Effects of COVID-19 on the Dutch labour market

An aggregate, sectorial, and individual analysis

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Louvain la Neuve, 30 May 2022

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Academic year 2021-2022

In order to obtain the double degree:

Master of Science in Economics

(Maastricht University, School of Business and Economics)

and

Master 120 en Sciences économiques, Orientation générale, Finalité spécialisée

(UCLouvain, Economics School of Louvain)

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Acknowledgements

First of all, I would like to thank my first thesis supervisor, Bart Golsteyn, and my internship supervisor, Jessie Bakens, for all the valuable knowledge, insights, and advice provided throughout my thesis process. Second, I would also like to acknowledge Jean Hindriks, my second thesis supervisor, for his constructive thoughts on the project. Third, I want to thank the Research Centre for Education and the Labour Market (ROA) for providing me the internship conducted for this project, as well as access to the data alongside Statistics Netherlands. Finally, I want to thank my family for supporting me throughout my whole academic journey.

Abstract

This thesis analyses the effect of COVID-19 on the Dutch labour market through a general analysis, a sector analysis, and an individual analysis. To investigate this, I observed the employment and full time equivalent (FTE) working hour trend throughout 2015-2021, alongside examining the sectors that lost most employment and investigating the characteristics that make individuals switch sectors. My results show that there was a decrease in employment and FTE during the first quarter of 2020 and the last quarter of 2021, highlighting that accounting for the trend and persistence of employment and FTE are essential to correctly estimate the effect. Sectors which require social contact lost most employment during the pandemic. Lastly, individuals most likely to switch from an affected sector to a different one and find new employment were older, female, native-born, working less hours, with a higher wage, with a temporary contract, and with a higher education. These results provide insight for policy makers to target social policies to individuals likely to switch to facilitate and encourage the change, as well as assisting those who are less likely to switch. Additionally, information is provided on what sectors lost most formal employment and the time periods to create greater targeted aid.

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1 Introduction

The first case of COVID-19 in the Netherlands was diagnosed on the 27th of February 2020 (Governement of the Netherlands, 2020). Since then, the Dutch government has had to impose restrictions regarding social distancing, as well as confinement. The measures taken place to limit the infections of the disease have slowed down economic activity, if not completely stopped it for some sectors such as restaurants and hotels, or art and entertainment. In the second quarter of 2020, there was a contraction of 8.4% in the Dutch economy compared to the quarter before (Centraal Bureau voor de Statistiek, 2021). Many workers have reduced their working hours or lost their job. For instance, in the Netherlands in May 2020 there was an 18% decrease in the hours worked per worker (Institute of Labor Economics, 2021). Given these large employment shocks both in the extensive and intensive margin, it is essential to investigate more deeply the effects of the COVID-19 shock on the labour market as well as on the people affected.

The aim of this thesis is to investigate the effects of COVID-19 on the labour market at a general level, at the sector level, and at an individual level. I first want to provide a general overview of the effect of COVID-19, highlighting after the heterogenous impact in different sectors, and lastly understanding the heterogenous impact of the labour shock among individuals within a sector focusing on their resilience. To start, I analyse the employment trend and the trend in the number of hours worked (Full Time Equivalent (FTE)) from 2015 until 2021. I determine whether there is a trend break after COVID-19 and quantify the effect on employment and hours worked for each post-pandemic quarter. I take into account that the shock may have persistent effects. Due to the heterogeneous effect of COVID-19 across sectors, as a following step I concentrate on the sector effect of COVID-19, assessing which sectors were the most affected based on employment loss. To end, I narrow down the analysis to an individual level, as the shock of COVID-19 might also be heterogenous among the population. In particular, I want to analyse the job profiles of workers and their individual characteristics to assess which individuals are more prone to switching sectors after COVID-19. If an individual is recently unemployed and looking for employment, they can choose to search in the same sector or in more than one sector. Being able to search for a job in different sectors increases the probabilities of finding employment and indicates the resilience of the individual.

The data used for this analysis are from the Statistics Netherlands (CBS). The dataset for this thesis is constructed from several datasets, mainly SPOLISBUS which provides information on the job and wages of Dutch employees according to the tax registrations, GBA which represents the municipality population register, and HOOGSTEOPLTAB which provides information on the highest obtained education level of individuals. The data are resister data from the Dutch population. Such complete and unique data provides many advantages such as investigating detailed sections of the economy or individuals, which is necessary for this analysis.

The empirical strategy is divided into three sections according to the aggregate, sectorial, or individual analysis. First, I investigate the effect of COVID-19 on aggregate employment and Full Time Equivalents (FTE) through a fixed effects regression. I run the analysis with raw data, then with seasonally adjusted data, followed by adding two lags of the dependent variable into the equation, and taking the first differences as a last step. This is done for both aggregate employment and FTE employment. Second, I focus on what sectors were most hit during the pandemic. I do this by taking the difference in employment from the start of the pandemic (first quarter 2020) and one year later as a short-term measure, and two years later as a medium-term measure, showing a list of the sectors most affected. As a third and final step, I further analyse the characteristics of the workers in hotels, restaurants, and cafés or catering (from now on referred as horeca), as it was one of the most affected sectors in the economy. I compare individuals that stayed in horeca to those who changed sector in a one-year period and in a two-year period, exploring their job and personal characteristics. I then expand this exploration to the complete sample considering if workers remained in the same sector or switched to another sector within the same time frames.

The main findings are the following. First, it is necessary to seasonally adjust the data because the seasonal component of the time series will otherwise under or overestimate the effect of the pandemic depending on the quarter of the year it is in. Second, once the data are seasonally adjusted, it is very important to add a time trend as the employment has a positive trend. If not accounted for, the effect of the pandemic will be underestimated. Moreover, given that employment trends may be persistent it is necessary to add yearly lags to the regression, two in my case. Furthermore, for stationary reasons I investigate whether the time series has a unit root, which means that the coefficients of the sum of the lags of the dependent variable equals 1. In my analysis, I cannot reject this hypothesis, so it is necessary to take first differences. The graphical analysis and the regressions show that the most impacted periods after COVID-19 are the second quarter of 2020 and the fourth quarter of 2021. The former is attributed to the start of COVID-19 as the effects of the first lockdown in March were only seen in April (quarter two 2020). The latter refers to another strict lockdown in the Netherlands due to the Omicron variant at the end of the year (Governement of the Netherlands, 2021). The graphical and regression analyses show that employment decreases for these two periods, whilst for the rest there is an increasing trend with a similar slope to pre-COVID-19. Hence, COVID-19 caused a decrease in employment during the second quarter of 2020, and in the last quarter of 2021. Similar findings occur when using FTE. Once controlled for the persistence in the employment and the yearly trend, coefficients decrease signalling that the employment effect may not be as large as what can be first perceived in the descriptive analysis.

For the second part of the analysis the three most affected sectors were food and beverage locations, job placement agencies and personnel management, and lodgement in the short run. In a two-year period, the sectors most affected are retail sector (not cars), food and beverage locations, and job placement agencies and personnel management. For the third part of the analysis, in the horeca sector individuals more likely to switch were older, female, native-born, working less hours, with a higher wage, with a temporary contract, and with a higher education. For the complete sample, the individuals that were more prone to switching were younger, male, native-born, working less hours, with a lower wage, a temporary contract, and highly educated. These results show that individuals most affected in the horeca sector, had to search for employment elsewhere and some did so in a different sector that may be more secure. For instance, women are less likely to switch, as suggested by the analysis on the complete population, but were forced to search for employment elsewhere if they were employed in the horeca sector at the start of the pandemic.

Even though COVID-19 is relatively recent, this crisis has gained much interest in the academic literature. Béland, Brodeur, and Wright (2020) investigate the effects of COVID-19 on the US labour market, showing that the pandemic has decreased the hours of work, increased unemployment, and decreased labour force participation. Data presented by the Institute of Labor Economics (2021) demonstrate that in May 2020, the Netherlands witnessed a higher decrease in actual hours worked, with -18%, compared to the modest decrease in employment of -2.2%. From March to May 2020, there was a drop in employment of more than 200 thousand people (Institute of Labor Economics, 2021). The Dutch government has implemented the “Temporary Emergency Bridging Measure for Sustained Employment”, from now on called NOW. The NOW provides firms subsidies for the wages of employees who are not working during a period of time due to COVID-19 related situations (Netherlands Enterprise Agency, 2022). Employment losses have been contained given the government subsidies mitigating the negative shock, although actual hours worked have decreased significantly in the periods of lower economic activity (European Comission, 2021)..

Eurostat (2021) finds a large decrease of hours worked for quarter two of 2020, also verified for essential jobs by OECD (2022). The data do not provide information for quarter four of 2021 (Eurostat, 2021). Much of the research about COVID-19 is very recent, therefore not all data is updated. My research will provide a study until 31 December 2021 which is important given that one of the largest employment decreases in my analysis occurred in the last quarter of 2021. In this thesis, I observe the employment and FTE trend from 2015 until 2021 and analyse the effect of COVID-19. More precisely, I analyse what quarters were most affected from 2020 and 2021, their magnitude, as well as the persistence of the pandemic shock effect in the time trend.

For the second part of my analysis, I will look into the most affected sectors which has also been a topic in previous literature. The European Comission (2021) declares that contact intensive services such as trade, transport and accommodation, arts or entertainment were most affected by COVID-19. Sectors intensive in high-skilled employees as well as those with a high possibility for remote working were less affected, for instance ICT, finance, or real estate. The accommodation and food services sector (horeca) is the hardest hit in a short-term assessment period in the European Union (January 2020 until December 2020) (European Comission, 2021). The results from this thesis extend this finding to the Netherlands.

Battistini and Stoevsky (2021) show that in the largest European countries, and in the Netherlands, recreational services presented the largest economic losses among sectors. In line with these results, del Rio-Chanona, Mealy, Pichler, Lafond, and Farmer (2020) focus on the US economy emphasising that the most affected sectors in the short term are entertainment, restaurants, and tourism. As a second analysis in the thesis, I will calculate the employment loss in a one-year period, as well as a two-year period to observe the sectors that were most affected by employment loss in the Dutch economy in the short and medium run.

Regarding the third part of the analysis, some earlier analyses focus on the personal and job characteristics of those individuals that were most affected, nevertheless no earlier studies investigated how characteristics that individuals had before COVID-19 induced them to search employment in a different sector after the start of the pandemic, signalling resilience.

Many studies conclude that the individuals most affected by the labour shock of COVID-19 where women (Fana, Tolan, Torrejón, Brancati, & Fernández-Macías, 2020; Moen, Pedtke, & Flood, 2020), younger individuals (Béland et al., 2020; Fana et al., 2020; Gupta et al., 2020; Moen et al., 2020; OECD, 2022; Zwetsloot et al., 2021), lower educated (Béland et al., 2020; Gupta et al., 2020; OECD, 2022; Pouliakas & Branka, 2020; Zwetsloot et al., 2021)., migrants (OECD, 2022; Pouliakas & Branka, 2020; Zwetsloot et al., 2021), workers earning low wages (Béland et al., 2020; OECD, 2022; Pouliakas & Branka, 2020), and employees with a temporary contract (Institute of Labor Economics, 2021).

Lee, Park, and Shin (2021) provide a prime analysis of the individual characteristics of the population showing which individuals were most vulnerable to the pandemic. They use gender, race and ethnicity, education level, and the worker's industry. They conclude that women, minorities, less educated workers, and young individuals are most vulnerable even after controlling for sector, which I also control for.

Much literature indicates the characteristics of individuals most vulnerable to the employment shock produced by COVID-19. My contribution to the literature is to use these characteristics to investigate which individuals are most prone to switch to another sector and look for employment elsewhere. I will conduct this analysis in the Dutch labour market at short- and medium-term periods.

The thesis structure is as follows. Section 2 presents the data used for the analysis as well as a description of the variables. Section 3 provides the empirical strategy. Section 4 discusses the results of the analyses. Followed by section 5 which provides a conclusion.

2 Data

This section of the thesis describes the data used for the analysis. Subsection 2.1 addresses the dataset description, and subsection 2.2 provides details and descriptives of the main variables used.

2.1 Dataset description

The data used for this research were obtained through Statistics Netherlands (CBS) with the assistance of the Research Centre for Education and the Labour Market (ROA). I constructed a unique dataset in which I combined tax registry data for employees with employee specific characteristics and job specific characteristics.

The original datasets used include the jobs and wages according to tax administration (SPOLISBUS) which contains quantitative and qualitative data on jobs and wages of employees at Dutch companies for a specific reporting year or part of a reporting year (Centraal Bureau voor de Statistiek, 2022b). Employees from the public sector such as health or education are also included. Individuals who do not have a job or are self-employed are not in the dataset. The workers who are under temporary unemployment subsidised by NOW are included in the dataset and appear as employed as long as they are still registered with a valid work contract. The municipal population register (GBA) includes a population register used by the municipalities containing information on personal characteristics such as gender or age, among other variables that will be further discussed in section 2.2. Additionally, the highest achieved/attained level of education (HOOGSTEOPLTAB) will also be used. This dataset provides information on the educational background of the Dutch population (Centraal Bureau voor de Statistiek, 2022a).[1]

The dataset is constructed as a panel data set, where it is possible to follow individuals throughout time. The time frame consists of seven years, from 1 January 2015 until 31 December 2021. It is presented in quarters, meaning there are four time periods per year, 28 time periods in total. Each observation contains the individual's ID, the job characteristics (permanent contract, sector, hours worked, and wage), as well as personal characteristics (gender, age, migrant background, and education). These are the variables that will be used throughout the analysis.

2.2 Variables

This section will put forward the variables used during the analysis, accompanied by their respective descriptive statistics as well as any data cleaning criterion used to compose the dataset.

2.2.1 Job Characteristics

The job characteristics used in this analysis are the employment sector of the individual, type of contract, the hours worked, and the wage. Given that these were used for only 2020 and 2021, the descriptive characteristics will include this period.

The first variable concerns the sector the individual is employed in. I use a two-digit sector code containing 86 different sectors. A list containing the sectors can be found in appendix 7.2. The sectors relevant for the analysis will be brought up in their respective sections in the thesis.

Permanent contract is a dummy variable where a flexible contract is represented by 0 (31%), and a fixed or permanent contract by 1 (69%). Table 1 shows the distribution.

Moreover, the hours the individual worked in that time period at one job are also recorded and used in the analysis. The hours worked denote the number of paid hours minus over time hours. The hours worked refer to one specific job, meaning an individual could have three jobs in one time period but the hours worked would be registered for each different job. The mean hours worked are 318 per quarter, with a standard deviation (SD) of 138. Table 1 presents the distribution. In the aggregate analysis, the hours worked are transformed into Full

[1] The educational background used in the analysis refers to the level of education an individual has on the 1st of October of 2020.

Time Equivalents (FTE) which corresponds to 40 working hours per week (Eurostat). This was done to compare full time and part time positions.

The last variable used as a job characteristic is wage. Wage will appear as hourly wage in the analysis, which was computed with the basic wage excluding special rewards, allowances and overtime wages given to an individual for a time period, divided by the hours worked in that same time period. All the observations with an hourly wage lower than three euros and higher than 500 euros were dropped as this did not seem realistic. The mean hourly wage is 21.83 euros, with a SD of 13.20.

Table 1. Descriptive statistics of job characteristics.

Variable	Classification	Values
Permanent contract	Temporary (0)	1,733,227 (31.41%)
	Permanent (1)	3,784,512 (68.59 %)
	Total	5,517,739
Hours worked	Mean	318.21
	SD	138.39
Hourly wage	Mean	21.83
	SD	13.20

Source: own calculations based on SPOLISBUS, GBA, and HOOGSTEOPLTAB Statistics Netherlands.

2.2.2 Employment

I use the variable employment in different forms throughout the thesis. I will use total employment over all sectors, employment per sector, a dummy variable reflecting whether the individual was employed at the beginning and the end of a given period for the same sector or a different one.

Aggregate employment over all sectors includes all the jobs in the dataset at a given time period. One individual may have several jobs, and these jobs will be counted as separate observations. Employment is reflected as a quantitative variable which varies through time. Aggregate employment per sector represents all the jobs in a given sector during that time period. The total employment is the total observations in the sample, given that the observations account for the individuals employed, which is 5,517,739.

2.2.3 Personal Characteristics

The variables that will be used as personal characteristics are age, gender, education, and migration background. Table 2 shows the descriptive statistics of these variables.

Age was calculated taking the difference between the birth date of the individual and 1 January 2020. Then the number of days were divided by 365.25 so that age is measured in years. The mean age is 39 years old.

The variable female is 0 if male (49.44%), and 1 if female (50.56%).

Education is the highest education completed by the individual. It is a categorical value with three levels. One represents low educated (17.12%), two represents middle educated (43.23%), and three represents highly educated (39.64%). The corresponding levels to the Dutch education system can be found in Appendix 7.2.

The variable migrant presents the migrant background of an individual. The dummy variable represents a zero for native individuals as well as second generation migrants (90.28%), one represents first generation migrants (9.72%).

Table 2. Descriptive statistics of personal characteristics.

Variable	**Classification**	
Age	Mean	38.76
	SD	13.61
Gender	Male (0)	2,727,982 (49.44%)
	Female (1)	2,789,757 (50.56%)
	Total:	5,517,739
Education	Low educated (1)	944,866 (17.12%)
	Middle educated (2)	2,385,400 (43.23%)
	Highly educated (3)	2,187,473 (39.64%)
	Total	5,517,739
Migrant	Native-born (0)	4,981,458 (90.28%)
	Foreign-born (1)	536,281 (9.72%)
	Total	5,517,739

Source: own calculations based on SPOLISBUS, GBA, and HOOGSTEOPLTAB Statistics Netherlands.

3 Empirical Strategy

The purpose of my thesis is to investigate the effects of COVID-19 on employment at an aggregate level, at a sectorial level, and at an individual level. I start with an employment trend analysis, where I investigate graphically and analytically the fluctuations in employment.

Analytically, this is done through a fixed effects model where employment is the dependent variable, and as independent variables I use quarter dummies after the shock and a year trend. Furthermore, I investigate the changes in employment of the sectors at a two-digit level (86 sectors) to observe which sectors lost or gained most employment. The analysis observes the short-term effects within one year, as well as using a medium-term approach of two years after the shock. From the results, I choose a sector that was severely hit by the COVID-19 crisis to proceed with the next section of the study. Choosing the horeca sector, I focus on the individual level of the analysis. I observe what characteristics have an effect on individuals switching sectors in one year, as a short-term approach, and I use a two year-period, as a medium-term approach. I also do this analysis for the full population including all the sectors. It is then possible to observe what personal or job characteristics are most correlated with the likelihood of switching to a different sector for different time frames.

3.1 Employment trend

To start the analysis, I introduce a general overview of the effects COVID-19 had on employment in the Netherlands. The formal analysis uses fixed effects regressions. This technique allows to control for time-invariant characteristics that may arise from the different sectors in the panel data. The fixed effects aim to control for sector characteristics and use the 86 sectors in the data.

Model 1

$$Employment = \alpha_0 + \sum_{t=1}^{8} \alpha_t * quarter_t + \alpha_9 * year + \varpi + \varepsilon$$

Model 1 found above, uses aggregate employment ($Employment$) as a dependent variable and as independent variables there are eight quarter dummies that account for the quarters after COVID-19 hit the economy: from quarter one of 2020 ($t = 0$) until quarter four of 2021 ($t = 7$), as well as a year trend. It is important to include a year trend to account for the positive employment growth per year. The sector fixed effects are included in ϖ, and ε is the error term.

The data for employment needs seasonal adjustment given that the seasonal component of the time series is very pronounced, mainly a lower employment is found in the first quarter of every year. Given this issue, I adjust the data to obtain the employment trend without the seasonal component. To do this, I first compute the mean of employment per year and sector. I then take each time period and subtract the employment from the yearly average computed. As a third step, I calculate the average deviations for the four quarters throughout the seven years by sector, and finally I subtract the average deviations per quarter from the employment of each time period. The subsequent models all include seasonally adjusted employment.

Model 2

$$Employment_{sa} = \beta_0 + \sum_{t=1}^{8} \beta_t * quarter_t + \beta_9 * year + \pi + \upsilon$$

Model 2 above, has seasonally adjusted aggregate employment ($Employment_{sa}$) as a dependent variable, and as main independent variables include eight quarter dummies from quarter one of 2020 ($t = 0$) until quarter four of 2021 ($t = 7$), and I include a linear trend in employment called $year$. The fixed effects are represented by π, and the error term is υ.

Model 3

$$Employment_{sa} = \gamma_0 + \sum_{t=1}^{8} \gamma_t * quarter_t + \gamma_9 * year + \gamma_{10} * L_1.Employment_{sa} + \gamma_{11} * L_2.Employment_{sa} + o + \varrho$$

However, given that employment might be heavily determined by past employment I include lags of employment in model 3 above. Not doing so may bias the results because employment shocks can persist across time. The optimal lag amount depends on several factors. First, it is possible to use the Akaike's information criterion (AIC) as well as the Bayesian information criterion (BIC) to determine the optimal lags. This was calculated for model (2) adding up to four employment lags. Table 3 shows the results highlighting that the optimal model would be that of four lags with an AIC and BIC of 41,583 and 41,656 respectively.

Table 3. AIC and BIC

Model	**N**	**df**	**AIC**	**BIC**
Model A (0 lags)	2,408	9	52,376.54	52,428.62
Model B (1 lag)	2,322	10	46,801.46	46,858.96
Model C (2 lags)	2,236	11	45,010.95	45,073.79
Model D (3 lags)	2,150	12	43,257.12	43,325.20
Model E (4 lags)	2,064	13	41,583.60	41,656.82

Source: own calculations based on SPOLISBUS, GBA, and HOOGSTEOPLTAB Statistics Netherlands.

Nevertheless, when running the model only the first and second lag are significant at a 5% significance level. Therefore, I take two lags as adding more lags reduces the number of observations. o is the fixed effects term, and ϱ is the error term in the equation. Moreover, robust standard errors will be used, given that when testing for heteroskedasticity with the Wald test, it is not possible to reject the null hypothesis of homoskedasticity. Furthermore, serial correlation was tested with the Born & Breitung Bias-corrected LM-based test for serial correlation (Wursten, 2018). It is not possible to reject the null hypothesis of no serial correlation up to order 2 at a 5% significance level.

Model 4

$$D.Employment_{sa} = \delta_0 + \sum_{t=1}^{8} \delta_t * D.quarter_t + \delta_9 * D.year + \delta_{10} * L.D.Employment_{sa} + \delta_{11} * L_2.D.Employment_{sa} + \mu + \varsigma$$

If lags of the dependent variable are introduced in a model, it is necessary to test if the sum of the lags is equal to one. This is called a unit root and implies that a time series is not stationary. To test this, an Augmented Dickey Fuller test was used. It is not possible to reject the null hypothesis of unit root ($p = 0.9998$). In order to correct this, first differences must be used denoted with "D.". Model 4 above presents the equation, with μ as the fixed effects term and ς as the error term. Model 4 reveals no serial correlation up to order two, and no unit root. I use robust standard errors to correct for heteroskedasticity.

Model 5

$$FTE_{sa} = \theta_0 + \sum_{t=1}^{8} \theta_t * quarter_t + \theta_9 * year + \kappa + \zeta$$

Model 6

$$FTE_{sa} = \rho_0 + \sum_{t=1}^{8} \rho_t * quarter_t + \rho_9 * year + \rho_{10} * L.FTE_{sa} + \rho_{11} * L_2.FTE_{sa} + \vartheta + \varphi$$

Model 7

$$D.FTE_{sa} = \tau_0 + \sum_{t=1}^{8} \tau_t * D.quarter_t + \tau_9 * D.year + \tau_{10} * L.D.FTE_{sa} + \tau_{11} * L_2.D.FTE_{sa} + \eta + \psi$$

The same analysis will be done with the employment variable in FTE to compare the outcomes. Following the same exploration as for employment, the data needs seasonal adjustment given the pronounced seasonal trend. Given the persistence of FTE, and the lags display a unit root, I run the three fixed effects models shown above. The terms κ , ϑ and η are the fixed effect terms for the models 5, 6, and 7 respectively. The terms ζ, φ and ψ are the error terms for the models 5, 6, and 7 respectively.

3.2 Sector analysis

The aggregate analysis provides an overview of the pandemic effects on the labour market. Nevertheless, there is a heterogeneity of the effects of the shock on different sectors. It is likely that the sectors that gained employment during the pandemic compensate to a small extent for those sectors that lost employment. To further investigate the effects per sector I calculate the sector employment change at a short- and medium-term period. First, the change in employment is calculated for all the sectors subtracting the employment in quarter one of 2020 from the employment in quarter four of 2020 for the short term. For the medium term, the aggregate employment per sector was calculated subtracting the employment of the first quarter of 2020 from the employment of the fourth quarter of 2021. This shows how many jobs were lost or gained in a sector for one year and for two years.

3.3 Individual characteristics

After the sector analysis, one sector is chosen to investigate further the characteristics of the individuals that were hit harder by the COVID-19 crisis, given the heterogenous impact of the shock. The horeca sector was chosen to perform this analysis as it was one of the sectors most affected. [2] This analysis can provide insights on what individuals were the most resilient and found employment in another sector after the labour shock.

Model 8

$$Switch\ Horeca = \lambda_0 + \lambda_1 * age + \lambda_2 * age^2 + \lambda_3 * female + \lambda_4 * migrant + \lambda_5 * hours\ worked + \lambda_6 * hourly\ wage + \lambda_7 * contract\ type + \lambda_8 * education + \chi$$

The dependent variable of model 8 shown above is a dummy variable that reflects whether an individual was employed in the horeca sector on the 1 January 2020 but was employed at a different sector at any point in time for a given post pandemic period, which ends on 31 December 2020 for the short-term analysis and 31 December 2021 for the medium-

[2] It is important to note that the horeca sector data is limited given that there are many self-employed individuals working in this sector, and I do not have data these workers.

term analysis. Zero represents an individual who was employed at the beginning of the period in the horeca sector as well as their last job recorded. For instance, an individual who is employed in the horeca sector and enters (temporary) unemployment and then obtains another (the same) job in the horeca sector will still be considered in the same sector, therefore labelled as zero. One reflects an individual switching sectors, meaning they were employed in the horeca sector at the beginning of the period, and at least one job recorded in the set period was in a different sector.

The independent variables are age, age squared, female, migrant, hours worked, hourly wage, permanent contract, and education, all measured at the job held on January 1, 2020. These variables were chosen given that the literature presented above presented them as characteristics of individuals that are more vulnerable to COVID-19. The error term is represented by χ.

Model 9

$$Switch\ Sector = \xi_0 + \xi_1 * age + \xi_2 * age^2 + \xi_3 * female + \xi_4 * migrant + \xi_5 * hours\ worked + \xi_6 * hourly\ wage + \xi_7 * contract\ type + \xi_8 * education + \sum_{i=9}^{95} \xi_i * sector + \iota$$

Furthermore, a similar analysis to model 8 is computed but including the complete sample with the different sectors. Model 9, found above, has a dependent dummy variable that represents individuals that switched sectors at any point during the time period. Similarly, to the dependent variable in model 8, one represents the individuals who changed sectors, and zero represents individuals who stayed in the same sector throughout the complete the period. Moreover, model 9 also includes sector dummies at a two-digit level to control for sectorial effects. The error term is represented by ι.

4 Results

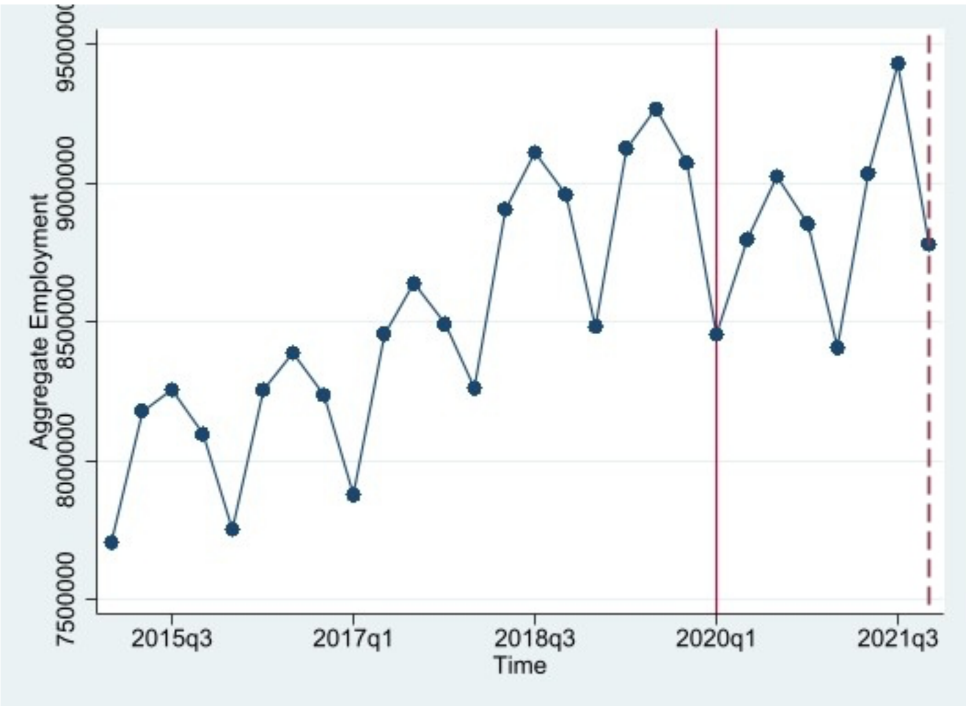
In this section of the thesis, I will present the results of the analyses conducted. First, I will look into the employment trend in the Netherlands, if there was a trend break after COVID-19, and which time periods were most relevant. Second, I will observe which sectors were most affected. Third, I will investigate the characteristics of the individuals and their jobs in one of the most affected sectors, horeca, and afterwards replicate the analysis with the complete sample controlling for sector effects.

4.1 *Employment trend*

4.1.1 Employment analysis

The study will first start with a descriptive analysis of employment. Figure 1 shows the employment plotted from the first quarter of 2015 until the fourth quarter of 2021 using the raw data. The graph shows strong seasonality where there is a significant decrease in employment during the first quarter of each year. The full vertical line signals the first quarter of 2020, the start of the COVID-19 pandemic, and the dashed vertical line signals the Omicron lockdown.

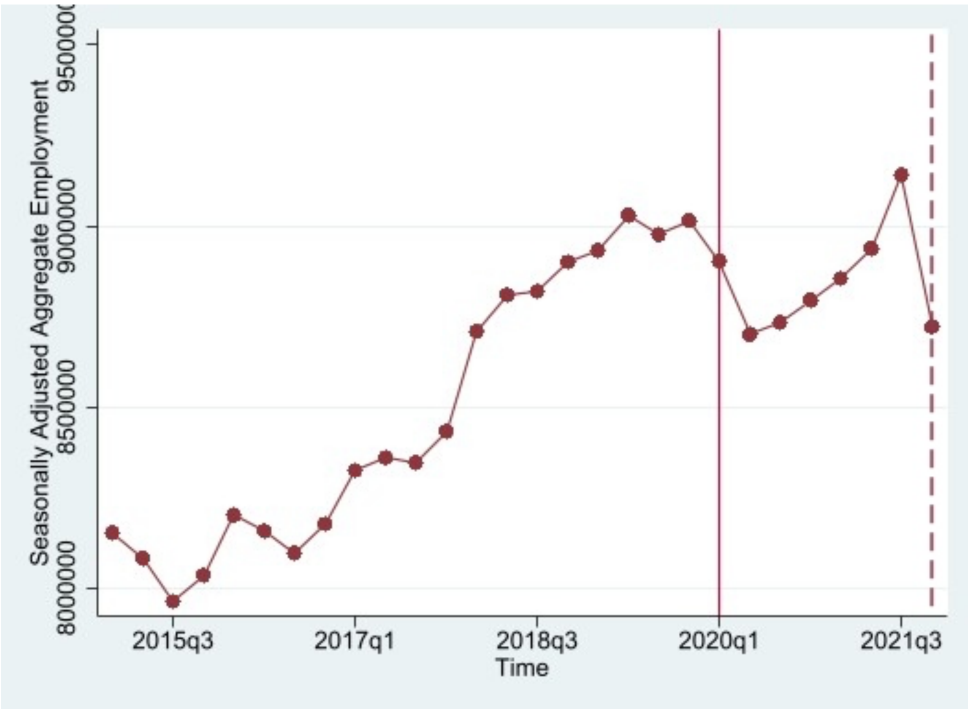
Figure 1. Aggregate employment with raw data.



Source: own calculations based on SPOLISBUS, GBA, and HOOGSTEOPLTAB Statistics Netherlands.

With the data seasonally adjusted, it is possible to properly observe the employment trend in red as shown in figure 2. The effects on employment of the pandemic can be observed with a drop in the first quarter of 2020 compared to the fourth quarter of 2019. Nevertheless, there is a much larger effect in the second quarter of 2020 where employment decreases approximately double the amount. Furthermore, employment from the third quarter of 2020 until the third quarter of 2021 increases at a steady pace. Lastly, in the fourth quarter of 2021, employment drastically drops to similar levels to the ones found in the second quarter of 2020. The full vertical line symbolizes the start of the pandemic, and the dashed vertical line shows the lockdown due to the Omicron variant. To summarize, there are three quarters that should be highlighted, quarter one of 2020, quarter two of 2020, and quarter four of 2021. Figure 2 shows a positive linear trend before the shock. After the shock there is the same increasing trend with a similar slope until the third quarter of 2020, which precedes the decrease in quarter four of 2021. A linear year trend will be added to the analysis to account for this. At a first glance, it is possible to say that COVID-19 decreased formal employment in quarters one and two of 2020 and quarter four of 2021.

Figure 2. Seasonally adjusted aggregate employment 2015-2021.



Source: own calculations based on SPOLISBUS, GBA, and HOOGSTEOPLTAB Statistics Netherlands.

In order to test the employment trend change by COVID-19 formally, I run models one to four. Table 4 displays the results of the models starting from the main regression and including necessary elements progressively. Column 1 presents a model with fixed effects regression with the raw data. Column 2 portrays a fixed effects regression with seasonally adjusted data. Column 3 is a fixed effects regression with seasonally adjusted data, and with two lags. Column 4 puts forward a fixed effects regression with seasonally adjusted data, two lags, and with first differences. When discussing the results, I will apply a 5% significance level to report significant results.

Column 1 provides the fixed effects regression of employment on the quarter dummies after COVID-19, and a year trend as well as clustering per sector. The year trend shows that for each one-year increase, there is an employment increase of 2,921 ($p = 0.001$). The dummy quarters are the deviations from the year trend. In quarter one of 2020, there is a statistically significant decrease of 9,013 jobs compared to the expected amount ($p = 0.041$). Moreover, quarter one of 2021 shows a statistically significant decrease of 12,490 jobs compared to what was expected ($p = 0.021$). The last statistically significant result occurs in the fourth quarter of 2021 with 8,142 jobs less than expected by the trend.

Column 2 provides the results for the same regression but executed on seasonally adjusted data. The year trend shows an expected increase of 2,921 jobs per year. Compared to model 1, Quarter one of 2020 is not statistically significant and quarter two of 2020 presents a significant decrease of 6,159 jobs from what was expected based on the trend. Quarter one of 2021 shows insignificant results at a 5% level. Nevertheless, quarter one and two of 2020 are significant at a 10% level with a decrease in employment of 7,276 ($p = 0.058$) and 6,314 ($p = 0.075$) respectively, relative to the expected trend. As in column 1, the last quarter of 2021 is significant with a decrease of 8,835 jobs less compared to the yearly trend.

Column 3 presents a model with seasonally adjusted data and including two lags of the dependent variable. The persistence of the time series is 0.85. [3] Using the persistence estimates, one can compute long run effects of the shocks. The long run effect of the initial shock at quarter one of 2020 is for instance $-16{,}415$.[4] The year trend presents a 541 job increase per year increase. It is important to highlight that the year trend is considerably smaller in this model relative to the earlier models. Regarding the quarter dummy variables, quarter two of 2020 has a significant decline of 3,302 jobs compared to the expected amount ($p = 0.000$). Moreover, quarter four of 2021 shows a significant employment decrease of 6,761 jobs compared to the expected trend ($p = 0.001$).

Adding the lags of the dependent variable drastically decrease the coefficients of the quarter dummy variables. Accounting for the persistent effects of the employment shows that the consequences of COVID-19 on formal employment were not as large as one would expect from the graphical analysis.

Furthermore, column 4 provides a model with seasonal adjustment, two lags, and additionally first differences given that the unit root (i.e., the coefficient of the sum of the lags of the dependent variable equalling one) could not be rejected. The year trend, significant at

[3] The persistence of the time series is calculated by adding the coefficients of the lagged dependent variables.

[4] The long run effect (also known as the long run propensity) was computed by dividing the coefficient of 2020q1 by 1 minus the sum of the coefficients of the lagged dependent variables $\left(\frac{-2440.43}{1-(1.07-0.21)}\right) = -16{,}415.11$.

the 1% level, indicates that the difference in employment from one year to the next increases by 1299 jobs. For this model, all quarter dummies are significant at the 1% level, except the first quarter of 2020 which is significant at the 10% level.

Regarding the R^2, models 1, 2, and 4 have low within R^2 signalling that there is little variation of employment captured within sectors in the models. Model 3 has a R^2 of 0.99.

To summarise, formal employment decreased in quarters two of 2020 and quarter four of 2021, which coincides with the two strict lockdowns in the Netherlands at the beginning of the pandemic, and for the Omicron variant. Formal employment decreased during these periods, even though the NOW government program was in place. The effect found in the regressions is not as large as the descriptives results suggest, and when including the persistence effects of employment, the effect decreases substantially highlighting the importance to account for such aspects.

Table 4. Aggregate employment regressions.

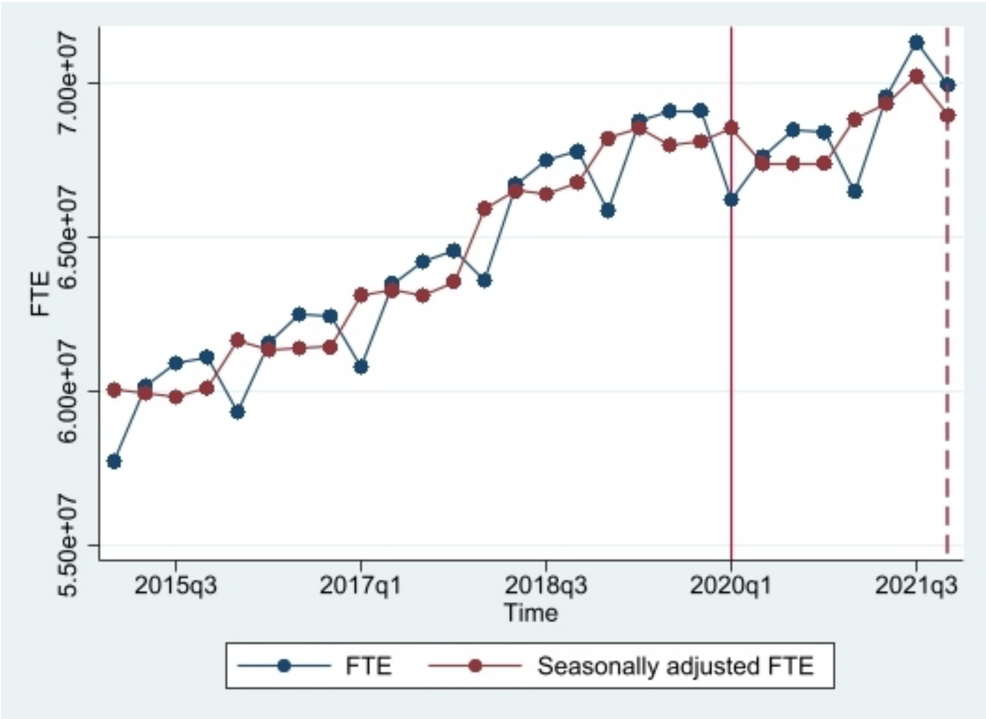
	(1)	(2)	(3)	(4)
	Employment count	**Employment count (sa)**	**Employment count (sa)**	**D. Employment count (sa)**
2020q1	-9012.91**	-3799.07	-2440.43*	-3047.40*
	(4341.75)	(2835.34)	(1385.77)	(1574.74)
2020q2	-5027.45	-6158.69*	-3302.25***	-5549.25***
	(3205.99)	(3529.16)	(894.88)	(2032.89)
2020q3	-2379.36	-5769.66	-672.57	-5224.32***
	(2948.09)	(3691.24)	(479.86)	(1889.13)
2020q4	-4354.30	-5046.58	-884.73*	-5008.75***
	(3095.87)	(3367.89)	(461.01)	(1736.50)
2021q1	-12490.19**	-7276.35*	-1422.99*	-6055.31***
	(5300.08)	(3793.99)	(725.27)	(1972.19)
2021q2	-5183.04	-6314.28*	-1042.68*	-5513.615***
	(3177.32)	(3502.48)	(530.80)	(1619.50)
2021q3	-561.10	-3951.40	441.69	-3611.68***
	(2178.52)	(2811.38)	(335.04)	(1124.99)
2021q4	-8142.29**	-8834.58**	-6760.91***	-9147.43***
	(3647.17)	(3951.20)	(1995.36)	(2568.62)
Year	2921.28***	2921.28***	540.78***	1298.93***
	(860.54)	(860.54)	(131.30)	(382.56)
Constant	-5793668***	-5793668***	-1075762***	350.82***
	(1735718)	(1735718)	(263150.20)	(119.57)
Lag 1 employment count (sa)			1.07***	.14
			(.09)	(-.04)
Lag 2 employment count (sa)			-.21**	-.04
			(.11)	(.04)
One time period difference for all variables	No	No	No	Yes
Robust standard errors	Yes	Yes	Yes	Yes
Observations	2,408	2,408	2,236	2,150
R^2 Within	0.07	0.09	0.81	0.06
R^2 Between	0.01	.	1.00	0.89
R^2 Overall	0.01	0.01	0.99	0.07

Source: own calculations based on SPOLISBUS, GBA, and HOOGSTEOPLTAB Statistics Netherlands.
Note: All regressions have clustered standard errors by sectors (86 sectors). Standard errors in parenthesis.
*** p<0.01. ** p<0.05. *p<0.1.
The aggregation level for the observations is the employment in each of the 86 sectors throughout 28 quarters (2015q1-2021q4) which leads to 86*28=2,408.

4.1.2 FTE analysis

A similar analysis is done for FTE. Figure 3 below shows the raw and seasonally adjusted data for FTE. The seasonally adjusted FTE exhibits a positive linear trend, which is accounted for in the regressions. In the FTE there is a limited impact of the pandemic, as there is a decrease in FTE, nevertheless not as pronounced as employment. Given that FTE is based on the number of paid hours of an individual minus the overtime hours, it could be a measure of the effectiveness of the NOW program installed by the Dutch Government to produce temporary unemployment instead of formal unemployment.

Figure 3. FTE raw and seasonally adjusted data over time (2015-2021).



Source: own calculations based on SPOLISBUS, GBA, and HOOGSTEOPLTAB Statistics Netherlands.

Column 1 in table 5 provides the results taking FTE_{sa} as a dependent variable of model 5. The linear year trend exhibits a 24,891 FTE increase per year. Not accounting for the linear trend may underestimate the effects of COVID-19 on FTE_{sa} because of the positive growth it exhibits per year. The coefficients of quarters one and four of 2021 are significant at a 10% level. The coefficients present a decrease of 41,986 and 40,485 FTE with regard to the expected FTE in those quarters respectively.

Column 2 in table 5 shows model 6 with two lags of the dependent variable. The year trend presents a yearly increase of 3,246 FTE, which is much lower than the year coefficient in column 1 if no lags are included. The quarters with the largest and significant coefficients are quarter two of 2020, and quarter four of 2021. Quarter two of 2020 presents a 21,812 FTE decrease compared to the expected, whilst quarter four of 2021 shows 25,501 FTE less than expected for that quarter. These results are in line with the large decreases found in the employment analysis. Regarding the lagged variables, the persistence of the time series is 0.89. The medium run effect of the shock of quarter one in 2020 is −26,002.

Given the unit root of model 6 in column 2, first differences are added presenting model 7 in column 3. Regarding the year trend, the difference in FTE from one year to the next increases by 19522 FTE, significant at a 1% level. All the quarter dummy variables are significant at a 1% level except quarters one and two of 2020, which are significant at a 5% level.

Regarding the R^2 of the models, models in columns 1 and 3 have low values whilst column 2 has 0.99. This could mean that the models could be underfitted or overfitted respectively.

Similar to the employment, an important take away is that adding the possible persistence effect of FTE through lags decreases the coefficients. If the persistence was not accounted for, the effect of COVID-19 on FTE would be overestimated. Additionally, not including the year trend that is appreciated in the graph would underestimate the pandemic effect. Lastly, the regression and graphical analyses show that the largest impacts of FTE were noticed during the second quarter in 2020 and the last quarter of 2021, in line with the employment analysis.

Table 5. Aggregate FTE regressions

Table 5. Aggregate FTE regressions.

	(1) **FTE (sa)**	(2) **FTE (sa)**	(3) **D. FTE (sa)**
Year	24891.17*** (6609.717)	3245.70*** (868.15)	19522.57*** (4478.47)
2020q1	-20197.99 (15817.04)	-2821.69 (5290.14)	-15151.71** (7370.52)
2020q2	-33654.68 (21389.33)	-21812.62*** (6456.80)	-29828.09** (12217.38)
2020q3	-33706.80 (21698.01)	-5333.56*** (1704.84)	-26991.41*** (9467.62)
2020q4	-33532.99 (20700.93)	-8379.78** (4033.51)	-27659.19*** (9478.48)
2021q1	-41985.77* (23774.08)	4602.90 (3103.42)	-30979.65*** (9876.94)
2021q2	-35927.07 (22293.45)	-7956.35** (3179.25)	-28572.69*** (9597.22)
2021q3	-25716.18 (17974.55)	-617.32 (2767.58)	-19034.62*** (5930.67)
2021q4	-40485.4* (22790.63)	-25501.20*** (8295.95)	-35856.99*** (11872.69)
Constant	-4.95e+07*** (1.33e+07)	-6462729*** (1736543)	197.11 (1200.05)
Lag 1 FTE (sa)		1.13*** (.11)	0.21 (.14)
Lag 2 FTE (sa)		-.24* (.13)	-.04** (.02)
One time period difference for all variables	No	No	Yes
Robust standard errors	Yes	Yes	Yes
Observations	2,408	2,236	2,150
R^2 Within	0.14	0.89	0.06
R^2 Between	.	1.00	0.96
R^2 Overall	0.01	0.99	0.08

Note: All regressions cluster for 86 sectors. Standard errors in parenthesis. *** p<0.01. ** p<0.05. *p<0.1

Source: own calculations based on SPOLISBUS, GBA, and HOOGSTEOPLTAB Statistics Netherlands.

4.2 *Sector analysis*

In this section, I will explore the heterogeneity of the impact of COVID-19 on the different sectors of the economy. In the aggregate analysis it was possible to see an employment decrease, but some sectors were more hit than others. Therefore, I will calculate the employment changes in the short run, at a one-year period, and in the medium run, at a two-year period, to investigate this difference.

Table 6 presents the 10 sectors that lost the most employment in the short run and medium run, at a two-digit level. For the short run, the first is food and beverage locations (56) with a job loss of 59,292, the second sector is job placement agencies and personnel management (78) with an employment loss of 32,714, the third is lodgement (55) with a decrease in employment of 14,668, and the fourth is sports and recreation (93) with a decrease of 9,003 jobs.

For the medium run, the first sector most affected is the retail sector (not cars) (47) with an employment loss of 53,857 jobs, followed by the food and beverage locations (56) with 34,514 lost jobs over two years. The third sector most affected in the medium run is the job placement agencies and personnel management (78) with an employment loss of 14,747. The fourth sector most affected was lodgement (55) with an employment loss of 12,195.

All the sectors (except the retail sector in the medium run) most affected by COVID-19 are sectors that require social interaction as literature suggests (Battistini & Stoevsky, 2021). Prevention measures, social distancing measures, including lockdown periods prevented the economic activity of these sectors to advance and many jobs were therefore lost.

Table 7 presents the 10 sectors that gained most employment in the short and medium run. For the short run, the sectors that gained most employment were the retail sector (not cars) (47) with an increase of 34,687, the healthcare sector (86) with an increase of 11,230 jobs, followed by public administration, public services, and compulsory social insurance (84) with a job increase of 8,020. The fourth is education (85), gaining 5,217 jobs. It is interesting to note that the retail sector (not cars) (47) was the first sector that gained most employment in the short run but lost most employment in the medium run.

In the medium run, the sectors that gained most employment are education (85) with an increase of 16,732, and public administration, public services, and compulsory social insurance (84) with an employment increase of 15,842.

Given that the horeca sector was first in the short run and second in the medium run as sector most affected, the following analysis will take a deeper look into this section of the labour force.

Table 6. Employment changes in the short and medium run for the 10 sectors most affected.

	Short run	Medium run
1	56. Food and beverage locations (-59291)	47. Retail (not cars) (-53857)
2	78. Job placement, employment agencies and personnel management (-32713)	56. Food and beverage locations (-34513)
3	55. Lodging (-14367.57)	78. Job placement, employment agencies and personnel management (-14746)
4	93. Sports and recreation (-9002.711)	55. Lodging (-12194)
5	46. Wholesale trade and brokerage services (excluding motor vehicles and motorcycles) (-5940.156)	81. Facility management, cleaning, and landscaping (-11464)
6	49. Land transport (-5924.422)	93. Sports and recreation (-7226)
7	81. Facility management, cleaning, and landscaping (-4858)	79. Travel mediation, travel organisation, tourist information and reservation agencies (-6855)
8	90. Art (-4436)	77. Rental and lease of cars, consumer goods, machines, and other movable goods (-6200)
9	79. Travel mediation, travel organisation, tourist information and reservation agencies (-3430)	49. Land transport (-6155)
10	96. Wellness and other services; funeral industry (-3301)	45. Trade and repair of cars, motorcycles, and trailers (-6031)

Note: The employment count in absolute numbers is found between brackets.

Source: own calculations based on SPOLISBUS, GBA, and HOOGSTEOPLTAB Statistics Netherlands.

Table 7. 10 sectors that gained most employment in the short and medium run.

	Short run	Medium run
1	47. Retail (not cars) (34686)	85. Education (16731)
2	86. Healthcare (11230)	84. Public administration, government services and compulsory social insurance (15842)
3	84. Public administration, government services and compulsory social insurance (8020)	86. Healthcare (5857)
4	85. Education (5216)	62. Information technology service activities (5137)
5	65. Insurance and pension funds (no compulsory social insurance) (3886)	82. Other business services (2417)
6	87. Nursing, care, and guidance with overnight stay (3231)	35. Production, distribution and trade in electricity, natural gas, steam and refrigerated (2188)
7	53. Post and couriers (2596)	72. Research and development work (2142)
8	64. Financial institutions (excluding insurance and pension funds) (1894)	63. Information service activities (1745)
9	1. Agriculture, hunting and services for agriculture and hunting (1612)	43. Specialized work in construction (1556)
10	21. Manufacture of pharmaceutical raw materials and products (1046)	53. Post and couriers (1225)

Note: The employment count in absolute numbers is found between brackets.

Source: own calculations based on SPOLISBUS, GBA, and HOOGSTEOPLTAB Statistics Netherlands.

4.3 Individual characteristics

The final section of the results focuses on individuals and their characteristics. I look further into the horeca sector, and the characteristics of the individuals employed. To do this, I investigate the relationship between switching sectors and the job and personal characteristics of the individuals. Workers can stay in the same job, or if fired, they can search for another employment in the same sector or in a different sector. Given that there were so many job losses in the horeca sector in the short run and in the medium run, it is interesting to see which individuals searched for employment outside their sector and what characteristics made these individuals more resilient and more open to other occupations.

This will be done with a one-year sample, and a two-year sample. Furthermore, to increase the scope of the examination, the same analysis will be conducted for the full population including all the sectors. With this, I aim to investigate what characteristics made workers switch between sectors and their importance. In this last regression, sectors will be included to control for the differences between them.

4.3.1 Horeca sector

The first column of table 8 shows a regression with the dependent variable "switch" which signals whether an individual has switched from the horeca sector to a different one in a one-year time period. For the short run, all characteristics are statistically significant at the 1% level. First, age shows that as an individual increases their age by one year, they are on average 0.87 percentage points (p.p.) less likely to switch sectors. Extrapolating this result: an individual who is 10 years older will be 8.7 p.p. less likely to switch sectors than a younger individual. The parabolic shape indicates that the top of the parabola is reached at 33.25 years of age. Additionally, women are 2.05 p.p. more likely to switch than men. A first-generation migrant is 2.16 p.p. less likely to switch sectors than a native worker. Furthermore, the more hours employees work, the less likely they are to switch to a different sector: an increase in one hour decreases the probability of switching by 0.08 p.p. An increase of a standard deviation (12.16 hours per week, 146 hours per quarter) would lead to an individual being 11.68 p.p. less likely to switch. Moreover, workers with a one-euro higher wage, are 0.46 p.p. more likely to switch sectors. An increase of a standard deviation (€5.95) will lead to individuals being 2.74 p.p. less likely to switch sectors. Earning high wages in horeca induces workers to switch sectors when out of employment, this could be due to firms laying off workers with a higher wage due to the larger financial burden for the company. Contract type reflects that if the individual's contract is permanent, they are 3.91 p.p. less likely to switch sectors. Intuitively, if an individual has a permanent contract, it is less likely they are fired, and they do not lose their job. Therefore, there is no need to find a different one in another sector. Lastly, the most important factor seems to be education. A one level increase in education will induce individuals to change sector by a 6.52 p.p. [5]

Column 2 shows the medium-term results for a switch in the horeca sector. In the medium-term, age becomes less important than in the short term, with an increase in one year resulting in a 0.45 p.p. lower likelihood to switch. The optimal age to switch provided by the parabolic shape has decreased to 19.58 years of age compared to column 1. In the medium run, it is more optimal to switch at a younger age than in the short run. Women are 3.28 p.p. more likely to switch to switch than men. On the other hand, even though migrants are more affected by COVID-19, foreign-born are 3.91 p.p. less likely to switch than native-born. An increase in one hour worked decreases the likelihood to switch by 0.07 p.p., a one standard deviation increase (12.5 hours per week, 150 hours per quarter), will decrease the likelihood of leaving by 11.77 p.p. Hourly wage is not significant in the medium run for the switch from the horeca to another sector. Contract type increases its importance compared to the short run, reflecting that if an individual has a permanent contract, they are 4.94 p.p. less likely to switch. Education also gains importance, with a one level increase in education leading to the individual to be 7.64 p.p. more likely to switch.

In the horeca sector, many of the results are in line with the individuals most vulnerable to the COVID-19 shock. Staring with age, the literature suggests that younger individuals are more affected than their older counterparts (Béland et al., 2020; Fana et al., 2020; Gupta et al., 2020; Moen et al., 2020; OECD, 2022; Zwetsloot et al., 2021). This finding could explain why younger individuals are more willing to switch sectors given that they may be laid off with a higher likelihood. Similarly, studies find that women are more affected by COVID-19 than men (Fana et al., 2020; Moen et al., 2020). More affected employees like women who are more likely to lose their job, will be more prone to find another employment in a different sector to increase the probabilities of finding a job. On the other hand, migrants seem to be less likely to switch sectors as presented in my analysis compared to native-born individuals, even though they are found to be more affected by the labour shock of the pandemic than native-born (Béland et al., 2020; Gupta et al., 2020; OECD, 2022; Pouliakas & Branka, 2020; Zwetsloot et al., 2021). Eurostat (2021) shows that slightly under 70% of all first-generation migrants are employed, whilst for the native-born, over 85% are employed showing the difference in labour

[5] Education level is divided into low educated (1), middle educated (2), and highly educated (3).

activity between the groups. Migrants are not equally represented in the economy, mainly employed in sectors with high percentages of low-skilled employees (OECD, 2020a). Low skilled workers were also found to be less likely to switch in my analysis, which may have an effect on the migrant switch pattern. Many studies confirm that lower educated individuals are more vulnerable to the labour shock of COVID-19 (Béland et al., 2020; Gupta et al., 2020; OECD, 2022; Pouliakas & Branka, 2020; Zwetsloot et al., 2021). Nevertheless, in my analysis high-educated individuals were found to be more likely to switch than low-educated ones. It is possible that higher educated individuals may have a higher skill transferability to other sectors and therefore more job opportunities in different sectors. Low wage workers are corroborated by the literature to be more impacted by COVID-19 than high wage individuals (Béland et al., 2020; OECD, 2022; Pouliakas & Branka, 2020). I find that the higher the wage of the individual in the horeca sector, the more likely they are to switch. It is possible that those firms in the horeca sector that have not been covered by subsidies, or that have substantial financial losses lay off individuals with higher wages before those with low wages to decrease the overall loss. Then high-wage individuals decide to look for employment in other sectors that may provide greater earnings. The mean hourly wage in the horeca sector is €11.67 whilst the mean hourly wage from all the sample is higher at €38.76. Ending with contract type, individuals working with a non-standard type of labour contract are more vulnerable to the labour shock of the pandemic (Institute of Labor Economics, 2021). This finding is strongly corroborated in my study, suggesting that workers that are more vulnerable with a temporary contract are therefore more likely to be laid off and will search for employment in another sector.

These findings highlight that individuals who were harder hit and were laid off from their job had to search for employment elsewhere. Such employment is found by many in another sector that may be more secure and, for instance, functioning even when COVID-19 measures are in place. Additionally, previous literature presents the most vulnerable individuals however my research shows that out of these vulnerable individuals, many of them are resilient and decide to find employment in a different sector, such as women, highly educated individuals, or workers with a temporary contract among others. Knowing which individuals are more prone to switch and find employment in other sectors also provides essential information for governments about who is more resilient. This indicates the population that could benefit the most from targeted training and skill building programs or other assistance to aimed at helping them find employment in other sectors.

Table 8. Individual characteristics regression

	(1) **Horeca Short term**	(2) **Horeca Medium term**
Dependent variable	Switch sectors from horeca	Switch sectors from horeca
Age	.0087***	.0047***
	(.0004)	(.0005)
Age^2	-.0001***	-.0001***
	(6.09e-06)	(6.69e-06)
Female	.0204***	.0328***
	(.0015)	(.0017)
Migrant	-.0215***	-.0390***
	(.0023)	(.0026)
Hours worked	-.0008***	-.0007***
	(6.55e-06)	(7.27e-06)
Hourly wage	.0046***	.0001
	(.0001)	(.0002)
Permanent contract	-.0391***	-.0494***
	(.0016)	(.0018)
Education	.0652***	.0764***
	(.0013)	(.0015)
Constant	.2203***	.4618***
	(.0066)	(.0072)
Sector Control	No	No
Observations	329,180	306,084
R^2	0.0790	0.0966

Note: Standard errors in parenthesis. *** p<0.01. ** p<0.05. *p<0.1

Source: own calculations based on SPOLISBUS, GBA, and HOOGSTEOPLTAB Statistics Netherlands.

4.3.2 *Complete labour market*

Column 1 in table 9 presents the model with the complete sample and all sectors. The dependent variable is whether the individual has switched sectors in one year. Sector dummies are included to control for the heterogeneity between the sectors. Compared to the horeca sector, age is now negative. An increase in one year of age for an individual translates in a 0.22 p.p. lower likelihood to switch, an increase of 10 years yields to a 2.2 p.p. lower likelihood to switch. The optimum age established by the parabolic shape is past the retirement age (at 332.08 years). Moreover, women are 1.69 p.p. less likely to switch in the whole sample. Foreign-born are 0.32 p.p. less likely to switch than natives. An increase in one hour worked decreases the likelihood to switch to another sector by 0.06 p.p. Hence a one standard deviation increase (11.5 hours per week and 138 hours per quarter) will decrease the likelihood to switch by 8.47 p.p. Moreover, if hourly wage increases by one euro, the likelihood of switching decreases by 0.06 p.p., which is 0.79 p.p. for one standard deviation (€13.2). A permanent contract will decrease the likelihood of switching by 4.07 p.p. An increase in one level of education will lead to a 2.79 p.p. increase in the likelihood of switching.

Column 2 shows the medium-term analysis for an individual switching from a sector to another controlling for the sectorial differences. In the medium run, a one-year increase in age results in a 0.82 p.p. decrease in the likelihood of switching. The optimal age to switch is at 78.27 years, past retirement. A woman is 1.17 p.p. more likely to switch to another sector than a man. A foreign-born is 0.88 p.p. less likely to switch to another sector than a native born. Similarly, to the short term, a one hour increase in hours worked will decrease the likelihood of switching by 0.06 p.p., where one standard deviation (11.5 hours per week and 138 hours per quarter) will decrease the switching likelihood by 0.69 p.p. A one euro increase in hourly wage will decrease the likelihood of switching by 0.06, and a one standard deviation (€13.2) will decrease it by 0.79 p.p. An individual with a permanent contract will be 7.7 p.p. less likely to switch, which seems to be the most important factor in column 4. An increase in one level of education will increase the likelihood of switching by 3.25 p.p.

The results between the complete population analysis, and the horeca sector analysis bring out differences in three variables: female, age, and hourly wage. The incentives for switches may be very different among sectors, as the whole population includes sectors that were positively hit, or not hit at all. Switching sectors may be seen as a risk for individuals. Research shows that women are more risk averse than men in financial as well as other environments, which could be one of the reasons to explain why there is a higher switch for men (Borghans, Heckman, Golsteyn, & Meijers, 2009; Halek & Eisenhauer, 2001; Jianakoplos

& Bernasek, 1998). Other literature also states that risk aversion increases with age (Halek & Eisenhauer, 2001; Morin & Suarez, 1983). Moreover, some studies find a lower turnover for older workers with higher tenure compared to younger workers (Arnold & Feldman, 1982; McQuaid, 2006). Which could restrain older workers switching sectors. Whilst the complete working population in the sample shows a mean age of 38.75, the mean age of the horeca sector is 28.59. Horeca workers are younger which also incentives employees to switch sectors.

Workers who enter or leave an occupation earn lower wages than those who stay (Böhm, Gaudecker, & Schran, 2019). Minimum wage workers are more likely to be new entrants, where changes in occupation are important to improve the financial compensation of minimum wage earners (Even & Macpherson, 2003). For the complete sample, the theory may corroborate the results found. Nevertheless, for the horeca sector only wage in the one-year period is significant, signalling that the higher the wage in the horeca sector the higher likelihood to switch. The mean wage in the horeca sector in my sample is €11.82 whilst the mean wage in the complete sample is €21.83.

These differences show that the horeca sector is different to the complete population given its restrictions during the COVID-19 measures. Individuals who were harder hit and laid off were in need of employment and searched for a job in another sector, even though they would be less likely to switch in a standard circumstance shown by the analysis on the full sample.

Table 9. Individual characteristics regression

	(1) **All sectors Short term**	(2) **All sectors Medium term**
Dependent variable	Switch sectors	Switch sectors
Age	-.0022***	-.0081***
	(.0001)	(.0001)
Age^2	3.36e-06***	.0001***
	(9.24e-07)	(1.10e-06)
Female	-.0169***	-.0116***
	(.0003)	(.0003)
Migrant	-.0032***	-.0088***
	(.0004)	(.0005)
Hours worked	-.0006***	-.0006***
	(1.32e-06)	(1.57e-06)
Hourly wage	-.0004***	-.0006***
	(.0001)	(.0001)
Permanent contract	-.0407***	-.0778***
	(.0003)	(.0004)
Education	.0279***	.0324***
	(.0002)	(.0002)
Constant	.4790***	.7260***
	(.0087)	(.0104)
Sector Control	Yes	Yes
Observations	5,517,739	5,517,739
R^2	0.1204	0.1629

Note: Standard errors in parenthesis. *** p<0.01. ** p<0.05. *p<0.1

Source: own calculations based on SPOLISBUS, GBA, and HOOGSTEOPLTAB Statistics Netherlands.

5 Conclusion

This thesis aims to assess the effects of Covid-19 on the labour market at a general level, at a sectorial level, and at an individual level. First, I looked at the employment and FTE trends from 2015 until 2021, concluding that there were two significant drops: in the first quarter of 2020, and the fourth quarter of 2021. These drops are in line with the first lockdown when the pandemic started, and an additional lockdown due to the Omicron variant of the virus. An important finding is the necessity of considering a time trend, as well as lagged dependent variables. If a time trend is not considered, the effect of COVID-19 on employment and FTE is underestimated as the positive trend will counteract the negative shock. Employment and FTE trends may be persistent and determined by its past level. Therefore, it is necessary to include lags. When including lags, the coefficients considerably decrease.

Second, I produced a list with the sectors that lost most employment in the short and medium run after COVID-19 given the heterogeneity of the shock across occupations. The sectors most affected were food and beverage locations (horeca), job placement agencies and personnel management, lodgement, and the retail sector (not cars) in the medium run.

As a third finding, the effects of the characteristics on switching sectors differed whether the horeca sample was used or the complete population. Short and medium run results were alike for both samples but with different magnitudes. In the horeca sector, individuals more prone to switching were older, female, native-born, working less hours, with a higher wage, with a temporary contract, and with a higher education. Wage was not significant in the medium run. On the other hand, for the complete sample the individuals that were more prone to switching were younger, male, native-born, working less hours, with a lower wage, a temporary contract, and highly educated. The findings of the horeca sector are in line with literature on the most affected individuals by the pandemic. Individuals who have recently lost their job are more likely to search for another job in a different sector compared to individuals who are still employed. For the complete population other factors could play a role, such as risk aversion being higher for male than female or younger people having a higher turnover rate. It is interesting to note that foreign-born were less likely to switch sectors in both instances than native-born.

This thesis may provide important policy implications. Being aware of the most resilient individuals provided by their propensity to switch can enlighten social policy to target programs to provide skills, education, or training to the individuals that are most prone to switching to facilitate the job search and decrease unemployment in an effortless way. Providing assistance to individuals who are motivated and want to improve their future prospects would be an effective and rapid way to decrease unemployment. On the other hand, the analysis also provides information on who is less likely to search employment in different sectors, such as migrants. It may be necessary then to dedicate social policy to enhance the prospects and induce these workers to find employment in other sectors. Moreover, recognizing the sectors most affected as well as the time periods where most employment was lost offers additional insights to provide targeted social aid.

A limitation in the individual part of the analysis involves the content of the data. Many horeca workers are self-employed, and these individuals do not form part of the data used for this analysis. This can also be applicable to the aggregate analysis mitigating the actual effect given that literature shows that self-employed individuals have been hit harder than employees (OECD, 2020b).

For future research, it would be interesting to estimate the employment trend taking into consideration that subsidies were provided. In this thesis, I compare employment and FTE which yield to the same results. Nonetheless, it would be enlightening to observe how the employment trend would have been without the NOW help from the Dutch government or differentiating for the temporary unemployment. Additionally, it would be interesting to follow which sectors the individuals went to after switching. An initial guess would be to those sectors that grew in size such as the health sector, although this may differ in the medium or longer-term. Another interesting topic for analysis is to investigate whether individuals that changed sectors in the medium run decide to return to their initial sector or whether the labour shock created a permanent switch. Lastly, another approach to this research would be to perform a difference in difference analysis taking one of the unaffected sectors as the control group and observe how sectors that were hit or sectors that grew changed with respect to the control group.

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7 Appendix

7.1 Levels of education

These are the levels of education and their equivalents in the Dutch education system.

Level	Description
1 Low education	Basisonderwijs Vmbo-b/k, mbo1 Vmbo-g/t, havo-, vwo-onderbouw
2 Middle education	Mbo2, Mbo3, and Mbo4 Havo, vwo
3 High education	Hbo-, wo-bachelor Hbo-, wo-master, doctor

Table 10. Levels of education and Dutch education equivalent.

7.2 Sector list

1 Agriculture, hunting and services for agriculture and hunting

2 Forestry, forestry exploitation and forestry services

3 Fishing and farming of fish and shellfish

6 Extraction of petroleum and natural gas

8 Extraction of minerals (excluding oil and gas)

9 Mineral extraction services

10 Manufacture of food products

11 Manufacture of beverages

12 Manufacture of tobacco products

13 Manufacture of textiles

14 Manufacture of clothing

15 Manufacture of leather, leather goods and shoes

16 Primary woodworking and manufacture of articles of wood, cork, reed and fleece.

17 Manufacture of paper, cardboard and carton and cardboard products

18 Book or newspaper printing, reproduction of recorded media

19 Manufacture of oil products and petroleum processing

20 Manufacture of chemical products

21 Manufacture of pharmaceutical raw materials and products

22 Manufacture of rubber and plastic products

23 Manufacture of other non-metallic mineral products

24 Manufacture of metals in primary form

25 Manufacture of metal products (excluding machines and equipment)

26 Manufacture of computers, electronic and optical equipment

27 Manufacture of electrical equipment

28 Manufacture of other machines and equipment

29 Manufacture of motor vehicles, trailers and semi-trailers

30 Manufacture of other means of transport

31 Manufacture of furniture

32 Manufacture of other goods

33 Repair and installation of machines and equipment

35 Production, distribution and trade in electricity, natural gas, steam and refrigerated..

36 Extraction and distribution of water

37 Wastewater collection and treatment

38 Waste collection and treatment; preparation for recycling

39 Remediation and other waste management

41 General civil and utility construction and project development

42 Earth, hydraulic and road construction (no earthmoving)

43 Specialized work in construction

45 Trade and repair of cars, motorcycles and trailers

46 Wholesale trade and brokerage services (excluding motor vehicles and motorcycles)

47 Retail (not cars)

49 Land transport

50 Water transport

51 Aviation

52 Storage and services for transport

53 Post and couriers

55 Lodging

56 Food and beverage locations

58 Publishers

59 Production and distribution of films and television programs; creating and publishing.

60 Providing and broadcasting radio and television programs

61 Telecommunication

62 Information technology service activities

63 Information service activities

64 Financial institutions (excluding insurance and pension funds)

65 Insurance and pension funds (no compulsory social insurance)

66 Other financial services

68 Real estate rental and trade

69 Legal services, accountancy, tax advice and administration

70 Holdings (not financial), group services within own group and management advice

71 Architects, engineers and technical design and consultancy; inspection and control

72 Research and development work

73 Advertising and market research

74 Industrial design, photography, translation and other consultancy

75 Veterinary services

77 Rental and lease of cars, consumer goods, machines and other movable goods

78 Job placement, employment agencies and personnel management

79 Travel mediation, travel organisation, tourist information and reservation agencies

80 Security and detection

81 Facility management, cleaning and landscaping

82 Other business services

84 Public administration, government services and compulsory social insurance

85 Education

86 Healthcare

87 Nursing, care, and guidance with overnight stay

88 Social services without overnight stay

90 Art

91 Cultural lending centres, public archives, museums, zoos and botanical gardens

92 Lotteries and games of chance

93 Sports and recreation

94 Philosophical and political organisations, interest and ideological organisations

95 Repair of computers and consumer goods

96 Wellness and other services; funeral industry

97 Households as employers of domestic workers

98 Undifferentiated production of goods and services by private households.

99 Extraterritorial organizations and bodies

Appendix C: Declaration of Originality MSc Thesis *

By signing this statement, I hereby acknowledge the submitted MSc Thesis titled

Effects of COVID-19 on the Dutch labour market.
An aggregate, sectorial, and individual analysis
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