A bridge between sentiment indicators: What does Google Trends tell us about COVID-19 pandemic and employment expectations in the EU new member states?

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ABSTRACT

The sentiment indicators tend to reflect better the social tensions caused by COVID-19 pandemic. In this context, the aim of this paper is to reflect the relationship between employment expectations and tensions related to new coronavirus. The impact of COVID-19 pandemic on employment expectations is assessed using the data collected by Google Trends in Panel Autoregressive Distributed Lag (panel ARDL) models and Bayesian multilevel model. The results indicated that COVID-19 searched on Google had a negative impact on employment expectations in the EU New Member States on the period March 2020-May 2021. The unemployment and inflation rate had also a negative effect, while improvement in economic sentiment indicator has increased the employment expectations. These results are the support of economic policies to reduce labour market tensions and improve employment expectations.

1. Introduction

The global COVID-19 pandemic became an event of exceptional impact to the society and economy. To save the citizen's health and lives, countries worldwide make drastic political decisions which significantly shook the global economy and changed social reality. According to Laing (2020), the impact of Covid-19 on the world can only be matched by the Great Depression.

One of the main challenges of COVID-19 pandemic is the connection between labour market and digital transformation. New social restrictions affected labour market, changing employment expectations and intensifying the society digitalization as a solution for solving the tensions on labour market. Therefore, we will present the way in which COVID-19 epidemic affects employment expectations conditioned by digital transformation.

Beland et al. (2020) showed that there are more channels through which COVID-19 affects employment and consequently, the employment expectations. The first channel is represented by the deterioration of human capital. The labour supply is negatively affected because of the health state of infected people. Friends and other relatives of these people might be affected (Currie and Madrian, 1999). In this context, the reduction of labour supply because of the ill people decreases the

employment expectations.

The pandemic accelerated uncertainty and social tension which influenced the consumer behaviour. Baker et al. (2020) proved that overall spending decreased, but the consumption in few sectors increased: food, retail, credit card spending. On the other hand, consumer sentiment decreased during the pandemic (Curtin, 2020). The deterioration of consumer sentiment might be a cause of the deterioration of employment expectations.

The social distance requirements to customers and other workers reduced activity in some sectors. Baker et al. (2020) suggested that some occupations are riskier than other ones. In this situation, higher wages could be paid to people having these risky occupations, while other people might be forced or might wish to stop working or work less (Garen, 1988). These two tendencies could reduce the employment expectations and intensify the risk of social exclusion.

On the other hand, more people worked home during the epidemic compared to pre-COVID-19 period. The employees in health system had to work more. From this point of view, the employment expectations grew in health sector and those sectors that required working at home. The digital skills were more and more required during the pandemic and people with these competences found easier a job. On the other hand, people without digital skills or with low level of these skills hurried to

give up to their jobs or to retire faster.

Digital transformation is one of the EU targets during and after the COVID-19 pandemic together with green economy. The employment expectations in the sectors implying digital competences will increase. In the context of accelerating the economy digitalization during the COVID-19 epidemic, online services, but also the promotion and sale of goods through online networks have increased. According to Microsoft, the number of people using the company's software for online collaboration has increased by about 40% in just one week (UNCTAD, 2020).

The digital challenges brought by pandemic could connect with labour market also through Internet searches for jobs or for epidemic evolution to anticipate employment expectations. In this framework, we propose a novel approach by connecting Internet searches related to COVID-19 to a sentiment indicator provided by official data sources at macroeconomic level. Actually, the main aim of this paper is to explain the employment expectations based on people searches on Google related to COVID-19. This approach could help us in provide better and real time forecasts of employment expectations as a state of the labour market in the EU New Member States (NMS). The tool used to collect that related to Internet searches on Google for keyword *COVID-19* is Google Trends. It allows us to compute indexes for these searches in the NMS.

We assume the hypothesis that COVID-19 searches on Google as a sentiment indicator of population based on microdata had a negative influence on employment expectations as an official sentiment indicator based on managers' opinions. Under this hypothesis, the paper is structured as follows: after an overview of current studies related to the impact of pandemic on socio-economic changes and labour market in particular, we describe the methodology and present empirical findings of the research. The paper ends with theoretical insights about role of social behaviour to economics.

2. The overview of current studies related to the impact of pandemic to socio-economic changes

The COVID-19 pandemic has negatively impacted various areas of society's structure and life, such as democracy, human rights, education, gender equality, jobs and income (Alon et al., 2020; Mahler et al., 2020; Sumner et al., 2020; Reisch et al., 2020). Due to special constraints on people's mobility being massively introduced, the balance between the supply and demand of many products and services has changed. The production was being decreased in most cases while a lot of businesses have stopped. The related layoffs decreased the possibilities for employment and increased poverty (Barua, 2020; McKibbin and Vines, 2020; Forsythe et al., 2020; Coibion et al., 2020).

In general, the shake-ups created by the pandemic have influenced a turn from globalization to deglobalization (Tokic, 2020; Mckibbin and Roshen, 2020). Changes are observed not only in trade but also finance and currency markets in both global and local regions (e. g. Czech, 2020). Most countries change their behaviour in markets seeking to reduce their dependency on foreign partners (Baldwin and Tomiura, 2020). Moreover, due to near-global quarantine, the intensiveness of economic activity has decreased which endangered the countries' financial stability (Boot et al., 2020; Mckibbin and Roshen, 2020). On the other hand, it becomes obvious that no single country can be a separate island in the system of global economy. All countries remain closely connected with each other (McKibbin and Roshen, 2020). Sweden's example has shown that even when business and social mobility constraint policies differ in model from the rest of the world are applied, the negative socio-economic consequences cannot be avoided. As research by Juranek et al. (2020) in Scandinavian countries found out, the situation has worsened to the same degree in Sweden as in neighbouring countries, only with a delay of 2 to 3 weeks.

The evaluation of pandemic's economic impact is very important for policy-makers (Scott et al., 2020). However, the unprecedented situation introduces high uncertainty. Governments find it difficult to form

an appropriate macroeconomic policy response to the circumstances faced with because the social impact of the disease is still difficult to foresee (Mckibbin and Roshen, 2020). Meanwhile, forecasting requires at least minimal stability of the situation. It is illustrated by the current statistics which is different from the economic forecasts published during the early period of Covid-19 (e. g. Ng, 2020). Today more than ever can it be ascertained that citizens' health has direct impact on the countries' economic welfare (Mckibbin and Roshen, 2020; Lin, Meissner, 2020). However, this connection is ambiguous. Strict policy of disease control is saving lives but at the same time directly influences economic decline (Eichenbaum et al., 2020). What is more, the effect of long-term quarantine may cause a hysteresis of economic consequences, e. g. destruction of supply chains which would cause a massive deceleration of the global economy (Eichenbaum et al, 2020). According to International Monetary Fund (IMF 2020a), the global economy may shrink by 3 percent, which is more than the economic recession observed during the global financial crisis of 2008-2009. Economic recession may put millions of people in long-term poverty (Suryahadi et al., 2020). Small businesses will suffer the most, evidence for which already exists. For example, around 50 percent of workers in the USA work in small business, the majority of which are in retail. By executing the disease control policy, drastic measures were put in place due to which, during the first months of Covid-19, around 43% of the sector's businesses were temporary closed while the employee busyness has decreased by around 40% (Bartik et al., 2020a). Similar tendencies are also observed in Europe and the UK. Countries which implemented a strict „stay-at-home" policy and left employees at home with only a part of their pay also observed an increased number of unemployed people, especially in small businesses and among those with least income (Forsythe et al., 2020) as well as increase in income inequality. This is the main aspect by which Covid-19 crisis differs from the earlier economic crisis, when mostly large-scale production, construction and similar businesses stopped while the most impacted were those with the highest income (Bartik et al., 2020; Campello et al., 2020). Nevertheless, it is difficult to objectively evaluate the situation due to contradicting data. For example, job loss statistics are relatively improved by the fact that a part of employees retired early. Due to this reason, higher number of people quitting their jobs rather than becoming unemployed is observed (Coibion et al., 2020).

As Coibion et al. (2020) explained, the lockdown because of pandemic generated a significant decline in employment and consumer spending. The characteristics of supply and demand changed significantly. To prevent a total economic collapse, many countries worldwide assigned allowances for organizations suffering due to the crisis and people who lost their jobs. Unfortunately, allowances did not ensure the same level of income and caused lesser consumption. With decreased demand, organizations constrained the volume of less-demanded products and services. To prevent collapse, organizations were forced to make business optimization decisions which decreased the number of functions that were no longer needed as well as the employees carrying them out. As a result, part of employees lost their jobs by decision of the employer while the rest quit their jobs due to downtime and decreased income. With businesses stopping, finding a new job and restore income has come difficult or even impossible. On the other hand, due to various constrains to contain Covid-19 remaining and individuals getting better at living with lesser income and decreased needs, a lot of workers lost their motivation to work. This is shown by the statistics of employment supply and demand. For example, in Lithuania, although unemployment grew from 7,9 percent in October, 2019, to 14,9 percent in November, 2020 (Statistics Lithuania, 2020), certain sectors lack employees because the unemployed refuse to work even for an average country's wage (Rakauskė, 2020; Žilionis, 2020).

Evidently, many various upheavals were caused by the pandemic, such as shake-ups in (job) supply, product demand, financial, uncertainty shake-ups etc. (Lin and Meissner, 2020). These resulted in a high uncertainty in communities (Binder, 2020; Bartik et al., 2020; Coibion

et al., 2020; Scott et al., 2020; Bloom et al., 2020) and businesses (e. g. Bloom et al, 2020; Meyer et al., 2020) because there is a lack of critical knowledge which would allow to reasonably evaluate, understand and effectively fight a new situation that is unfamiliar from the past (McKibbin and Roshen, 2020; Chang and Velasco, 2020). Uncertainties will remain after the pandemic because it is unclear whether economic and social disturbances caused by COVID-19 are reversible. It is becoming clear that after evaluating the socio-economic changes in the world caused by the control of Covid-19 outbreak, the conception of sustainability will need an essential rethinking (Nicola et al., 2020).

While rethinking sustainability, the role of human behaviour must be taken into consideration. Both during the pandemic and in the world after Covid-19, the necessity to research and understand specific social behaviour nuances and their connection to economic processes will increase. For example, the research by Fetzer et al. (2020) which examined how economic anxiety about the virus spreads in the society of the United States has ascertained that providing information about the coronavirus strongly influences the participants' understanding of the crisis and possible economic concerns. Proof about the influence of shake-ups on increasing uncertainty, anxiety and stress in the society were also provided by other authors, like Reisch et al. (2020), Hanspal et al. (2020), Bloom et al. (2020). The expectations of individuals and individual groups are formed by the understanding of the situation, morale, and opinions in the society, while the latter influence behaviour. The impact of expectations on decisions were illustrated by examples by scientists from Germany (Buchheim et al., 2020), Japan (Tanaka et al., 2020), USA (Roth and Wohlfart (2020) and other countries. Unfortunately, with the pandemic introducing new revelations, politicians and medics being unable to control the widespread of the disease and scientists having no somewhat accurate forecasts, the society's trust in scientific research staggered. The amount of conspiracy theories and fake news in societies have reached levels unseen from the middle-ages. As Bratianu (2020) notices, "human behaviour bears an inherent component of irrationality, due to which the behaviour should be evaluated as a non-linear phenomenon which is difficult to capture in a mathematical model. That explains why mathematical models that were designed to investigate the development of COVID-19 crisis could not foresee the booming in the number of infected people after the state of emergency".

Another problem that forecasting runs into is sudden and critical changes. Scott et al. (2020) provides the example of United States and highlights that in February of 2020, the level of unemployment in the US was 3.5%, which was the lowest in the last 67 years while after only six weeks, almost ten million Americans applied for unemployment checks. As the author denotes, due to the suddenness of this change, it is difficult to expect that methods based on regression statistical analysis and historic data will provide suitable means of modelling the future.

During this period of massive global socio-economic shakeups, the tendency to exclusively trust quantitative research methods in social sciences is experiencing a shock on its own. Social research and change forecasting methods require being updated with qualitative research methods. As societal research papers published during the pandemic (e. g. Fetzer et al., 2020; van der Wielen and Barrios, 2020) show, some quite modern methods, for example Google Trends, allow to reach balance between quantitative and qualitative research and to ensure a possibility to analyse the tendencies of changes in the society categorically, without generalizing the conclusions but leaving space to sensitively evaluate the society's morale and foresee the perspectives of possible turns in societal behaviour.

Though the pandemic was indeed the point where Google Trends unraveled its full potential, studying the literature that made Google Trends ready for COVID-19 use is essential for the completeness of any future work. Therefore, the use of Google Trends in various studies for nowcasting unemployment rate in the EU NMS is presented taking into account the pre-pandemic period and the COVID-19 epidemic. As a novelty for literature, we predicted employment expectations, a

sentiment indicator, rather than an official statistic (unemployment rate).

Jun et al. (2018) provided a comprehensive research on the implications of Google Trends in what concerns the Big Data use in real life, covering various fields beside economics and business: medicine, health, IT, communication. Our study treats a specific issue in economics: unemployment as a tension on labour market with many social and psychological implications.

First, the relationship between unemployment rate and Google searches related to this issue was the subject of extensive research in developed countries where the Internet penetration is higher compared with CEE countries in the EU. The seminal papers of Askitas and Zimmermann (2009 a) and Askitas and Zimmermann (2009b) nowcasted unemployment rate in Germany during the recent economic crisis based on Internet searches like *job search, most popular search engines in Germany, labour office, unemployment office or agency, unemployment rate, Personnel Consultant* and *short-term work*. Following the German initiative, a lot of papers focused on forecasts for unemployment rate for countries in the Southern Europe: Italy (D'Amuri and Marcucci (2017) and Francesco (2009) consider *offerte di lavoro* (job offers) as the most popular key-word in Italy, while Naccarato et al. (2018) improved Italian unemployment forecasts by combining official data with Internet predictions), France (Fondeur and Karamé (2013) consider *emploi* as the most popular key-word while searching for work), Spain (Vicente et al. (2015) focused on jobs offers to explain unemployment rate: *oferta de empleo, oferta de trabajo*).

Only few studies explained unemployment in CEEs using Internet searches, because the lower Internet penetration might make this tool ineffective in some countries. For example, Simionescu (2020) improved the unemployment rate forecasts in Romanian regions by combining official statistics with Internet data. Like in the case of Simionescu (2020) we will employ a panel data approach in our study, but the cross-sections are represented by countries that joined the EU since 2004 or later. Moreover, beside panel data models, we will employ a Bayesian multilevel model to confirm the robustness of the results based on panel approach. The superiority of Google data in predicting monthly unemployment better than official forecasts was proved by Pavlicek and Kristoufek (2015) for four NMS: Poland, Slovakia, Czech Republic and Hungary for the period 2004-2013. For countries outside the EU the evidence is mixed: for Turkey, Chadwick and Sengül (2015) showed that Google data provided better forecasts related to labour market, while in Ukraine Internet data did not explain unemployment because of low Internet penetration (Oleksandr, 2010).

The COVID-19 pandemic enhanced the digital transformation and the Internet penetration and use. In this context, Google searches for key-words related to new coronavirus have rapidly grown making labour market issues more predictable using Internet data. Caperna et al. (2020) nowcasted the monthly unemployment rate in the EU-27 at the beginning of the COVID-19 pandemic showing an increase in unemployment expectations. Moreover, the searches for jobs using Internet grew by 30% during the lock-down in these countries compared to pre-pandemic period. Fenga and Son-Turan (2020) predicted NEET unemployment in Italy for the period 2020-2021 using Internet data showing that the epidemic effects are absorbed quite fast. Penalized Regression with Inferred Seasonality Module predicted better unemployment during the 2008-2009 financial crisis and during the pandemic compared to traditional methods (Yi et al., 2021). However, for Poland, Drachal (2020) showed that the inclusion of Internet data in dynamic model averaging model did not outperform the predictions based on ARMA model, even if COVID-19 pandemic enhanced the utilization of Internet to search for jobs.

3. The impact of COVID-19 on labour market

At world level, millions of employees have been negatively affected by measures taken to limit the spread of coronavirus. The contraction of

economic activity has led to a significant decrease in employment, an increase in unemployment, social tensions and in-work poverty, the deterioration of human capital. If in 2019, the number of young unemployed people aged 15 to 24 was three times higher than that of adult unemployed, the new global economic situation determined by COVID-19 can increase youth unemployment, but also the quality of jobs by engaging in the informal sector and extending part-time and "zero-hour" contracts. In addition to young people, other groups vulnerable to unemployment during the epidemic were women, low-educated workers and with low wages (Adams-Prassl et al., 2020; Evans and Dromey, 2020). Also, the labour market tensions have negatively influenced the employment perspectives of immigrants (Borjas and Cassidy, 2020).

This significant decrease in labor demand in some sectors of activity was correlated with the widening of the labor shortage in other sectors. A possible solution to alleviate these imbalances and make the labor market more flexible is to transfer the available human resources in certain sectors of activity to those sectors that require labor (Costa Dias et al., 2020). This approach can be made possible by removing barriers in labor-intensive sectors and by facilitating loans and grants to ensure the training and retraining of labor resources. However, retraining and reallocation of labor to other sectors could have negative effects once work resumed under normal conditions in all areas by ending ties with the sectors in which they originally had a job.

The shocks to the labor market generated by the new medical context are also captured by various surveys organized during the COVID-19 pandemic. Based on real-time surveys conducted in the UK, Germany and the US, Adams-Prassl and others (2020) showed that the effects of the coronavirus pandemic were lower in Germany compared to the US and the UK due to long-term work schedules. short well established. Thus, 18% of the individuals analyzed lost their jobs in the USA, 15% of British respondents were fired due to the SAR-CoV-2 pandemic and only 5% of Germans were laid off. A lower percentage of 16.5% of Americans lost their jobs, according to the survey organized by Bick and Blandin (2020). Other surveys analyzed by Evans and Dromey (2020) also describe the situation on the UK labor market:

- The YouGov poll from the end of March 2020 reveals the loss of a job immediately after the outbreak of the pandemic of one in ten people, while 16% of respondents claim a reduction in salary or number of hours worked;
- The survey conducted by academia at the end of March 2020, before the announcement of the business support authorities, shows that 8% of workers became unemployed and 35% expected salary reductions in the next four months;
- The survey of the National Statistics Office between March 9-22, 2020 establishes the reduction of short-term staff in over half of the companies providing food and accommodation services, while similar trends were observed in the administrative, cultural and support services sector;
- The survey of the Institute of Personnel and Development suggests that 52% of employers gave up their jobs during the coronavirus pandemic, a quarter of them make fewer jobs, 14% hire as normal, and 4% of companies hire a lot;
- The British Chamber of Commerce survey from the beginning of April 2020 indicates the same trend of staff reductions, even anticipating reductions of at least 50% for almost half of employers in the next week.

The Eurofound survey conducted in April-June 2020 to assess the impact of COVID-19 on young people in the EU revealed significant declines in well-being and the fact that young people are the category most affected by job losses. NEET young people were among the people most affected by the Great Recession from 2008-2013, and the effects of COVID-19 on them are expected to be even stronger. The explanations could be related to the fact that these young people tend to work more in sectors that have reduced their activity during the pandemic, have temporary contracts or work in precarious working conditions. Therefore, they are more susceptible to dismissal or reduced working time, which prevents them from entering the labor market or puts them at risk of long-term unemployment.

The evolution of the unemployment rate during the coronavirus epidemic also depends on the response of each country through appropriate economic policies to limit the economic consequences of the medical crisis. Thus, countries that have supported wage benefit schemes in favor of unemployment benefits to maintain the link between employees and employers have recorded lower unemployment rates. On the other hand, states that have allocated more funds to support the unemployed should create and / or recreate new jobs and ensure that the unemployed have not lost their skills and are encouraged to reintegrate into the labor market (Tetlow et al., 2020).

Although the macroeconomic framework is highly uncertain, future labor market policies should pursue five main directions mentioned by Evans and Dromey (2020): prevention of long-term unemployment, greater support for young people, greater use of capital skills. ensuring the security of citizens even in conditions of high unemployment, ensuring urgent support only where necessary.

Globally, government measures taken to limit the effects of the pandemic on the labor market have focused, in particular, on: adjusting existing social spending and social assistance programs, implementing new aid programs, allocating additional funds, administrative improvements, reform of taxation systems, new packages of fiscal measures to support business and protect vulnerable groups. However, these measures need to be improved to support migrants and those working in the informal sector as well.

The initial measures taken worldwide to limit the negative economic effects of COVID-19 on the labor market involved:

- aid schemes consisting in granting grants and loans to those companies in the sectors most affected by coronavirus, subsidies amounting to 80% of the value of income held by employees temporarily laid off to keep skilled workers and limiting their standard of living;
- temporary transfer of redundant workers to sectors with labor shortages;
- making structural-occupational changes on the labor market (Deb et al., 2020).

It is now unclear how these decisions by governments and organizations will affect the socio-economic situation of countries and changes in the labour market, and what the challenges will be if the pandemic continues for a long time. Governments and businesses will have to respond to disease-induced changes in the global situation and develop unprecedented strategies based on available information without at least some more reliable forecasts. To this end, it makes sense to monitor and analyse people's general attitudes, which, as the studies mentioned in the previous section show, sometimes allow behaviour to be predicted much more reliably than statistical calculations based on time series. In the following, we present exactly this - a study of people's expectations and attitudes related to work.

4. Methodology

The aim of this empirical research is to explain employment expectations based on COVID-19 searches on Google. The microdata related to searches for COVID-19 key-word are collected using Google Trends.

Google Trends (GT) tool was introduced in 2008 and provides a public view for relative internet search volumes of some queries identified by keywords. The main advantage of Google search is related to nowcasting and forecasting in real time which is a solution of macroeconomic indicators that are released late (Simionescu and Zimmermann, 2017). The data are based on a representative subsample permanently updated.

GT provides a time series index to show the queries volume of users that introduced into Google search a certain keyword. The users are located in a certain country or region. The monthly query index is based on the ration between total query volume for that keyword in a certain space and total number of queries in that zone and in that month. The normalization to 100 is done to maximum query share in that month and the normalization to 0 to reflect minimum query share in that month (Choi and Varian, 2012). In our particular case, the monthly Google Trends index (GTI) as a proxy of sentiment analysis is computed as geometric mean of the daily indexes. The statistical nature of the indicator (index) recommends the use of geometric mean instead of arithmetic average.

The "sessionization" reduces noise from, typing errors, frivolous repetitions, rewrites and other acts. However, Google Trends offers only an aggregate image for the microdata behaviour. It is conditioned by internet penetration rate in that country and volume of searches.

From mathematical point of view, if the number of searches for a query q is n(q,l,t) where l is the location (country) and t is the period, the relative popularity of the query is:

$$RP(q, l, t) = \frac{n(q, l, t)}{\sum_{q \in Q(l,t)} n(q, l, t)} \cdot D_{(n(q,l,t) > \tau)}$$

Q(l,t)- set of all queries made during t from the area l, $D_{(n(q,l,t) > \tau)}$ is a dummy variable with value 1 for enough popular query ($n(q, l, t) > \tau$) and else it is 0. The resulted values are scaled on a range from 0 to 100 based on the proportion of that topic in the total number of search terms. The GTI is calculated as:

$$GTI(q, l, t) = \frac{RP(q, l, t)}{\max\{RP(q, l, t)_{t \in 1,2,...,T}\}} \cdot 100$$

GTI takes the value zero for queries with low search volume. The searches made repeatedly from the same machine in a short period are not considered and queries with apostrophes and special characters are filtered. The GTIs are available since the first of January up to 36 hours prior the search.

The Google Trends time series were retrieved on June 4th, 2021. The period was set from March 1st 2020 to May 31st 2021, and the category selected was "All categories". The countries examined were Bulgaria, Czech Republic, Slovakia, Slovenia, Romania, Poland, Malta, Cyprus, Lithuania, Estonia, Latvia, Hungary, and Croatia. All were individual searches, not comparisons. The keyword selected was *COVID-19* and it was considered as "search term", not a "topic". Quotes or strings including "+" were not used in this key-word that registered massive increase at the beginning of the pandemic in the analyzed countries. The most searches for this term were made in March 2020 in Estonia, Latvia, Romania, Malta, Croatia, Czech Republic, in April 2020 in Hungary, Slovakia, Slovenia, in August 2020 in Bulgaria, in October 2020 in Poland, in April 2021 in Lithuania and Cyprus. The related topics to COVID-19 and similar searches also registered a massive increase during March 2020-May 2021.

"Coronavirus" could be am alternative keyword, but it was not considered in this study since *COVID-19* term was more popular than it. Moreover, our proposed keyword is identical in each country, while "coronavirus" has different translations in the languages of some countries in the sample. Some users may search the term "coronavirus" in English while others in the language of the country of residence. However, the consideration of this keyword will be the subject of a future study.

We explain employment expectations using as explanatory variables the Google Trends index related to COVID-19 and some control variables: unemployment rate (%), according to ILO definition and harmonized index of consumer prices (HICP, where 2015=100). The data for control variables and employment expectations are provided by Eurostat. Seasonally adjusted data were used for all the variables.

The unemployment rate is based on the ratio between the number of unemployed people in a country and the total number of people in the labour force of that specific country.

$$\text{unemployment rate } (\%) = \frac{\text{no. of unemployed people}}{\text{total no. of persons in the labour force}} \times 100$$

HICP is based on a common methodology and it reflects the modification over time in the prices of goods and tariffs of services that were acquired.

The economic sentiment indicator is an aggregate indicator provided by the European Commission through the Directorate General for Economic and Financial Affairs (DG ECFIN) and it tracks GDP growth that is directly connected to employment expectations.

The employment expectations indicator (denoted by EEI) represents a composite indicator that is provided by the DG ECFIN. It shows managers' employment perspectives in four business sectors: services, industry, construction, and retail trade. This indicator is computed as a weighted average of these managers' employment expectations in the mentioned business sectors. If the values are greater than 100, managers' employment expectations are high, while the values below 100 indicate low expectations.

Our analysis is made only for the EU NMS in the first months of pandemic (March 2020-May 2021) for these countries. The relationship between employment expectations and COVID-19 searches is described using a panel ARDL models based on pooled mean group (PMG) estimators and a Bayesian multilevel model.

All in all, our statistical analysis is based on more steps:

a) Data collection and primary processing: computation of Google Trends monthly indexes for key-word COVID-19 using daily indexes for each country (geometric mean) and data collection for the rest of the variables using Eurostat database;
   Ø monthly data referring to the same period are used for all variables;
   Ø employment expectations and economic sentiment indicators are considered as proxies for the managers' opinions in those particular months.
b) Preliminary tests before estimations on panel data to check for heterogeneity, cross-sectional dependence, unit root, cointegration;
c) The selection of the most suitable panel data model based on the results of preliminary tests (panel ARDL models based on PMG estimators);
d) Robustness check based on additional control variable (economic sentiment indicator) and another method (Bayesian multilevel model).

4.1. Preliminary tests

Few types of tests are applied before establishing the most suitable panel data model to describe employment expectations in the NMS: tests for heterogeneity and cross-sectional dependence due to unobservable common factors or spill over effects, unit root and cointegration tests. The heterogeneity hypothesis is confirmed since there are differences between the NMS related to labour market flexibility, Internet penetration and speed of economic development. The cross-sectional dependence is explained by the fact that the COVID-19 pandemic acted like a common factor that influenced the employment expectations in all the NMS. From statistical point of view, the cross-sectional dependence is checked using CD Pesaran (2007) test that is not influenced by the sample size and it is recommended for short periods like in this case (15 months). The test is based on the following hypotheses:

$$H_0: \rho_{ij} = \rho_{ji} = cor(e_{it}, e_{jt}) = 0, i \neq j$$

$$H_1: \rho_{ij} = \rho_{ji} \neq 0, \text{ for some } i \neq j$$

ρ_{ij}- pair-wise correlation coefficient of the disturbances

$$\rho_{ij} = \rho_{ji} = \frac{\sum_{t=1}^{T} e_{it} \cdot e_{jt}}{\sqrt{\sum_{t=1}^{T} e_{it}^2} \cdot \sqrt{\sum_{t=1}^{T} e_{jt}^2}}$$

For balanced panels, the CD Pesaran (2007) test is based on the following statistic:

$$CD = \sqrt{\frac{2}{N(N-1)}} \cdot \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{\rho}_{ij}$$

T_{ij}- number of common observations for two countries (*i* and *j*)

$$\widehat{\rho}_{ij} = \widehat{\rho}_{ji} = \frac{\sum_{t \in T_i \cap T_j} \left(\widehat{e}_{it} - \overline{e}_i\right) \left(\widehat{e}_{jt} - \overline{e}_j\right)}{\sqrt{\sum_{t \in T_i \cap T_j} \left(\widehat{e}_{it} - \overline{e}_i\right)^2} \cdot \sqrt{\sum_{t \in T_i \cap T_j} \left(\widehat{e}_{jt} - \overline{e}_j\right)^2}}$$

$$\overline{e}_i = \frac{\sum_{t \in T_i \cap T_j} \left(\widehat{e}_{it}\right)}{\left(T_i \cap T_j\right)}$$

Under the cross-section dependence, the Breitung test is used to check for unit root in balanced panels like in this case.

4.2. Panel Autoregressive Distributed Lag model (panel ARDL)

The panel ARDL is built in case of no cointegration was detected with the previous tests or in case of data with different orders of integration. The data nature does not allow us to utilize the GMM estimator. The relationship between employment expectations and other variables is analyzed using a specific estimator presented by Pesaran et al. (1999): pooled mean group (PMG) estimator.

We will start from ARDL model:

$$\exp_{it} = \alpha_i + \sum_{l=1}^{p} \beta_0 \exp_{it-1} + \sum_{l=0}^{q} \beta_1 \mathrm{ur}_{it-1} + \sum_{l=0}^{q} \beta_2 \mathrm{index}_{it-1} + \sum_{l=0}^{q} \beta_3 \mathrm{HICP}_{it-1} + \mathrm{e}_{it}$$

i is index for country and *t* is index for month, *emp* is the employment expectations indicator, *ur* is the unemployment rate, *index* is the Google Trends index associated to the key-word COVID-19, *HICP* is the harmonised index of consumer prices, $\alpha_i, \beta_0, \beta_1, \beta_2, \beta_3$ -coefficients, p and q- lags.

After parameterization, the previous equation becomes:

$$\Delta \exp_{it} = \alpha_i + \Phi_i(\exp_{it-l} - \theta_1 ur_{it-l} - \theta_2 index_{it-l} - \theta_3 HICP_{it-l}) + \sum_{l=1}^{p-1} \lambda_{il} \Delta \exp_{it-l}$$

$$+ \sum_{l=0}^{q-1} \lambda'_{il} \Delta \mathrm{ur}_{it-l} + \sum_{l=0}^{q-1} \lambda''_{il} \Delta index_{it-l} + \sum_{l=0}^{q-1} \lambda'''_{il} \Delta HICP_{it-l} + e_{it}$$

In this case, $\lambda, \lambda', \lambda'', \lambda'''$ represent the short-run parameters associated to lagged endogenous variable, unemployment rate, Google Trends index and HICP respectively. $\theta_1, \theta_2,$ and θ_3 are the long-run parameters. The speed of adjustment is represented by Φ_i.

The PMG estimator considers homogenous long-run equilibrium across countries and heterogeneous short-run relationship. The heterogeneity associated to countries could be explained by different responses to external shocks.

4.3. Robustness check: Additional variable and other method (Bayesian multilevel model)

The robustness of estimations based on PMG estimator will be checked adding economic sentiment indicator as control variable in the previous models. Moreover, the robustness will be checked using a Bayesian multilevel model.

The multilevel model (MLM) based on OLS method to explain employment expectations based on COVID-19 searches index and other variables starts from:

employment expectations$_t \sim$ Normal (μ_t, σ_e)

$\mu_t = \alpha + \beta_1 \mathrm{COVID\_19\,index}_t + \beta_2 \mathrm{unemployment\,rate}_t + \beta_3 \mathrm{HICP}_t$

These relationships represent the likelihood of the model and might be written as:

employment expectations$_t = \alpha + \beta_1 \mathrm{COVID\_19\,index}_t$
$$+ \beta_2 \mathrm{unemployment\,rate}_t + \beta_3 \mathrm{HICP}_t + \varepsilon_t$$

$\varepsilon_t \sim$ Normal$(0, \sigma_\varepsilon)$

We assume that employment expectations follow a normal distribution around a mean μ_t with some error σ_ε. This means that errors are normally distributed around 0. Starting from this, the multilevel model is represented as:

employment expectations$_t \sim$ Normal (μ_t, σ_e)

$\mu_t = \alpha_{i[t]} + \beta_1 \mathrm{COVID\_19\,index}_t + \beta_2 \mathrm{unemployment\,rate}_t + \beta_3 \mathrm{HICP}_t$

$\alpha_j \sim$ Normal (α, σ_α) (prior distribution describing the population of intercepts)

$\alpha_{i[t]}$ shows that each group (country) is given a single intercept from a normal distribution centered on α which suggests the existence of different mean values of employment expectations for each country.

σ_ε - residual standard deviation

σ_α - standard deviation associated to changing intercepts distribution

The intra-class correlation is the variation of the coefficient α between countries *i* (Nalborczyk et al., 2019).

5. Data and results

Our approach considers employment expectations as an indicator of sentiment related to behavioural economics. We consider that the managers' expectations expressed in a certain month for the next three months are a proxy for their behaviour in that specific month on which we focus on. This behaviour is determined by many factors, including the economic ones and the new medical challenge given by COVID-19 pandemic.

Beside Google Trends indexes reflecting searched of COVID-19 keyword each month, other control variables are used in the models: harmonized unemployment rate, harmonized index of consumer prices and economic sentiment indicator. The Google Trends indexes are computed by authors as geometric means of the daily values provided by Google Trends (https://trends.google.com/trends/). For each month we selected the values of the Google Trends indexes registered each day in each country. The period of one specific month and the country are directly selected in the Google Trends website. The data for the rest of the variables are provided by Eurostat.

All the countries, excepting Cyprus, registered the minimum value of employment expectations indicator in April 2020 because of emergency states, while Cyprus reached the lowest employment expectations in February 2021. Excepting Cyprus, Romania and Bulgaria, all the other states registered the maximum value of employment expectations indicator in May 2021, at the end of the analyzed period due to elimination of many restrictions. In October 2020, Cyprus proved the most optimistic expectations related to employment while Bulgaria and Romania showed this in April 2021, very close to the end the analyzed period. These optimistic expectations in Cyprus are explained by the low number of cases of new coronavirus. In Bulgaria, the unemployment rate decreased by 0.4 percentage points in April 2021 compared to March

2021. On the other hand, in April 2021 the business confidence indicators have improved in this country compared to previous month in all sectors (industry, construction, services, retail trade). Fig. 1

According to descriptive statistics in Table 1, the minimum interest for COVID-19 searches was registered by Bulgaria in September 2020 which is explained by the fact that this country lifted most of the restrictions starting with the 1st of June 2020. The highest interest for searched on pandemic was observed in Slovenia in October 2020, because that month the government expanded restrictions after doubling the cases of infected people in only one week of October.

Czech Republic reached the minimum unemployment rate at the beginning of the epidemic in March 2020, while Cyprus registered the highest unemployment in the region in October 2020 (10.2%). The lowest inflation was observed in Cyprus in January 2021, while Hungary registered hyperinflation in May 2021. The most optimistic employment expectations were expressed by Slovenian managers in May 2021, while the Romanian managers were the most pessimistic in the zone at the beginning of the pandemic in April 2020 when the country was in the middle of emergency state. In May 2020, Polish managers were the most pessimistic regarding the future economic growth, while the managers from Malta expect economic recovery in May 2021. As expected, in the first months of epidemic, the managers were the most pessimistic regarding the perspectives on employment and economic growth, while in the last analyzed month of pandemic the situation is more optimistic.

According to CD Pesaran's test, the hypothesis of corss-sectional independence is rejected for all variables at 5% level of significance (Table 2). Therefore, under the cross-section dependence and balanced panels, the Breitung test is applied to check the stationary in panel for data in level.

The results of Breitung test indicates that the data series in level for COVID-19 index is stationary at 5% level of significance, while the rest of the data are non-stationary. The Levin-Lin-Chu in unbalanced panels suggests that for all the variables excepting COVID-19 index the data in the first difference are stationary (Table 3).

After applying panel data unit roots tests, we can conclude that the COVID-19 index series is stationary, while the data for the rest of the variables are integrated of order 1. Therefore, cointegration between employment expectations and the rest of the variables is checked to establish a possible long-run relationship.

The results of Kao test and Pedroni test in Table 4 suggest that all panels are cointegrated at 5% level of significance. Given the fact that the variables do not present the same order of integration, the long-run and short-run relationships are identified using panel ARDL model.

The short-run behaviour should be heterogeneous since there are specific gaps between countries. Therefore, the PMG estimator is the best choice in this case. Analyzing the values of all the error correction

Table 1
Descriptive statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
COVID-19 index	32.18078	14.7893	1.56667	69.93549
Unemployment rate	5.903077	1.935184	1.9	10.2
HICP	108.377	4.133719	98.41	120
Economic sentiment indicator	88.04923	10.83935	59.5	118
Employment expectations indicator	94.71231	9.789614	59.6	116.7

Source: own calculations in Stata 15

Table 2
The results of CD Pesaran's test

Variables	Statistics	p-values
COVID-19 index	16.76	<0.05
Unemployment rate	13.02	<0.05
Employment expectations indicator	25.28	<0.05
HICP	22.99	<0.05
Economic sentiment indicator	30.52	<0.05

Source: own calculations in Stata 15

Table 3
The results of panel unit root tests

Variable	Statistic of Breitung test (constant & trend) (no lag) data in level	Statistic of Breitung test (constant & trend) (one lag) data in level	Adjusted statistic of Levin-Lin-Chu data in the first difference
COVID-19 index	-3.7224*	-1.8386*	-
Unemployment rate	0.7925	-1.0803	-3.8681*
Employment expectations indicator	-1.3400**	-0.6620	-3.6692 *
HICP (2015=100)	4.9130	2.1387	-1.6203**
Economic sentiment indicator	0.3942	0.2023	4.1470*

Source: own computations in Stata 16. Note: * significant at 5% level of significance; ** significant at 10% level of significance

terms in Table 5, the highest speed of adjustment of 74.2% (−0.742) is obtained from PMG in the first model which suggests a correction of 74.2% for the discrepancy of this estimation when economic sentiment
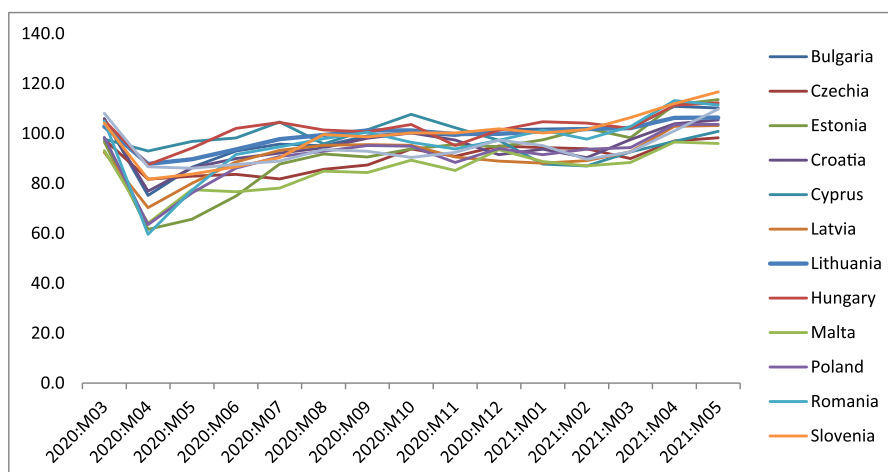

Fig. 1. The evolution of the employment expectations indicator in NMS (March: 2020-May: 2021) Source: own graph based on Eurostat data.

Table 4

The results of Kao and Pedroni cointegration tests

Kao test	Statistic	p-value	Pedroni test	Statistic	p-value
Modified Dickey-Fuller t	-3.2884	0.0005	Modified Phillips-Perron	3.0838	0.0010
Dickey-Fuller t	-4.8458	<0.05	Phillips-Perron t	-1.9114	0.0280
Augmented Dickey-Fuller t	-2.3962	0.0083	Augmented Dickey-Fuller t	-5.7743	<0.05
Unadjusted modified Dickey-Fuller t	-3.9058	<0.05			
Unadjusted Dickey-Fuller t	-5.0549	<0.05			

Source: own computations in Stata 15

Table 5

PMG estimators to explain employment expectations in A13 countries (March: 2020-May:2021)

	Variable	PMG1	PMG2
Long-run relationship	COVID-19 index	-0.003*	-0.002*
	Unemployment rate	-3.833*	-2.624*
	HICP	-4.381*	-0.092
	Economic sentiment indicator	-	0.511*
Error correction term	-		-0.742*	-0.595*
Short-run relationship	COVID-19 index	-0.019*	-0.007*
	Unemployment rate	-19.057*	-2.810*
	HICP	-0.066	1.458*
	Economic sentiment indicator		0.432*
	Constant	-301.364*	26.446*
Residuals	I(0)	I(0)	I(0)

Source: own computations in Stata 15

indicator is not included among the explanatory variables.

The results of estimations in Table indicate a significant long-run relationship between variables. In PMG1, there is a negative and long-run connection between employment expectations and COVID-19 searches on Google, inflation and unemployment rate. The short-run relationship is indirect and significant in case of COVID-19 index and unemployment rate. On the other hand, economic sentiment indicator is positively correlated with employment expectations both on short and long-run, as economic theory suggests. However, when this variable is introduced in the model for robustness check, inflation rate is significantly correlated with employment expectations only on short-run.

The robustness of the estimations is also checked using a different method. According to Bayesian multilevel model in Table 6, COVID-19 Google Trends index, unemployment rate and HICP had a negative effect on employment expectations in the NMS in the period March: 2020-September: 2020.

According to Fig. 2, there are similar patterns of posterior distributions of random intercepts for certain groups of countries. For example, there are left-skewed distributions of coefficients in the case of Czech Republic, and Estonia. Right-skewed distributions are observed for Croatia, Latvia, Lithuania, Slovenia, Slovakia. The distributions are almost symmetric for the other countries.

In the case of both models, searches of key-word *COVID-19* on Google and unemployment rate had a negative impact on employment expectations. Moreover, the increase in unemployment and inflation negatively affects the opinions on employment perspectives. The results are consistent with the economic expectations since unemployment expansion and more tensions reflected by more searches for employment reduce the employment expectations.

The first step, as Coates et al. (2020) mentioned, is to solve the health crisis. After that, economic measures should be implemented: significant financial stimulus to ensure the expansion of aggregate demand. The governments in the EU countries should support more the companies to

Table 6

Bayesian multilevel model to explain employment expectations in the NMS (March: 2020-May: 2021)

Variable	Mean	Standard deviation	MCSE
COVID-19 Google Trends index	-0.137	0.137	0.0030
Unemployment rate	-0.749	1.496	0.109
HICP	-0.097	0.551	0.186
Constant	106.203	61.262	1.787
Country Constant: variance	66.512	65.958	6.143
Constant for:			
Bulgaria (1)	0.3697203	4.77971	0.152961
Czech Republic (2)	-4.438333	6.594413	0.468893
Cyprus (3)	7.626711	6.354317	0.470293
Croatia (4)	3.421721	5.742293	0.410962
Estonia (5)	-8.238133	4.979064	0.237517
Latvia (6)	0.269058	5.150721	0.297261
Lithuania (7)	7.026892	6.126025	0.397598
Malta (8)	-10.8533	5.687147	0.398492
Poland (9)	-4.582714	5.487007	0.337046
Romania (10)	-0.5582815	4.293737	0.177375
Slovenia (11)	3.145243	4.541451	0.171461
Slovakia (12)	2.222557	4.427087	0.193693
Hungary (13)	5.760411	5.0481	0.215312

Source: own computations in Stata 16

ensure the cash flow for covering the actual costs. The financial stability at macroeconomic level should be achieved in order to diminish the long-run damage to capacity of production in the economy. Low and middle- income households should be supported more. The states should pay benefits for people with part-time jobs during the pandemic to cover the losses in wages. The reforms in economic field should boost productivity in order to ensure better living standards during and after the COVID-19 pandemic. The recovery after this pandemic should follow certain directions: labour force participation, tax, innovation, competition, land-use planning.

6. Conclusions

The results of the research confirmed that unemployment rate has a large-scale negative impact on employment expectations. We found that a rise of unemployment in one percentage point increases individuals' anxiety about work by three up to seven percentage points.

Based on the research results, it can be stated that the majority of people show an active emotional response only to changes in a relatively close environment and do not make presumptions about the future through insights of wider environment. The research has also shown that people's employment expectations were more positive in countries where the spread of Covid-19 was lesser in scope and government applied less restrictive quarantine constraints on social contacts and organizations' activities, causing the unemployment curve to be smoother than in countries which were impacted worse by the Covid-19. Our research confirmed Juranek's et al. (2020) observation that countries cannot exist as separate islands in the global economy during the pandemic. Sooner or later, the situation becomes similar to that of neighbouring countries. Our research provided the example of Cyprus, where the employment expectations remained high for longer, but decreased to the level similar to other countries in respective region with the increasing number of Covid-19 cases.

However, unemployment statistics and objective situation of the crisis does not always allow to forecast the employment expectations accurately. Our research shows that in some regions, the situation between neighbouring countries were significantly different, although the Covid-19 situation was similar and non-critical. Baltic states could be distinguished as an example. The Latvian citizens' employment expectations were higher than those of Lithuanian citizens' not only at the beginning of the pandemic but during summertime, although neither of the countries suffered catastrophic consequences of Covid-19 during the analysed period. Due to a lack of objective evidence, we can only assume
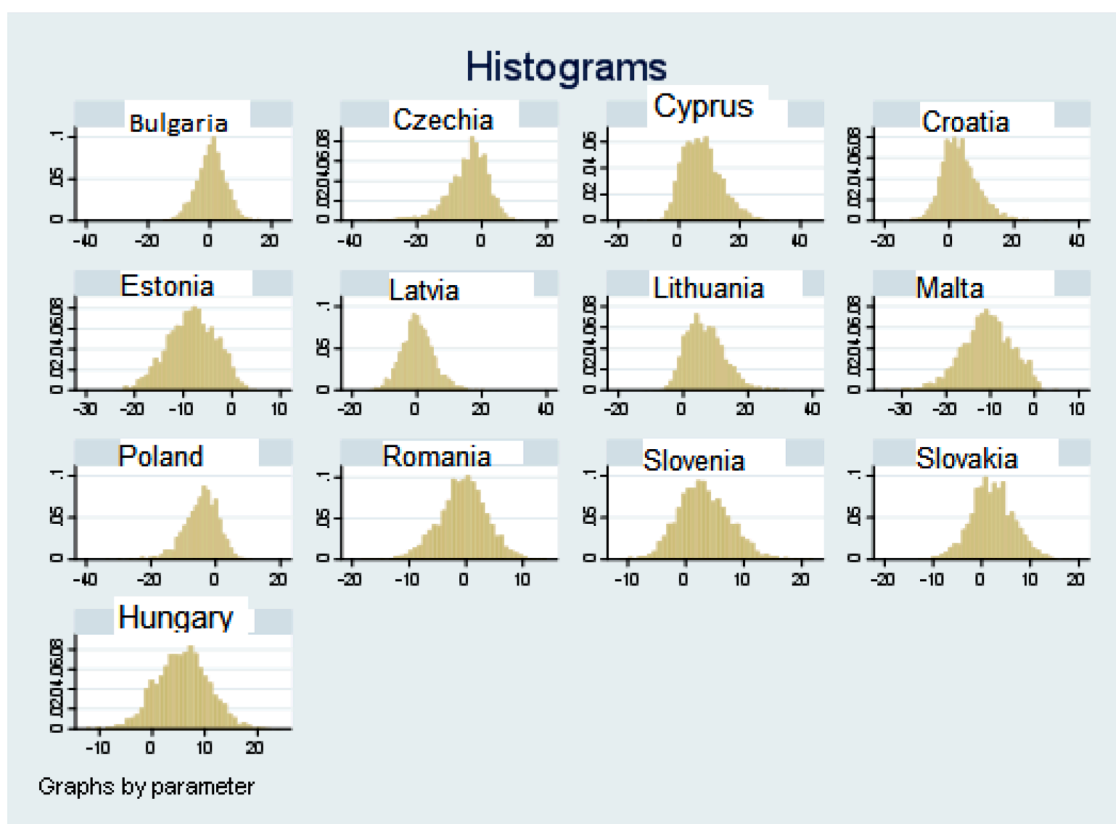
Fig. 2. Posterior distributions of random intercepts Source: graphs in Stata 16 Source: graphs in Stata 16

that other factors, forming society's opinion were meaningfully different – first and foremost, the communication from the government. Either way, our research proves that employment expectations are not formed by one single factor which would unambiguously impact the society's morale in the same way and scale.

Our results have specific policy implications that allow us to make some recommendations.

Firstly, governments should realize the undeniable importance of what information is provided to the society, as the society's morale is influenced not only by objective facts.

Secondly, it is irrational to expect that individuals will construct their behavioural strategies by observing the neighbouring countries. Thus, to reduce the consequences of the pandemic, it is meaningless to appeal to individuals' consciousness. It is important to make decisions which regulate the society's behaviour appropriately for the situation. As our research shows, society's understanding of the situation changes only by reacting to a worsening situation rather than proactively.

Speaking of unemployment control, the scale of support for both businesses and people who temporarily or permanently lost their jobs is questionable. Naturally, businesses do not abolish jobs only while the government helps to sustain them and demand for the products or services does not decrease. If support is discontinued or (due to a pandemic) demand decreases, organizations stop their activity. The job market shrinks. It seems that by observing such a process, the society loses trust in business and government and as a result, employment expectations worsen. In this context of uncertainty, distrust but also government grants, the decrease in number of individuals looking for a job does not seem inexplicable. In addition, due to income guaranteed by government grants, inflation becomes rationally explained with reduced demand (Barone, 2020; Reinsdorf, 2020).

As theoretical insight and practical implication of our research we can state that objective environmental and socio-economic situation does not necessarily call out adequate emotional response from the society. This is not a new insight in the aspect of social psychology. However, it seems that in economy, where decisions are made by timeline-based forecasting, it is quite forgotten.

Author Contribution Statement

The paper was written by the two authors. They declare no conflict of interest.

Mihaela Simionescu wrote the sections:

- Introduction
- A part of the section "The overview of current studies related to the impact of pandemic to socio-economic changes"
- The impact of COVID-19 on labour market
- Methodology
- Data and results

Agota Giedrė Raišienė wrote:

- A part of the section "The overview of current studies related to the impact of pandemic to socio-economic changes"
- Conclusions

References

Adams-Prassl, A., Boneva, T., Golin, M., & Rauh, C. (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys.

Alon, T.M., Doepke, M., Olmstead-Rumsey, J., Tertilt, M., 2020. The Impact of COVID-19 on Gender Equality. National Bureau of Economic Research, Cambridge, MA, USA.

Suryahadi, Asep, Izzati, Ridho Al, Suryadarma, Daniel, 2020. Estimating the impact of Covid-19 on poverty in Indonesia. Bull. Indonesian Econ. Stud. 56 (2), 175–192. https://doi.org/10.1080/00074918.2020.1779390.

Askitas, N., Zimmermann, K.F., 2009a. Google econometrics and unemployment forecasting. Appl. Econ. Q. 55 (2), 107–120.

Askitas, N., Zimmermann, K.F., 2009b. Googlemetrie und Arbeitsmarkt. Wirtschaftsdienst 89 (7), 489–496.

Baker, S.R., Farrokhnia, R.A., Meyer, S., Pagel, M., Yannelis, C., 2020. How does household spending respond to an epidemic? Consumption during the 2020 covid-19 pandemic (No. w26949. National Bureau of Econom.

Baldwin, R.E., Tomiura, E., 2020. Thinking ahead about the trade impact of COVID-19. Economics in the Time of COVID-19. Centre for Economic Policy Research, London, UK, pp. 59–71.

Barone E. (2020, October 30). The pandemic is costing americans more money than official numbers suggest, Time, https://time.com/5905902/covid-19-inflation/.

Bartik, A.W. Bertrand, M., Lin, F., Rothstein, J., Unrath, M. (2020). Measuring the labor market at the onset of the COVID-19 crisis, Brook. Paper. Econ. Activ. Natl. Bureau Econ. Res., Working Paper 27613, DOI 10.3386/w27613.

Bartik, A.V., Bertrand, M., Cullen, Z., Glaeser, E.L., Stanton, Ch., M., 2020a. The impact of COVID-19 on small business outcomes and expectations. Proc. Natl. Acad. Sci. 117 (30), 17656–17666. https://doi.org/10.1073/pnas.2006991117.

Barua, Suborna (2020): Understanding Coronanomics: The economic implications of the coronavirus (COVID-19) pandemic. MPRA Paper No. 99693, SSRN Electron. J., DOI: 10.2139/ssrn.3566477 https://doi.org/10.1016/j.jmacro.2020.103230.

Beland, L. P., Brodeur, A., & Wright, T. (2020). COVID-19, stay-at-home orders and employment: evidence from CPS data.

Bick, A., & Blandin, A. (2020). Real-time labor market estimates during the 2020 coronavirus outbreak. Available at SSRN 3692425.

Binder, C, 2020. Coronavirus fears and macroeconomic expectations. Rev. Econ. Stat. 102 (4), 721–730. https://doi.org/10.1162/rest_a_00931.

Bloom, N., Bunn, P., Mizen, P., Smietanka, P., Thwaites, G., 2020. The impact of Covid-19 on businesses' expectations: evidence from the Decision Maker Panel, Bank of England. Q. Bull. 2020, Q3.

Boot, A.; Carletti, E.; Kotz, H.-H.; Krahnen, J.P.; Pelizzon, L.; Subrahmanyam, M. The coronavirus and financial stability. Available online: https://voxeu.org/content/coronavirus-and-financial-stability 2020.

Borjas, G.J., Cassidy, H., 2020. The Adverse Effect of the COVID-19 Labor Market Shock on Immigrant Employment (No. w27243). National Bureau of Economic Research.

Bratianu, C., 2020. Toward understanding the complexity of the COVID-19 crisis: a grounded theory approach, Management & Marketing. Challeng. Knowl. Soc. 15 (s1), 410–423. https://doi.org/10.2478/mmcks-2020-0024. Doi.

Buchheim, Lukas;, Dovern, Jonas;, Krolage, Carla;, Link, Sebastian, 2020. Firm-Level Expectations and Behavior in Response to the COVID-19 Crisis, CESifo Working Paper, No. 8304. Center for Economic Studies and Ifo Institute (CESifo), Munich.

Campello, M., Kankanhalli, G., Muthukrishnan, P. (2020). Corporate Hiring Under COVID-19– Labor Market Concentration, Downskilling, and Income Inequality, Vol. 27208, NBER working paper series, National Bureau of Economic Research, p. 44, ISSN 0898-2937.

Caperna, G., Colagrossi, M., Geraci, A., & Mazzarella, G. (2020). Googling unemployment during the pandemic: inference and Nowcast using search data. Available at SSRN 3627754.

Chadwick, M.G., Sengül, G., 2015. Nowcasting the unemployment rate in Turkey: let's ask google. Central Bank Rev. 15 (3), 15.

Chang, R., Velasco, A. (2020). Economic policy incentives to preserve lives and livelihoods, National Bureau of Economic Research, Working Paper, Working Paper Series No. 27020, doi: 10.3386/w27020.

Coates, B., Cowgill, M., Chen, T., Mackey, W., 2020. Shutdown: Estimating the COVID-19 Employment Shock. Grattan Institute, Melbourne, Victoria.

Coibion, O., Gorodnichenko, Y., Weber, M., 2020. The Cost of the Covid-19 Crisis: Lockdowns, Macroeconomic Expectations, and Consumer Spending (No. w27141). National Bureau of Economic Research.

Coibion, O.; Gorodnichenko, Y.; Weber, M. (2020): Labor Markets during the Covid-19 Crisis: a preliminary view, CESifo Working Paper, No. 8238, Center for Economic Studies and ifo Institute (CESifo), Munich.

Costa Dias, M., Joyce, R., Postel-Vinay, F., Xu, X, 2020. The challenges for labour market policy during the Covid-19 pandemic. Fiscal Studies 41 (2), 371–382.

Currie, J., Madrian, B.C., 1999. Health, health insurance and the labor market. Handbook Labor Econ. 3, 3309–3416.

Curtin, R., 2020. More Aid Urgently Needed. Michigan Surveys of Consumer.

Czech, K., Wielechowski, M., Kotyza, P., Benešová, I., Laputková, A., 2020. Shaking Stability: COVID-19 Impact on the Visegrad Group Countries' Financial Markets. Sustainability 12, 6282.

D'Amuri, F., Marcucci, J., 2017. The predictive power of Google searches in forecasting US unemployment. Int. J. Forecast. 33 (4), 801–816.

Deb, P., Furceri, D., Ostry, J. D., & Tawk, N. (2020). The economic effects of Covid-19 containment measures.

Drachal, K., 2020. Forecasting unemployment rate in Poland with dynamic model averaging and internet searches. Global Bus. Econ. Rev. 23 (4), 368–389.

Eichenbaum, M.S., Rebelo, S., Trabandt, M. (2020). The Macroeconomics of Epidemics, NBER Working Papers 26882, National Bureau of Economic Research, Inc.

Evans, S., & Dromey, J. (2020). Coronavirus and the Labour Market: Impacts and Challenges. Learning and Work Institute, Leicester.

Fenga, L., & Son-Turan, S. (2020). Forecasting youth unemployment in the aftermath of the COVID-19 pandemic: the Italian case.

Fetzer, T., Hensel, L., Hermle, J., Ch, Roth, 2020. Coronavirus perceptions and economic anxiety. Rev. Econ. Stat. 0 0:ja 1–36 https://doi.org/10.1162/rest_a_00946.

Fondeur, Y., Karamé, F., 2013. Can Google data help predict French youth unemployment? Econ. Modell. 30, 117–125.

Forsythe, E., Kahn, L.B., Lange, F., Wiczer, D.G., 2020. Labor demand in the time of covid-19: evidence from vacancy postings and UI claims. J. Public Econ. 189, 104238 https://doi.org/10.1016/j.jpubeco.2020.104238.

Francesco, D.A., 2009. Predicting unemployment in short samples with internet job search query data. MPRA Paper 18403, 1–18.

Garen, J. (1988). Compensating wage differentials and the endogeneity of job riskiness. Rev. Econ. Stat., 9-16.

Hanspal, T.; Weber, A.; Wohlfart, J. (2020). Income and Wealth Shocks and Expectations during the COVID-19 Pandemic, CEBI Work. Paper Ser., No. 13/20. 10.2139/ssrn.3578472.

Jun, S.P., Yoo, H.S., Choi, S., 2018. Ten years of research change using Google Trends: from the perspective of big data utilizations and applications. Technol. Forecast. Soc. Change 130, 69–87.

Juranek, S., Paetzold, Jörg and Winner, Hannes and Zoutman, Floris, Labor Market Effects of COVID-19 in Sweden and its neighbors: evidence from novel administrative data (2020). CESifo Working Paper No. 8.

Laing, T., 2020. The economic impact of the Coronavirus 2019 (Covid-2019): Implications for the mining industry. Extr. Ind. Soc. 2020 (7), 580.

Lin, Z., Meissner, Ch.M. (2020). Health vs. Wealth? Public Health Policies and the Economy During Covid-19, National Bureau of Economic Research Working Paper Serie, No. 27099. DO - 10.3386/w27099.

Mahler, D.G.; Lakner, C.; Castaneda Aguilar, A.R.; Wu, H. Updated estimates of the impact of COVID-19 on global poverty. Available online: https://blogs.worldbank.org/opendata/updated-estimates-impact-covid19-global-poverty (accessed on 28 June 2020).

McKibbin, W., Vines, D., 2020. Global macroeconomic cooperation in response to the COVID-19 pandemic: a roadmap for the G20 and the IMF. Oxf. Rev. Econ. Policy graa032. https://doi.org/10.1093/oxrep/graa032.

McKibbin, W.; Roshen F. (2020). The global macroeconomic impacts of COVID-19: seven Scenarios, CAMA Working Paper No. 19/2020, 10.2139/ssrn.3547729.

Meyer, B. H., Prescott, B., Sheng, X. S., (2020). The Impact of the COVID-19 pandemic on business expectations, 10.2139/ssrn.3690489.

Naccarato, A., Falorsi, S., Loriga, S., Pierini, A., 2018. Combining official and Google Trends data to forecast the Italian youth unemployment rate. Technol. Forecast. Soc. Change 130, 114–122.

Nalborczyk, L., Batailler, C., Lœvenbruck, H., Vilain, A., Bürkner, P.C., 2019. An introduction to Bayesian multilevel models using brms: a case study of gender effects on vowel variability in standard indonesian. J. Speech Lang. Hear. Res. 62 (5), 1225–1242.

Ng, W.L., 2020. To lockdown? When to peak? Will there be an end? A macroeconomic analysis on COVID-19 epidemic in the United States. J. Macroecon. 65, 103230.

Nicola, M., Alsafi, Z., Sohrabi, C., Kerwan, A., Al-Jabir, A., Iosifidis, C., Agha, M., Agha, R., 2020. The socio-economic implications of the coronavirus pandemic (COVID-19): A review. Int. J. Surg. 78, 185–193.

Oleksandr, B., 2010. Can Google's Search Engine be used to Forecast Unemployment in Ukraine (Doctoral dissertation). Kyiv School of Economics.

Pavlicek, J., Kristoufek, L., 2015. Nowcasting unemployment rates with google searches: evidence from the visegrad group countries. PLoS One 10 (5), e0127084.

Pesaran, MH, 2007. A simple panel unit root test in the presence of cross-section dependence. J Appl Econ 22 (2), 265–312.

Rakauskė, R. (2020, November 9). Esant rekordiniam nedarbui, darbdaviai neranda norinčių dirbti: juodais pinigais susirenka daugiau, https://www.delfi.lt/verslas/verslas/esant-rekordiniam-nedarbui-darbdaviai-neranda-norinciu-dirbti-juodais-pinigais-susirenka-daugiau.d?id=85667337.

Reinsdorf, M., 2020. Data Disruption: The Impact of COVID-19 on Inflation Measurement. November 10. International Monetary fund. https://blogs.imf.org/2020/11/10/data-disruption-the-impact-of-covid-19-on-inflation-measurement/.

Reisch, T., Heiler, G., Hurt, J., Klimek, P., Hanbury, A., Thurner, S. (2020). Behavioral gender differences are reinforced during the COVID-19 crisis, arXiv:2010.10470v1.

Roth, C., Wohlfart, J., 2020. How do expectations about the macroeconomy affect personal expectations and behavior? Rev. Econ. Stat. 102 (4), 731–748. Iss.

Scott, R.B., Bloom, N., Davis, S.J., Terry, S.J., 2020. COVID-Induced Economic Uncertainty, Working Paper 26983. National Bureau of Economic Research, Inc. https://doi.org/10.3386/w26983

Simionescu, M., 2020. Improving unemployment rate forecasts at regional level in Romania using Google Trends. Technological Forecasting and Social Change 155, 120026.

Simionescu, M., & Zimmermann, K. F. (2017). Big data and unemployment analysis (No. 81). GLO Discussion Paper.

Statistics Lithuania (2020, November 12). Labour market situation, October 2020. Overview, https://osp.stat.gov.lt/en/informaciniai-pranesimai?articleId=8178607.

Sumner, A., Hoy, C., Ortiz-Juarez, E., 2020. Estimates of the impact of COVID-19 on global Poverty. WIDER Working Paper, 43rd ed. UNU-WIDER, Helsinki, Finland. Volume 2020, ISBN 978-92-9256-800-9.

Tanaka, M., Bloom, N., David, J.M., Koga, M., 2020. Firm performance and Macro forecast accuracy. J. Monet. Econ. 114, 26–41. https://doi.org/10.1016/j.jmoneco.2019.02.008 p.

Tetlow, G., Pope, T., & Dalton, G. (2020). Coronavirus and unemployment: the importance of government policy: a five nation comparison.

Tokic, D. Long-term consequences of the 2020 coronavirus pandemics: Historical global-macro context. J Corp. Account. Financ. 2020.

UNCTAD (2020). Coronavirus reveals need to bridge the digital divide https://unctad.org/en/pages/newsdetails.aspx?OriginalVersionID=2322.

van der Wielen, W and S Barrios (2020), "Fear and employment during the COVID pandemic: evidence from search behaviour in the EU", JRC Working Papers on Taxation and Structural Reforms No 08/2020, European Commission.

Vicente, M.R., López-Menéndez, A.J., Pérez, R., 2015. Forecasting unemployment with internet search data: does it help to improve predictions when job destruction is skyrocketing? Technological Forecasting and Social Change 92, 132–139.

Yi, D., Ning, S., Chang, C. J., & Kou, S. C. (2021). Forecasting unemployment using Internet search data via PRISM. J. Am. Statist. Assoc., 1-12.

Žilionis, M. (2020, June 12). Už 1 tūkst. eurų dirbančių neranda – vešis dar daugiau užsieniečių; https://www.delfi.lt/verslas/verslas/uz-1-tukst-euru-dirbanciu-neranda-vesis-dar-daugiau-uzsienieciu.d?id=78494347.

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