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Measuring The Impact Of Non-Pharmaceutical Interventions On Youth Unemployment Rate In European Countries

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Abstract

In order to slow down the spread of the coronavirus, European governments have implemented a variety of non-pharmaceutical interventions (NPIs). Next to the intended consequences, NPIs also cause psychological and economic damage. Insight into these negative consequences can assist policy makers with the task of balancing the pros and cons of NPIs and better tailor interventions to the current needs. One unwanted consequence of NPIs is a rise in youth unemployment. Youth unemployment can have far-reaching consequences in the short and long term and in both personal and economic terms. This thesis aims to be a starting point in contributing to a more comprehensive and holistic view of NPIs capturing new unwanted consequences. The data used is a combination of data concerning NPI implementation, general trends in real gross domestic product and youth unemployment rate changes. A straightforward non-negative least square optimization algorithm is applied in combination with the econometric principle of Okun's law, i.e., the relationship between changes in economic output, measured in gross domestic product (GDP), and unemployment rate. When it comes to policy recommendations, our results show that the closure of public transport and the limitation of non-essential shops are measures that do not offer much benefit in terms of the reduction of the reproduction number, whilst showing significantly large impacts on youth unemployment rate and therefore proving inadvisable. In contrast, measures that limit private and mass gatherings show promise in limiting negative effects while still significantly helping to stop the infections. Measures like wearing a mask are universally advisable due to their relatively low costs, whereas the closure of education is a measure that should only be considered in extreme situations. Our overall goal in this thesis was to stack medical pros against economical cons. Extrapolating from the results from a youth unemployment perspective, we can conclude that research towards additional economical drawbacks of NPIs can assist policy makers in navigating such a balance through implementing sets of NPIs. We see that NPIs are more or less suitable in varying situations, all depending on the desired balance or priorities defined by policy makers. We offer insight from the perspective of youth unemployment, and show up paths for future research to extend perspectives and create a more complete picture.

1. Introduction

Since March 2020, the world has been dealing with the coronavirus outbreak. In response to this outbreak, countries in Europe have implemented several non-pharmaceutical interventions (NPI), such as stay-at-home orders and the closure of non-essential businesses. These interventions were intended to limit the spreading of infections over time, in order to reduce the number of people simultaneously needing medical attention. This way the number of people needing medical attention due to covid-19 or other illnesses is kept within the healthcare capacities of a country. The effectiveness of NPIs in accomplishing this goal has been studied thoroughly (e.g., Brauner et al., 2021; Chang et al., 2021; Dehning et al,. 2020; Ferguson et al., 2020). A measure of this effectiveness is often expressed in a predicted reduction in total infections or the currently well-known R value, which expresses the average number of people a single contagious person infects. Brauner et al. (2020) estimated the effects of several individual NPIs, such as gatherings of people and closing of schools, with the aim to focus on the most effective NPIs and thus minimising the strain on society.

The need to limit the amount of active NPIs as much as possible has a motivation that looks beyond the positive medical consequences of such NPIs. It illustrates the need for a more nuanced and holistic view of NPIs, taking into account their possible negative side effects. A study researching the psychological effects of a strict lockdown in New Zealand by Every-Palmer et al. (2020) reported a significant increase in psychological distress, anxiety and a marked reduction of psychological well-being. These negative effects were more prominent among young people, people who lost their jobs, those with poor health and those who were diagnosed with mental illness in the past. Such negative psychological consequences are also expected to continue even after the outbreak (Sood, 2020).

Beside these negative psychological effects, the negative effects of the pandemic can also be expressed in economic terms. To gain a clearer overview of the economic situation during the pandemic, it is useful to look at a few recent reports presented by the International Monetary Fund (IMF). In a report published in June 2020, global economic growth was forecasted to be -4.9% in 2020. This projection was 1.9% worse than what was expected in April 2020. This illustrates that the economic impact on the first half of 2020 was more severe than anticipated. However, a report from October 2020 projects economic growth to be -4.4%, which is a slightly less pessimistic outlook compared to the first report of 2020. In April 2020, the final global economic growth was estimated at -3.3%. This indicates that the main economic shock was more heavily felt in the first part of 2020 and could be interpreted as a sign that economies were adapting to a new way of working.

This general economic downturn might also give an indication of the situation in more specific economic branches. An example of such a branch is the labour market. Lemieux et al. (2020) looked at changes in employment and aggregate hours worked between February 2020 and April 2020 in Canada. They found a 32% decline in working hours for people between the ages of 20 and 65 and a 15% decline in employment. The decline in employment was mainly concentrated among people with public-facing jobs in the most heavily affected sector (accommodation and food service) and young people. This negative employment trend is also visible in other parts of the world (Foley, 2020; Pouliakas & Branka, 2020; Bell & Blanchflower, 2020). The pandemic might, however, not affect all groups in the same manner when it comes to unemployment shocks; Unemployment in the EU among young people aged 15-24 has increased significantly (Tamesberger & Bacher, 2020). This increase in youth unemployment rate (YUR) is both visible in EU countries with an initially high YUR (Greece, Spain, Italy) and an initially low YUR (Netherlands, Poland, Slovenia) (Lambovska et al., 2021). Also, according to a report from the OECD (2021), the unemployment rate among young people was significantly higher than the overall unemployment rate at the end of 2020 in most countries. Again, this trend was not limited to a single part of the world. Inanc (2020) observed a steep shift in YUR in the US. The main reasons that youth unemployment might be particularly impacted by the pandemic, is the tendency for this demographic to work in the sectors that are more heavily affected (OECD, 2021; Inanc, 2020), young people more frequently work with a temporary contract (OECD, 2021) and most of their jobs cannot be done from home (Inanc, 2020).

But why is the rise in youth unemployment a problem? The disproportionate effect of pandemic policies on unemployment among young people could have more permanent and long-term consequences if political responses are too hesitant (Tamesberger & Bacher, 2020). Personal consequences of early unemployment can be in terms of future reduced earning, labour force participation in later life and long-term health and social consequences (Arulampalam, 2001; Gregg 2001; Schwandt & van Wachter, 2020). Arulampalam (2001) found that an unemployment spell early in life causes the most damage, and could lead to an income loss of up to 6% on re-entry in Britain. Similarly, De Fraja et al., (2017) also found such a wage penalty and reported a loss of income of up to 2% when unemployed for one month between the ages of 18 and 20. In terms of labour force participation, Gregg (2001) found that depending on certain background characteristics, an extra three months of youth unemployment (before the age of 23) leads to an additional 1.3 months out of work between the ages of 28 and 33 years. Schwandt & van Wachter (2020) emphasise that these 'scars' could be something long-term and add possible health and social consequences like lower self-esteem and higher obesity rates. Next to these personal consequences, high unemployment rates among young people also bring costs from a broader economic perspective. Eurofound (2015) (the European Foundation for the Improvement of Living and Working Conditions) calculated that in 2013, the total costs of young people not engaged in the labour market was about 163 billion Euros, which is an increase of about 9 billion compared to the 2012 estimate.

Youth unemployment is therefore a problem stretching from the macro to the micro levels. With the clearly observed rise of YUR in the pandemic, it is necessary to apply policies to limit its further rise. The coronavirus outbreak demands policy measures to ensure hospitals do not overflow and keep infections in check. Careful deliberation between necessary health benefits and the rising YUR requires a more holistic view of pandemic policy impacts. Hence, this thesis will be focussing on estimating the effects of non-pharmaceutical interventions (NPIs) on YUR to balance the knowledge about the impact of NPIs on a number of infections and R value. This will allow policy makers to 1) more deliberately and carefully pick and choose NPIs with more knowledge of the possible negative collateral effects and 2) implement additional policies to counteract these negative collateral effects. To limit the scope of the research somewhat, the focus of this study will be on European countries.

The research question for this thesis therefore is formulated as follows:

How do individual non-pharmaceutical interventions (NPI) affect the unemployment rate among people between the ages of 15-24 in European countries?

In order to answer this question, the main research question is divided into 4 sub-questions;

1) How are the main concepts (youth unemployment, non-pharmaceutical interventions) defined?

The exact dimensions and definitions of the main concepts must first be clarified in order to properly interpret the results of the quantitative study.

2) How and why is YUR affected by NPIs?

The effects and consequences of NPIs on youth unemployment must be critically assessed (as mentioned above). These can be used to formulate hypotheses for the results.

3) What are the determinants of youth unemployment and how can it be modelled?

When predicting YUR, the independent variables that shape this concept should be investigated and defined. This will help to define how NPIs might affect YUR.

4) How can NPIs be related to youth unemployment from a modelling perspective?

Assessing the ways in which NPIs impact and influence these defined determinants in the previous question is crucial to be able to investigate the effects of NPIs on youth unemployment.

2. Literature Review

In this section, the first two sub-questions (i.e., *How are the main concepts -youth unemployment, non-pharmaceutical interventions- defined?* and *How and why is YUR affected by NPIs?*) formulated in Chapter 1 will be addressed. Because of the rapidly expanding literature surrounding the relation between NPIs and their economic costs, this section will display a brief overview of some of the relevant literature in this relatively new research stream. The goal of this overview is to explore and understand how NPIs might influence different economic measures (the labour market in particular) and how these influences might vary for different groups of people.

2.1 Pandemic Policy And General Economic Consequences

A commonly measured economic factor in relation to the implementation of NPIs are production-related metrics such as GDP and value-added. The ways in which NPIs can affect these economic metrics can vary. Huang et al. (2020) and Zhang et al. (2020) considered the reduction of mobility as the consequence of pandemic policy to estimate the effects on production. Both studies use the correlation between mobility and economic performance as a bridge between NPI and economic impact. Other studies point out that the disruption of global supply chains as a consequence of NPIs has a large effect on economic measures such as GDP, which is not restricted to the countries that implement such policy measures (Guan et al., 2020; Inoue & Todo, 2020). König & Winkler (2021) found that the strategy with which NPIs, or bundles of NPIs, are implemented (suppression vs mitigation) have a significant effect on economic factors like GDP. Therefore, some examples of how NPIs might affect more general economical metrics is through a reduction in mobility, disruption of supply chains and NPI implementation strategy. Within the context of this thesis, the ways in which NPIs can disrupt labour markets is of particular interest.

2.2 Pandemic Policy And Labour Market Consequences

The fact that NPIs have an effect on overall employment rates is not surprising. However, the exact nature of this relationship is worth examining more in-depth. First, closing of businesses naturally has a negative effect on employment which is, however, often damped by policy measures that counter this effect, such as the NOW (Noodmaatregel Overbrugging Werkgelegenheid) in the Netherlands. Another factor that plays a role is the redistribution of customers due to pandemic policy. Goolsbee & Syverson (2021) find that the social distancing policy is not responsible for the whole unemployment shock, but has had a significant effect in reallocating customers from ‘non-essential’ to ‘essential’ businesses and from restaurants and bars towards grocery stores and other food sellers. Goolsbee & Syverson (2021) used mobile phone usage in points of interest to look for changes in mobility and customer behaviour in the US during March, April and May of 2020. Similarly, Forsythe et al., (2021) found that the employment shock is not entirely caused by NPIs like stay-at-home orders. They also observed that ‘essential’ retail took a much smaller hit, whilst ‘non-essential’ retail and leisure and hospitality services took the biggest hit in the US. Bodenstein et al., (2022) similarly made use of mobility data to look for the effects of social distancing on employment. Their findings suggest that, next to the reallocation of customers to other sectors, the ability of workers to work from home is an important factor in policy impact on employment. Both the reallocation of customers and the ‘tele-workability’ of workers seem like mechanisms through which NPIs can affect the labour market. However, in a more general sense, a change (both in terms of frequency and intention) in mobility also seems to be a contributing factor in unemployment rate changes.

Understanding the mechanisms through which pandemic policy influences employment is useful to be able to counter it. However, the demographic of the people affected by this is still overlooked. It would be wrong to assume that pandemic policy affects the population homogeneously. The initial distribution of workers plays an important role in the heterogeneous way the consequences of NPI policies are felt (Reichelt et al., 2021; Fairlie et al., 2020). Reichelt et al., (2021) found a difference in the impact between men and women, while Fairlie et al., (2020) found a similar discrepancy among different ethnicities in the US. Additionally, Gupta et al., (2020) found that about 60% of the employment shock in the US was due to social distancing policies and that this unemployment shock was indeed not felt homogeneously among the population. Workers in 'non-essential' industries, especially lesser-educated workers in these industries and younger workers were hit hardest. That workers in 'non-essential' industries are hit harder is not surprising, as policy was concentrated among these industries. However, Gupta et al., (2020) explicitly voice and raise concerns for the possible long-term consequences of the finding that younger workers suffer more severe consequences.

2.3 Pandemic Policy And Youth Unemployment Rate Consequences

Papers that research the impact of pandemic policy measures on youth unemployment rate in particular are not frequent. An example of a paper that specifically looks at youth unemployment in the pandemic context is a paper by Churchill (2021). This author researched the impact of social distancing and lockdown on the youth unemployment rate in Australia, specifically the differences between males and females. In agreement with earlier discussed papers, Churchill (2021) found that young people were hit harder compared to older people. Additionally, he found that young women were exposed to more economic fallout compared to young men. Again, Churchill (2021) points to the pre-pandemic distribution of workers, explaining that young women are over-represented in the hardest hit industries like accommodation, food and recreation services. Another paper that looked at YUR in direct relation to COVID-19 policies is a study by Lambovska et al., (2021). Similarly to the research question for this thesis, their analysis was centred within Europe. Lambovska et al., (2021) found that YUR was significantly higher in European countries as a consequence of pandemic policies to stop the spread of the disease. Additionally, they found that the effects of pandemic policy significantly differ per country. This study, however, only offers a surface data analysis and does not go into detail about possible reasons for the observed effects. Another paper that researches the relation between pandemic policies and youth unemployment rate is by Henehan (2021). She looked at this relationship in the UK and compared the effects of several different demographic groups within youth unemployment. The author finds differences among groups with differing educational backgrounds, ethnicities and gender. However, for the scope of this thesis, Henehan (2021) reiterates the finding in other papers that the portion of 18 to 24-year-olds that worked in the hard-hit sector was nearly twice as large as the share of 25 to 65-year-olds.

The studies mentioned in this section of the thesis relate to the central research question on different levels. Some relate through the fact that they estimate economic effects of specific NPIs. Other papers take a broader perspective and estimate the economic effect of 'social distancing measures' in general. When it comes to economic consequences of a policy in terms of unemployment, studies take the latter perspective. More specifically, the papers that look at YUR during the coronavirus pandemic are rather limited. This thesis aims to both fill the gap that exists when it comes to estimating consequences of more specific policy measures, and the gap in the literature when it comes to knowledge about the short-term effect of this policy on YUR. Furthermore, this thesis takes a European perspective, whilst most other related papers take an American or (even single) country perspective.

2.4 Hypotheses

Pandemic policies yield benefits and incur costs. The benefits are in terms of infection reduction and protection, while this comes with significant economic costs in terms of general output and unemployment. This economic downturn in the labour market proved not to be divided homogeneously among those affected. Several studies conclude that younger workers, those between the ages of 18 and 24, suffer more severe consequences of the pandemic policy than their older peers. Even within this group, the consequences are not divided evenly. Unfortunately, these negative short-term consequences can have great ramifications in the long run. The uneven distribution of the downturn seems to be centred around three main reasons. First, younger workers are often concentrated in industries that are classified as ‘non-essential’ and are thus hardest hit by policies. Second, young people often have jobs that have a low ‘tele-workability’, they cannot do their job from home and thus have a lower level of flexibility in the way they carry out their jobs. Finally, reduction in mobility seems to play a role in the increase of overall unemployment rates. Additionally, mobility historically plays an important role in youth unemployment (Brandtner et al., 2017; Vince et al., 2003).

Based on these findings, some hypotheses can be formulated. These hypotheses are seen as the expected outcomes of the central research question. They are formed based on existing knowledge (e.g., the papers that have been described in this section). Hypotheses in this thesis are used to link the literature to the results and to interpret and explain these results. We form three hypotheses:

Hypothesis 1: *Non-pharmaceutical interventions that target non-essential industries are highly impactful on YUR.*

Hypothesis 2: *Non-pharmaceutical interventions that stimulate or force people to work from home are highly impactful on YUR.*

Hypothesis 3: *Non-pharmaceutical interventions that reduce population mobility in general have a large effect on YUR.*

3. Method

This section presents an overview of the method that was used to answer the overall research question and the hypotheses. First, we explain the sources of the data and the way in which the data has been processed. Second, we present the concepts of Okun’s law and Okun’s coefficient and the accompanying formulas. Third, we describe the way the dataset will be used to calculate results. Finally, we defend the main assumption in this method.

3.1 Data

The final dataset that is used to answer the research question consists of a combination of three separate datasets. Ideally, the datasets have similar characteristics in terms of frequency and countries taken into account. However, this is often not the case, because not all datasets were available on a monthly (or even more frequent) basis. As an alternative we decided to use quarterly data. This decision has the drawback that there are less data points and the results are therefore less precise. Additionally, some countries had to be omitted due to missing data points.

The first data that is collected and used concerns NPIs that have been implemented during the period 2020 -2022 in European countries. The dataset is taken from the site of the European Centre for Disease Prevention and Control (ECDC). It contains information of 30 countries and is reviewed and updated every two weeks. It comprises the start date and end date of NPI implementation per country. The dataset does state some limitations. First, the ECDC warns that the same NPI can differ from country to country in terms of enforcement and specific rules. This means that NPIs that are classified as the same NPI in the dataset can have practical differences. Second, NPIs reported in the dataset are on a national level, while NPIs are often preceded by NPIs on a local level. Also, start dates are taken from official government sources but in practice implementation can be delayed. In order to use this dataset for the purposes of this thesis, the data is transformed to show the number of days a certain NPI is active during a fiscal quarter (a period of 3 months) per country. In order to do this, a python script using the ‘numpy’ and ‘datetime’ modules is written. This script counts the number of days a specific NPI specified in the script is active during a given period (the start and end data of quarters between 2020 and 2021) per country. A selection of certain NPIs is made in order to keep the scope of the research limited. The NPIs that are selected are believed to be the most relevant in testing the hypotheses described in Chapter 2. The output of this script is then put into an excel file.

The second dataset employed is the nominal gross domestic product (GDP) per quarter for European countries taken from Eurostat (Eurostat, 2022). The data ranges from quarter one of 2010 to quarter four of 2022. In order to get real GDP (which is nominal GDP adjusted for inflation), nominal GDP is divided by a GDP deflator, which is available from the same dataset on Eurostat. To more accurately measure the impact of NPIs on the economic situation, the long term real GDP trend is calculated (from 2010 to 2019) and is extrapolated until 2022. The percentage difference between this trend and the actual real GDP for 2020 until 2022 is used in the final dataset, see Figure 3.1 below for a visualised example. The extrapolation of the long term trend line is calculated by adding the average increase (or decrease) per quarter for the last 9 years to quarter four of 2019 onwards. To bridge the gap to youth unemployment, data for the monthly youth unemployment rate is taken from Eurostat. ‘Youth’ is defined as people aged between 15 and 24 and unemployment is expressed as a percentage of the labour force. This dataset ranges from 2000 to 2019.

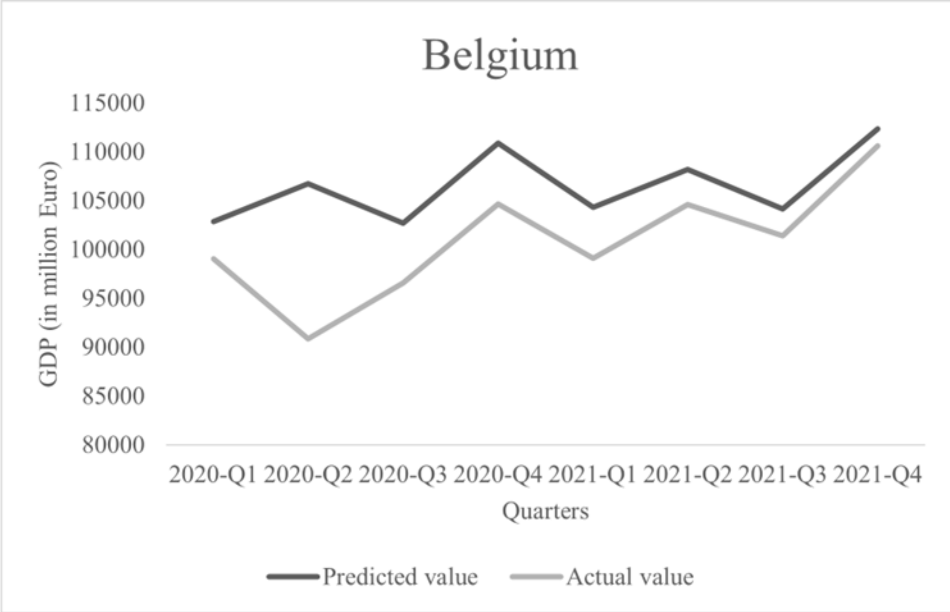

Figure 3.1. Example of the difference between predicted GDP values (long-term extrapolated trend) and the actual values for Belgium.

3.2 Okun's Law

In order to estimate the impact of NPIs on YUR, the principle of Okun's law is used. The relationship between growth rate and unemployment rate is referred to as Okun's law (Okun, 1962). Originally, Okun documented that U.S. unemployment tended to decrease by 1% when GDP increased by 3%. This ratio is referred to as Okun's coefficient. In this original ratio, GDP is connected to the overall unemployment rate exclusively in the U.S. In more recent literature, the value of Okun's coefficient is found to be closer to a two-to-one ratio instead of the earlier proposed three-to-one ratio. The robustness of this ratio has been subject to debate, with several studies questioning the universality of Okun's law (e.g., Gordon, 2011; Meyer and Tasci, 2012). However, in a more recent study, Ball et al. (2017) found that Okun's law describes a strong relationship between unemployment rates and output in most countries, and is found to be quite stable over time. The major deviation from the originally proposed universality of Okun's law is that the coefficient of the relationship differs per country. These differences might be a reflection of varying national labour market characteristics.

In the literature, the papers that administer Okun's coefficient can be divided into papers that employ the original equations suggested by Okun (1962), which uses solely GDP growth as the independent variable, and approaches that include some additional variable(s) on the right side of the equation. These original equations are divided into the difference and gap model. The difference model (3.1) is based on percentage differences between unemployment rate (U) and GDP growth (Y) in a certain time period (t). In this equation, β is denoted as Okun's coefficient.

$$\Delta U_t = \alpha + \beta \Delta Y_t + \varepsilon_t. \tag{3.1}$$

The other equation proposed by Okun (1962) is the so-called gap version. The name refers to the nature of this equation. Unlike the difference equation (3.1), the gap equation (equation 3.2) uses the difference (or gap) between the observed value for unemployment rate (U_t) and the long-term trend (or potential) unemployment rate (U_t^*) as the dependent variable and the difference between the natural log of real GDP (Y_t) and the natural log of potential real GDP (Y_t^*) as an independent variable. For the GDP rate this is called the output gap, whilst for unemployment this is called the unemployment gap. The idea behind the gap version is that when actual GDP exceeds its potential, it creates an overall downward trend in the unemployment gap (or the inverse):

$$U_t - U_t^* = \alpha + \beta_t(Y_t - Y_t^*) + \varepsilon_t. \quad (3.2)$$

In this study, the approach used will be a variation of the gap model originally proposed by Okun (1962). The reason for using a variation of the gap version is the fact that the GDP impact of NPIs is derived in a similar manner (difference between long-term trend and actual observations). Therefore, the gap approach fits the methodology better than the difference version. The variation used in this thesis is referred to as an autoregressive distributed lag model (ADL) and includes (max) 2 additional time lags for the dependent and the independent variables as used in Obst (2022). The formula reads

$$\begin{aligned} U_t - U_t^* = \alpha &+ \beta_0(Y_t - Y_t^*) + \beta_1(Y_{t-1} - Y_{t-1}^*) + \beta_2(Y_{t-2} - Y_{t-2}^*) \\ &+ \delta_1(U_{t-1} - U_{t-1}^*) + \delta_2(U_{t-2} - U_{t-2}^*) + \epsilon_t, \end{aligned} \quad (3.3)$$

where U_t is YUR at time t, Y_t is the natural log of GDP. The variables U_t^* and Y_t^* are the potential versions (long-term trend) of youth unemployment rate (YUR) and real GDP (natural log), respectively. Both the potential YUR and GDP have been estimated with the Hodrick-Prescott (HP) filter (Hodrick & Prescott, 1997). This version allows for a lag between a change in output gap and a reaction in unemployment rate. Including this lag is theoretically plausible, as Okun (1962) pointed out that labour is a quasi-fixed factor. Adjusting employment is costly, so firms are more inclined to deal with short-run output fluctuations by adjusting hours worked per worker or to increase the workers' labour intensity (Ball et al., 2017). Additionally, lagged terms of the dependent variable are included to tackle serial correlation in the model. The presence of serial correlation is tested using the Breusch-Godfrey test (Breusch, 1978; Godfrey, 1987). Because formula (3.3) is a so-called level-log regression, β is divided by 100 to help the interpretation of the coefficient. The final output needed from this model for the purposes of this thesis is Okun's coefficient (OC) (Ψ). In the ADL variant, this is calculated as follows:

$$\Psi = \sum_{i=0}^{n}(\beta_i/100) \ /(1 - \sum_{i=0}^{n}\delta_i). \quad (3.4)$$

3.3 GDP Impact

Because Okun's law is used to bridge the gap between GDP impact and unemployment, a first connection between NPIs and GDP impact must be established. For this, the NPI dataset and the real GDP dataset are combined. As independent variables, we take a selection of NPIs that will help answer the hypotheses formulated in Chapter 2 (more detail is provided later). These variables consist of the number of days an NPI was active in a country during a quarter (between Q2 2020 and Q4 2021, Q1 2020 has been omitted because NPIs were not active during the whole quarter) divided by the number of days in that quarter. As a dependent variable, the difference between potential real GDP and actual real GDP during these quarters per country will be taken. The final dataset will be formed by stacking the different quarters.

Combining all the data points implicitly assumes two things. First, it assumes that the effect of NPIs on GDP is stable over time. It would stand to reason that differences in coronavirus variants do not necessarily change the impact of the same NPI on GDP, but that different NPIs are used. The second assumption is that NPIs impact GDP similarly across the different European countries. The latter assumption has been researched by Konig & Winkler (2021). They distinguished two main NPI strategies, mitigation and elimination. Konig & Winkler (2021) find that a difference in NPIs strategy results in different levels of GDP growth. NPI strategy in this case is referred to as the strength and speed with which countries respond to waves of infections. This finding implies that it is not possible to just assume universal GDP impact, but further investigation is required to underpin this assumption.

3.4 Clustering

Whilst an NPI strategy is found to affect GDP growth, it is necessary to explore if there are significant differences in the data in terms of NPI strategy. In order to test this, we will construct a dataset containing the frequency (number of days) of strict NPIs active per country. The difference to the NPI dataset described earlier is that it includes more NPIs (no partial NPIs or recommendations) and that the days active for each included NPI are summed up. The result is a dataset that shows the density of (strict) NPIs for each country in Q1 2020 until Q4 2021. Konig & Winkler (2021) used the response to waves of infections as strategy. However, due to the fact that the selection of countries in this thesis consists of only European countries the timing of waves of infections is similar for all countries in the sample. Including the frequency and timing of NPIs in the countries is therefore sufficient to estimate the strategy.

In order to determine if the NPI strategies differ significantly, we use the concept of principle component analysis (PCA) (Jolliffe, 2002). PCA is a technique that creates new variables (or components) from existing variables with the objective to reduce the dimensions of the dataset by including as much of the total variance as possible in fewer variables. The PCA processed dataset will include the minimum number of components that cover 80% of the total variance. The dataset with these variable components will be used by a k-means clustering algorithm to determine if there are clusters in the data (Lloyd, 1982). K-means clustering is an unsupervised machine learning algorithm that essentially tries to group similar data points to look for underlying patterns. The number of groups (centroids) that the algorithm will take into account has to be specified beforehand. Therefore, to determine the optimal number of groups, one to twenty centroids will be tried. For each of those we calculate the silhouette score (Rousseeuw, 1987). The silhouette score is a metric that quantifies the quality of the clustering technique and varies between -1 and 1, where -1 means that the clusters are assigned in the wrong way, 0 means that the clusters are indifferent and insignificant and 1 means that clusters are clearly apart from each other. The score is calculated using the intra-cluster distance and the inter-cluster distance. The advantage of using the silhouette score is that it not only tells the best number of centroids to use, but also quantifies the quality of the clustering.

3.5 Calculating YUR Impact

In order to calculate the impact on YUR, answer the research question and test the hypotheses, the NPI dataset described in section *3.3 GDP Impact* is employed. This dataset is extended with the calculated OC (Ψ) using (3.3) and (3.4). The dependent variable, the percentage difference between long-term real GDP trend and actual real GDP for each country is multiplied by its respective Ψ. The resulting dataset is divided depending on the country clusters that are found using PCA and the K-means algorithm. The results for each of the datasets corresponding to the different groups will be calculated applying a non-negative least squares optimization method. The non-negativity of the algorithm is used because it is assumed that NPIs have a negative effect on real GDP and YUR. To facilitate this, the dependent variable is multiplied by -1, meaning that a positive number indicates a negative impact.

4. Results

In this section, we present and discuss the results of (3.3) and (3.4), as well as the results of the clustering. Next, the results concerning the NPI impact on YUR are presented in three figures. Then we will interpret and explain the findings. Finally, we revisit the hypotheses and central research question and discuss the limitations and options for future research.

4.1 Okun's Coefficient

The results in Table 4.1 show the sensitivity of the youth unemployment gap to changes in the output gap per country. First, we notice that OC is negative for all countries. This makes sense and is expected, it stands to reason that an increase in output leads to a decrease in unemployment rate. For most of the countries, the inclusion of a single lag term for the unemployment gap solved the issue of serial correlation in the regression, except for Romania and Slovakia where an extra term was used. Also, most of the R squared values are rather high, with the lowest being 0.311 for Belgium and the highest being 0.935 for Spain. The overall high R squared scores indicate that the regression model explains a substantial proportion of the variability.

The most interesting results are those for OC (Ψ). Table 4.1 shows that Poland seems to have the greatest sensitivity to output gap changes in terms of youth unemployment gap, while Hungary has the lowest. The average OC among all countries is -1.070 but there are clear discrepancies from this median value among countries, indicating a high variability among them. This result confirms that OC is indeed country specific. Comparing these results with the findings from Obst (2022), who calculated OC for the overall unemployment rate, show that YUR seems to be overall much more sensitive to output changes and also less stable between countries as opposed to overall unemployment rates.

During the calculation of OC, some countries did not show a significant (at least on the 10% level) effect of output gap on youth unemployment gap. These countries have been omitted from the analysis. While most countries show a statistically significant relationship at least on the conventional 5% level, some countries show relationships with a p-value of between 0.05 and 0.10. These countries are Belgium, Croatia, Cyprus, Ireland, Slovenia and Sweden. Despite these slightly higher p-values, these countries are still included in the analysis. For the purposes of this exploratory research and its main goal to give an indication of NPI effects on the YUR, a higher error rate (1/10 for 10%, as opposed to a minimum of 1/20 for 5%) is tolerated to facilitate more data points to extract NPI effects.

Country	β_0	β_1	β_2	δ_1	δ_2	R2	OC (Ψ)
Belgium	-72.7013*		-73.7596***	0.1923***		0.311	-1.813
Bulgaria	-41.5608***			0.6434**		0.562	-1.165
Croatia	-20.8250*			0.6647***		0.562	-0.621
Cyprus		-65.4124*	54.1254**	0.5865***		0.576	-0.273
Germany	-11.1594**		8.5673**	0.7863***		0.782	-0.121
Denmark	-23.9900***			0.5709***		0.555	-0.559
Spain	-122.4731***	51.6444**	53.4623***	0.8196***		0.935	-0.963
Finland	-13.2117**	-26.5961***		0.4143***		0.735	-0.680
France	-67.8545***			0.6849***		0.717	-2.153
Greece	-30.4577***		-14.5883***	0.6373***		0.896	-1.242
Hungary		-29.0431**	27.3648**	0.7854***		0.652	-0.078
Ireland		-4.8825*		0.9238***		0.869	-0.640
Italy	-49.3237***			0.6316***		0.654	-1.339
Netherlands	-15.8168**	-15.6676**		0.7622***		0.803	-1.324
Poland	-34.5719**			0.9057***		0.867	-3.666
Portugal	-69.7514***			0.7335***		0.726	-2.617
Romania			-17.4662***	0.6562***	-0.2467**	0.399	-0.296
Slovakia	-25.9190***			1.2241***	-0.4154***	0.894	-1.355
Slovenia	-29.0697*			0.2606***		0.378	-0.393
Sweden	-17.0424*			0.6100***		0.603	-0.437

*Table 4.1. Statistical significance is depicted by ***, ** and * on the 1%, 5% and 10% level, respectively. Results from the regression use formula 3.1 and 3.2 including R squared (R2) value to illustrate regression fit. Data used in the regression concerns real GDP (GDP corrected for inflation) and youth unemployment rate (people aged between 15 and 24) as a percentage of the labour force. Data is quarterly and between Q1 2000 and Q4 2019.*

4.2 NPI Strategy Clustering

In order to detect significant groupings in the data with regards to NPI strategy among the European countries in the dataset, the first step is to run a PCA analysis on the data. For the determination of the amount of principal components to consider for the K-means algorithm, it is useful to look at the explained variance for the generated components. The graph showing the cumulative percentage of explained variance per additional component is presented in Figure 4.1 below. In Chapter 3 of this thesis, the cut-off for the minimum percentage of explained variance was set at eighty percent. According to Figure 4.1, the inclusion of three principal components satisfies these conditions. Therefore, three principle components are used.

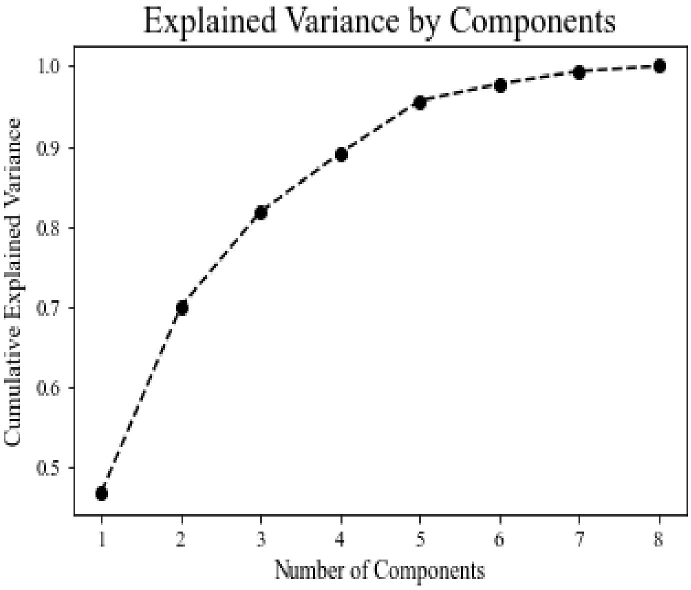

Figure 4.1. Cumulative curve of percentage of explained variance by amount of principal components.

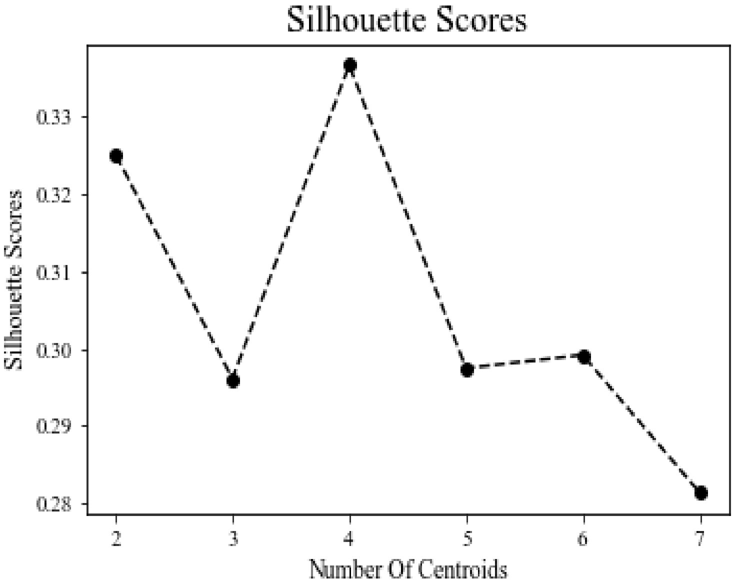

Figure 4.2. Silhouette scores for two to seven centroids.

Using these components, a k-means clustering algorithm is applied. However, one of the parameters of the k-means clustering algorithm is the number of centroids used, hence these have to be specified beforehand. In order to do this, the silhouette scores for two to seven centroids are calculated and shown in Figure 4.2. The silhouette score for 4 centroids is the highest with a score of 0.34. Therefore, splitting the data into 4 subgroups would result in the best distinguished groups both in terms of intra group closeness and inter group distance. However, a silhouette score of 0.34 does not provide much evidence that these groups are significantly different from each other. It is thus not clear if this data can be grouped sufficiently. In order to get a more detailed view, these groupings are plotted in Figures 4.3. In this figure, the first two principal components are plotted (just the first two are included for visualisation purposes). The different colours represent different group labels.

For more detail, Figure 4.3 offers some additional insight. This figure plots the first two principal components with a colour label for each group. It is useful to look at the plots and judge them on the same terms as the silhouette scores, intra-group closeness and inter-group distance. In terms of intra-group closeness, the red (3) and green (2) group display the longest distance inside the group itself. For the red group this is more generally applicable to all points as opposed to the green group. In the latter group there seem to be one or two outliers while the other points can be seen as much closer together. However, the most likely explanation for the lower silhouette score is the overall short inter-group distance. Overall, all the points are rather close together. There is even a slight overlap between blue (0) and green. The red and blue group do not overlap, although they are also rather close together. The only group that is visibly and collectively distant from the others is the orange (1) group. In conclusion, the visualisation of the data supports the suspicion indicated by the silhouette scores.

In the context of the European countries in the sample, this conclusion is not surprising according to Konig & Winkler (2021). They formulated some characteristics that play a role in the chosen NPI strategy. According to their research, island countries or countries that have not more than two bordering neighbours are much more likely to implement a stricter NPI strategy. Also, reliance on trade openness (sum of imports and exports divided by GDP in 2018) seems to have a negative effect on implementing a strict elimination NPI strategy. In the country sample used in this thesis, these variables do not differ significantly. This further supports the finding that there do not seem to be any significant groupings in terms of NPI strategy in the dataset. This results in the assumption that the same NPI affects GDP similarly in all countries in the sample, a finding that is hence retained in the analytical method for this thesis.

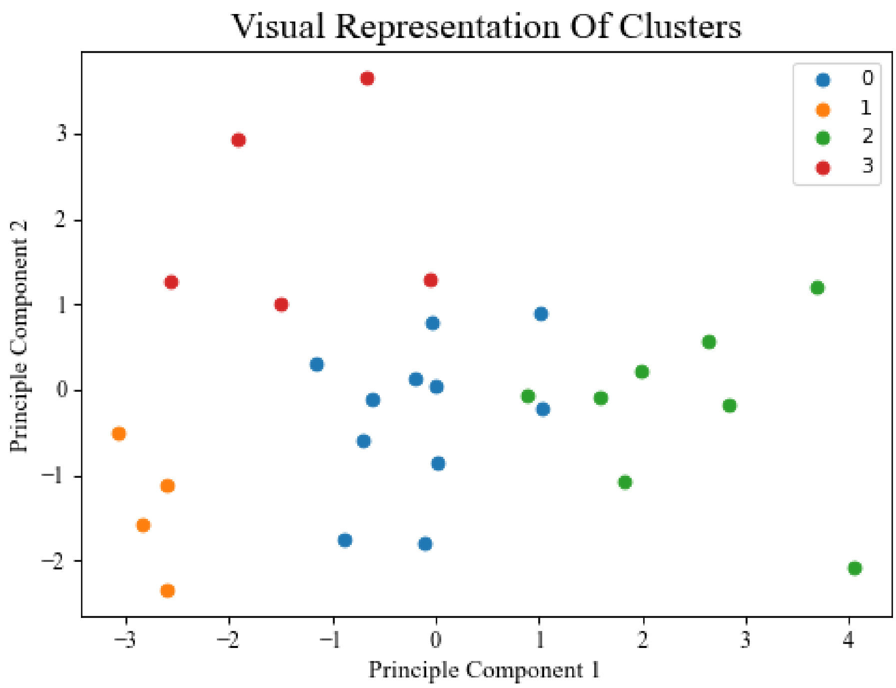

Figure 4.3. First two principal components plotted with a colour label.

4.3 Youth Unemployment Results

In this part of Chapter 4, the previous results are combined and the main results concerning youth unemployment rate are presented. A selection of NPI has been made out of the original dataset. The reason for the selection of the NPI in the analysis is that these NPIs provide a good overview to test the hypotheses formulated in Chapter 2. Figure 4.5 shows that the least impactful measure relative to the others is the mandatory wearing of masks, which did not have much significance at all. Also at the lower end of the spectrum, the restrictions of private gatherings can be found. The most impactful measures seem to be the closing of educational institutions (day-cares, primary/high schools, universities etc.), the closure of non-essential shops and the restrictions in public transport. The cancellation of mass gatherings and teleworking (working from home) can be classified as moderately impactful measures. When interpreting these results, it must be taken into account that they are relative to each other: They do not mean anything in absolute terms and must be considered in the context they are presented in.

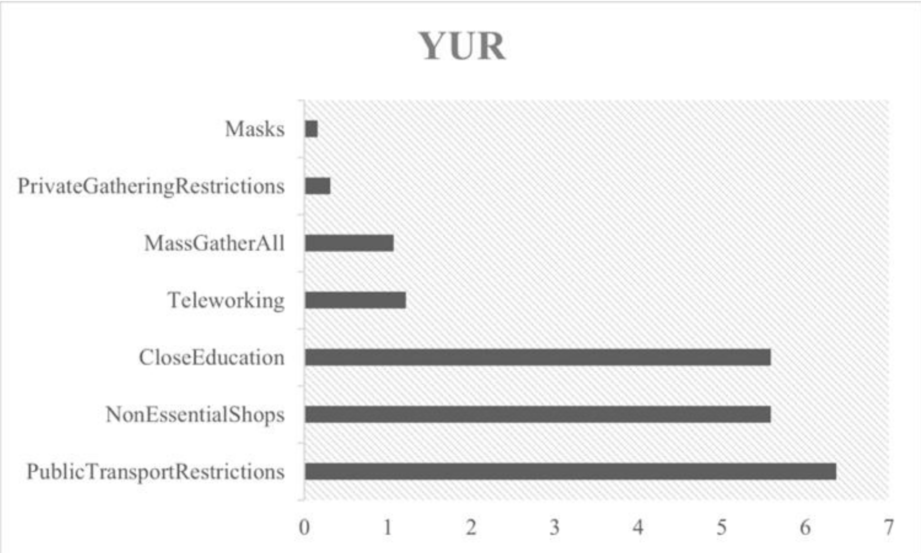

Figure 4.5. Non-negative least squares results ranked from least impactful (top) to most impactful (bottom).

Due to the fact that the results in Figure 4.5 are estimated using GDP data, it is interesting to look at the difference between the GDP impact results and the YUR impact results. Figure 4.6 shows the percentual difference between the contribution of the NPIs towards GDP growth impact and towards YUR changes (e.g., Figure 4.6 illustrates that the contribution of Teleworking towards YUR is significantly bigger than towards GDP growth). Figure 4.6 thus does not tell anything about the absolute size of the contribution, but only something about the percentual change of this contribution.

There are both positive and negative changes for the NPI. The negative changes (GDP impact is higher than on YUR) are the closure of educational institutions, the wearing of masks, the closure of non-essential shops and the cancellation of mass gatherings. The cancellation of mass gatherings and masks show the biggest percentage difference and a closure of educational institutions shows the least. Three NPIs show positive change, teleworking, private gathering restrictions and public transport restrictions. Teleworking and private gathering restrictions have a significantly large effect as both measures more than double. Restrictions for public transport show the least positive change.

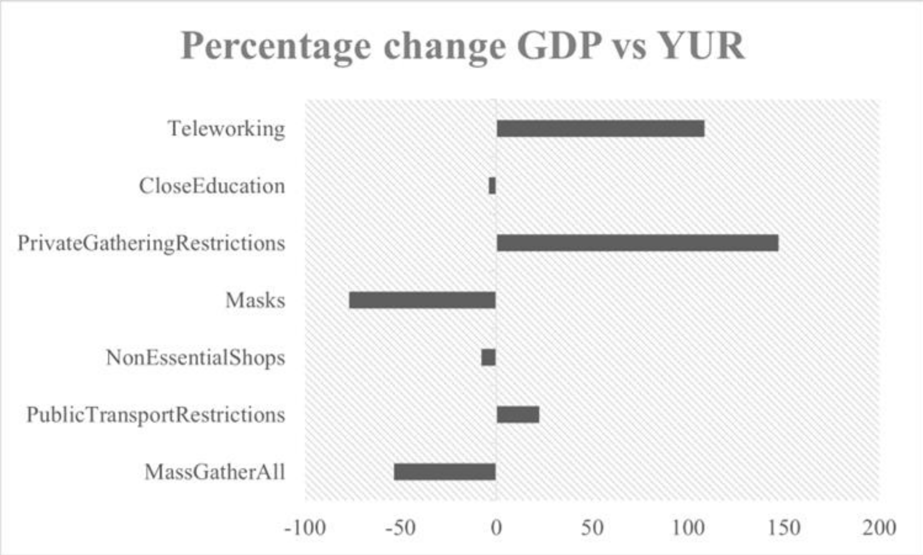

Figure 4.6. Percentual difference between the non-negative least squares results for each NPI for GDP impact and YUR impact.

The goal of estimating the relative impact of these NPIs is to ultimately assist policy makers in balancing maximising medical utility (stopping the spread of a virus) and minimising economic impact (youth unemployment in this case). To visualise this choice based on these results, Figure 4.7 shows a normalised score for the change in the reproduction (R) number for each NPI. This number quantifies the rate at which a disease spreads among the population. These scores are estimated by Haug et al. (2020).

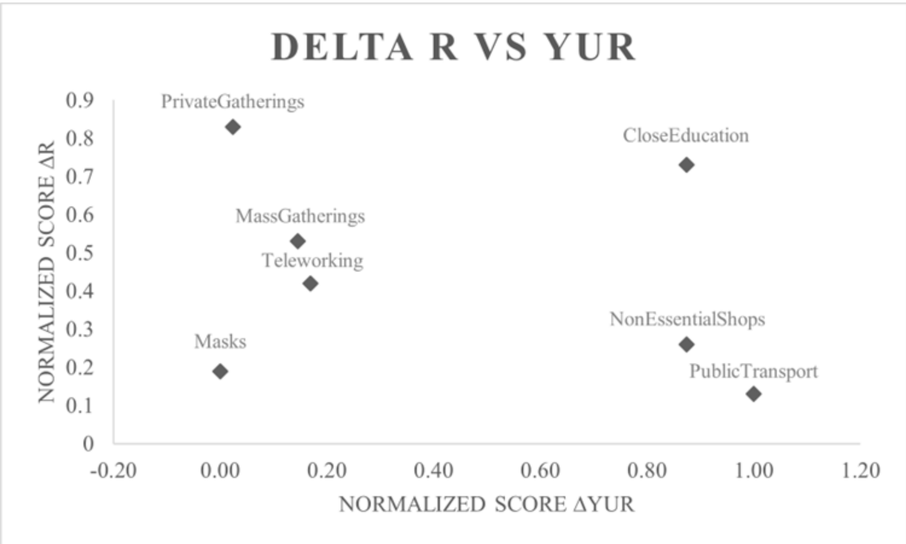

Figure 4.7. Normalised scores for the change in R value (Haug et al., 2020) and YUR.

The definitions of the NPIs for the ECDC dataset (used to estimate YUR impact) and the dataset used by Haug et al., (2020) do not match perfectly. Therefore, the positions of the NPIs in Figure 4.7 should not be interpreted as precise positions but rather as an indication of the relative position. Ideally, an NPI that scores high on the R impact (vertical axis) and low on the YUR impact (horizontal axis) is best from the perspective of a policy maker. This would maximise the reduction of disease spread and minimise the impact on YUR. In Figure 4.7, such NPIs are in the top left corner. Similarly, the NPI in the opposing corner (bottom right) are the worst as their balance is skewed towards YUR impact as opposed to impact on R.

5. Discussion

In this section, we interpret and discuss the results presented in Figures 4.5, 4.6 and 4.7. By doing this, we discuss and answer the main research question. Additionally, we revisit the hypotheses that are proposed in Chapter 2. Finally, we discuss the limitations of this thesis.

5.1 Results Interpretation

When looking at Figure 4.5, a most conspicuous result is that closure of educational institutions shows to have a big impact on youth unemployment rates. However, this result might not be that straightforward. At first sight, a lack of education should logically have a negative effect on the youth. However, one would expect this effect not to be instantaneous (or perceived within the time window of a single fiscal quarter) but rather become visible in the time frame of years. In fact, school closures are shown to have some relatively short-term effects on GDP, mostly due to absenteeism and a loss in productivity of the parents, who will have to take care of their child while working (Lempel et al., 2009). Through the methodology used in this thesis, this naturally gives rise to a high estimated impact on YUR. However, short-term impact on unemployment is more prevalent for people older than 24 (e.g., parents with young children) (Amuedo-Dorantes et al., 2020). Therefore, we believe that the results for the closure of educational institutions (in the short-term) are rather inflated. The effects on youth in the long run are significant, though, and cannot be underestimated (Psacharopoulos, 2020). Additionally, the results from Figure 4.6 show a slight decline in effect on YUR as opposed to GDP. This supports the idea that the impact found in Figure 4.5 is at least partly due to the high impact on GDP, hence the impact on YUR should be less in the time frame for this study.

However, the biggest impact is estimated for public transport restrictions. Public transport is used mostly by young people between the ages of 15-19 (Ganesh et al., 2018). Moreover, Brandtner et al., (2019), find that public transport plays an important role in youth unemployment rates, especially in car-independent cities. Similarly, transport was found to be the most significant barrier for young people accessing employment and training opportunities in rural areas (Vince et al., 2003). Although these studies are not directly related to the coronavirus pandemic, it is clear that a link between public transport and youth unemployment is there. When combined with the frequent inability for youth workers to work from home (see related work section), it is not surprising to see public transport restrictions as a highly harming measure. According to Figure 4.6, public transport measures are even more impactful on YUR than they are on overall GDP. The same can be said for teleworking. Although public transport restrictions are about 20% more impactful, teleworking more than doubles. These numbers further indicate that mobility (or a lack thereof) plays an important role in the impact of NPIs on youth unemployment.

Another high impact is estimated for the closure of non-essential shops. The fact that NPIs regarding limitations or closing of non-essential shops impact youth unemployment is not surprising, as many young people work in sectors that are classified as non-essential (Barford et al., 2021). It is surprising, though, that there is a decline from GDP impact percentage to youth unemployment percentage, visible in Figure 4.6. This is, however, a relatively small change, meaning that this NPI has significant impact for both GDP and YUR. NPIs that can be grouped with restrictions on non-essential shops are the cancellation of mass gatherings and private gatherings, as both these NPIs interact mostly with the leisure and service industries (e.g., bars, parties, events). However, the main distinction between the two is that mass gatherings are usually set in a commercial environment, planned and organised by professionals, and private gatherings are less reliant on organisations. The results in Figure 4.5 support this notion, as the limitations on mass gatherings are estimated to impact YUR significantly more than restrictions on private gatherings.

Figure 4.7 shows the findings from Figures 4.5 and 4.6 in a wider perspective. The figure shows a Pareto distributed pattern, with an NPI like private gathering restrictions well balanced and an NPI like public transport restrictions to be non-advisable. A measure that does not fall along the Pareto line is the closure of educational institutions. Its place suggests that it can be seen as a measure that is highly impactful both in terms of stopping the spread of a virus and in terms of economic costs. The term 'economic costs' is used here instead of YUR as it was previously established that the effect on YUR should be delayed and GDP and unemployment for people older than 24 are impacted more directly. On the opposite side of the closure of education is a measure like mandatory wearing of masks, which has a relatively low impact on reproduction number (R) but poses no costs for YUR.

Based on the results in Figure 4.3, policy makers are advised to consider implementing measures that fall into the top-left corner. Focusing on the restriction of private and mass gatherings can help limit the spread of coronavirus while also limiting economic impact. Measures like masks that do help reduce the spread of the virus but pose no significant costs are always advised. When the spreading of the virus cannot be sufficiently halted with these measures, it is advised to start picking measures that fall closer to the bottom-left corner of Figure 3, like enforcing working from home. A measure like the closure of educational institutions should only be considered when the priority on stopping the spreading outweighs that of economic impact. Finally, limiting/eliminating public transport and closing and limiting non-essential shops is not advisable from either perspectives.

5.2 Hypotheses And Research Question Revisited

In Chapter 2 of this thesis, we proposed three hypotheses as to how certain types of NPIs might impact YUR. Now the results have been presented and discussed, these hypotheses can be revisited. Hypothesis 1 was stated as '*Non-pharmaceutical interventions that target non-essential industries are highly impactful on youth unemployment'.* According to the results, this hypothesis is partially accepted. Non-essential shop limitations and closure is found to be highly impactful. However, this hypothesis would suggest that NPIs like mass gathering restrictions are highly impactful too, which is not reflected in the results. Hypothesis 2 (*Non-pharmaceutical interventions that stimulate or force people to work from home are highly impactful on youth unemployment rate)* and hypothesis 3 (*Non-pharmaceutical interventions that reduce population mobility in general have a large effect on youth unemployment rate)* are quite similar in the sense that they both deal with mobility. For Hypothesis 2, teleworking seems not to be highly impactful, but it does show a big increase in percentage contribution compared to GDP. The results suggest, therefore, that teleworking is impactful for YUR, but not as highly as was expected. Hypothesis 3, however, is supported more strongly by the results. A limitation of public transport is the most impactful measure in the NPI taken into account.

In the introduction of this thesis, the central research question reads; '*How do individual non-pharmaceutical interventions (NPIs) affect the unemployment rate for people between the ages of 15-24 in European countries?'.* This question has been regarded from both a quantitative and explanatory perspective, using the hypotheses as a link between both perspectives and provide context to the numerical results. The findings of this thesis show that people who work in non-essential industries, have limited options to work from home and are reliant on public transport, are hit the hardest. Unfortunately, young people tend to be disproportionately hit by the economic downturn of such measures because this demographic is over-represented in jobs that satisfy these conditions. Next to these explanatory findings, the quantitative findings offers additional insight for policy makers as to which measures to consider to limit negative employment effects for young workers.
The results show that the closure of public transport and the limitation of non-essential shops are measures that do not offer much upside in terms of the reduction of the reproduction number, while showing significantly large impacts on the YUR. In contrast, measures that limit private and mass gatherings show promise in limiting negative effects while still significantly helping to stop the

infections. Measures like masks are universally advisable due to their relatively low costs, while the closure of education is a measure that should only be considered in extreme situations.

5.3 Limitations

This research is subject to some limitations, and the results and conclusions of this thesis should be considered with these limitations in mind. First, most of the NPIs were implemented simultaneously with others. This means that it is difficult to isolate the effect on GDP and YUR in the data for each NPI. One way to tackle this issue in future research is to extend the dataset by either adding more countries with similar NPI strategies or by increasing the frequency of the data (quarterly in this thesis). This would logically allow for more variations in NPIs and a better estimation of isolated effects. This ties in with another limitation of this thesis. The extended data needed was not available or easily accessible, meaning that some concessions had to be made, like changing time frequency and omitting data from some countries. Second, the effects that are seen in the data are only relatively short term. In this methodology, there is no way to estimate the effects of the implemented NPIs that stretch beyond one quarter. Ideally, a way to also look at the long-term effects of NPIs would offer a better picture for policy makers of the potential economic costs. Finally, the usage of Okun's law and Okun's coefficient come with inherent limitations, as the concept of Okun's law and Okun's coefficient relies on a linear relation between output and unemployment. Such linear (long-term) relations are naturally subject to insecurities and variability. Therefore, it is important to interpret the results produced by this method with the required variability. It is thus not possible to infer precise impacts of NPIs using this method, but rather indications of the internal relative relations. However, we believe that this method provides valuable information for policy makers when implementing NPIs in the future.

5.4 Future Research

This thesis can be seen as a starting point for estimating and quantifying economic effects of individual NPIs in terms of unemployment rate. The method outlined in this thesis is rather straightforward. It relies on a small number of variables and can be reproduced quickly, given the right data. While this has its drawbacks which have been discussed earlier, it also offers flexibility. The proposed method can, in theory, be used to estimate relatively short-term effects of NPI on a wider collection of unemployment demographics. Next to a regular unemployment rate, variations in age groups, ethnical groups, gender or education level, for example. This would help create a more complete picture of the negative effects of pandemic policy options, and provide policy makers with more context and information to make decisions when it comes to initial implementation and possible countermeasures to dampen these negative effects. Also, the findings in this thesis can be a starting point to research a particular NPI in more detail in terms of YUR. It might be particularly rewarding to further investigate the possible short- and long-term effects of the closure of educational institutions on YUR for different age groups. However, in order to do this, more data on the longer term numbers is necessary.

From a more general standpoint, this thesis is meant to be a part in the broader puzzle involving economic consequences of non-pharmaceutical interventions by governments. The overarching goal is to offer policy makers as much context and as complete a picture of the total consequences as possible, in order to optimise policy decisions when it comes to costs and benefits. Future work should therefore be centred around this goal and aim to contribute to completing the overall picture.

5.5 Conclusion

The conclusion of this thesis is twofold: First, conclusions can be drawn based on the results of this thesis within the scope and perspective of NPI effects on YUR. Second, there is a more general conclusion beyond the central perspective of this thesis. This section, therefore, will target both.

From this thesis, we learned that measures like the closure of non-essential shops and restrictions of public transport do not contribute to a balanced compromise between the reduction of infections and costs in terms of YUR. Additionally, we learned that the closure of educational institutions is a measure that should only be employed in a situation where the priority of the balance is skewed towards the reduction of infections. An NPI that attributes positively to this balance is the cancellations of private gatherings and is thus a prime candidate to consider as one of the first NPIs to implement. The wearing of masks is an NPI that seems to have zero to no costs in terms of YUR but still has a significant contribution to the reduction of infections and can therefore be considered to be relevant in practically every scenario (when NPIs are deemed necessary in the first place). From these results, we learned that there are optimal solutions when it comes to the balancing of medical pros and economical cons when implementing NPIs. The word ‘optimal’ is hereby subject to the perspective and the desires of the policy makers. We learned that research towards additional economical drawbacks of NPIs can assist policy makers navigating such a balance through implementing sets of NPIs.

The primary function of this thesis was to act as an initial step into offering policy makers a more holistic view of the pros and cons of implementing NPIs. Therefore we believe that the conclusion of this thesis should reflect this overarching goal and offer a more general lesson. The results show that NPIs differ in severity in both their benefits and costs. However, these two are not always balanced. Relatively small benefits compared to costs makes an NPI harder to implement, while the opposite makes the NPI more generally applicable. We believe that this thesis shows that research into the costs of NPIs can be immensely helpful in giving policy makers a more complete picture of the costs and benefits of NPIs and aid in their decision making. Therefore, we conclude that complementary research with the goal to add new cost perspectives further completes the picture and will be crucial in assisting policy makers to 1) make better informed decisions when implementing NPIs and 2) anticipate the consequences of these NPIs.

Summary

In order to slow down the spread of the coronavirus, European governments have implemented a variety of non-pharmaceutical interventions (NPIs). Next to these intended consequences of NPIs, pandemic policy also causes psychological and economic fallout. Some of the psychological negative effects include psychological distress, anxiety and low wellbeing (Every-Palmer et al., 2020). Such negative psychological consequences are also expected to continue even after the outbreak (Sood, 2020). Economic fallout includes a decrease in overall economic output as can be measured by gross domestic product (GDP). However, the economic fallout of NPIs reaches further than just overall GDP. An example of this is the labour market, or more specifically, the unemployment rate. However, the increase in unemployment rate is not divided homogeneously among the population. A group that is affected adversely are younger people, as unemployment in the EU among young people aged 15-24 has increased significantly (Tamesberger & Bacher, 2020). But why is the rise in youth unemployment a problem? The disproportionate effect of pandemic policies on the unemployment among young people could have more permanent and long-term consequences if political responses are too hesitant (Tamesberger & Bacher, 2020). These long-term consequences can be both in personal and broader economic terms. Keeping the rise of youth unemployment to a minimum while also stopping the spread of the virus to limit pressure on hospitals, requires a more holistic view of NPIs and their consequences. This will allow policy makers to 1) more deliberately and carefully pick and choose NPIs with more knowledge of the possible negative collateral effects and 2) implement additional policies to counteract these negative collateral effects. Therefore, the central research question of this thesis is formulated as follows:

How do individual non-pharmaceutical interventions (NPI) affect the unemployment rate for people between the ages of 15-24 in European countries?

It is clear that pandemic policy has both benefits and costs. The benefits are in terms of infection reduction and protection, while this comes with significant economic costs in terms of general output and unemployment. This economic downturn in the labour market is shown to not be divided homogeneously among those affected. Several studies conclude that younger workers, those between the ages of 18 and 24, suffer more severe consequences of the pandemic policy than their older peers (Churchill, 2021; Henehan, 2021; Gupta et al., 2020). Even within this group, the consequences are not divided evenly. Unfortunately, these negative short-term consequences can have great ramifications in the longer term. The uneven distribution of the downturn seems to be centred around three main reasons. First, younger workers are often concentrated in industries that are classified as 'non-essential' and are thus hardest hit by policy. Second, young people often have jobs with a low 'tele workability', they cannot do their job from home and thus have a lower level of flexibility in the way they carry out their jobs. Lastly, reduction in mobility seems to play a role in the increase of overall unemployment rates. Additionally, mobility historically plays an important role in youth unemployment (Brandtner et al., 2017; Vince et al, 2003). Based on these findings, some hypotheses can be formulated:

Hypothesis 1: *Non-pharmaceutical interventions that target non-essential industries are highly impactful on youth unemployment rate.*

Hypothesis 2: *Non-pharmaceutical interventions that stimulate or force people to work from home are highly impactful on youth unemployment rate.*

Hypothesis 3: *Non-pharmaceutical interventions that reduce population mobility in general have a large effect on youth unemployment rate.*

In order to test these hypotheses, datasets from a combination of sources will be used. First, data concerning the frequency of implementation of a NPI from 2020 to 2022 in European countries. The dataset consists of the start and end date of NPI implementation per country. The data points are converted to the amount of days a NPI is active during a quarter. A selection is made of the NPIs in the dataset to keep the scope limited. The NPIs that are selected are believed to be the most helpful in testing the hypotheses. The second dataset that is used is the nominal gross domestic product (GDP) per quarter for European countries. The data ranges from quarter one of 2010 to quarter four of 2022. In order to get real GDP (which is nominal GDP adjusted for inflation), nominal GDP is divided by a GDP deflator, which is available from the same dataset on Eurostat. To more accurately measure the impact of NPIs on economic impact, the long term real GDP trend is calculated (from 2010 to 2019) and is extrapolated until 2022. The percentage difference between this trend and the actual real GDP for 2020 until 2022 is used in the final dataset. The extrapolation of the long-term trend line is calculated by adding the average increase (or decrease) per quarter for the last 9 years to quarter four of 2019 onwards. To bridge the gap to youth unemployment, data for the monthly youth unemployment rate is taken from Eurostat. 'Youth' is defined as people aged between 15 and 24 and unemployment is expressed as a percentage of the labour force. This dataset ranges from 2000 to 2019.

In order to estimate the impact of NPIs on the YUR, the principle of Okun's law is applied. The relationship between GDP growth rate and unemployment rate is referred to as Okun's law (Okun, 1962). Okun originally proposed two variations of Okun's law. One is based on the percentual differences between unemployment rate and GDP growth and is called the difference version. The other variation uses the difference between the observed value for the unemployment rate and the long-term trend (or potential) unemployment rate and the difference between the natural log of real GDP and potential real GDP. This variant is referred to as the gap version. In this thesis, the approach used will be a variation of the gap model originally proposed by Okun (1962). The reason for doing so, is because the GDP impact of NPIs is derived in a similar manner (difference between long-term trend and actual). Therefore, the gap approach fits the methodology better than the difference version. The variation employed in this thesis is referred to as an autoregressive distributed lag model (ADL) and includes (max) 2 additional time lags for the dependent and the independent variables as employed in Obst (2022). The final output needed from this model for the purposes of this thesis is Okun's coefficient (Ψ), which will be applied to calculate the results.

The ADL model is used to bridge the gap between Economic impact (in terms of GDP growth rate changes) and youth unemployment rate. However, in order to answer the central research question, a bridge between NPIs and GDP growth rate is required. For this, the NPI dataset and the real GDP dataset are combined. As independent variables, a selection of NPIs is made that will help answer the hypotheses. These variables consist of the amount of days a NPI was active in a country during a quarter divided by the amount of days in that quarter. As a dependent variable, the difference between potential real GDP and actual real GDP during these quarters per country will be taken. The final dataset will be formed by stacking the different quarters. To include the youth unemployment factor, the dependent variables are multiplied by their respective Ψ. The results are calculated using a non-negative least squares optimization method. The non-negativity of the algorithm is applied because it is assumed that NPIs have a negative effect on real GDP and YUR.

According to the results, the least impactful measure relative to the others is the mandatory wearing of masks, which did not have much significance at all. Also at the lower end of the spectrum, the restrictions of private gatherings can be found. The most impactful measures seem to be the closing of educational institutions (daycares, primary/high schools, universities etc.), the closure of non-essential shops and the restrictions in public transport. The cancellation of mass gatherings and teleworking (working from home) can be classified as moderately impactful measures. When interpreting these results, it must be taken into account that these results are relative to each other, in the sense that they do not mean anything in absolute terms and must be considered in the context they are presented in. When looking at the difference between impact on GDP growth and YUR, restrictions on private gatherings and teleworking are found to be most highly different compared to the other NPIs. This means that these NPIs have significantly more impact on the YUR than on GDP growth. In order to place these results into context and answer the research question, normalised scores for the impact of these NPI on the reproduction (R) number (taken from Haug et al., 2020) are compared with normalised scores for youth unemployment. For a policy maker, an NPI that scores high on the delta R axis and low on the youth unemployment axis would be ideal. An NPI that is closest to this is the restrictions of private gatherings, while the restrictions of non-essential shops and public transport are shown as the least ideal. Other opposites are masks and the closure of educational institutions. Masks show little to no impact on youth unemployment while still showing some impact on R, whereas closure of educational institutions show both a high impact on YUR and on R value.

After calculating these results, it is possible to revisit the earlier defined hypotheses and the central research question. Based on the results, the first hypothesis is partially accepted. Non-essential shop limitations and closure is found to be highly impactful. However, this hypothesis would suggest that NPIs like mass gathering restrictions are highly impactful too, which is not reflected in the results. For Hypothesis 2, teleworking seems to not be highly impactful, but it does show a big increase in percentage contribution compared to GDP. The results suggest, therefore, that teleworking is impactful for YUR, but not as high as expected. Hypothesis 3, however, is supported more strongly by the results. A limitation of public transport is the most impactful measure in the NPI taken into account. The overall central research question has been regarded from both a quantitative and explanatory perspective, using the hypotheses as a link between both perspectives and provide context to the numerical results. The findings of this thesis show that persons who work in non-essential industries, have limited options to work from home and are dependent on public transport, are hit hardest. Unfortunately, young people tend to be disproportionately affected by the economic downturn of such measures because this demographic is over-represented in jobs that satisfy these conditions. Next to these explanatory findings, the quantitative finding offers additional insight to policy makers as to what measure to consider to limit negative employment effects for young workers.

In terms of policy recommendations, the results show that the closure of public transport and the limitation of non-essential shops are measures that do not offer much benefit in terms of the reduction of the reproduction number, while showing significantly large impacts on youth unemployment rate and are thus not advisable. In contrast, measures that limit private and mass gatherings show promise in limiting negative effects while still significantly helping to stop the infections. Measures like masks are universally advisable due to their relatively low costs, while the closure of education is a measure that should only be considered in extreme situations.

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