Title: Big Data Measures of Well-Being: Evidence from a Google Well-Being Index in the United States

Short title: Big Data Measures of Well-Being

Authors: Yann Algan[a], Elizabeth Beasley[b], Florian Guyot[c], Kazuhito Higa[d], Fabrice Murtin[e], Claudia Senik[f]

Classification: Social Sciences, Economic Sciences

Keywords: Subjective Well-Being; Big Data; Bayesian statistics;

[a] yann.algan@sciencespo.fr, Department of Economics, Sciences Po, Paris 75006, France

[b] elizabeth.beasley@cepremap.org, Well-Being Observatory, CEPREMAP, Paris 75014, France

[c] florian.guyot@sciencespo.fr, Department of Economics, Sciences Po, Paris 75006, France

[d] Kazuhito.higa@oecd.fr; OECD, Statistics Directorate, Paris 75016, France

[e] Fabrice.Murtin@oecd.org; OECD, Statistics Directorate, Paris 75016, France (corresponding author)

[f] senik@pse.ens.fr; Université Paris-Sorbonne and Paris School of Economics, Paris 75014, France

SIGNIFICANCE (120 WORDS)

Subjective well-being – for example, how happy or satisfied people are with their lives - has great promise as an indicator of social progress. It can potentially be used as a better measure of the impact of policy or different types of events on well-being. Data on subjective well-being is costly to obtain through surveys, and there remains some uncertainty about what is driving responses to subjective well-being questions. We use internet search volumes to build a model that accurately forecasts subjective well-being in the United States and also gives information on what aspects of life are correlated with well-being. We find that searches related to employment, financial security, family life and leisure are particularly important in predicting well-being. This model can be used to produce data at a much higher frequency and granularity than is available through survey data.

ABSTRACT

We build an indicator of individual wellbeing in the United States based on Google Trends. The indicator is a combination of keyword groups that are endogenously identified to fit with weekly time-series of subjective wellbeing measures collected by Gallup Analytics surveys. We show that such information from Big Data can be used to build a model that accurately forecasts survey-based measures of subjective well-being. The model successfully predicts the out-of-sample evolution of most subjective wellbeing measures at a one-year horizon. This opens up the possibility to use Big Data as a complement to traditional survey data to measure and analyze the well-being of population at high frequency and very local geographic level. We show that we can also exploit the internet search volume to elicit the main life dimensions related to well-being. We find that keywords associated with job search, financial security, family life and leisure are the strongest predictors of the variations in subjective wellbeing in the United States. This paper contributes to the new research agenda on data sciences by showing how Big Data can improve our understanding of the foundations of human wellbeing.

Introduction

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 wellbeing, 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.[1] 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 both in measurement and interpretation (Kahneman and Deaton, 2010; Deaton 2012; Deaton and Stone, 2013; Krueger and Stone, 2014); and alternative approaches such as the Day Reconstruction Method (Kahneman et al., 2004, Stone and Mackie, 2014) and Time Use Surveys (Krueger et al., 2015) have been developed to address some of these issues.

This paper contributes to this new research agenda by showing how Big Data can improve our understanding of the foundations of wellbeing. A major consequence of the accelerated digitization of social life is the traceability of attitudes, feelings, and social relations, embedded in large datascapes, such as Google, Facebook, Twitters or the Blogosphere. The quantification of those social traces should be 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 measure and the analysis of human wellbeing.

The first advantage of these data is that they offer social scientists the possibility to observe people's behavior, such as searches on Google, to make inferences about attitudes and feelings, rather than statements about attitudes and feelings. 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.

The second main 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.

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 wellbeing. Our methodology allows us to construct a model that has four important qualities: it is grounded in theory and the existing literature on well-being, it is testable and has strong out of sample

[1] 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).

performance, it is reasonably transparent, and it is adaptable and can potentially be used to predict well-being on a continuous and recurrent basis.

This paper builds on the growing literature that seeks to exploit search engine data. The early contribution of Ettredge et al. (2005) used internet search data to forecast the unemployment rate in the US. 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). 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.

This paper demonstrates the capacity of search engine data to track and replicate the trends in subjective affects 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 wellbeing 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 wellbeing, 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 wellbeing. In practice, we run a simple variance decomposition to quantify the contributions of each dimension to predict well-being. For all subjective wellbeing 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 wellbeing.

Results

A Model of SWB in the United States

To facilitate estimation, interpretation, and the robustness of the model, Google 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 (*Family Stress, Family Time, Civic Engagement* and *Personal Security*), and Health and Wellness (Healthy Habits, Health Conditions, Summer Activities and Education and Ideals)[2]. The composition of each category is described in the Supporting Information. Note that the search terms in *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

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

alpha[3] (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). Table 1 shows the composite categories and their components.

(TABLE 1 ABOUT HERE)

Table 2 presents the results from the model for each SWB variable[4]. The coefficients are generally consistent for positive and negative affects. Categories of search terms that are consistently associated with higher wellbeing (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 wellbeing are *Job Search, Financial Security, Health Conditions,* and *Family Stress*.

(TABLE 2 ABOUT HERE)

Overall, these findings are in line with the literature on subjective wellbeing. The consistent negative relationship of *Job Search* (which seems to relate to searching for a job from unemployment) confirms the importance of employment as a foundation of subjective wellbeing: having a job is one of the strongest correlates of life satisfaction and happiness, while, conversely, being unemployed is highly detrimental to life satisfaction, notwithstanding 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 generally difficult to disentangle with confidence as reported health status may be a proxy of subjective wellbeing and as such are highly correlated (see Deaton, 2008, for instance). In addition, there is evidence that higher levels of well-being themselves lead to better health outcomes (Howell et al, 2007).

Civic Engagement is related to the importance of social capital, which has been amply demonstrated to be strongly associated with subjective wellbeing (see for instance Helliwell and Wang 2011 or 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 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 wellbeing are summarized in The World Happiness Report (2013, 2015).

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 (note that generally, living in a high crime area is associated with lower SWB as argued by Lelkes, 2006).

---

[3] Cronbach's alpha is a normalized index of correlation that indicates the degree to which a set of variables measures a single latent variable. It is often viewed as an indicator of internal consistency.

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

Variance Decomposition

Simple variance decomposition as described can help to quantify the contributions of each covariate to the explanatory power of the model (see Supporting Information for details). Table 3 reports the results. Overall, it appears that, for all subjective wellbeing variables except 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 healthy habits.

(TABLE 3 ABOUT HERE)

Predicting SWB in the United States and Reliability of the Model

The model is quite reliable in out of sample tests. 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 1 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*. A major finding of this paper is that the correlations remain high in out-of-sample testing periods for most subjective well-being variables. 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 AND FIGURE 1 ABOUT HERE)

Note that a high correlation does not necessarily imply an accurate prediction, since the correlation measures the degree to which the two data move together, rather than whether they are equal. For example, the 2008 test period has a very high correlation for *Life evaluation*, but visual inspection of the graph shows that while the series move together, the predicted series is much higher. 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). The objective of this exercise is to obtain a combination of keywords that is able to predict the evolution -and not the level- of subjective wellbeing, 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 wellbeing beyond GDP

Discussion

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 wellbeing. Moreover, the model successfully predicts the out-of-sample evolution of most subjective wellbeing measures at a one-year horizon. Regarding future research, this paper presents an original methodology that lays the groundwork to construct 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 well-being in the United States.

Materials and Methods

Data

The SWB data is taken from Gallup Analytics, which is 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, learn, life evaluation 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. Additional detail is given in Supporting Information

The 'Big Data' in this paper is the search frequency of keywords on Google, which are available from Google Trends. The data on search volume present many challenges for empirical estimation which are discussed in detail in Supporting Information. 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 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 that 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 a cherry picking of 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.

Empirical Framework

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 first aim to avoid 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. 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). Formally, let X denote the set of all possible categories and $X_\gamma \in X$ a given subset. We use the BMS package for R (Feldkircher and Zeugner, 2015), where the 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. Asa 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].

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 (see George, 1999, Brock and Durlauf, 2001, and Durlauf, Kourtellos and Tan, 2012), and it can be addressed by using a preliminary factor analysis in order to reduce the number of potential explanatory variables. In practice, 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.

The grouping of words into categories must be coherent both logically and statistically. The words grouped together must meet a common sense test, 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. 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. Further detail on the categories is given in Supporting Information, and here we note only that many of the constructed categories match trends observed in

[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.

administrative data linked to the underlying construct (though the frequency of the administrative data makes a detailed empirical analysis of this relationship difficult). For example, the *Financial Stress* category matches the yearly trend of Chapter 11 filings in the United States fairly well, and *Family Stress* is decreasing over the period along with reports of Intimate Crime as provide by the FBI. 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.

Regarding model selection and out-of-sample prediction, 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 is used for the training set, while data from 2008 to 2009 is 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.

In practice, we first identify the most robust categories by applying BMA to the training data. All categories with a PIP larger than 0.7 are pre-selected as a potential determinant of the subjective well-being variable. The PIPs of the various categories found in the exploratory analysis are reported in the Supporting Information. 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.[6]

[6] 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 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.

ACKNOWLEDGEMENTS

Algan, Beasley and Senik are grateful to CEPREMAP for financial support. Yann Algan has received the financial support of the ERC Advanced Grant. This paper has received the technical support from the Medialab at Sciences Po and the authors are especially grateful to Paul Girard, Guillaume Plique and Mathieu Jacomy. We also thank Melissa Leroux for excellent research assistance. This document expresses the views of the authors and does not reflect the official views of the institutions with which the authors are affiliated. All errors are our own.

REFERENCES

Askitas, N. and K.F. Zimmermann (2010), 'Google Econometrics and Unemployment Forecasting', Technical Report, SSRN 899. [Cited 1 April 2012] Available from: http://papers.ssrn.com/sol3/papers.cfm?abstract_id¼1465341.

Baker, S. and A. Fradkin (2014), 'The Impact of Unemployment Insurance on Job Search: Evidence from Google Search Data', Working Paper Stanford.

Benjamin D., O. Heffetz, M. Kimball and N. Szembrot, "Beyond Happiness and Satisfaction: Toward Well-Being Indices Based on Stated Preference", *American Economic Review* 104.9 (2014): pp. 2698-2735.

Biddle, S.J., and P. Ekkekakis (2005), Physically active lifestyles and well-being, *The science of well-being*, pp. 140-168.

Buddelmeyer H., D. Hamermesh and M. Wooden (2015), "The Stress Cost of Children", IZA Discussion Paper No. 8793.

Choi, H. and H. Varian (2009), 'Predicting Initial Claims for Unemployment Insurance Using Google Trends', Technical report, Google. [Cited 1 April 2012] Available from: http://research.google.com/archive/papers/initialclaimsUS.pdf.

Choi, H. and H. Varian (2012), 'Predicting the Present with Google Trends', *The Economic Record*, Vol. 88, pp. 2-9.

Clark A. and A. Oswald (1994), "Unhappiness and Unemployment", *Economic Journal*, 104, pp. 648-659.

Clark A., E. Diener, Y. Georgellis and R. Lucas (2008), "Lags and Leads in Life Satisfaction: A Test of the Baseline Hypothesis", *Economic Journal,* 118 (529).

D'Amuri F. and J. Marcucci (2010), "Google it! Forecasting the US Unemployment Rate with a Google Job Search Index", Social Science Research Network. [Cited 1 April 2012] Available from: http://papers.ssrn.com/sol3/papers.cfm?abstract_id¼1594132.

Deaton A. (2008), "Income, Health and Well-Being around the World: Evidence from the Gallup World Poll", *Journal of Economic Perspectives*, 22(2), pp. 53-72.

Deaton A. (2012), "The Financial crisis and the well-being of Americans", in *Investigation in the Economics of Aging*, Chicago, IL: Chicago University Press.

Deaton A. and A. Stone (2013), "Do context effects limit the usefulness of self-reported well-being measures?" *Research Program in Development Studies Working Paper*, n° 288.

Eicher T.S., C. Papageorgiou and A.E. Raftery (2011), "Default priors and predictive performance in Bayesian model averaging, with application to growth determinants", *Journal of Applied Econometrics*, Vol. 26 (1), pp. 30-55.

Ettredge M., J. Gerdes and G. Karuga (2005), "Using Web-based Search Data to Predict Macroeconomic Statistics", Communications of the ACM, 48 (11), pp. 87-92, [Cited 1 April 2012] Available from: http://portal.acm.org/citation.cfm?id¼1096010.

George D. and P. Mallery (2003), SPSS for Windows step by step: A simple guide and reference, 11.0 update (4th ed.), Boston: Allyn & Bacon.

Helliwell J. and S. Wang (2011), "Trust and Wellbeing", *International Journal of Wellbeing*, (1), pp. 42-78.

Helliwell J., C. Barrington-Leigh, A. Harris and H. Huang (2010), International Evidence on the Social Context of Well-Being, in Diener E., Helliwell J. & Kahneman D. (eds.), *International Differences in Well-Being*, Oxford University Press.

Helliwell J., R. Layard and J. Sachs (2015), World Happiness Report, United Nations.

Hoeting J.A., D. Madigan, A.E. Raftery and C.T. Volinsky (1999), "Bayesian Model Averaging: A Tutorial", *Statistical Science* 14, pp. 382-417.

Howell R.T., M.L. Kern and S. Lyubomirsky (2007), "Health benefits: Meta-analytically determining the impact of well-being on objective health outcomes", *Health Psychology Review*, *1* (1), pp. 83-136.

Kahneman D., A. Krueger, D. Schkade and A. Stone (2006), "A Survey method for characterizing daily life experience: The day reconstruction method", *Science* 306 (5702), pp. 1776-1780.

Kahneman D. and A. Deaton (2010), "High income improves evaluation of life but not emotional well-being", *Proceedings of the national academy of sciences*, *107* (38), pp. 16489-16493.

Krueger, A. Eds (2009), *Measuring the Subjective Well-Being of Nations: National Accounts of Time Use,* University of Chicago Press, Chicago.

Krueger A. and Stone, A., "Progress in measuring subjective well-being", *Science* 346, (6205), pp. 42-43

Lelkes O. (2006), "Knowing what is good for you: Empirical analysis of personal preferences and the objective good", *The Journal of Socio-Economics*, *35* (2), pp. 285-307.

Mavridis D. (2015), "The unhappily unemployed return to work faster", IZA Journal of Labor Economics, 4 (1), pp. 1-22.

Nunnally J.C. (1978), "Assessment of Reliability". Psychometric Theory (2nd ed.), New York: McGraw-Hill.

OECD (2013), *OECD Guidelines on Measuring Subjective Well-being*, OECD Publishing, Paris, DOI: http://dx.doi.org/10.1787/9789264191655-en

Penna N.D. and H. Huang (2009), "Constructing Consumer Sentiment Index for U.S. Using Google Searches", Technical report, University of Alberta, [Cited 1 April 2012]. Available from: http://econpapers.repec.org/paper/risalbaec/2009_5f026.htm.

Preis T., D. Reith and H. Eugene Stanley (2010), "Complex Dynamics of Our Economic Life on Different Scales: Insights from Search Engine Query Data", Philosophical.

Radinsky K., S. Davidovich and S. Markovitch (2009), "Predicting the News of Tomorrow Using Patterns in Web Search Queries", Proceedings of the 2008 IEEE/WIC/ACM International Conference on Web Intelligence (WI08), [Cited 1 April 2012] Available from: http://www.cs.technion.ac.il/~shaulm/papers/pdf/Radinsky-WI2008.pdf.

Raftery A.E. (1988), “Approximate Bayes Factors for Generalized Linear Models”, Technical Report No. 121, Department of Statistics, University of Washington.

Schwartz H.A., J.C. Eichstaedt, M.L. Kern, L. Dziurzynski, M. Agrawal, G.J. Park, S.K. LakshmikanthJha, M.E.P. Seligman, L. Ungar and R.E. Lucas (2013), “Characterizing Geographic Variation in Well-Being using Tweets”, Proceedings of the Association for the Advancement of Artificial Intelligence.

Scott S.L. and H.R. Varian (2012), “Bayesian Variable Selection for Nowcasting Economic Time Series”, Working Paper Berkeley.

Scott S.L. and H.R. Varian (2014), “Predicting the present with Bayesian structural time series”, International Journal of Mathematical Modelling and Numerical Optimisation, Vol.5, No.1/2, pp.4-23

Shields M.A. and S.W. Price (2005), “Exploring the economic and social determinants of psychological well-being and perceived social support in England”, *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *168* (3), pp. 513-537.

Stiglitz J., A. Sen and J.P. Fitoussi (2009), Rapport de la Commission sur la mesure des performances économiques et du progrès social. France: La Commission.

Stone A. and C. Mackie, Eds. (2014), *Subjective Well-Being: Measuring Happiness, Suffering, and Other Dimensions of Experience*, National Research Council, National Academies Press, Washington, DC.

Suhoy T. (2009), “Query Indices and a 2008 Downturn: Israeli Data”, Technical report, Bank of Israel, [Cited 1 April 2012], Available from: http://www.bankisrael.gov.il/deptdata/mehkar/papers/dp0906e.pdf.

Transactions of the Royal Society of London, pp. 5707-19. [Cited 1 April 2012] Available from: http://rsta.royalsocietypublishing.org/content/368/1933/5707.

Van Praag B. and A. Ferrer-I-Carbonell eds. (2008), *Happiness Quantified: A Satisfaction Calculus Approach,* Oxford University Press.

Zeugner S. and M. Feldkircher (2015). “Bayesian Model Averaging Employing Fixed and Flexible Priors: The BMS Package for R”, *Journal of Statistical Software*, 68(4), 1-37. doi:10.18637/jss.v068.i04

Figure Legends

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	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.

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.

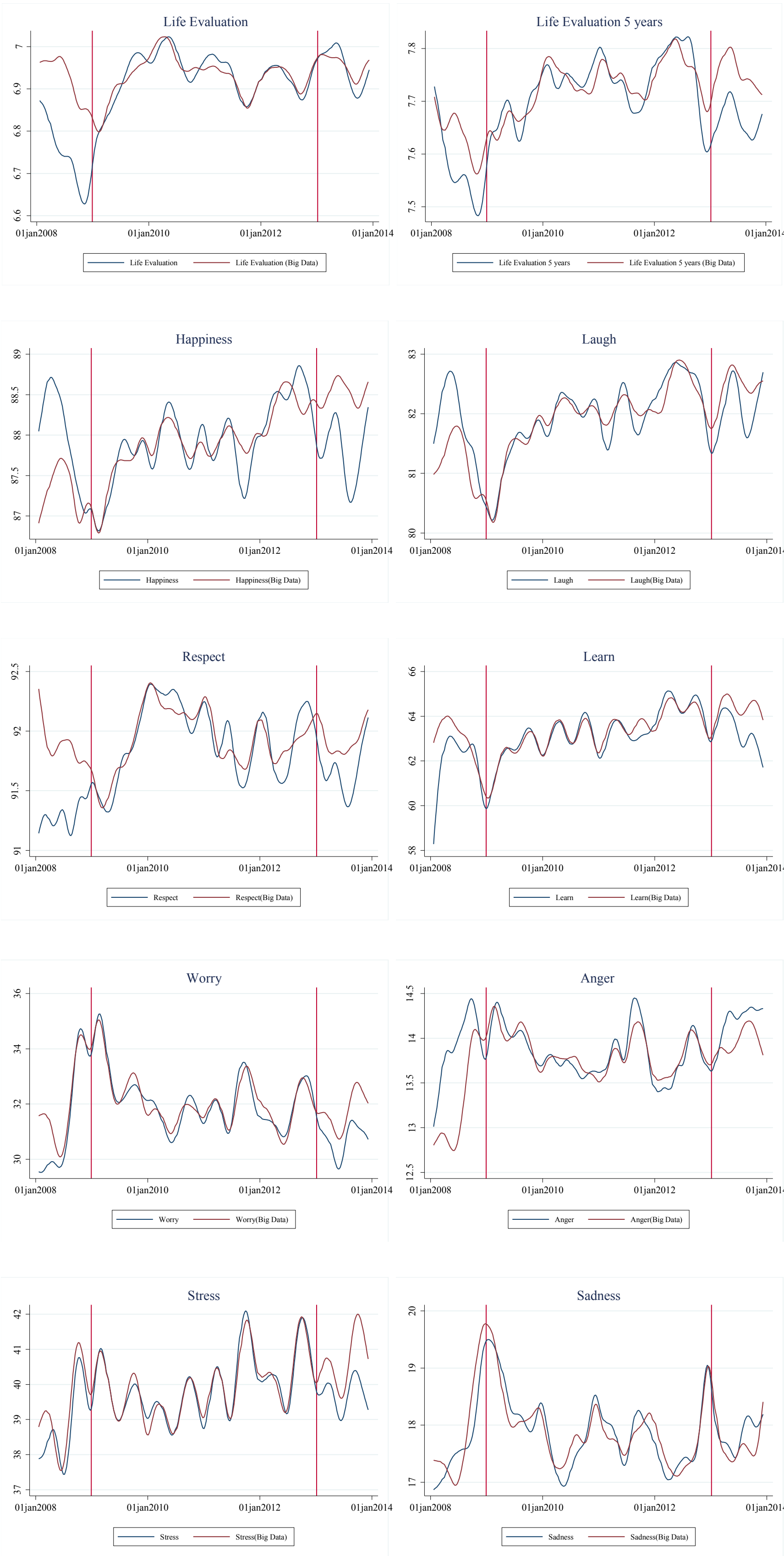
Table 3. Decomposition of the Explained Variance of SWB variables

	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**

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

Figure 1. Predictions and Observed SWB (Training Data inside the red lines, Test Data outside)



Big Data Measures of Well-being:
Evidence from a Google Well-Being Index in the United States

SUPPORTING INFORMATION

Data on Subjective Well-Being

Figure S1 depicts the 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* have dropped significantly in 2008-2009, while the percentages of people experiencing worry, anger, stress and sadness have increased at the same time. A second observation concerns the cyclicality of these variables, which all display large seasonal swings.

(FIGURE S1 ABOUT HERE)

Data challenges with search volumes

The search volumes obtained from Google Trends pose several challenges for estimation. 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).

Spikes

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 the divorce of Kim Kardashian (an American celebrity) from Kris Humphries in October 2010 is shown in Figure S2. This is a concern for estimation as it 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 to dampen the importance of a shock in any individual keyword.

(FIGURE S2 ABOUT HERE)

Cliffs

Other search terms show "cliffs", where volume is at or near zero for some substantial period (see Figure S3), 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 not 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 S3 ABOUT HERE)

The January 2011 Discontinuity

We 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 Figure S4. We believe this discontinuity to be related to the change in the algorithm used by Google to localize the searches in January 2011. To adjust for this discontinuity, 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 are undoubtedly losing some information with this adjustment, there should not be any bias introduced.

Time Trends

Many of the search terms have a strong time trend. The example given in Figure S5 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, as described in the Methods section) 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.

(FIGURE S5 ABOUT HERE)

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 trend. 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).

Additional Information on Categories

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 with 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. The factor loadings for each of the categories are given in Tables S1-S3.

(TABLES S1-S3 ABOUT HERE)

Figure S6 shows the evolution of the category variables over time, and Figure S7 provides some comparison of those trends to other social trends reflected in administrative data. *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, and *Job Search* 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. 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. *Family Life* shows an increasing trend over the period, whereas *Family Stress* decreases after the financial crisis, and the decrease in *Family Stress* maps onto the decrease in Intimate Crime incidents reported by the FBI. *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 S1. Subjective Well Being Variables over time

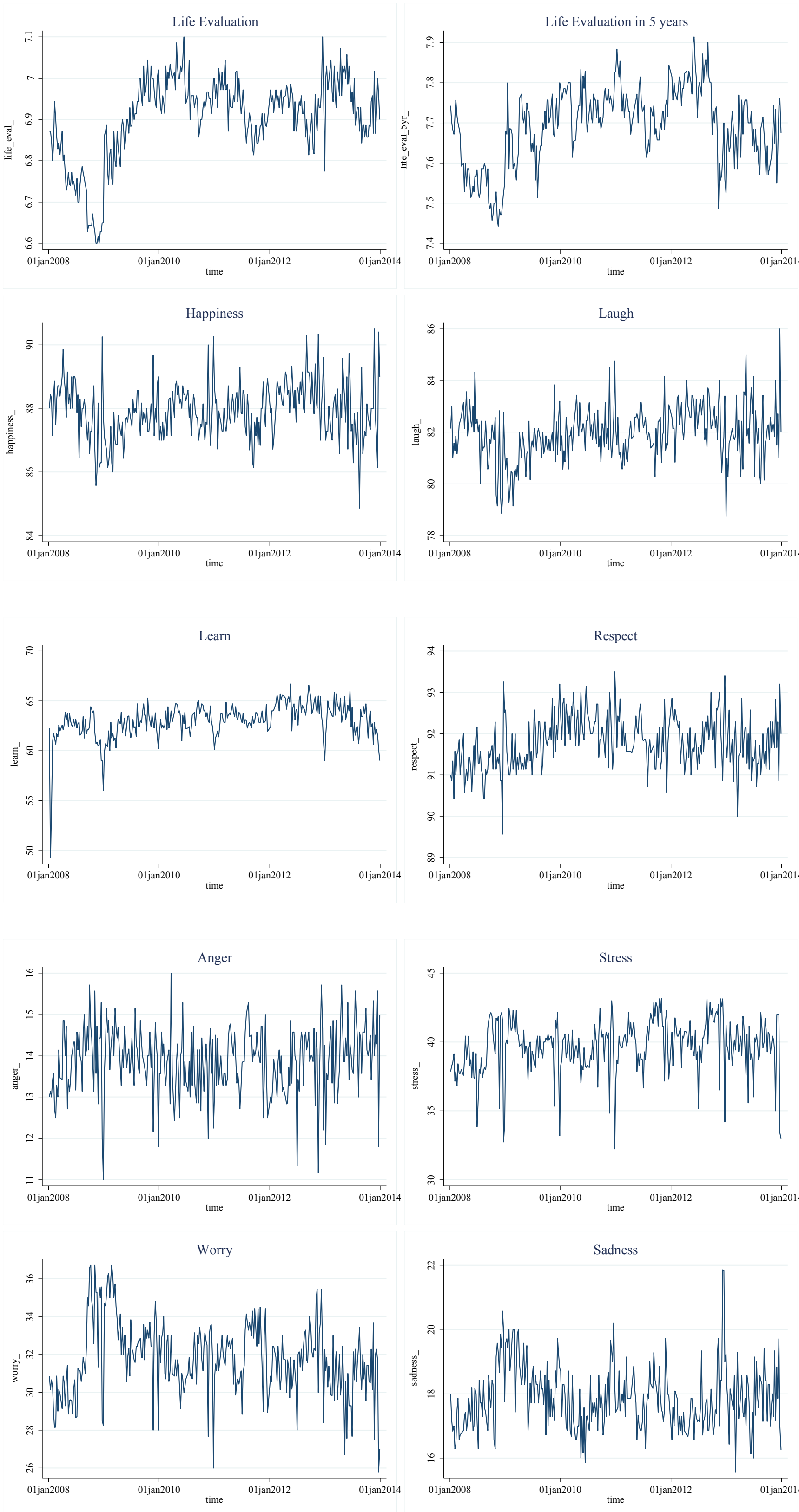
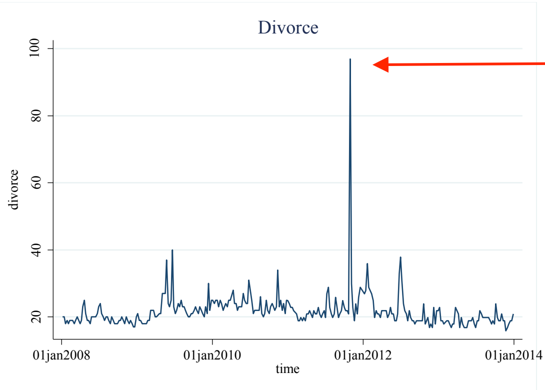


Figure S2. "Spikes" and the Divorce of Kim Kardashian



October 31, 2011: Kim Kardashian files for divorce from Kris Humphries after 72 days of marriage

Figure S3. "Cliffs" and Mace Spray

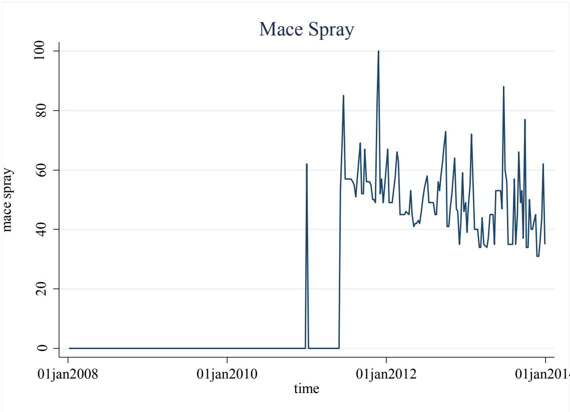
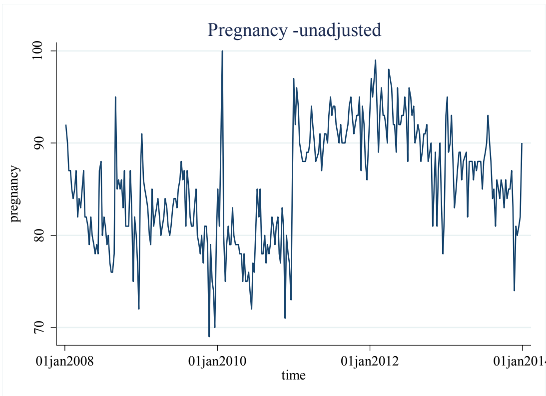


Figure S4. Adjustment for the January 2011 Discontinuity



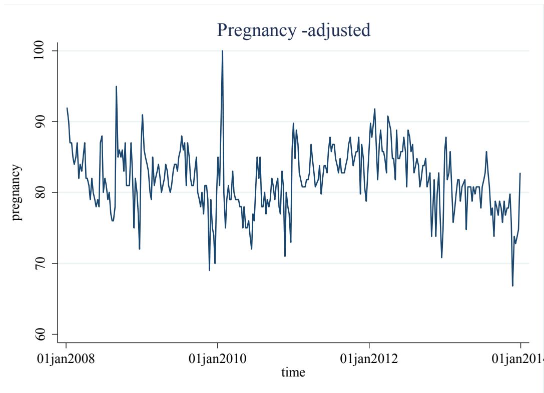


Figure S5. Time trends in "Teeth hurt"

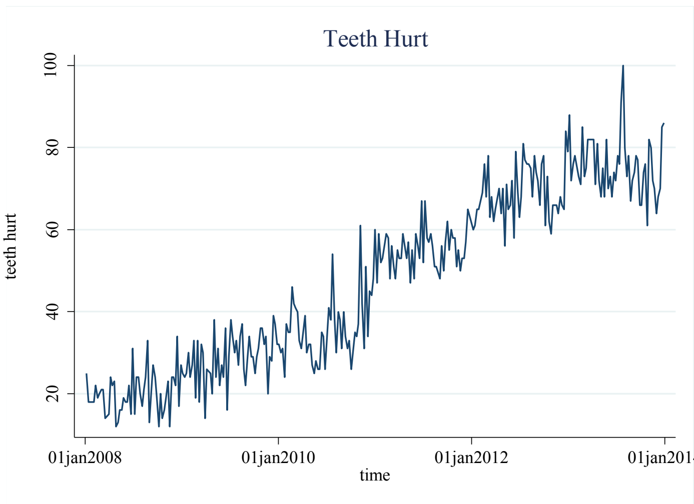


Figure S6. Category Variables over time

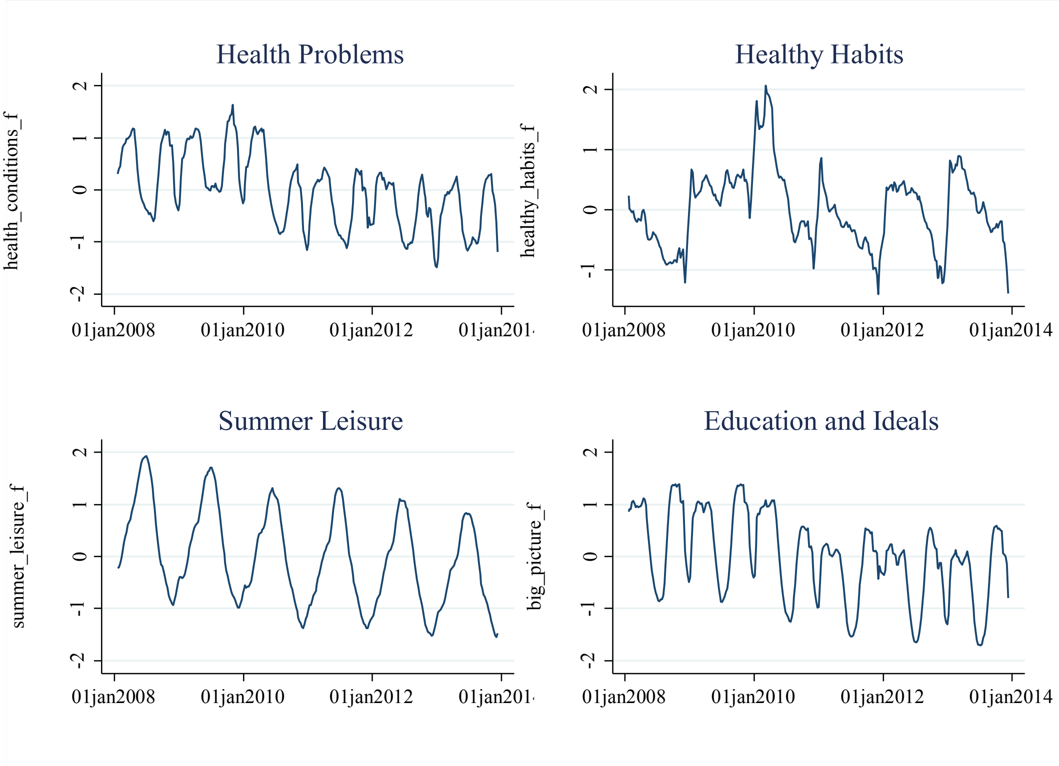
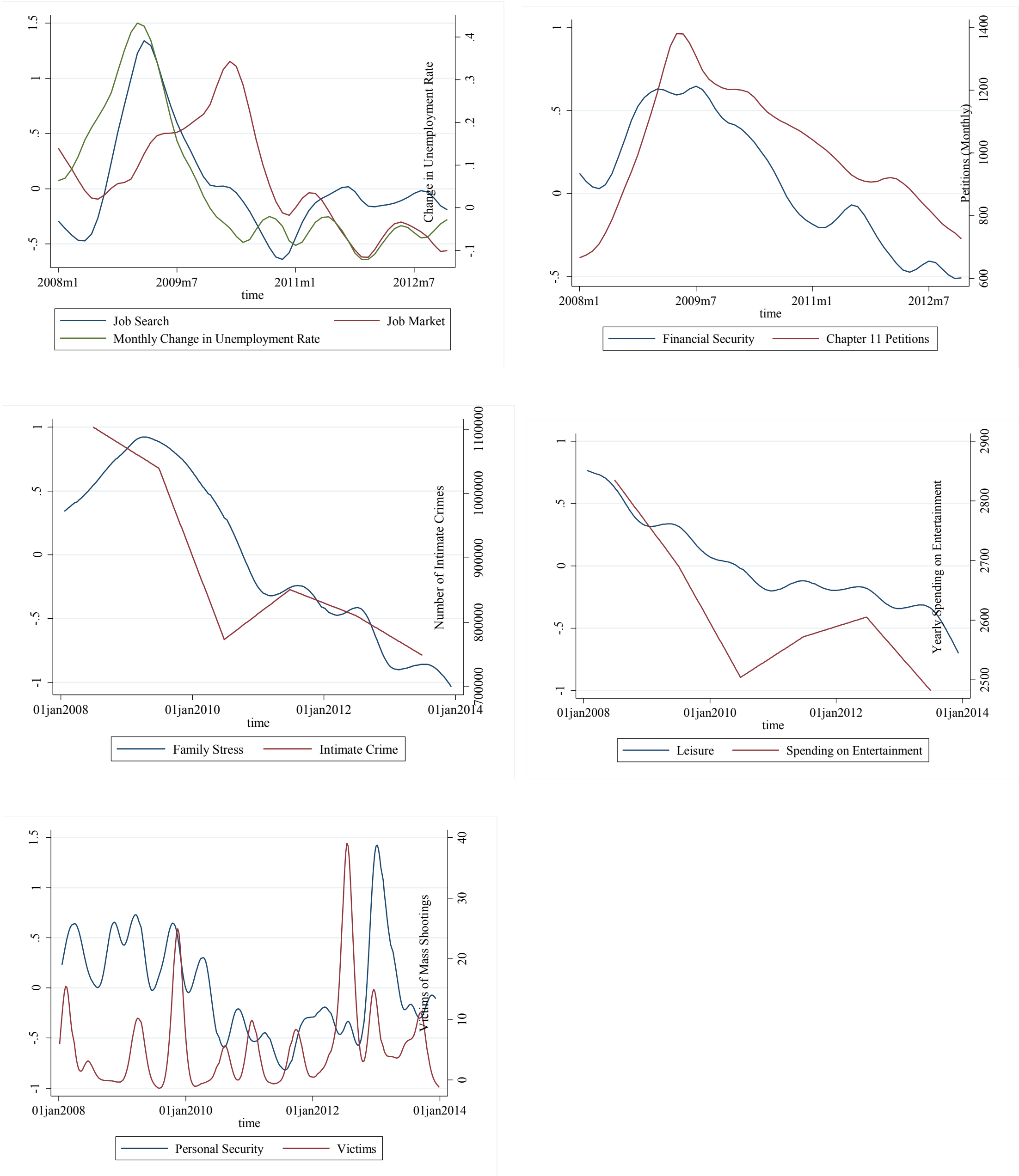

Health Problems
Healthy Habits
Summer Leisure
Education and Ideals
health_conditions_f
healthy_habits_f
summer_leisure_f
big_picture_f
01jan2008
01jan2010
01jan2012
01jan2014

Figure S7. 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).

Table S1. 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 S2. 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 S3. 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

TABLE S4: 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				