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Research article

The impact of the Covid-19 pandemic on the business interruption insurance demand in the United States

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A R T I C L E I N F O

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A B S T R A C T

The article investigates the Covid-19 pandemic related changes in the demand for insurance services in the Unites States due to business interruptions by employing panel vector autoregression models to a dynamic panel data set of 50 states and District of Columbia for three periods of time: 01 January, 2004 to 28 June, 2020; 01 January, 2004 to January 21, 2020 (pre-Covid period); January 22, 2020 to June 28, 2020 (Covid-period). This paper is the first attempt to obtain estimates by applying Google Trends with a search key word "Business Interruption Insurance". The data was collected and reduced to a single scale by US states within the widest possible time span. Google Trends Hits and Initial Claims for Unemployment Insurance Benefits are used as endogenous variables in the built models. In the constructed models, the impact of the exogenous variable New Covid Cases is compared with that of over US billion-dollar natural disasters. The impulse responses show a positive relationship between the Google Trends Hits and Initial Claims with the Covid-factor having a significant impact on the responses. The conducted analyses reveal that the demand for insurance services due to the Covid-19 outbreak in the United States can be expected to increase 2–6 times, with the total amount of the incurred costs for the economy due to the virus ranging from 0.3 to 7 percent of the US-2019 GDP. The results lay the foundation for recommending the insurance market participants to lobby for adoption of public-private protection schemes being able to secure a more efficient response to the pandemic-related losses that may occur in the future.

1. Introduction

The Covid-19 pandemic and the measures taken to limit the spread of the virus have significantly disrupted economic activity worldwide, with uncertainty about the future of the global trading system and international cooperation being on the rise. The novel coronavirus has had a more negative impact on economic growth in the first half of 2020 than anticipated, which has resulted in the downward revision of the global expansion from –3% in April 2020 (IMF 2020a) to –4.4% in October 2020 (IMF 2020b).

The vast majority of the losses owing to the coronavirus looms as an onerous burden on businesses, governments and insurance companies, with private insurance coverage for economic losses caused by pandemics being limited (Hartwig et al., 2020). Judging by the available data, the pandemic impact on the insurance market is similar to that of a natural disaster (Aaronson et al., 2020; Ludvigson et al., 2020). However, the pandemic cannot be fully covered by the insurance industry as it is not a regionally concentrated event; thus, losses might exceed the worldwide capacity of the industry as a whole (Richter and Wilson 2020). As any disaster, the spread of COVID-19 has already resulted in significant business interruption (BI) losses with exact figures still being under assessment due to the long-term and continuously renewed lockdowns. While property damage is an important insurable consequence of suspension of production or commercial activities and is relatively easy to define and verify, BI is much more complex (Mills and Jones 2016). In an annual survey by global insurer Allianz, more than 2700 risk management experts from around the world rank business interruption risks at the top of their list of concerns (Allianz Risk Barometer 2021).

Under most BI insurance policies cover is provided for business damage in the event of material damage to the insured building, inventory and/or property with the impact being called "direct physical loss of or damage". However, in the majority of cases, premises will not have been "damaged" by the coronavirus and in those cases there seems to be no business interruption cover. Still, globally there are already thousands of lawsuits pending in which policyholders take the view that the concept of 'material damage' should be interpreted broadly and include the consequences of the COVID-19 pandemic with policyholders already having significant achievements both in the United States and

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Europe, including a victory before the English High Court in the UK Financial Conduct Authority's COVID-19 Business Interruption Test Case (Macinnes et al., 2020).

One of the tools to obtain the necessary estimates of the demand for BI insurance services can be Google search statistics with the search query "Business Interruption Insurance". This method fails to provide absolute values of demand, but it allows assessing the trends (Gergaud and Ginsburgh 2017). By comparing the responses of these searches to disasters and the pandemic, it is possible to predict the consequences of the pandemic for insurance companies. This paper compiles the statistics of Google searches related to business interruption concerns. This data is further linked to disaster statistics including the Covid pandemic.

The market under study is the US market as it is the largest world insurance market with life and nonlife direct premiums written amounting to 39,1% of total world premiums in 2019 (Swiss Re 2020). The second reason for focusing on the US is that it is above other countries in the rankings on the number of the confirmed COVID-19 cases (Gharehgozli et al., 2020). In this context, the primary aim of the study is to assess the change in demand for BI insurance due to the Covid pandemic by applying Google Trends data. The obtained results also allow forecasting the impact of the pandemic on the US output.

Business interruptions are inevitably followed by changes on the labour market, which are reflected in the number of unemployment insurance (UI) benefits applications (Borup and Schütte 2020). Google Trends reflect fear and intent with random deviations being significant (Challet and Ayed 2013). Theoretical considerations confirm that initial claims measuring the number of Americans filing new claims for UI benefits is one of the most sensitive official statistics used to detect changes in the country real activity (Ludvigson et al., 2020) which could improve the quality of the built models (Borup and Schütte 2020). Since the mutual influence of Google Trends and Initial Claims is assumed, both variables have signs of endogeneity, the nature of this influence is set in the panel vector autoregression (PVAR) model (Gujarati 2004).

The findings suggest that the Covid-19 pandemic has greatly boosted demand for BI insurance services in the first 6 months of 2020, and this trend may last, which may partially compensate enormous losses the insurers incur under BI policies issued prior to the pandemic outbreak. The study also reveals that the Covid-19 related losses may reach up to 7% of the 2019 US GDP.

The paper is arranged as follows. The following section reviews the literature. The subsequent section describes the incorporated data and details the employed methodology. The results and extended specifications of the empirical research are provided in the "Results and Discussion" section. Conclusions and suggestions are given in the final section.

2. Literature review

The literature documents that natural disasters are associated with a destruction of physical and human capital and therefore have substantial implications for economic activities and political stability (Noy 2009; Noy and Vu 2010; Oh and Reuveny 2010; Strobl 2012), which may impact the insurance demand.

Many households decide not to insure against natural disasters as they are mostly confined to relatively concentrated areas (Anderson, 1974: 579), their probability is rather low (Schwarze and Wagner 2007), insurance industry has a proper risk management strategy and can play a significant role in disaster loss reduction (Arnold 2008), government assistance programs can help mitigate the corresponding risks (Raschky et al., 2013). Despite the stated reasons for refraining from insurance purchases, Kunreuther (1984) and Gerber (2007) emphasize that it is critically important both for households and businesses to obtain insurance in order to reduce natural disaster losses as the available capacity may be unable to compensate the incurred damage. On the basis of a sample of 39 countries for the period 1984–2009, Chang and Berdiev (2013) study the influence of external factors, such as political risks and natural disasters on the insurance market development. The obtained results in their study confirm that the occurrences of natural disasters and deaths attributable thereto motivate individuals to purchase both life and non-life insurance policies.

Pandemic risks, whose impact may be compared to that of natural disasters', are intensifying as globalization and urbanization proceed at full speed, potentially costing as much as USD 23.5 trillion over the next 30 years (Hilsenrath 2020). However, Hartwig et al. (2020) outline that insurance demand can be reduced by people's perception that in case of a truly disastrous pandemic event governments are likely to intervene and provide assistance. Meanwhile, the same authors stress that the overwhelming majority of pandemic risk is uninsured. The Covid-19 pandemic forces market players to reconsider many traditional approaches as insurance companies face the impacts of confinement measures and staff absences which result in reduced revenues as the demand for various types of insurance coverage (event cancellation, travel, household insurance, etc.) declines (Organisation for Economic Co-Operation and Development, 2020).

On the other hand, the scale of the disruption is such that the industry and the state would not in any event be able to cover the whole loss amount. In this respect, Brunette et al. (2013) may have come to the justified findings that regardless of the form of governmental support, the ambiguity context makes individuals and business more willing to pay extra to be fully insured than in the risk situation. It coincides with the opinion of Eeckhoudt and Kimball (1992) showing that the presence of background risk reinforces the propensity to insure. It has been estimated that business continuity losses alone in the United States may reach USD 1 trillion per month (Hartwig and Gordon 2020), with the total capital resources of the U.S. property-casualty insurance industry standing at approximately USD 744,9 billion during the first quarter of 2020 (Best 2020).

So far, there have been no studies on the pandemic-related business interruption insurance demand. The present study is the first attempt to investigate the problem by applying Google Trends platform which has already been successfully used for the forecasting purposes in the earlier literature. Several researchers have investigated the use of web search volume data for economic prediction.

One of the first such applications was presented in Ettredge et al. (2005), which made an analysis of the relation between WorldTracker's Top 500 Keywords Report data and unemployment in the US and revealed a positive, significant association between employment-related searches by Internet users and official unemployment levels disclosed by the US government. Ginsberg et al. (2009) opened the door for the use of Google Trends in research studies demonstrating that Google Trends traced and predicted the spread of influenza earlier than the Centers for Disease Control and Prevention. Google Trends analysis has been used in a growing number of studies to "nowcast" the spread of disease, including now COVID-19 (Carneiro and Mylonakis 2009; Mavragani 2020; Mavragani et al., 2018; Nuti et al., 2014; Strzelecki and Rizun 2020; Walker et al., 2020). Choi and Varian (2009) emphasized the variety of time series nowcasts which can be improved with Google Trends indicators, such as automobile sales, home sales, retail sales, and travel behaviour. Google-searches based variables may provide a measure of consumer's readiness to spend (Vosen and Schmidt 2011, 2012; Choi and Varian 2012).

Aaronson et al. (2020), Goldsmith-Pinkham and Sojourner (2020), Forsythe et al. (2020) apply Google Trends to demonstrate the Covid-19 related surge in the demand for unemployment insurance in the US. Capema et al. (2020) show that, in the aftermath of lockdowns, such indicator rose by about 30% in the EU Member States compared to the pre-pandemic average.

3. Methodology

3.1. Data

3.1.1. Google Trends Hits

The analysis is based upon the Google Trends web search data (Google Trends 2020) over the period 01.01.2004–28.06.2020 in a panel of 50 US states and District of Columbia (D.C.). The lower bound corresponds to the date from which the Google Trends data is available. While searching the Google Trends data the query "Business interruption insurance" was used. After the set of transformations described in Appendix 1, the data was scaled down to a single scale with weekly frequency across 50 states and D.C. Descriptive statistics for this data set are summarized in Table A2.1.

The expression "Business Interruption Insurance" has become the search object for the following reason. The book "Business Interruption Insurance" (Klein 1950) gives credit to Frederick C. White for coining the phrase and providing the title of "business interruption insurance." This name of insurance product has become a certain cliché since the turn of the 21st century due to the globalization of industry, the increased dependence on electronic data and cyber security risk, terrorism events, increased frequency, and severity of natural catastrophes. Therefore, I assumed that searching for the protection of their businesses due to the interruption of production or service activities, entrepreneurs would use nothing but the term "Business Interruption Insurance". Anyway, synonymous words have also been considered though they have demonstrated a low level of representativeness as compared to the chosen search expression. Table 1 shows the results of the searches with the highest level of completeness (nonzero searches), as well as cross correlation between the searches.

Fig. A 3.1 shows search results for the whole country as well as two separate states, i.e., New York and Georgia. Google Trend Hits are measured in relative units from 0 to 100 by weeks and by states. Google Trends define the largest number of searches as 100 over the entire observation range. All other searches are defined as a fraction of this number.

3.1.2. Weather and climate billion-dollar disasters

The data is obtained from the NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (NOAA, 2020). The observation period fixed 7 types of the costliest natural and social disasters (civil disorder in Baltimore in April 27–28, 2015). The list of disasters, incurred losses as well as and other characteristics are provided in Table 2.

Initially, the data has daily frequency and covers 49 US states and District of Columbia. Hawaii is excluded as there were no billion US dollar-scale disasters over the observation period. The data on the disasters and losses was converted to a weekly frequency so that its frequency is consistent with other time series. If the disaster occurred in several states, then its cost in the data series is uniformly distributed among these states. If the disaster lasted for several days, its cost is uniformly distributed between these days. Descriptive statistics of the disaster data are given in Table A2.2. The costs of the disasters in the paper are measured in USD million per week in a given state.

Table 1. Google Trend search results with different keywords. by months and for the whole period.

N	Keyword	Number of zeros in the search	Cross correlation between the searches			
			1	2	3	4
1	Business Interruption Insurance	27	1.000	0.274	0.204	0.066
2	Business Interuption Insurance ("r" is missed)	150		1.000	0.066	-0.109
3	Business Disruption Insurance	191			1.000	-0.025
4	Business Stop Insurance	114				1.000

Source: Author's estimations.

Table 2. Weather and climate disasters list with characteristics.

N	Disaster	Number of cases	Cost, million USD	Percent of all	Number of days it lasted	Deaths
All 01.01.2004–28.06.2020						
1	Baltimore	1	24	0.0024	4	0
2	Drought	215	91325	9.1584	60573	286
3	Flooding	107	67714	6.7906	4384	256
4	Freeze	28	4444	0.4457	160	1
5	Severe_Storm	753	181099	18.1613	2853	1106
6	Tropical_Cyclone	140	580479	58.2127	815	2924
7	Wildfire	118	61942	6.2118	23054	275
8	Winter_Storm	70	10166	1.0195	303	113
All		1,431	997169	100	92142	4961
Covid 22.01.2020–28.06.2020						
1	Severe Storm	94	16590	-	243	70

Source: Author's estimations based on NOAA, 2020.

Unemployment weekly data by states is retrieved from The US Department of Labor (2020). I used seasonally unadjusted data for initial claims with weekly frequency 50 states and D.C. Descriptive statistics of the Initial Claims data are shown in Table A2.3.

Fig. A 3.2 shows Initial Claims for the whole country as well as two states, i.e., New York and Georgia for the three periods underlying PVAR Models. Initial Claims are measured in numbers per week in a given state.

Daily Covid cases data is obtained from The Covid Tracking (2020) and ranges from 22 January, 2020 to 28 June, 2020. The daily data is provided for 50 states and 6 territories with the number being reduced to the standard 50 states and D.C. for other samples and the data being converted to a weekly format. Descriptive statistics for the New Covid Cases data are summarized in Table. A2.4.

Fig. A 3.3 shows New Covid Cases for the entire US as well as two states, i.e., New York and Georgia. New Covid cases are represented in numbers per week by states.

3.2. Methods

In this work, the entire range of observations, which is the time interval from 01 January, 2004 to 28 June, 2020 is divided into two periods. The first period consists of data prior to the official registration of the first cases of Covid in the United States. This is the time interval from 01 January, 2004 to 21 January, 2020. There were registered two positive cases in Wyoming at 22.01.2020 (Table A2.5). The second period is the remaining time interval from January 22, 2020 to June 28, 2020. Dividing the observation range into intervals allows estimating the adjustments made by the pandemic for the nature of the relationship between Google Trends Hits and Initial Claims.

Google Trends Hits with the Business Interruption Insurance search query are assumed to reflect the demand for business interruption insurance services. This variable is the subject of primary interest. The sensitivity of Google Trends Hits to the emergence and spread of Covid infection is evaluated. This compares the responses of Google Trends Hits to Initial Claims amid the pandemic and prior to Covid-19.

For the entire observation period, as well as for each of the intervals, PVAR models were constructed, which differ in the sets of variables. They can be combined by the equation

$$Y_{it} = \sum_{\tau=1}^{p} B_{\tau}^{k} Y_{it-\tau} + B_{p+1}^{k} X_{it}^{k} + \alpha_i + U_{it}^{k} \tag{1}$$

where k is a time interval indicator; Y represents an endogenous variables vector; p refers to a lags depth in PVAR model; X^k is an exogenous variables vector for time interval k; $\alpha_i$are fixed effects by states; i is a state number; t is week number from the beginning of 2004. Time interval indicator takes three values:

k = 1 – the entire observation interval (All Model); k = 2 – observation interval preceding Covid (Before Covid Model); k = 3 – the interval from the beginning of the official registration of Covid-19 (Covid Model) in the United States.

For each interval, the vector of endogenous variables is as follows:

Y = (Hits, Initial Claims).

The vector of exogenous variables X^k in Eq. (1) includes indicators of catastrophes observed in the corresponding period. Table 2 provides a list of recorded major social and natural disasters. The very reflection of the fact of a catastrophe by means of a binary variable taking values of 0 or 1 does not allow measuring its scale and consequences for the economy. Therefore, it was decided to measure catastrophes by the magnitude of economic losses. As published in NOAA (2020), the consequences of disasters are shown for the whole period of their duration with the total amount for each state where they occurred provided. Due to the lack of estimates of the distribution of losses by state and duration, in this paper a uniform distribution is assumed for each dimension.

For k = 1 and k = 3, the vector of exogenous variables includes the number of new cases of Covid-19. The paper does not simply record the presence or absence of Covid-19 cases in the respective state. The number of new cases shows the degree of Covid-19 impact on the economic, social and psychological life of society.

4. Results and Discussion

In accordance with Eq. (1), PVAR models were constructed for three periods of time. Table 3 displays statistic and p-values of unit root tests results with an intercept for endogenous variables used in the models (Im et al., 2003).

Figure 1 (a, b, c) shows the stability test results for each of the three models (Lütkepohl, 2007). Inverse unit roots are located inside the unit circle, which proves that the models are stable.

The lag length in the PVAR model is set according to the minimum values of the information criteria (Akaike 1973; Schwarz 1978; Hannan and Quinn 1979). In each of the three models, the lag length is 4 which is set according to Schwarz (1978) criterion in All Model and Hannan and Quinn (1979) criterion in Covid Model.

Table 4 shows that there are significant reciprocal causal relationships between the variables Google Trends Hits and Initial Claims (Granger 1969). For each of the three models, Google Trends Hits are the reason for Initial Claims. This justifies the inclusion of Initial Claims in the list of endogenous variables and, as a consequence, the choice of PVAR as a model. In the All and Before Covid models, lagged Initial Claims are the reason for Google Trends Hits.

The left panel of Figure 2 shows Google Trends Hits responses to Initial Claims impulses. Comparing Figure 2 a and Figure 2 e, we see that the responses differ insignificantly, although the observation ranges and, accordingly, the sample sizes are significantly different. The presence of an exogenous factor in the form of new cases of Covid-19 combines the responses of the upper and lower panels. New Covid-19 cases dominate the link between Google Trends Hits and Initial Claims. The very relationship between these variables is positive. The impulse of one variable causes an increase in the second one with some lag. Initial Claims momentum is tantamount to unemployment growth. Google Trends Hits reflect the demand for business interruption insurance. Rising unemployment increases the demand for business interruption insurance.

Figure 2 c illustrates Google Trends Hits response to Initial Claims impulse in Before Covid Model. It can be seen that in the second week there is an increase in Google Trends Hits, which is 2–6 times less, then in All and Covid Models, and quickly becomes insignificant. An increase in the demand for insurance against business interruption triggered by the rise in unemployment in the period before Covid is several times lower than amid Covid.

After the 4th week, the response becomes negative. This was not in All and Covid Models. The rise in unemployment and the decline in production lead to the funds allocated for insurance against business interruption being reduced over time.

The right panel in Figure 2 shows Initial Claims responses to Google Trends Hits impulses. Figure 2 b and Figure 2 f show responses in All and Covid models, whose shapes differ little. There is a positive relationship. The growth in demand for business interruption insurance can be viewed as a forecast for interruption with a high occurrence probability. As a result of the business shutdown, unemployment rises.

Figure 2 d shows Initial Claims responses to Google Trends Hits impulses in Before Covid Model. It can be seen that the absence of the Covid factor changes the nature of the relationship between Initial Claims and Google Trends Hits to the opposite. Business interruption insurance is in demand any time. However, prior to Covid, investors expected and feared changes and therefore were interested in business interruption insurance. But that period was favourable compared to what happened after the Covid-19 outbreak. Employment grew with a simultaneous decrease in the number of applications for unemployment benefits. The pandemic has changed the motivation for searching jobs.

Table 5 shows the estimates of the parameters of PVAR models for three time periods, obtained in accordance with Eq. (1). Lagged Initial Claims have a significant impact on Google Trends Hits in each of the three models. The parameter estimates in the All and Covid models differ insignificantly, which indicates the stability of the constructed dependencies. Initial Claims appear to be a good predictor of Google Trends Hits, and hence the demand for business interruption insurance.

Among the disasters presented in Table 2, Severe Storm should be highlighted. Losses from this type of disasters are in second place after Tropical Cyclone and account for more than 18% of all losses. As per Table A2.6 providing the descriptive statistics of this variable, Severe Storms are fairly common and widespread throughout the United States. Severe Storms significantly affect Google Trends Hits and Initial Claims, but only in the Covid era. In the Before Covid model, no significant influence of this variable was revealed.

In the Covid model, the Severe Storm disaster was the only one from the list of Table 2. The rest of the catastrophes in this time interval were not observed. Its descriptive statistics are given in Table A2.7 which shows that despite a relatively short period of time, this type of disaster was common in a significant number of states. Since in the Before Covid Model Severe Storm is not significant, it was in the Covid model that the influence of this type of disaster was decisive.

According to Table 5, one new case of Covid in All Model initiates 1.97 Hits. The total number of Covid cases in the United States as of

Table 3. Unit roots null hypothesis statistic and p-value. Source: Author's estimations.

Variable	Model					
	All 01.01.2004–28.06.2020		Before Covid 01.01.2004–21.01.2020		Covid 22.01.2020–28.06.2020	
	statistic	p-value	statistic	p-value	statistic	p-value
GT Hits	-81.8054	0.0000	-85.3325	0.0000	-2.1396	0.0162
Initial Claims	-47.0393	0.0000	-28.2672	0.0000	-2.5244	0.0058

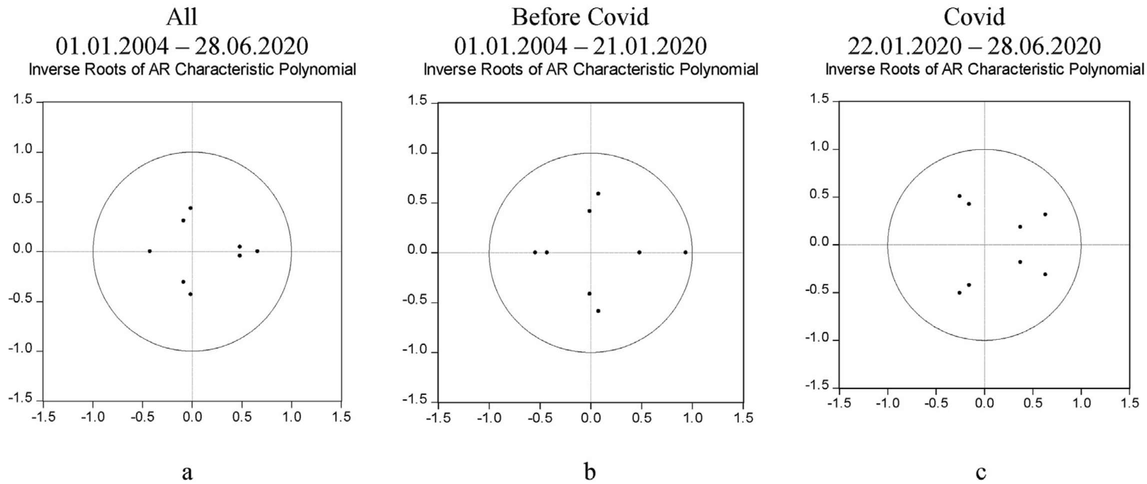

Figure 1. Inverse unit roots graphs. **Source:** Author's estimations.

Table 4. P-values of Granger test for causality dependent variables.

Model	Variable with lags from 1 to 4		are cause for
	Google Trends Hits	Initial Claims	
All	0.0000	-	Initial Claims
Before Covid	0.0000	-	
Covid	0.0000	-	
All	-	0.0001	Google Trends Hits
Before Covid	-	0.0034	
Covid	-	0.2348	

Source: Author's estimations.

June 28, 2020 was 2,533,559 in 50 states and D.C. (The Covid Tracking, 2020). Assuming a linear relationship, as in (1), we obtain $1.97 \cdot 2533559 = 5 \cdot 10^6$ increase in Hits from the total number of new Covid cases.

Severe Storm in All Model, with a USD million loss, increases Hits by 3.35 (3.35 Hits/USD Million). In order to determine Severe Storm losses to cause a $5 \cdot 10^6$ Hits increase, I divided $5 \cdot 10^6$ by 3.35 and got USD $1.5 \cdot 10^6$ million. If we measure the impact on Hits, then the total number of Covid cases produced the same effect as Severe Storm with losses of USD $1.5 \cdot 10^6$ million. In 2019, the US GDP (in current USD) was USD $21.4 \cdot 10^6$ million (The World Bank, 2020). According to the obtained estimate, Covid acted like a Severe Storm resulting in a loss of 7% of the 2019 US GDP. After making similar calculations in the Covid Model, I got USD $6.5 \cdot 10^4$ million or 0.3% of the US GDP.

The obtained estimates are very rough. Linear approximation (1) was built in the range of Hits values [0; 5429] (Table A2.1), Severe Storm Costs [0; 1245] (Table A2.5) and New Covid Cases [0; 66754] (Table A2.4). Forecasting for Hits, Severe Storm Costs and New Covid Cases that are thousands of times as much as the model building range may not be accurate (Gujarati 2004). However, these estimates provide some indication of the disaster scale.

The estimates of the influence parameters of Initial Claims lagged values on Google Trends Hits shown in Table 5, demonstrate little difference in All and Covid Models. This indicates the decisive influence of Covid in this function. The surge in Hits during the Covid period basically formed the dependencies of Google Trends Hits on Initial Claims lagged values.

The estimates of the parameters of the dependence of Initial Claims on Google Trends Hits lagged values (Table 5) are similar in All and Before Covid Models, which indicates that the nature of this function is long-term and depends little on the conjuncture associated with the pandemic.

On balance, the business sentiment reflected by the number of initial claims has turned out to be particularly responsive to the pandemic. Business interruptions resulting from restrictions on economic activities have propelled BI insurance claims (OECD, 2021) and led to a sharp rise in unemployment (Gezici and Ozay 2020). The significant impact of the Covid-19 pandemic on the US unemployment rate is also confirmed by Groshen (2020) and Milani (2021).

Though there is little evidence that the US unemployment schemes may have discouraging impact on the willingness to work (Finamor and Scott 2021; Dube 2021), government support with particularly generous treatment for low earners relative to the wages they can command or the wage subsidies available makes them unwilling to return to work (Tetlow et al., 2020). As a result, the struggling businesses face extra losses due to the decreased numbers of work applicants (Morath 2021). This trend may contribute to the further growth of business sentiment uncertainty and thus boost business interruption insurance demand.

The mutual influence of BI insurance demand and Initial Claims has never been investigated before; however, the obtained results on the interdependence of these two indicators demonstrate that in the face of the pandemic businesses are forced to build resilience with business interruption remaining their primary concern and thus BI insurance demand growing. The revealed trend is in line with that highlighted by Richter and Wilson (2020) and Liedtke (2021).

The findings on the Covid-19 related losses are not as pessimistic as those given by Walmsley et al. (2021) forecasting US GDP losses from Covid-19 ranging from 14.8% to 23.0% in a 2-year period. In general, the obtained results do not contradict either the data of Ludvigson et al. (2020), where the decline in industrial production due to Covid was estimated at 12.75% or an estimated contraction of the US economy by 3.6% in 2020 provided by The World Bank, 2021.

5. Conclusions and suggestions

The conducted research is the first attempt to study the trends in demand for insurance amid the Covid-19 pandemic by collecting and reducing to a single scale the search results with the search query "Business Interruption Insurance" from 01.01.2004, when Google Trends data became available.

There was a surge in searches due to business interruption in 2016–2018 up to 200 units across the United States. Similar surges were observed in 2006 and 2012. The Covid pandemic increased the frequency of business interruption searches by 3.5 times to 700. The pandemic,

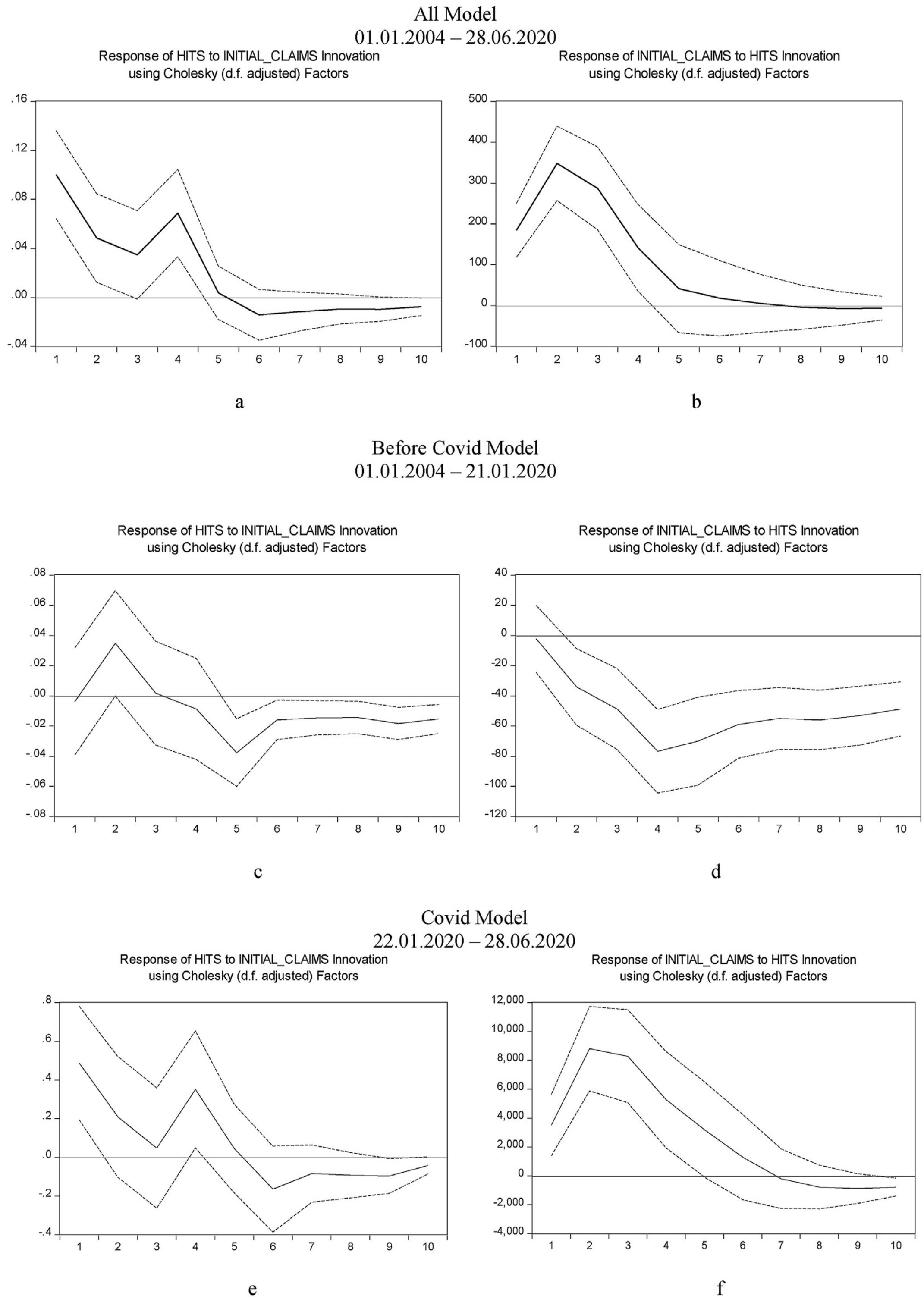

Figure 2. Google Trends Hits and Initial Claims mutual impulse responses for different time periods. **Source:** Author's estimations.

unlike other crises, has affected all states. Its cumulative effect was manifested throughout the United States, with relatively small surges in individual states.

It was decided to reach the aim of the research by studying the interaction between Google Trends Hits and Initial Claims, with the latter also reflecting business sentiment. During the 2008 crisis, Initial Claims peaked at 950,000 units. However, during the pandemic, the peak values were 6 times higher than before and reached 6 million units with individual states showing similar surges.

Impulse responses (Figure 2), as well as Granger tests for PVAR models (Table 4) prove the interdependence of Google Trends Hits and Initial Claims. This interdependence is determined by both economic and psychological reasons. As dynamic changes in Initial Claims reflect the economic situation (Martin et al., 2020), unemployment claims rise as business activity is interrupted and economic worries grow (Gezici and Ozay 2020). As a consequence, amid economic policy uncertainty which can trigger bankruptcies and firm shutdowns (Stolbov and Shchepeleva 2020), a surge in Initial Claims which is statistically recorded by the

Table 5. PVAR models estimates according to (1).

Coefficients	Dependent variables					
	All Model		Before Covid Model		Covid Model	
	Hits	Initial Claims	Hits	Initial Claims	Hits	Initial Claims
HITS (-1)	46.82832***	0.055727***	-9.336334***	0.037533***	1099.217***	0.291244***
HITS (-2)	-2.756136	0.039744***	-8.15865***	0.036428***	-74.4412	-0.108055***
HITS (-3)	-19.36783**	0.025460***	-12.49947***	0.01411***	29.59779	0.16222***
HITS (-4)	-12.19021	0.039744***	-5.088795*	0.0356***	-99.12225	-0.067397**
INITIAL_CLAIMS(-1)	0.95084***	6.20E-06**	0.549633***	1.48E-05	0.91125***	1.81E-06
INITIAL_CLAIMS(-2)	-0.228714***	-1.71E-06	0.094121***	-8.33E-06*	-0.287113***	-6.06E-07
INITIAL_CLAIMS(-3)	0.068076***	6.66E-06*	0.059143***	-5.85E-06*	0.094088**	7.16E-06
INITIAL_CLAIMS(-4)	-0.029745***	-9.28E-06***	0.18082***	-1.51E-05	-0.095895***	-8.33E-06**
COST_BALTIMORE	-41.73397	-0.021101	-37.79623	-0.021051		
COST_DROUGHT	0.134631	-0.000314	0.370781	-0.000241		
COST_FLOODING	-0.174533	-0.000194	-0.111872	-0.000191		
COST_FREEZE	0.51493	0.002719	0.412537	0.002668		
COST_SEVERE_STORM	3.348256***	0.001006***	0.083879	0.000428	65.67156***	0.010113***
COST_TROPICAL_CYCLONE	-0.057167	-2.17E-05	-0.022387	-2.36E-05		
COST_WILDFIRE	-0.428797	0.000555	-0.200815	0.000549*		
COST_WINTER_STORM	5.001485	-0.001847	1.617692	-0.001373		
NEW_COVID	1.968599***	9.86E-05***			1.689848***	6.51E-05*

*p<10%; **p<5%; ***p<1%. Constant and fixed effects estimates α_i for states are not included in the table for the sake of compactness.
Source: Author's estimations.

business community (data on Initial Claims is published weekly) encourages searching for protection against business interruption; therefore, BI insurance demand rises.

On the other hand, expectations of economic situation changes are reflected by Initial Claims through the business sentiment. Assuming any downward trends in the future, entrepreneurs begin a cycle of production cuts and layoffs (Yu et al., 2021), thus boosting the demand for BI insurance and provoking an increase in Initial Claims.

Google Trends Hits responses to Initial Claims impulses are shape-stable under the influence of the Covid-19 (All and Covid Models). First, comparing the impulse responses of Hits during the pandemic and its absence allowed establishing that Covid is a decisive factor in their formation. New cases of Covid intensify the amplitude of responses by 2–6 times. A similar growth rate should be expected for the demand for business interruption insurance services.

The Covid-19 pandemic manifested itself with a high level of significance (Table 5) in the constructed models. The latter include exogenous factors such as states fixed effects, social and natural disasters, and the Covid-19 pandemic. Among the catastrophes, Severe Storms demonstrated high significance (Table 5). This type of disaster is typical of the United States and occurs quite often. During the pandemic alone (158 days from 22 January, 2020 to June 28, 2020), the total duration of these disasters across all states was 243 days, with the loss amount reaching USD 16,590 million (Table 2).

Next, by comparing the response of Google Trends Hits to Covid and Severe Storm changes it was estimated that Covid-related costs may range from 0.3% to 7% of the 2019 US GDP.

Overall, the findings of the paper provide evidence that the coronavirus pandemic caused a sharp decline in production with long-lasting lockdowns disrupting the service sector. In this regard, demand for business interruption insurance services due to the pandemic outbreak increased, which simultaneously implies higher written premiums for insurers and increased claims payments under the policies signed prior to the Covid-19. The new reality made it necessary for most insurance companies to reconsider their policy wordings ahead of the renewal period and more legislators to consider statutory changes (Frankel 2020) to force the industry to provide retroactive coverage to policyholders, regardless of the language of their insurance contracts. In respect of increasing the efficiency of business interruption insurance coverage in the years to come, it may be recommended to take a closer look at the idea of public-private partnerships on a par with a pandemic-related loss allocation model suggested by a global insurance and reinsurance company Chubb Ltd. (Moorcraft 2021). The project seems to be more beneficial as compared to other federal-backed protection initiatives as it calls for the mobilisation of much more capital from public and private markets.

To lend support to the findings of the present research, future research, thus, may include additional indicators of economic activity such as Business Formation Statistics. In the future study, in case of data availability, it would be useful to consider major alterations to the legislation and claim settlement procedures, which would lead to a greater understanding of the Covid-19 pandemic impact on the US insurance market.

Declarations

Author contribution statement

Elena Nebolsina: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Additional information

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