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ABSTRACT

We build an indicator of individual subjective well-being in the United States based on Google Trends. The indicator is a combination of keyword groups that are endogenously identified to fit with the weekly time-series of subjective well-being measures disseminated by Gallup Analytics. We find that keywords associated with job search, financial security, family life and leisure are the strongest predictors of the variations in subjective well-being. The model successfully predicts the out-of-sample evolution of most subjective well-being measures at a one-year horizon.

RÉSUMÉ

Un indicateur de bien-être subjectif est construit pour les États-Unis sur la base des données de Google Trends. L'indicateur est une combinaison de mots-clés qui sont identifiés pour reproduire les séries hebdomadaires de bien-être subjectif de Gallup Analytics. Nous trouvons que les mots-clés associés à la recherche d'emploi, à la sécurité financière, à la vie de famille et aux loisirs sont les plus forts prédicteurs des variations du bien-être subjectif. Le modèle prévoit l'évolution hors échantillon de la plupart des mesures de bien-être à l'horizon d'un an.

TABLE OF CONTENTS

Tables

Figures

1. Introduction

1. There is a growing interest in social sciences in going beyond the income-based approach of human development by using new measures of wellbeing (Stiglitz et al., 2009). In particular, GDP does not measure non-market social interactions such as friendship, family happiness, moral values or the sense of purpose in life. This motivates the recourse to subjective self-reported measures of well-being, such as Life Satisfaction (i.e. answers to the question: "All things considered, how satisfied are you with your life as a whole those days?"), which economists increasingly use as a direct measure of utility.[2] Political leaders have embraced this move by calling for representative surveys of well-being to guide their policy, as illustrated by the Cameron's commission of well-being in UK. In spite of these achievements, subjective well-being measures still raise a number of challenges and concerns among economists. First, they are not based on revealed behavior and choices, and are affected by the limits inherent to all self-reports (Deaton, 2013). Subjective well-being is also multidimensional (Kahneman and Deaton, 2010; Steptoe *et al.* 2014) and some aspects, especially pain or chronic disability are difficult to capture. Second, survey questions on subjective well-being are limited in coverage, time and space, which most of the time eliminates the possibility of measuring it with the appropriate business-cycle frequency and local level for policy decisions. Third, questions are sensitive to wording and ordering effects if the survey is changed (Deaton, 2013).

2. This paper contributes to this new research agenda by showing how Big Data can improve our understanding of the foundations of well-being. A major consequence of the accelerated digitization of social life is the traceability of social relations, embedded in large datascapes, such as Google, Facebook, Twitters or the Blogosphere. The quantification of those social traces is of considerable interest for social scientists. However, as stated by Lazer et al. (1999), while the capacity to collect and analyze massive amount of data has transformed the fields of physics and biology, such attempts have been much slower in social sciences. This paper illustrates the potential use of Big Data for both the measurement and the analysis of subjective well-being.

3. The first advantage of these data is that they offer social scientists the possibility to observe people's behavior, such as Google queries, and not just opinions. Second, rather than relying on the answers to pre-defined questions, social scientists can listen to what people say. This approach of revealed preferences unveils a reflexive picture of society because it allows the main concerns of citizens (and the priority ranking of those concerns) to emerge spontaneously, and it complements as such the information captured by GDP. In a nutshell, these data are based on the actual behavior of people when they search for information and they endogenously elicit the relative importance of people's concerns.

4. The second advantage of these data is their timeliness as they offer an immediate source of information for policy-makers, who are often confronted with short-term horizons and data scarcity in the midst of the decision-making process. Moreover, they are available at a local level - as long as internet penetration and use is sufficient to obtain statistical representativeness. Finally, Big Data are often made available for free.

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[2] Subjective well-being measures have been used to test a variety of potential determinants of wellbeing such as income, unemployment, inflation, health status, income inequality and income comparisons (see, for example, Helliwell et al. 2015).

5. This paper demonstrates the capacity of search engine data to track and replicate the trends in subjective states that are traditionally captured by surveys and to elicit and identify the type of activities that predict subjective well-being. We construct robust predictors of subjective well-being measures in the United States using a very large amount of search engine data covering the years 2008-2013. We measure the life dimensions whose search intensity is robustly associated with self-reported well-being collected by the Gallup Healthways Wellbeing survey, such as life evaluation (Cantril ladder) or the percentage of people who declare that they have experienced happiness, stress or worry "during a lot of the day yesterday". With our composite categories, we predict a time-series that tightly fits the Gallup survey trends in subjective well-being, and also behaves nicely out of sample. This method allows identifying the type of behaviors, activities and experiences that are associated with higher or lower subjective well-being. In practice, we run a simple variance decomposition to quantify the contributions of each dimension to predict well-being. For all subjective well-being variables, material conditions are the most important family of predictors, followed by social factors and health/wellness categories. At the category level, we find that keywords related to job search, financial security, family life and leisure are the most important predictors of subjective well-being.

6. However, the volume of Big Data to be treated is potentially enormous and it is a statistical challenge to disentangle signal from noise and to identify the relevant piece of information while avoiding cherry picking. We identify several issues with the dataset that we use (Google Search volumes) and propose several solutions, in particular the construction of categories reflecting different dimensions of life as well as the use of Bayesian techniques to select the most robust determinants of subjective well-being. Our methodology allows us to construct a model that has four important qualities: i) it is grounded in theory and the existing literature on subjective well-being; ii) it is testable and has strong out of sample performance; iii) it is reasonably transparent; and iv) it is adaptable and can potentially be used to predict subjective well-being on a continuous and recurrent basis.

7. This paper builds on the growing literature that seeks to exploit search engine data (see Reimsbach-Kounatze, 2015, for a survey). The early contribution of Ettredge et al. (2005) used internet search data to forecast the unemployment rate in the United States. The same idea was explored by Askitas and Zimmermann (2010), D'Amuri and Marcucci (2010) and Suhoy (2009), while Baker and Fradkin (2014) use a measure of job search based on Google search data to study the effects of unemployment insurance and job finding. Choi and Varian (2009, 2012) have explained how to use search engine data for forecasting macroeconomic indicators of unemployment, automobile demand, and vacation destinations, while several papers have analyzed consumer sentiment (Radinsky et al., 2009; Penna and Huang, 2009; Preis et al., 2010).

8. Regarding subjective well-being, Stephens-Davidowitz (2013) used Google data to study trends of depression. Schwartz et al. (2013) used tweets and found that words related to outdoor activities, spiritual meaning, exercise and good jobs correlate with increased life satisfaction (controlling for socio-economic variables). To the best of our knowledge, our paper is the first to use search data to identify the nature of life dimensions that best predict subjective well-being.

9. The paper is organized as follows. Section 2 describes the statistical framework, Section 3 presents the results, and the last section concludes.

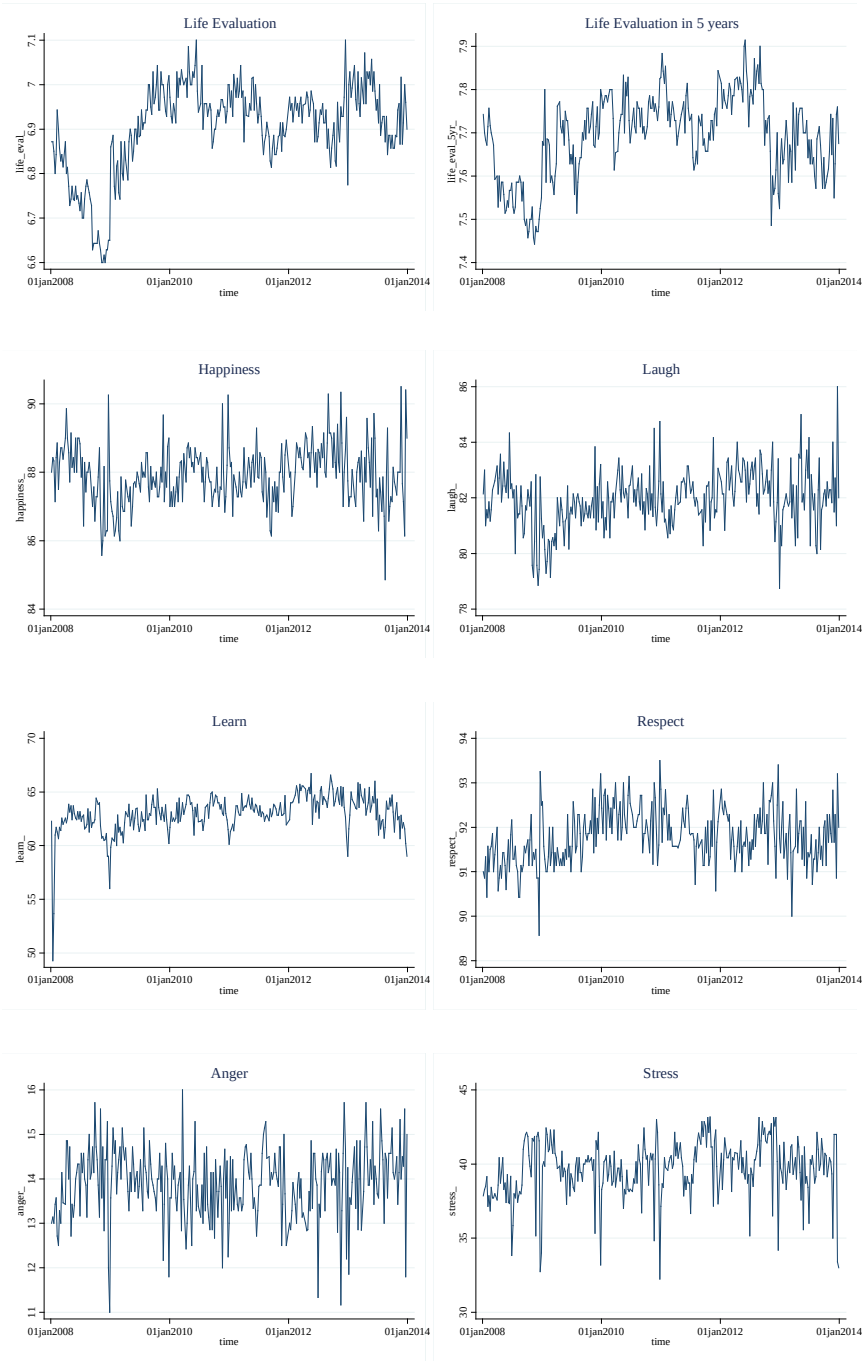
2. The Data

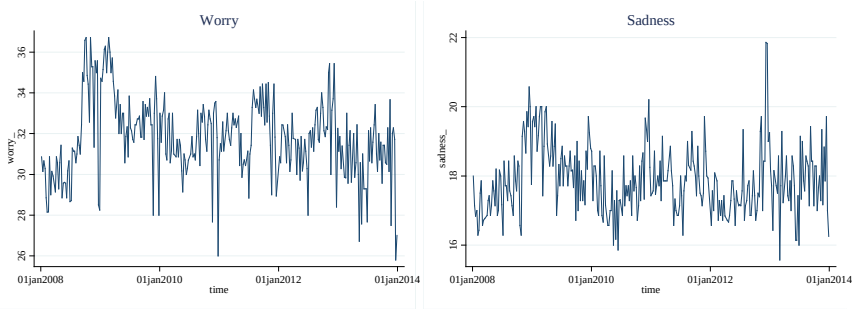
2.1. Gallup Data

10. The SWB data are taken from Gallup Analytics, which include data from a daily telephone survey of at least 500 Americans aged 18 and older. More than 175,000 respondents are interviewed each

year, and over 2 million interviews have been conducted to date since the start of the survey in 2008. The survey includes 6 measures of self-reported positive emotions (happiness, learning, life evaluations today and in 5 years, laugh, being respected) as well as 4 measures of negative emotions (anger, sadness, stress, worry). The time span covers 300 weeks from January 6, 2008 to January 4, 2014.

Figure 1. Subjective Well Being Variables over time





11. Figure 1 depicts these ten indicators over the period. The consequences of the Great Recession are visible on most SWB indices: *life evaluation* today and in 5 years, *happiness* and *laugh* dropped significantly in 2008-2009, while the percentages of people experiencing worry, anger, stress and sadness increased at the same time. A second observation concerns the cyclicality of these variables, which all display large seasonal swings.

2.2. Google Trends Data

12. Our 'Big Data' here consist of the search frequency of keywords on Google, which are available from Google Trends. The initial list of keywords is selected as follows. We extract two long lists of keywords potentially linked to SWB outcomes. The first one comes from the OECD Better Life Index Online Database, which records answers from data users to the question "What does a Better Life mean to you?" The second one is based on the American Time Use Survey, which records the daily activities undertaken by US citizens as well as the positive or negative emotions that are associated with these episodes. This selection method allows us to avoid cherry picking a limited set of search queries on Google. On the other hand, survey-based keywords may be disconnected from the day-to-day life of Americans if they do not include their usual internet queries or do not reflect their practical living conditions. As a consequence, we have added a set of keywords that were likely to be relevant to different life experiences related to subjective well-being: this ranges from job concerns (e.g. the website 'getajob'), poverty ('coupons') or family stress ('women shelter'). In total, the initial database contains 845 keywords, split into 144 for the BLI, 95 for the US time-use data and 606 from our own judgment.

13. The search volumes obtained from Google Trends pose several challenges for estimation.[3] First, there may be sharp spikes in the popularity of a word. While some of these spikes are surely related to the degree to which the concept represented by this word is important in people's lives, others are less directly related. The example of the spike in "divorce" searches induced by Kim Kardashian's precipitous divorce from Kris Humphries in October 2010 is shown in Appendix A. This is a concern for estimation as it

3 The Google Trends data on search volume is not the raw search volume; rather it is the proportion of total searches over a given period that included that keyword, normalized so that the highest volume over the period is equal to 100. This has several consequences: first, the value of the series obtained directly from Google Trends is difficult to interpret, as it depends not only on the volume of searches for a given word but also on the volume of other searches. Second, the value of the series on any given day cannot be compared between terms, since they are normalized to the maximum value by term. To deal with this issue, we normalize all search volumes so that they have a mean of zero and a standard deviation of one, since we are interested in how volume changes within a given term (rather than which terms have the highest search volumes overall).

creates a risk of over-fitting: if a sufficient number of search terms have a sufficient number of spikes, one could predict almost any series perfectly (though with poor out of sample performance). We address this by smoothing the data using a simple three period moving average and by creating composite category indicators (discussed below) to dampen the importance of a shock in any individual keyword. We also observed an unexplained discontinuity in many series from the last week of December 2010 to the first week of January 2011. An example for the word "pregnancy" is provided in the Appendix. To adjust for this discontinuity, we calculate the average index in December and January for the unaffected years, the average change during the unaffected years, subtract this unaffected average change from the observed change from December 2010 to January 2011, and adjust all data from 2011 onwards using this difference. That is, we assume that the change from December 2010 to January 2011 should be the same as in the other years, and we adjust accordingly. While we are undoubtedly losing some information with this adjustment, there should not be any bias introduced.

14. Second, many of the search terms have a strong time trend. The example given in the Appendix is "teeth hurt", where the time trend from 2008 to 2014 explains 89% of the variance in frequency. The consistent relative increase in the search volume of "pain" may be due to at least two possibilities: people are feeling more pain, or people are feeling the same amount of pain but are turning towards the internet for medical care as a general cultural shift. We would like to capture the first, but we have no way to distinguish it from the second. In this case we chose to drop all words where the adjusted R^2 (using training data only, see below) from a regression of time on the keyword is greater than 0.6, and to visually investigate words between 0.5 and 0.6. This process reduces the number of available keywords from 845 to 554. We may be losing some important information in this step, but we feel the danger posed by conflating shifts in the way internet is used with how people are actually feeling is more severe.

15. Finally, many search terms exhibit extreme seasonality (particularly those that have to do with leisure). Since some of the subjective well-being variables also exhibit seasonality, this is a major concern, as search terms might be well-correlated with a given subjective well-being variable merely because they follow the same seasonal pattern. We guard against this by using month dummies in all specification with one small modification: the months of December and January exhibit consistent and dramatic intra-month patterns, presumably due to the Christmas holidays and New Year's Eve. We thus also construct additional dummy controls for the each of the four weeks of those two months (and so the December and January month dummies are dropped).

3. Empirical Framework

16. Our empirical goal is to build a model that accurately predicts the evolution subjective well-being using a type of revealed information, that is, searches on Google. We seek to construct a model that is grounded in theory and the existing literature on subjective well-being, is testable, has strong out of sample performance, is reasonably transparent, is adaptable and can potentially be used to predict subjective well-being on a continuous and current basis. Our overall approach is to use composite categories of keywords tested using out of sample predictions, which meets these criteria.

3.1. Big Data, Noisy Data and High Dimensionality

17. A simple model would be a regression of subjective well-being variables on a large number of keywords, controlling for months, and keeping those that are strong predictors. However, this strategy risks overfitting of the dependent variable. For instance, using all of the available Google keywords and month dummies would result in a model with extremely high explanatory power and a R-squared statistics near 1, but a very low predictive power, as the model would essentially fit random variations in the sample rather than actual relationships. Conversely, using too few Google keywords creates a risk of underfitting of the

dependent variable, which also would yield poor predictions, given that it is likely that all Google keyword variables are noisy signals of an underlying latent good predictor of SWB.

18. This dual problem is pervasive in the world of 'Big Data', which is often characterized by the availability of a lot of information (i.e., in our setting, a large number of potential explanatory variables) and a lot of noise (each variable being a poor predictor of the dependent variable). To cope with the first problem of high dimensionality, Bayesian Model Averaging (BMA) is commonly viewed as a powerful means of selecting the most robust determinants (e.g. Sala-i-Martin et al., 1997; Fernandez et al., 2001). However, BMA analysis can be distorted when there are many redundant or highly correlated covariates in the sense that the detection of robust and distinct predictors gets diluted away from covariates that are not highly correlated with other predictors. This well-known problem is related to the 'independence of irrelevant alternatives' problem in discrete choice models (George, 1999; Brock and Durlauf, 2001; and Durlauf, Kourtellos and Tan, 2012) and can be addressed by using a preliminary factor analysis in order to reduce the number of potential explanatory variables.

19. Using exploratory factor analysis to create meaningful *composite* terms substantially reduces the number of the potential explanatory variables, and also has the virtue of addressing several of the data issues discussed above. We start from the assumption that individual Google keywords may be noisy predictors of underlying life dimensions, which correspond to the latent variables in factor analysis. Following this, we combine individual search terms into composite categories that are used as predictors of SWB, which has the added advantage of limiting the noise due to any individual variable. This approach opens up the possibility of continuous and ongoing prediction of subjective well-being, as it will allow us to remove any search term that may become unusable in the future due to internet 'cascades' or cultural change, without greatly altering the significance of its category as a predictor of SWB. In addition, constructing categories offers more visibility on the nature of correlates of SWB variables, and allows disentangling the aspects of life (e.g. housing, employment, health, leisure…) that correlate most with different types of SWB variables, such as short-run emotional affects (e.g. feelings of happiness, stress and worry) and cognitive variables such as life evaluation.

3.2. Category Construction

20. The grouping of words into categories must be coherent both logically and statistically. The words grouped together must meet a common sense test (should "boy scouts" be grouped with "diabetes"?), and they must also pass a statistical test, which implies first conducting factor analysis (using only the training data) and then calculating the Cronbach alpha, which measures the cross-correlation of the components and is an estimate of the internal consistency and reliability of the constructed category. As many keywords exhibit seasonality (as discussed above), and different keywords may exhibit similar patterns of seasonality without sharing the same meaning, we used the residuals of a regression over month and week dummies (to remove seasonal effects) in order to test the coherence of the word grouping. However, we used the raw data (without the removal of season variations) in order to construct the categories. Search terms were excluded if the factor loading was negative or less than 0.3, and many search terms were not used because they did not fit consistently with any category grouping. We use 215 keywords of the 554 words available after cleaning. We only used search terms with a positive factor loading. Note that the fact that two words are grouped into the same category does not imply that they mean the same thing, but only that the search pattern over time is similar for the two words. For example, "racism" and "Buddhism" are grouped together (into "Education and Ideals"), due to the fact that the timing of Google search for these words is similar. Detailed factor loadings are presented in Appendix B.

21. Search terms were grouped into twelve domains that can be organized into three aspects of life: Material Conditions (*Job Search, Job Market, Financial Security* and *Home Finance*), Social Aspects (*Family Stress, Family Time, Civic Engagement* and *Personal Security*), and Health and Wellness (Healthy

Habits, Health Conditions, Summer Activities and Education and Ideals)[4]. The composition of each category is described in Table 1. Note that *Job Market* and *Job Search* do not group together, and the types of words in each category give some intuition as to why: *Job Search* seems to be related to searching for a job (any job) from unemployment, while *Job Market* seems to be related to job quality, which might reflect searching in a looser job market. The lowest Cronbach's alpha (for *Healthy Habits*) is 0.84, which is still reassuringly high. A commonly accepted rule of thumb sets 0.7 as a threshold for an acceptable degree of internal consistency (Nunnally, 1978; George and Mallery, 2003).

[4] As explained below, Home Finance is excluded in the analysis that follows but we present the results on the category.

Table 1. Category Components

Life Aspects	Category	Cronbach's Alpha	Component Keywords
Material Conditions	Job Search	0.8720	part_time_job layoffs jobfair apprenticeships severance_pay unemployment_rate careerfair jobs unemployment_benefits
	Job Market	0.9315	jobbenefits employmentcontract careercenter coverletter pension certification_program retirement work_experience entrylevel qualifications discrimination employeebenefits
	Financial Security	0.9101	401k banking familybudget housingauthority section8 inflation studentloans school_loans interestrate fired financial_crisis loans eitc socialsecurity coupons medicaid fileforbankruptcy shelter eviction foodbank homeless
	Home Finance	0.9618	mortgagerates mortgagecalculator mortgage refinancing houseprice homeloan housing_crisis mortgagepayment
Social Aspects	Family Stress	0.8818	domesticabuse marriagehelp marriageprob custody marriagecounseling familysupport womensshelter
	Family Time	0.9140	snacksforkids weekends adhd daycare child_care_center pta kidsparty volleyball play_football reading recipe housework laundry toddler babyshower bullying kids_books ideasforkids tuition
	Civic Engagement	0.9148	volunteering blood_donation homeownersassociation boyscouts kiwanis citycouncil freemasons bingo teaparty lionsclub club communitymeeting civic_engagement rotaryclub towncouncil
	Personal Security	0.8657	firearm victims gun gunsafety violent_crime crime_rate assault securitycamera murder selfdefense aggression risks homealarm mugging
Health and Wellness	Health Conditions	0.9051	stress hypertension diabetes obesity panicdisorder illness tobacco_use lung_cancer heartdisease obsessivecompulsive cancer relax_tech antidepressant health_status fracture arthritis asthma relaxation self_care sleepprob mayoclinic depression_symptoms symptomchecker suicide_rates drug_use chronicfatigue
	Healthy Habits	0.8441	exercise weights healthydiet dental_care fruits_and_veg life_expectancy lose_weight health_care quitsmoking
	Summer Activities	0.9417	golf fishing motorcycle ponds hiking biking water_sports boating tours beachcottage sightseeing bedandbreakfast baseball softball playpool
	Education and Ideals	0.9862	middleschool juniorhigh economics homework stateuniversity moral individualism billofrights human_capital constitution politicalaction social_justice dropout reading_books grammar tutor buddhist school highschool ethics philosophy studies study mathematics learning skills secondary_education writing worship creativity psychologist therapy selfesteem morality povertyonlinecourses literature degree language science literacy feminist rights relations freedomofspeech civilrights religion religious propertyrights racism governments freespeech rituals infant_mortality spirituality

Note: Chronbach alpha calculated using seasonally adjusted search volumes.

22. Categories are constructed on the basis of a simple average of the z-scores. This is to avoid the structure of a category from depending on the inclusion of a single word, and to facilitate future construction and revision of the categories, in case one of the components needs to be dropped due to an unexpected peak. Using an estimate of a latent variable calculated from the factor loadings produces substantially similar results.

23. Figure 2 describes the constructed categories, while Figure 3 compares some of them with administrative data that are helpful to understand their variations over time. Observing the trends of the composite categories and their relationship to social trends and other data series gives us confidence that our categories are not random associations, but reflect actual trends and social phenomena which correspond to our interpretation of the categories.

24. *Job Search* and *Job Market* both show the severity of the crisis in 2008-2009 and the subsequent improvement of labor market conditions. Note that *Job Search* peaks in 2009, when the unemployment rate was increasing the most quickly, and *Job Market* peaks in early 2010, when the unemployment rate was stabilizing and starting to drop (Figure 3); *Job Search* also shows less of a seasonal drop around Christmas than *Job Market*. Similarly, the declining trend in *Financial Security* and *Home Finance* seem to indicate that Americans have been less and less preoccupied by housing conditions and their financial conditions over the period. *Financial Security* also closely tracks bankruptcy (Chapter 11) petitions in US courts (Figure 3). Personal *Security* shows a slow decrease from 2009 to 2012 but a marked jump around December 2012 – one possibility is that this jump shows the fears and grief of the public following the Sandy Hook Elementary School shooting on December 14, 2012 (Figure 3). *Family Life* shows an increasing trend over the period, whereas *Family Stress* decreases after the financial crisis, which maps onto the decrease in Intimate Crime incidents reported by the FBI (Figure 3). *Civic Engagement* is somewhat higher during the financial crisis but not markedly so, as are *Health Problems* and *Education and Ideals*. *Healthy Habits* showed a rebound as the economy began to recover; its sharp discontinuities every January are remarkable and probably reflect New Year's Eve resolutions. Finally, *Summer Leisure* exhibits a slight downward trend with a high seasonality, and the smoothed and seasonally adjusted series maps onto consumer spending on entertainment (Figure 3).

Figure 2. Category Variables over time

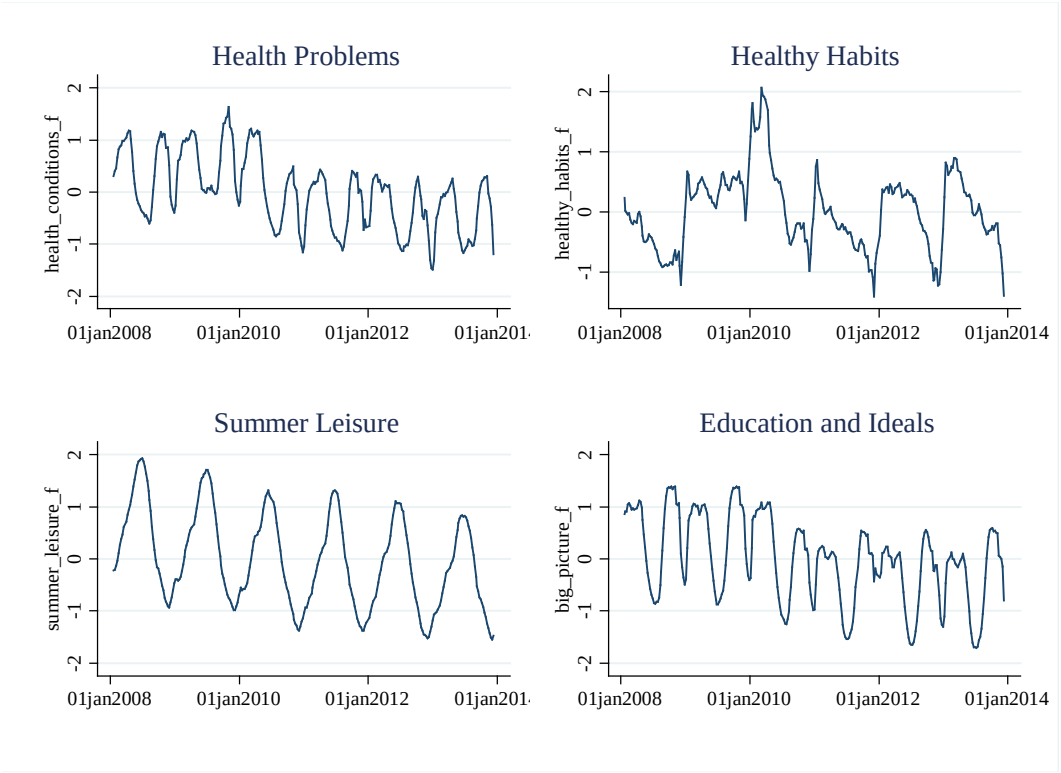
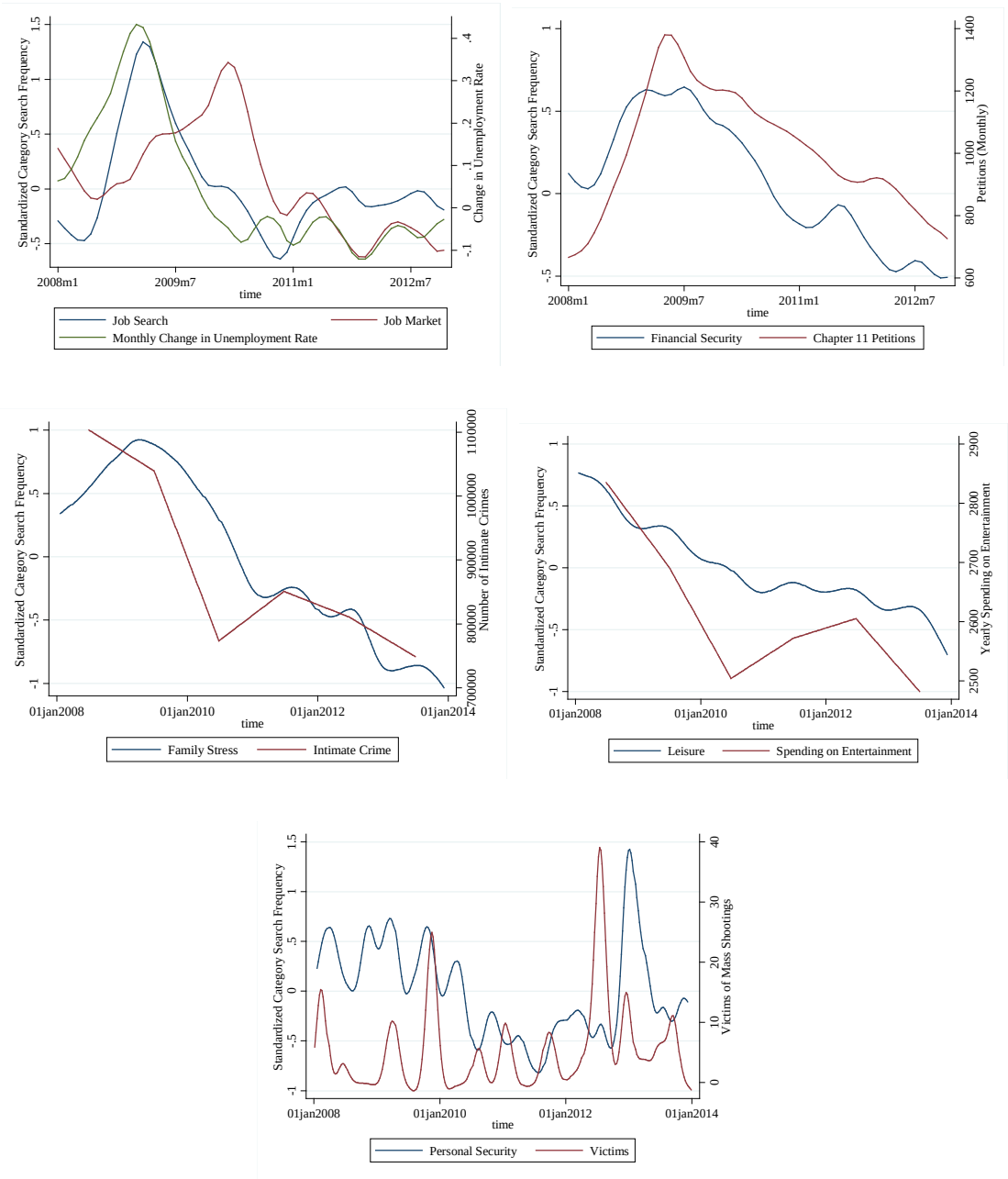

Health Problems
health_conditions_f
-2
-1
0
1
2
01jan2008
01jan2010
01jan2012
01jan201
Healthy Habits
healthy_habits_f
-1
0
1
2
01jan2008
01jan2010
01jan2012
01jan2014
Summer Leisure
summer_leisure_f
-2
-1
0
1
2
01jan2008
01jan2010
01jan2012
01jan201
Education and Ideals
big_picture_f
-2
-1
0
1
2
01jan2008
01jan2010
01jan2012
01jan2014

Figure 3. Comparison of selected category composites to administrative data series



Source: Bureau of Labor Statistics (Unemployment Rate and Spending on Entertainment), Bankruptcy Data Project at Harvard (Chapter 11 Petitions), FBI (Intimate Crime), Mother Jones (Victims of Mass Shootings).

3.3. Bayesian Model Averaging

25. We use a Bayesian Model Averaging (BMA) approach to select the subset of category variables among the potential candidates that are the most robust correlates of SWB variables. Formally, let X denote the set of all possible categories and $X_\gamma \in X$ a given subset. The BMS approach simply consists of evaluating a very large number of models M_γ of the following form:

$$y = \alpha_\gamma + \beta_\gamma X_\gamma + \varepsilon \quad \varepsilon \sim N(0, \sigma^2 I)$$

with *y* being the SWB outcome, α_γ a constant, β_γ the coefficients and ε a normally distributed error term of variance σ^2. As a matter of fact, most of SWB dependent variables surveyed by Gallup are approximately normally distributed. Evaluating the model M_γ with regressors X_γ can be done through the posterior model probability (PMP) which is from Bayes' rule:

$$PMP_\gamma = p(M_\gamma|y, X) = \frac{p(y|M_\gamma, X)p(M_\gamma)}{p(y|X)}$$

The quantity $p(y|X)$ is independent of the model considered and can be viewed as a constant. As a result, the PMP can be calculated as the model prior $p(M_\gamma)$ times the conditional marginal likelihood $p(y|M_\gamma, X)$. In a second step, these PMPs are used to infer the Posterior Inclusion Probability (PIP) of each category variable, which is simply the sum of the PMPs of all models in which a given category variable is included.[5]

3.4. Model Selection and Out-of-Sample Testing

26. Our methodology is designed to ensure that the weights on the categories used in the model do not suffer from overfitting, spurious correlation, and constitute credible predictors of SWB variables. First, we divide the sample into a "training" and "test" sample, and use the training sample to build the model, and evaluate its performance on the test sample. Data from 2009 to 2013 are used for the training set, while data from 2008 to 2009 are used for one test set and from 2013 to 2014 for the other. The reason for the symmetrical test sets is that we would like to construct an index that predicts as well for periods of crises (i.e. the 2008 economic crisis) as for periods of relative stability.

27. In practice, we first identify the most robust categories by applying BAM to the training data. All categories with a PIP larger than 0.7 are pre-selected as a potential determinant of the SWB variable. The PIPs of the various categories found in the exploratory analysis are reported in Annex C. On a second step, we refine the model by simply regressing the dependent SWB variable on selected categories while using the training dataset, and we remove any category with a non-significant coefficient. Finally, we use the coefficients from the final model (estimated over the training period) to predict SWB over the whole period, namely both training and test sub-periods. The next section evaluates how well the predictions fit the actual data.

28. We intentionally exclude *Home Finance* from the model. While we recognize that financing a home is an important life event for many Americans, the predominance of words related to home finance ("mortgage", for example) during this period is also critically linked to the financial crisis, and so the importance of these words in predicting SWB is likely to be highly time-specific. As such, this category

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[5] We choose the model prior most commonly used in applied studies, namely the uniform distribution that assigns equal prior probability $p(M_\gamma) = 2^{-K}$ to all 2^K possible models. The use of the uniform model prior was first suggested by Raftery (1988) while Hoeting et al. (1999) reviewed the evidence supporting the good performance of the uniform model prior. It should be noted BMA does not compute the marginal likelihood and the posterior distribution for each possible model. Instead, it identifies the subset of models where the mass of the model posterior probability is concentrated. This is achieved with the help of a Metropolis-Hastings algorithm that walks randomly through the model space but visits its most important part. In practice, we use the "birth-death" sampler that randomly chooses one of the K variables at each step of the algorithm, and excludes it from the model if it is already included in it, or includes it otherwise.

might dominate the prediction in the training data, and risk yielding poor results in the out of sample tests, and having poor power to extrapolate to the future.

4. How to Google Subjective Well-Being in the United States?

4.1. A Model of SWB in the United States

29. Table 2 presents the results from the selected regression model for each SWB variable.[6] The coefficients are generally consistent for positive and negative affects. Categories that are consistently associated with higher subjective well-being (excluding the Learn and Respect SWB variables, for which our model does not perform well, as discussed below) are *Job Market*, *Civic Engagement*, *Healthy Habits*, *Summer Leisure*, and *Education and Ideals*. Categories that are consistently associated with lower subjective well-being are *Job Search*, *Financial Security*, *Health Conditions*, and *Family Stress*.

6 The dependent and explanatory variables have been standardized to allow for a comparison of the magnitude of the effects at stake.

Table 2. Regression of Categories on Subjective Well-Being Data

	Positive Affects						Negative Affects			
	Life Evaluation	Life Evaluation 5 Years	Happiness	Laugh	Learn	Respect	Anger	Stress	Worry	Sadness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Material conditions										
Job Search	-0.772***			-0.293***	-0.466***	-0.452***	0.571***	0.387***	0.751***	0.619***
	(0.075)			(0.058)	(0.061)	(0.070)	(0.067)	(0.051)	(0.042)	(0.069)
Job Market	0.552***		0.294**		-0.297***	1.261***				
	(0.121)		(0.145)		(0.101)	(0.150)				
Financial Security	-0.327***	-0.712***	-0.596***	-0.481***	-0.415***	-0.657***	1.234***	0.402***	0.438***	0.440***
	(0.112)	(0.066)	(0.114)	(0.079)	(0.088)	(0.110)	(0.180)	(0.078)	(0.057)	(0.109)
Social										
Family Life			0.251***	0.266***	0.403***		0.416***	0.478***		-0.367***
			(0.080)	(0.065)	(0.057)		(0.082)	(0.049)		(0.077)
Family Stress	-0.381***		-0.269***							
	(0.091)		(0.096)							
Civic Engagement	0.477***							-0.182**		
	(0.115)							(0.088)		
Personal Security	0.199***	-0.410***		-0.266***						0.282***
	(0.049)	(0.067)		(0.055)						(0.049)
Health and Wellness										
Healthy Habits	0.203**	0.785***	0.460***	0.551***	0.267***	-0.203*		-0.373***	-0.402***	-0.280***
	(0.079)	(0.076)	(0.103)	(0.059)	(0.066)	(0.110)		(0.057)	(0.048)	(0.078)
Summer Leisure							-1.521***	-0.881***	-0.786***	-0.906***
							(0.308)	(0.143)	(0.135)	(0.212)
Health Conditions					0.478***			0.262**		
					(0.113)			(0.116)		
Education and Ideals							-1.092***	-0.393***		-0.654***
							(0.182)	(0.139)		(0.150)
Month dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	*200*	*200*	*200*	*200*	*200*	*200*	*200*	*200*	*200*	*200*
R^2	*0.798*	*0.652*	*0.688*	*0.828*	*0.861*	*0.662*	*0.606*	*0.904*	*0.868*	*0.816*
Adj. R^2	*0.770*	*0.614*	*0.650*	*0.806*	*0.843*	*0.623*	*0.557*	*0.890*	*0.853*	*0.791*

*note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Week dummies included for weeks in December and January, month dummies included for all other months.*

30. Overall, these findings are in line with the literature on subjective well-being. The consistent negative relationship of *Job Search* (which, as discussed above, seems to relate to searching for a job from unemployment) confirms the importance of employment as a foundation of subjective well-being: having a job is one of the strongest correlates of life satisfaction and happiness while, conversely, being unemployed is highly detrimental to life satisfaction, beyond the loss of income that this entails (see, for example, Clark and Oswald, 1994), and is most difficult to adapt to (Clark et al. 2008). There is evidence that objective health shocks (such as heart attacks) are negatively correlated with SWB (Shields and Wheatley Price, 2005), though this relationship is more difficult to disentangle with confidence as reported health status may be a proxy of subjective well-being and as such are highly correlated (Deaton, 2008). In addition, there is evidence that higher levels of subjective well-being themselves lead to better health outcomes (Howell et al, 2007).

31. *Civic Engagement* is related to the importance of social capital, which has been amply demonstrated to be strongly associated with subjective well-being (Helliwell and Wang, 2011; Helliwell et

al., 2010). *Healthy Habits*, notably physical exercise, are associated with less depression and anxiety and improved mood (Biddle and Ekkekakis, 2005). *Education and Ideals* is a grouping of words that includes references to religion, political goals, philosophy, and education, and which is associated with higher SWB, consistent with the literature that finds higher subjective well-being associated with religious activity (Clark and Lelkes, 2005; Helliwell, 2003). Finally, family, health and security are identified, through choices, as extremely important in terms of people's happiness by Benjamin et al. (2014) and these categories coincide with the "satisfaction domains" that have been explored by the Leyden school (van Praag and Ferrer-i-Carbonell, 2008). Many of these patterns of subjective well-being are summarized in *The World Happiness Report* (Helliwell et al., 2013, 2015).

32. Two categories have inconsistent signs. *Family Life* is associated with more Happiness and Laughter, and less Sadness, but also with more Anger and Stress. (The finding of inconsistent associations of *Family Life* may reflect the complicated nature of interactions with children, consistent with the finding in Deaton and Stone (2014) that parents experience both more daily joy and more daily stress than non-parents: see also Buddelmeyer et al., 2015.) *Personal Security* is positively associated with Life Evaluation (today), but negatively associated with Life Evaluation in 5 years and Laughter, and positively associated with Sadness. We cannot explain this difference. [7]

33. These associations remain silent on causality since the different dimensions could be correlated to each other or related to an omitted variable. Nevertheless, bearing this caveat in mind, we generally observe that material condition aspects play an important role in our model, with job search and financial security showing large, highly significant and consistent associations with almost all of the subjective well-being categories. *Job Search* has the largest coefficient for all of the categories for *Life Evaluation* and *Worry; Financial Security* has the largest coefficient for *Life Evaluation in 5 years, Happiness, Laugh, Learn* and *Anger*, and is close to the largest for *Respect* and *Sadness*.

34. Social aspects play a large role in predicting *Life Evaluation* and other positive affects, though the coefficients tend to be relatively smaller than the Material Conditions aspects. Health and Wellness aspects are most significant with respect to predicting negative affects, with the exception of *Healthy Habits*, which is consistently significant for every affect except *Anger*. Note also that *Healthy Habits* has a relatively large coefficient with respect to *Life Evaluation in 5 years*. *Summer Leisure* is consistently associated with lower negative affects but not with higher positive affects, and the largest coefficient is associated with reduced *Anger*.

4.2. Variance Decomposition

35. Simple variance decomposition can help to quantify the contributions of each covariate to the R^2. It simply follows from the equality:

$$R^2 = Var\left(\sum_i \lambda_i X_i\right) = Cov\left(\sum_i \lambda_i X_i, \sum_j \lambda_j X_j\right) = \sum_i \underbrace{\lambda_i \sum_j \lambda_j Cov(X_i, X_j)}_{X_i \text{ contribution to } R^2}$$

[7] Note that, generally, living in a high crime area is associated with lower SWB as argued by Lelkes, 2006.

Note that some contributions can be negative if the covariance terms are larger than the individual variance of variable X_i and are negative. This case typically occurs when a given variable is highly correlated with others but has the opposite sign.

36. Table 3 reports the results, which refine the conclusions stated above. Overall, it appears that, for all subjective well-being variables but stress, material conditions are the most important family of predictors, followed by social factors and health/wellness categories. At the category level, the most important variables are job search, financial security, summer leisure and family life. Regarding the stress variable, it appears to be mostly explained by family life, summer leisure and health habits.

37. It is interesting to note that SWB variables display very different degrees of cyclicality, as indicated by the contribution of time dummies to the explained variance. For instance, time dummies explain almost nothing of the variations in *Life Evaluation* today and in 5 years, while they entail significant variations in *Happiness, Laugh, Learn, Respect, Anger* and *Stress*.

Table 3. Decomposition of the Explained Variance of SWB variables

	Life Evaluation	Life Evaluation 5 Years	Happiness	Laugh	Learn	Respect	Anger	Stress	Worry	Sadness	Average
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*
Material conditions	**0.594**	**0.268**	**0.214**	**0.469**	**0.486**	**0.347**	**0.649**	**-0.027**	**0.643**	**0.299**	**0.394**
Job Search	*0.433*			*0.195*	*0.182*	*0.205*	*0.274*	*0.108*	*0.510*	*0.184*	*0.261*
Job Market	*0.118*		*-0.099*		*0.032*	*0.086*					*0.035*
Financial Security	*0.043*	*0.268*	*0.313*	*0.274*	*0.271*	*0.056*	*0.376*	*-0.135*	*0.133*	*0.114*	*0.171*
Social	**0.103**	**0.191**	**0.182**	**0.204**	**0.249**		**0.061**	**0.344**		**0.271**	**0.201**
Family Life			*0.051*	*0.076*	*0.249*		*0.061*	*0.330*		*0.128*	*0.149*
Family Stress	*0.075*		*0.130*								*0.102*
Civic Engagement	*0.033*							*0.014*			*0.023*
Personal Security	*-0.004*	*0.191*		*0.128*						*0.143*	*0.114*
Health and Wellness	**0.067**	**0.151**	**-0.067**	**-0.089**	**-0.068**	**-0.032**	**-0.422**	**0.403**	**0.247**	**0.259**	**0.045**
Healthy Habits	*0.067*	*0.151*	*-0.067*	*-0.089*	*-0.046*	*-0.032*		*0.148*	*0.046*	*0.061*	*0.027*
Summer Leisure							*-0.252*	*0.352*	*0.201*	*0.288*	*0.147*
Health Conditions					*-0.022*			*0.058*			*0.018*
Education and Ideals							*-0.170*	*-0.155*		*-0.089*	*-0.138*
Contribution of time dummies	**0.034**	**0.042**	**0.360**	**0.244**	**0.194**	**0.347**	**0.318**	**0.184**	**-0.021**	**-0.013**	**0.169**
R^2	**0.798**	**0.652**	**0.688**	**0.828**	**0.861**	**0.662**	**0.606**	**0.904**	**0.868**	**0.816**	**0.809**

4.3. Predicting SWB in the United States and Reliability of the Model

38. The model is quite reliable out of sample. Table 4 displays the correlations between the predicted values and the actual values of SWB variables for both the training and the test sub-periods, while Figure 4 depicts the predicted and observed SWB variables. During the training sub-period (that is, the dataset with which the model was estimated) correlations between the predicted and actual series are generally high, ranging from 0.87 for *Anger* to 0.97 for *Learn* and *Stress*. Do these correlations remain high over the out-of-sample testing sub-periods? A major finding of this paper is that this is indeed the case in a majority of cases. Out of 20 tests, 16 yield correlations over 0.60, 13 over 0.70, and 11 over 0.80. Two of the ten affects stand out as being particularly difficult to predict (out of sample): *Learn* (0.47 in 2008 and 0.55 in 2013) and *Respect* (-0.58 in 2008 but a respectable 0.80 in 2013). One possible reason for this is that these affects are not well defined or understood.

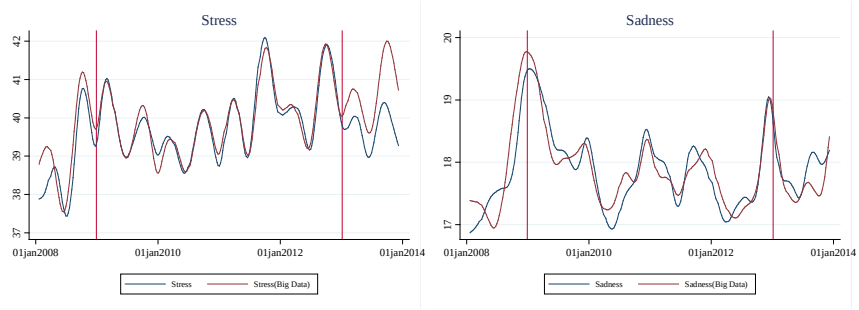
Table 4. Correlation between Predicted and Observed SWB values (Smoothed)

	Life Evaluation	Life Evaluation 5 Years	Happiness	Laugh	Learn	Respect	Anger	Stress	Worry	Sadness
Training	0.93	0.87	0.90	0.96	0.96	0.92	0.91	0.97	0.96	0.94
Test 2008	0.85	0.76	0.63	0.85	0.47	-0.58	0.60	0.92	0.94	0.89
Test 2014	0.92	0.86	0.47	0.86	0.55	0.80	0.61	0.82	0.84	0.70

39. In the case of *Life evaluation* this may be due to the change in the ordering of questions in the Gallup survey that took place at about this time, and is thought to depress the overall *Life evaluation* measure, as reported by Deaton (2011).

40. However, the objective of this exercise is to obtain a combination of keywords that is able to predict the evolution — rather than the level — of subjective well-being, both cognitive and emotional. With respect to this objective, it seems that such an exercise is not out of reach, at least over a 12 month period. Big Data creates a new avenue for constructing a high-frequency indicator of subjective well-being beyond GDP

Figure 4. Predictions and Observed SWB (Training Data inside the red lines, Test Data outside)



5. Conclusion

41. This paper proposes an original methodology to construct robust predictors of subjective well-being variables in the United States from a very large amount of search engine data covering the 2008-2014 period. Our framework is simple and transparent, has strong validity, is grounded in theory and the existing literature on subjective well-being, and allows for continuous updating of the predicted series. In particular, we make use of a sensible statistical arsenal to filter out the relevant information among a large number of noisy measures, which is often an important concern when working with Big Data. As a result, we find that keywords related to job search, financial security, family life and summer leisure are the most important predictors of subjective well-being. Moreover, the model successfully predicts the out-of-sample evolution of most subjective well-being measures at a one-year horizon. Regarding future research, this paper presents an original methodology that lays the groundwork to construct subjective well-being indices at the local level (state or metropolitan area), which might then be used to measure the impact of local shocks or policy reforms on subjective well-being in the United States.

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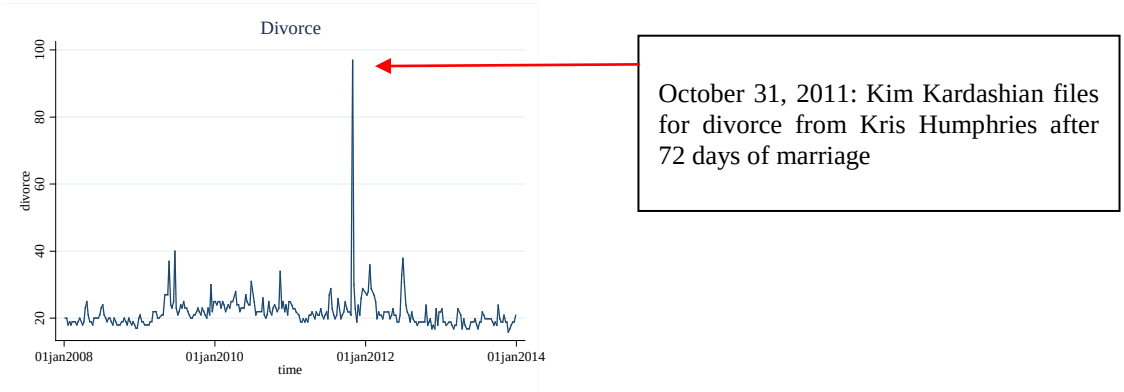
APPENDIX A. BIG DATA ISSUES

This Appendix gives additional detail on problems encountered with the data on search volume downloaded from Google Trends. There are four main types of problems: spikes, cliffs, the January 2011 discontinuity, and time trends.

Spikes

Many search terms show large spikes. These spikes might either be related to the importance of the underlying word, related to a tangential cultural event, or be unexplained. The spikes pose two different problems. The first problem is that if they are unrelated to the underlying concept of interest (see, for example, Figure A1, showing the divorce of Kim Kardashian, an American celebrity as the likely cause of the spike in searches that include the term "divorce" during the last week of October, 2011), they will add a large amount of statistical noise. The second is that even if they are related to the underlying concept, they will lead to large outliers in the explanatory variables. If a sufficient number of explanatory variables have such outliers, the risk of overfitting increases (in principal, if there are as many explanatory variables with spikes as there are data points, one could fit the series perfectly). We address this problem in two ways. First, we use a five-period moving average in the analysis, which dampens shocks within an individual keyword. Second, the composite indicators dampen the shock present across keywords.

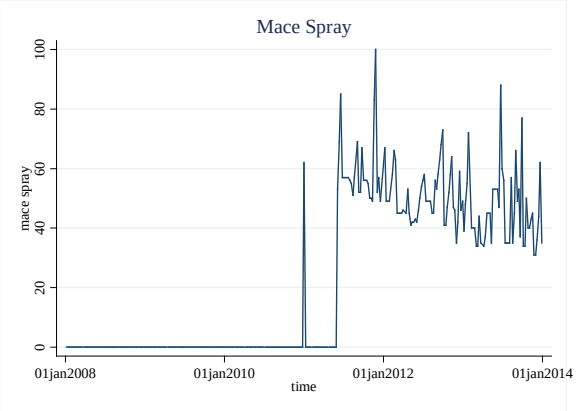
Figure A1. "Spikes" and the Divorce of Kim Kardashian



Cliffs

Other search terms show "cliffs", where volume is at or near zero for some substantial period (see Figure A2 below), and it is difficult to know whether it is because volume was zero or because there is an issue with the way the Google trends data is compiled. These cliffs pose an issue similar to that of the spikes, especially since words have cliffs at different points (that is, it is into a uniform discontinuity). However, we do not wish to exclude all zeros, because some zeros reflect zero volume. To address this issue, we dropped any search term with more than five zeros during the period (changing the number of allowable zeros does not substantially change the results). This results in a loss of information, as we have to exclude many terms that are potentially salient and important (such as mace spray).

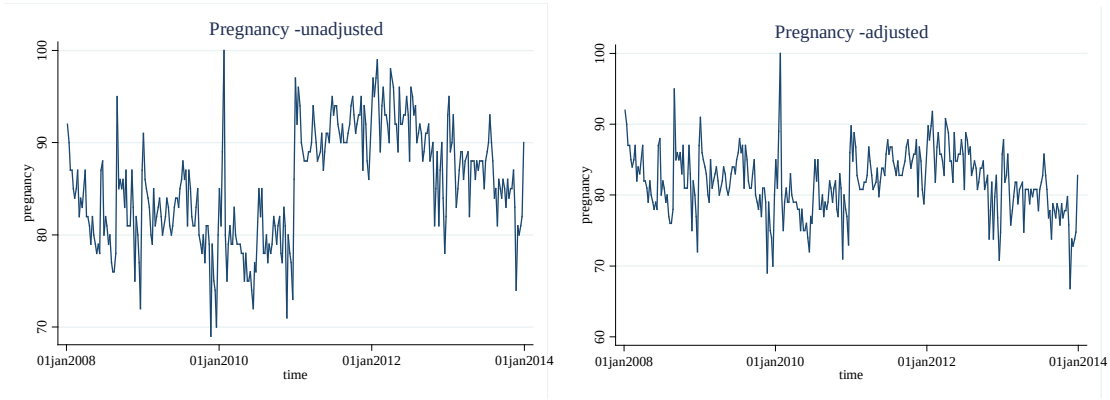
Figure A2. "Cliffs" and Mace Spray



The January 2011 Discontinuity

We observed an unexplained discontinuity in many search term volumes from the last week of December, 2010, to the first week of January, 2011. An example for the word "pregnancy" is provided in Figure A3. To adjust for this discontinuity, which we believe to be related to the localization used by Google in treating the data, we calculate the average index in December and January for the unaffected years, we take the average change during the unaffected years, subtract this unaffected average change from the observed change from December 2010 to January 2011, and adjust all data from 2011 onwards using this difference. That is, we assume that the change from December 2010 to January 2011 should be the same as in the other years, and we adjust accordingly. While we may lose some information with this adjustment, there should not be any bias introduced.

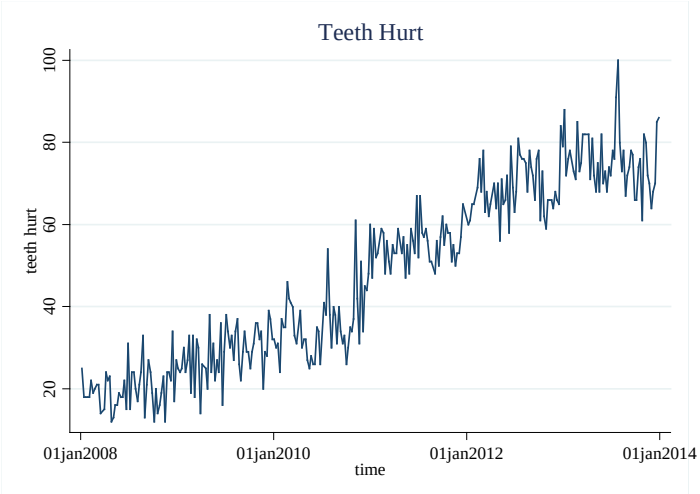
Figure A3. Adjustment for the January 2011 Discontinuity



Time Trends

Some search terms (see "teeth hurt" in Figure A4) exhibit strong time trends. There are several possibilities for this. First, it may be that the importance of this term is increasing – that is, either people have more tooth pain or it bothers them more, and that this trend continued fairly consistently for six years. Second, it may be that people experience the same amount of discomfort from tooth pain, but they are turning more and more to the internet for advice on this type of problem (either because of cultural shifts or external factors such as increasing health care costs). There might also be a third reason related to the compilation of the search data within Google that we do not know. The time trends are problematic for at least two reasons. First, a positive coefficient on a term with a strong time trend might lead to large and unrealistic predictions for subjective well-being in the future. Second, as our estimation strategy relies on creating statistically coherent composite variables, we risk grouping together words that are unrelated but share a common time trend. To avoid these issues we drop all words where the adjusted R2 (using training data only) from a regression of time on the keyword is greater than 0.6, and we individually examine the series for words between 0.5 and 0.6 and drop the word if the trend is consistent over the period.

Figure A4. Time trends in "Teeth hurt"



APPENDIX B. EXPLORATORY FACTOR ANALYSIS

To group the search terms into coherent categories, we took the following steps. First, we removed seasonality by regressing month and, for January and December, week dummies on the search volume, to avoid grouping terms together only because they shared seasonal patterns. Second, we roughly grouped the words into a priori related categories (such as jobs or family). Third, we ran a factor analysis, removing any terms which had a factor loading of less than 0.3. These removed terms might also form a separate category (so jobs was divided into *Job Search* and *Job Market*). The factor loadings from the final categories are given below. In order to preserve the option of future application of the categories, we use a z-score average to compute the actual category rather than the factor loadings. Using the factors rather than the z-score averages produces almost identical results.

Table B1. Factor Loading for Material Conditions Variables

Job Search	Factor Loadings	Job Market	Factor Loadings	Financial Security	Factor Loadings	Home Finance	Factor Loadings
part time job	0,734	jobbenefits	0,528	401K	0,478	mortgage rates	0,962
layoffs	0,879	employment contract	0,864	banking	0,790	mortgage calculator	0,913
jobfair	0,874	careercenter	0,871	family budget	0,374	mortgage	0,995
apprenticeships	0,825	coverletter	0,888	housing authority	0,712	refinancing	0,934
severance pay	0,817	pension	0,557	section8	0,500	houseprice	0,780
unemployment rate	0,798	cert prog	0,482	inflation	0,770	homeloan	0,927
careerfair	0,626	retirement	0,901	studentloans	0,764	housing crisis	0,849
jobs	0,408	work experience	0,568	school loans	0,858	mortgage payments	0,764
unemployment benefits	0,473	entrylevel	0,755	interestrate	0,839		
		qualifications	0,905	fired	0,562		
		discrimination	0,806	financial crisis	0,782		
		employee benefits	0,903	loans	0,954		
				eitc	0,837		
				socialsecurity	0,692		
				coupons	0,492		
				medicaid	0,413		
				file for bankruptcy	0,622		
				shelter	0,726		
				eviction	0,623		
				foodbank	0,755		
				homelessshelters	0,716		

Table B2. Factor Loading for Social Variables

Family Stress	Factor Loadings	Family Time	Factor Loadings	Civic Engagement	Factor Loadings	Personal Security	Factor Loadings
domestic abuse	0,889	snacksforkids	0,821	volunteering	0,855	firearm	0,845
marriagehelp	0,763	weekends	0,380	blood donation	0,656	victims	0,771
marriage problems	0,776	adhd	0,558	homeowners association	0,817	gun	0,728
custody	0,690	daycare	0,543	boyscouts	0,645	gunsafety	0,754
marriage counseling	0,822	child care center	0,555	kiwanis	0,920	violent crimes	0,858
familysupport	0,870	pta	0,758	citycouncil	0,767	crime rate	0,870
womensshelter	0,432	kidsparty	0,402	freemasons	0,642	assault	0,647
		volleyball	0,359	bingo	0,548	securitycamera	0,558
		play football	0,792	teaparty	0,496	murder	0,481
		reading	0,470	lionsclub	0,653	selfdefense	0,552
		recipe	0,602	club	0,779	aggression	0,303
		housework	0,397	community meeting	0,439	risks	0,245
		laundry	0,820	civic engagement	0,364	homealarm	0,246
		toddler	0,810	rotaryclub	0,889	mugging	0,314
		babyshower	0,820	towncouncil	0,559		
		bullying	0,637				
		kids books	0,881				
		ideasforkids	0,919				
		tuition	0,782				

Table B3. Factor Loading for Health and Wellness Variables

Health Conditions	Factor Loadings	Healthy Habits	Factor Loadings	Summer Leisure	Factor Loadings	Education and Ideals	Factor Loadings
stress	0,772	exercise	0,824	golf	0,934	middleschool	0,493
hypertension	0,583	weights	0,679	fishing	0,952	juniorhigh	0,798
diabetes	0,841	healthydiet	0,814	motorcycle	0,905	economics	0,866
obesity	0,834	dental care	0,735	ponds	0,921	homework	0,690
Panic disorder	0,748	fruits and vegetables	0,591	hiking	0,925	State university	0,872
illness	0,559			biking	0,939	moral	0,879
tobacco use	0,832	life expectancy	0,800	water sports	0,610	individualism	0,893
lung cancer	0,776	lose weight	0,355	boating	0,878	billofrights	0,825
heartdisease	0,776	health care	0,773	tours	0,880	human capital	0,633
obsessive compulsive disorder	0,885	quitsmoking	0,383	beachcottage	0,588	constitution	0,880
				sightseeing	0,874	politicalaction	0,587
				bedandbreakfast	0,839	social justice	0,530
cancer	0,429			baseball	0,323	dropout	0,419
relax tech	0,642			softball	0,420	reading books	0,681
antidepressant	0,871			playpool	0,617	grammar	0,909
health status	0,339					tutor	0,861
fracture	0,316					buddhist	0,774
arthritis	0,625					school	0,866
asthma	0,866					highschool	0,906
relaxation	0,615					ethics	0,944
self care	0,506					philosophy	0,941
sleepproblems	0,638					onlinecourses	0,476
mayoclinic	0,775					literature	0,976
depression symptoms	0,620					degree	0,598
						language	0,940
symptomchecker	0,543					science	0,942
suicide rates	0,772					literacy	0,942
drug use	0,776					studies	0,941
chronicfatigue	0,638					study	0,625
						mathematics	0,953
						learning	0,966
						skills	0,725
						secondary education	0,876
						writing	0,952
						worship	0,812
						creativity	0,523
						psychologist	0,896
						therapy	0,850
						selfesteem	0,894
						morality	0,809
						poverty	0,931
						feminist	0,547
						rights	0,951
						relations	0,933
						freedomofspeech	0,731
						civilrights	0,830
						religion	0,509
						religious	0,932
						propertyrights	0,672
						racism	0,772

						governments	0,361
						freespeech	0,775
						rituals	0,850
						infant mortality	0,837
						spirituality	0,802

APPENDIX C. BAYESIAN AVERAGING MODEL RESULTS

Life Evaluation		**Life Evaluation in 5 Years**		**Happiness**		**Laugh**		**Learn**	
Category	PIP	Category	PIP	Category	PIP	Category	PIP	Category	PIP
Job Search	1	Family Stress	.9999999	Family Life	.9999308	Job Search	1	Job Search	1
Family Stress	.9999345	Financial Security	.9999994	Job Market	.9988018	Family Life	1	Family Life	.9999999
Job Market	.9959486	Job Search	.9987293	Financial Security	.9612713	Personal Security	.9987682	Health Conditions	.9926389
Healthy Habits	.9756049	Personal Security	.9867251	Job Search	.7824603	Summer Leisure	.9339863	Financial Security	.9868134
Civic Engagement	.896345	Job Market	.9126053	Summer Leisure	.5180083	Health Conditions	.9287642	Healthy Habits	.8700904
Financial Security	.4405012	Family Life	.7997323	Education and Ideals	.3740062	Financial Security	.7978849	Job Market	.7783921
Summer Leisure	.0798991	Education and Ideals	.1033073	Family Stress	.2125029	Civic Engagement	.5212126	Family Stress	.2353987
		Civic Engagement	.0968726	Civic Engagement	.1982485	Job Market	.4633149	Summer Leisure	.136816
		Summer Leisure	.0882474	Health Conditions	.0954218	Family Stress	.1317561	Education and Ideals	.0983368
		Health Conditions	.0730709	Personal Security	.0713978	Education and Ideals	.1096197	Civic Engagement	.0924329
								Personal Security	.0689583

Respect		**Anger**		**Stress**		**Worry**		**Sadness**	
Category	PIP	Category	PIP	Category	PIP	Category	PIP	Category	PIP
Job Market	1	Job Search	1	Family Life	1	Job Search	1	Job Search	1
Job Search	.9999644	Financial Security	.9999973	Job Search	1	Summer Leisure	.9999992	Personal Security	.9999999
Financial Security	.9995359	Summer Leisure	.9999353	Healthy Habits	.9999991	Healthy Habits	.9999803	Family Life	.9998972
Healthy Habits	.2881511	Education and Ideals	.9795223	Summer Leisure	.9999747	Financial Security	.9998447	Summer Leisure	.9981101
Personal Security	.1305427	Civic Engagement	.0981886	Financial Security	.9726784	Family Stress	.6311848	Education and Ideals	.9921088
Family Stress	.1250909	Health Conditions	.0951104	Education and Ideals	.7365542	Education and Ideals	.5506082	Financial Security	.9878952
Summer Leisure	.0748373	Job Market	.0887169	Civic Engagement	.4862978	Health Conditions	.5280867	Healthy Habits	.9852301
		Personal Security	.0664031	Health Conditions	.3005131	Personal Security	.5102105	Health Conditions	.1115238
		Family Stress	.0663557	Family Stress	.2364499	Civic Engagement	.0752305	Civic Engagement	.0924093
				Personal Security	.1218278	Family Life	.067823	Family Stress	.0690964
				Job Market	.0749033				

Output from Bayesian Model Selection routine carried out in R using BMS package, with 1M iterations. Fixed effects were included for weeks during the months of December and January, and months during the rest of the year. PIP indicates the posterior inclusion probability. To avoid overfitting, the categories used for each SWB variable were restricted to those that increased the adjusted R2 when included in a regression with month and week controls.