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# Economic sentiment during the COVID pandemic: Evidence from search behaviour in the EU☆

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ABSTRACT

The COVID-19 pandemic has inflicted an economic hardship unprecedented for the modern age. In this paper, we show that the health crisis and ensuing lockdown, came with an unseen shift in households' economic sentiment. First, using a European dataset of country-level and regional internet searches, we document a substantial increase in people's business cycle related searches in the months following the coronavirus outbreak. People's unemployment concerns jumped to levels well-above those during the Great Recession. Second, we observe a significant, coinciding slowdown in labour markets and consumption. Third, our analysis shows that the ensuing shift in sentiment was significantly more outspoken in those EU countries hit hardest in economic terms. Finally, we show that unprecedented fiscal policy actions, such as the short-time work schemes implemented or reformed at the onset of the COVID-crisis, however, have not eased economic sentiment.

## 1. Introduction

It is now beyond question that the COVID-19 pandemic is not only a global health emergency, but is also leading to a major global economic downturn as the deaths toll rises and economies are intentionally shut down. Most EU countries, for instance, have responded to the COVID-19 shock by adopting a lock-down survival strategy, with leading figures coining the COVID-induced recession the Great Lockdown (e.g. Gopinath, 2020). Preliminary indicators on job destruction and unemployment benefit claims across EU countries suggest that the impact of the COVID-19 pandemic is likely to be exceptionally high. While the global job loss is more difficult to gauge, the decline in working hours thus far already exceeds 195 million full-time jobs (International Labour Organization, 2020).

Traditional, backward looking measures of economic sentiment derived from statistical models' fit to macroeconomic data are not well suited to quickly capture shifts associated with sudden, surprise developments like the COVID-19 crisis. Real-time, more high-frequency measures of economic agents' sentiment and perceived uncertainties are thus proving vital for nowcasting and the formulation of effective stabilisation and recovery policies. Therefore, the existing early-warning indicators in the policymakers' toolbox are being expanded or new ones proposed (Baker et al., 2019, 2020; Altig et al., 2020a, b; Müller and Hornig, 2020).

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The purpose of this paper is to document the changes in households' economic sentiment in the EU following the outbreak of the COVID-19 pandemic and ensuing lockdown. To this end, we employ a rich dataset of country-specific internet searches in the EU. Contrary to more traditional approaches such as consumer surveys, internet search data are freely available in near real-time and at a high-frequency, allowing policymakers to observe shifts as they arise. Furthermore, these non-traditional data have been show to track well actual unemployment and consumption, and possibly, even cover aspects of consumer sentiment not captured by consumer surveys.

Our main conclusions are threefold. First, we document a substantial change for the worse in people's economic sentiment in the months following the coronavirus outbreak as well as a significant, coinciding slowdown in labour markets and (durable) consumption. These results complement earlier findings for Great Britain, the US and select EU countries, both in scope and type of data used (e.g. consumer surveys and transaction data). Interestingly, whereas supporting the claim that drop in households' consumption spending was partly driven by the spread of the virus regardless of mobility restrictions, our European data tend to attribute a larger share to the impact of the lockdowns than the existing US evidence (e.g. Goolsbee and Syverson, 2020).

Second, our analysis shows that the ensuing shift in sentiment was significantly more outspoken in those EU countries hit hardest in economic terms. As these countries labour market conditions were often already less favourable at the onset of the crisis, the risk of a widening gap between EU member states thus seems likely in absence of a commensurate (and coordinated) policy response. This result is very much in line with earlier findings suggesting that a higher share of jobs are at risk in southern Europe and France (Doerr and Gambacorta, 2020). Previous evidence on the impact of the financial crisis in these countries points to a risk of persistent high level of unemployment during the post-crisis phase, against the background of high debt levels, low population and productivity growth, see Boeri and Jimeno (2016) and Galí (2015).

Third, using monthly search data for the past decades, we show that the shift in economic sentiment during the first wave of the COVID-19 pandemic is similar or higher than during the Great Recession of 2007–2009. This is especially the case for unemployment-related sentiment.[1] Following the pandemic, unemployment-related web searches have jumped far beyond those observed during the Great Recession. This difference is even more outspoken for wage compensation queries in countries that had short-time work (STW) schemes present during both crises, thus highlighting their relevance during the heat of the pandemic. The (intensified) use of STWs, however, does not seem to have eased economic sentiment relative to countries without such schemes; although there is suggestive evidence that during the Great Recession countries with STWs in place had less unemployment-related concerns, as measured by corresponding internet searches. While this does not have to affect the ability of STWs to save jobs, it supports the idea that the labour market impact of this crisis is more pervasive, at least in the people's minds, which might fuel animal spirits (Akerlof and Shiller, 2010) and/or heighten the risk of unemployment hysteresis in countries most directly affected by the pandemic.

The rest of the paper is organised as follows. We start by presenting an overview of the related literature in Section 2. Section 3 then describes in more detail the Google search data and the econometric identification. Next, Section 4 presents the estimation results for the EU panels in terms of business cycle, labour market and consumption trends, respectively. Section 5 concludes.

## 2. Related literature

### 2.1. Economic sentiment and economic activity

Economic sentiment captures "*economic agents' views of future economic developments that may drive the economy because they influence agents' decisions today, a view that may reflect rational arguments and facts but also a mood of optimism or pessimism*" (Nowzohour and Stracca, 2020, p. 691).[2] Economic sentiment can be decomposed into (Knight, 1921): (i) confidence, a strong belief in (positive) future economic developments, which may be the result of animal spirits and/or news about future economic developments; and (ii) uncertainty, which can refer to either the range of possible outcomes of future economic developments (i.e. risk) or the lack of knowledge of the probability distribution from which future economic developments are drawn (i.e. Knightian uncertainty).

Ideally, one would like to measure and analyse each of these separately. Unfortunately, this is commonly complicated by the fact that each component may influence the behaviours observed in the data. In their recent survey, Nowzohour and Stracca (2020), for instance, conclude that there is an important common component in uncertainty and confidence measures, with the principal component explaining up to half of the variation. For example, a higher stock market volatility signals larger uncertainty and (perceived) downside risks as well as lower investor confidence. Our analysis is no exception to this. Our analysis primarily measures households' economic sentiment as a whole.[3] Internet searches have been proven to provide a good measure of the economic sentiment, both among investors (Beer et al., 2013; Da et al., 2015) and households (see, e.g. Choi and Varian (2012) for unemployment and Vosen and Schmidt (2011) and McLaren and Shanbhogue (2011) for consumption).

The idea that sentiment is a driver of economic activity is moreover gaining ground. Analysing a set of common measures of confidence and uncertainty, Nowzohour and Stracca (2020) for example find that most of the correlations with economic and financial variables are contemporaneous or forward-looking (espec. consumer confidence). Sentiment may affect the real economy in a variety

[1] This conclusion is in line with the more traditional sentiment indicators for the EU. In the two months after the arrival of the virus, the European Commission's monthly survey-based Economic Sentiment Indicator (ESI) and, in particular, the Employment Expectations Indicator (EEI) have surpassed their lows observed during the Great Recession.

[2] See Algaba et al. (2020) for a recent overview of the methodological details of measuring economic sentiment.

[3] Moreover, the ad hoc character of the search data is more likely to capture (short-run) uncertainty and news, rather than long-held beliefs.

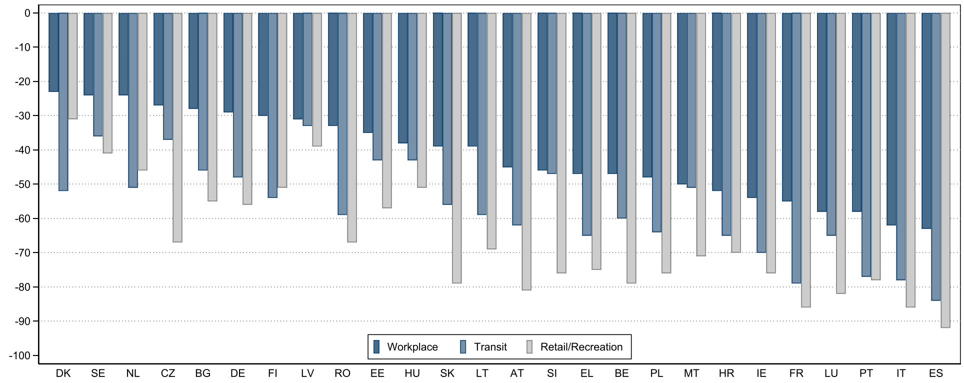



**Fig. 1.** Google Mobility – percentage changes w.r.t. median mobility on the same day of the week in the weeks leading up to the crisis. *Note:* Data were extracted on April 16th 2020. Data covering the period February 15th to April 11th, 2020.

of ways. Under the animal spirits hypothesis, consumers and business sentiment can drive economic activity (see e.g. Benhabib and Spiegel, 2019). Uncertainty, in particular, has recently been documented to find its way into the business cycle via a variety of channels.[4] For instance, the resulting increases in risk premia may reduce growth by raising the cost of financing. Uncertainty, moreover, may make firms more cautious about investment and hiring, since adjustment costs often make reversion expensive (Bloom, 2009). Households' expectations, on the other hand, may be affected too and, by consequence, their precautionary savings, consumption and investment, triggering a fall in aggregate demand and supply (Roth and Wohlfart, 2020). Even accounting for their socio-economic characteristics, people with more uncertain expectations exhibit more precaution in their consumption, credit, and investment behaviour (Ben-David et al., 2018).[5] Recent Eurostat data for the euro area, for example, suggest an unprecedented surge in saving rates, from 12.7% in the fourth quarter of 2019 up to 16.9% in the first quarter of 2020, due mainly to the exceptional fall in consumption expenditure.[6] Finally, uncertainty has been linked to equilibria with persistently higher unemployment as the result of steady-state indeterminacy, so-called sunspots (Farmer, 2012; Benigno and Fornaro, 2018). Fontaine (2020), for example, goes to show that under price stickiness uncertainty shocks may lead to declines in firms' profits, fewer vacancies being posted and decreases in labour force participation.

### *2.2. Non-traditional high-frequency data*

The limitations of traditional, backward looking measures of sentiment in terms of suitability and availability, have recently led to a variety of new indicators emerging, e.g. the Weekly Economic Index by Lewis et al. (2020) and the Daily News Sentiment Index by Buckman et al. (2020). At the same time, researchers started employing a broad range of non or less traditional data sources to gauge the economic impact of the COVID-19 pandemic, including web scraped consumer prices, (credit card) transaction data, online job postings, satellite imaginary, traffic flows, electricity consumption, cellular phone records and natural language processing of news and social media.

One way of measuring the impact of the crisis, for example, is the severity of the disruption to movements and presence at the workplace. For example, on April 11th the percentage changes vis-à-vis the median mobility on the same day of the week in the five weeks leading up to the crisis show a generalised (and exceptional) reduction in mobility, which was particularly pronounced for movements related to retail and recreation, which are specific to tourism and leisure activities, see Fig. 1. In fact, mobility data have been shown to capture the impact of COVID-19 confinement measures, explain the spread of the pandemic and, hence, provide relevant information for policy design (Iacus et al., 2020a; b; Santamaria et al., 2020; Yilmazkuday, 2020). Moreover, from European mobility data (Fig. 1), it becomes clear that countries that are generally considered to have been hit hardest by the health crisis (e.g. Italy and Spain), have also suffered the most drastic shifts in activity, especially in the tourism sector; capturing the extent of the confinement measures and ensuing economic standstill necessary to combat the virus.[7]

[4] Fernandez-Villaverde and Guerron-Quintana (2020) provide a model-based illustration of the various mechanisms through which how higher level uncertainty are linked to the business cycle.

[5] Many consumers moreover associate bad times with high inflation. Binder (2020) observes that greater concern about the coronavirus is associated with higher inflation expectations. Interestingly, provision of information about the Fed announcement leads some consumers to become more optimistic about unemployment and revise inflation expectations downward. Coleman and Nautz (2020) their results in turn indicate that the credibility of the ECB's inflation target has significantly decreased, particularly in the course of the coronavirus pandemic.

[6] Nevertheless, high saving rates might prove insufficient for households to weather the crisis and therefore for consumption to resume, especially for low-income ones with a high spending propensity, see Gambacorta et al. (2020).

[7] Similar trends can be observed from Apple's mobility data.

Another source proven useful is Google Trends data, as popularised by Choi and Varian (2012).[8] Google Trends data have some distinct advantages. First, the time series are freely accessible. Conducting consumer surveys, by contrast, is relatively expensive. Second, Google Trends data are available in near real-time, in various frequencies up to the daily level. More traditional (survey-based) sentiment indicators can have delays in the availability. For example, the European Commission's monthly Economic Sentiment Indicator is only available at the end of each month. Third, and probably most importantly, they have been show to track well the variables of interest. In addition to the detection of influenza epidemics (Ginsberg et al., 2009), Google Trends data have been successfully used to predict (un)employment (Askitas & Zimmermann, 2009; Borup & Schütte, 2020; D'Amuri & Marcucci, 2017; Fondeur & Karamé, 2013; Mulero & García-Hiernaux, 2020; Naccarato, Falorsi, Loriga, & Pierini, 2018; Niesert, Oorschot, Veldhuisen, Brons, & Lange, 2020), inflation (Guzman, 2011), consumer behaviour (Goel et al., 2010; Chamberlin, 2010), car sales (Du and Kamakura, 2012; Fantazzini and Toktamysova, 2015), tourism (Camacho and Pacce, 2018), oil consumption (Yu et al., 2019), warning signs of stock market moves (Preis et al., 2013) and more general macroeconomic aggregates (Koop and Onorante, 2019; Ferrara and Simoni, 2019).[9]

Given their power, internet searches serve as a measure of economic sentiment. As a result, Google Trends data have been used for the measurement of investor sentiment, including by Beer et al. (2013), Mao et al. (2015), Da et al. (2015), and Brochado (2020). Similarly, as illustrated by among others Choi and Varian (2012) and Vosen and Schmidt (2011), internet searches provide a good measure of the economic sentiment among households. McLaren and Shanbhogue (2011), for instance, conclude there is evidence that these data may be used to provide additional insight on a wider range of issues that traditional business surveys might not cover. In response to the recent crisis, the European Commission, for example, actively monitored citizens' health, economic and social isolation concerns using Google search data.[10] Using a large panel of search data, Fetzer et al., 2020 show that economic sentiment took a substantial turn for the worst after the virus had reached a country. Furthermore, Caperna et al. (2020) document a surge of about 30% of European unemployment searches in the wake of lock-downs.

Our contribution to the literature is double. First, we provide a topical application of Google Trends data for the measurement of economic sentiment among European households. Doing so, we document strong shifts in sentiment the months following the spread of the coronavirus, thereby complementing evidence using other alternative real-time measures (e.g. stock market volatility, newspaper and Twitter-based uncertainty measures, forecaster disagreement and business expectation surveys). For example, Altig et al. (2020) also document huge jumps in reaction to the pandemic. Second, our analysis takes a more granular look at the labour market and consumption component of households' sentiment across EU countries.

### 2.3. Labour and consumption during the pandemic

The labour market trends we observe for Europe using search query data are in line with those documented for the UK and US at the outset of the crisis using alternative methods. Using a large-scale household survey, Coibion et al. (2020), for instance, conclude that US citizens losing their jobs are not actively looking to find new ones. Furthermore, using vacancy postings, Forsythe et al. (2020) and Costa Dias et al. (2020) observe that firms' job postings collapsed at the outset of the crisis in the US and UK, respectively. While UK vacancies fell across the whole wage distribution, the fall was sharpest in low-paid occupations directly affected by social distancing measures, but new vacancies for higher-paid jobs in legal and managerial professions also experienced steep falls. Similarly, US trends in job postings showed little difference depending on whether they are deemed essential and whether they have work-from-home capability, suggesting the collapse was not caused solely by lockdown measures. By contrast, Campello et al. (2020) find that US firms have cut back on postings for high-skill jobs more than for low-skill jobs, with small firms nearly halting their new hiring altogether. Binder (2020), moreover, observe more pessimistic unemployment-related sentiment among their survey respondents following the virus outbreak.

Additionally, the slowdown in consumption following the coronavirus outbreak indicated by our analysis concurs with the consumption trends documented for other countries or panels. For example, according to Chronopoulos et al. (2020) their transaction data, household spending in Great Britain declined as the imposed lockdown became imminent, and continued to decline throughout the lockdown period. The authors also find evidence for a strong increase in groceries spending consistent with panic buying and stockpiling behaviour in the two weeks following the World Health Organisation (WHO) announcement describing COVID-19 as a pandemic. Similarly, Carvalho et al. (2020a) find evidence of initial stockpiling followed by significant decreases in spending using Portuguese electronic payment data. Carvalho et al. (2020b), on the other hand, find no changes prior to the lockdown, but large, and sustained expenditure reductions after in Spanish transactions. Yilmazkuday (2020a) uses transaction data to explore how American households adapted their consumption amid the epidemic. He documents absolute decreases in spending on all sectors (except for groceries), but increases in relative consumption of products and services that can be consumed at home or bought online. Using survey data, Baker, Farrokhnia, Meyer, Pagel, & Yannelis, 2020 also find that, after an initial hike in spending, greater levels of social

[8] Jun et al. (2018) provide an overview of the uses of Google Trends data over the past decade. Askitas and Zimmermann (2015), moreover, present a survey of the potentials and challenges of internet data for social sciences.

[9] Google Trends' series, however, do not seem to have predictive value for improving housing market forecasts (Limnios and You, 2018). Finally, in light of the COVID-19 pandemic, Aaronson et al. (2020) and Borup et al. (2020) use Google Trends to predict US unemployment insurance claims, showing significant improvements in predictive power.

[10] See all weekly reports at https://ec.europa.eu/knowledge4policy/projects-activities/tracking-eu-citizens%E2%80%99-concerns-using-google-search-data_en.

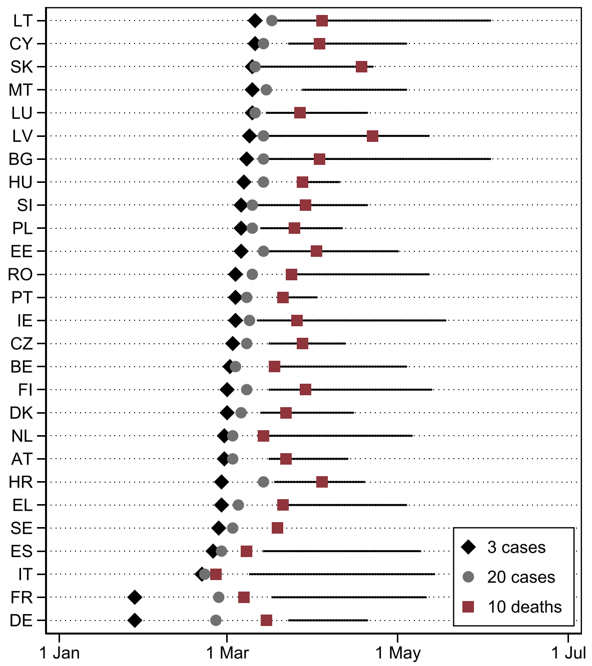



**Fig. 2.** Overview of respective cut-off dates for COVID-19 arrival. *Note:* Data on the number of confirmed cases, active cases and COVID-19 related deaths were obtained from John Hopkins. Emergency lockdowns (as indicated by the vertical lines) were obtained from a variety of sources, including Wikipedia and (online) newspapers.

distancing are associated with drops in spending, particularly in restaurants and retail. Evidence using transaction data from Denmark and Sweden, on the other hand, suggests that the observed drops in aggregate spending may be caused by the virus – and its multiplicity of implications – itself, regardless of social distancing measures (Andersen et al., 2020a, b). The latter also aligns with our results showing a significant impact at the time of arrival of the virus, which pre-empts the lockdowns, in EU member states. Moreover, it aligns with the findings based on cellular phone records data on customer visits in the US, suggesting that traffic started dropping before the legal orders were in place and was highly tied to the number of COVID deaths (Goolsbee and Syverson, 2020).

## 3. Data and methodology

For our analysis we rely on panels of internet search intensity data from Google Trends. We construct two panels. The first panel is a country-level panel for the 27 EU member states covering business cycle, labour market and consumption related queries (including e.g., crisis, recession, unemployment, social benefits) for the days in January through April 2020. The second panel, on the other hand, covers a subset of these variables on a monthly basis since 2004.[11]

Google Trends queries can be constructed based on individual search terms or search topics, which encompass groups of related individual search terms, i.e. capturing a broader set of search terms. We employ a combination of both. One reason for using individual search terms and their country-specific (translated) equivalents, is because the automatic stabilisers and policy measures acting in response to the crisis not only differ in name but also in type across countries. Similarly, the most frequently used job boards for finding vacancies differ substantially across countries.

For each query, the Google Trends platform generates a measure of search intensity scaled from 0 to 100, with 100 representing the highest proportion among the queried terms within a selected country and time frame. Seven-day moving averages are used to rid the series of day of week effects.[12] In addition, we normalise the search intensity covered by the series at the country level using the mean search intensity prior to the surge of the coronavirus in each country. This normalisation makes the coefficient estimates interpretable as percentage changes relative to pre-coronavirus levels. The normalisation of the series has an important benefit. By default the intensity series may capture queries not solely driven by new developments and information affecting sentiment. Nonetheless, such searches are captured by the baseline level used to normalise the series. For example, searches for a concept like unemployment or recession occur on a continuous basis. However, the excess searches in crisis times are unlikely to be driven by common interest, but much more by people confronted by the related health and economic risks, either directly or indirectly. Consequently, normalising the

[11] The authors also constructed a regional-level panel for the four biggest European economies (Germany, Spain, France and Italy) to highlight important inter-regional differences of relevance for catering policy responses. This analysis, however, is beyond the scope of this paper.
[12] The results are robust to refraining from any averaging of the series.

series helps to guarantee that our series capture what we want them to capture.

As our baseline, we estimate the following econometric specification to capture the impact of the arrival of the coronavirus:

$$y_{c,t} = \alpha + \beta D_{c,t} + \varepsilon_{c,t} \tag{1}$$

where $y_{c,t}$ measures the search intensity in country $c$ on day $t$ for a specific topic. Coefficient $\beta$ is the coefficient of interest. The coefficient captures the difference in search intensity before and after the onset of the crisis.[13] $D_{c,t}$ is a dummy variable set to one as soon as the pandemic reaches a country. To this end, we merge in data on the number of confirmed cases, active cases and COVID-19 related deaths from the primary source available, cf. John Hopkins. To determine the pre and post-COVID outbreak period, we exploit the precise timing of coronavirus arrival in a country by constructing different cut-off dummies. As the default, we set $D_{c,t}$ to one when the number of confirmed cases exceeds 3. However, this seems to push forward France and Germany (see Fig. 2), hence we also tested and confirmed robustness of our results to a higher cut off (20 confirmed cases), which is more constant across countries. Alternatively, we set the cut off for $D_{c,t}$ based on the number of COVID-related deaths (i.e. exceeding 10), since this is likely to be more disconcerting to people. Finally, $\varepsilon_{c,t}$ comprises panel fixed effects, day-of-the-week fixed effects and the error term.

Alternatively, we estimate the following difference-in-difference (DiD) regression:

$$y_{c,t} = \alpha + \sum_{\tau=-6}^{6} \beta_\tau D_{c,\tau} + \varepsilon_{c,t} \tag{2}$$

where $D_{c,\tau}$ are relative week dummies centred around the arrival of the pandemic in the country. The latter specification has the benefit that, in addition to quantifying the difference between pre and post-COVID search queries, it captures the evolution in search behaviour in the weeks following the COVID outbreak.

## 4. Results

### *4.1. Business cycle*

We first show that the arrival of the coronavirus resulted in a turn for the worse in economic sentiment. In particular, we look at searches capturing well the economic sentiment in Europe regarding the economy as a whole. Table 1 reports the results of baseline specification (1) for four different search queries: crisis, recession, unemployment and unemployment benefits.[14] As the pandemic hits European countries, a significant increase in the searches for “crisis” and “recession” is observed, as concerns about an impeding economic slowdown rose substantially over Europe.[15] This is also confirmed by the difference-in-difference estimates from (2), as shown in Fig. 3, with peaks up to three weeks after the first COVID-cases. This is a troublesome harbinger, since Fetzer et al., 2020 found that real GDP growth and real growth in consumption and imports are significantly lower, both in a statistical and economic sense, in quarters following increases in “recession” searches. Households’ concerns took on very concrete forms as shown by the last two panels of Table 1. People actively googled more for information on unemployment and unemployment benefits, with the latter only significant at a later cut-off date.[16] Fig. 3, however, shows that both queries remained significantly larger up to six weeks after the arrival of the virus. This is in line with the more pessimistic unemployment expectations following the virus outbreak observed in the US (Binder, 2020) and the surge of unemployment-related searches in Europe after the lockdown (Caperna et al., 2020).

In addition, the impact is found to be substantially larger in those countries hit hardest in economic terms. In Table 2 we replicate the earlier estimates splitting the sample based on the recorded revisions to GDP.[17] We distinguish between those countries with the relatively largest revisions (more than 5.5 pp.) to their GDP growth. The GDP growth revision is computed as the difference between the 2020 growth rate in the European Commission’s Spring Forecast minus the one originally foreseen (before the crisis) in the Autumn Forecast. The subset of countries with relatively large revisions includes (in order of the size of the revision): Italy, Spain, Greece, France, Croatia, Belgium, Lithuania, the Netherlands and Germany. Concerns about an impending recession were significantly larger in those countries expected to be hit hardest economically in the course of 2020. The corresponding output from model (2) is illustrated in Fig. 4. Allowing for a time dimension in the estimation highlights a difference: several weeks after the arrival of the virus recession

[13] In this set-up, the $p$-value of the cutoff coefficient boils down to a Wald-test for a structural break at the cutoff point. Alternatively, we performed Im–Pesaran–Shin tests for a unit root in the respective search series, confirming our conclusions.

[14] The number of countries covered by each specification depends on the quality of the series for the country-specific queries. Countries with insufficient non-zero observations are excluded from the analysis. For all countries included, the same time frame (January–April 2020) and number of observations is considered.

[15] As expected, we observe earlier hikes in those countries hit earlier in the year, e.g. Italy.

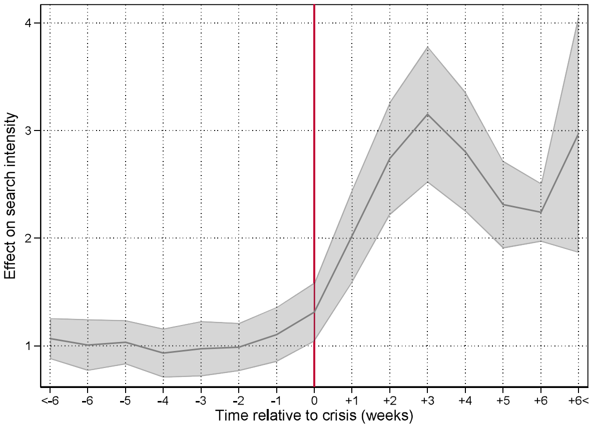
[16] Since the goal is to measure sentiment as a whole, it does not matter for the analysis whether these searches are performed by people who are facing the possibility of losing their jobs or whom have actually already transitioned into unemployment.

[17] Similar results are obtained by interacting the cut-off dummy with the large-revision dummy (instead of splitting the sample), see Table 6 in the online appendix.

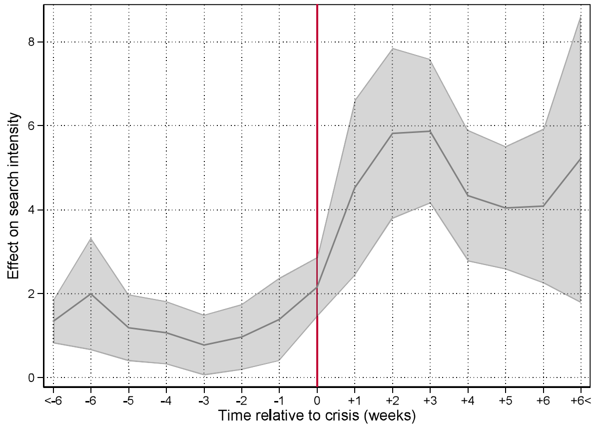
**Table 1**
Business cycle – baseline specification.

| | Crisis | | | Recession | | | Unemployment | | | Unemp. benefit | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| COVID I | 1.461*** | | | 3.914*** | | | 2.340*** | | | 4.420 | | |
| | (0.187) | | | (0.906) | | | (0.750) | | | (3.573) | | |
| COVID II | | 1.647*** | | | 3.544*** | | | 2.502*** | | | 5.130 | |
| | | (0.246) | | | (0.739) | | | (0.828) | | | (4.130) | |
| COVID III | | | 1.347*** | | | 2.017** | | | 1.559*** | | | 0.926*** |
| | | | (0.311) | | | (0.779) | | | (0.394) | | | (0.149) |
| Constant | 0.998*** | 0.970*** | 0.822*** | 1.150** | 0.936*** | 0.753*** | 1.031** | 1.058*** | 0.891*** | 0.877 | 0.911 | 0.922*** |
| | (0.109) | (0.117) | (0.122) | (0.466) | (0.298) | (0.211) | (0.381) | (0.377) | (0.183) | (1.892) | (2.013) | (0.076) |
| Day FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Panel FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *F*-statistic | 10.46 | 12.50 | 12.67 | 5.200 | 10.18 | 13.03 | 8.271 | 13.04 | 15.77 | 2.112 | 2.036 | 10.03 |
| *p*-value | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.081 | 0.092 | 0.000 |
| *R* squared | 0.284 | 0.324 | 0.296 | 0.115 | 0.133 | 0.071 | 0.082 | 0.095 | 0.162 | 0.018 | 0.022 | 0.168 |
| # obs. | 2352 | 2352 | 2352 | 2156 | 2156 | 2352 | 2548 | 2548 | 2548 | 2450 | 2450 | 2450 |
| # panels | 24 | 24 | 24 | 22 | 22 | 24 | 26 | 26 | 26 | 25 | 25 | 25 |

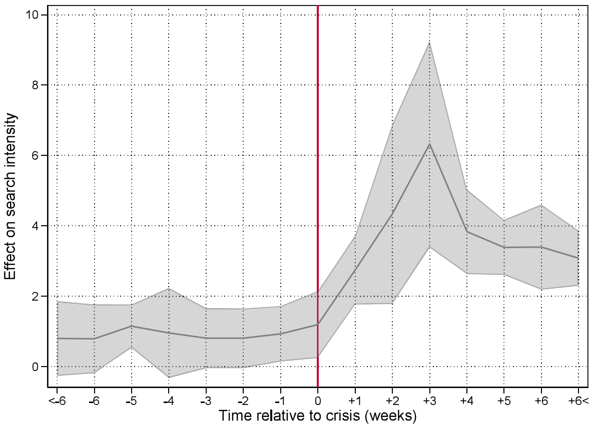
*Note:* The dependent variable is the seven-day moving average search intensity for country-specific terms (crisis, recession, unemployment and unemployment benefit), normalised by the mean search intensity before the COVID-19 outbreak. COVID I, II and III are dummies taking the value one once the number of confirmed cases exceeds 3, the number of confirmed cases exceeds 20 and the number of COVID-related deaths exceeds 10, respectively. Cluster-robust standard errors are noted in parentheses: * p<0.10, ** p<0.05 and *** p<0.01.



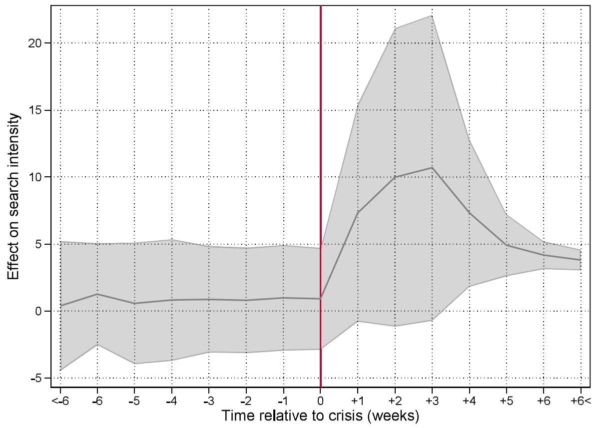

(a) Crisis




(b) Recession




(c) Unemployment



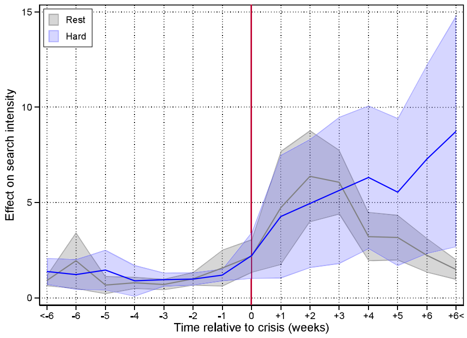

(d) Unemployment benefit

**Fig. 3.** Business cycle – marginal impact on search intensity by week. *Note:* The plot shows the marginal impact on search intensity by week, relative to the 3-cases cut-off, from the DiD-model (2) and their 95% confidence intervals.

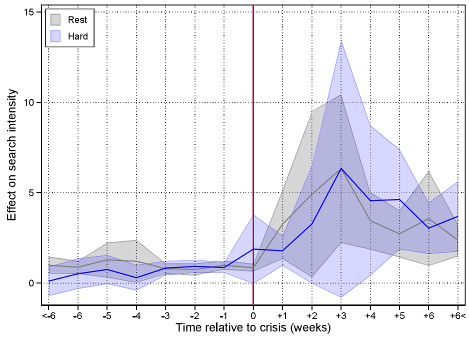
**Table 2**
Business cycle – split by size of GDP revision.

| | Crisis | | Recession | | Unemployment | | Unemp. benefit | |
|---|---|---|---|---|---|---|---|---|
| | (Hard) | (Rest) | (Hard) | (Rest) | (Hard) | (Rest) | (Hard) | (Rest) |
| COVID dummy | 2.069** | 0.838*** | 4.124** | 0.574*** | 2.180** | 1.165*** | 0.690** | 1.087*** |
| | (0.649) | (0.181) | (1.726) | (0.188) | (0.904) | (0.293) | (0.218) | (0.196) |
| Constant | 0.867** | 0.809*** | 0.908* | 0.702*** | 0.812 | 0.944*** | 0.950*** | 0.901*** |
| | (0.286) | (0.073) | (0.455) | (0.071) | (0.471) | (0.114) | (0.120) | (0.096) |
| Day effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Panel effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *F*-statistic | 11.85 | 14.00 | 5.378 | 15.04 | 16.89 | 18.56 | 4333 | 7.705 |
| *p*-value | 0.001 | 0.000 | 0.015 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Goodness-of-fit | 0.372 | 0.261 | 0.116 | 0.041 | 0.194 | 0.133 | 0.207 | 0.174 |
| No. of obs. | 882 | 1470 | 882 | 1470 | 882 | 1666 | 882 | 1568 |
| No. of countries | 9 | 15 | 9 | 15 | 9 | 17 | 9 | 16 |

*Note:* The dependent variable is the seven-day moving average search intensity for country-specific terms (crisis, recession, unemployment and unemployment benefit), normalised by the mean search intensity before the COVID-19 outbreak. The COVID cut-off dummy switches value when the number of COVID-related deaths exceeds ten. Cluster-robust standard errors are noted in parentheses: * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$. The set of hard hit countries covers those countries with GDP growth revisions larger than 5.5 pp.




(a) Recession




(b) Unemployment

**Fig. 4.** Marginal impact on search intensity by week - By size of GDP revision. *Note:* The plot shows the marginal impact on search intensity by week, relative to the 3-cases cut-off, from the DiD-model (2) and their 95% confidence intervals. The set of hard hit countries (in blue) covers those countries with GDP growth revisions larger than 5.5 pp. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

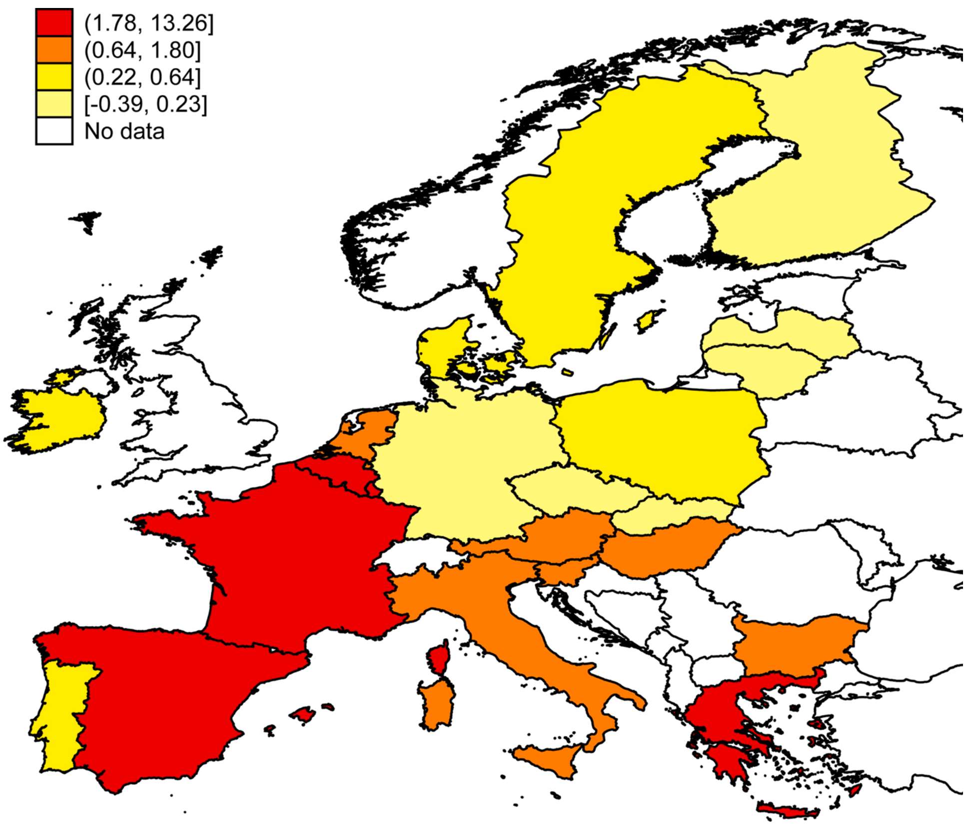
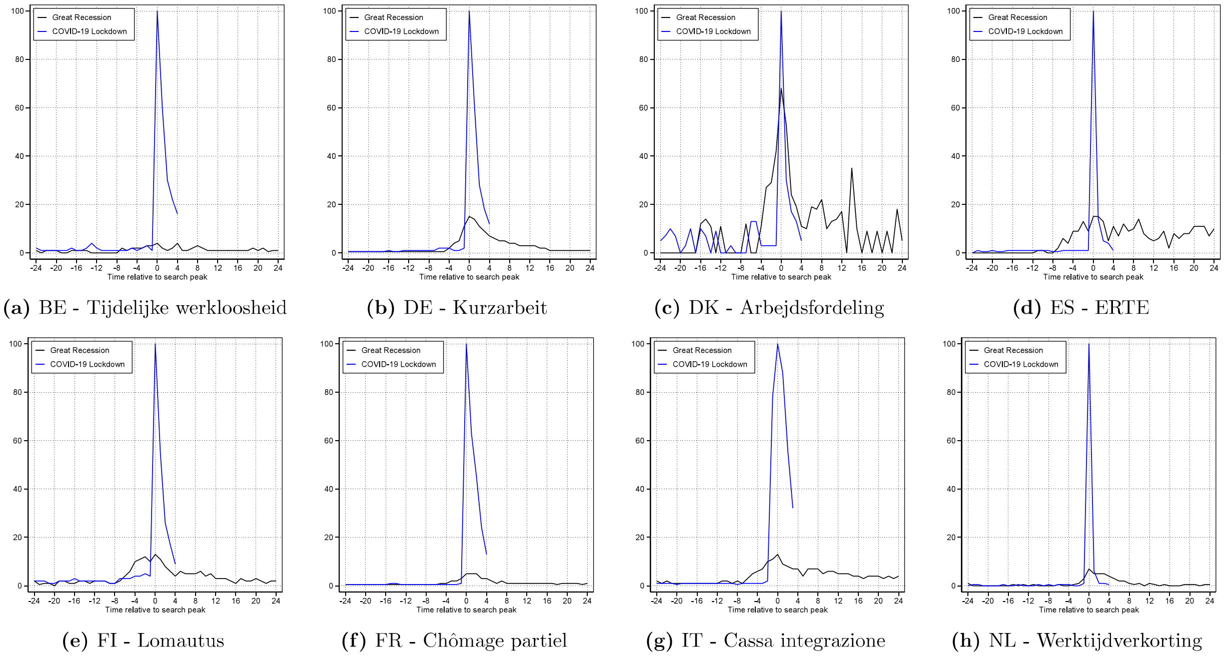



**Fig. 5.** Difference between the average unemployment-related searches before and after the Corona outbreak. *Note:* The series of Google searches were normalised and represent 7-day moving averages. The COVID cut-off dummy used, is that based where the number of COVID-related cases exceeds three. (For interpretation of the references to color in this figure citation, the reader is referred to the web version of this article.)




(a) BE - Tijdelijke werkloosheid (b) DE - Kurzarbeit (c) DK - Arbejdsfordeling (d) ES - ERTE

(e) FI - Lomautus (f) FR - Chômage partiel (g) IT - Cassa integrazione (h) NL - Werktijdverkorting

**Fig. 6.** Google Searches for pre-existing short-time work schemes (STWs) during the Great Recession and the Lockdown.

related queries kept increasing in those countries hit hardest, while they started fading in the other countries.[18]

The overall divergence across European countries is also illustrated graphically in Fig. 5, plotting the difference in the average search intensity before and after the crisis by country. The result plotted in this figure reveals an interesting pattern, in particular concerning the perceived importance of unemployment, which is especially high in countries with high pre-crisis level of unemployment (possibly with the exception of Belgium and Luxembourg). The population-weighted unemployment rates before the COVID-19 crisis (i.e. as of February 2020, source: Eurostat) shows a clear differential pattern between the four country groups considered: those countries with the highest search intensity for unemployment (displayed in red) had an average unemployment rate of 10.3%, while the other country groups had average unemployment rates of 7.5% (orange), 4.7% (dark yellow) and 3.4% (light yellow) respectively. This evidence suggests that the sentiment related to the employment consequences of the COVID-19 crisis reflects to some extent the pre-crisis performance of country-specific labour markets.

In addition to increases in comparatively generic searches, we also observe consistent spikes in queries for very specific wage compensation schemes, such as the Cassa Integrazione in Italy, Kurzarbietergeld in Germany, chômage partiel in France and the ERTE (expedientes de regulación temporal de empleo) in Spain. Fig. 6, for example, plots the monthly search intensity for some of the most well-known short-time work schemes in Europe.[19] All eight cases show clear peaks during the first wave of the COVID-19 pandemic. They, however, did not supplement the general searches for unemployment information.[20]

The increases in searches are also substantially larger than those observed during the Great Recession. For ease of comparison, each of the graphs is centred around the peak of both crises. In each case, except Denmark, the search intensity for information regarding the short-time work systems was more than five times larger during the recent crisis. Despite coverage by wage compensation schemes being expanded recently, the number of EU countries with short-time work schemes in place during the Great Recession was non-negligible. Moreover, research has shown that many of the pre-existing schemes were effective at saving a considerable number of jobs during the Great Recession, see, e.g. Cahuc et al. (2018) for France; Hoffmann and Schneck (2011), Crimmann et al. (2012), Brenke et al. (2013), Balleer et al. (2016) and Gehrke and Hochmuth (2020) for Germany; Giupponi and Landais (2018) for Italy; and Efstathiou et al. (2018) for Luxembourg. For example, mid-2009 the number of Germany's short-time workers reached 1.5 million. With estimates that up to 0.87 jobs per short-time worker may save in an economic crises (Gehrke and Hochmuth, 2020), this implies a clearly non-trivial number of households affected. Therefore, the prior that one would observe comparatively strong increases in

[18] Differences among the groups are not only observed in terms of recession queries. We also find significantly different recovery patterns for consumption related searches (e.g. furniture), as described in Section 4.3. The recovery in searches, after the initial steep drop, appears to have been slowest in those EU member states hit hardest in economic terms.

[19] Unfortunately, the series plotted in Fig. 6 do not allow for a comparison of the demand for each country's short-time work system. The series are relative. The series are indexed at 100 on the moment the searches peak. For example, both the unadjusted ERTE and Kurzarbeit series would peak at the same level, even if these peaks may represent different volumes. What is possible is a comparison of the relative changes, i.e. using the difference in the mean search intensity before and after the crisis by country.

[20] See Fig. 12 in the online appendix.

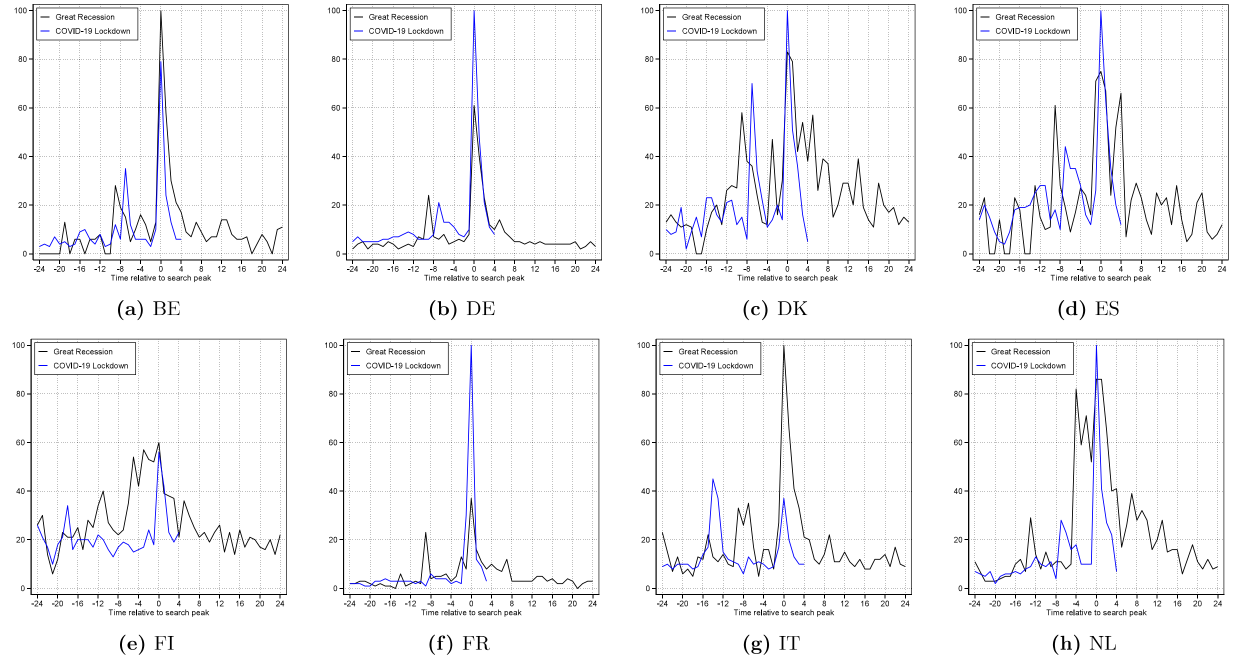



**Fig. 7.** Google Searches for recession during the Great Recession and the Lockdown.

business cycle or at least STW-related searches during the Great Recession does not appear very limiting.[21] On the bright side, the persistence of the shock seems to be less outspoken this time around. In the case of Denmark, Spain and the Netherlands the level of searches four months after the peak has dropped below its level for the Great Recession.

Finally, the comparatively large increase in STW searches does not seem to have curtailed changes in households' business cycle related sentiment, relative to the Great Recession. Given the potential for STWs to save jobs (Boeri and Bruecker, 2011; Lydon et al., 2019), one might expect their availability to (indirectly) diminish economic uncertainty and, by extension, uphold sentiment, especially in light of their recent extensions. Nonetheless, in countries with STWs (with the exception of Italy) recession and unemployment concerns appear to have been similar or even higher during the first wave of the COVID-19 pandemic (Fig. 7). Estimating the search intensity for recession or unemployment around the crises' peak during both the Great Recession and COVID-19 lockdown using specification (2), adjusted to monthly data, we observe no significant differences in responses between those countries that had STWs in place and those that had not (Fig. 8).[22] Statistically, the biggest difference between the two groups is observed in terms of unemployment concerns during the Great Recession (panel (c) of Fig. 8), suggesting that countries with STWs portrayed lower unemployment concerns during the Great Recession.[23] This result, however, does not extend to the COVID-19 crisis, despite the regained attention (and general deployment of) for STWs. Finally, while there is little to no difference between countries with and without STWs, the difference in unemployment concerns between the two crises is striking.

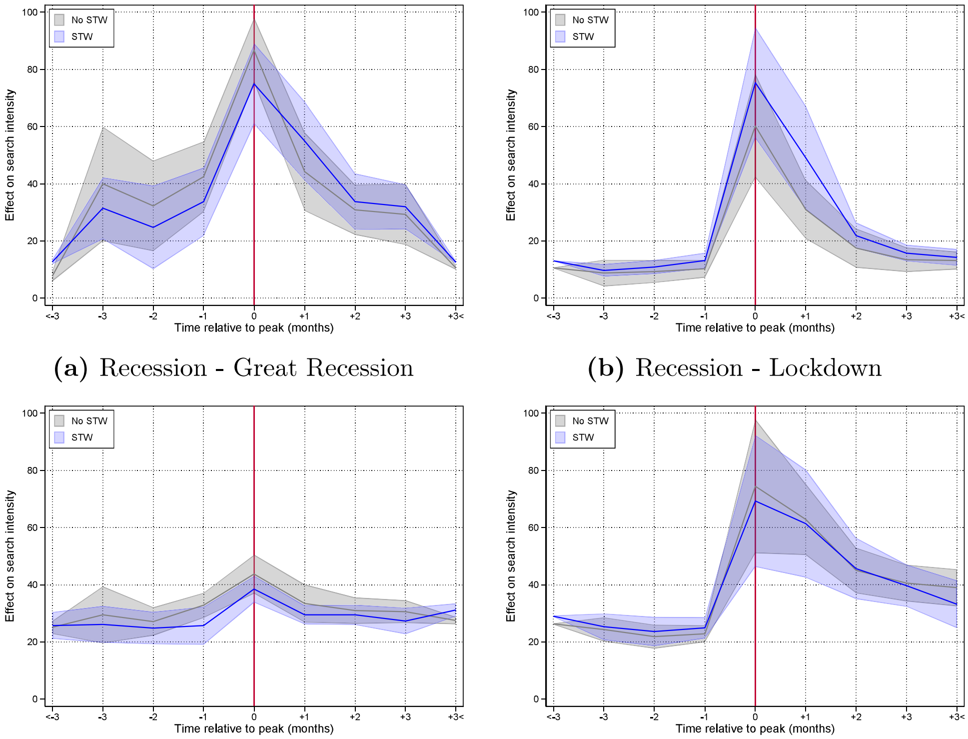
### *4.2. Labour markets*

Having established the general shift in economic sentiment, we now turn to the impact of the pandemic on more specific concerns on the people's minds, using a novel set of labour market related search queries. First, we analyse changes in households' searches for vacancies. Specifically, Table 3 and Fig. 9 report the estimation results of specifications (1) and (2) for search queries regarding country-specific job boards, internationally active employment agencies, the online career platform LinkedIn and generic searches common for job applicants. The $\beta$-coefficient for the search queries on job boards and employment agencies are negative and significant, suggesting a 30% drop in interest relative to the pre-corona period. The data on the major employment agencies is slightly more noisy, as not all of them are (as) active (as others) in all EU member states. Nonetheless, the result seems to be consistent across queries. In the same vein, a smaller, but significant drop in searches for the international platform LinkedIn is observed. The drop in searches for resume is smallest, yet significant. Consequently, our results extend to the EU the earlier survey-based findings for the US

[21] For those systems only introduced for the first time, spikes in searches are not uncommon either, since newly introduced benefit systems often go hand-in-hand with high levels of searches.

[22] The subset of countries with STWs in place includes Belgium, Germany, Denmark, Spain, Finland, France, Italy, Luxembourg and the Netherlands.

[23] For an alternative specification without the relative time dimension, but interacting the dummies for each crisis period with an STW dummy, showing a clear significant impact, see Table 7 in the online appendix.




(a) Recession - Great Recession

(b) Recession - Lockdown

(c) Unemployment - Great Recession

(d) Unemployment - Lockdown

**Fig. 8.** Marginal impact on search intensity by month – by presence of STW. *Note:* The plot shows the marginal impact on search intensity by week, relative to the crisis peak, from the DiD-model (2) and their 95% confidence intervals. The set of STW countries (in blue) covers those countries with short-time work schemes in place. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

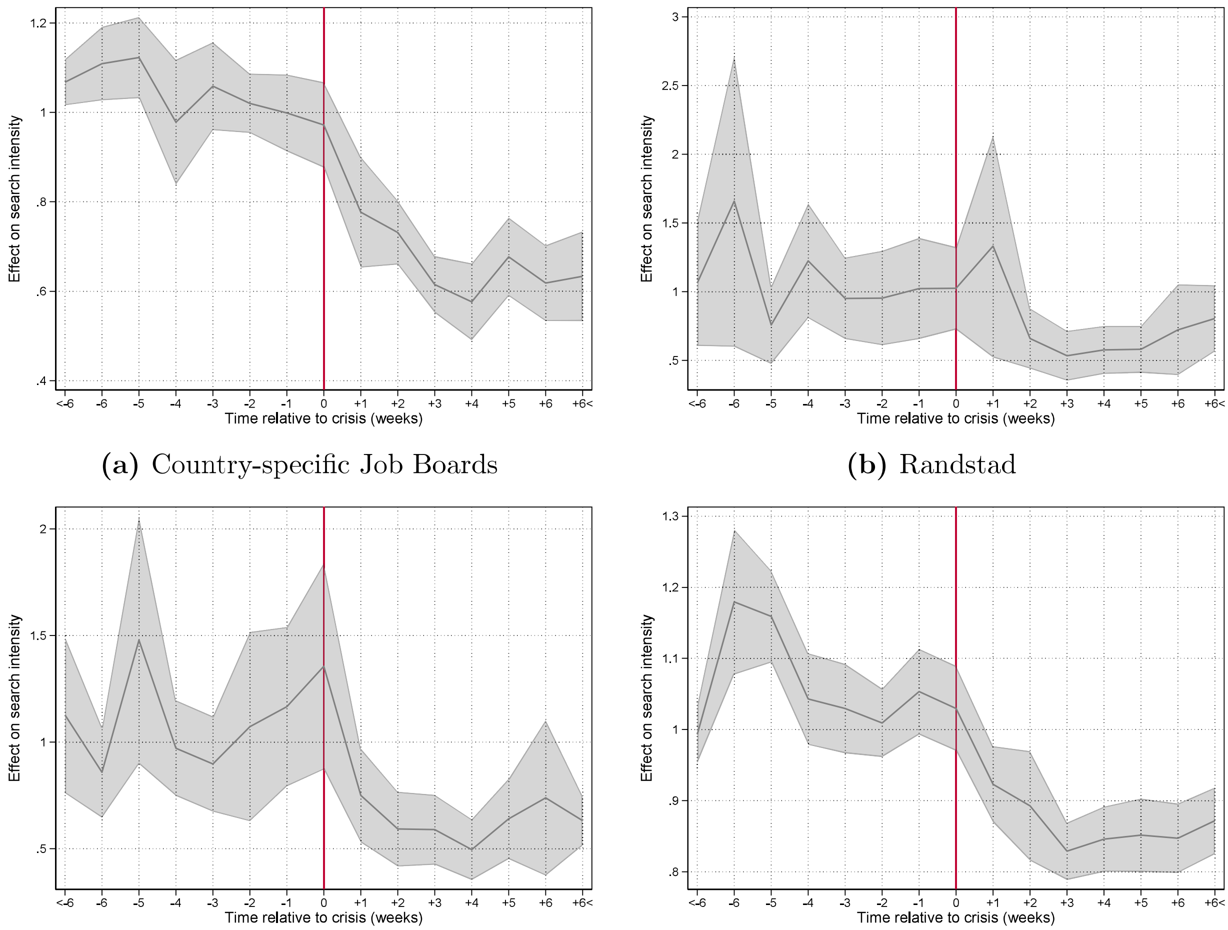
**Table 3**
Labour markets – job search.

| | Job Board (1) | Manpower (2) | Randstad (3) | Adecco (4) | Indeed (5) | LinkedIn (6) | Curriculum (7) | Resume (8) |
|---|---|---|---|---|---|---|---|---|
| COVID dummy | − 0.364*** | − 0.228*** | − 0.311*** | − 0.366*** | − 0.314*** | − 0.179*** | − 0.156 | − 0.123*** |
| | (0.0202) | (0.060) | (0.056) | (0.047) | (0.032) | (0.017) | (0.106) | (0.034) |
| Constant | 0.996*** | 0.934*** | 0.986*** | 0.979*** | 1.003*** | 1.005*** | 0.996*** | 1.013*** |
| | (0.012) | (0.039) | (0.036) | (0.036) | (0.020) | (0.010) | (0.039) | (0.021) |
| Day effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Panel effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *F*-statistic | 70.35 | 10.92 | 17.98 | 39.17 | 35.96 | 22.52 | 11.41 | 4.28 |
| *p*-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.003 |
| Goodness-of-fit | 0.395 | 0.020 | 0.030 | 0.049 | 0.104 | 0.235 | 0.010 | 0.016 |
| No. of obs. | 2352 | 2646 | 2156 | 2548 | 2646 | 2646 | 2646 | 2646 |
| No. of countries | 24 | 27 | 22 | 26 | 27 | 27 | 27 | 27 |

*Note:* The dependent variable is the seven-day moving average search intensity for country-specific job boards, internationally active agencies and general queries, normalised by the mean search intensity before the COVID-19 outbreak. The COVID cut-off dummy switches value when the number of COVID cases exceeds three cases. Cluster-robust standard errors are noted in parentheses: * p<0.10, ** p<0.05 and ***p<0.01.

that currently unemployed are not (as) actively looking to find new jobs (Coibion et al., 2020).

Interestingly, the job search trends do not seems to differ all that much between those countries hit harder in economic terms and the others (cf. Table 4). For example, the country-specific job board searches tend to drop by 36% to 38% in both subpanels. The use of LinkedIn, on the other hand, seems to be affected less in those countries hit hardest. The biggest difference is the significantly larger drop in searches for curriculum related information in the pool of hardest hit countries. This may, nonetheless, be the counterpart of




(a) Country-specific Job Boards (b) Randstad

(c) Adecco (d) LinkedIn

**Fig. 9.** Labour supply – marginal impact on search intensity by week. *Note:* The plot shows the marginal impact on search intensity by week, relative to the 3-cases cut-off, from the DiD-model (2) and their 95% confidence intervals.

**Table 4**
Labour markets – job search, split by size of the GDP revision.

| | Job Board | | LinkedIn | | Curriculum | | Resume | |
|---|---|---|---|---|---|---|---|---|
| | (Hard) | (Rest) | (Hard) | (Rest) | (Hard) | (Rest) | (Hard) | (Rest) |
| COVID dummy | – 0.380*** | – 0.358*** | – 0.153*** | – 0.192*** | – 0.340*** | – 0.073 | – 0.091 | – 0.138*** |
| | (0.037) | (0.025) | (0.014) | (0.024) | (0.068) | (0.149) | (0.072) | (0.038) |
| Constant | 1.002*** | 0.994*** | 1.009*** | 1.001*** | 1.004*** | 1.004*** | 1.007*** | 1.015*** |
| | (0.028) | (0.012) | (0.007) | (0.014) | (0.034) | (0.050) | (0.033) | (0.028) |
| Day effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Panel effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *F*-statistic | 367.1 | 76.35 | 227.1 | 15.77 | 22.87 | 14.28 | 13.30 | 3.607 |
| *p*-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 | 0.014 |
| Goodness-of-fit | 0.427 | 0.377 | 0.257 | 0.241 | 0.152 | 0.002 | 0.018 | 0.017 |
| No. of obs. | 784 | 1568 | 882 | 1764 | 882 | 1764 | 882 | 1764 |
| No. of countries | 8 | 16 | 9 | 18 | 9 | 18 | 9 | 18 |

*Note:* The dependent variable is the seven-day moving average search intensity for job boards and general queries, normalised by the mean search intensity before the COVID-19 outbreak. The COVID cut-off dummy switches value when the number of COVID cases exceeds three cases. Cluster-robust standard errors are noted in parentheses: * p<0.10, ** p<0.05 and *** p<0.01. The set of hard hit countries covers those countries with GDP growth revisions larger than 5.5 pp.

**Table 5**
Consumption – baseline specification.

| | 2nd hand platforms (1) | Furniture (2) | 2nd hand car platforms (3) | AutoScout (4) | Auto1 (5) | BMW (6) | Peugeot (7) | Skoda (8) | Volvo (9) |
|---|---|---|---|---|---|---|---|---|---|
| COVID dummy | − 0.082* | − 0.048** | − 0.133** | − 0.140* | − 0.245** | − 0.106*** | − 0.180*** | − 0.180*** | − 0.155*** |
| | (0.039) | (0.021) | (0.047) | (0.080) | (0.104) | (0.026) | (0.034) | (0.031) | (0.029) |
| Lockdown | − 0.125** | − 0.131*** | − 0.318*** | − 0.277** | − 0.351*** | − 0.199*** | − 0.305*** | − 0.323*** | − 0.254*** |
| | (0.047) | (0.031) | (0.059) | (0.115) | (0.102) | (0.028) | (0.039) | (0.041) | (0.033) |
| Constant | 1.008*** | 1.027*** | 1.010*** | 0.997*** | 1.005*** | 1.000*** | 0.993*** | 1.000*** | 0.995*** |
| | (0.014) | (0.011) | (0.024) | (0.034) | (0.036) | (0.012) | (0.013) | (0.012) | (0.011) |
| Day effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Panel effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *F*-statistic | 54060 | 65.00 | 43.41 | 11.48 | 22.33 | 21.92 | 36.55 | 69.36 | 43.06 |
| *p*-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Goodness-of-fit | 0.291 | 0.179 | 0.474 | 0.065 | 0.082 | 0.559 | 0.643 | 0.664 | 0.636 |
| No. of obs. | 882 | 2548 | 1176 | 2646 | 2058 | 2548 | 2254 | 2058 | 2450 |
| No. of countries | 9 | 26 | 12 | 27 | 21 | 26 | 23 | 21 | 25 |

*Note:* The dependent variable is the seven-day moving average search intensity for furniture purchases, country-specific platforms for second hand goods or second hand cars, internationally active platforms for car sales and car manufacturers, normalised by the mean search intensity before the COVID-19 outbreak. The COVID cut-off dummy switches value when the number of COVID cases exceeds three cases. The lockdown dummy is one when legal mobility restrictions are in place (cf. Fig. 2). Cluster-robust standard errors are noted in parentheses: * $p<0.10$, ** $p<0.05$ and *** $p<0.01$.

the significantly larger decrease in searches for resume related info in the least hard-hit countries. Extending the estimation using (2), however, does not show any significant differences among the two panels for these queries, only a slower decline in LinkedIn searches.

### 4.3. Consumption

Finally, we document a drop in households' consumption related search queries. In particular, we investigate the impact of the pandemic on the purchase of durable goods as such consumption is often preceded by an information gathering process (e.g. for price comparison) and therefore search data are a good proxy for (near-term) purchases. For example, we look at the intention of car purchases, which tend to be negatively correlated with income fluctuations and are usually considered a good proxy of consumer sentiment and the business cycle, see Dunn (1998) for evidence from the US and Casalis and Krustev (2020) for recent evidence for the euro area.[24]

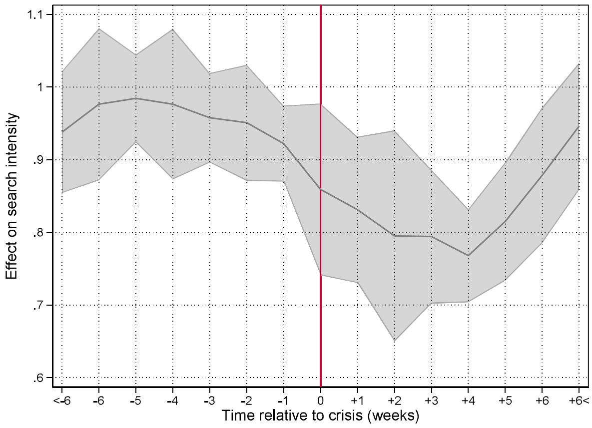
Table 5 summarises the results from baseline specification (1), controlling for the mobility restrictions imposed as well. Figs. 10 and 11 plot the corresponding results from specification (2). Following the spread of the pandemic, we observe a large and significant drop in searches for furniture and car purchase related terms. Interest for common (premium and non-premium) car brands, internationally active second-hand car platforms (such as AutoScout and Auto1) and country-specific second-hand car platforms drops by approximately 15 to 20 percent in the weeks following the outbreak.[25] Interestingly, a statistically significant decline in queries for furniture products appears to already set in one week before the arrival of the pandemic, followed by a more severe drop upon the arrival, thereby confirming the slowdown seen for car searches. Unlike furniture, queries regarding car brands, however, do not or hardly tend pick up in the six weeks following the arrival of the pandemic.[26]

Additionally, we find suggestive evidence that a similar, yet smaller pattern possibly also affected less-durable consumption. Overall, the consumption of non-durable goods is harder to gauge using search data, since it is generally preceded by less of a search effort and comparison on part of the consumer. Nonetheless, interest in peer-to-peer second-hand goods platforms may provide a proxy for non-durable consumption or at least less-durable consumption. Table 5 and panel (a) of Fig. 10 offer some suggestive evidence that

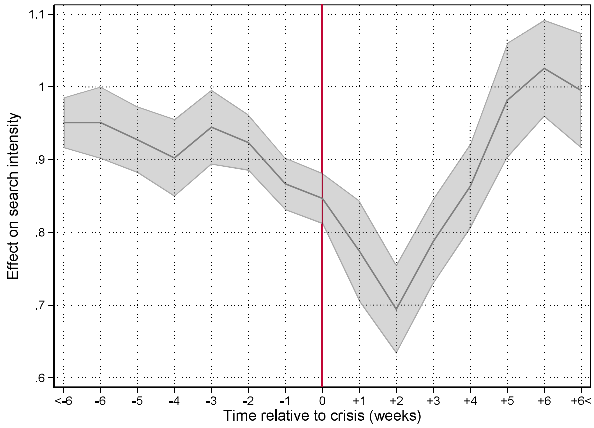
[24] While we cannot establish a causal link between households' business cycle related sentiment and the observed consumption responses, we do observe a clear negative correlations between business cycle related searches (e.g. crisis and recession) in one week and consumption related search queries in the following week (see Fig. 13 in the online appendix).

[25] In addition to the brands displayed in Table 5 and Fig. 11, we also tested other car manufacturer brands, including Fiat, Ford, Mercedes-Benz, Renault and Volkswagen. With minor variations on the size of the drop in search intensity and timing, all showed very similar trends.

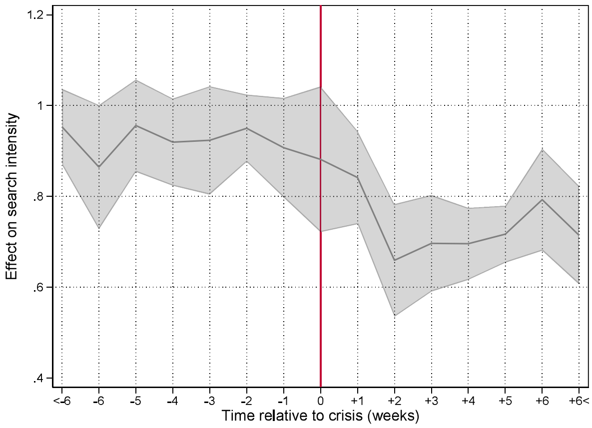
[26] The recovery in terms of search queries several weeks after the pandemic appears to have been slowest in those EU member states hit hardest in economic terms. Therefore, the higher need to upgrade home offices due to persistent teleworking in these countries, for instance, does not seem to have fully eased the recovery in terms of likely furniture sales.



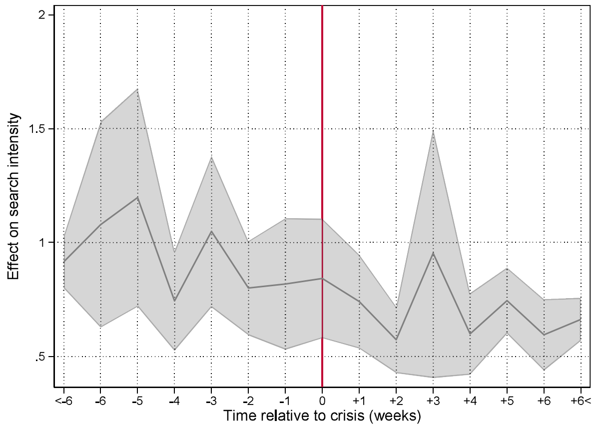

**(a)** Country-specific second-hand platforms




**(b)** Furniture




**(c)** Country-specific second-hand car platforms




**(d)** AutoScout

**Fig. 10.** Consumption – marginal impact on search intensity by week. *Note:* The plot shows the marginal impact on search intensity by week, relative to the 3-cases cut-off, from the DiD-model (2) and their 95% confidence intervals.

the drop observed for durables is also present for less-durable goods, although to a smaller extent.

Importantly, we also find a significant negative impact of the lockdowns for each of the consumption proxies in our analysis. Moreover, the impact of the legal mobility restrictions tends to be larger than that of the spread of the pandemic. Consequently, whereas supporting the claim that the drop in aggregate spending was partly driven by the spread of the virus regardless of mobility restrictions (Andersen et al., 2020b), our European data tend to attribute a larger share to the impact of the lockdowns than the existing US evidence (e.g. Goolsbee and Syverson, 2020). Nevertheless, even when we correct for the impact of the mobility restrictions, we still find significant negative effects on consumption related searches in the weeks following the arrival of the virus in EU countries.

In sum, the high-frequency non-traditional time series employed in our analysis provided real-time insights in the slowdown in consumption as it developed following the pandemic. The official statistics available now, e.g. quarterly national accounts, point to a 17% drop in EU households' consumption expenditure in the second quarter of 2020 (relative to the same quarter in 2019), peaking at − 23.9% in Spain. The relatively unsophisticated, real-time data source employed in our analysis seems to approximate this shift surprisingly well, boosting confidence to claims to include it in policymakers' toolboxes.

## 5. Conclusion

In this paper, we used a large panel of real-time search data for the EU to show that the recent health crisis and ensuing lockdown, came with an extraordinary shift in economic sentiment. Consequently, innovative data sources, such as the Google Trends data, have proven indispensable during the sudden, surprise developments of the COVID-19 crisis, complementing the traditional, backward looking indicators used by policymakers. In this light, the current paper analyses more carefully some of the sentiment's aspects most relevant to public policymakers, with a particular focus on consumption and labour market developments.

We documented a substantial increase in people's business cycle related web searches in the months following the coronavirus outbreak. Such real-time trends are not to be taken lightly. Search data have been shown to closely track economic sentiment.

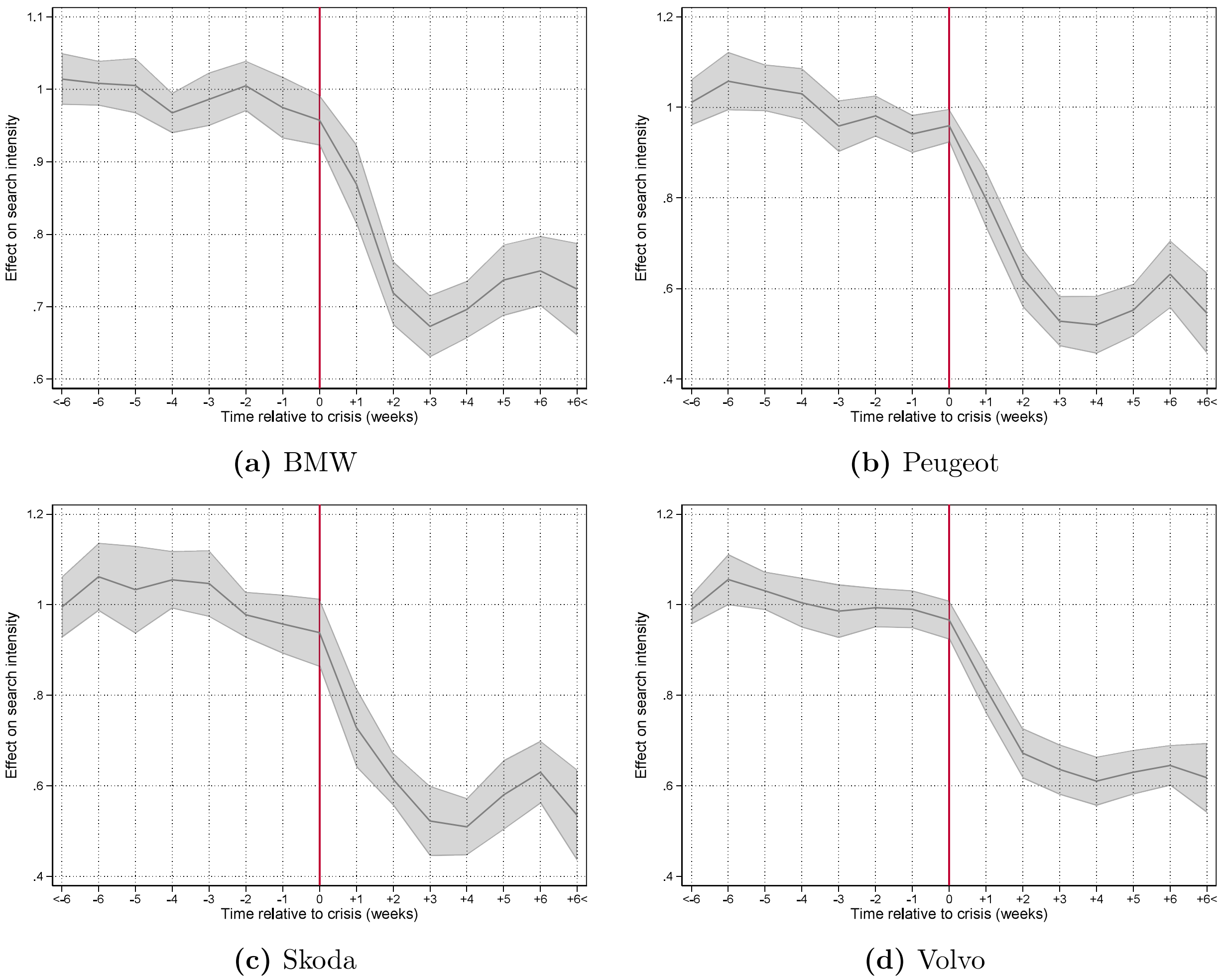



**Fig. 11.** Car manufacturers – marginal impact on search intensity by week. *Note:* The plot shows the marginal impact on search intensity by week, relative to the 3-cases cut-off, from the DiD-model (2) and their 95% confidence intervals.

Moreover, economic sentiment and, in particular, economic uncertainty are not only a transmission channel, but may affect an economy directly; and by extension the global economy as effects spill over (Punzi, 2020). Economic sentiment, for instance, may affect households' expectations and (future) consumption behaviour (Roth and Wohlfart, 2020) and the survival of firms as their business is affected (Ghosal and Ye, 2019). In fact, we observe a significant, coinciding slowdown in labour markets and (durable) consumption. We found that especially the unemployment-related sentiments have shifted well beyond the observed values at the peak of the Great Recession, thereby confirming that the labour market impact of this crisis is more pervasive, at least in the people's minds.

Given the exceptional labour market concerns following the COVID-19 pandemic, a targeted policy response is necessary to support economic recovery and limit the risks of unemployment hysteresis. Especially since labour market conditions in countries where the shifts in sentiment were significantly more outspoken were often already less favourable at the onset of the crisis. Interestingly, the availability and extensions of European short-time work schemes, while highly sought after during the heat of the pandemic, however, did not seem to have supported the countries' economic sentiment relative to countries without such schemes. This is somewhat surprising, since we do find suggestive evidence that countries with STWs in place portrayed less unemployment-related search queries during the Great Recession.

## Conflict of interest

None declared.

## Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jeconbus.2020.105970.

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