Divorce during COVID-19 Pandemic : Google knows best ?

Analysis of Divorce-related Google Queries during COVID-19 Pandemic and Nowcasting of Crude Divorce Rates in the United States.

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Résumé

Dans cet article, nous étudions les réactions à la pandémie de COVID-19 et aux politiques sanitaires sur les recherches Google liées au divorce aux États-Unis. Nous avons également prédit les taux bruts de divorce pour 2020 grâce aux données Google Trends. Les modèles d'*event study* et de triple-différence tendent à identifier un effet important du confinement plutôt qu'un effet de la pandemie. Le confinement entraîne une diminution des volumes de recherche relatifs correspondant aux recherches liées au divorce, sauf pour les caractéristiques financières du divorce qui montrent une augmentation de recherche importante. Le taux brut moyen de divorce pour 2020 que nous estimons grâce aux données Google Trends reste stable, et est même estimé légèrement plus élevé qu'en 2017 et 2018 lorsque les données de chômage sont incluses dans le modèle de panel.

Abstract

In this paper, we study the reactions to COVID-19 pandemic and sanitary policies on divorce-related queries on Google search engine in the United States. We also nowcast the crude divorce rates for 2020 thanks to Google Trends data. Event studies and triple-difference analyses tend to identify a prominent lockdown effect over a pandemic effect. The lockdown renders a decrease in relative search volumes related to divorce queries, except for financial features of divorce which shows an important increase. The averaged crude divorce rate for 2020 that we estimate thanks to Google Trends data remains at a stable level, and is even estimated slightly higher than in 2017 and 2018 when unemployment data are included in the panel data model.

1 Introduction

The novel coronavirus 2019 (COVID-19) [1] is undoubtedly an unprecedented shock in the last few decades which has a worldwide impact and moreover an influence on almost every aspect of the life of individuals. To fight against the pandemic, strict sanitary measures such as testing policies, tracking of sick persons or confinement policies were applied around the world, beginning with China and the province of Hubei, before spreading in most countries. Responses to the pandemic did vary but a majority of countries implemented lockdowns to minimize the propagation speed of the virus. Within the federal structure of the United States (U.S.), the sanitary crisis is not handled uniformly leading to different responses between states. Our approach exploits these differences in responses to the pandemic (variation in the implementation of a lockdown and variation in the severity of the pandemic) to inform demographic issues that could be impacted by the pandemic both in the short-term and in the mid-term. Since the end of March and the beginning of April, some places in China emerged from a severe lockdown and it has been said that there was a rise in divorce filings in impacted cities [2, 3]. It seems that many couples did not survive a prolonged time confined together. If this example warns us about the potential effects of this global shock, many questions remain unanswered.

While the effects of COVID-19 pandemic on divorce rates in the U.S. remain unclear and with the current lack of systematic data on this issue, this work tries to fill the void in estimations of the pandemic impact on divorce at the aggregate level. The reaction to the pandemic and to lockdown policies is addressed through the lens of Internet use - more precisely the use of Google search engine. We will analyse the evolution of the interest for divorce-related issues on Google amid COVID-19. Then using this data we will seek to nowcast the divorce rates for 2019 and 2020.

A plethora of press articles were published in the U.S. to assess or counter the argument of a possible surge in divorces due to the pandemic [4, 5, 6, 7]. These articles ground their assumptions on the apparent growing concern on divorce showed by an increasing number of divorce-website visits and by figures provided by *Legal Templates*, a company providing legal documents. According to the report they delivered [8], the rise in sales of divorce agreements papers is up to 34% compared to the same period in 2019. These numbers are supported by previous scientific

1. We will refer to the disease with the common abbreviation «COVID-19» rather than the actual abbreviation (2019-nCoV) or formal name «severe acute respiratory syndrome coronavirus 2» (SARS-CoV-2).

2. https://www.bloomberg.com/news/articles/2020-03-31/divorces-spike-in-china-after-coronavirus-quarantines

3. https://www.sixthtone.com/news/1005435/spousal-distancing-thechinese-couples-divorcing-over-covid-19

4. https://www.ny1.com/nyc/all-boroughs/news/2020/06/27/has-the-coronavirus-pandemic-created-a-spike-divorces-

5. https://nypost.com/2020/09/01/divorce-rates-skyrocket-in-u-s-amid-covid-19/

6. https://www.reformaustin.org/coronavirus/divorce-rates-not-what-youd-expect-during-pandemic/

7. https://www.abc.net.au/news/2020-04-25/family-courts-to-fast-track-cases-coronavirus/12184498

8. https://legaltemplates.net/resources/personal-family/divorce-rates-covid-19/

studies which identify traumatic events as the possible trigger of marital dissolution decisions. Nevertheless COVID-19 pandemic is a really specific framework because of the prolonged time of forced cohabitation when under lockdown and because of the shutdown of administrative facilities. Difficulties to track divorces during the pandemic are obvious because each county has its own rules regarding divorce: depending on the state and county, divorce courts and services could be closed, assured through Internet or even totally opened. It is not an easy task to assess if divorces occurring after the pandemic are due to the potentially traumatic event or simply to a postponement because of the sanitary restrictions. Moreover, distinguishing the divorces due to the pandemic and the divorces conducted for usual reasons is not obvious at the aggregate level. The varying duration of the legal process to achieve divorce makes it also difficult to collect data quickly to address this demographic issue.

Many reasons are invoked to explain these relationships strains. The confinement can force couples to live with each other more than they usually do which make them come to the realization that they do not want to pursue their relationships. Existential self-questioning tends to be more prominent when in contact to deaths or life-threatening events and could lead to these marital decisions. The financial stress due to the lockdown - jobs losses or wage cuts for instance - is also one of the main reasons people seek for divorce. The domestic issues are numerous to explain the divorce framework - housework division, domestic violence, child care, etc. - with a well-informed effect of lockdown policies putting more of the burden on the shoulders of women (Dang and Viet Nguyen (2020), Leslie and Wilson (2020)).

To overcome the fact that divorce data are not immediately available, we use search engine data in this study and more precisely Google Trends data. Google Trends provides data on the queries made by users on Google search engine which may be salient to estimate effects of the pandemic on U.S. divorces. While suffering form limitations and not being a measure of behaviours, these Internet data are informative and almost immediately available. The analysis of divorce-related queries during the lockdown period and their relations to the actual divorce rates for the precedent years give us hints about the amount of divorces occurring in 2020. These estimations must be cautious and confronted to ground data on divorce when available. The main contribution of this work is to extend the nowcasting framework with Google Trends to marital issues while the field of demographic research has only marginally used these techniques and data to this day.

This work proceeds as follows: Section 2 presents the literature review, focusing on divorce and Google Trends. Section 3 presents a set of hypotheses to understand the evolution of divorce-related queries amid COVID-19 pandemic. Section 4 describes the different sets of data. Sections 5 and 6 develop the econometric methodologies to analyse the reactions of Google users regarding divorce topics during the pandemic and to nowcast the divorce rates for 2019 and 2020. Section 7 presents the results. Section 8 discusses the results and provides elements for further research. Section 9 concludes.

2 Literature Review

At the time this study is released - December 2020 - little insight on the evolution of divorce rates in times of COVID-19 pandemic is available. The yearly release of divorce rates delays the interpretations of COVID-19 effects on the aggregated mass of divorces. Furthermore it is obvious that the measures of divorce rates for 2020 will be subject to different effects - plausibly postponement of divorces and increase or decrease in the demand for divorces - due to the abnormal conditions of living during a pandemic. The divorce rates may be impacted for more than one year. While the subject has been largely discussed in the media arena as stated in the introduction, only a few research works addressed the issue, mostly through the lens of domestic violence (Zhang (2020)) and family relations (Biroli et al. (2020)). Even in China which was first hit by the pandemic no systematic data are available to assess a shifting pattern of divorce rates during COVID-19 pandemic. Smyth et al. (2020) who directly focus their study on separating and separated families in Australia during the pandemic affirm that the inherent tensions due to the sanitary measures are higher for these persons. The disruption of romantic or family relationship patterns is obvious with the uncertainty brought by the pandemic and the economic downturn. Guetto et al. (2020) show that the marital decisions are directly impacted by this uncertainty. Biroli et al. (2020) also raise this issue of growing tensions within families thanks to a survey-based study. Numerous works inform the worsening in mental health during the lockdowns (Patrick et al. (2020), de Pedraza et al. (2020), Brodeur et al. (2020)) and the increase of domestic violence (Usher et al. (2020), Hsu and Henke (2020), Leslie and Wilson (2020), Zhang (2020)). Both are directly linked to divorce patterns. As shown by Bowlus and Seitz (2006) domestic violence in the household tends to increase the probability of divorce. The worsening of well-being and mental health is due to life stressors which can be detrimental to every couple due to the global scale of the pandemic. These stress spillovers are an additional burden for couples and can conduct to the incapacity to cope with the marital relationship (Buck and Neff (2012)). The article of Pietromonaco and Overall (2020) sheds the light on the principal hypotheses concerning effects of COVID-19 pandemic on romantic relationships using relationship science. Looking at marital responses to natural disasters may be informative since COVID-19 encompasses the same features (life-threatening event, economic downturn, administrative shutdown, etc.) but at a much larger scale. The work of Cohan and Cole (2002) is an influential one in this domain: the authors show in the framework of a natural experiment that following hurricane Hugo in 1989 the counties of South Carolina hit by the hurricane reported significantly higher divorce rates than the ones that were not hit. Another channel through which the divorce rates might be affected lies in the financial strains that households are facing. A large part of the literature focusing on divorce tries to identify the correlation between the economic context and the divorce patterns. Studies suggest that there exists a paradoxical effect of unemployment between the individual level and the macroscopic level. Individual job losses appear to destabilize marriages while macroeconomic studies find modest evidence of pro-cyclicity of divorce rates along the business cycle. For instance Amato and Beattie (2011) and Hellerstein and Morrill (2011) both find that state crude divorce rates are negatively correlated to state unemployment rates during the last two decades. This supports the idea that the deterioration of the economy pushes the number of divorces downward at least in the short-term. This paradox in the transition between the individual and aggregate levels may be due to the fact that macroeconomic conditions could influence divorce probabilities even for the population that does not experience an economic shock. But what will be the link when the shock is global? With the COVID-19 crisis and its global impacts the effects still remain to estimate but papers have tried to overcome the lack of data using alternative sources of information. Notably Brodeur et al. (2020) and Berger et al. (2020) use Google Trends data to track the interest in the divorce issue during the pandemic. The latter finds that the share of searches associated with divorce declined at the beginning of lockdowns and then returns to its average level and even increased two and a half months after the lockdown beginning when compared to pre-pandemic periods.

Since the seminal paper of Ginsberg et al. (2009) which uses Google search engine queries volumes to track influenza outbreaks (Google Flu Trends), Google Trends data have been widely used among numerous scientific fields. For a systematic review of Google Trends use in the scientific domain, you can refer to Jun et al. (2018). The most prominent fields on this ground are economics and health. Works as those of Choi and Varian (2012) using Internet data to predict sales of different natures (vehicles, homes, etc.) or Askitas and Zimmermann (2009) finding strong correlations between chosen keywords searches and monthly German unemployment rates in the practice of forecasting have boosted researches in this domain. Vosen and Schmidt (2011) introduces Google Trends indicators to forecast private consumption, which outperform traditional indicators (survey-based) for in-sample and out-of-sample forecasts. All this has nourished enthusiasm about Internet data but the demographic area has mostly remained on the sidelines in the exploitation of this type of data. Demographic contributions using Google Trends remain punctual while it provides new possibilities especially for nowcasting. One of the major advantages of these data is indeed their almost immediate availability and high frequency when demographic measures and estimations are released with important lags and very low frequency. Some works have assessed correlations of Google Trends data with variations in socio-demographic structures and behaviours such as abortion rates (Reis and Brownstein (2010)) or fertility rates (Ojala et al. (2017)). One major contribution for our study is the work of Billari et al. (2016). This study assesses the possibility to use Google Trends data to predict fertility rates in the United States. Their augmented-model with Google Trends indicators carries more predictive power than the traditional ones in a short-term horizon. In the period of COVID-19 pandemic, with all demographic structures being affected, Internet data can deliver insights to nowcast and forecast the effects of the crisis on these structures. On these grounds the infodemiology [9] is much more developed than is the use of Internet data

9. «the science of distribution and determinants of information in an electronic medium, specifically the

in demographic research. Mavragani and Ochoa (2019) have made an attempt in providing a methodological framework to adequately use Google Trends in health researches. With the violent outbreak of COVID-19 the use of Internet data has revealed interesting to track and monitor epidemics (Higgins et al. (2020), Effenberger et al. (2020)). To quickly test hypotheses of the effects of COVID-19 on demographic structures researchers have been forced to turn themselves to Internet data since survey-based date are not yet available. Brodeur et al. (2020) have studied well-being informed on Internet with chosen Google Trends topics - among those is the topic of divorce but the authors do not dwell on the results *i.e.* a large drop in the share of searches related to divorce. To provide a short-term forecast of the fertility rates in the U.S. Wilde et al. (2020) have joined the lineage of Billari et al. (2016) using Google Trends data and their variations amid COVID-19 pandemic. Finally an influential work for our study is the one of Berger et al. (2020) which analyses the aggregate reactions of Google users to COVID-19 for demographic topics and notably for the keyword «divorce». Adopting both of these latter approaches we will estimate the effect of COVID-19 pandemic and lockdowns on divorce-related searches and on divorce rates. The contribution of this work lies in the nowcasting exercise of divorce rates which has not been carried out up this day to our knowledge.

3 Theoretical Model

Our central hypothesis supported by numerous previous studies across various fields is that Google Trends data could be salient for a chosen issue. We assume that searches made on Google search engine enable access to a selected set of information for users. Note that queries including the same keywords do not necessarily carry the same meaning but a variety of meanings that might be related to the keyword issue (Mellon (2013)). Measuring the aggregate demand for a keyword over Google search engine and its evolution over time might then be informative of a spectrum of thoughts and behaviours held by users relatively to the keyword issue. With COVID-19 pandemic the social and marital behaviours of the individuals might obviously change. The searches amount - and share among the overall number of searches - might also evolve. While Google Trends data do not deliver an adequate measure of behaviours, we make the assumption that the series might inform the evolution of the interest over an issue among the population - of Google search engine users. We will further detail the structure of the Google Trends data in subsection 4.1. The basic idea is that Google Trends series render points measuring an interest over a keyword among all searches at a precise time point - the literature refers to these values as Relative Search Volumes (RSV). Notice that the overall use of Internet has known a sharp increase during the COVID-19 lockdowns as mentioned in Feldmann et al. (2020). The values corresponding to our selected keyword searches during this period are expressed relatively to this increase in volume.

Internet, or in a population, with the ultimate aim to inform public health and public policy», Eysenbach (2009).

Because of theoretical assumptions developed in the previous section as peaks in unemployment, decrease in mental health and well-being during the pandemic, it appears that marital functioning has been put under huge stress pushing towards an increase in the global demand for divorce. Studies suggest that lockdown policies might exacerbate this effect. Moreover closure of administrative facilities dealing with divorce could lead to more people seeking information on Internet which remains accessible. Divorce is a social issue amongst others that will probably be strongly impacted by the COVID-19 pandemic. This has drawn a growing interest on this issue. From this we hypothesize that the absolute number of divorce-related searches has increased with the pandemic and especially during the lockdown period. Notice that this hypothesis of increase in divorce-related searches does not mean an increase in relative search volumes. It depends on the evolution of the overall number of searches. Furthermore the media nourishing the divorce issue during COVID-19 pandemic might produce contagion effects with people not directly impacted or even concerned by marital problems searching for divorce-related keywords. From this we make the assumption that relative search volumes for divorce-related queries might increase during the lockdown and remain at a higher level than the usual for a short period after it because of the postponement of divorce filings.

Nevertheless several reasons might push the relative search volumes of divorce-related queries downward. As written in section 2 there is modest evidence that a context of economic crisis (the main empirical results concern the Great Recession of 2008-2011) conducts to a decrease in the number of divorces. Following this argument it is possible that the absolute number of divorce-related searches has diminished with the pandemic. The closure of divorce courts might also postpone researches that would normally be conducted. Moreover several reasons advocate for a decrease in relative search volumes. Lockdown forced most people to work from their home and pursue leisure activities inside their household. Feldmann et al. (2020) show that the Internet use has largely increased during this period. But users behaviours have also changed (Feldmann et al. (2020), Böttger et al. (2020)). Entertainment activities on Internet grew sharply with the lockdown and this type of activity on Internet can be repeated without consuming all the utility associated with this activity. Searching divorce on the Internet appears as a research for information where there is no gain in utility to research again divorce-related keywords when all wanted information is gathered. Internet is a tool which conducts to different usages with some representing a larger share of the overall use and growing more than divorce-related searches. However the return to a normal Internet traffic after lockdown (but still within the pandemic) would yield to an adequate comparison to pre-lockdown period where relative search volumes inform the effect on divorce demand more clearly at this time. We hypothesize that relative search volumes for divorce-related keywords might decrease during lockdowns even if mitigated by a growth in absolute number of searches.

Previous studies on families during the pandemic suggest that confinement policies might increase tensions among couples (Biroli et al. (2020) for instance). On the one hand, these tensions might increase the global interest for divorce in the population. On the other hand, with more leisure time at home - leading to more time spent on Internet -, the overall search volume on Google search engine might also increase. This increase in overall search volume tends then to hide the increase in global interest for divorce since our data are relative search volumes - and not absolute ones. From this we suppose that the states implementing lockdowns will yield to different effects in the aggregated volume of searches. The coefficients associated to the lockdown periods will be superior for states having lockdown than for those not having one. If the relative search volume for a divorce-related keyword increases we expect a larger increase in the lockdown states. And if the the relative search volume for a divorce-related keyword decreases we expect this decrease to be of less magnitude in these states. This effect should be reduced with the end of the lockdowns.

4 Data

4.1 Google Trends Data

4.1.1 What is Google Trends?

The first set of data comes from the Google tool, Google Trends [10], a website which enables us to extract time series about one or several keywords informing about the research intensity for this topic on Google search engine, as illustrated by Figure 1. The figure compiles the time series related to the term «divorce» for all states and the District of Columbia (light gray lines) and also their average value (black line). Google Trends was launched in 2006. Google Insights for Search, another similar tool was merged into Google Trends in 2012. It appears that during the first years of the functioning of Google Trends, the data were not regularly updated as it is the case now. This could explain what we observe during the first years of our series with data being of lower quality or noisier (this noisiness could be spotted for the window 2004-2008 on Figure 1). Google Trends presents a relative flexibility for the observation of various time series. Indeed the time series period and location can be adjusted to personal preferences. When choosing a sampling period, the time series could go back to 2004 and the location choices include different levels - world, country, states or regions, counties and cities. Depending on the chosen sampling period, the point frequency differs. Monthly data are provided for time series longer that five years, weekly data for queries between nine months and five years ans daily data for time series shorter than nine months. The aim of Google Trends is to render time series which give the relative interest for a keyword in the aggregate base of queries and its evolution over time. To obtain this, one just needs to search for a keyword or a combination of keywords on Google Trends. Some additional features not detailed here are provided by the website.

As documented by Google (2020) and explained by Stephens-Davidowitz and Varian (2014),

10. https://trends.google.com

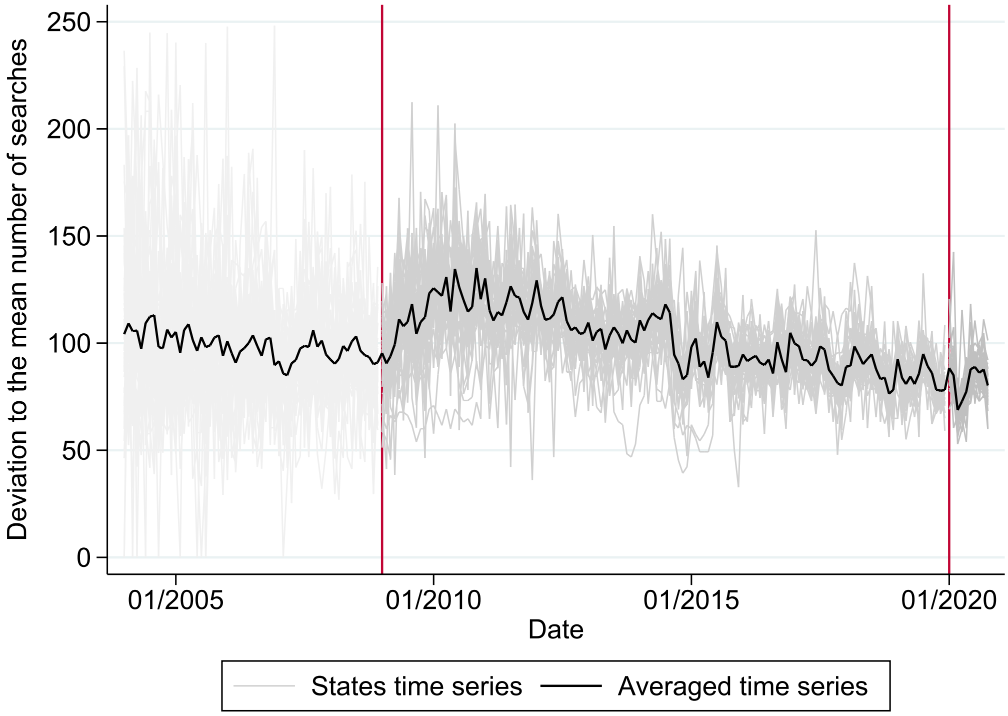

Figure 1 – Search interest associated to the keyword «divorce»

these time series do not return absolute levels for the number of topic-related searches but are relative to the overall searches in each point of time for the chosen location. It is not possible to directly infer a volume of searches based on these data. The rate of topic-related searches among all searches is calculated for each point. The observation returning the highest rate for searches about the keyword(s) among all other searches in the area and for this point-period is given the value 100. Then every other rate is evaluated relatively to this maximum. We can not assume the number of searches associated to a point value because it depends of the overall searches during the length of this observation. It is possible that a point which takes the value 50 reflects the same number of topic-related searches (in absolute terms) as the point taking the value 100 in a different period, just because the overall searches is two times bigger for the first point than for the second one.

As an illustration, we present Table 1 to clarify the data processed by Google Trends. The example of Table 1 is purely fictional but respects the normalization process delivered by Google Trends. Remember that the absolute number of searches (overall or keyword-related) are never given by Google Trends. Here the time series counts 4 observations. We exhibit the number of overall searches and the number of searches related to the chosen keyword for each unit of time. The ratio of the latter to the overall volume of searches gives us the column *Search rate*, which represents the share of the keyword-related searches among all searches. The data of the series are relative and not absolute. Once all rates are calculated for each period of time, the highest rate (here it is 0.01 for the second period) is considered the reference observation and is given the value 100. The multiplier column represents the coefficient by

Period	Overall searches	Keyword searches	Search rate	Multiplier	GT normalization
1	20 000	150	0.0075	0.75	75
2	20 000	200	0.01	1	100
3	40 000	200	0.005	0.5	50
4	100 000	400	0.004	0.4	40

Table 1 – Example of the normalization process implemented by Google Trends

which we must multiply the highest rate to obtain the search rate for a given period. Once multiplied by 100, this gives us exactly the values rendered by Google Trends. This fictional example allows us to tackle some potentially wrong assertions. Firstly, the Google Trends values are dependent of the absolute number of keyword-related searches. When we compare for the period 1 and 2, we see that the overall volume of searches remains constant, but the keyword-related searches grow. Consequently the search rate grows in the same proportion and the Google Trends value is bigger for the second period. The Google Trends value also depends strongly on the overall volume of searches. when we compare the period 2 and 3, we observe that the number of keyword-related searches remains constant - equal to 200 - but the overall volume of searches grows. The search rate for the period 3 is then lower than the one for the period 2. The corresponding Google Trends value is then lower even if the absolute number of keyword-related searches remains the same. Finally, we can compare the observation at period 4 to the observation at period 2 - it works the same if compared to period 1 or 3. We see that the number of keyword-related searches has doubled between these periods. But in the same amount of time, the overall volume of searches has been multiplied by 5. Consequently the search rate is strongly lower for the period 4 while the absolute number of keyword-related searches is at its highest point. The interpretations have to be cautious when commenting the Google Trends series values because a lower point does not necessarily mean less searches. Since Google Trends does not provide the overall volume of searches, the only valid interpretation is in terms of share in the overall queries at the time of the observation. We will discuss this issue further in the work.

Due to this normalization process, the interpretation of the Google Trends data is not straightforward. Notice also that every time series is independent from one another, and one must not try to draw a direct comparison between variables or states.

4.1.2 Series Selection and Retrieval

The aim of this study is to analyse Google queries related to the divorce topic and ensure the validity of these observations as salient variables to explain and predict divorces. Some previous works as the famous Google Flu presented by Ginsberg et al. (2009) adopted an approach where the exploration of statistically significant relationships with the dependent variable (the number of influenza cases in this example) is automatic. Since the dependent variable is compared to a high number of Google Trends (several millions) indexes, it is possible that some indices are correlated by chance. To avoid this data mining approach, we partially follow the methodology developed by Mellon (2014) ensuring first face validity of our variables and then their content validity. The first step - face validity - consists in selecting keywords or combination of keywords that are *a priori* relevant to measure the concern of the chosen domain. For instance the keywords «alimony» or «spousal support» seem to be relevant to estimate the interest for the financial benefits or payments associated to divorce. The second step of the methodology is to assess the content validity of the *a priori* chosen variables. It means that the queries made with the selected keywords have to inform the domain they are chosen for and not be attached to other topics we do not want to measure. Mellon (2014) assesses the validity of the variables by ensuring that the most requested terms for the keywords are relevant. For instance, the keyword «divorce» appears as relevant to the domain of divorce, but there are also searches associated to celebrities divorce as Kim Kardashian's one. Whether it is relevant or not to explain the aggregate divorce rates is an open question. We could advocate that these media divorces have an impact on people and have an indirect effect on the divorce rates. In this paper we make the assumption that they do not have an effect on divorces, direct (let aside their own divorce obviously) or indirect but only render a media effect. Moreover, it often appears that these unrelated events are causing extreme values in the time series. A feature of Google Trends is the command «-» which enables to forbid keywords in the queries. The confounding terms can be eluded thanks to this and the new selected combinations of keywords better approximate the domain studied.

After these steps, we have selected different sets of keywords referring to the following domains: divorce, legal procedures in divorce, administrative features in divorce, financial traits in divorce, divorce questioning and a set of control keywords. The package *gtrendsR* of Massicotte and Eddelbuettel (2020) allows us to extract the variables detailed in the Table 7 in appendix at the state level and at a monthly frequency.

4.1.3 Normalization Procedure

To avoid any misleading interpretation, we conduct a normalization procedure after extracting the raw series, as described hereafter. Let $\tilde{R}_{st}$ be the observation provided by Google Trends for the variable $\tilde{R}$ in state s at date t. The normalized variable of interest is noted R_{st}. We normalized every time series extracted, by state and by variable, applying the following method:

$$R_{st} = \frac{\tilde{R}_{st}}{\overline{\tilde{R}_s}} * 100$$

where $\overline{\tilde{R}_s}$ is the mean of the series. This normalization procedure makes it clearer how to interpret the observed values. 100 being the mean for all the observations over the global period (2009-01 - 2020-10) after this re-normalization, all observations are defined as deviations to this mean. If a point takes the value 200, it means that this point is twice as big as the mean of the series.

We are trying to identify the varying interests of people for divorce and its specific procedures at a precise time and in a precise area. Still after normalization, our time series remain noisy since a lot of exogenous events are influencing the search rates for our variables, which is something we do not want to include in the analysis, unless it also influenced the divorce rates in any manner possible. We already evoked media events which could cause the presence of outliers. For instance, after Kim Kardashian files for divorce from Kris Humphries the 31^{st} October 2011, the initial data extracted show a great peak for November 2011 in most states for some of our variables. In addition of being something we do not want to measure, it will bias the results of our analysis on two grounds: the normalization procedure will not be optimal, all the more if the maximum value of the raw series (point of reference for all the time series observations) is due to this exogenous event, and the inclusion of month fixed-effect in our analysis will render this type of exogenous event endogenous if we do not exclude them properly.

To avoid this kind of interference, we decided to conduct three tests to identify different types of outliers for each time series: (i) Chauvenet's Criterion, (ii) Hampel Filter, (iii) outliers according to a Seasonal Trend decomposition using Loess. We precsise the testing process in appendix. Each test is conducted using the observations from 2004 to 2019, thus avoiding any influence of the potential effects of the COVID-19 pandemic, which we want to identify. An observation is declared an outlier when all the three tests declared it an outlier. A checking procedure can then be done, searching which event is related to this extreme value: using Google Trends tool, we narrow the window of the time series around this abnormal point and look at the most frequently requested associated keywords on this narrowed period. It usually gives hints on what can cause this outlier. Once we have identified the main outliers that tend to bias our analyses, two methods could be conducted in order to exclude them.

1. The first one consists in adding dummies for the observations identified as outliers, nullifying the effect of this extreme point in the estimation of other effects. That is what Berger et al. (2020) do in their analyses. This has the advantage to avoid pre-treatments before the regression analysis.

2. The second one consists in re-extracting the series of interest while subtracting for the searches associated to the outliers (with the same method detailed earlier). That is the method we choose, that presents the advantage to directly reduce the bias risk induced by the abnormal points. That is why many of our variables forbid the combination of divorce-related terms and celebrities, under the assumption that the event we decided to push aside has no effect (directly or indirectly) on the probability of divorce of the person searching for this specific combination.

The exclusion of the outliers is necessary in this normalization framework because eluding this step will directly bias the normalized values. Let us consider that each value can be decomposed into two parts: a *real* part r_{st} seizing the personal interest for an issue which is

salient in the estimation of the effects and an *outlier* part e_{st} induced by unrelated events or errors which introduces noisiness in the estimation.
Formally: $\tilde{R}_{st} = r_{st} + e_{st}$ and $\forall\ (s,t),\ r_{st}\ \in\ [0,100],\ e_{st}\ \in\ [0, r_{st}]$.
The ideal normalization process without bias would lead to the following equation:

$$R_{st} = \frac{r_{st} \times 100}{\frac{1}{T}\sum_{t=1}^{T} r_{st}} \tag{1}$$

Nevertheless within our framework the we obtained the following equation (details are provided in appendix):

$$R_{st} = \frac{r_{st} \times 100}{\frac{1}{T}\sum_{t=1}^{T} r_{st}} \underbrace{\left(1 - \frac{\sum_{t=1}^{T} e_{st}}{\sum_{t=1}^{T} r_{st} + \sum_{t=1}^{T} e_{st}}\right)}_{\boldsymbol{A}} + \underbrace{\frac{e_{st} \times 100}{\frac{1}{T}\sum_{t=1}^{T} r_{st}} \left(1 - \frac{\sum_{t=1}^{T} e_{st}}{\sum_{t=1}^{T} r_{st} + \sum_{t=1}^{T} e_{st}}\right)}_{\boldsymbol{B}} \tag{2}$$

$\boldsymbol{A}$ and $\boldsymbol{B}$ identify a possible decomposition of the bias. Notice that

$$\frac{\sum_{t=1}^{T} e_{st}}{\sum_{t=1}^{T} r_{st} + \sum_{t=1}^{T} e_{st}} = \frac{\sum_{t=1}^{T} e_{st}}{\sum_{t=1}^{T} \tilde{R}_{st}}$$

which means that the multiplicative bias $\boldsymbol{A}$ is due to the total share of outliers information within the series. Note also that $\boldsymbol{B}$ can be decomposed as follows:

$$B = \frac{e_{st} \times 100}{\frac{1}{T}\sum_{t=1}^{T} r_{st}} \left(1 - \frac{\sum_{t=1}^{T} e_{st}}{\sum_{t=1}^{T} r_{st} + \sum_{t=1}^{T} e_{st}}\right) = \underbrace{\frac{e_{st} \times 100}{\frac{1}{T}\sum_{t=1}^{T} r_{st}}}_{\boldsymbol{B_1}} - \underbrace{\frac{e_{st} \times 100}{\frac{1}{T}\sum_{t=1}^{T} r_{st}} \left(\frac{\sum_{t=1}^{T} e_{st}}{\sum_{t=1}^{T} r_{st} + \sum_{t=1}^{T} e_{st}}\right)}_{\boldsymbol{B_2}} \tag{3}$$

$\boldsymbol{B_1}$ is the bias induced by the share of the outlier part in the normalized observation, while $\boldsymbol{B_2}$ is the same multiplicative bias as $\boldsymbol{A}$ but applied to the outlier part of the observation. We have assumed that outliers can only change the observed values in a positive way. The outlier part e_{st} is always positive or equal to 0. Because of this assumption, $\boldsymbol{A}$ and $\boldsymbol{B_2}$ always have a negative effect. On the other hand $\boldsymbol{B_1}$ always have a positive effect. The bias evaluation is not straightforward and strongly depends on the point estimated (due to its outlier part).

4.1.4 Advantages and Limitations

Sparsity issues

Yet, some issues remain with Internet data. When the number of searches is not sufficient for a time series (given a threshold in absolute numbers set by Google and that we are unaware of), we only obtain missing values. It is especially the case for the states with a low population, all the more when the selected keywords are quite specific and precise. We must point out that some variables may be too specific: if the time series returned is not a series of missing values, it can also happen that the series actually displays a lot of zeroes. When the threshold of searches (set by Google) is not exceeded for a point, it will return 0, ending with a noisy series with strong ups and downs. Finally, data from the first years of Google Trends seem to be of bad quality and then give a lot of outliers for our automatic identification. One of our robustness checks is to remove these first years for the model estimation.

Representativeness

Another issue comes with the representativeness of Google Trends data. This is very plausible that the data are not correctly representing the overall population. Between geographic entities like countries or even states the coefficient of Internet penetration could be different leading to different quality for the data and to different samplings due to a different distribution of Internet use among demographic groups. Choosing to restrict the analysis to the U.S. will reduce the bias risk on this ground - we indeed assume that Internet is broadly used across the country. Zagheni and Weber (2015) evoke this problem and try to implement a methodology to solve it, which remains theoretical. Another problem arises when we take into account that Google search engines is not the only search engine available on the web. This remark is mitigated by the overwhelming percentage of Internet users choosing Google as search engine: according to *Statcounter*[11] more than 90% of queries are made on Google. Nevertheless it is possible that we do not observe other types of Internet behaviours that only exist on other search engines. Finally shifts for Internet behaviours across time is also a possibility: Mellon (2014) evokes the time specificity of terms used which is why we require a step of keyword validity. Internet behaviours might evolve smoothly over the years but may also shift drastically in a period of crisis as for the Great Recession or COVID-19 pandemic. Using Internet data instead of traditional data as surveys may get round - or at least reduce - the bias of social desirability[12]. Since queries are not immediately thought as data that will be analyzed and also because they are anonymous it leads to a decrease in the social desirability bias.

Volume problems

The most important problem related to Google Trends data is the unknown quantity of absolute volume - both queries and overall search volumes. The Google black box concerning volumes yields to question the validity of the analyses. Indeed Siliverstovs and Wochner (2018)

11. https://gs.statcounter.com/

12. «Social desirability is the tendency of some respondents to report an answer in a way they deem to be more socially acceptable than would be their «true» answer.», Lavrakas (2008)

develop a method to analyse the matching between Google Trends queries and actual data in the tourism sector in Switzerland, but can only do this comparing queries by pairs. The fact that we observe Relative Search Volumes and not absolute ones is problematic since we can not assess that a temporal variation for a query rendered by Google Trends is due to a variation in request or a variation in overall search volume. Already illustrated by Table 1, this binds researchers to cautious approaches and interpretation, moreover when the Internet behaviours and patterns are shifting quickly which is the case with COVID-19 pandemic. We should also underline a point raised by Lazer et al. (2014) who write that search behaviours are not just exogenously determined - and so adequately correlated with external events - but are endogenously cultivated by Google, the service provider to achieve commercial purposes. This bias is put forward by the authors to explain the failure of Google Flu Trends (Ginsberg et al. (2009)) after a few years to achieve its objectives, major example that should warn us about the caution to adopt to interpret these data, and the necessity to confront the results to traditional data to assess the validity of interpretations. Another issue concerning the data volume is the nature of the searches which may be linked to external events in different way: people may search for an issue because they are personally interested with it or because they have only heard of it. Cervellin et al. (2017) show that there is a media coverage bias - here in an infodemiology analysis - when people search for informations on Google after having heard of it in another medium. With the example of Ebola fever they demonstrate that there is no correlation between the local epidemiological context in Italy (no cases) and the data corresponding which present a peak related to media coverage of Ebola epidemics in Africa.

4.2 Ground Data

The divorce and wedding data come from the National Vital Statistics System, within the Centers for Diseases Control and Prevention, and they are found by following this link: `https://www.cdc.gov/nchs/nvss/marriage-divorce.htm`. The data are given at a state-level and at an annual frequency. They concern the divorce and wedding rates per 1000 inhabitants of the state (also called Crude Divorce Rate and Crude Wedding Rate), for 1990, 1995 and between 1999 and 2018. We choose to restrict our sample to 2004-2018 to match our Google Trends data. We could already point out that our work will be partial and incomplete because of missing observations for certain states, which choose not to report their rates: California, Hawaii, Indiana for the whole analysis period, Georgia between 2004 and 2016, Louisiana between 2004 and 2012, Minnesota since 2005 and New Mexico since 2016. The Figure 2 shows the crude divorce rates for all states reporting their data (light gray lines) and the average rate of all these series (red dashed line) between 2004 2018. The estimates for state population and its age characteristics between 2004 and 2019 are provided by the US Census

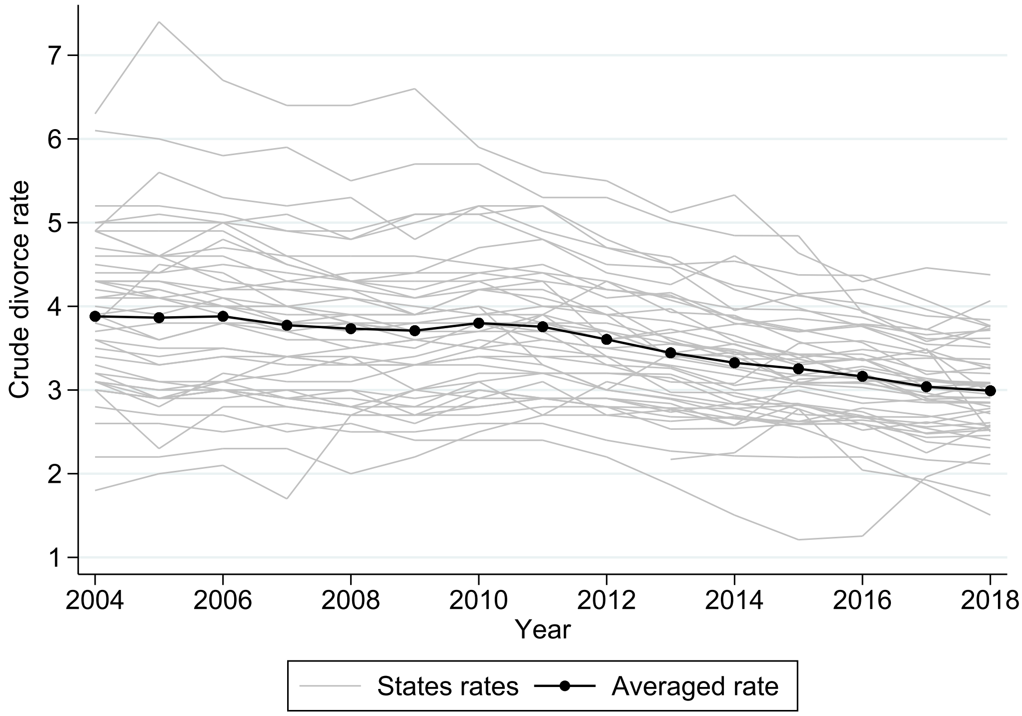

Figure 2 – States crude divorce rates and averaged crude divorce rate

Bureau [13, 14, 15] and the 2020 state population projections come from the Weldon Cooper Center (2018). We bring the monthly unemployment rates at the state level to enrich our analysis, from the Bureau of Labor Statistics: https://www.bls.gov/lau/. Unemployment rate is often considered in the literature as a good and synthetic indicator for the state of the economy, even if not complete. Moreover, an abundant literature tries to understand the mechanisms linking unemployment and divorce: Bremmer and Kesselring (2004), Amato and Beattie (2011), Hellerstein and Morrill (2011) just to cite a few. We also include the annual averages for this variable. To integrate control variables such as deaths due to COVID-19 or confirmed cases, we choose to refer to the daily updated time series delivered by the Johns Hopkins University on this link: https://github.com/CSSEGISandData/COVID-19. We compute these variables for the same period as the rest of our analysis, until October 2020. For these variables, we use new confirmed cases and deaths per month and by state, in absolute numbers and proportional to the state population. The lockdown dates (beginning and end) are based on Stay-At-Home Orders and Shelter-In-Place Orders given at a state-scale. We do not consider the counties Stay At-Home Orders. We counted 8 states where a statewide stay-at-home order was not issued: Arkansas, Iowa, Nebraska, North Dakota, Oklahoma, South Dakota, Utah, Wyoming. Since we defined lockdowns here as the consequences of stay-at-home orders, we should note that every

13. https://www.census.gov/data/tables/time-series/demo/popest/intercensal-2000-2010-state.html
14. https://www.census.gov/data/tables/time-series/demo/popest/2010s-total-housing-units.html
15. https://www.census.gov/data/tables/time-series/demo/popest/2010s-national-detail.html

order has not the same nature: they could be (i) mandatory for all persons, (ii) mandatory only for persons in certain areas of the jurisdiction, (iii) mandatory only for persons at increased risk in the jurisdiction, (iv) mandatory only for persons at increased risk in certain areas of the jurisdiction, (v) advisory or recommendation (*i.e.* nonmandatory). For now, these differences are not showed in our model [16].

5 Analysis of the Google Queries Related to Divorce During the COVID-19 Pandemics

5.1 Motivation

The COVID-19 pandemics has been a global unexpected shock which has affected the behaviors and policies. It is not absurd to assume that the Internet searches will be affected by this crisis too. The Google Trends series associated with the divorce topic seems to vary

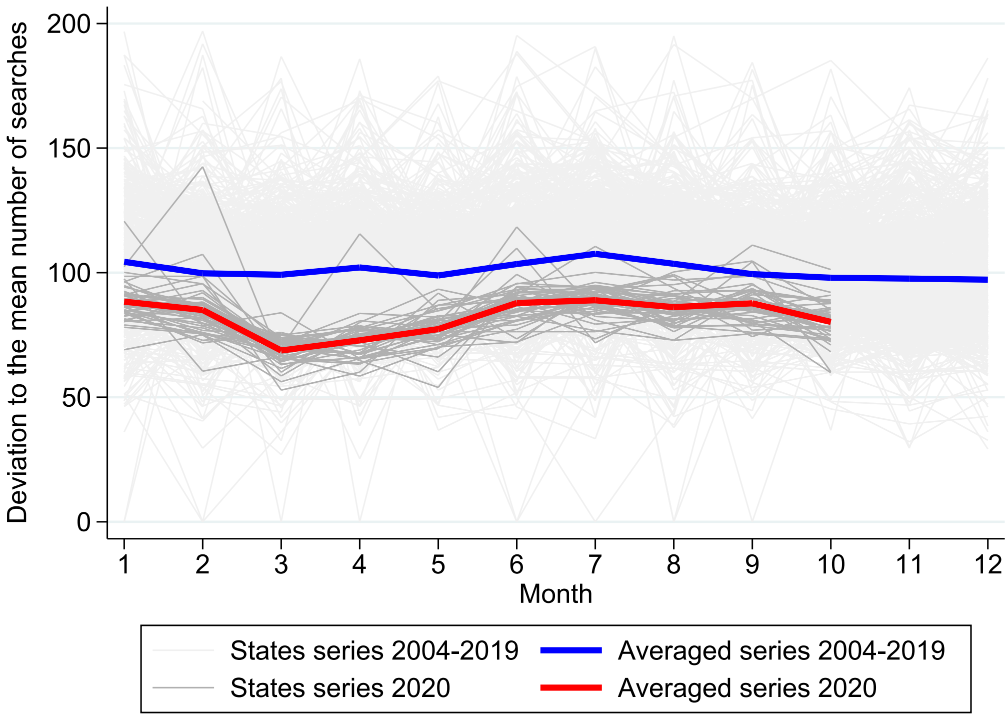

Figure 3 – Search rates associated to the keyword «divorce»

during the period of the COVID-19 pandemics, as suggested by the Figure 3. The searches that includes the term «divorce» seem to strongly decrease during the pandemics compared to the years before. With 100 being the mean value for the whole sampling period, it means that the search rate associated to the keyword «divorce» has known a really sharp decrease in March 2020 (around 60) compared to this mean. We will conduct an econometric analysis to assert the

16. Refer to Moreland et al. (2020) for more detailed information.

significance of these variations and to disentangle the potential effects that induce these shifts for the Google queries we are interested in. Asserting the significance of the variations since around February 2020 [17] for the Goggle Trends series is indeed not an easy task since many reasons could explain these sharp changes in the observed points. Structural and temporal grounds could partially induce these differences between the series: it is quite plausible that the states are very heterogeneous in terms of divorce. This institution might not have the same weight for each state and thus the reaction to the pandemic for the divorce queries might also be heterogeneous between states as shown in Reis and Brownstein (2010). Moreover changes in the institution and in the perception of divorce have been described for instance by Stevenson and Wolfers (2007) and they need to be noticed to fully understand potential trends and breaks in our time series. The heterogeneity between states might also exist for the use of Internet, with populations being very different across states in terms of age distribution, ethnic composition, religions distribution, etc. inducing different Internet behaviours and consequently different search rates. This issue is developed by Zagheni and Weber (2015) who propose a methodology to assess the validity of Internet data representativeness against ground data. Since the data have a temporal dimension, the decomposition of this factor at different scales is also necessary. Firstly, we must take into account a potential seasonality: if there are fewer searches related to divorce in December than any other month based on administrative or cultural grounds, and this for every year, we could not directly deduce an effect from a decrease of the search rate in December. This motivates the inclusion of fixed-effects in our analysis, more precisely month fixed-effect. At a different scale, heterogeneity between years is a potential bias as we mentioned above, referring to secular changes in the trends for divorce. But this potential heterogeneity may also be due to more recent and localized behaviours, as shifts in the use of the Internet since 2004, or because of changes in the framework of our topic (divorce and all that comes with it) in a state. We could evoke for instance the debated reform of the alimony law in Florida around April 2013. The Figure 4 shows this peak for the searches about «alimony» or «spousal support» in April 2013 in Florida while the rest of the time series seems to be quite close to the averaged time series. Including month, year and state fixed-effects in our analysis seems to be the best solution to reduce the biases in our model, accounting for a part of the heterogeneity between the observations. Furthermore, clustering at the state level seems to be appropriate so that we allow for the correlation of the regression errors within a state but not across the states.

We will now discuss directly the object of our study, *i.e.* the divorce-related topics on Internet - more precisely on the Google search engine, even if this precedent generalization might be quite correctly estimated from our analysis according to statistics on Internet use (*cf.* section 4). We want to render the perception and interest for divorce through the analysis of topic-related Google Trends series. It remains unsure that our time series are adequately

17. The COVID-19 outbreak was declared a pandemic by the World Health Organization the 11^{th} March 2020: https://www.euro.who.int/en/health-topics/health-emergencies/coronavirus-covid-19

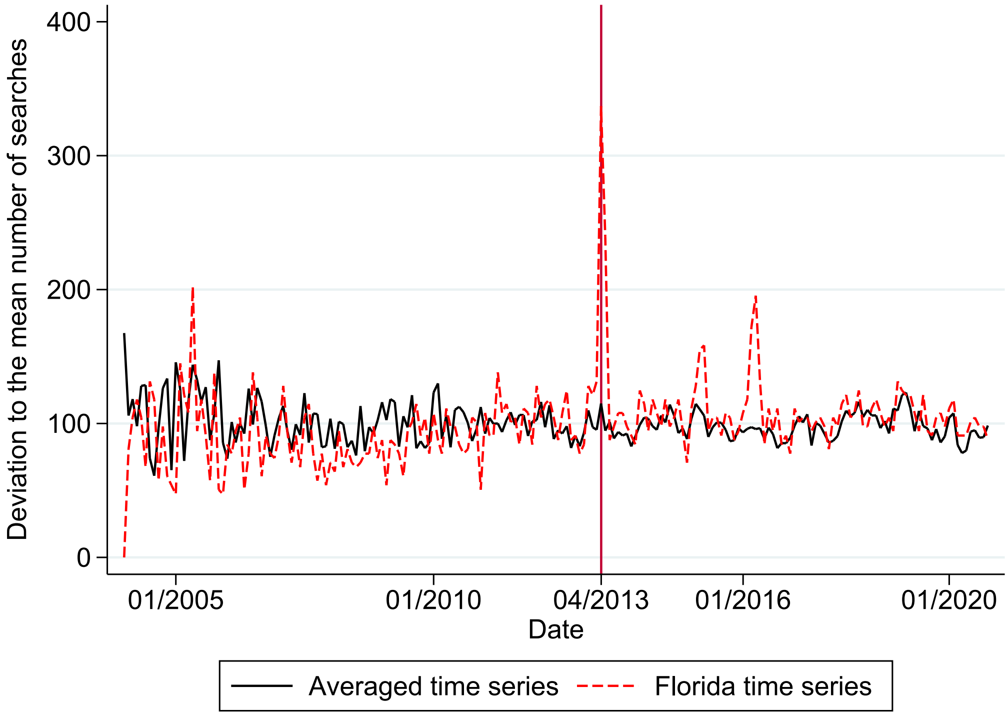

Figure 4 – Search rates associated to the terms «alimony» or «spousal support»

chosen, since they are strongly subject to be influenced by exogenous events. As depicted in the previous section, during the first stage of our work, we had not eluded the term «Kardashian», elusion which strongly changes the characteristics of our time series. Indeed, we could observe a large spike in the searches referring to «divorce»in November 2011, for most of the states, right after that Kim Kardashian files for divorce from Kris Humphries the 31^{st} October 2011. We have also demonstrated that not eluding this event biases the normalization process. In addition this will lead to a largely greater month fixed-effect on the month of this specific observation, changing our results. Following Berger et al. (2020), we make the assumption that this type of events is exogenous and does not influence the divorce behaviour of the Internet users. Therefore, the time series has to be re-computed, eluding the outliers created by these exogenous events. Our results will be biased if the assumption made above turns out to be wrong, meaning that the events we eluded does have an impact on the divorce behaviour of individuals, directly or indirectly.

5.2 Pandemic Index Construction

We want to identify the effect of the COVID-19 lockdowns on the Google Trends data solely, disentangling it from the global effect of the pandemic. It is possible that the lockdown did not have any effect. This would mean that the administrative or legal framework is not causing variation in the Internet behaviour in that case, meaning that we can infer that the observed variations in the search rates are due to the disease [18]. The United States is a particularly interesting case to study since it offers many variations in the reactions to this sanitary crisis. 42 states and the district of Columbia have instituted a Shelter-In-Place-Order or a Shelter-At-Home-Order (Moreland et al. (2020)), while the eight remaining - Arkansas, Iowa, Nebraska, North Dakota, Oklahoma, South Dakota, Utah, Wyoming - have not. The dates of statewide lockdowns are detailed in Table 6 in appendix. These COVID-19 lockdowns have not all been instituted at once, so that we can measure a temporal variation for this «treatment». Another spatio-temporal variation that we exploit in our analysis is the date when a certain state is considered to have reach a certain level of pandemic, measured by the excess of a fixed threshold. We measure the presence of the epidemic by the excess of a threshold of new cases or new cases per state population within the state and report it as the date of reference for the beginning of the epidemic in the state. This date of reference is susceptible to be different between states because of the initial conditions of arrival of the virus in the U.S., because of the transmission rate which is somehow linked with the density of population, with the age structure, with implemented policies and voluntary responses, *etc.* (Allcott et al. (2020a); Dowd et al. (2020)). These significant temporal differences found for instance by Allcott et al. (2020a) are the the foundations of our analysis which aims to disentangle policies effects and pandemic effects. To identify and possibly disentangle the effects of the lockdown and of the pandemics, a variation is needed between our two indicators - lockdown and pandemic threshold. Otherwise identification of the corresponding coefficients will be doomed. The Figure 5 and Figure 6 show the varying number of states exceeding a defined threshold, based on the number of new monthly cases in absolute terms or proportional to the population. Constructing a pandemic threshold with a quite high number of new cases appears as an adequate way to seize the pandemic effect since we want to consider the variations between states: on the one hand if this threshold is too low, every state will be considered as hit by the pandemic in the beginning of March; on the other hand if the threshold is too high only a few number of states will be considered as hit by the pandemic, which will go against the definition of a pandemic itself. From this point of view, the chosen thresholds deliver enough variation for the time the states are hit by the pandemic while still having the «pandemic attribute»: in October, for both types of thresholds more than 40 states are hit by the pandemic. These two variations, for the legal and epidemiological frameworks, could be considered as events and «treatments»: we will apply an event study methodology and a triple-difference approach on these grounds. The pandemic «treatment» enables the definition of subgroups which are the months impacted by the pandemic (for each state), thus allowing the disentanglement of the pandemics effect and of the lockdown effect in the classic DDD approach. Before coming to the baseline model, we ensured that the thresholds chosen for our pandemic indexes (blue lines in Figures 5 and 6, *i.e.*

18. That comes under the assumption that we correctly control for the other grounds of changes, and biases, and that we are not eluding any other phenomenon that could explain the sharp shift for the time series observations. Given that within the period we study, the focus on COVID-19 was omnipresent and that this shock undoubtedly supplants other changes in the period, that appears as a reasonable assumption.

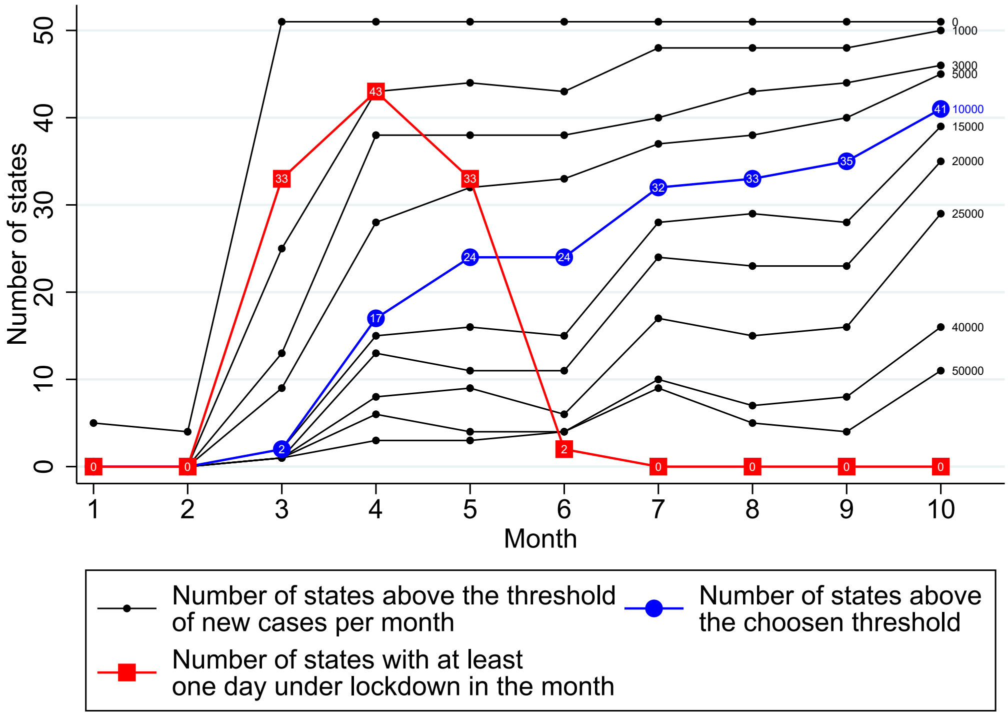

Figure 5 – Number of states under lockdown and exceeding a threshold of new confirmed cases during the year

10,000 cases in absolute numbers and 3,000 cases for one million inhabitants) were suitable. To do so, we ran our main regression while varying the thresholds and reported the coefficients of interest to make sure they were not subject to sharp changes due to the integration of only one marginal state in the pandemic-hit group. Figure 7 shows the coefficients of interest for the varying thresholds for the variable *div_ law*, which corresponds to the keywords «divorce law», «divorce laws» and «divorce legal» [19]. We observe that the chosen thresholds correspond to what appears as a robust coefficient estimation, while the same analysis with lower thresholds would yield less robust estimates - since we can observe sharp shifts for the corresponding coefficients values. As mentioned, we will adopt an event study approach first and a triple-difference approach in the second place.

5.3 Event Study Analyses

COVID-19 pandemic will obviously have demographic consequences, and divorce is one phenomenon that will without a doubt be impacted (period of economic uncertainty, fewer movements on the marital market due to the sanitary crisis, worsened access to the institutions which deal with family, health issues of the married and divorced people, etc.). Searches about divorce on Google will correlatively be impacted by the pandemic. That can be illustrated with Figure 8, which depicts a strong increase in the search rates for the term «child support» for April and May 2020, compared to the others recorded years. As a measure to fight against

19. The remaining figures are available on request.

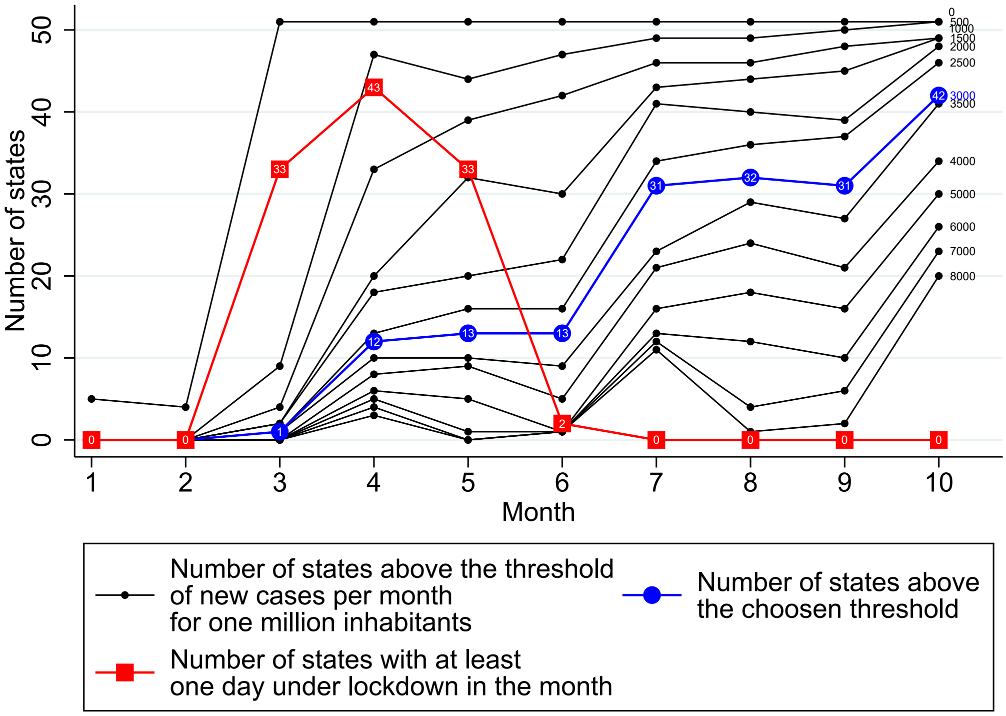

Figure 6 – Number of states under lockdown and exceeding a threshold of new confirmed cases proportional to state population during the year

the sanitary crisis, numerous states implemented a statewide lockdown (Safer-At-Home-Order or Shelter-In-Place-Order). It is not absurd to suppose that in a state implementing a lockdown, this latter will also have an impact on the divorce phenomenon with the access to legal institutions being blocked as written by Smyth et al. (2020), with more time spent with the spouse which could theoretically have ambiguous effects, and thus on the searches related to divorce during this period. Our outcome variable, the divorce-related Google searches, is then determined not only by the pandemic «treatment », but also by the lockdown. For instance, referring to Figures 5, 6 and 8, we observe that the peak in search rates for «child support» in 2020 corresponds mostly to the months when states were under lockdown, but the correlation with our constructed pandemic index remains unsure. We could assume that the lockdown has been causing financial distress - jobs losses, shops closures, etc. - to divorced or currently divorcing people creating an incentive to search for this source of income, distress that is not caused by the pandemic itself but by the shutdown of the economic and administrative infrastructures due to the SIPO and SAHO. Another possible explanation is the shock reaction: the uncertainty due to the pandemic and the sanitary measures implied with it is causing the sharp growth in the search rates for April and May 2020, but it appears only as a transitory shock with mean reversion because individuals adapt later to the pandemics. In this case, the variation is not due to the lockdown itself but to the pandemic-induced dynamics and the novelty of these events. Because all lockdowns have begun at the beginning of the epidemic (March or April) and ended at the latest in June, we can not infer that this last explanation is wrong even

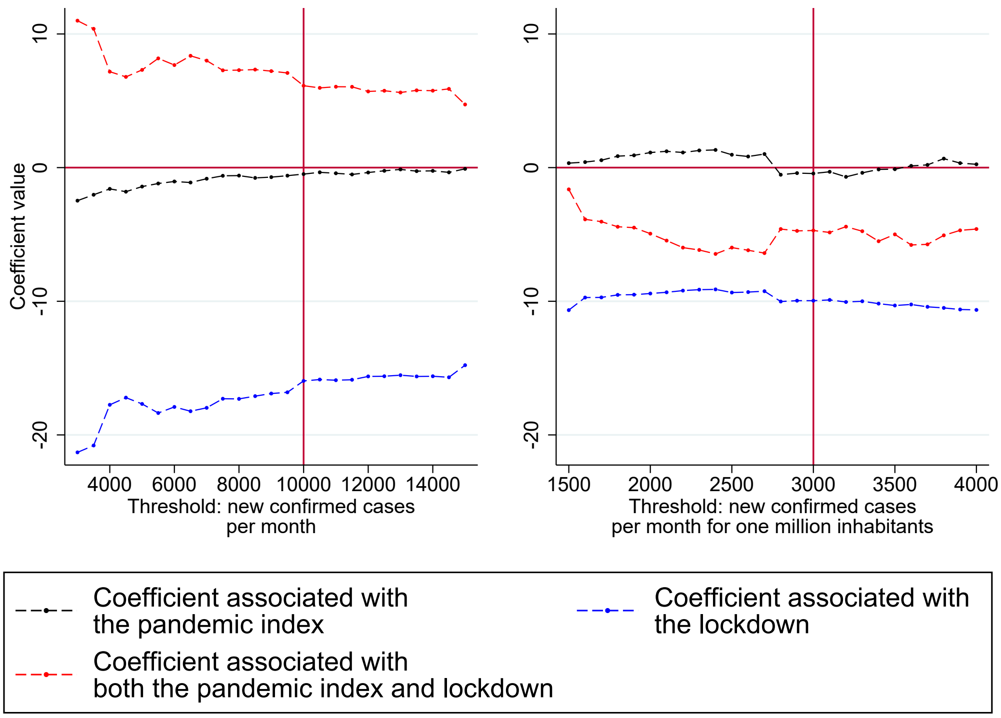

Figure 7 – Coefficients of interest for the variable *div_ law* depending on the thresholds of cases for the pandemic index

if we capture an effect for the lockdown. A way to overcome this obstacle would be to observe the new variations induced by a new lockdown at another period of the year in case of a second wave of SAHO and SIPO, as it is happening in some European countries since November 2020.

We must point out that the beginnings of the «treatments» are always state-dependent since each lockdown is implemented at the state-level and each threshold of cases is exceeded at a date depending of the state. We can not find a sole *pre* period and a sole *post* period, because the lockdown «treatment» is auto-referential for each state. Moreover it theoretically implies that the treatments are «temporal»: what is actually «treated» is not the state itself but the months under lockdown for the state, and the months after the outbreak of the pandemic for the state. To define it more clearly, the treated and control groups are the years, and the *pre* and *post* periods are defined at the month-level.

The dynamic effect of the lockdown and of the pandemic could be seized thanks to the event study methodology. We generate a full set of dummy variables on the sampling period. Adopting an event-study methodology means that we want to evaluate one effect related to an event (the reference dummy: $t = 0$), event which can happen at different dates for each observed unit i.e. for each state. Before the occurrence of the event the associated dummies take the value 0 and after the occurrence of the event, the corresponding dummies take the value 1. As a first step in the analysis, we built event-study models that corresponds to the occurrence of only one event.

First, we want to identify the potential dynamic effect of the lockdown which implies that

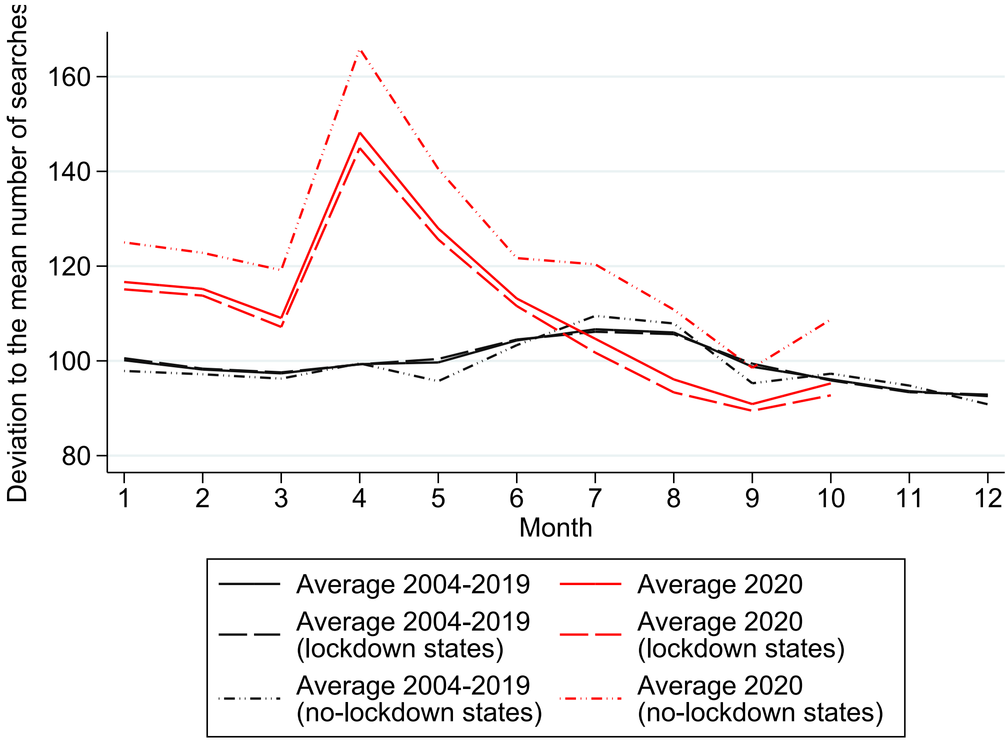

Figure 8 – Searches associated to the combined keywords «child support» and avearged time series for the states with and without a lockdown

our event evaluated is the lockdown. The date of reference for each state is the beginning month of the lockdown (at least one day under lockdown during the corresponding month). We are well aware that this process will not account for the same amount of lockdown days depending on the date of implementation of the SAHO-SIPO within the month. This will yield to bigger standard errors for the months evaluated under lockdown, which is not detrimental to our analysis since it will drive a more conservative result. Some states have not instituted a lockdown, so we exclude them from this analysis.

To nourish the analysis developed in the previous subsection, we use the pandemic index to distinguish the pandemic treatment. For a given state, the month of the exceeding of the chosen thresholds corresponds to the event «pandemic». The same approach as the framework presented above is adopted, only distinguishing between two «cohorts» of states. As can suggest Figures 5 and 6, two waves of the pandemic can be identified thanks to the thresholds of cases. The first one corresponds to the states exceeding the thresholds between March and June, while the second correspond to the states entering the pandemic state in July and August. Adding this feature of first and second cohort has the other advantage to disentangle totally the effect of the pandemic from the lockdown effect for the states concerned (since every lockdown ended at last in June).

Note that the last states to implement a lockdown have done so in April 2020, meaning that it gives us 6 more observations with all the states (*cf.* Figures 5 and 6). The first states to implement a lockdown have done it in March letting two anterior observations for 2020 (*cf.*

Figures 5 and 6). Since we also want to account for a potential difference between the years 2019 and 2020, we let the observation for January 2020 out of the scope of our analysis to estimate the 2020 fixed-effect. Concerning the two cohorts of states for the pandemic treatments, we estimate the models separately. The month when the first states have been hit by the pandemic according to our indicator is March which gives us two anterior observations per state in 2020 - we use the same procedure as for the lockdown analysis with the observation of January 2020. Since we allow the entry into the treatment until June for the first cohort, we can estimate four more coefficients after the occurrence of the events. For the second cohort with the entry into the treatment allowed until August, we can estimate two more coefficients after the event occurrence. There is an exception for the second cohort when using the pandemic index corresponding to absolute cases because no new state has been hit by the pandemic in August: we can estimate three more coefficients after the event occurrence.

Let us denote t the number of months before or after the event. t is equal to 0 for the first month where we observe the corresponding event. We estimate the following event-study model for each treatment detailed above:

$$R_{myst} = \beta_0 + \sum_{\tau=t_{pre}}^{t_{post}} \beta_\tau \mathbb{1}\{t = \tau\} + \alpha_m + \alpha_y + \alpha_s \tag{4}$$

$t_{pre} = -1$ for the models with the lockdown event and with the pandemic event applied to the first cohort of states, $t_{pre} = -2$ for the model with the pandemic event applied to the second cohort of states and t_{post} is respectively equal to 6, 4, 3 and 2 for the lockdown, for the pandemic in the first cohort, for the pandemic in the second cohort using the threshold in absolute numbers and for the pandemic in the second cohort using the threshold of cases proportional to the state population. R_{mys} is the value of the variable R in the state s for the month m and the year y. The month fixed-effect, year fixed-effect and state fixed-effects are respectively denoted by α_m, α_y and α_s. The monthly fixed-effects α_m account for the seasonality of the Google Trends series within a year. The year fixed-effects α_y account for the heterogeneity between years. And the state fixed-effects absorb the differences between states. In order to make robust inferences, the error terms are clustered by state which allows for intra-group correlation, and consequently yields to bigger standard errors as the standard ones. The event study methodology presents the advantage to retrace the full trajectory of the effects. Moreover it yields to precise estimates by exploiting the state-level variation in the event time. These variations for the date of occurrence of the event allow us to identify the set of dummies which captures the dynamic event effects. Note that we could obviously rule out a causal inverse relationship (divorce-related searches causing the lockdown or the pandemic) which validates our identifying approach of these events.

We complete the baseline specification by estimating heterogeneous effects for the lockdown event study between the two cohorts of states describes previously for the pandemic. This could be compared to an exposure-response (or dose-response) analysis where the states in the first cohort are hit by the pandemic with more severity - at least more quickly. If the results are somehow different, it will probably indicate an impact of the pandemic at the state-level. If not, it will advocate for the strength of the lockdown effect over the pandemic effect.

5.4 Triple Difference Analyses

5.4.1 Model Framework

We adopt in this subsection an approach in term of treatments instead of events. To disentangle both effects of the pandemic and of the lockdown, which we want to identify, we will implement a first-stage differencing strategy on the pandemic «treatment» in order to better identify the lockdown effect. The pandemic «treatment» is in a way a confounding variable that blurs the actual effect of the lockdown. Berck and Villas-Boas (2016) show that this further differencing step can in some cases reduce the bias induced by the other variable than the treatment in the determination of the outcome variable. Here, including the pandemic index will moreover avoid an endogeneity problem since this variable influences both the dependent variable (the search rates) and the independent variable (the lockdown). The triple-difference approach, as initiated by Gruber (1994), is commonly used to remove the bias induced by an other variable in the estimation of the effect of a treatment in a difference-in-difference approach. Olden and Møen (2020) show that the triple-difference model can be identified as the combination of two difference-in-difference. Our analysis relies on this idea: we estimate the effect of the pandemic «treatment», of the lockdown «treatment», and we jointly estimate the effect of the lockdown and pandemic «treatments».

The «treated» year is 2020 for each state and for both the pandemic and the lockdown. The years 2004 to 2019 constitute the control group. Let $T_{L'}$ denote the year a state imposed a lockdown, $T_{P'}$ denote the year a state was hit by the pandemic. Let L' denote the period (*i.e.* the months) of the year when a lockdown is imposed (*e.g.* $L' = \mathbb{1}\{m \in [m^0_{L'}; m^1_{L'}]\}$, where m denotes the month in the year, $m^0_{L'}$ denotes the month the lockdown started and $m^1_{L'}$ denotes the month the lockdown ended). Let P' denote the period of the year when the state is hit by the pandemic with the same logic as L' above. P' is a dummy variable taking the value 1 if the threshold of new cases per month (10000 new cases in absolute terms, 3000 new cases per million inhabitants) is exceeded in the state, and 0 otherwise. Moreover, we take into consideration the fact that the lockdowns do not always last a full month so that the dummy variable L' becomes a continuous variable between 0 and 1, taking the value of the ratio of the days under lockdown to the total number of days in the month. It accounts for the intensity of the lockdown within a month. Notice that both the pandemic and lockdown «treatments» are not irreversible: once they have taken the value 1, they could take the value 0 again later. The lockdown «treatment» is thus focused on the months between March and June included. The general triple-difference model for the outcome variable R is written as follows:

$$R_{mys} = \beta_0+\beta_1 L'+\beta_2 P'+\beta_3 L'*P'+\beta_4 L'*T_{L'}+\beta_5 P'*T_{P'}+\beta_6 L'*T_{L'}*P'*T_{P'}+\alpha_m+\alpha_y+\alpha_s\epsilon_{mys} \quad (5)$$

The DDD estimator is the estimated coefficient β_6, associated with both the lockdown and the pandemic index. This general framework can be greatly simplified since L', P' and $L' * P'$ are redundant with the month fixed-effects α_m. Because both the lockdown and the pandemic happened in 2020, we can write $T_{L'} = T_{P'} = T$, which is redundant with the year fixed-effects α_y. Let's denote $L = L' * T$ and $P = P' * T$. Our baseline model is therefore:

$$R_{mys} = \beta_0 + \beta_1 L + \beta_2 P + \beta_3 L * P + \alpha_m + \alpha_y + \alpha_s + \epsilon_{mys} \quad (6)$$

Note that due to the treated and control groups being constituted of years, the model can be estimated for only one state by removing the state fixed-effects. We know that eight states have not implemented a lockdown during this period, so we consider this case. Formally, for a given state of this type we always have: $L = 0$. The model for this specific case becomes:

$$R_{my} = \beta_0 + \beta_2 P + \alpha_m + \alpha_y + \epsilon_{my} \quad (7)$$

This model is actually a simple difference-in-difference with β_2 being the estimated coefficient for the pandemic «treatment». Moreover, because of the construction of the pandemic threshold, some states have implemented a lockdown but have never being considered as hit by the pandemic. Formally, for a given state of this type we always have: $P = 0$. For this case, the model becomes:

$$R_{my} = \beta_0 + \beta_1 L + \alpha_m + \alpha_y + \epsilon_{my} \quad (8)$$

Once again we can identify here a simple difference-in-difference model where is only evaluated the lockdown «treatment». In all cases, the model is identified at the state level, as long as there is enough variation in the start and end months of the lockdown and for the month above the pandemic threshold. It may not be the case. A special case is when the pandemic and the lockdown start and end on the very same months, in which case $L = P = L * P$. If there is no variation, the lockdown effect is not separately identified from the pandemic impact. But we have constructed a threshold for the pandemic index ensuring that not all states implementing a lockdown are considered as hit by the pandemic at the time they implement the SIPO or SAHO. Table 2 informs of the states that are not considered as hit by the pandemic according to the two chosen thresholds. From the cases detailed above, we conclude that only the Wyoming does not yield to the adequate estimation of at least one of the coefficients of interest in the case of the pandemic threshold in absolute terms (but not for the pandemic threshold proportional to the state population). This state then helps us for the identification of the constant term in the regression analysis.

Threshold / Lockdown	*Less than 10000 new cases for all months (abs.)*	*Less than 3000 new cases per million inhabitants for all months (pop.)*
Yes	Alaska, District of Columbia, Delaware, Hawaii, Maine, New Hampshire, Rhode Island, Vermont	Maine, New Hampshire, Oregon, Vermont, Washington
No	Wyoming	

Table 2 – States not being hit by the pandemic according to the implementation of a lockdown and to the chosen pandemic threshold

We develop here formally the identification strategy. Admitting that L can be either a dummy variable or a continuous one which only changes the intensity of the treatment in our framework, we demonstrate that the coefficients are identified in the binary framework. We have:

$$\begin{cases} \mathbb{E}\left[R_{mys}|L=0,P=0\right] & = \beta_0+\alpha_m+\alpha_y+\alpha_s=\beta_0' \\ \mathbb{E}\left[R_{mys}|L=1,P=0\right] & = \beta_0'+\beta_1 \\ \mathbb{E}\left[R_{mys}|L=0,P=1\right] & = \beta_0'+\beta_2 \\ \mathbb{E}\left[R_{mys}|L=1,P=1\right] & = \beta_0'+\beta_1+\beta_2+\beta_3 \end{cases} \tag{9}$$

From these equation, we can write the coefficients:

$$\begin{cases} \beta_0' & = \mathbb{E}\left[R_{mys}|L=0,P=0\right] \\ \beta_1 & = \mathbb{E}\left[R_{mys}|L=1,P=0\right]-\mathbb{E}\left[R_{mys}|L=0,P=0\right] \\ \beta_2 & = \mathbb{E}\left[R_{mys}|L=0,P=1\right]-\mathbb{E}\left[R_{mys}|L=0,P=0\right] \\ \beta_3 & = \mathbb{E}\left[R_{mys}|L=1,P=1\right]-\mathbb{E}\left[R_{mys}|L=0,P=0\right] \\ & -\left(\mathbb{E}\left[R_{mys}|L=1,P=0\right]-\mathbb{E}\left[R_{mys}|L=0,P=0\right]\right) \\ & -\left(\mathbb{E}\left[R_{mys}|L=0,P=1\right]-\mathbb{E}\left[R_{mys}|L=0,P=0\right]\right) \end{cases} \tag{10}$$

β_1 is correctly identified by the states that implemented a lockdown but that were not directly hit by the pandemic during this lockdown - we know they exist according to the Figures 5 and 6. β_2 is correctly identified by the states that were hit by the pandemic but that did not implement a lockdown - we can refer to Table 3 here who informs about these states. Notice that the DDD estimator β_3 can be be simplified:

$$\begin{aligned} \beta_3 = & \left(\mathbb{E}\left[R_{mys}|L=1,P=1\right]-\mathbb{E}\left[R_{mys}|L=1,P=0\right]\right) \\ & -\left(\mathbb{E}\left[R_{mys}|L=0,P=1\right]-\mathbb{E}\left[R_{mys}|L=0,P=0\right]\right) \end{aligned} \tag{11}$$

State	Threshold	Month					
		5	*6*	*7*	*8*	*9*	*10*
Arkansas	abs.	0	1	1	1	1	1
	pop.	0	1	1	1	1	1
Iowa	abs.	1	0	1	1	1	1
	pop.	1	0	1	1	1	1
North Dakota	abs.	0	0	0	0	1	1
	pop.	0	0	1	1	1	1
Nebraska	abs.	0	0	0	0	1	1
	pop.	1	0	1	1	1	1
Oklahoma	abs.	0	0	1	1	1	1
	pop.	0	0	1	1	1	1
South Dakota	abs.	0	0	0	0	0	1
	pop.	0	0	0	1	1	1
Utah	abs.	0	1	1	1	1	1
	pop.	0	1	1	1	1	1
Wyoming	abs.	0	0	0	0	0	0
	pop.	0	0	0	0	1	1

Table 3 – Pandemic index for the states not implementing a lockdown

As mentioned above, it corresponds to a double difference-in-difference applied to the pandemic «treatment» in presence of the lockdown and in its absence. If the model does not suffer of misspecification and the coefficients are separately estimated, β_1 gives the average effect of the lockdown «treatment» on the search rates, disentangled from the pandemic impact.

As for the event study approach we estimate heterogeneous effects between the cohort of states separated thanks to the timing impact of the pandemic.

5.4.2 Required Assumptions to Yield Causal Inferences

As noted above, the DDD model is an extension of the simple DD model, which relies on the Common Trend Assumption. The required assumption to draw causal inferences from this DDD model is therefore quite similar as detailed by Olden and Møen (2020): considering the lockdown as the treatment evaluated, it requires that the differential in outcomes issued from the difference-in-difference on the pandemic «treatment» trends similarly in the presence of the lockdown as in its absence. We are fully aware that the lockdown is never independent from the occurrence of the pandemic. Nevertheless the construction of the pandemic index ensures that some states are legally experiencing a lockdown while not being hit by the pandemic. Table 3 presents the pandemic index for the states not implementing a lockdown - before May it is always 0. From this Table 3 we see that since May there is always at least one of the eight states above the pandemic threshold. As presented in Figure 8 we see that the averaged series for the states implementing a lockdown on the one hand, and those not implementing one on the other hand seem to trend similarly whether we consider the control years or the «treated» year for the variable about child support - considering the first months of the year, before COVID-19 outbreak. The similar trends considering the groups (control year and treatment years) and the subgroups (states with and without lockdown) are a sufficient condition to assert the adequate estimation of the coefficients of interest. The similar figures for the other variables are available on request. Based on these descriptive graphs, we do not reject the common trend assumption for the search rates of divorce-related terms on Google between the states experiencing a lockdown and those not experiencing one. The DDD model conducts to differences amongst the estimated coefficient whether the state has implemented a lockdown or not. It is possible that we have to deal with a selection problem if this selection of states is endogenous to our evaluation. The question is then to know on what criteria this selection could be done and to observe if it is somehow related to the Google search rates for divorce-related topics. Policy and behaviour responses to the pandemic have been widely studies in the area of political sciences. Many studies as the ones from Allcott et al. (2020b) or Gollwitzer et al. (2020) point out the differences in responses derived from a partisanship framework. We thus assume that the selection problem is not endogenous to our study. As detailed above, the differences between the «lockdown states» and «no-lockdown states» do not seem to be correlated with our variables of interest. We therefore let aside this problem.

6 Nowcasting Divorce Rates Using Google Trends

6.1 Google Trends predictors selection

The main purpose of this section is not to draw causal inferences but to assert the predictive power of adequately chosen Google Trends series to nowcast demographic phenomena. Following Wilde et al. (2020), we adopt a data-driven and iterative approach to select our predictor variables. Based on the results of previous studies across different scientific fields (*cf.* section 2) we assume that adequately chosen keywords render us Google Trends series that are correlated with the outcome we measure. In our case it means that divorce-related queries may be informative of marital structures. We should point out that Google Trends data is a macroscopic measure which aggregates all microscopic queries. Our hypotheses and results must be interpreted only at this scale. Moreover we insist on the fact that Google Trends data does not only capture the legal process of divorce but a myriad of behaviours in the spectrum of divorce. A lot of these queries may be done by people thinking about divorce but not pursuing one *in fine*. The link between these data and the crude divorce rates may thus not be stable across time and across states all the more during a period of global crisis. We nevertheless assume that there is a relative stability in the relationship between the Google Trends series (which are an aggregate index of interest on Internet) and divorce rates [20].

We build a first model based on static panel regression analysis. To do so, we have to

20. Note that this assumption is central. If it does not hold because the COVID-19 crisis has altered the relation between the Google Trends series and the outcome, the prediction will be based on a wrong assumption. The only way to know is to wait for the actual divorce rates and compare them to the ones we nowcast

account for the mixed frequencies of our variables (monthly or annual). On the one hand the divorce rates are compiled by the CDC-NVSS based on the annual reports delivered by the willing states. On the other hand, the Google Trends series over several years yields to monthly observation points. Several methods are proposed to solve this problem as showed by Foroni and Marcellino (2013), and we will begin by the most basic one which is to aggregate the high-frequency observation to match the low-frequency observations. Nevertheless, our main objective is to find good predictors of the probability to divorce (which is only indirectly observed once in a year, calibrated in December in our analysis) and so the aggregation of the variable is not straightforward. Indeed, we could assume that different searches are made at different times: people thinking about the divorce may search for more general information about divorce, whereas people engaged in the divorce process might be more interested in precise divorce issues. It is even possible that people are searching for divorce-related terms even after that the divorce has been issued, with for instance the questions referring to rights in the post-divorce state (alimony, child support, etc.). Including lead variables would conduct to the disappearance of the last observations for 2020: since we want to nowcast, we do not adopt this approach even through it is relevant. Therefore, we decided to include lagged variables, *i.e.* that the aggregation to obtain an annual observation could be done with a monthly lag. Let us denote l the value of the monthly lag or lead. The value of the Google Trends predictors for the state s and the year y is expressed as follows:

$$\begin{cases} R^a_{syl} = \dfrac{1}{12} \times \displaystyle\sum_{t=l-11}^{l} R_{syt} \text{ for the years 2004 to 2019} \\ R^a_{syl} = \dfrac{1}{10} \times \displaystyle\sum_{t=l-9}^{l} R_{syt} \text{ for the year 2020} \end{cases}$$

The maximum number of lags allowed is 11 and the maximum numbers of leads is 6. Having built the Google Trends Indicators, a selection of the most predictive variables is conducted. It takes place in an iterative approach allowing a forward selection of the best predictors combined with cross-validation. We dispose from the divorce rates for the years 2004 to 2018 for 44 states (*cf.* section 4.2). A basic panel regression is implemented to fit these divorce rates, first only estimating the state fixed-effects and an intercept. We drop the observations for the year 2004 because the lagged variables renders missing values. To be sure to avoid commonly known errors in the forecasting domain (*e.g.* overfitting or spurious correlations), we use a cross-validation technique, *leave-p-out*. In our case, we willingly let aside a 2-year window which we predict thanks to the panel model fit on the other years. Two models are estimated each time: the baseline model and the baseline model adding only one variable. Once the prediction is done for each model, we compute a metric measuring the predicted error of our models. The metric used is the Mean Squared Prediction Error (MSPE) which is defined as follows:

$$MSPE := \frac{1}{n}\sum_{i=1}^{n}\left(D_i - \hat{D}_i\right)^2$$

n is the number of predicted points, D_i is the real value (that we have previously let aside) and the corresponding $\hat{D}_i$ is the predicted value based on the training set. This metric measures the quality of the prediction.

We implement this procedure for each two-year window possible between 2005 and 2018 and for each variable. Finally, we compute the mean of the MSPE on all windows associated to the addition of a variable in the baseline model. The variable which minimizes the mean MSPE among all variables is added to the baseline model. Then we do the same procedure again to select the next best predictors. We stop this routine when the difference in the mean MSPE between the baseline model and the model with an added Google Trends Indicator is less than 1% of the first baseline model (simple panel regression with control variables). This procedure identifies the best Google Trends Indicators avoiding a correlation «by chance» thanks to the cross-validation framework.

6.2 Static Panel Data Model

Once the Google Trends Indicators have been selected, we estimate state crude divorce rates with the following panel data model on the whole sampling period:

$$D_{sy} = \sum_{w\, \in\, W} \beta_w R_{syw} + \beta_U U^l_{sy} + \beta_X X_{sy} + \alpha_s + \epsilon_{sy} \tag{12}$$

This equation corresponds to the within estimator accounting for state heterogeneity by implementing state fixed-effects α_s. The selected Google Trends Indicators (potentially with lags or leads) belong to the group of variables W. X_{sy} is a group of control variables which account for the differences in age distribution and sex ratio between states. U^l_{sy} is the state annual average for the unemployment rate. Notice that we go through the same process of cross-validation to choose the unemployment variable, i.e. the annual average with monthly lags (denoted by l) with the most predictive power. It seems that unemployment may have different effects whether we consider different timing as written by Amato and Beattie (2011). Including lags is a way to detect the most prominent effect of unemployment on divorce rates and its timing. The estimated coefficients will further enable us to nowcast the divorce rates for the years 2019 and 2020, having the Google Trends Indicators available. This baseline specification for the panel data model only requires the Google Trends Indicators to nowcast the divorce rates.

7 Results

7.1 Event Study Results

Table 4 is the main table of results for the event study approach concerning lockdown. It compiles the coefficients associated with the event dummies for the variables *lock*, *div*, *div_ law*, *child_ support*, *alimony*, *div_ how*, *div_ papers* and *div_ court*. The various fixed-effects (month, year, state) are not reported here for the sake of clarity.

Table 4 – Event study on Google Trends Indicators depending on the statewide lockdowns

	lock	*div*	*div_ law*	*child_ support*	*alimony*	*div_ how*	*div_ papers*	*div_ court*
-1	975.3*	-3.659*	-1.190	4.593**	-0.741	-1.519	-8.247	-7.819**
	(404.5)	(1.364)	(2.023)	(1.386)	(5.015)	(4.327)	(5.070)	(2.799)
0	3121.5***	-13.02***	-12.30***	10.18**	-22.93***	-16.75***	-18.28***	-17.17***
	(305.6)	(0.948)	(1.892)	(3.045)	(2.498)	(2.599)	(4.574)	(2.267)
1	1098.0***	-8.222***	-12.44***	29.54***	-22.59***	-17.60***	-27.64***	-17.00***
	(99.83)	(1.482)	(1.429)	(4.087)	(3.753)	(2.883)	(3.454)	(1.784)
2	704.6***	-1.064	-7.969***	10.13**	-12.19**	-6.146*	-22.93***	-9.955***
	(76.06)	(0.994)	(1.876)	(3.621)	(3.868)	(2.701)	(4.278)	(2.305)
3	269.4***	0.119	-6.090**	-6.987*	-1.076	-5.842	-10.74***	-3.719
	(33.51)	(0.694)	(2.073)	(2.895)	(3.963)	(3.066)	(2.444)	(2.841)
4	167.9**	0.678	-4.351**	-16.17***	-8.101*	-5.216*	-10.53*	2.985
	(49.84)	(0.925)	(1.571)	(3.636)	(3.328)	(2.443)	(4.940)	(2.408)
5	71.80***	3.238*	-2.375	-19.78***	-8.573**	-6.020	-7.140	2.030
	(16.57)	(1.230)	(1.447)	(2.123)	(3.146)	(3.480)	(4.269)	(2.934)
6	64.56***	6.016***	-3.263	-15.63***	1.961	-4.155	-9.458*	-6.765**
	(14.41)	(0.888)	(2.314)	(1.019)	(3.453)	(2.590)	(4.209)	(2.400)
Cons.	7.599	102.5***	111.8***	78.61***	108.4***	89.28***	114.9***	93.57***
	(6.623)	(3.024)	(3.923)	(3.348)	(4.307)	(3.214)	(6.900)	(3.906)
R^2	0.757	0.568	0.663	0.331	0.133	0.209	0.151	0.150
Obs.	6106	6106	5822	6106	6106	6106	5680	5964

Standard errors in parentheses $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

It is clear that there is a strong lockdown effect, as depicted in Figure 9 for the variable *div*. We assume based on the event study analyses that the most relevant effect is lockdown effect and not a pandemic effect. Indeed, we can observe the additional Tables 8 and 9 presented in appendix which apply the methodology of the event study taking as event the exceeding of pandemic threshold for states hit by the first wave and for states hit by the second waves. What is striking is the dilution of the effects observed following lockdowns on different months because of the temporal variation of the pandemic outbreak. The relevant event to evaluate the evolution of relative search volumes for divorce-related queries is most probably the lockdown and not the pandemic itself. This analysis could be pursued by mentioning Tables 10 and 11 in appendix applying the event study on lockdown with heterogeneous effects (cohorts of states hit by the first or the second waves). The results are very similar to those shown in Table 4:

every variable presents the same pattern for each cohort of states, the only difference being sometimes on the magnitude of the effects, but this remains marginal. This marginal difference could suggest the presence of a minor pandemic effect.

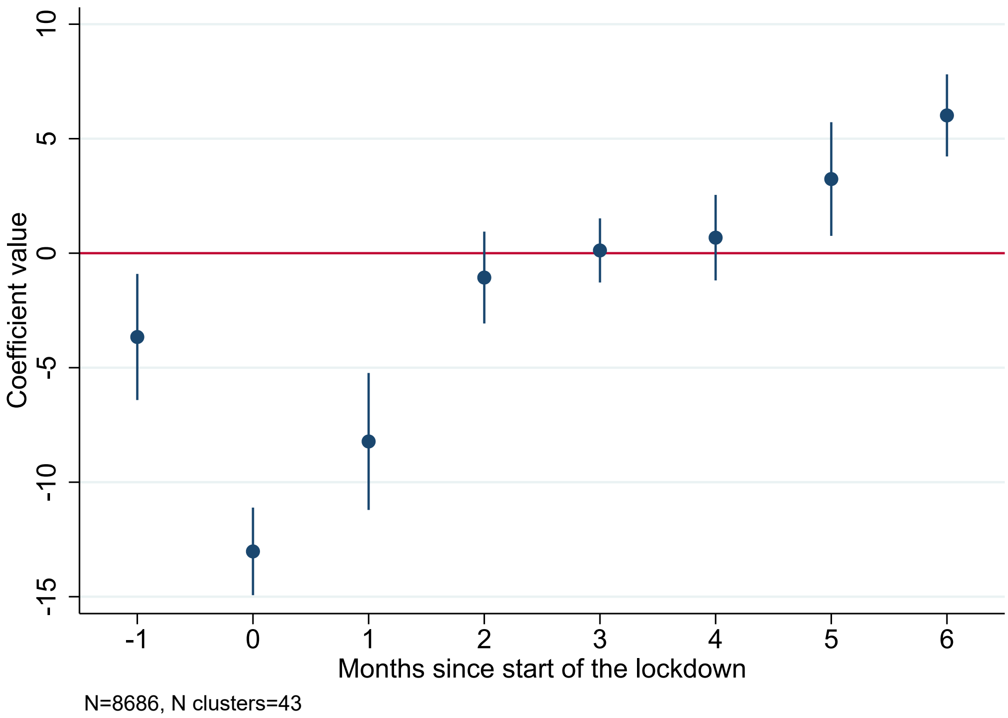

Figure 9 – Event study analysis for the variable *div*

Except for the variables *child_ support* and *lock* - this one being more a control variable than a variable of interest - an important and significant decrease in relative search volumes is recorded for the months following the lockdown beginning (associated to the dummy $t = 0$). Besides the particular pattern of *child support* which will be described later, every variable of interest presented in Table 4 present a decrease of magnitude between 8 and 23 for time dummies 0 and 1. Every domain of divorce for Google queries is thus impacted by the sanitary policies. While we can question the correctness of the event study approach for long-term effects - since the sanitary crisis and policies are evolving across time - it seems that we could observe a mean reversion for most of our variables, denoted by returns that are not significant for the last months analyzed which renders levels in relative search volumes quite similar to stable levels observed in previous years. That is not actually the case for all variables as we can observe significant coefficients for the dummy $t = 6$ for the variables *div* and *div_ court*. The lockdown effect might thus be a transitory effect still with repercussions in the mid-term horizon.

The variable *child_ support* is the only one to present a special pattern, with the lockdown effect expressing itself in a strong increase compared to decreases for other variables. A clear spike is identified following the lockdown ($t = 1$) with a coefficient of value 29.54. Even though the financial topic associated with divorce is also rendered by the variable *alimony*, this one follows the same pattern as described above. This difference must reside in the different nature between these two payments: the first is a periodic one supposed to provide financial help aimed at care and support of children whereas the second payment is occurring before or after a legal process to end a marital relationship. Therefore alimony corresponds to a one-time process and is a fund that can not be re-mobilized. On the other hand, child support is a periodic revenue that can be more quickly mobilized and demanded. In our opinion this sharp increase in relative search volume for the «child support» query corresponds more to a situation of financial stress or uncertainty for divorcing or divorced persons who search for revenues that can be mobilized quickly. The lockdown policies which causes economic uncertainty might have led people to take action and engage in legal procedures corresponding to this divorce feature. This could advocate for the hypothesis of *cost of divorce perspective* presented in economic literature: couples tend to avoid or postpone divorce in times of recession or economic uncertainty. More than the sanitary crisis, we could think that the most prominent channel through which we will observe an impact on divorce might be the one of economic consequences. Following this idea, it appears as normal to observe a global decrease in relative search volumes for almost any variable since divorce is not therefore a priority, or at least is somehow financially prevented. Moreover, an information effect may be at stake: the sanitary crisis and policies of these magnitudes are a total novelty for the United States, novelty which might shift daily routines and what appears as normal events. Putting aside what does not appear as a priority could lead to this decrease in relative search volumes for most of our Google Trends Indicators.

One possible interpretation is also one in terms of stocks and flux. Considering information as the good pursued on Internet, we could hypothetically explain the patterns for *div* (*cf.* Figure 9) or *child_support* where the coefficients for the last time dummies present a significant effect of opposite direction to the initial decrease or increase due to lockdown policies. People inform themselves less (or more for *child_support*) during this period which implies that the the «stock» is decreasing (or growing). To remain at a normal «stock» level in the long-term we thus observe a catch-up effect. Theoretically this could imply if relative search volumes for divorce-related queries are correlated to divorce figures that we will only observe some kind of postponement of the divorces due to sanitary policies. The estimations of the effects being restricted to the short-term, we will then be unable to estimate the actual effects of the lockdowns on divorce, which will only be rendered in the long-term.

Finally all these results concern the relative search volumes and not the absolute ones - and still less marital behaviours - since Google Trends give these figures without a measure of overall search volume. We want to remain cautious in the absence of these data since Internet use has been clearly impacted by lockdown policies (telecommuting, leisure time at home, etc.). That is why we speak in terms of share of interest on Google search engine at a precise moment and nothing else.

7.2 Triple Difference Results

The triple-difference allows us to include all states in the analysis whether they implemented a lockdown or not. The main results are detailed in Table 5.

Table 5 – Triple-difference analysis on Google Trends Indicators

	lock	*div*	*div_law*	*child_support*	*alimony*	*div_how*	*div_papers*	*div_court*
Lock.	1263.1***	-8.960***	-9.958***	35.60***	-23.43***	-14.13***	-23.43***	-10.09***
	(195.6)	(0.978)	(1.270)	(6.135)	(2.995)	(1.947)	(3.579)	(2.133)
Pand.	-381.0***	3.476***	-0.439	-10.76***	-1.977	-0.456	-6.136	5.209**
	(97.54)	(0.832)	(1.306)	(2.980)	(2.585)	(1.180)	(3.624)	(1.662)
Lock. * Pand.	-15.87	-3.573	-4.703	-10.95	5.185	-2.265	-3.416	-18.74***
	(225.4)	(2.398)	(3.005)	(11.09)	(6.312)	(3.797)	(5.765)	(4.753)
Cons.	19.45**	102.5***	122.0***	79.14***	109.8***	90.26***	116.5***	95.16***
	(7.109)	(2.927)	(3.754)	(3.271)	(4.316)	(3.314)	(6.768)	(3.985)
R^2	0.456	0.558	0.652	0.313	0.120	0.188	0.138	0.145
Obs.	7242	7242	6958	7242	7242	7242	6532	7100

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results of the triple-difference approach clearly confirm a lockdown effect over the pandemic effect concerning divorce-related queries. All the coefficient corresponding to the lockdown effect for our main Google Trends Indicators return a strongly significant effect with the same pattern as depicted in the previous subsection: a decrease in relative search volumes for every variable besides the variable corresponding to child support - which shows a strong increase. While we can not examine a dynamic response as in the previous approach, we still could conclude to the catch-up effect concerning the variables *div* and *child_support*. Indeed as the pandemic progresses over time and impacted more and more states, we see that the coefficient associated with the pandemic variable is significant for these two Google Trends Indicators. In our opinion this variable captures a temporal evolution more than an adaptive behaviour of Internet users to the path of the pandemic. The dynamic response is thus diluted in this variable. The conclusions drawn form these results are quite the same as those detailed above. The relative search volumes for every Google Trends Indicator show a significant decrease - except for *child_support* - rendering a lower share among Google queries at that time.

Once again it is not obvious to assert that it corresponds to a lower interest for divorce in absolute terms since figures for the overall search volume on Google are not available. This decrease could purely be the result of an increase volume of queries while divorce-related queries remain at the same level in absolute terms. Note that even if the overall search volume has increased as suggested by Feldmann et al. (2020) the number of queries associated to child support has increased in a larger magnitude. The potential decrease due only to the shift in Internet behaviours during lockdown is more than compensated with the coefficient taking the value of 35.60. In times of sanitary and economic uncertainty, Internet users might mobilize the most accessible means to regain some certainty which explains the focus on financial issues and funds that can be periodically demanded.

7.3 Robustness

To assert the significance of our results, several robustness tests were conducted. To extend our data range, we run the baseline models taking the observations since 2004 - including prior data that appear noisier. Another regression does not include the mean population of the state over the years sampled as a weight for our observations which means that each state has the same weight. The interpretation of the coefficients must then be done at the state-level and not at the individual level. Further regressions include trends, linear and linear-quadratic or control variables of the severity of the pandemic, which are the number of new confirmed cases or deaths per month proportional to the state population. Finally we simulate a pandemics and a lockdown for the years 2018 and 2019. These placebo events are included as the «treatments» in this robustness regression, so that we assert the significance for the evaluated effects in 2020 and the insignificance for the other years. Tables 14 and 15 are reported in appendix as examples, and all tables are available on request. In the sight of the results of these tests, the results returned by our analyses are quite robust.

7.4 Panel Data Model

After all the process described in section 6 has been applied, the selected variables to nowcast the divorce rates are the following: *div*, *div_ law* » with a 7-month lag, *div* with a 11-month lag - and the annual average of the monthly unemployment rates. The selected control variables for the panel prediction are the sex ratio and median age per state. As already said, these variables do not yield causal inferences but correspond to strong correlations not due to chance - because of the cross-validation process. It would be false to infirm that divorce-related queries cause the divorce figures. The central hypothesis is that the correlation between these queries relative volumes and the states (crude) divorce rates observed between 2004 and 2018 remains for the years 2019 and 2020. The Figure 10 summarizes graphically the results of this nowcasting analysis. Even though the selected Google Trends Indicators present a decrease in relative search volume during the lockdowns period, note that the estimated points in 2020 are higher than a naive trend could suppose. Two effects may be at stake with the Google Trends Indicators. Indeed the variable *div* with a 11-month lag does not take recent events concerning the pandemic into account. It might account for the divorcing intentions that are not obligatorily linked with the pandemic crisis. On the other hand, *div_ law* with a 7-month lag implies that the points used in the prediction go until March. This variable accounts for the first effects of the pandemic, notably the significant decrease in relative search volume for the queries related, but this does not take the mean reversion into account in the regression. Finally the variable *div* without lag includes all the effects of the pandemic *i.e* the significant decrease in the beginning of the year but also what has been described as a catch-up effect which is a

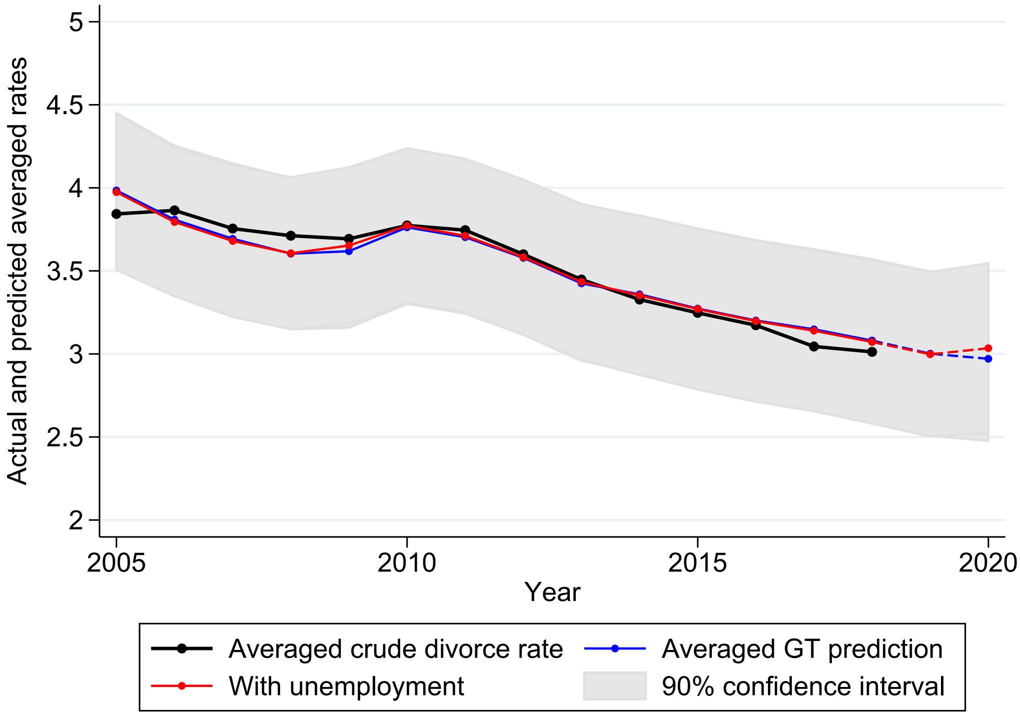

Figure 10 – Nowcasting of the average crude divorce rates in the United States

significant increase in the mid-term horizon. All these effects combined with different timings make it difficult to know at first glance the lockdown and pandemic effects on divorce rates.

In a second time, we included the annual average for the monthly unemployment rates in the panel data model. This correspond to the red line in the Figure 10. Obviously, this variable is positively correlated with the crude divorce rates which tends to push the prediction for 2020 upwards. It is noticeable that there is a clear difference between the points estimated with or without the unemployment variable in 2020 since such a difference never appears in the previous years. Obviously the economic crisis induced by the pandemic might be a strong channel to explain the coming divorce figures - even though it is not the only one. This result can comfort the strong link between marital structures and economic conditions developed in numerous articles. The effect still is difficult to seize since it tends to go against the *cost of divorce perspective*. This hypothesis which is slightly favoured by some researchers as Hellerstein and Morrill (2011) or Amato and Beattie (2011) at the aggregate level is not rendered here. The prediction for the crude divorce rate [21] in 2020 is a stable level or higher level than the one predicted in 2019. Contrary to what appears as a trend in the previous decade, the point for 2020 does not correspond to a decline in the divorce figures most probably due to the repercussions of the lockdown and pandemic effects. We will discuss these results and their validity in the next section.

21. The graph is averaged at the country level, but the results are also available at the state level on request.

8 Discussion

8.1 Limitations

The major limitation of this study is a data induced limitation. As already depicted in section 4, Google Trends data come with advantages but with important limitations too. The volume problem is the most dramatic one since it prevents us to draw final conclusions on the evolution of chosen queries. Interpretations can be done speaking in terms of interest share on Google search engine but it remains unsatisfying to be able to analyse wisely Internet behaviours. We will not dwell on this issue since it has been detailed all along this study.

Another limitation concerning the panel prediction lies in the hypothesis supporting the analysis, which is that the correlation between Google Trends Indicators and crude divorce rates between 2004 and 2018 remains stable for 2019 and 2020. That is a strong assertion that cannot be verified. What is problematic is the feature for 2020 which is a global crisis. We have already evoked the fact that Internet behaviours during lockdowns have shifted from normal behaviours due to many reasons. By assuming the link between Internet behaviours and marital behaviours to be stable, we fail to consider the case where this shift does not transpose in the divorce figures with the same pattern as during the previous years. Google Trends Indicators are variables which are somehow linked to divorce intentions and not directly to divorces. Our model can present a bias because in a period of crisis, nothing indicates that the proportion of people presenting divorce intentions and actually pursuing a divorce *in fine* is the same as for less troubled years.

COVID-19 pandemic at the time of achieving this work is clearly not over. The repercussions on marital structures may last longer and be visible only in the long-term. A lot of frameworks are possible concerning the evolution of divorce rates, but the prediction model here can only render short-term effects.

8.2 Extensions

Several extensions to this current work can be made to complete our results. The first one would be to use more precise data concerning divorce *i.e.* use refined divorce rates (number of divorces per 1,000 women married to men) instead of crude divorce rates. Even through crude divorce rates may be quite similar to refined divorce rates, having the last set of data would avoid the presence of a «marriage bias» [22]. Concerning the triple-difference analysis, a few remarks could be made concerning the «treatments». The pandemic treatment is only a binary variable which takes 0 before the exceeding of the chosen threshold of cases and 1 after. This does not account for the severity of the pandemic even if robustness tests tend to include control variables for this. In the same manner, one could consider the lockdown treatment

22. It could appear for instance as higher crude divorce rates due to higher marriage rates in some states - and not as higher propensities to divorce

as incomplete. Indeed, it accounts for the quantity (variable taking a value between 0 and 1 depending on the number of days under lockdown) but not for the intensity - or stringency. Moreover we focus in this paper on statewide lockdowns but some have been implemented at a much granular level (counties). An extension would thus be to refine the treatments in the analysis.

The problem of mixed-frequency arises with the panel model, which we handle by the most basic technique: aggregating the high-frequency data to obtain the same frequency as the low-frequency data. Some analysis tools have been proposed in the literature to face this problem without losing the richness of the high-frequency data. Notably we could mention the works of Ghysels et al. (2004) who propose the Mixed-data sampling (MIDAS) regression to handle this mixed-frequency problem. A substantial literature is now available on this topic, but to our knowledge only Havranek and Zeynalov (2019) have combined Google Trends data with this type of regression. Furthermore this opens a new area for research in the continuity of this work which is to elaborate on divorce-related searches seasonality and divorces seasonality. Since data about state divorce rates are only delivered at a yearly frequency, these Internet data and econometric tools could help us in seizing the pattern of divorce decisions and process along a year at the aggregate level.

9 Conclusion

COVID-19 pandemic and the following sanitary policies are shaking up the classical patterns in demography. The issue of divorce has been widely discussed in the media arena, often because of the fear of a surge in divorces due to confinement measures. An event study methodology and a triple-difference analysis are applied on Google Trends data in this work in order to seize the interest of people - on Google search engine - for divorce topics amid COVID-19 pandemic. The results of these analyses tend to identify a lockdown effect over a pandemic effect, which presents modest evidence of repercussions in the mid-term horizon. Besides financial features who have aroused relatively more interest on Google search engine during lockdowns periods, every domain related to divorce has shown a decrease in relative search volumes. However this work tends to show the limited avenues of Google Trends data to yield robust results in social sciences due to limitations and biases that have largely been ignored in most of the preceding scientific literature.

Another section of this report focuses on the task of nowcasting divorce rates for 2020 using Google Trends data which are almost immediately available. A panel data model coupled with a cross-validation framework enables the completion of this prediction. Our model tends to refute a decline in divorce rates in 2020 and shows a stable level based on Google Trends Indicators and even slightly increasing when adding unemployment data.

Many questions remain at the time of delivering this research article, the most prominent one being that the pandemic is not over yet. The long-term effects of COVID-19 on marital structures are thus not evaluated in this paper and several propositions of extensions are let for future research.

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10 Appendix

10.1 Lockdowns

Alabama	04/04/2020 - 30/04/2020	Montana	28/03/2020 - 26/04/2020
Alaska	28/03/2020 - 24/04/2020	Nebraska	—
Arkansas	—	Nevada	01/04/2020 - 09/05/2020
Arizona	31/03/2020 - 16/05/2020	New Hampshire	27/03/2020 - 15/06/2020
California	19/03/2020 - 25/05/2020	New Jersey	21/03/2020 - 09/06/2020
Colorado	26/03/2020 - 26/04/2020	New Mexico	23/03/2020 - 31/05/2020
Connecticut	23/03/2020 - 20/05/2020	New York	22/03/2020 - 28/05/2020
District of Columbia	01/04/2020 - 29/05/2020	North Carolina	30/03/2020 - 08/05/2020
Delaware	24/03/2020 - 31/05/2020	North Dakota	—
Florida	03/04/2020 - 30/04/2020	Ohio	23/03/2020 - 29/05/2020
Georgia	03/04/2020 - 30/04/2020	Oklahoma	—
Hawaii	25/03/2020 - 31/05/2020	Oregon	23/03/2020 - 15/05/2020
Iowa	—	Pennsylvania	01/04/2020 - 08/05/2020
Idaho	25/03/2020 - 30/04/2020	Rhode Island	28/03/2020 - 08/05/2020
Illinois	21/03/2020 - 30/05/2020	South Carolina	07/04/2020 - 03/05/2020
Indiana	24/03/2020 - 04/05/2020	South Dakota	—
Kansas	30/03/2020 - 03/05/2020	Tennessee	31/03/2020 - 30/04/2020
Kentucky	26/03/2020 - 11/05/2020	Texas	02/04/2020 - 30/04/2020
Louisiana	23/03/2020 - 14/05/2020	Utah	—
Maine	02/04/2020 - 31/05/2020	Vermont	25/03/2020 - 15/05/2020
Maryland	30/03/2020 - 15/05/2020	Virginia	30/03/2020 - 15/05/2020
Massachusetts	24/03/2020 - 18/05/2020	Washington	23/03/2020 - 31/05/2020
Michigan	24/03/2020 - 28/05/2020	West Virginia	24/03/2020 - 04/05/2020
Minnesota	27/03/2020 - 17/05/2020	Wisconsin	24/03/2020 - 13/05/2020
Mississippi	31/03/2020 - 27/04/2020	Wyoming	—
Missouri	06/04/2020 - 03/05/2020		

Table 6 – Lockdown dates for the U.S. states and the District of Columbia

10.2 Google Trends Variables

Keywords Set	**Variables**	**Keywords**	**Missing States**
Control	*div_cov*	divorce coronavirus	Alaska, North Dakota, South Dakota, Vermont, Wyoming
	lock	lockdown - love - six - r6	
Divorce	*div*	divorce - kardashian - blake - katie - jon - evans - mccartney - britney - heidi	
	div_cov_media	divorce - kardashian - blake - katie - jon - evans - mccartney - britney - coronavirus	

Legal	*div_court*	divorce court + divorce attorney	Vermont
	div_law	divorce law + divorce laws + divorce legal	Alaska, Vermont
	div_lawyer	divorce lawyer + divorce lawyers	Alaska
	div_legal	divorce court + divorce lawyer + divorce lawyers + divorce attorney + divorce legal + divorce law	
Administrative	*child_custody*	child custody	
	div_file	divorce file - kardashian - katie - jon - obama	Alaska, Montana, North Dakota, Rhode Island, South Dakota, Vermont, Wyoming
	div_papers	divorce papers - kardashian - katie - jon - obama	Alaska, District of Columbia, New Hampshire, Rhode Island, South Dakota, Vermont, Wyoming
Financial	*alimony*	alimony + spousal support	
	child_support	child support	
Questioning	*div_how*	how divorce	
	div_long	how long divorce	Alaska, District of Columbia, Delaware, Hawaii, Maine, Montana, North Dakota, New Hampshire, Rhode Island, South Dakota, Vermont, Wyoming
	div_much	how much divorce	Alaska, District of Columbia, Delaware, Maine, Montana, North Dakota, New Hampshire, Rhode Island, South Dakota, Vermont, West Virginia, Wyoming

Table 7 – List of detailed Google Trends variables

10.3 Testing for Outliers

10.3.1 Chauvenet's Criterion

We consider the observations $(P_i)_{i \,\in\, \mathbb{N}}$. An observation P_i is an outlier if it verifies the following equation :

$$erfc\left(\frac{|P_i - \overline{P}|}{S_p}\right) < \frac{1}{2n}$$

where $\overline{P}$ is the mean of the observations, S_p the standard deviation, n the number of observations and $erfc(.)$ the error complementary function defined as follows: $erfc(x) = \frac{2}{\sqrt{\pi}} \int_x^{\infty} e^{-t^2}\,\mathrm{d}t$.
For further information refer to the review of Rochim (2016).

10.3.2 Hampel Filter

Consider the observation P_i. A window of odd length centered on the evaluated point is implemented. The local median M_i and standard deviation S_i of the sample are computed. An observation P_i is an outlier if it verifies the following equation :

$$|P_i - M_i| < n_S \times S_i$$

where n_S is a threshold allowing for the maximal number of standard deviations corresponding to the median absolute deviation. In our study the window is of length 13 (6 points on both sides of the evaluated point) and the chosen threshold is 3 to conform to the 3σ-rule.
For further information refer to the work of Hampel (1974).

10.3.3 Seasonal Trend Decomposition Using Loess

Following Cleveland et al. (1990) we decompose each point of the time series into three parts: trend, seasonality and remainder. Considering P_i, we have:

$$R_i = P_i - T_i - S_i$$

where R_i, T_i and S_i are respectively the remainder, trend and seasonal parts. Robustness weights are applied to the observations, which means that outlier points with large remainder parts will have a vey small or zero weight. The process is the following:
With $h = 6\ median\,(|R_i|)$, we have the robustness weight ρ_i:

$$\rho_i = B\left(\frac{|R_i|}{h}\right)$$

where $B(.)$ is the bisquare weight function:

$$B(x) = \begin{cases} (1 - x^2)^2) & \text{for } 0 \leq x < 1 \\ 0 & \text{for } x > 1 \end{cases}$$

10.4 Detailed Explanation for the Biases due to Outliers for the Mean Normalization Procedure

10.4.1 Normalization Procedure

Let us denote $\tilde{R}_{st}$ the raw value given by Google Trends for the state s and time t. Writing R_{st} the normalized value, we compute the normalization as follows:

$$R_{st} = \frac{\tilde{R}_{st}}{\overline{\tilde{R}}_s} \times 100, \tag{13}$$

where we have the mean of the series:

$$\overline{\tilde{R}}_s = \frac{1}{T} \sum_{t=1}^{T} \tilde{R}_{st} \tag{14}$$

T denotes the number of observations in the series.

10.4.2 Outliers Introduction

By definition, the series given by Google Trends are scaled between 0 and 100. Let us consider that each value can be decomposed in two parts: a *real* part seizing the personal interest for an issue which is salient in the estimation of the effects and an *outlier* part induced by unrelated events or errors which introduces noisiness in the estimation. Formally:

$$\tilde{R}_{st} = r_{st} + e_{st} \tag{15}$$

$\forall \ (s,t), \ r_{st} \in [0, 100], \ e_{st} \in [0, r_{st}]$.
We deduce the following:

$$\overline{\tilde{R}}_s = \frac{1}{T} \sum_{t=1}^{T} r_{st} + \frac{1}{T} \sum_{t=1}^{T} e_{st} \tag{16}$$

Combining (13), (15) and (16), we have:

$$R_{st} = \frac{r_{st} \times 100}{\frac{1}{T} \sum_{t=1}^{T} r_{st} + \frac{1}{T} \sum_{t=1}^{T} e_{st}} + \frac{e_{st} \times 100}{\frac{1}{T} \sum_{t=1}^{T} r_{st} + \frac{1}{T} \sum_{t=1}^{T} e_{st}} \tag{17}$$

10.4.3 Side Calculus Note

Let $(a, b, c) \in \mathbb{R}^3,\ a \neq 0,\ b \neq 0$. We resolve the following equation:

$$\frac{c}{a+b} = \frac{c}{a} + x$$

$$\begin{aligned}
\frac{c}{a+b} = \frac{c}{a} + x &\iff x = \frac{c}{a+b} - \frac{c}{a} \\
&\iff x = \frac{c \times (-b)}{a(a+b)} \\
\frac{c}{a+b} = \frac{c}{a} + x &\iff x = \frac{-c}{\dfrac{a^2}{b} + a}
\end{aligned}$$

10.4.4 Biases Identification

Using (17) and the solution developed in the Side Calculus Note, we calculate the biases of the normalized values. We identify:
$a = \frac{1}{T}\sum_{t=1}^{T} r_{st},\ b = \frac{1}{T}\sum_{t=1}^{T} e_{st},\ c = r_{st} \times 100$. We have:

$$\frac{a^2}{b} + a = \frac{\left(\dfrac{1}{T}\displaystyle\sum_{t=1}^{T} r_{st}\right)^2}{\dfrac{1}{T}\displaystyle\sum_{t=1}^{T} e_{st}} + \frac{1}{T}\sum_{t=1}^{T} r_{st} = \frac{1}{T}\sum_{t=1}^{T} r_{st}\left(\frac{\displaystyle\sum_{t=1}^{T} r_{st}}{\displaystyle\sum_{t=1}^{T} e_{st}} + 1\right)$$

Therefore:

$$\frac{-c}{\dfrac{a^2}{b} + a} = \frac{-r_{st} \times 100}{\dfrac{1}{T}\displaystyle\sum_{t=1}^{T} r_{st}\left(\dfrac{\displaystyle\sum_{t=1}^{T} r_{st}}{\displaystyle\sum_{t=1}^{T} e_{st}} + 1\right)}$$

Identifying c as $e_{st} \times 100$ and following the same steps:

$$\frac{-c}{\dfrac{a^2}{b} + a} = \frac{-e_{st} \times 100}{\dfrac{1}{T}\displaystyle\sum_{t=1}^{T} r_{st}\left(\dfrac{\displaystyle\sum_{t=1}^{T} r_{st}}{\displaystyle\sum_{t=1}^{T} e_{st}} + 1\right)}$$

10.4.5 Final Bias Equation

Using (17) and the precedent developments in Biases Identification we can write:

$$R_{st} = \frac{r_{st} \times 100}{\frac{1}{T}\sum_{t=1}^{T} r_{st}} - \frac{r_{st} \times 100}{\frac{1}{T}\sum_{t=1}^{T} r_{st}\left(\frac{\sum_{t=1}^{T} r_{st}}{\sum_{t=1}^{T} e_{st}} + 1\right)} + \frac{e_{st} \times 100}{\frac{1}{T}\sum_{t=1}^{T} r_{st}} - \frac{e_{st} \times 100}{\frac{1}{T}\sum_{t=1}^{T} r_{st}\left(\frac{\sum_{t=1}^{T} r_{st}}{\sum_{t=1}^{T} e_{st}} + 1\right)}$$

A possible decomposition of the bias is the following:

$$\boxed{R_{st} = \frac{r_{st} \times 100}{\frac{1}{T}\sum_{t=1}^{T} r_{st}} \underbrace{\left(1 - \frac{\sum_{t=1}^{T} e_{st}}{\sum_{t=1}^{T} r_{st} + \sum_{t=1}^{T} e_{st}}\right)}_{\mathbf{A}} + \underbrace{\frac{e_{st} \times 100}{\frac{1}{T}\sum_{t=1}^{T} r_{st}} \left(1 - \frac{\sum_{t=1}^{T} e_{st}}{\sum_{t=1}^{T} r_{st} + \sum_{t=1}^{T} e_{st}}\right)}_{\mathbf{B}}} \tag{18}$$

Notice that

$$\frac{\sum_{t=1}^{T} e_{st}}{\sum_{t=1}^{T} r_{st} + \sum_{t=1}^{T} e_{st}} = \frac{\sum_{t=1}^{T} e_{st}}{\sum_{t=1}^{T} \tilde{R}_{st}}$$

which means that the multiplicative bias A is due to the total share of outliers within the series. Note that B can be decomposed as follows:

$$\boxed{B = \frac{e_{st} \times 100}{\frac{1}{T}\sum_{t=1}^{T} r_{st}} \left(1 - \frac{\sum_{t=1}^{T} e_{st}}{\sum_{t=1}^{T} r_{st} + \sum_{t=1}^{T} e_{st}}\right) = \underbrace{\frac{e_{st} \times 100}{\frac{1}{T}\sum_{t=1}^{T} r_{st}}}_{B_1} - \underbrace{\frac{e_{st} \times 100}{\frac{1}{T}\sum_{t=1}^{T} r_{st}} \left(\frac{\sum_{t=1}^{T} e_{st}}{\sum_{t=1}^{T} r_{st} + \sum_{t=1}^{T} e_{st}}\right)}_{B_2}}$$

B_1 is the bias induced by the share of the outlier part in the observation normalized, while B_2 is the same multiplicative bias as A but applied to the outlier part of the observation.

10.4.6 Biases Effects

We have assumed that outliers can only change the observed values in a positive way. The outlier part e_{st} is always positive or equal to 0. Because of this assumption, A and B_2 always have a negative effect. On the other hand B_1 always have a positive effect. The bias evaluation is not straightforward and strongly depends on the point estimated (due to its outlier part).

10.5 Pandemic Event Studies

Table 8 – Event study on Google Trends Indicators depending on the first wave of the pandemic

	lock	*div*	*div_law*	*child_support*	*alimony*	*div_how*	*div_papers*	*div_court*
-1	853.2	-3.191	-4.242*	9.289***	-4.744	-3.344	-8.571	-4.860*
	(470.0)	(2.411)	(1.563)	(1.732)	(5.809)	(3.279)	(4.587)	(2.216)
0	292.6	-1.620	-5.898**	6.714	-7.161	-4.191	-11.87*	-8.025
	(396.6)	(2.919)	(1.906)	(6.812)	(5.118)	(4.485)	(4.966)	(4.570)
1	-75.32	0.793	-4.874	-6.594	-0.532	-3.146	-8.719	-3.009
	(240.4)	(2.006)	(2.541)	(7.016)	(4.034)	(3.001)	(5.657)	(3.847)
2	-374.2	1.912	-1.303	-19.40**	0.0881	-3.573	-1.131	0.714
	(242.3)	(1.831)	(1.983)	(6.704)	(3.250)	(3.254)	(3.656)	(2.842)
3	-517.1**	5.845*	-0.665	-22.17***	1.818	-0.0631	-2.607	7.500*
	(163.9)	(2.408)	(1.869)	(4.627)	(3.744)	(2.562)	(3.643)	(3.586)
4	-559.8***	4.958**	3.634	-20.47***	0.187	-2.100	5.178	4.904
	(143.9)	(1.426)	(2.000)	(2.455)	(3.125)	(2.675)	(5.376)	(3.189)
Cons.	92.38***	103.9***	125.8***	87.41***	103.1***	92.13***	121.5***	107.4***
	(9.421)	(2.219)	(2.978)	(4.367)	(4.201)	(2.777)	(4.721)	(3.398)
R^2	0.442	0.641	0.705	0.319	0.129	0.213	0.161	0.173
Obs.	3976	3976	3976	3976	3976	3976	3834	3976

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9 – Event study on Google Trends Indicators depending on the second wave of the pandemic

	lock	*div*	*div_law*	*child_support*	*alimony*	*div_how*	*div_papers*	*div_court*
-2	-284.3***	3.723**	-4.452	10.52*	-3.987	-0.265	-27.69***	-1.189
	(40.08)	(1.184)	(3.027)	(4.282)	(7.993)	(6.828)	(3.557)	(4.107)
-1	-771.4***	4.934***	-2.628	-5.629	5.902	5.764*	-1.791	1.961
	(23.38)	(1.018)	(1.806)	(3.571)	(7.225)	(2.341)	(5.128)	(1.660)
0	-732.8***	5.623***	-7.134*	-13.50***	1.594	5.781	-12.66	8.191*
	(48.78)	(1.003)	(3.148)	(2.842)	(3.640)	(3.231)	(9.231)	(3.516)
1	-982.7***	7.136***	2.022	-23.12***	-4.592	6.558	-5.314	10.22*
	(65.73)	(1.658)	(3.836)	(3.033)	(6.877)	(5.539)	(8.181)	(4.423)
2	-1030.7***	12.87***	2.832	-22.65***	9.158	2.413	9.270	-3.560
	(75.06)	(1.413)	(3.040)	(1.577)	(7.203)	(3.641)	(6.654)	(3.437)
Cons.	61.31***	96.50***	123.1***	74.19***	100.4***	88.13***	105.0***	84.02***
	(3.991)	(6.844)	(9.521)	(2.651)	(8.604)	(9.507)	(16.87)	(7.592)
R^2	0.423	0.475	0.580	0.438	0.151	0.216	0.133	0.142
Obs.	2130	2130	1988	2130	2130	2130	1846	2130

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

10.6 Heterogeneous Effects

Table 10 – Event study with heterogeneous effects: first wave

	lock	*div*	*div_law*	*child_support*	*alimony*	*div_how*	*div_papers*	*div_court*
-1	1389.1*	-4.933**	-2.915	5.624*	-4.081	-3.594	-12.14*	-7.274
	(525.2)	(1.554)	(2.385)	(2.224)	(5.404)	(6.293)	(5.506)	(4.019)
0	2711.0***	-12.54***	-12.01***	12.78**	-27.03***	-15.84***	-20.92***	-16.10***
	(313.4)	(1.244)	(1.856)	(3.612)	(2.871)	(3.254)	(5.442)	(3.253)
1	993.3***	-6.043**	-12.50***	24.77***	-19.23***	-12.84***	-27.00***	-16.56***
	(101.9)	(1.802)	(1.945)	(5.640)	(4.887)	(3.054)	(4.384)	(2.151)
2	665.1***	-0.319	-7.571***	6.274	-11.82**	-5.357	-20.60***	-9.287**
	(99.40)	(1.260)	(1.843)	(5.018)	(3.752)	(3.229)	(4.073)	(3.065)
3	263.9***	0.0573	-6.119*	-10.72*	1.246	-4.550	-10.51**	-1.387
	(36.89)	(1.033)	(2.696)	(3.847)	(5.013)	(4.232)	(2.975)	(4.045)
4	110.4***	0.951	-2.827	-21.43***	-9.889*	-6.032	-6.141*	3.633
	(11.49)	(1.247)	(1.726)	(4.373)	(4.360)	(2.967)	(2.866)	(3.131)
5	60.51**	4.442**	-3.738*	-23.05***	-9.611**	-5.264	-7.543	3.382
	(19.81)	(1.566)	(1.702)	(2.465)	(3.327)	(4.667)	(4.170)	(3.887)
6	74.57***	6.409***	-3.522	-16.33***	1.544	-4.692	-14.40*	-4.087
	(17.71)	(0.926)	(3.182)	(1.575)	(4.036)	(3.408)	(5.402)	(2.786)
Cons.	17.92**	104.5***	126.4***	85.57***	103.6***	91.35***	122.1***	105.9***
	(5.904)	(2.317)	(3.141)	(4.631)	(4.452)	(2.659)	(4.887)	(3.249)
R^2	0.718	0.655	0.716	0.351	0.154	0.235	0.195	0.182
Obs.	3408	3408	3408	3408	3408	3408	3266	3408

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11 – Event study with heterogeneous effects: second wave

	lock	*div*	*div_law*	*child_support*	*alimony*	*div_how*	*div_papers*	*div_court*
-1	175.4	-1.157	4.266	1.871	8.926	-0.301	6.627	-8.870
	(329.1)	(2.194)	(3.790)	(1.310)	(10.33)	(4.979)	(16.33)	(5.645)
0	3946.9***	-13.32***	-14.45*	4.878	-18.56***	-16.28**	-5.159	-21.69***
	(368.7)	(1.043)	(4.764)	(4.950)	(3.781)	(4.878)	(5.891)	(2.811)
1	1307.9***	-12.55***	-12.81***	38.47***	-26.95***	-24.88***	-29.17**	-20.37***
	(161.4)	(1.692)	(2.315)	(6.087)	(4.454)	(3.497)	(8.694)	(2.606)
2	784.4***	-2.065	-10.31*	18.04**	-15.22	-5.928	-29.81**	-10.47*
	(112.8)	(1.601)	(4.457)	(5.397)	(10.85)	(5.552)	(8.555)	(3.731)
3	297.6**	-0.389	-8.214*	1.101	-4.627	-3.340	-7.492	-7.521*
	(70.71)	(0.633)	(3.645)	(3.936)	(10.53)	(2.662)	(4.109)	(2.828)
4	301.7*	0.449	-9.793***	-6.451*	-8.671	-0.152	-20.59	1.963
	(119.7)	(1.410)	(0.880)	(2.438)	(5.879)	(2.815)	(11.98)	(3.398)
5	95.29*	1.882	-0.313	-14.07***	-10.50	-2.938	-7.434	-0.113
	(34.63)	(2.138)	(2.084)	(1.754)	(7.719)	(5.134)	(13.00)	(5.536)
6	44.50	6.669*	-1.795	-14.11***	0.778	-2.675	4.136	-11.32*
	(28.39)	(2.256)	(3.488)	(1.369)	(8.594)	(3.717)	(9.237)	(4.493)
Cons.	25.40*	96.60***	123.0***	71.19***	98.77***	88.80***	102.5***	83.70***
	(10.68)	(7.190)	(9.935)	(2.787)	(7.520)	(9.825)	(15.81)	(7.618)

R^2	0.903	0.489	0.589	0.455	0.168	0.248	0.136	0.154
Obs.	1704	1704	1562	1704	1704	1704	1562	1704

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12 – Triple-difference with heterogeneous effects: first wave

	lock	*div*	*div_law*	*child_support*	*alimony*	*div_how*	*div_papers*	*div_court*
Lock.	1187.8***	-8.786***	-9.648***	36.18***	-24.11***	-12.70***	-19.05**	-12.81***
	(300.6)	(1.311)	(1.911)	(6.627)	(4.472)	(3.406)	(5.782)	(2.583)
Pand.	-424.4**	4.613***	0.966	-12.32**	-0.669	-0.233	-3.054	4.161
	(144.2)	(1.024)	(1.498)	(3.393)	(2.365)	(1.482)	(2.911)	(2.134)
Lock. * Pand.	50.34	-3.599	-5.446	-6.206	4.097	-1.881	-8.434	-16.81**
	(321.2)	(2.550)	(3.467)	(11.67)	(6.751)	(4.293)	(8.016)	(5.166)
Cons.	31.86***	104.4***	126.4***	85.90***	104.5***	92.99***	122.8***	108.5***
	(7.390)	(2.241)	(3.015)	(4.547)	(4.354)	(2.810)	(4.731)	(3.405)
R^2	0.455	0.643	0.705	0.323	0.133	0.215	0.163	0.177
Obs.	3976	3976	3976	3976	3976	3976	3834	3976

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13 – Triple-difference with heterogeneous effects: second wave

	lock	*div*	*div_law*	*child_support*	*alimony*	*div_how*	*div_papers*	*div_court*
Lock.	1402.7***	-10.45***	-11.96***	27.85**	-24.99***	-16.29***	-32.48***	-9.267*
	(261.9)	(1.438)	(2.474)	(7.662)	(4.014)	(2.289)	(4.995)	(3.883)
Pand.	-351.9**	1.842	-3.662*	-8.941	-6.762	0.919	-13.48	4.686
	(105.4)	(0.880)	(1.482)	(4.755)	(7.135)	(2.112)	(7.712)	(2.846)
Cons.	9.464	96.83***	123.9***	72.96***	101.6***	88.88***	107.1***	84.48***
	(14.57)	(6.906)	(9.423)	(2.874)	(8.474)	(9.627)	(16.78)	(7.454)
R^2	0.476	0.475	0.580	0.441	0.154	0.218	0.134	0.143
Obs.	2130	2130	1988	2130	2130	2130	1846	2130

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

10.7 Robustness

Table 14 – Triple-difference robustness tests for the Google Trends Indicator *div*

	DDD	No Weight	Linear	Quadratic	Cases Control	Deaths Control	Rob 2004
Lock.	-8.960***	-11.06***	-10.47***	-9.151***	-9.007***	-9.095***	-10.09***
	(0.978)	(1.230)	(1.217)	(0.967)	(0.967)	(0.956)	(1.277)
Pand.	3.476***	1.977*	5.123***	7.316***	2.600	3.257***	1.861*
	(0.832)	(0.840)	(0.877)	(1.247)	(1.830)	(0.892)	(0.853)
Lock. * Pand.	-3.573	0.826	-3.032	-7.709**	-3.473	-4.764	0.743
	(2.398)	(2.929)	(3.485)	(2.813)	(2.397)	(3.225)	(2.252)
Cases (pop.)					0.177		

					(0.241)		
Deaths (pop.)						3.479	
						(3.649)	
Cons.	102.5***	104.7***	105.9***	157.4***	102.5***	102.5***	100.7***
	(2.927)	(1.327)	(1.334)	(2.915)	(2.924)	(2.927)	(1.532)
R^2	0.558	0.492	0.608	0.648	0.558	0.558	0.395
Obs.	7242	7242	7242	7242	7242	7242	10302

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15 – Placebo lockdown for the years 2018 and 2019

	div 2019	*div 2018*	*div_ law 2019*	*div_ law 2018*
Placebo Lock.	-0.799	5.309***	0.0903	0.247
	(0.850)	(1.312)	(2.282)	(1.565)
Placebo Pand.	0.795	-2.079**	-1.210	-1.055
	(0.638)	(0.661)	(1.091)	(1.489)
Placebo Lock. * Placebo Pand.	-2.552	-0.136	1.237	-1.595
	(2.201)	(2.900)	(4.056)	(4.143)
Cons.	102.4***	102.2***	121.8***	121.7***
	(2.854)	(2.815)	(3.702)	(3.623)
R^2	0.509	0.455	0.628	0.604
Obs.	6630	6018	6370	5782

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All robustness tests for other variables are available on request.