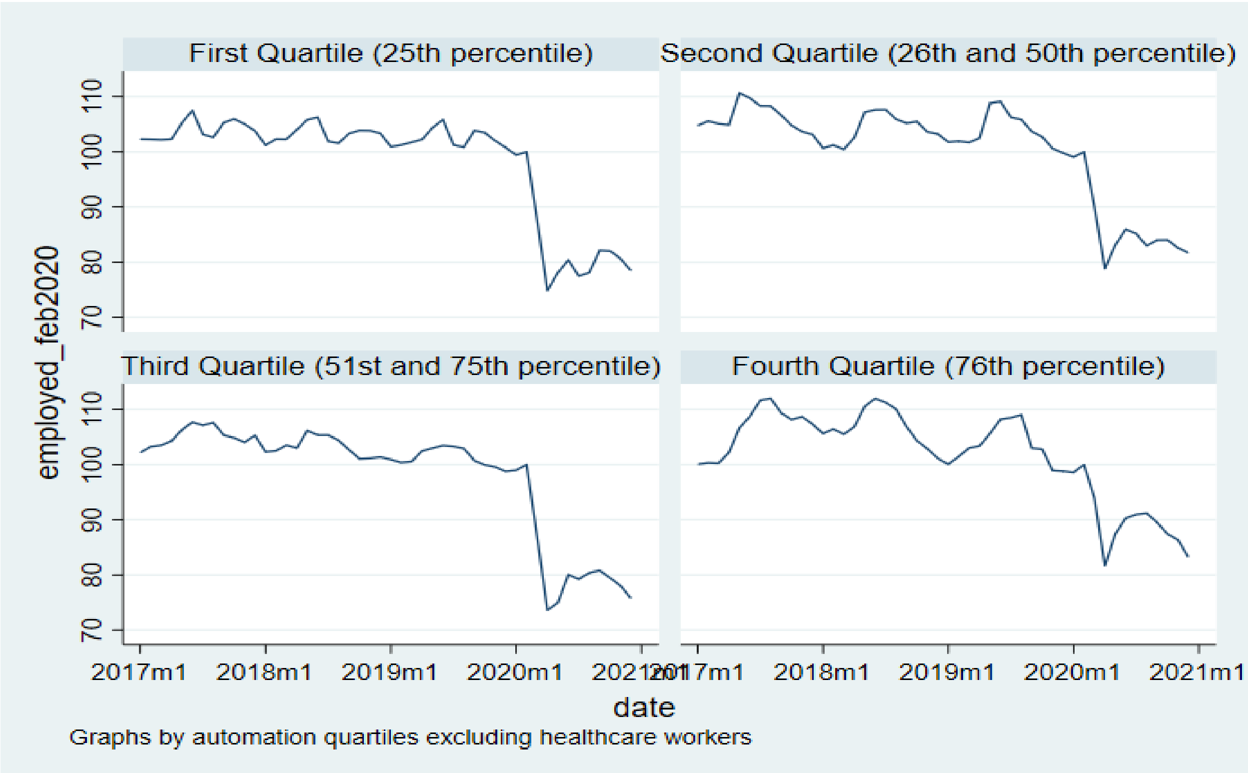

Figure 7. Employment based on the automation quartiles, excluding healthcare workers.

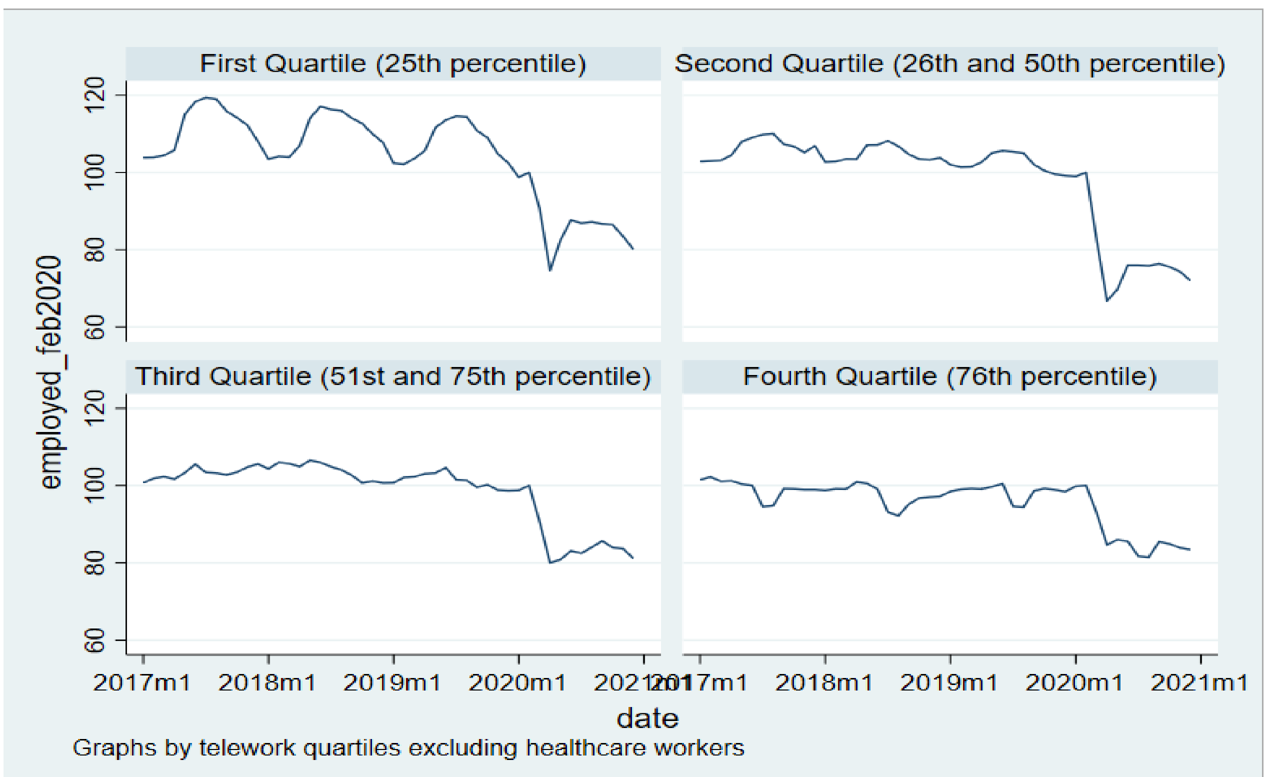

Figure 8. Employment based on the telework quartiles, excluding healthcare workers.