The life satisfaction literature has boomed in the last decades since economists have access to more accurate databases allowing to test the impact of alternative variables on subjective well-being. A still unexplored issue is the relationship between financial crises and life satisfaction, due to the difficulty of collecting aggregate information at high frequency. Our proxies of life dissatisfaction used to overcome such difficulty are the normalized number of individuals searching the world happiness from Italy and from Germany on Google.

We propose a simple model to explain the relationship among life dissatisfaction, Google happiness search and the level of the spread between the 10-year yields of Italian and German government bonds. We empirically find a strongly significant and positive correlation between the spread and happiness, net of the impact of confounding controls, as predicted by our model. When testing the direction of the nexus we find that the spread Granger causes the Google “happiness” search, showing that financial crises decrease well-being.

Keywords: life satisfaction, financial crises, spread

JEL Numbers: D31,D53, I31,G01
1. Introduction

Research on happiness has made considerable progress during the last decade. Economists have built theoretical models with utility/happiness functions based on stringent assumptions on individual preferences, since data on subjective well-being were not available. More recently, however, the wide availability of databases measuring life satisfaction for large samples of individuals in many countries has made possible to test the validity of the assumptions on preferences.

A still unexplored issue is, however, the investigation of the link between happiness and the fear of losing one’s own material wellbeing due to the risk of financial crises. One of the reasons is the scarcity of aggregate high frequency data on subjective well-being which prevents the analysis of the relationship between financial volatility and happiness. Currently available large panels (such as the German Socioeconomic Panel, Eurobarometer, World Value Survey or the British Household Panel Survey) provide yearly life satisfaction data. There are also surveys which use the momentary affect approach, recording changes in life satisfaction during the day for a limited sample of individuals (for an overview see Kahneman and Kreueger, 2006). Even in the presence of high frequency data (as in the case of the Gallup Healthways Well-being Index providing daily values for well-being in the US) the use of self-reported well-being, even though inspiring fundamental contributions in the literature, has several limits, since data may be influenced by the way questions are formulated, the order of questions, the actual mood and the period in the life cycle of respondents. Schwarz (1987) documents experimentally that individuals tend to overweight most recent events in their subjective wellbeing evaluations, while Schwarz and Clore (1983) demonstrate that atmospheric conditions affect life satisfaction answers. Distortions may also arise since many individuals are tempted to hide true emotions to conform to their self-image, for fear to be

\textsuperscript{1} Note however that part of the fear involves that of losing employment which is not just related to an economic but as well to a psychological loss as documented by Winkelmann and Winkellman (1998).
criticised, desire to appear better, happier or to be commiserated. Another possible cause for lack of sincerity is the tendency to give socially desirable answers (Furnham, 1986; Konow and Earley, 2008). Since socially desirable opinions are culture-dependent, the propensity to report distorted levels of happiness is highly variable across countries (Diener and Lucas, 2000).

Our paper aims to bridge this gap by constructing a high frequency indicator of life satisfaction based on the normalized number of individuals searching on Google the word “felicità” (happiness in Italian) from Italian web addresses and “glück” (happiness in German) from German web addresses. A major advantage of using our proxy is that it successfully deals with the well known ordinality and interpersonal comparability problems of a subjective qualitative indicator as life satisfaction\(^2\). The choice of searching the word happiness on the web is interpersonally comparable and the number of people who search can be counted and aggregated.

We study whether this variable is affected by the level of the spread between the 10-year yields of Italian (BTP) and German (Bund) long term government bonds. Our empirical results test a hypothesis derived from a simple theoretical model. We assume individuals’ happiness as depending on income (beyond other factors which are not the focus of our analysis). Individuals are risk averse and a higher spread increases the probability of a financial crisis. An increase in the probability of a financial crisis raises the perceived volatility of income, thereby reducing happiness. Since high frequency aggregate happiness cannot be measured, we proxy it with the number of people searching for the word “happiness” on Google. The link between the change in

\(^2\) One of the most recent methodological advancements to tackle the problem of interpersonal comparability of self-assessment is the vignette approach (see Corrado and Weeks, 2010). The approach identifies “anchoring vignette questions” illustrating the situation of an individual whose life satisfaction must be evaluated by all survey respondents (King and Wand, 2007). Differences in evaluating the common situations are then used to tune individuals’ heterogeneous life satisfaction scales when evaluating their own subjective wellbeing response. To clarify with an example, Danes have usually very high average life satisfaction levels. If however they report on average higher life satisfaction values when evaluating the common vignette question with respect to respondents of another nationality (who reported for themselves a lower average life satisfaction level), their apparently superior life satisfaction is in part due to their tendency to inflate life satisfaction evaluations and answers on their subjective wellbeing have to be considered upward biased. Recent contributions however show that the two assumptions on which the validity of the vignette approach holds (vignette consistency and response equivalence) are not always supported by empirical evidence (Bago d’Uva et al., 2011; Ferrer-I-Carbonell et al., 2010).
aggregate happiness and our proxy is the following: happiness maximizing individuals search the word “happiness” on the web if benefits from search are higher than costs. Benefits are modelled in terms of the expected value of search which corresponds to the probability of finding on the web information which may increase one’s own happiness times the happiness gap, that is, the difference between the maximum attainable happiness and its current level. Costs of search are modelled as being invariant across individuals. As a consequence, the benefit from search is higher for individuals with a lower happiness level.

A prediction of our model is that an increase in the spread raises the probability of a financial crisis, which in turn raises the number of individuals searching the word happiness on the web.

Our empirical findings do not reject the hypothesis that the number of people searching the word “happiness” on the web correlates positively with the spread after controlling for this confounding factor. The result is significant in both countries but is stronger for Italy than for Germany where costs and benefits of the financial crisis are not so clear cut especially at high spread levels. The result in Italy is robust econometrically and Granger causality tests highlight a clear direction of causality from the spread to the Google search for happiness. Overall, our empirical results provide novel evidence of the adverse effects of financial crises on well-being.

The paper is divided into six sections (introduction and conclusions included). The second section illustrates the theoretical framework for the model that it is built in section three. The fourth section presents descriptive findings and the database. The fifth section discusses econometric findings. The sixth section concludes.

2. Happiness, money and financial crises

The growing interest for understanding the relation between money and happiness has been stimulated by the discrepancy between average per capita GDP and life satisfaction over time observed in several countries, most notably in the US, in the second post-war period. Despite the
fact that the research on the money-happiness nexus dates back to the work by Malthus (1798/1970), Marshall (1890), Veblen (1899), Duesenberry (1949) and, more recently, by Hirsch (1976), the policy relevance of the money-happiness paradox was first illustrated by Easterlin (1974).

The literature originated by the Easterlin paradox finds that the relationship between money and income tends to be concave, consistently with the shape postulated for standard utility functions. Returns from increased income in terms of life satisfaction tend to be high when starting from low levels of economic wellbeing, while becoming much smaller when the initial level of economic affluence is high. Recent work has employed exogenous shocks on income to overcome endogeneity and reverse causality problems, confirming positive but decreasing returns on subjective wellbeing. Notable examples are tsunami related effects on income (Becchetti and Castriota, 2007), lottery wins (Gardner and Oswald, 2007) or changes in real income in Russia and East Germany after transition and reunification (Frijters et al., 2004a, 2004b and 2006). The paradox is confirmed by Blanchflower and Oswald (2004) in the period going from the early 1970s to the late 1990s, for United States, Great Britain, Belgium and Japan. Similar results are obtained by Veenhoven (1993) in Japan over the period 1958-1987 and Frey and Stutzer (2002) on a large sample of countries using data from the World Database of Happiness and the U.S. Bureau of Census. The paradox has been recently challenged by Stevenson and Wolfers (2008) to whom Bartolini et al. (2008) and Easterlin and Angelescu (2009) replicate.

The relation between happiness and capital markets has, however, been less explored. There are interesting analyses of the link between confidence in economic conditions and capital markets and a recent work showing the relation between stock market volatility and happiness but no studies, to our knowledge, investigating the effects of financial crises on happiness.

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3 Lowell (1975), Otoo (1999), Howrey (2001), Fisher and Statman (2003), Ludvigson (2004), using the Consumer Sentiment Index, measured by the University of Michigan and the Conference Board’s Consumer Index, have tried to
The nature of the adverse effects on happiness caused by financial crises is arguably one of the most important issues on the research agenda. Socioeconomic status is an important predictor of a range of health and illness outcomes (Baum et al. 1999). According to psychological and medical studies, financial distress generate both mental and psychical health problems that affect the adults’ individual well-being, independently of their age but depending on their income level (Dooley et al., 1996; Drentea and Lavrakas, 2000; Bagwell and Kim, 2003; O’Neil et al., 2005; Garman et al., 2007). For instance, financial difficulties are proven to increase the level of anxiety and depression in students (Lange and Byrd, 1998; Andrews and Wilding, 2004): daily financial stress affects individual’s perceptions regarding the sustainability of their current financial situation and their ability to understand the underlying reasons, undermining their sense of control and self-esteem. Financial strain is also proved to increase emotional health risk and absenteeism for employees (Prawitz et al., 2006, 2010) and depression for elderly adults, especially for those who have inadequate information support (Krause, 1987). Financial and economic crises determine a raise in income inequality, social polarisation and significant pro-rich inequalities fostering three main psychopathologies: depression, suicidal thoughts and suicidal attempts (Hong et al., 2011), which in turn produce losses in terms of standard economic indicators, such as productivity and hours worked. To sum up, financial crises are expected to generate consequences on economic variables, thereby affecting through them subjective wellbeing and generating psychological costs which have in turn feedback effects on standard economic variables. If this is the case there should be an empirically testable causality nexus going from the fear of financial crises to life satisfaction,

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explore the connection between the confidence in expected business conditions, and capital market evolution. High stock returns increase consumer confidence since households perceive changes in stock prices as a leading indicator of future labor income. Otto (1999) and Ladwigson (2004) found the same effect for individuals that own stock compared with those who do not. In addition, investors fail to fully understand stock markets and believe that good stocks are just stocks of good companies. The use of consumer index sentiment to explain the correlation between sentiments and capital markets is subject to the criticism that they do not add new information not already available from standard financial market indicators. Using the Gallup Healthways Well-being Index, Standard&Poor’s S&P 500 and the VIX volatility index, Murgea and Reisz (2012) show a strong and statistically significant negative impact of stock market volatility on well-being.
Our paper aims to contribute to this growing literature by proposing an innovative way of measuring happiness and empirically testing a theoretical model linking financial crises with happiness.

3. The model

3.1. Motivation

The starting point in our model is the assumption that the number of people searching the world “happiness” on the web is inversely correlated with aggregate life satisfaction, based on the presumption that individuals are more likely to search for something when they do not have it, that is, they are searching “happiness” because they are not happy.

Our reasoning goes as follows: if utility/happiness maximising individuals are already happy they do not need to find on the web what happiness is. This is because, for them, the marginal benefit from the “happiness” search on the web is likely to be lower than the marginal (opportunity cost) of searching such word. The marginal benefit would be in fact given by a further increase in happiness which is nil or negligible if they are already happy. On the contrary, if individuals are in a state of unhappiness, the marginal benefit of finding something inspiring on the web about happiness may more than compensate the opportunity cost of browsing, which is conveniently assumed to be equal between those who are happy and those who are not.

This hypothesis is confirmed by evidence on the behaviour of web surfers, increasingly looking for information when they have (or are afraid to be affected by) some illness (Brodie et al., 2000; Dickerson et al., 2004; Ybarra and Suman, 2006). These individuals run the cost of looking for information on something not nice since the expected benefit of solving their doubts is larger than for individuals that are not (or not afraid to be) affected by that illness.
Consider that the top ranked sites appearing on Google when clicking the word “felicità” (happiness) are a definition of happiness from Wikipedia and happiness quotes from Wikiquotes. This is followed by videos and definition of happiness (see Figure 1). Something similar happens when we digit the word “glück” from German websites or the word “happiness” from Italian and German websites. Hence, searching for the word happiness on the web may provide inspiration and ideas on how to be happy, ideas which are more precious for those who are not happy than for those who are.

In the next section we describe our simple theoretical model, based on the assumptions discussed.

3.2. The model

Individuals decide to search the word happiness on the internet only if the expected utility exceeds the cost of browsing. Starting from this assumption, let us define the individual happiness/utility as depending on income:\(^4\):

\[ U(Y) \text{ with } U[0, U_{\text{max}}] \]  \hspace{1cm} (1)

The benefits from happiness web search are:

\[ B_{\text{gs}}(t) = \pi \delta(a) \Delta U t \text{ with } \pi, \delta \in [0,1], \quad \delta \cdot (a) > 0 \]  \hspace{1cm} (2)

where \( \pi \) is the probability of finding something on the web (by searching on Google) which may contribute to increase one’s own happiness, \( \delta \) is the amount of the gap which a successful research is expected to bridge, while \( \Delta U t = (U_{\text{max}} - U t) \) is the gap between the maximum attainable level of

\(^4\)As we know from the literature life satisfaction depends on many other nonfinancial factors beyond income which are uncorrelated with the spread and the likelihood of a financial crisis. Utility depends also on other financial factors (such as changes in wealth and probability of being employed in the future) which we omit for simplicity since we assume that the spread affects them in the same way as it affects income.
happiness \((U_{\text{max}})\), and the current individual happiness level \((U_t)\). We also assume that the amount of the happiness gap bridged depends on the individual search ability \(a = H^B A^V\) where the latter is in turn function of education \((H)\) and age \((A)\): \(B_{Gs}\) can therefore be considered as the expected value of happiness web search.

On the other side, costs of search are defined as:

\[
C_{Gs(t)} = H^e A^d
\]

where the cost of browsing is assumed to be a decreasing function of education and an increasing function of age.

Utility maximizing individuals decide to search the word “happiness” on the web if benefits from search are higher than costs, or \(S_w = 1 \mid B_{Gs} > C_{Gs}\) with \(S_w\) being a dichotomous variable which takes value one if individuals decide to search and zero otherwise.

It can immediately be noted that, the lower the happiness level in \(t\), the higher the happiness gap and therefore, \textit{ceteris paribus}, the higher the probability that the individual will find it optimal to search the word “happiness” on the web.

We can now introduce in the model the effect of financial crises. A financial crisis produces a fall in wealth, income and increases the probability of job loss (Baldacci \textit{et.al.}, 2002; Fallon and Lucas, 2002; Deaton, 2012) and is thereby expected to produce a significant fall in happiness. Assume now that a higher BTP-Bund spread \((S)\) raises the probability of a financial crisis, which could likely lead to the euro breakdown.

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\]

\(^5\) We assume for simplicity that \(U_{\text{max}}\) is the same for every individual.

\(^6\) A higher level of education may significantly increase the capacity of classifying and selecting information on the web, thereby increasing search ability.
More formally, we assume that income has a stochastic component which is amplified by the spread (i.e., the variance depends positively on the spread). The modified standard utility function which takes into account uncertainty becomes:

\[ U = (Y) - \gamma \sigma^2 Y(S) \]  

(4)

where \( \gamma \) is a coefficient of risk aversion and the spread \( S \) acts as a shock on individuals’ happiness levels inducing the fear that a financial crisis would reduce their wealth or make their future economic and working conditions more uncertain. The spread does not affect costs of search which depend on education and age but affects the benefits which can be obtained by searching on the web. For risk averse individuals, and assuming that income positively affects happiness, an increase in the spread would produce a negative effect on happiness \( U \) and, in turn, a positive impact on aggregate “happiness” Google search. This is because it reduces individual’s utility due to its effects on income, volatility.

This can be easily formalized by assuming that individuals, given their idiosyncratic characteristics and the impact of other factors affecting happiness which are not influenced by the spread, are uniformly distributed on the normalised unit segment \([0, Y_{\text{max}}]\) and have for simplicity the same costs of web access.

By defining \( Y^* \) as the level of income of the individual which gives him an utility such that he/she is indifferent between searching or not on the web, that is, the individual for which \( B_{G^s} = C_G \), we get

\[ Y^* = \frac{\pi \delta - H^d A^d}{\pi \delta} + \gamma \sigma^2 \gamma Y. \]

\( Y^* \) also measures on the unit segment the share of individuals who will find it optimal to search on the web. Hence, the increase of the spread will produce a downward

\[^7\text{As it is well known, the utility function in (7) can be the transformation of either a quadratic or a constant relative risk aversion function}\]

\[^8\text{The substance of our conclusions does not change if we assume non uniform distribution and heterogeneity in search costs since search costs are assumed to be unaffected by the spread. However our results are much more intuitive under these assumptions.}\]
shift in utility of all individuals in the segment thereby raising $Y^*$ and increasing the number of those who search on the web $\frac{\partial Y^*}{\partial S} > 0$.

Based on this simple theoretical framework the null hypothesis to be tested in the following empirical sections which follow is

$H_0$: an increase in the spread raises the number of searches on Google of the word “happiness”

In what follows we discuss potential objections to our model, check whether the correlation exists and is significant and further discuss how we control for potential confounders which may make such correlation spurious.

3.3. Discussion of model assumptions

The model could raise objections related to the high cost of search for depressed individuals, curiosity as a potential motivation for the search, the particular well-being pattern in web users or differences in the cost of access to the web according to age and education.

A first objection to our theoretical assumption that the cost of search may be prohibitively high for very depressed individuals is tantamount to say that costs of search may be proportional to the happiness gap or just steeply increase below a given threshold of life satisfaction. This does not seem to be the case if we think of health and web search. There is plenty of anecdotal evidence documenting that, when someone is very worried about her/his health, she/he is more likely to go on the web to get information about her/his illness even at the risk of discovering frightening news about it (Fox and Rainie, 2002; Hart et al., 2004). This evidence seems to confirm that more concerned individuals tend to have a psychological pressure to search information on the web.
Another objection may be that individuals search for the word “happiness” because they are just curious even if they are already very happy. However, this contradicts our assumption of rational utility maximizing individuals who are mainly driven by the expected gain from the search in terms of subjective well-being. Even if costs are progressively lower, opportunity costs of going on the web and searching are always nonzero. Note that we are working on a large number of people. Hence, even though there might be exceptions such as very depressed people with prohibitively high search costs or just curious happy individuals, it is rather likely that, by the law of large numbers, the utility maximizing behaviour tends to be the rule.

A new growing research field explores the relation between internet use and well-being. A potential objection that could be raised is that internet users have a different well-being level than non-users, and therefore the conclusion from our study may not be extended to all the population, despite the large number of internet users. The literature shows, however, both negative and positive effects of the internet use on well-being. Internet communication could displace face-to-face communication which psychologists describe as being of higher quality in terms of contribution to well-being. Well-being could decrease due to a less developed social life, weaker social ties and the decrease in leisure time associated with pursuing social connections and extending working time from home (Kraut et al., 1998; Leung and Lee, 2005). On the other side, listening to music from CD/MD/MP3, non-pathological use of computer games, chat rooms or discussion forums are proved to be beneficial for well-being (for instance the medical literature points out the positive effects of using discussion groups on the internet for the caregivers of patients with Alzheimer or patients with AIDS)\(^9\). Hence, there is no evidence that Internet profoundly changed the way people live their lives or their general well-being levels. (Tyler, 2002).

Last, we need to take into account also the effects of changes in the cost of access to the web, age and education. Easier access to the web should increase the number of people searching the world

\(^9\) For further details see Brennan et al., (1991), Gallienne et al.,(1993) and Brennan et. al., (1995)
“happiness” on the web, independently of their happiness levels. It is however unreasonable to assume that easier web access affects differently happier than less happy individuals. Note as well that the effects of education and ageing, which are likely to compensate each other, may be controlled with linear time trends.

The empirically testable hypothesis derived from our model - the number of searches for the word happiness increases with the spread - will be verified in the next sections.

3. Data and descriptive evidence

Our empirical analysis aims to test the nexus between the spread and the number of individuals searching the word “felicità” in Italy and “glück” in Germany on Google, as a proxy for individual happiness.

The spread is based on Friday market close Bloomberg data and is calculated as the difference in the 10-year maturity yield of Italian BTP and German Bund government bonds. The time interval goes from January 2004 to July 2012. The number of individuals searching the word “felicità” in Italy (from Italian web addresses) and “glück” in Germany (from German web addresses) on Google is taken from the Google “Insights for search” statistics which automatically normalize on a 0-100 scale the information in the selected interval. The Google week interval goes from Monday until Sunday (and therefore is not influenced by the following week market opening).

10 Touching the screen of one’s own I-phone involves almost no costs (if we are in a free wi-fi area) and therefore the criticism to our model hardly applies.

11 The available data are the weekly number of web searches normalized with respect to the week of maximum search contained on our time interval which is conventionally set at 100. Details on the reliability of the information and the methodology adopted can be found in the web page http://www.google.com/trends/correlate.

12 Our findings do not change if we use the average of the daily spreads during the week. Note that our use of the Friday market close reflects the fact that individuals have more time to search on the web in the weekend and therefore this value is expected to influence strongly the weekly Google search values measured till Sunday.
In Table 1 we report descriptive findings for all other variables used in the econometric analysis which will be presented in section 4. The spread reaches in our database a maximum at 527 basis points in the 1-6 January 2012 week and a minimum at 8.7 basis points (Table 1) in the 21-28 November 2004 week. The peak in the number of individuals searching for the word “felicità” on the web in Italy is in the same 1-6 January week. The peak in the number of “spread” searches on financial websites in Italy is at the beginning of November (6 to 13) 2011 when the spread increases over the threshold of 450 basis points.

When the spread is below 100 basis points the normalized number of “felicità” searches is 13.77 on average. When the spread is between 100 and 200 basis points, it rises to 18.25, while it moves up to 20.85 in the 200-300 basis point intervals. It rises to 23.61 in the 300-400 interval, 23.86 in the 400-500 interval and becomes almost three times higher (64) when the spread is above 500 basis points (Figure 2). The dynamics of searches of the word “glück” in Germany is also increasing in the spread.

These data document a positive correlation between the spread and the number of web happiness searches. It should not be surprising that also Germans’ and not only Italians’ web search is negatively affected by the spread. This is consistent with our model where the spread (from whatever side we look at it) affects the fear of a financial crisis and the variability of income for both Germans and Italians, even though possibly for different reasons (the cost of rescuing countries in crisis for Germans and the cost of economic collapse for Italians).

It can be noted that the shapes of the two curves are different. The search for “felicità” in Italy is convex while the search for “glück” in Germany is concave and we even observe a decline on average for the highest spread levels in the last case. A possible interpretation is that in Germany the negative effect of the spread (in terms of expected costs of recovery for EU high debt countries) may be partially compensated by the “flight to quality” advantage on German bonds at high spread levels (the Bund rate is on average 3.59 when the spread is below 100 while 1.68 when the spread is
above 400). This side positive effect may explain the decline in “happiness” searches in the final part of the curve.

The significance and robustness of the nexus between the spread and happiness search on the web will be tested in the next section.

4. Econometric findings

In order to find whether the relationship is significant and robust we test the following benchmark specification

\[ H_i = \alpha_0 + \alpha_1 \text{Spread}_i + \sum \beta_i X_{it} + \epsilon_i \]

where the dependent variable is the normalized number of searches for the word “felicita’” (happiness) from Italy on Google. \( \text{Spread} \) is the Friday close difference in the 10-year yield between German and Italian government bonds and \( X \) are controls introduced with respect to a benchmark estimate in which \( \text{Spread} \) is the only regressor.

Results are presented in Table 2. The \( \text{Spread} \) variable is significant and positive in the simplest specification (column 1). In column 2 we add as control a linear time trend picking up the expected increase of people having access to the web and the improvement of web access over time also due to the diffusion of I-pads and -phones which allow internet connection at all moments of the day without a personal computer. Both of these factors should affect positively the number of people searching for the word “felicità” over time under the reasonable assumption of a positive correlation between overall web access and the number of people searching the word “felicità” on Google. Our assumption is supported by empirical evidence since the linear trend variable is positive and strongly significant. The spread remains however positive and significant even when we control for the linear trend variable. We finally consider that hours of daylight may affect both the number of
web connections and, via seasonal affective disorders (SAD), subjective wellbeing\textsuperscript{13}. We therefore introduce such variable in our estimate and find that it is negative and significant (column 3).

Descriptive evidence shown in Figure 2 evidences a nonlinear relationship between the spread and the number of “felicità” searches (the number of people searching increases with the spread moderately and progressively within the 500 basis point threshold, but becomes almost three times higher when the spread is higher than 500 basis points), consistently with the fact that the spread may increase nonlinearly the probability of a financial crisis. That is, the increase in the probability of a financial crisis is small and negligible when the spread moves from 100 to 200 basis points, while dramatically higher when it moves from 400 to 500 basis points. We therefore estimate a modified specification where the right hand side variable is the spread squared (column 4). The variable is positive and strongly significant. In columns 5 and 6, we find that the quadratic spread is also robust to the inclusion of the linear time trend and the daylight effect. Last, we also test whether the impact of the quadratic spread variable remains significant in an autoregressive model in which the number of people searching for the word happiness in the previous week is added among controls (column 7). The squared spread remains positive and significant when we include all our additional controls (column 9).

In order to verify whether the correlation between spread and happiness hides the expected causality nexus we perform a Granger causality test. We find that the spread Granger causes the search of the word “felicità” (happiness) on Google (Chi square 18.84, p-value 0.00) while the inverse is not true (Chi square 3.30, p-value 0.189). The direction of causality is confirmed if we replace the level with

\textsuperscript{13} The seasonal affective disorder (SAD) represents a subtype of depression characterized by changes in mood, energy, sleep, eating habits and social activities at the change of season, that highly impact on well-being levels. There are two types of SAD: winter-type and summer type, with rather distinctive features (Wehr et.al., 1991). Winter type SAD is triggered by light deficiency during fall and winter and is characterized by symptoms such as lack of energy, oversleeping, overeating and especially carbohydrate craving, due to the serotonin deregulation in the brain that cause several brain anomalies (Cohen et.al., 1992; Liotti and Mayberg, 2001). Summer type SAD is determined by heat and humidity. In this case the most common symptoms include agitation, insomnia and weight loss. Both winter type and summer type are more severe at extreme, higher or lower latitudes (Rosenthal et.al., 1984; Potkin et.al., 1986).
the squared spread. The squared spread Granger causes the search of the word “felicità” (happiness) on Google (Chi square 15.72, p-value 0.00) while the inverse is not true (Chi square 5.46, p-value 0.065).

Since Figure 2 has shown that the relationship between the spread and the number of happiness searches on Google for Italy is nonlinear (consistently with the idea that the probability of a financial crisis does not increase linearly but exponentially when the spread rises) a strong robustness check is to verify whether the relationship is significant when we exclude the top extreme spread values. We therefore repeat estimates without observations above the 500 basis points (Table 3) and find that the significance of the level of the spread is confirmed. The variable passes again the Granger causality test with the number of happiness Google searches even when we rule out the top extreme observations (Chi square 11.15, p-value 0.004). This check documents that even spread values below the top affect subjective wellbeing and happiness Google searches.

Conversely, we may think that the rise of the probability of a financial crisis is serious only when we exclude too low spread values. We therefore carry out all estimates for spread values above 100 basis points and find that our results remain significant and robust with Granger causality tests confirmed with both linear (Chi square 11.52, p-value 0.003) and quadratic (Chi square 12.66, p-value 0.004) spread, even though observations are now much lower and drop to 148 (Table 4).

We then repeat the same benchmark estimates of Table 2 for Germany using as dependent variable the web search of the word “glück” from Germany and average hours of daylight in Germany among regressors. We also add among regressors the Bund rate to capture “flight to quality” effects. The spread variable is positive and significant in all the specifications, but weakly significant when we add the lagged dependent variable (Table 5). Such weakness is not reduced if we eliminate the Bund rate variable from the estimate. Note as well that Granger causality tests are not conclusive in this case with both the linear and quadratic spread. The Bund rate has the expected sign (its reduction should increase happiness and therefore reduce happiness searches on the web) but its
significance is weak. Overall, estimates on Germany confirm what shown in Figure 2. The impact of the spread is stronger for Italians than for Germans even if the direction is the same. In Germany two opposite forces are at work: the negative effect of the Euro financial crisis is , especially at high spread levels, partially reduced by the positive effect of the flight to quality.

A final additional check on the general validity of the Google Insight for search variables can be performed by considering the relationship between the spread and the number of people that look for the word spread in the financial subsection of Google. We expect this correlation to be strong and significant if Google searches are significantly affected by real life events and if the spread is a real life event that matters. We find that this is the case since the significance of the spread variable if we replace the word “happiness” search with the word “spread” search on financial websites only in benchmark estimates of Table 2. We also find that the spread causes the Google search of the word spread (Chi square 90.68, p-value 0.00) but not vice versa (Chi square 0.222, p-value 0.90) (see Table 6).

### 4. Conclusions

Our paper contributes to the literature of the determinants of subjective wellbeing testing the significance of the nexus between happiness and (the fear of) financial crises. The issue has been so far unexplored also due to the scarcity of aggregate high frequency life satisfaction data. We overcome the problem by using a new variable (the number of people searching the word “happiness” on the web) as a proxy of aggregate subjective wellbeing. The proposed proxy has the merit of overcoming the problems of ordinality and interpersonal comparability of the standard life satisfaction survey measures since happiness web searches are not subjective evaluations but choices) which are observable and interpersonally comparable.
We study the nexus between such variable and the dynamics of the 10-year yield spread between the Italian BTP and the German Bund which has been in the years after the global financial crisis the key measure of the probability of a financial crisis increasing the likelihood of the collapse of the euro. We provide indirect evidence that our measure is sound and correlated to real life events by showing the strong relationship between the level of the spread and the number of web searches of the word “spread” in financial websites.

We then present a simple theoretical model to demonstrate that the number of web happiness searches grows (both in Italy and in Germany) when happiness is lower. Our theoretical hypothesis is supported by empirical evidence (robust to observable confounders) and Granger causality tests.

The negative correlation between happiness and (fear of) financial crises, consistent with medical evidence on the effects of the psychological costs of financial crises on subjective wellbeing and productivity, suggests that such costs increase the burden of financial volatility and financial crises on objective and subjective wellbeing measures, thereby making financial stability an even more fundamental and primary goal to be pursued by policymakers.
References


Lowel, M. C. (1975). ‘Why was the consumer feeling so sad?’, Brookings Papers of Economic Activity, vol.6(2), pp.473-479.


Appendix 1 Figures

Fig. 1. Google front page when searching the word “felicità”

Fig. 2. Bund – BTP spread and happiness web search

Figure 2 Legend. Vertical axis: the normalised number of Google “felicità” (happiness) search from Italy and “glück” (happiness) search from Germany. Horizontal axis: the spread between Italian and German 10-year government bonds.
Appendix 2 . Tables

Table 1. Descriptive statistics

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Spread: Friday market close difference in the 10-year maturity yield of Italian BTP and German Bund government bonds (Bloomberg data); FelicitàSearchItaly: weekly number of Google searches of the word “felicità” (happiness in Italian) from Italy normalized on the highest week number of searches (=100) from Italy in the sample period; GlückSearchItaly: weekly number of Google searches of the word “Glück” (happiness in German) from Italy normalized on the highest week number of searches (=100) from Germany in the sample period; SpreadSearch: weekly number of Google search of the word “spread” on financial websites from Italy normalized on the highest week number of searches (=100) from Italy in the sample period; DaylightItaly: weekly average of the hours of daylight in Italy; DaylightGermany: weekly average of the hours of daylight in Germany. Both series were constructed from the daily number of hours of daylight available from The United States Naval Observatory (http://aa.usno.navy.mil/data/docs/Dur_OneYear.php/)
**Table 2** The spread - yield difference between Italian (BTP) and German (Bund) long term government bonds - and “felicità” (happiness) Google search from Italy

Dependent variable: number of Google searches of the word “felicità” (happiness) from Italy

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Variable legend: see Table 1. T-stats in round brackets.

Granger causality:

- from Spread to FelicitàSearchItaly<sub>t-1</sub> ($\chi^2$ 18.44, p-value 0.00);
- from FelicitàSearchItaly<sub>t-1</sub> to Spread ($\chi^2$ 3.3, p-value 0.18);
- from [Spread]<sup>2</sup> to FelicitàSearchItaly<sub>t-1</sub> ($\chi^2$ 15.72, p-value 0.00);
- from FelicitàSearchItaly<sub>t-1</sub> to [Spread]<sup>2</sup> ($\chi^2$ 5.46, p-value 0.06)
Table 3 The spread - yield difference between Italian (BTP) and German (Bund) long term government bonds - and “felicità” (happiness) Google search from Italy (excluding observations where the spread is above 500 basis points)

Dependent variable: number of Google searches of the word “felicità” (happiness) from Italy

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N. of obs. 447 447 447 447 447 447 446 446 446
Adj. R$^2$ 0.589 0.603 0.615 0.641 0.642 0.652 0.784 0.781 0.785

Variable legend: see Table 1. T-stats in round brackets.

Granger causality:
from Spread to FelicitàSearchItaly ($\chi^2$ 90.68, p-value 0.00);
from FelicitàSearchItaly to Spread ($\chi^2$ .22, p-value 0.89);
from [Spread]$^2$ to FelicitàSearchItaly ($\chi^2$ 125.97, p-value 0.00);
from FelicitàSearchItaly to [Spread]$^2$ ($\chi^2$ 8.80, p-value 0.01)
Table 4 The spread - yield difference between Italian (BTP) and German (Bund) long term government bonds - and "felicità" (happiness) Google search from Italy (excluding observations where the spread is below 100 basis points)

Dependent variable: number of Google searches of the word “felicità” (happiness) from Italy

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Adj. R<sup>2</sup> 0.257 0.259 0.275 0.289 0.289 0.304 0.427 0.418 0.429

Variable legend: see Table 1. T-stats in round brackets.

Granger causality:
- from Spread to FelicitàSearchItaly (<chi>² 11.52, p-value 0.00);
- from FelicitàSearchItaly to Spread (<chi>² 2.95, p-value 0.22);
- from [Spread]<sup>2</sup> to FelicitàSearchItaly (<chi>² 12.66, p-value 0.00);
- from FelicitàSearchItaly to [Spread]<sup>2</sup> (<chi>² 5.67, p-value 0.06)
**Table 5. The spread - yield difference between Italian (BTP) and German (Bund) long term government bonds - and “glück” (happiness) Google search from Germany**

Dependent variable: number of Google searches of the word “glück” (happiness) from Germany

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Variable legend: see Table 1. T-stats in round brackets.

Granger causality:

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from GlückSearchGermany to Spread ($\chi^2 1.09$, p-value 0.58);
from [Spread]<sup>2</sup> to GlückSearchGermany ($\chi^2 1.64$, p-value 0.44);
from GlückSearchGermany to [Spread]<sup>2</sup> ($\chi^2 1.85$, p-value 0.40).
Table 6. The spread (yield difference between BTP and German bund yields) and “spread” Google search on financial websites from Italy

Dependent variable: number of Google searches of the word “spread” (happiness) from Italy

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N. of obs. 447 447 447 447 447 447 446 446 446
Adj. R² 0.589 0.603 0.615 0.641 0.642 0.652 0.784 0.781 0.785

Variable legend: see Table 1. T-stats in round brackets.

Granger causality:

- from Spread to SpreadSearch (χ² 125.97, p-value 0.00);
- from SpreadSearch to Spread (χ² 8.71, p-value 0.012);
- from [Spread]<sup>2</sup> to SpreadSearch (χ² 90.68, p-value 0.00);
- from SpreadSearch to [Spread]<sup>2</sup> (χ² 0.222, p-value 0.90)