Journal of Behavioral Economics for Policy, Vol. 6, Issue 1, 27-32, 2022

The nexus between unemployment and Covid-19 vaccine in the U.S. Evidence from Google trends

Georgios Garafas [1]*

Abstract
The current study explores how the anticipation of the Covid-19 vaccines has interacted with uncertainty and unemployment in the U.S during the period 3/7/2020 - 11/21/2020. It is estimated that Google Trends data for the topic of unemployment benefits can be a consistent proxy for insurance claims, while divergences in their movement can be attributed to fear and uncertainty. These divergences appear to be mitigated by the development of Covid-19 vaccines through the reduction of uncertainty. Thus, the relation between searches for unemployment and the Covid-19 vaccines has been proven that it is strong. Furthermore, when uncertainty is reduced, Google Trends and conventional data can be determined simultaneously.

JEL Classification: D84; F66; I12

Keywords
COVID-19 — unemployment — uncertainty — vaccine development — Google trends — wavelets

[1] *Department of Accounting and Finance, University of Ioannina, Greece*
***Corresponding author**: ggarafas@uoi.gr

Introduction

While seasonal influenza could kill 250,000 to 500,000 people worldwide, the World Health Organization (WHO) in 2004 was warning that a new strain of the flu virus could cause a pandemic and lead to millions of deaths due to lack of prior immunity (Ginsberg et al., 2009). Sixteen years later, on January 5, 2020, the WHO announced that WHO China Country Office was informed of cases of pneumonia of unknown cause in the city of Wuhan, China. On January 21, the Washington State Department of Health announced the first confirmed case of Covid-19 in the US, and on March 11, WHO stated the outbreak of Covid-19 to be a global pandemic.

Shortly before the end of 2020, the Covid-19 pandemic had caused more than 1.7 million deaths, while more than 81 million had been infected. But the pandemic of the novel coronavirus is more than a global public health crisis. People have lost their jobs or their incomes as they got sick or due to social and physical distancing policies that have been taken to mitigate the spread of the virus. The economic consequences of these policies could vary considerably. While tourism and other service industries have been hit, medical supplies and the food sector faced high demand due to panic buying (Nicola et al., 2020). However, the exceptions are not enough to reverse overall reduction of economic activity and severe shocks in labor markets due to the Covid-19 pandemic.

As shown in Table 1, in April 2020, the unemployment rate increased to 14,7% in the U.S., a monthly increase of 10,3 percentage points. This was the highest recorded value and the largest recorded over-the-month increase since the series was first built by the U.S. Bureau of Labor Statistics in 1948 (BLS, 2020). Coibion et al. (2020) argue that the unemployment rate is quite higher as they estimated that the actual loss of jobs is 20 million by April 6th, 2020, and is much higher than losses throughout the Great Recession. They also claim that many of those who lost their jobs cease to actively seek a new job.

Knipe et al. (2020) have investigated the impact of the pandemic on mental health through Google Trends data. They have found that fear is increasing and that there is a growing concern about unemployment and the economic consequences of the pandemic among indications. Despite the rise of fear and uncertainty, many governments around the world are only reacting in their crisis response underestimating the rapid propagation of the virus as Pac et al. (2020) claim. Nevertheless, the crisis is global and threatens all countries regardless of how many active cases it has. Indicatively the outbreak of the virus in Italy in mid-March fueled economic policy uncertainty in the U.S. (Garafas & Dimitriou, 2020). Things are getting even worse, as the economic anxiety raises when the virus reaches a country (Fetzer et al., 2020). People are changing their consumption behavior due to their reduced incomes or due to fear of economic uncertainty, and households and businesses spend less, especially on non-essential goods and services (Curdia, 2020). Therefore, fear and economic hardship appear to cause a decline in demand that could lead to a vicious circle that further increases unemployment and economic uncertainty. The expected vaccine apparently creates expectations for the end of the pandemic.

This article explores first if Google trends data can be a

	2019		2020										
Unemployment rate %	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov
	3,5	3,5	3,6	3,5	4,4	14,7	13,3	11,1	10,2	8,4	7,9	6,9	6,7

Source: U.S. Bureau of Labor Statistics

Table 1. Unemployment in the U.S.

	LOG(UNEM)	LOG(CLAIMS)
Mean	3.388114	14.05338
Median	3.563404	13.90372
Max.	4.459318	15.64190
Min.	1.098612	12.20798
Std. Dev.	0.670550	0.758966
Skewness	-1.415582	0.161838
Kurtosis	5.951421	3.299399
Jarque-Bera	26.48343	0.307809

Table 2. Descriptive Statistics

consistent proxy of conventional data and, secondly, whether the anticipation of the new vaccine interacts with uncertainty and searches for unemployment, based on Google Trends data.

The main findings outlined in this paper indicate that Google searches for unemployment benefits can be used as a proxy of the actual level of unemployment insurance claims, while the observed divergences can be attributed to fear and uncertainty. The latter is also supported by empirical analysis showing that Google searches for unemployment are closely linked with changes in the levels of concern and anxiety as reflected by the Google searches for the development of the Covid-19 vaccines.

The paper proceeds as follows. In "Data overview" section the data are analyzed with the help of diagrams and first assumptions are drawn which then are tested empirically in "Empirical analysis" section. Finally, conclusions are presented in the last section.

Data overview

There is a growing trend in literature, on studies using data based on online searches as proxies to conventional data. Google Trends normalizes search data and can be used as a source of reverse engineering data to monitor global interest in the pandemic (Strzelecki, 2020). The main reasons that Google Trends data may be preferred are that they are provided free of charge and in real-time. These two characteristics provide, not only the reproducibility of empirical analysis and, but also an opportunity to construct leading indicators (Castelnuovo & Tran, 2017). Moreover, another important advantage is that they are provided daily in contrast to most conventional ones.

Additionally, some of the limitations of Google Trends data are that they show search interest over time as normalized indexes rather than the actual number of searches. Moreover, further attention is required to their interpretation as they are a trend indicator, and their reliability may be reduced due to factors like variability in correlation attributed to media coverage or changes in levels of anxiety and concern. Asseo et al. (2020) show that the use of Google's research on the loss of taste and smell as an indication of the spread of the Covid-19 pandemic lost credibility from week to week while these symptoms were becoming known and recognized by CDC and WHO.

Nevertheless, Yilmazkuday (2020) shows that daily data of Google Trends can be consistent with relevant conventional data for different frequencies, such as unemployment, interest rates, and inflation. Following his analysis, unemployment insurance initial claims from the U.S. Department of Labor (weekly data) are compared with daily Google searches on the topic "unemployment benefits" in the U.S. from 3/7/2020 to 11/21/2020.[1] To do so, the latter were converted to weekly averages, and it was found that the correlation overtime is 0.88. As shown in Figure 1, the two series react quite similarly and, therefore, online searches can be a consistent proxy for the development of unemployment on a daily basis.

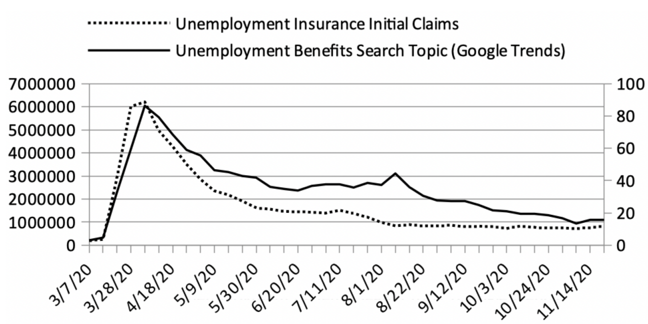

Figure 1. Initial Claims and Google searches for unemployment benefits

It is of particular interest, however, to study the divergences between changes in Google searches for unemployment benefits and changes in actual unemployment insurance

[1] Unemployment insurance weekly claims Data were obtained from: dol.gov/.

Data from Google trends can be found at: Google.com/trends

	Variable	Coefficient	Std. Error	t-Statistic	Prob.
Equation (1)	C	-1.970679	0.616924	-3.194362	0.0031
	LOG(CLAIMS)	0.711716	0.056873	12.51407	0.0000
	LOG(UNEM(-1))	0.766510	0.74026	10.35467	0.0000
	LOG(CLAIMS(-1))	-0.513827	0.090811	-5.658176	0.0000
	R-squared	**Adjusted R-squared**		**Durbin-Watson stat**	
	0.958334	0.954546		1.750581	

Table 3. Regression Output

claims. The existence of these differences may reveal an increase in financial uncertainty when Google searches grow faster than actual data (see Figure 1). This gap seems to be reaching the maximum in the first ten days of August and has been declining since then. Moreover, towards the end it is almost eliminated even though the reported new Covid-19 deaths in the US are on a rise towards the end of the period considered.

More detailed, Figure 2, shows unemployment benefit searches compared to the change in reported new Covid-19 deaths in the U.S.[2] Google searches for the unemployment benefits reached their peak earlier than the peak of the new confirmed Covid-19 deaths in the U.S., which confirms that fear had spread before the propagation of the novel coronavirus in the U.S. This was expected due to the outbreak of the virus that preceded in other countries. However, towards the end of the period considered, the Google searches for unemployment benefits were almost on a downward path even though as mentioned before new deaths relatively increased and although applications for unemployment benefits in the period between 10/24/2020 to 11/21/2020 had increased by 13,2%.

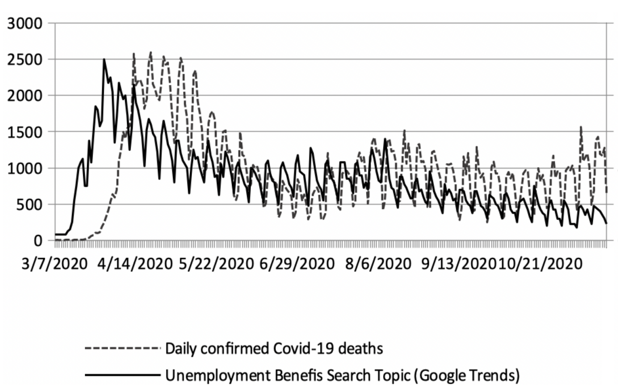

Figure 2. New Covid-19 deaths and Google searches for unemployment

A possible interpretation of that behavior is the expectation of the arrival of the vaccine for Covid-19. Figure 3 and the observation of the data show an increase of 125% in the searches for the vaccine on August 11, 2020, the day Russia announced the approval of the Sputnik V Covid-19 vaccine. Since then, and as mentioned before there has been a reduction in the divergence between the frequency of searches for unemployment benefits and the new claims. Another key date is November 9, 2020, when it was announced that Pfizer and Biontech's vaccine has more than 90% effectiveness, thereafter, the gap is even lower. This is a potential indicator of reduced financial stress.

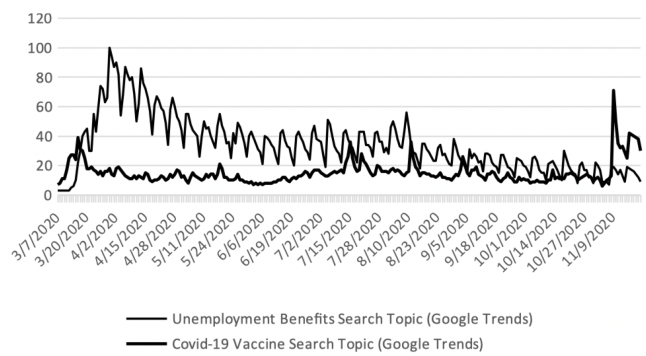

Figure 3. Google Searches for Unemployment and Covid-19 vaccine

Breusch-Godfrey Serial Correlation LM Test:			
H_0 : No serial correlation at up to 3 lags			
F-statistic	0.516817	Prob. F(3,30)	0.6739
Obs*R-squared	1.818252	Prob. Chi-Square (3)	0.6110

Table 4. Autocorrelation LM test

Empirical analysis

In this section, a series of econometric analyses are carried out to empirically test the assumptions that emerged from the data

[2]Daily confirmed Covid-19 deaths in the U.S. were obtained from Coronavirus Source Data by Hannah Ritchie available at ourworldindata.org/coronavirus-source-data

Heteroskedasticity Test: Breusch-Pagan-Godfrey:			
F-statistic	0.330026	Prob. F(3,30)	0.8037
Obs*R-squared	1.077753	Prob. Chi-Square (3)	0.7824

Table 5. Heteroskedasticity Test

Ramsey RESET Test:			
F-statistic	**Value**	**df**	**Probability**
t-statistic	0.653588	32	0.5180
F-statistic	0.427177	(1,32)	0.5180

Table 6. Ramsey Regression Equation Specification Error Test (RESET)

overview. The first hypothesis is that changes in unemployment drive, in part, the internet searches for unemployment benefits. The premise here is that Google searches can be used as consistent proxies of conventional data. To do so, the following equation is estimated for the U.S. during the period 3/7/2020 - 11/21/2020:

$$log(unem) = c(1) + c(2) * log(claims) \quad (1)$$
$$+c(3) * log(unem(-1)) + c(4) * log(claims(-1))$$

where:
unem: Google trends data on the topic: "unemployment benefits", weekly averages ; and *claims*: actual data for initial weekly insurance claims.

The estimation output as shown in Table 3 indicates that claims for insurance and lagged values of Google searches can explain over 95% of the variation in the Google searches for unemployment benefits. The LM test is then performed and as Table 4 shows there are no autocorrelation issues after we have introduced dynamics. Furthermore, based on the Breusch-Pagan-Godfrey test, there is no evidence of heteroskedasticity (Table 5), and the Ramsey RESET test shows that the model is well specified (Table 6). Finally, the plot of the Cumulative Sum (CUSUM) test stays within the 5% critical bounds, showing that the null hypothesis that all parameters are stable cannot be rejected (Figure 4).

The second hypothesis which has been tested empirically is whether Google searches for the new vaccine are determined by stress and uncertainty as expressed by Google searches for unemployment benefits. To do so, daily Google Trends data for the U.S. were employed in the period from 3/7/2020 to 21/11/2020 and the following equation was estimated:

$$log(vac) = c(1) + c(2) * log(unem) \quad (2)$$
$$+c(3) * log(vac(-1)) + c(4) * log(unem(-1))$$

	LOG(VAC)	LOG(UNEM)
Mean	2.629887	3.346709
Median	2.564949	3.433987
Max.	4.262680	4.605170
Min.	1.791759	1.098612
Std. Dev.	0.388291	0.646374
Skewness	1.072591	-1.042645
Kurtosis	4.693889	4.999186
Jarque-Bera	80.93654	90.40610

Table 7. Descriptive Statistics

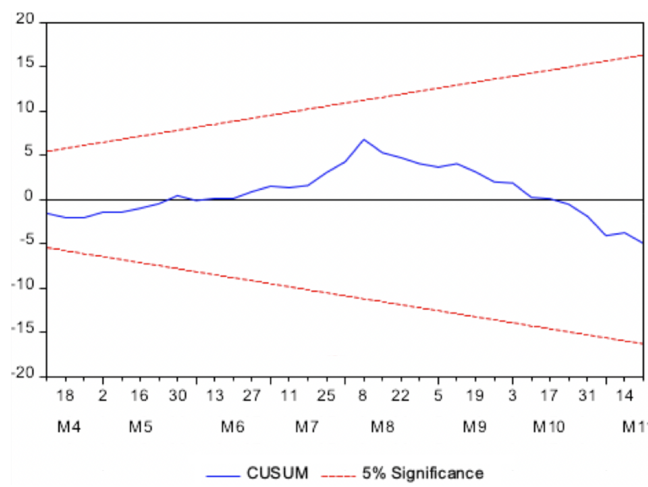

Figure 4. CUSUM plot

where:
unem: Google trends data on the topic: "unemployment benefits" ; and *vac*: Google trends data on the topic: "Covid-19 vaccine".

The estimation output as shown in Table 8 suggests that there is a statistically significant impact of Google searches for unemployment to searches for Covid-19 vaccine. Moreover, searches for unemployment benefits and lagged values of searches for the new vaccine can explain over 71% of the variation in searches for the Covid-19 vaccine. Regarding residual diagnostics, the LM test fails to show significant correlation amongst residuals (Table 9). Moreover, based on the Breusch-Pagan-Godfrey test, there is no evidence of heteroskedasticity (Table 10), and the Ramsey RESET test indicates that the model is well specified (Table 11). Also, the parameters of the model do not suffer from any structural instability as the CUSUM plot shows (Figure 5).

Papadamou et al. (2021) support their empirical research about the impact of the novel coronavirus pandemic on the correlation between stock and bond returns by using wavelets analysis that considers nonlinearity and coherence character-

	Variable	Coefficient	Std. Error	t-Statistic	Prob.
Equation (1)	C	0.466551	0.115014	4.056458	0.0001
	LOG(UNEM)	0.091473	0.045043	2.030767	0.0433
	LOG(VAC(-1))	0.848123	0.033489	25.32572	0.0000
	LOG(UNEM(-1))	-0.110080	0.044199	-2.490560	0.0134
	R-squared	**Adjusted R-squared**		**Durbin-Watson stat**	
	0.716702	0.713369		2.048923	

Table 8. Regression Output

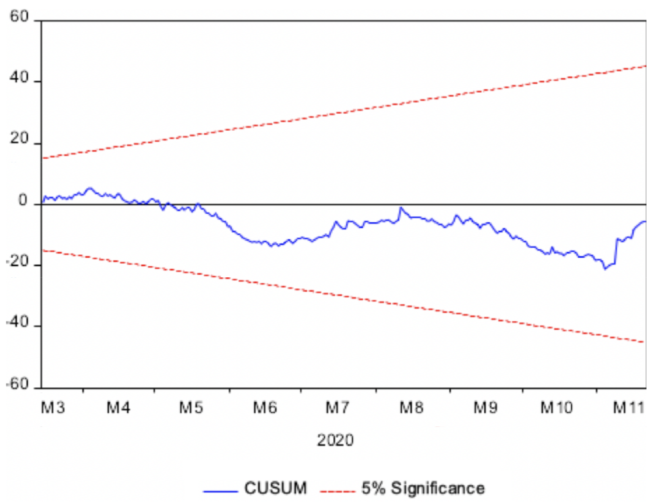

Figure 5. CUSUM plot

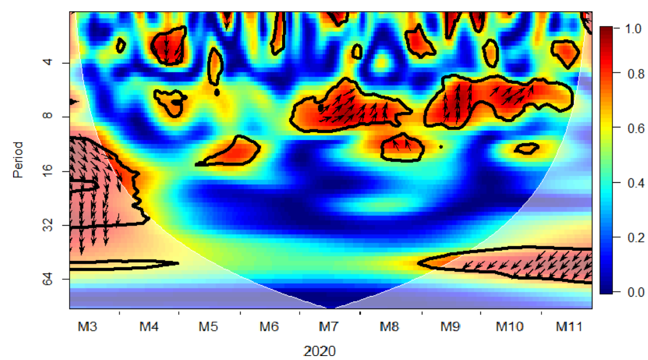

Figure 6. Wavelet coherence analysis between log(unem) and log(vac)

istics of the analyzed series. Similarly, in order to check the robustness of empirical analysis, this paper employs Morlet wavelet analysis to detect any significant consistency over time and frequency. Figure 6 shows the Wavelet coherence plot for the logarithmic form of Google trends data for unemployment benefits (log(unem)), and Covid-19 vaccines (log(vac)). A heat map identifies the different regions of coherency, which range from blue (low coherency) to red (high coherency). Y-axis measures frequencies and X-axis shows the time-period studied (3/7/2020 to 11/21/2020).

The heat map shows that there is high coherency between the two variables mainly in the second half of the period considered when expectations are emerging from the development of vaccines, and low or zero coherency during the long-run cycle (about 14 days and more). The arrows in the Wavelet plot indicate the phase differences between the two series. In periods of high coherency, the arrows mostly point to the right and up and that means that variables are in-phase having cyclical effects on each other and the first index is leading, i.e., unemployment searches cause searches for vaccines. Therefore, the previous findings reinforce the robustness of the preceded empirical analysis.

Breusch-Godfrey Serial Correlation LM Test:			
H_0 : No serial correlation at up to 3 lags			
F-statistic	1.374551	Prob. F(3,252)	0.2510
Obs*R-squared	4.169963	Prob. Chi-Square (3)	0.2437

Table 9. Autocorrelation LM test

Heteroskedasticity Test: Breusch-Pagan-Godfrey:			
F-statistic	0.240766	Prob. F(3,255)	0.8679
Obs*R-squared	0.731555	Prob. Chi-Square (3)	0.8658

Table 10. Heteroskedasticity Test

Conclusions

The current paper focuses on unemployment in the U.S. during the period from April to November 2020. During this period, the United States suffered massive job losses. The first concern of this study was to investigate whether unemployment can be approached through relevant research on the internet. An important conclusion of the study is that Google searches for the topic "unemployment benefits" can

Ramsey RESET Test:			
F-statistic	**Value**	**df**	**Probability**
t-statistic	0.388301	254	0.6981
F-statistic	0.150778	(1,254)	0.6981

Table 11. Ramsey Regression Equation Specification Error Test (RESET)

be a consistent proxy for initial insurance claims. Moreover, the differences observed in the changes in the two series may be due to changes in uncertainty. On key dates concerning the evolution of the vaccine for the novel coronavirus, it appears that the frequency of online searches for unemployment benefits is decreasing and more closely follows the changes in actual insurance claims. This is an indication of a decline in financial uncertainty as the start of vaccinations is expected to be the beginning of the end of the pandemic.

The empirical analysis has confirmed the above findings since current and lagged insurance claims and lagged values of internet searches can explain over 95% of the variation in the internet searches for unemployment benefits. Furthermore, the development of Covid-19 vaccines in the second half of the examined period is leading to an increase in searches for the new vaccine which seems to be affecting unemployment benefit searches mainly in the short-run.

The future researcher should be aware that reducing uncertainty, which in this case is marked with the development of the Covid-19 vaccine, is the key to increasing the consistency of Google Trends data compared to conventional ones.

References

Asseo, K., Fierro, F., Slavutsky, Y. et al. (2020). Tracking COVID-19 using taste and smell loss Google searches is not a reliable strategy. *Scientific Report, 10*, 20527 doi.org/10.1038/s41598-020-77316-3.

Bureau of Labor Statistics (2020). The Employment Situation – April 2020. *US Department of Labor News Release*, bls.gov/news.release/archives/empsit_05082020.pdf, accessed December 28, 2020.

Coibion, O., Gorodnichenko, Y., & Weber, M. (2020). Labor Markets During the COVID-19 Crisis: A Preliminary View. *NBER Working Papers* 27017. National Bureau of Economic Research, Inc.

Castelnuovo, E., & Tran, T. D. (2017). Google It Up! A Google Trends-based Uncertainty Index for the United States and Australia. *CESifo Working Paper Series*, 6695, CESifo.

Curdia, V. (2020). Mitigating COVID-19 Effects with Conventional Monetary Policy. *FRBSF Economic Letter*, Federal Reserve Bank of San Francisco, vol. 2020(09), pages 1-05, April.

Fetzer, T., Hensel L., Hermle J., & Roth, C., (2020). Coronavirus Perceptions And Economic Anxiety. Papers 2003.03848, arXiv.org, revised Jul 2020.

Garafas, G., & Dimitriou D. (2020). The Ides of March. Did Italian Covid-19 Crisis Fuel US Economic Policy Uncertainty? *Economia Internazionale/International Economics, 73*(4): 511-524.

Ginsberg, J., Mohebbi, M., Patel, R. et al. (2009). Detecting influenza epidemics using search engine query data. *Nature, 457*: 1012–1014. https://doi.org/10.1038/nature07634

Knipe, D., Evans H., Marchant A., et al. (2020). Mapping population mental health concerns related to COVID-19 and the consequences of physical distancing: a Google trends analysis [version 2; peer review: 2 approved]. *Wellcome Open Research, 5*: 82. doi.org/10.12688/wellcomeopenres.15870.2)

Nicola, M., Alsafi, Z., Sohrabi, C., Kerwan, A., Al-Jabir, A., Iosifidis, C., Agha, M., Agha, R. (2020, Jun). The socio-economic implications of the coronavirus pandemic (COVID-19): A review. *International Journal of Surgery, 78*: 185-193. doi.org/10.1016/j.ijsu.2020.04.018. Epub 2020 Apr 17. PMID: 32305533; PMCID: PMC7162753.

Pak, A., Adegboye, O. A., Adekunle, A. I., Rahman, K. M., McBryde, E. S., & Eisen, D. P. (2020). Economic Consequences of the COVID-19 Outbreak: the Need for Epidemic Preparedness. *Frontiers in Public Health, 8*, https://doi.org/10.3389/fpubh.2020.00241

Papadamou, S., Fassas, A., Kenourgios, D. & Dimitriou, D. (2021). Flight-to-quality between global stock and bond markets in the COVID era. *Finance Research Letters, 38*.

Strzelecki, A. (2020, Aug). The second worldwide wave of interest in coronavirus since the COVID-19 outbreaks in South Korea, Italy and Iran: A Google Trends study. *Brain, Behavior, and Immunity, 88*: 950-951. doi: 10.1016/j.bbi.2020.04.042. Epub 2020 Apr 18. PMID: 32311493; PMCID: PMC7165085.

Yilmazkuday, H. (August 28, 2020). Unequal Unemployment Effects of COVID-19 and Monetary Policy across U.S. States. *Journal of Behavioral Economics for Policy*, Forthcoming, Available at SSRN: https://ssrn.com/abstract=3559860 or http://dx.doi.org/10.2139/ssrn.3559860