Health and well-being in the great recession

Nikolaos Askitas
Institute for the Study of Labor (IZA), Bonn, Germany, and
Klaus F. Zimmermann
Institute for the Study of Labor (IZA), Bonn, Germany and Bonn University, Bonn, Germany

Abstract

Purpose – The purpose of this paper is to investigate the extent to which the authors can use internet search data in order to capture the impact of the 2008 Financial and Economic Crisis on well-being.
Design/methodology/approach – The authors look at the G8 countries with a special focus on USA and Germany and investigate whether internet searches reflect the "malaise" caused by the crisis. The authors focus on searches that contain the word "symptoms" and are thought to proxy self-diagnosis and those that contain "side effects" and are thought to proxy treatment.
Findings – The authors find that "malaise" searches spike in a fashion coincident with the crisis and its contagion timeline across the G8 countries. The authors show that results based on search recover previously known stylized facts from the economics of health, well-being and the business cycle.
Research limitations/implications – Internet penetration is high across the G8 countries. The authors nonetheless cannot get a good handle on the part of the population, which is not online. Moreover the authors cannot get a good grip on all confounding factors. More research would be necessary with access to search microdata.
Originality/value – The authors propose global proxies for diagnosis and treatment based on the "search buzz" for symptoms and side effects. The authors can thus capture trends on a global scale. This approach will become increasingly important.

Keywords Well-being, Symptoms, Economic crisis, Treatment, Diagnosis, Google Trends, Business cycle, Internet search, Side effects
Paper type Research paper

1. Introduction

Our paper's twofold aim is to investigate the extent to which we can use internet search data in order to study the impact of the 2008 crisis on health and well-being and by doing so to validate this type of data and alert social science workers to the possibilities it opens, as well as the issues it involves.

Looking at internet search activity in the USA during the crisis we are bound to find evidence of the crisis' impact[1]. We focus our attention on two types of Google searches, which we think are related to ill-being and health: those that involve "symptoms" (we will be referring to those as "symptoms searches") and those that contain "side effects" (referred to as "side effect searches"). Examples of such searches are "depression symptoms," "anxiety symptoms" or "heart attack symptoms," as well as "Prozac side effects" or "Xanax side effects." The union of the two types of searches

JEL Classification — C81, E32, I1, L86

The authors thank the Google Trends team for extensive discussions and clarifications regarding Google Trends Data in general, Hilmar Schneider, Konstantinos Tatsiramos and Rainer Winkelmann for reading earlier versions of the manuscript and the participants of IZA's Brown Bag Seminar for interesting comments. The authors also thank an anonymous referee for kind and helpful comments as well as Corrado Giulietti for acting as the Editor for this paper.

International Journal of Manpower
Vol. 36 No. 1, 2015
pp. 26-47

0143-7720
DOI 10.1108/IJM-12-2014-0260

will be referred to as "malaise searches." We show that spikes coincide with the crisis in the USA, Germany and across the G8 countries.

We document a delay in the German surge with respect to that in the USA, which is concordant with the contagion timeline of the crisis. Evidence such as the phase shift between the USA and Germany as well as the cross-sectional nature of the phenomenon significantly reduces the probability that the correlation of the crisis with the surge in symptoms and side effects searches is spurious. Furthermore it is reasonable to argue that malaise searches are bound to be related to well-being and health in one way or another. For instance, a search for "depression symptoms" may come from a hypochondriac, a medical buff, someone in psychological stress or has a loved one who is, or is an "e-patient," but all of these cases are nonetheless related to health and well-being[2]. Similarly a search for "Xanax side effects" most likely indicates someone who is consuming the known antidepressant or shopping for medication for oneself or for a loved one. In both cases a significant surge in the aggregate numbers of these searches is a phenomenon worth exploring, as the likelihood it implies increased malaise is more than apparent.

We know for example that "adults who, in the past 12 months, have provided unpaid care to a parent, child, friend, or other loved one" are one of the most likely groups to look online for health information. Our interpretation is that these searches do indeed indicate increased malaise: symptoms searches express self-diagnosis while side-effect searches imply that treatment is being applied. Since we cannot construct counterfactual societal realities in a lab, such as inserting or retracting a recession, our task is to make as airtight a case as possible for our narrative. We do so by means of alternative data sources or other statistical due diligence that helps us reject alternative hypotheses. Doing this solely based on aggregate data is of course not an easy task[3].

This paper is organized as follows: in Section 2 we reconstruct aspects of the timeline of the crisis and in Section 3 we review the available literature using Google Trends as well as that on the business cycle's effect on health and well-being. In Section 4 we describe the Gallup Well-Being Index, which gives us a first impression of the impact of the crisis on well-being. Section 5 describes our main data source, Google Trends, while in Sections 6.1 and 6.2 we discuss search intensity for "symptoms" and "side effects" and connect this with mental and physical well-being[4]. In Section 6.3 we perform statistical forensics in order to reject alternative hypotheses and strengthen our assertions, and Section 7 concludes our paper.

2. A brief timeline of the crisis

The 2008 economic crisis, which showed its first signs as early as 2007, was initially seen as a US financial crisis that became acute in the dramatic fall of 2008. It subsequently went on to "mutate" into an economic crisis "infecting" most of the industrialized world by the spring of 2009 and has been by many accounts underway for many years after. The crisis has impacted the world in profound ways, which policy and decision makers as well as economists are still busily sorting out.

As early as August 2007, US credit markets were impacted by the collapse of two mortgage-related hedge funds of Bear Stearns, at the time the fifth largest securities firm in the US. Bear Stearns ended up losing over 90 percent of its value soon after and was eventually bought by JPMorgan. The US labor market was beginning to show signs of a downturn since US unemployment had been falling since 2003 was only then beginning to inch upwards. At the same time the Dow Jones Economic Sentiment

Indicator (henceforth ESI) that measures the sentiment in press reporting was now becoming bleaker, having hovered between 60 and 70 points (on a scale of 0 to 100) since 2005. All the while more and more homeowners were falling behind on their mortgage payments.

By September 2008, Lehman Brothers – at the time the biggest US underwriter of mortgage-backed securities – was filing for bankruptcy while the two biggest US mortgage finance companies, Fannie Mae and Freddie Mac, were being nationalized. The labor market was deteriorating with unemployment up to 6.1 percent, compared to 4.1 percent at its previous low in October 2006. The ESI bottomed out at just over 20 points, having lost 60 percent of its value as of July 2007. On September 18, 2008, then Treasury Secretary Henry Paulson and Fed Chairman Ben Bernanke were meeting with legislators trying to secure a US$ 700 billion emergency backstop. Bernanke reportedly argued, "If we don't do this, we may not have an economy on Monday." The Troubled Assets Relief Program (henceforth TARP) was signed on October 3, 2008. This is our cut-off date. We mark this date on our time series plots and observe Google search behavior before and after the TARP date[5].

In Germany, as in the rest of Europe, the drama unfolding across the Atlantic was still being viewed and felt as if it was solely an American financial crisis. The DAX was following the Dow Jones Industrial Index but the economic consequences were still not fully visible and the only question was the extent to which a US collapse would take down US imports and with it the GDPs of export countries like Germany. German GDP showed mixed signs of a possible downturn in the first three quarters of 2008: while GDP was still growing year-over-year, it was dropping compared to previous quarters. By the time the German GDP plunged to its lowest point in the first quarter of 2009, *Kurzarbeit*[6] was at its peak and unemployment reached its high (considering the severity of the crisis, actually moderate) in March 2009, there was no doubt that there was also a German economic crisis. This is our mark for Germany where we start observing search spikes related to ill-being.

We think it is apparent that the business cycle may have an impact on emotional and psychological well-being[7]. Job uncertainty, housing market volatility, as well as income and equity erosion with the existential fears and anxiety they generate may reasonably be expected to impact mental health. Physical health may be expected to be impacted via the mental and psychological health channel, combined with the possible relaxation of on-the-job security precautions during a recession. This recession is different from any other in many qualitative ways – a fact many quantitative analysts often tend to forget. This signifies something beyond the usual loss of coherence in long time series. One of the ways this recession is different is that it has been as closely reported upon as no other in history[8]. This may very well have exacerbated the intensity of anxiety and malaise in the general population. In some way we may be witnessing "irrational sullenness" following "irrational exuberance"[9]. Our point is that while the causes may be exaggerated, the impact on health and well-being is real. This is comparable to expectations in financial markets: the "illusional" nature of optimistic or pessimistic expectations does not prevent them from having a real impact on market capitalization.

3. Relevant references

Our paper has a twofold aim: we want to use internet search data in order to explore the impact of the crisis on health and well-being and by doing so we want to validate this type of data and alert social science researchers to the possibilities it opens, as well as the issues it involves. We therefore want to devote this section to first reviewing the literature that has already used Google Trends, then subsequently review a portion of the literature dealing with well-being and the business cycle.

3.1 Google Trends in the literature

Google data has been used mainly to nowcast economic variables and, to be more precise, to "predict the present" (Varian and Choi, 2009; Askitas and Zimmermann, 2009). In this approach one exploits the real time availability of such data vs a significant lag in publishing "official data" (which is often subsequently revised) to predict economic variables of interest. In essence the core idea is that such data is readily available in real time and hence provides quality, fast, real-time reporting of reality. The official data then serves as the benchmark against which to check the reporting. The data has been used for consumption research (Kholodilin *et al.*, 2010; Schmidt and Vosen, 2009, 2010), housing prices (Kulkarni *et al.*, 2009), unemployment (Askitas and Zimmermann, 2009; D'Amuri and Marcucci, 2010), as well as finance (Sims, 2010) and policy (Bersier, 2010). It has also been used to enhance the performance of more traditional forecasting models as in Kholodilin *et al.* (2009). Our own exercise on short-term forecasting of German unemployment (Askitas and Zimmermann, 2009) served us well in predicting a quiet labor market at a time when most experts thought it was highly unlikely. In health analysis it has been used to predict flu trends (Ginsberg *et al.*, 2009). A paper similar to ours with a more restricted focus is Tefft (2011).

3.2 The business cycle and well-being

There is extensive literature on the impact of unemployment and the business cycle on health and well-being. The general picture appears to be that unemployment has a negative effect on well-being, as shown, for example in Clark and Oswald (1994). For a more comprehensive review of the relevant literature, the reader could consult Frey (2008). The effect of the business cycle on health using aggregate measures is treated in Brenner (1973, 1975, 1979) as well as in Ruhm (2000). The impact of recessions on physical health is studied for example in Arinaminpathy and Dye (2010) in the case of tuberculosis and in Martin-Moreno *et al.* (2010) for cancer. In short, the literature appears to point in the expected direction: unemployment and slow business cycles lead to increased malaise, although there may be a short-term reverse effect in both directions. By this we mean that a recession allows one to have more time to tend to health issues, which has a short-term positive effect on health but disappears in the long run. Similarly a booming economy may have a partially negative influence on health since it reduces time for caring for one's health.

4. Well-being and the crisis: a first look

The Gallup Well-Being Index provides us with well-being measurements in the US starting in January 2008. It has therefore captured some of the impact of this crisis on health and well-being. The indices are based on daily interviews of no less than a thousand, randomly selected respondents and what we plot here are publicly available monthly data. Figure 1 is our reproduction of these indices. Before we comment on the development of these indices we would like to briefly describe them for the purpose of our exposition[10].

PHI: the Physical Health Index is based on: sick days in the past month, disease burden, health problems that get in the way of normal activities, obesity, feeling well-rested, energy, colds, flu, headaches.

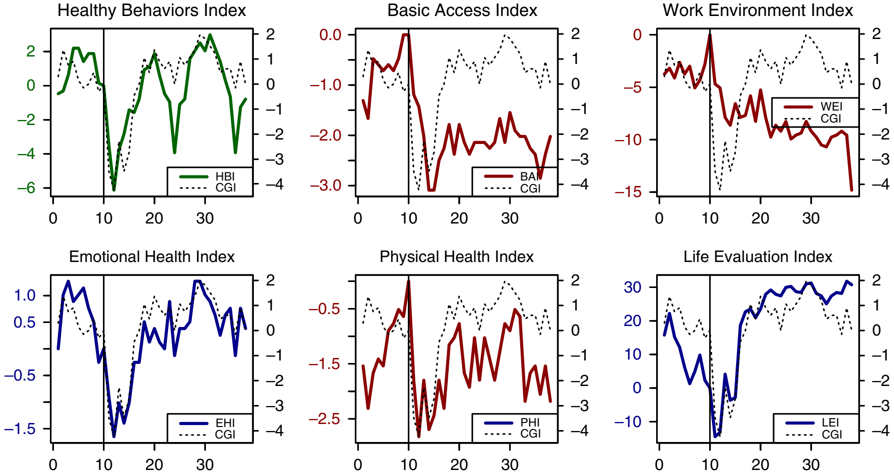


Figure 1.
Monthly (x-axis) Gallup Well-Being Indices starting in January 2008

Notes: Data were obtained from www.well-beingindex.com where information on the definitions may also be found. All series are expressed as percentage of change relative to their value at time t = TARP (so they are all zero on the TARP date $x = 10$). Each of the six plots contains the composite index in addition to a component of the Gallup Well-Being Index

WEI: the Work Environment Index measures the perception of one's work atmosphere and includes job satisfaction, ability to use one's strengths at work, supervisor's treatment (more like a boss or a partner), supervisor creates an open and trusting work environment.

BAI: the Basic Access Index measures access to necessities crucial to well-being and includes satisfaction with community or area, area getting better as a place to live, clean water, medicine, safe place to exercise, affordable fruits and vegetables, feel safe walking alone at night, enough money for food, enough money for shelter, enough money for healthcare, visited a dentist recently, access to a doctor and access to health insurance.

LEI: the Life Evaluation Index measures a self-evaluation of current and anticipated life situation (in five years).

EHI: the Emotional Health Index is based on respondents' daily experiences and includes smiling or laughter, being treated with respect, enjoyment, happiness, worry, sadness, anger, stress, learning or doing something interesting, depression.

HBI: the Healthy Behavior Index includes smoking, eating healthy, weekly consumption of fruits and vegetables, weekly exercise frequency.

Notice that the Emotional (EHI) and the Life Evaluation Indices (LEI) were dropping much earlier than October 2008 while the Basic Access (BAI), Work Environment (WEI) and Physical Health (PHI) Indices were increasing all the way up to the TARP and took a sharp turn downwards right after that. While anxiety levels were increasing early on in accordance with reports of a financial crisis in the making (underway since 2007), it is quite possible that the crisis was still being perceived as both an ambient nuisance and unrealized threat. At the culmination of the finance crisis and with the successive failures of the too-big-to-fail corporations, the threat began to materialize and people's physical health took the hit together with work environment conditions and access to basic goods.

It is also interesting to see that the subjective well-being indices (EHI and LEI) recovered relatively quickly (and in fact overcompensate) although the crisis was still in full swing – a well-known phenomenon called adaptation. The more "objective" indices such as PHI and BAI recovered much slower; the WEI even continued to worsen up until February 2011. One component we have so far left out is the HBI (top right), which shows a clear seasonality that changes between July's bikini-season high fitness vs the low during the Christmas season binge. The crisis can be seen here in the excesses of Christmas 2008: they were worse than those in 2007, 2009 and 2010, perhaps a sign of increased fatalism in the midst of an extremely over-reported finance crisis. Although healthy behaviors recovered quickly out of the deep 2008 dip, gaining two points in Christmas 2009, it clearly stagnated in 2010.

Finally the LEI (which contains subjective evaluation of the present life situation and that anticipated in five years' time) is the most volatile with a 30 percentage points spread when the BAI, EHI and PHI have an almost three-point spread and the seasonal HBI and the still falling WEI indices show a close to ten to 15 point spread. In the volatility of the LEI we see "animal spirits" and what we earlier called the real impact of "irrational sullenness."

It is clear from these indices that the crisis impacted the objective and subjective self-reported mental, emotional and physical well-being that was experienced and remembered.

5. Google Trends

In countries with high internet penetration, online is a "place" where a large and diverse portion of human activity occurs. Entertainment, shopping, porn, research, business, health, news, computing, home, automobiles, sports, travel, games, finance, and holidays are just some of the areas that span this online activity. Frankly speaking it is hard to imagine a human activity that would not have an internet component. Search is a vital component of this activity in that it indexes the enormous stock of online "documents" and makes it tractable for the user population. The study of general internet activity, particularly internet search, is therefore a natural scientific endeavor for the purpose of tuning the indexing and searching algorithms in order to make them more effective; another useful purpose is for the social sciences, which is our field of interest.

An internet search has several attributes such as: a Userid (who searches?), a Query (what is being searched?), a Query Time (when is the search performed?), the Click URL (which, if any, of the results was selected) and an Item Rank (what was the rank of the Click URL among all the results?). Localization attributes of the search origin are also tractable such as geo-coordinates, company, home or school network, etc. A query may be viewed as a short utterance by the user, i.e. as a short statement. In other words, a query may actually be an answer the user is giving us to a question we did not pose but that we can nonetheless guess with varying degrees of certainty. For example, a classical interview could ask a female user a question in the form, "Have you recently had unprotected sex?" and receive an answer or not. The answer may then be affirmative or negative and it may or may not be reliable. A search query such as "plan b cost" or "morning after pill" is quite likely an affirmative answer to the same question that we have now reverse-engineered. In a voluntary survey therefore we have certainty about the question but not about the answer whereas an internet query is an utterance (involuntary survey), supplying a reliable answer to a possibly unasked question. Being well aware of the interesting and difficult ethical issues involved, we can argue that search queries are honest answers given under the assumption of privacy and as such, they are valuable for research purposes.

Search microdata with demographics attached are not available at this time but we can to some extent make due with aggregate data. For example the share of searches including "job search" among all other searches on a daily, weekly or monthly basis may give us an idea of the intensity by which job searches are performed. The latter kind of search macro data is by and large free of ethical issues. Since the summer of 2008 Google Trends has made this type of aggregate data available[11]. The Google Trends service can be queried regarding the variation of the search intensity along any search term so long as it has sufficient volume (the restriction is meant to, among other things, prevent deanonymization).

A Google Trends query has several parameters, which can be chosen within some limits. These are regional, temporal, search-term specific and Google-category specific. Regional parameters may vary from country to city level depending on the country. Temporal parameters go as far back as 2004 and can be any desired interval (data is then daily or weekly depending on interval length) and the search term can be anything so long as it does not exceed a certain length. The search term may be composite in many ways. Disjunctions are possible, i.e. "employment+unemployment" will give you search intensity for all searches containing "employment" or "unemployment." Complements are also possible, i.e. "employment-unemployment" will give you search intensity for searches containing "employment" without counting searches which contain "unemployment." Finally, a keyword or phrase can be quoted to restrict counting to the searches, which contain the exact keyword or phrase.

Google divides each search in categories – such as Health or Automotive – and search intensity along a certain keyword may be measured relative to a category. For example in order to capture solely the health-related searches seeking "symptoms of depression," one must exclude the business cycle-related searches, and so one can limit the measurements to within the Health category. Comparative queries are possible: up to five search terms in a single geographic unit for any time interval or up to five geographic regions for a single search term and any time interval.

Google Trends delivers time series which are scaled and normalized as follows: all data points of the time series will be normalized by dividing the search term volume with the total search volume in the reference time interval (day, week, month). This means if the keyword K has K_i searches in the ith reference time point and the total Google search volume therein is G_i, then the measurement would be $N(K_i) = K_i/G_i$. The latter is then scaled by setting the maximum value equal to 100 and scaling the rest accordingly; i.e. the series we get from Google Trends would be $I(K_i) = 100 \times N(K_i)/\max_i\{N(K_i)\}$. Finally, sampling is involved in forming these numbers and the results are robust for values that are high enough. For low values, results may be unreliable and caution should be applied.

One of the advantages of looking at search data (besides the fact that it is easily available in real time) is that, unlike voluntary surveys, it has no observer effects. It is well known, for example that depression in men is underreported because "depression is a female disease" (see e.g. Porche, 2005; Wilhelm, 2010). The general picture is that as men grow older, they are less likely to report depression but more likely to commit suicide than women. Men, however, should have no inhibitions in searching for information about "symptoms of depression" in the privacy of their home and during their internet sessions. On the other hand, a survey question of the type "Are you aroused by children's sexual abuse?" is unlikely to get any affirmative answers[12].

6. Health searches

Since the advent of the internet there has been a democratization of knowledge whose consequences, both positive and negative, can be felt in all aspects of life. Now more often than before, patients confront their doctors with a possible diagnosis rather than describe their symptoms. According to data from the Pew Internet & American Life Project, 80 percent of internet users have looked online for health information, making it a widespread activity among internet users in the USA. We expect similar numbers in Germany and other locations where there is sufficient internet penetration. Our analysis of Google Search for "symptoms" and "side effects" is therefore well-founded on ubiquity and adoption and should therefore have little, if any, bias from a possible selection effect.

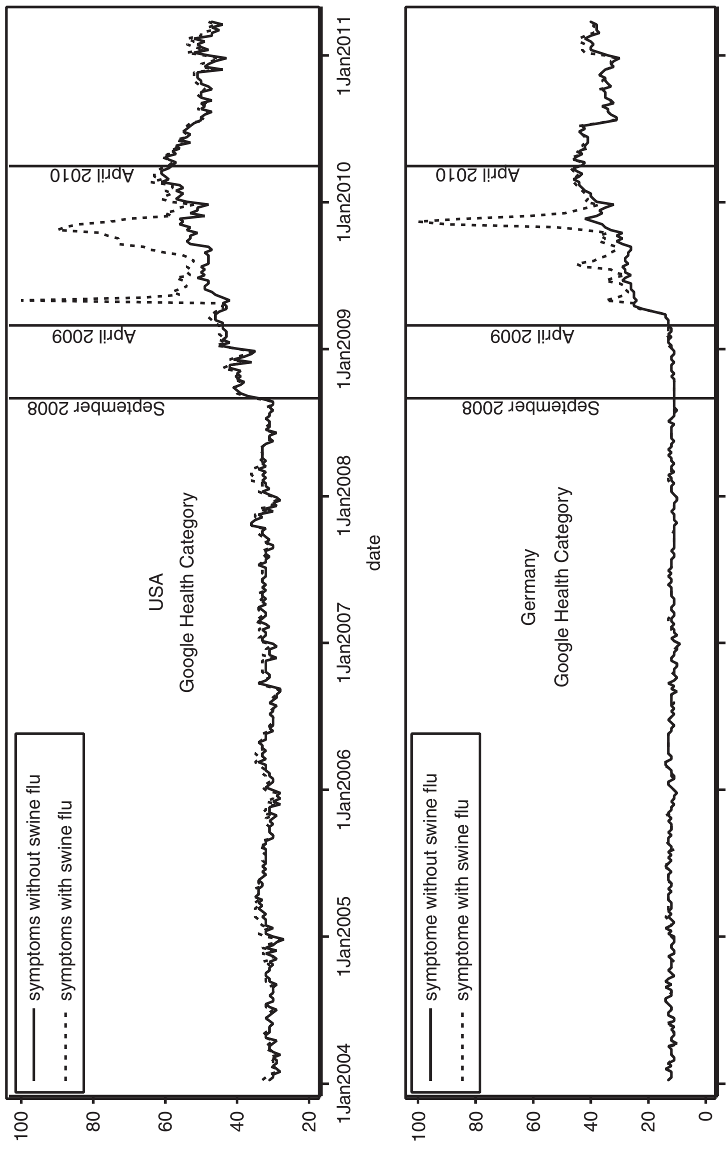
6.1 Symptoms

Typing "symptoms" as the first word of a query in Google returns several completion options such as "symptoms of mono," "symptoms of diabetes," "symptoms of pregnancy," etc. On the other hand by typing "depression," one is offered "depression symptoms" as one of the completion options and the same goes for "pregnancy," "anxiety," "heart attack," etc. So Google allows us a sneak peak at symptoms-related searches. There are many reasons why an internet user would search for symptoms of a disease. Many times it could be an attempt to self-diagnosis or do so for someone they care about. The reason people search (instead of say go to the doctor) may just be because there is a stock of knowledge out there that they can tap into, which then allows them to do many things such as better use a subsequent doctor's visit, learn about the experience of other patients with the same condition (e.g. pregnancy), diagnose themselves for malaise that they feel embarrassed about (i.e. men and depression symptoms, married and sexually transmitted diseases, etc.), or even because they are a hypochondriac or a medicine buff. In the USA the terms "e-patient" and "participatory medicine" are by now well-known[13]. Capturing the overall aggregate volume of this search activity is hence related in a multitude of ways to malaise.

Figure 2 shows us the intensity of symptoms searches in the USA and Germany. The rise started much earlier in the USA and in fact started soon after the dramatic September 2008 that was the break out of the financial crisis. In Germany, where the financial crisis had no immediate obvious impact, the surge occurred soon after April 2009 (the high point of a rather moderate rise in unemployment but also the high point of unemployment relief *Kurzarbeit*) at which point the financial crisis mutated to an economic crisis. They both peaked in April 2010.

We think that this clearly demonstrates that the crisis caused the surge in symptoms searches. Whether it means a rise in so-called participatory medicine or a rise in "pathogeny" and "malaise," it is at this point unclear and we will discuss it further.

Before we do so we would like to make two remarks on Figure 2. The dotted line shows us all searches containing "symptoms" (including the ones that contain "flu," "swine" or "H1N1"). The solid line shows us searches for symptoms without the aforementioned keywords in order to avoid the noise coming from the H1N1 epidemic, which is unrelated to the crisis. As a byproduct we see the impact of the epidemic on the searches for its symptoms. This is yet another verification that Google searches have content of interest for social sciences and epidemiology. We see in the graphs that there is indeed a significant impact of H1N1-related searches. Furthermore we see that the fact that the flu reached Europe with a delay is reflected in the difference between



Notes: While in the USA they surge as early as September 2008 (first vertical line), for Germany they do not do so until April 2009 (second vertical line). By April 2010 (third line) the searches more than doubled compared to the level before September 2008. We use "symptoms" and "symptoms flu – swine – H1N1" in the USA and "symptome" and "symptome – grippe – H1N1 – schweinegrippe" in Germany

Figure 2.
Symptoms searches in the Google Health Category in the USA and Germany

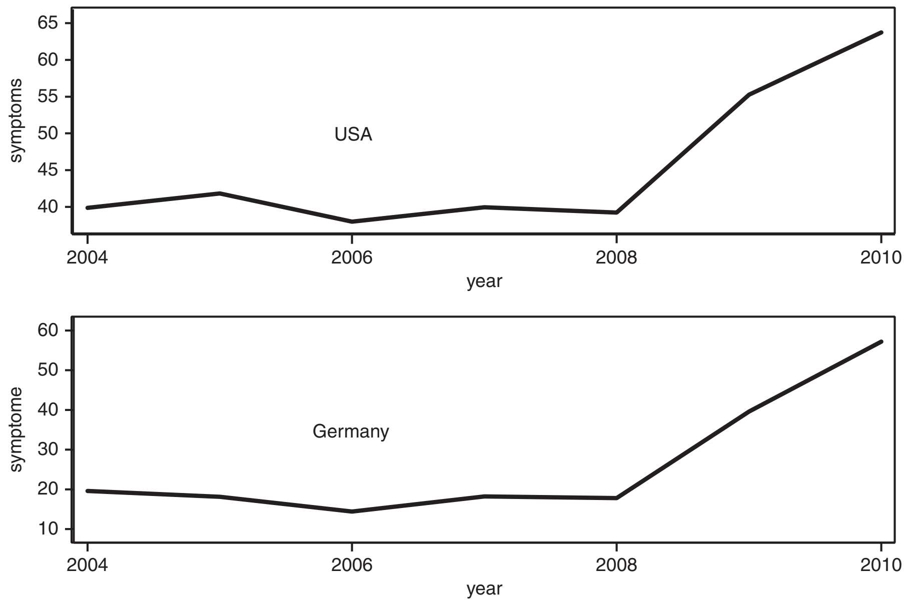
the first bumps in the USA case vs the German case and we also see that the flu has slowed down since.

Our second remark has to do with absolute volumes of these searches. While we cannot really determine how many searches included or how many people searched for the word "symptoms," we can use a ratio of search intensity for "symptoms" over search intensity for the most popular sport for which we have good intuition of its size: football. Figure 3 shows that in 2009 both ratios rise sharply. This serves as a kind of quantification of these numbers:

> In the US for every 100 football searches in 2007 we had about 40 for symptoms. By 2009 we had about 50 and by 2010 over 60. In the German case it went from under 20% to over 50% in 2010.

A few remarks are now due on Figure 3. The comparison is done globally (not in the Health category) because this would put football searches at a disadvantage. By doing so we inevitably introduce noise in the symptoms searches (non-health-related). The comparison is nonetheless helpful since over 75 percent of the symptoms searches fall within the Health Category in both countries. In order to get a feeling of the size of searches containing the word football or (fussball) we need to note that in Germany the mean of "*fussball+fußball*" searches since 2004 is a little over 50 percent of the mean of "porn" searches while in the US the comparison comes to a little under 50 percent. Considering that porn is the fourth most common activity on the internet (see Pass *et al.*, 2006), it gives us an idea of the volumes involved.

We performed a number of other explorations, all of which show that symptoms searches surge more intensely in comparison. One direction we looked at is other sports such as baseball or basketball. We also compared symptoms searches to "search white



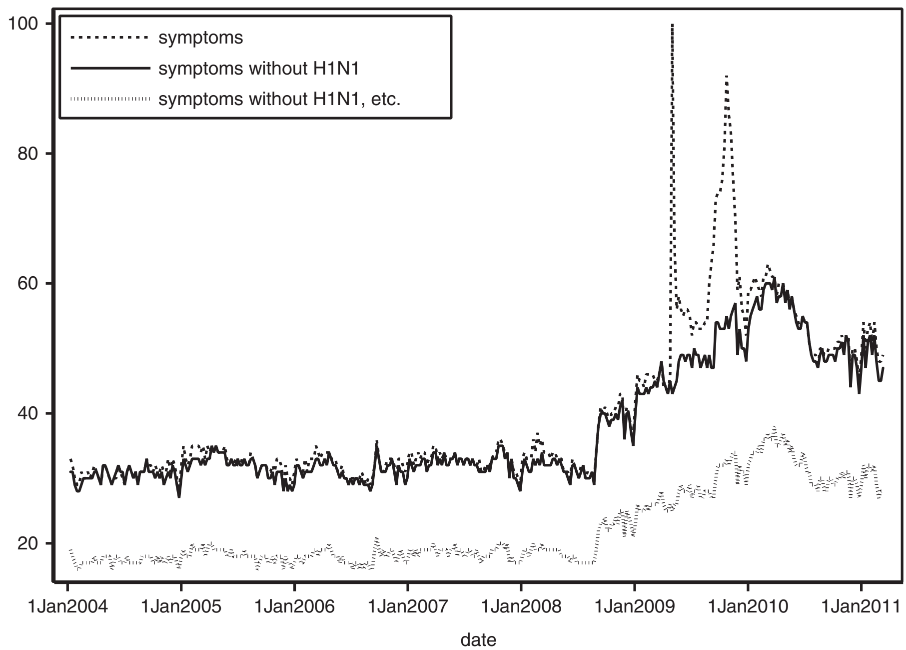
Notes: We use "football" and "symptoms – flu – swine – H1N1" in the USA and "fussball + fußball" and "symptome – grippe – H1N1 – schweinegrippe" in Germany

Figure 3. Annual averages of ratios of symptoms to football searches in the USA and Germany

noise" such as the disjunction of all days of the week, the disjunction of all months, all Arabic numerals, all Latin alphabet letters, etc. Finally we compared symptoms searches to searches containing each of the top ten most common English words[14].

We now want to return to the discussion of whether the crisis simply caused people to turn to the internet for health advice or whether it caused an increase of malaise. Quite likely it did both. Looking at Figure 4 we see that all symptoms searches spiked. In the graph we see the search intensity for symptoms broken down into three time series. The dotted line contains all symptoms searches. This time series contains the H1N1 epidemic so we subtract those and get a cleaned series (solid line). The dashed line is what we get by counting "symptoms" without those containing a number of associated terms. All series spike. Searches of symptoms of diseases with a lagged response to the crisis may contain more participatory medicine. For example while according to Martin-Moreno *et al.* (2010) cancer is expected to rise in economic downturns (changed working condition, cutting corners on safety, etc.), it is not something that spikes as easily as say anxiety symptoms. Nonetheless in the context of psychological distress and "irrational sullenness," even increases in symptoms searches of malaise with slow response may be an indication of generalized anxiety.

What supports the fact that the symptoms time series contains increased malaise is first that the surge begins with the financial crisis in September 2008 in the USA



Notes: This holds true even after we remove the following terms: H1N1, swine, flu, old, kidney, menopause, medical, herpes, withdrawal, Salmonella, and, allergy, infection, lyme, diabetes, AIDS, HIV, stroke, yeast, herpes, thyroid, autism, cancer, heart, attack, depression, anxiety, early, pregnancy. We stopped this exercise at the 30 word per query limit of Google Trends. The marvels of the long tail remain at this point a mystery

Figure 4.
A breakdown of symptoms searches in the USA shows us that all symptoms searches increase

whereas with the economic crisis in Germany in the spring of 2009; second, in Germany there is no organized "e-patient movement" and – unlike in the USA where less widespread health coverage may force people to self-diagnosis in times of economic downturn – despite a well-developed German social security system, "symptoms" searches still continued to increase. The Gallup Well-Being Index, along with its various components seen in Figure 1, also supports increased malaise in the USA. Finally from Figure 5 we see that the Google Category Health has grown by about 10 percent from its pre-crisis low to its post-crisis high, while symptoms searches grew significantly more. Moreover for more responsive types of searches such as "high blood pressure symptoms" we expect that a spike contains more malaise than patient participation than in the case of less responsive ones such as "chronic symptoms of Lyme disease."

Our conclusion is that while we cannot tell which part of the increase in symptoms searches is related to participatory medicine and which to the crisis causing increased malaise, we can say that it is due to both. The difficulty in validating this also has to do with the fact that in the searches there is malaise that may never express itself as a health-related expenditure or a doctor's visit either because of stereotyping (depression in men) or because the search spike is an expression of panic due to "irrational sullenness" or because the official numbers don't capture the truth (the unemployed cannot pay for a doctor's visit as easily in a recession).

We measured a number of other types of searches such as "heartburn relief," "acid reflux symptoms," "heart attack symptoms," "anxiety symptoms," "stroke symptoms" and "bipolar symptoms," all of which exhibit the same behavior. Figure 6 shows the search intensity for "symptoms of high blood pressure" in the USA. Here and elsewhere in the USA we see a shocking spike of the signal within a very short time around $t = \text{TARP}$. Finally in Figure 7 wescaled the US unemployment rate and symptoms

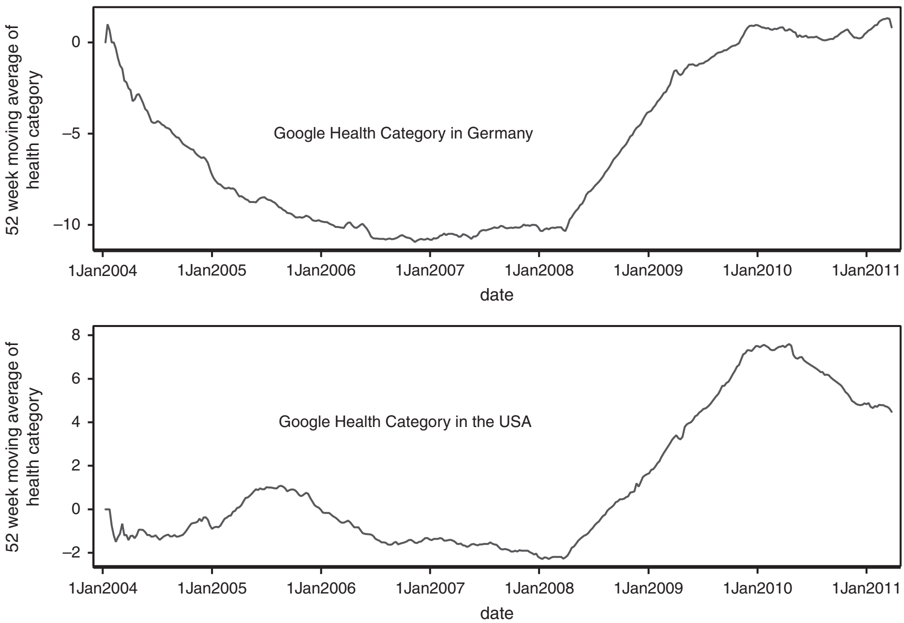


Figure 5. The growth of the google category: health

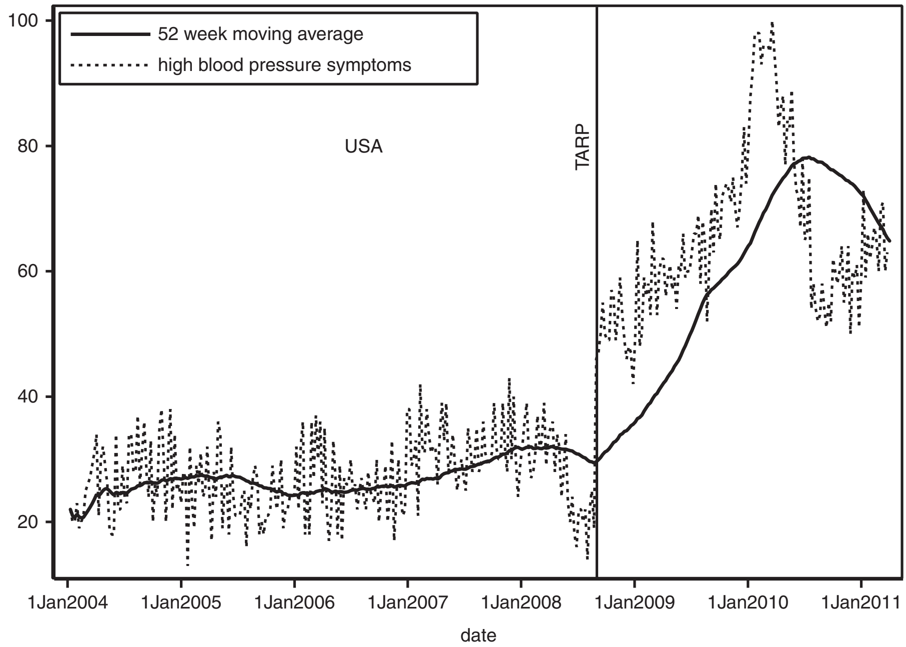


Figure 6.
Search intensity of "high blood pressure symptoms"

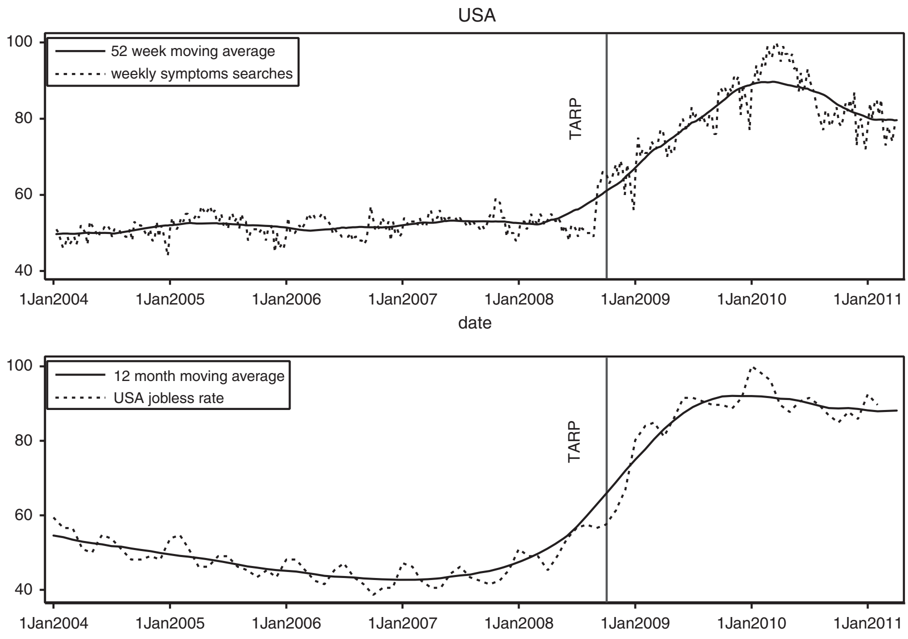


Figure 7.
Symptoms searches compared to changes in the labor market

searches in the USA with their own maximum value as a reference value. We see that the unemployment rate would "explain" symptoms searches well. The same is not true in Germany since unemployment rose only moderately but a combination of unemployment rate and *Kurzarbeit* would explain symptom searches well.

6.2 Side effects

US prescription sales grew by 5.1 percent in 2009 to over US$ 300 billion compared to 1.8 percent growth in 2008[15]. Moreover antidepressant sales grew by 4 percent in 2009 to 9.9 billion pushing the corresponding drug category one position up to number 4 in the list of the most consumed medications. This data is consistent with Figure 8, which shows the growth for side effectssearches in the USA, assuming an increase in searches for side effects implies an increase in the consumption of medication[16]. We believe this to be the case since the reason an internet user would search for say "Lexapro side effects" is because she or someone she cares about is currently consuming Lexapro or because she compares "Lexapro side effects" with "Xanax side effects" in order to decide which is best suited for her. We believe side effects searches to be closely correlated with medication and to be less affected by an increase in participatory medicine. In other words, unlike the case of symptoms searches – where we see a crisis-related increase, which is partly due to increased malaise and partly due to increased e-patient participation – in the case of side effects searches we believe that it is by far due to increased consumption of medicine. In the aggregate numbers this means an increase in searches of "side effects" implies an increase in medication consumption, which implies increased malaise. In the cases of prescription medicine we know that this is medically verified malaise. In the cases of over-the-counter medicine, we have self-reported subjective malaise. Both are significant.

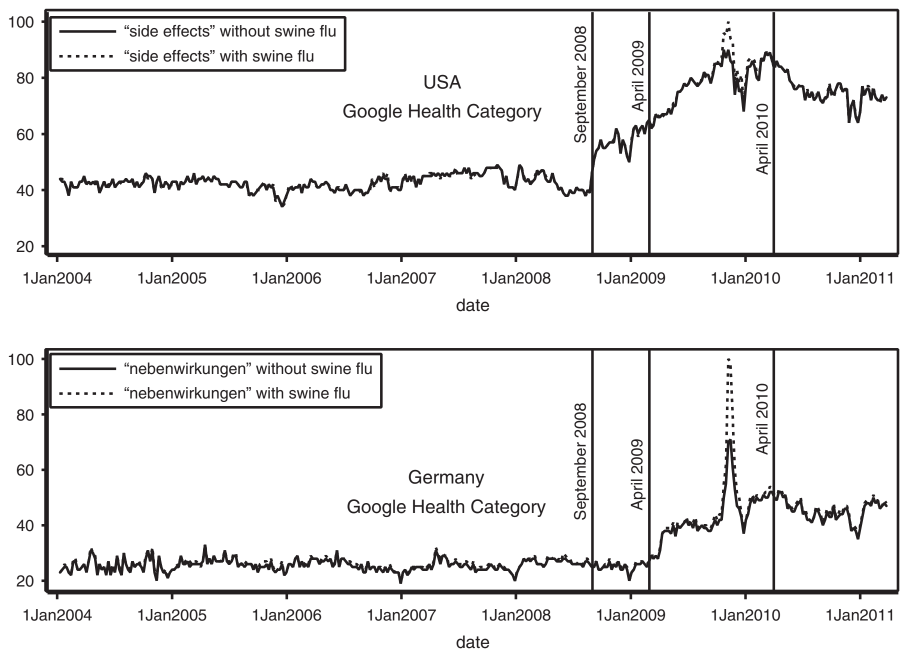


Figure 8.
Side effects search intensity: weekly series and smoothing

Explorations for side effects searches vs say football searches have similar results as for the symptoms searches in Section 6.1. Figure 9 shows us the searches for side effects of four well-known antidepressants: Lexapro, Celexa, Xanax and Zoloft. Similar increases can be observed in a series of other antidepressants[17]. The same lag in the spike is observed here as with symptoms.

Finally the surge in "symptoms" and "side effects" is to a large extent uniform across countries. Figures 10 and 11 show symptoms and side effects searches in the G8 countries. We see a surge in both kinds of searches around the TARP date. We note slight delays in all European countries except in France. Japan and Russia start surging before the TARP date, although in the Russian case the side effects search activity appears to be too small (an interesting fact in itself considering football searches between say Germany and Russia are comparable in volume across time). The numbers are relative so that volumes are not comparable across countries.

6.3 Further discussion

We observe a surge in malaise searches across the G8 and a closer look at the USA and German cases reveal a delay for the German surge, which is in concordance with the timeline of the crisis. These facts reasonably establish that the shock of the crisis caused the surge.

The obvious hypothesis that could have caused the spikes in these signals is that the crisis caused more people to be interested in symptoms or side effects information and hence more people were experiencing malaise of some kind (and taking some type of medication in the case of side effects). This is our preferred interpretation and in order to strengthen it we need to rebut alternative hypotheses that attempt to explain the

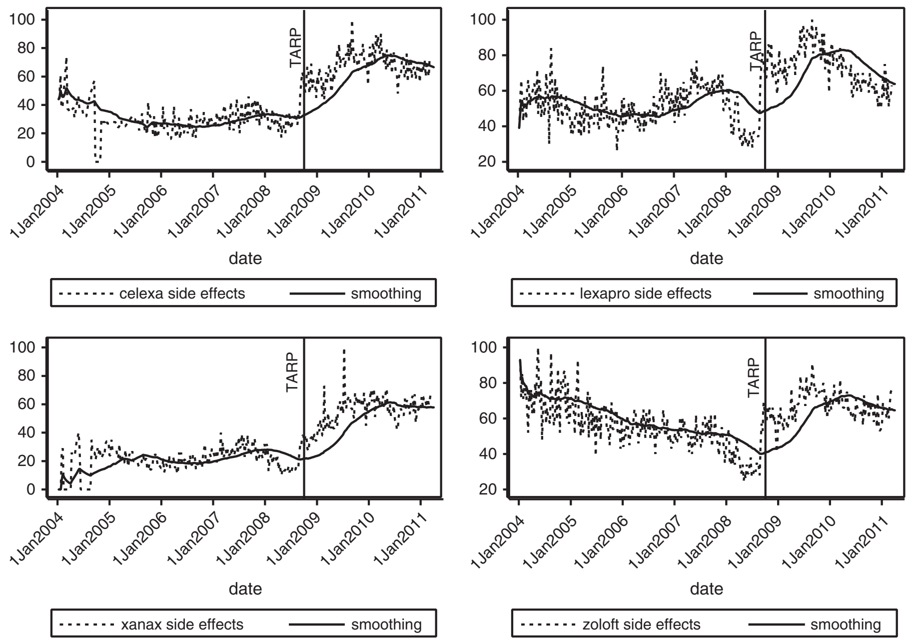


Figure 9.
Searches for the side effects of four well-known antidepressants: Celexa, Lexapro, Xanax, Zoloft

Note: Series are monthly and a 52-week moving average is added

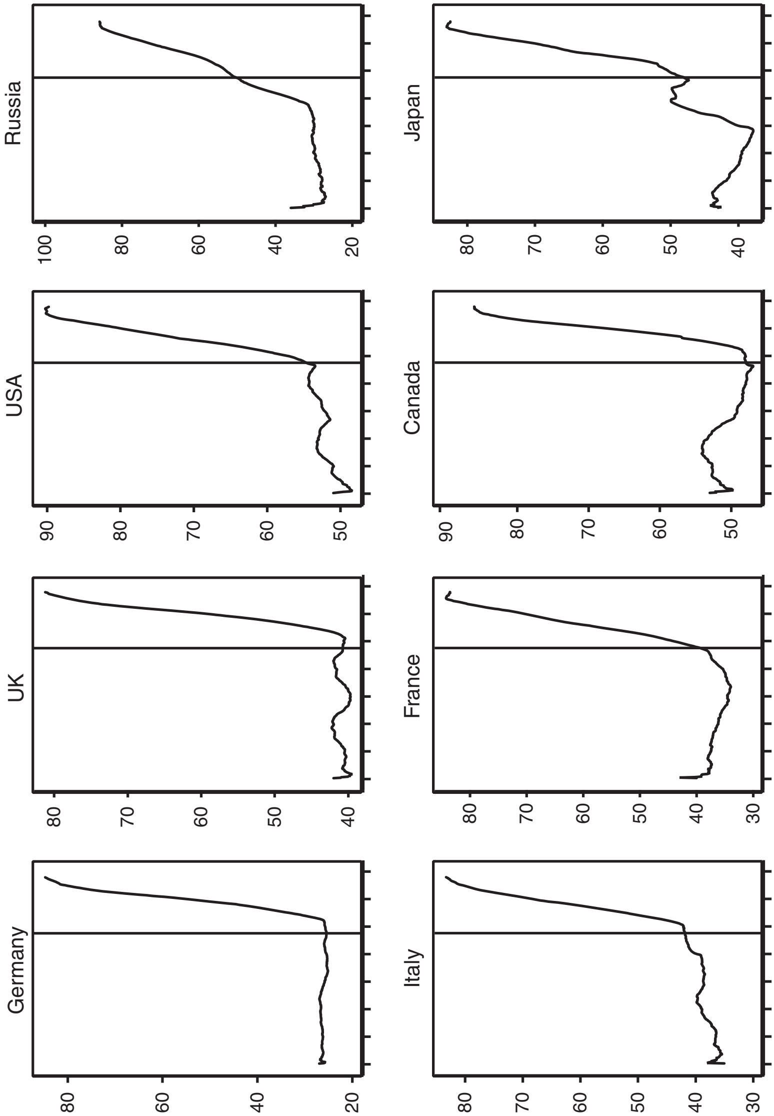


Figure 10.
Symptoms searches
in the G8

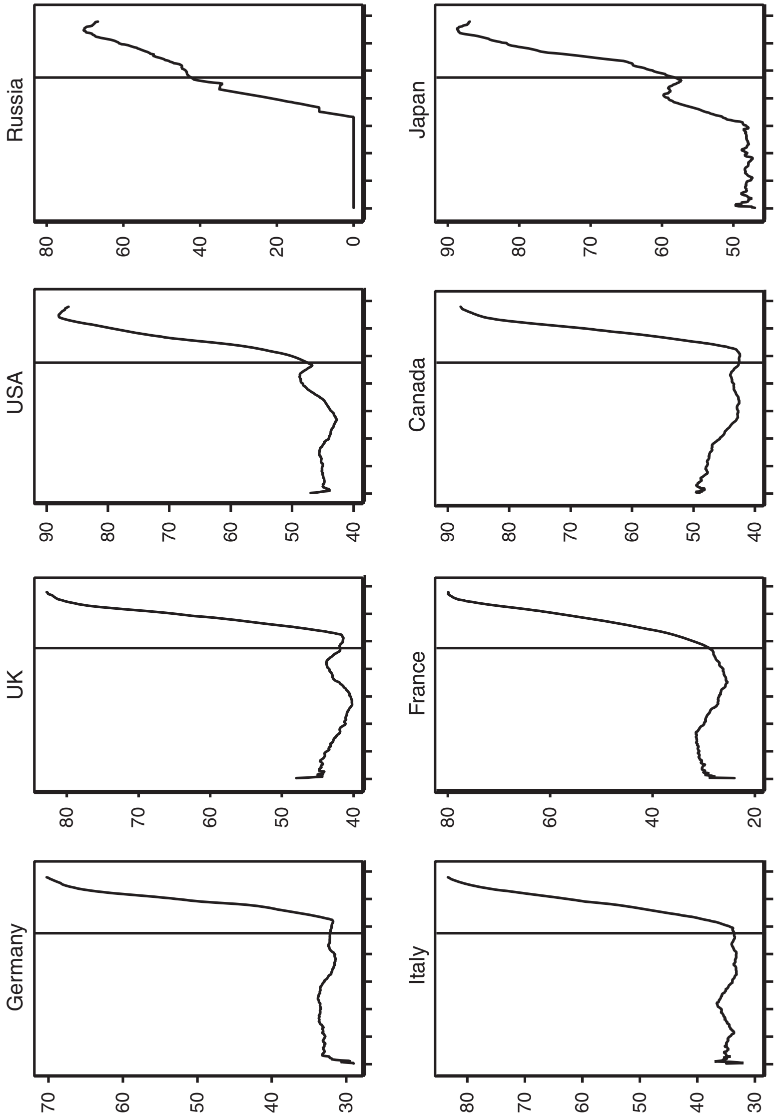


Figure 11.
Side effects searches in the G8

signal spikes in malaise searches without an increase in malaise. These stem from the reasonable assertion that the probability of uttering a certain word increases with the time or volume of utterance, just as the probability of finding a certain word in a text increases with the text's length. Alternative theories then propose that the signal spikes are not due to an increase in malaise but to increased reporting due to changes in the amount of time individuals allocate to searching.

In order to facilitate this discussion we need two formal definitions of the signal strength search volumes express. An individual's interest in certain documents (and lack of interest in others) is assumed to be a function of the individual's state and hence the individual's search queries attempting to discover these documents are as well.

These queries are therefore utterances worth investigating and monitoring the utterances may be thought of as an involuntary panel survey. On the aggregate level it is natural to define the signal $S_t(q)$ of a search query q or a disjunction thereof in a given reference time interval t. There are two obvious ways to do this. The first way is to simply count the number of respondents who searched for q within t and divide that by the number of respondents who searched for anything within t. A second definition is to weigh the contributions of individuals to the signal with a continuous function between [0,1] by dividing the number of times they searched for q by their total number of searches (one could also weigh by the number of clicks on the search results). The sum of all weighted contributions is then divided by the weighted sum of all searches within t and that will be the signal of q in that time interval t. We do not know which definition Google Trends uses, but we will try to make due without that knowledge.

The main difference between the two definitions is best captured by an epidemiological metaphor: the former definition counts the number of infections and is blind to their severity whereas the latter captures the severity. This means the latter cannot separate between surges in severity and surges in contagion.

One of the competing hypotheses, which would explain the signal spikes without increased malaise, suggests that the number of people (or even the group of people) who perform these malaise searches may remain fixed despite a strengthening signal. With our second signal definition this would mean that those experiencing malaise of some kind do so more intensely (starting at time $t = \text{TARP}$) but no new cases are added. It is certainly likely that say individuals with anxiety experience more malaise with any type of increased stress, but that alone would not suffice to explain the phenomenon as we know from the Gallup Well-Being Index that the self-reported malaise increased during the crisis very much at the same time as the malaise searches indicate.

Another, quite naturally arising, competing hypothesis proposes that, for example an ailing sports fan with limited leisure time may under normal circumstances first search for game results, rankings and interviews and may likely neglect searching for symptoms. However, if for some reason (like unemployment or slow business in the recession) the respondent spends more time searching, it may become more likely that she searches for symptoms. This way we get a spike in the signal but it reveals malaise, which was there to begin with. The crisis would then not cause new malaise but it would indirectly cause more reporting thereof because the real effect is that people have more time.

Data by Forrester (forrester.com) shows that while internet use has been increasing since 2004, it actually declined during the crisis years (i.e. from 2008 to 2009)[18]. This contradicts our alternative hypothesis since it implies increased internet time.

Moreover, the signal remained flat all the way through the increasing internet use between 2004 and 2008. For this hypothesis to remain true we would need to reveal preexisting malaise while at the same time have non-malaise searchers spending less time on the internet. This would imply that for some reason the crisis endowed ailing people with more time and healthy ones with less. While this could partially be the case (e.g. if ill people are fired first and the healthy ones still employed are now overworked), it does not seem to suffice as the sole explanation. This is most obvious in the case of side effects searches.

Another way in which increased signal due to newly revealed preexisting malaise can occur is that self-diagnosis substitutes a doctor's visit on financial grounds. This could hold in the case of the USA but it would certainly not hold in the German case where a more comprehensive social state is in place. Overall it is hard to imagine how this hypothesis would fit with side effects searches, which are very likely to be related to new treatments. In this case it would mean that at time $t = \text{TARP}$ medicated people decided to explore side effects that they had had all along.

7. Conclusions

We presented internet search data to show that the crisis impacted health and well-being in the USA, Germany, and the G8 countries and corroborated this evidence with data from different, more traditional sources. We performed due diligence checks in order to exclude several alternative hypotheses. The impact of the crisis on health and well-being has mainly been due to widespread welfare erosion but may well have been exacerbated by excessive reporting, which produced what we call irrational sullenness. Whichever the reason, its impact is real. Search data for symptoms and side effects across the G8 countries – where internet penetration[19] is high and such data are more reliable – show that mental, emotional and physical discomfort were severely affected very much in concordance with both the crisis' intensity and its contagion timeline.

Internet as a source of data, in our opinion, can be valuable for the social sciences; particularly relevant is search data, which can be viewed as a sort of involuntary panel survey. This is demonstrated via Google Trends, which – despite the loss of information that aggregation causes – provides us with unique insights into large-scale processes. The intensities of symptoms and side effects searches provide the basis for health indicators capturing self-diagnosis and treatment, respectively. We believe that with access to search microdata and more sophisticated techniques, these indicators could be important for public health policy-making and prevention.

Notes

1. "Some 69% of Americans have used the Internet to cope with the recession as they hunt for bargains, jobs, ways to upgrade their skills, better investment strategies, housing options, and government benefits": http://authoring.pewinternet.org/Reports/2009/11-The-Internet-and-the-Recession.aspx. Moreover, "eight in ten internet users look online for health information, making it the third most popular online activity": www.pewinternet.org/~/media//Files/Reports/2011/PIP_HealthTopics.pdf. Since 25 percent of adults are offline, it means that 59% of the total population seeks health information online.
2. The term "participatory medicine" is well-known in the USA.

3. We are well aware that a host of additional confounding factors exist which would require more research to shed line on. Access to good samples of search microdata would help clear some of the issues we will discuss but as researchers we are currently nowhere near an opportunity to accessing such data.
4. All data used in this paper are public and in fact freely available on the internet. Whenever the data is proprietary, we collected it from publicly available reports (available online) and occasionally we had to dissect a CGI or two to programmatically capture publicly plotted data (as in the case of the Gallup Well-Being Index).
5. The most dramatic time is the 60 days before that date but October 3, 2008 is by far the most memorable date to keep in mind.
6. *Kurzarbeit* ("short work") describes a labor market policy instrument that is used to absorb seasonal labor fluctuations. It does so by allowing employers to retain instead of firing employees; it was used in the crisis to stabilize the labor market. See for details also Brenke *et al.* (2013) and Rinne and Zimmermann (2012).
7. See Layard (2013) for the mental health issue.
8. The phenomenon is similar to the 2003 invasion of Iraq being like no other war: this was the birth of "embedded journalism."
9. "But how do we know when irrational exuberance has unduly escalated asset values, which then become subject to unexpected and prolonged contractions as they have in Japan over the past decade?" Alan Greenspan, Chairman of the Federal Reserve Board in Washington, DC in his speech "The Challenge of Central Banking in a Democratic Society" given at the American Enterprise Institute on December 5, 1996: www.federalreserve.gov/BOARDDOCS/SPEECHES/19961205.htm
10. More on the Gallup Well-Being Index and its methodology can be found at: www.well-beingindex.com/
11. www.google.com/trends/
12. This may be useful in many types of research. Since 2004, on average there have been three to four times more searches for "child porn" than for "girls volleyball."
13. In July 2009 the Society for Participatory Medicine was founded: http://participatory medicine.org
14. We used the ranking obtained from the American National Corpus, an open data repository for language research and education: www.americannationalcorpus.org/SecondRelease/data/ANC-written-count.txt
15. Data by IMS Health: www.imshealth.com
16. Pharmaceutical sales, as measured in total revenue, do not always reflect the amount of pharmaceuticals consumed. Shrinking revenue is not incompatible with increasing consumption. This can occur when patents expire and cheaper alternative brands or no-name drugs emerge. Also according to IMS Health, the reduced growth in 2008 was partly due to the economic downturn. It seems as though an ensuing downturn first affects consumption.
17. Side effects (*Nebenwirkungen*) searches in Germany spike similarly.
18. The report is proprietary but we can point the reader here: http://news.cnet.com/8301-1023_3-10297935-93.html
19. With the exception of Russia (53.3 percent) for G8 countries over 80% of their population are internet users. Identifying who the underprivileged non-internet users are and how this affects our narrative is an open question.

References

Arinaminpathy, N. and Dye, C. (2010), "Health in financial crises: economic recession and tuberculosis in central and Eastern Europe", *Journal of The Royal Society Interface*, Vol. 7 No. 52, pp. 1559-1569.

Askitas, N. and Zimmermann, K.F. (2009), "Google econometrics and unemployment forecasting", *Applied Economics Quarterly*, Vol. 55 No. 2, pp. 107-120.

Bersier, F. (2010), "Towards better policy and practice using real-time data", *SSRN eLibrary*, available at: http://ssrn.com/abstract=1614970

Brenke, K., Rinne, U. and Zimmermann, K.F. (2013), "Short-time work: the German answer to the great recession", *International Labour Review*, Vol. 152 No. 2, pp. 287-305.

Brenner, M.H. (1973), *Mental Illness and the Economy*, Harvard University Press, Cambridge.

Brenner, M.H. (1975), "Trends in alcohol consumption and associated illnesses: some effects of economic changes", *American Journal of Public Health*, Vol. 65 No. 12, pp. 1279-1292.

Brenner, M.H. (1979), "Mortality and the national economy", *The Lancet*, September 15, pp. 568-573.

Clark, A.E. and Oswald, A.J. (1994), "Unhappiness and unemployment", *The Economic Journal*, Vol. 104 No. 424, pp. 648-659.

D'Amuri, F. and Marcucci, J. (2010), "Google it. Forecasting the US unemployment rate with a google job search index", *SSRN eLibrary*, FEEM Working Paper No. 31, available at: http://ssrn.com/abstract=1594132

Frey, B.S. (2008), *Happiness: A Revolution in Economics*, CES, Munich.

Ginsberg, J., Mohebbi, M.H., Patel, R.S., Brammer, L., Smolinski, M.S. and Brilliant, L. (2009), "Detecting influenza epidemics using search engine query data", *Nature*, Vol. 457 No. 7232, pp. 1012-1014.

Kholodilin, K.A., Podstawski, M. and Siliverstovs, B. (2010), "Do google searches help in nowcasting private consumption? A real-time evidence for the US", KOF Swiss Economic Institute Working Paper No. 256, DIW Berlin Discussion Paper No. 997, available at: http://ssrn.com/abstract=1615453

Kholodilin, K.A., Podstawski, M., Siliverstovs, B. and Bürgi, C. (2009), "Google searches as a means of improving the nowcasts of key macroeconomic variables", DIW Berlin Discussion Paper No. 946, available at: http://ssrn.com/abstract=1507084

Kulkarni, R., Haynes, K.E., Stough, R.R. and Paelinck, J.H.P. (2009), "Forecasting housing prices with google econometrics", GMU School of Public Policy Research Paper No. 2009-10, available at: http://ssrn.com/abstract=1438286

Layard, R. (2013), "Mental health: the new frontier for labour economics", *IZA Journal of Labor Policy*, Vol. 2, p. 2, doi:10.1186/2193-9004-2-2.

Martin-Moreno, J.M., Alfonso-Sanchez, J.L., Harris, M. and Lopez-Valcarcel, B.G. (2010), "The effects of the financial crisis on primary prevention of cancer", *Eur J Cancer*, Vol. 46 No. 14, pp. 2525-2533.

Pass, G., Chowdhury, A. and Torgeson, C. (2006), "A picture of search", *InfoScale '06: Proceedings of the 1st international conference on Scalable information systems*, Hong Kong.

Porche, D.J. (2005), "Depression in men", *The Journal of Nurse Practicioners*, Vol. 1 No. 3, pp. 138-139.

Rinne, U. and Zimmermann, K.F. (2012), "Another economic miracle? The German labor market and the great recession", *IZA Journal of Labor Policy*, Vol. 1, p. 3, doi:10.1186/2193-9004-1-3.

Ruhm, C.J. (2000), "Are recessions good for your health?", *Quarterly Journal of Economics*, Vol. 115 No. 2, pp. 617-650.

Schmidt, T. and Vosen, S. (2009), "Forecasting private consumption: survey-based indicators vs Google Trends", Ruhr Economic Paper No. 155, available at: http://ssrn.com/abstract=1514369

Schmidt, T. and Vosen, S. (2010), "A monthly consumption indicator for Germany based on internet search query data", Ruhr Economic Paper No. 208, available at: http://ssrn.com/abstract=1692719

Sims, G. (2010), "The demand for information", *SSRN eLibrary*, available at: http://ssrn.com/abstract=1630244

Tefft, N. (2011), "Insights on unemployment, unemployment insurance, and mental health", *Journal of Health Economics*, Vol. 30 No. 2, pp. 258-264, available at: http://dx.doi.org/10.1016/j.jhealeco.2011.01.006

Varian, H.R. and Choi, H. (2009), "Predicting the present with Google Trends", Google Research Blog, available at: http://ssrn.com/abstract=1659302

Wilhelm, K.A. (2010), "Men and depression", *Australian Family Physician*, Vol. 38 No. 3, pp. 102-105.

Further reading

Celjo-Hörhager, S. and Niessen, A. (2006), "How do self-fulfilling prophecies affect financial ratings? – an experimental study", CFR-Working Paper No. 06-13, CFR, Cologne.

Classen, T.J. and Dunn, R.A. (2011), "The effect of job loss and unemployment duration on suicide risk in the United States: a new look using mass-layoffs and unemployment duration", *Health Economics*, Vol. 21 No. 3, pp. 338-350.

Lewis, G. and Sloggett, A. (1998), "Suicide, deprivation, and unemployment: record linkage study", *BMJ*, Vol. 317 No. 7168, pp. 1283-1286.

Linn, M.W., Sandifer, R. and Stein, S. (1985), "Effects of unemployment on mental and physical health", *Am J Public Health*, Vol. 75 No. 5, pp. 502-506.

Murphy, G.C. and Athanasou, J.A. (1999), "The effect of unemployment on mental health", *Journal of Occupational and Organizational Psychology*, Vol. 72 No. 17, pp. 83-99.

Narayan, P.K. (2010), "Modelling health and output at business cycle horizons for the USA", *Health Economics*, Vol. 19 No. 7, pp. 872-880.

Wilcox, W.B. (2009), "The Great Recession's Silver Lining", *The State of our Unions: Marriage in America*, pp. 15-22.

About the authors

Dr Nikolaos Askitas is the Director Data and Technology of the Institute for the Study of Labor (IZA, www.iza.org). His published Mathematics research is in the areas of four-dimensional topology and knot theory. His current research interests are in the areas of technology and economics and game theory and economics. He is a Member of the Experts Committee of the Data Documentation Initiative (DDI alliance, ddialliance.org), an Advisor at the Open Data Foundation (ODaF, odaf.org), and a Speaker of the German Research Data Infrastructure (FDI) to the German Data Forum (RatSWD, ratswd.de). He is an Inventor and a Coorganizer of EDDI (eddi-conferences.eu) the Annual European DDI Conference.

Klaus F. Zimmermann is a Professor of Economics at the Bonn University, the Director of IZA, an Honorary Professor of Economics at the Free University of Berlin and an Honorary Professor at the Renmin University of China in Beijing. He is a Member of the German Academy of Sciences Leopoldina, Academia Europaea, has advised many national governments, the World Bank and the European Union Commission, and is the author or editor of 49 books and 143 papers in refereed research journals and 145 chapters in collected volumes. Professor Klaus F. Zimmermann is the corresponding author and can be contacted at: zimmermann@iza.org

This article has been cited by:

1. Nikolaos Askitas, Klaus F. Zimmermann. 2015. The internet as a data source for advancement in social sciences. *International Journal of Manpower* **36**:1, 2-12. [Abstract] [Full Text] [PDF]