# Wellbeing and Unemployment

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**Abstract**

Using micro-data from the European Values Survey over several decades, we analyze the effects of individual unemployment status and local unemployment rates on individual subjective wellbeing. In particular, we innovate on the existing literature in three key ways. First, we aggregate several survey items related to wellbeing and happiness into a single measure of subjective well-being using principal components analysis. Second, we use a double-Lasso procedure to select controls from a high-dimensional dataset in a principled, data-driven manner, thereby introducing machine learning techniques into the research on happiness. Finally, we try to identify plausibly exogenous variation in individual unemployment and local unemployment rates by using exogenous local labor demand shocks as an instrument. We find that *negative* indirect / group effects of unemployment on wellbeing are not robust to including plausible controls for other macroeconomic channels in the data. Moreover, we find suggestive - but not conclusive - evidence that indirect negative effects of unemployment are not causal.

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# 1 Introduction

In a seminal study, Clark and Oswald (1994) found that mental distress was higher among the unemployed than among the employed in Great Britain, but observed that this gap was smaller in the British regions with a higher unemployment rate. Tella et al. (2003) show that self-reports of subjective wellbeing co-move with macroeconomic indicators over the business cycle. Of particular interest, the authors found that increases in the unemployment rate in Europe and the United States tend to have a large, negative effect on subjective wellbeing and that the magnitude of this effect is much larger than that the effects of movements in GDP per capita.

In this paper, we focus on how unemployment affects self-reported subjective wellbeing. We are interested in how subjective wellbeing differs between the unemployed and the rest of the population. In addition, we also analyze whether variation in local unemployment "spills over" to the rest of the population. That is, does subjective well-being change for those that remain employed and out-of-labor force in times of high unemployment? To answer these questions, we use four waves of the European Value Survey (EVS), which contains high-quality, micro-data on self-reported subjective well-being that covers over 40 countries over three decades. This enables us to analyze how subjective wellbeing changes across a variety of locales and macroeconomic conditions.

We employ an eclectic approach that innovates on the existing literature in several ways. First, we aggregate sixteen survey items into a single measure of subjective wellbeing. The EVS asks respondents a battery of questions assessing their satisfaction, happiness and general feelings towards life. Each of these is plausibly correlated with the unobservable subject wellbeing of the respondent. As a result, we pool the noisy information in each survey item by extracting an underlying latent factor using principal components analysis. This constructed index is used throughout the analysis.

Second, we reproduce several specifications that relate individual subjective well-being to individual employment status and local unemployment in the existing literature such as Clark and Oswald (1994). However, in addition, we add to this approach in two key ways. First, we take seriously the risk of including "bad controls" that may lie on the causal pathway from unemployment to subjective well-being. Bad controls may have attenuated prior estimates of the effect of unemployment on subjective well-being towards zero (Angrist and Pischke, 2008). Second, we take a data-driven approach to control variable selection by using the double-Lasso procedure recently developed in Belloni et al. (2014a) and Belloni et al. (2014b). This approach allows us to exploit the high-dimensionality of the EVS and introduces machine learning techniques such as the Lasso into happiness research.

Finally, we identify plausibly exogenous variation in individual employment status and local unemployment rates by using industry-employment shocks or "local demand shocks" as an instrument. These are commonly referred to as "Bartik Shocks." The existing literature on the relationship between unemployment and subjective well-being such as Tella et al. (2003) and Clark and Oswald (1994) cannot make causal claims about this relationship as it cannot escape reasonable omitted variable bias concerns. By introducing a popular technique for credible identification in labor economics into the literature on happiness research, we are one of the first papers to make causal statements about the effects of local unemployment on subjective well-being. While our results in this area are only suggestive as the data is not fine-grained enough to estimate precise causal effects, we show how instrumental variable approaches using techniques developed by Bartik (1991), Notowidigdo (2011), Goldsmith-Pinkham et al. (2018)

among others might be used in the wellbeing context.

We find that negative indirect group effects of regional or national unemployment rates on individual wellbeing are not robust to the inclusion of controls for an alternative channel operating through income - they turn positive once income at the group level is controlled for.

The remainder of the paper proceeds as follows. Section 2 provides a brief framework to discuss the identification of the regression coefficients of interest in the presence of social interactions. Section 3 describes our data and measures of wellbeing, unemployment and income. Section 4 further describes our empirical approach. Section 5 presents the results and Section 6 concludes.

## 2 Identification with Social Interactions

As we are considering a model in which observable variables can affect an individual-level outcome variable both through their individual exposure and also through the group level mean, we first clarify the identification problem using a simple model of spatial interactions following the notation in Gibbons et al. (2015).

Consider a group of $n$ individuals in geographic locale. Let $y$ denote the $n$-dimensional vector of stacked individual outcomes $y_i$ (wellbeing in this case) for each individual. Assume that the individual-level outcome can be written as a function of an individual-level observables $U_i$ (unemployment in this case). Let $U$ denote the $n$-dimensional stacked vector of individual observables. Assume that wellbeing is a function of unemployment in the following way [1]:

$$y = U\beta + G_U U\gamma + u \tag{1}$$

where $G_U$ is a $n \times n$ spatial weights matrix. The $i$-th row of $G_U$ contains the weights for the effect of other individuals' values $U_j$ for $j \in \{1, \ldots, n\}$ on $y_i$. For instance, suppose $G_u = \frac{1}{N} ll'$, where $l$ is the $n$-dimensional vector of all ones. In this case, $G_u U$ is unemployment rate at the relevant level of aggregation.

We may worry that the error term also contains unobservables that have group-level effects with

$$u = G_\nu \nu \lambda + \epsilon \tag{2}$$

where $G_\nu$ is another $n \times n$ spatial weight matrix and $\nu$ is an $n$-dimensional stacked vector of individual-level unobservables $\nu_i$. This situation may arise due to some location-specific omitted variable that directly affects $y$ or due to self-sorting of similar individuals on unobservables across locations. In the wellbeing-unemployment context, this may be the effect of local "culture", which affects both attitudes towards human capital investment and lifestyle choices that affect life-satisfaction.

We may try to solve the problem of potential omitted variable bias by "spatial differencing." That is, we multiply both sides of Equation (1) by $I - G_\nu$. In the case where $G_\nu$ is the mean-generating matrix, this is equivalent to adding fixed effects at the relevant-level of aggregation. Substituting Equation (2) into Equation (1) and pre-multiplying by $I - G_\nu$, we have that

$$(I - G_\nu)y = (I - G_\nu)U\beta + (G_U - G_\nu G_U)U\gamma + (G_\nu - G_\nu G_\nu)\nu\lambda + \epsilon \tag{3}$$

[1] Additional controls could easily be included by writing a matrix of observables $X$ in addition to $U$ and adapting the rest of the notation accordingly. Alternatively, interpret $y, U$ as the residuals from the linear projection of $y$ and $U$ onto $X$.

The identifying assumption is that $plim(G_\nu - G_\nu G_\nu)\nu = 0$ and if true, we can consistently estimate $\beta, \gamma$ with OLS. A sufficient condition for this is that $G_\nu$ is idempotent in the population. Suppose that this condition holds but that $G_U = G_\nu$. That is, the spatial structure of the effect of the observed outcome $U_i$ on individual outcomes $y_i$ is the same as the effect of the unobservable $\nu_i$. We can no longer identify $\gamma$, the parameter of interest. In the simplest case where $G_\nu = G_U$ is the mean-generating matrix and individual outcomes depends on average group observables and unobservables, $\gamma$ cannot be identified in a regression that includes group-level fixed effects.

To avoid this identification problem, there are no great solutions. In the following empirical analyses we can only identify $\gamma$, the effect of aggregate mean unemployment under the additional assumption that there is no omitted variable bias from aggregate-level unobservables that covary with the group unemployment rate. That is,

$$E[G_U U G_\nu \nu] = 0 \tag{4}$$

However, in a later section we will try to obtain identification under weaker assumptions by using an instrumental variables approach that exploits shocks that plausibly move $G_U U$ without affecting $G_\nu \nu$.

# 3 Data

## 3.1 European Values Study

Our individual-level data come from the European Values Study (EVS). The EVS is a repeated-cross-sectional survey conducted in over 40 European countries that collects information about respondents' beliefs, values, attitudes, and outcomes for key dimensions of their lives.[2] The survey has been conducted four times – in 1981, 1990, 1999, and 2008 – thus providing researchers with a unique way to investigate how Europeans thoughts and outcomes in topics such as family, work, religion, politics, and society have changed over several decades.

The data is nationally representative of the adult population within each country for the given collection year. Each country randomly sampled adults through a multi-stage procedure until some specified quota was met (e.g., each country aimed for 1,200 respondents in 1981). In some years, countries over sampled specific populations, but the EVS provides sample weights to recover nationally representative samples. In most years and countries, the survey was conducted as face-to-face interviews, but there are some instances where countries collected responses using other methods (e.g., phones, online, postcards). See GESIS Leibniz Institute for the Social Sciences (2015) for more details about the country-level quotas over the years and for a discussion of how some specific countries might have deviated from the sampling procedure.

[2]Specifically, the EVS contains responses from Albania, Armenia, Austria, Belarus, Belgium, Bosnia-Herzegovina, Bulgaria, Canada, Cyprus, Northern Cyprus, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Georgia, Germany (East/West), Great Britain, Greece, Hungary, Iceland, Ireland, Northern Ireland, Italy, Kosovo, Latvia, Lithuania, Luxembourg, Malta, Republic of Macedonia, Republic of Moldova, Republic of Montenegro, the Netherlands, Norway, Poland, Portugal, Romania, Russian Federation, Serbia, Slovak Republic, Slovenia, Spain, Switzerland, Sweden, Turkey, Ukraine, and USA. Not all countries are represented in each year of the survey. See GESIS Leibniz Institute for the Social Sciences (2015) for a more detailed description of which countries were sampled in which years. Note that although Canada and USA are not European, for convenience, we will continue to refer to the sample as "Europe" or "European" throughout.

The EVS dataset contains 164,997 observations with almost 1,400 variables for each individual.[3] The construction of our measures of wellbeing and and unemployment are described in more detail below. The specific control variables we use and the various processes we used to select them are described in Section 4.

## 3.2 Measures of wellbeing

Each individual survey item that elicits respondents to evaluate a particular aspect of their life satisfaction and happiness captures a different dimension of subjective wellbeing. A priori, it is unclear which survey item best captures the "true" subjective wellbeing of the respondent. As a result, we take an eclectic approach and consider a variety of measures. We use four measures of wellbeing, three of which are the raw responses to survey items and another that we aggregate from 16 survey items.

We first consider the survey items that elicit respondents' overall life satisfaction (*A170*), feelings of happiness (*A008*) and overall job satisfaction (*C033*). Each of these survey items appears in each wave of the European Value Survey and so, they provide the most coverage of respondents. Each of these measures have appeared in the literature on subjective wellbeing. For example, Tella et al. (2003) uses a survey measure of general life satisfaction in its analysis of Europe and a survey measure of overall feelings of happiness in its analysis of the United States. Diener (2006) argues that subjective wellbeing also incorporates assessments of job-satisfaction.

Finally, we construct our own measure of subjective wellbeing from the European Values Survey that aggregates responses from 16 survey items across the four waves. There are a variety of survey items in the European Values Survey that elicit an assessment of the quality of life from respondents. In addition to the three measures described above, survey items ask respondents to describe their state of health, satisfaction with the financial situation of their household, satisfaction with their home life, whether they have ever felt depressed and many more. Each of these survey items provides a noisy measure of the respondent's "true" subjective wellbeing that is unobservable and so, we may wish to aggregate these responses into a single measure of subjective wellbeing.

This suggests modeling the subjective wellbeing of a respondent as a latent factor that we extract from survey responses using principal components analysis. In particular, a respondent's subjective wellbeing is the first principal component that underlies their responses to 16 wellbeing related survey items. These items are further described in Table 5 of the appendix. Several survey items are missing for respondents either because the respondent did not answer or because the item was not asked in a given wave. We use an expectation-minimization (EM) algorithm that simultaneously computes the principal components and imputes missing values following Stock and Watson (2002). In short, the EM algorithm iteratively updates the imputed missing values as the fitted values from the factors and loadings of the previous step. The principal components are then re-estimated using the data with the newly imputed missing values. The algorithm iterates until convergence. The results are summarized in Figure 1 below. As can be seen, each survey item is highly correlated with one another. This gives confidence that the principal components analysis extracts some unobserved, common signal underlying this array of items. The estimated first-principal component mostly loads onto the life satisfaction, financial satisfaction, job satisfaction and happiness survey items.

[3]Note that we do not include 538 potential duplicate observations in our analysis sample.

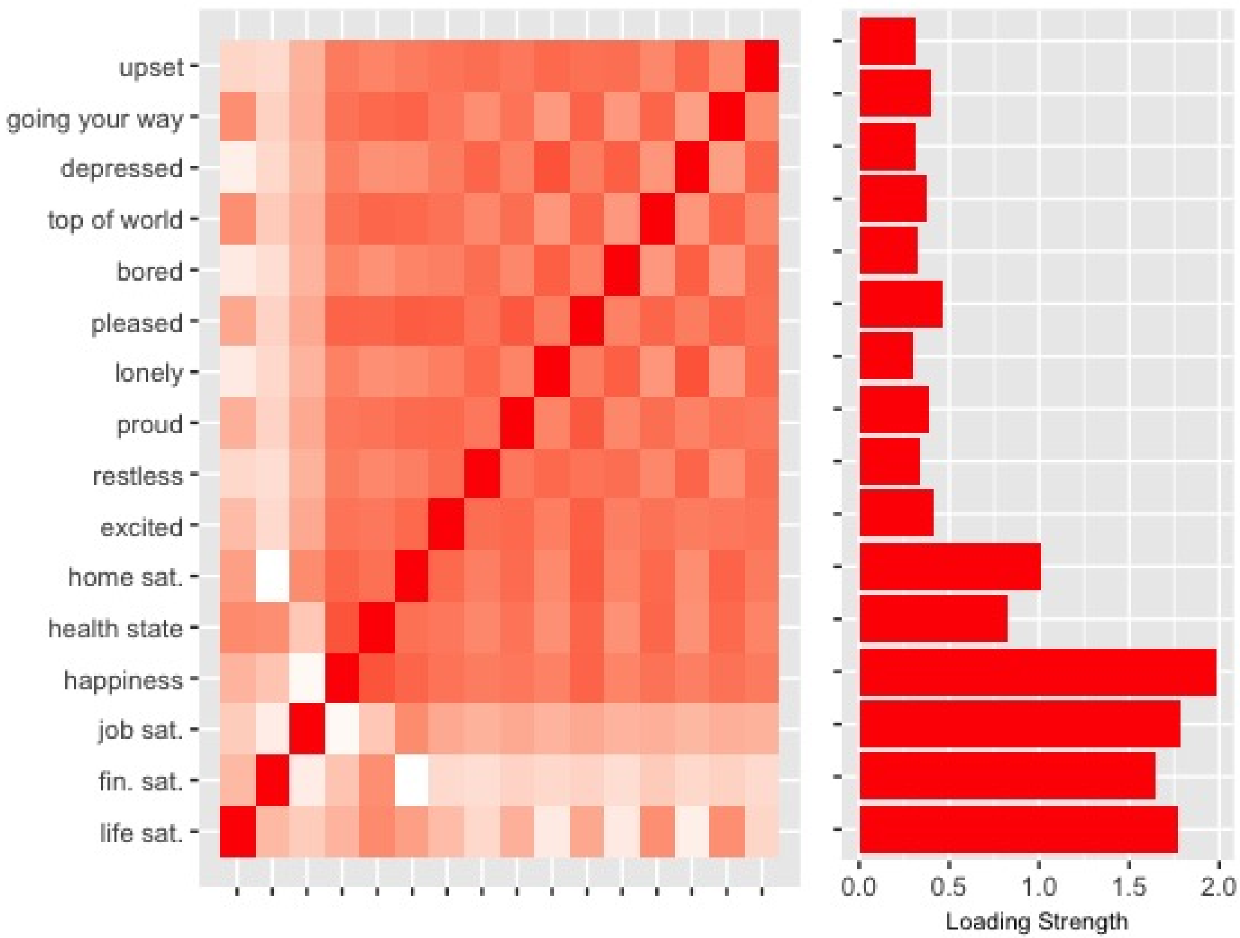


Figure 1: Pairwise correlation heatmap of wellbeing survey items and factor loadings of the first principal component

## 3.3 Measures of unemployment and income

We obtain two different measures of unemployment for our analysis. At the individual level, we use micro data from the European Value Survey (EVS), where each respondent is asked her employment status as employed (full-time, part-time or self), out-of-labor force (retired, housewife, student) or unemployed. We treat respondents that reply "other" as being out of the labor force. Using these responses, we flag respondents as unemployed or not.

The aggregate regional or national unemployment rate is then calculated by summing all the unemployed and employed individuals to obtain the labor force and calculating the unemployment rate as the share of the labor force that is unemployed. More precisely, in all the regressions at the individual level, we will be using leave-one-out estimates of regional and national unemployment rates, that is, omitting each individual's own unemployment status from the aggregate included in their regression in order to avoid a mechanical correlation between the aggregate status and the individual's.

As an alternative measure, to be used in cross-country regressions, we also use national unemployment rates obtained from the World Bank World Development Indicators (WDI), based on the definition used by the International Labor Organization (ILO).[4] This measure provides a standardized definition of unemployment that is consistent across countries and survey years.

Similarly, we use two different measures of income: On the one hand, we again construct leave-one-out estimates of regional and national average incomes for each individual using data from their respective EVS wave. Alternatively, we also employ an estimate of real GDP per capita in PPP terms,[5] for each country, which is also sourced from the World Bank WDI.

## 3.4 Industry employment by region

In order to identify exogenous regional shocks to employment (for the last survey wave only), we construct regional-level employment by industry for the years preceding the 2008 survey. We obtain data at the NUTS 2 regions level for all available industries at the NACE Level 1 classification[6] from Eurostat. The included industries are: Mining and quarrying; Manufacturing; Electricity, gas, and water supply; construction; Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods; Hotels and restaurants; Transport, storage and communication; Real estate, renting and business activities.

For each industry, we obtain the number of people employed for each year from which we subsequently construct country totals for the included industries. After dropping missing observations, we end up with 314 and 320 NUTS 2 regions, respectively, for which we can construct 2002-2007 or 2006-2007 industrial employment growth shocks using the methodology detailed in the section on Bartik shocks below.

[4] The ILO defines unemployment as "All persons of working age not in employment, seeking employment and available to take up employment given a job opportunity, during a specified reference period," (International Labour Organization, 2013) which is somewhat different from the status-based measure constructed within the EVS data.

[5] Values of real GDP per capita PPP correspond to values in constant 2005 local currency units, converted to U.S. dollars using 2005 purchasing power parity estimates from the World Bank.

[6] NACE refers to the "Statistical Classification of Economic Activities in the European Community". Level 1 of the industry classification includes 21 industries.

# 4 Empirical Approach

## 4.1 Individual level unemployment effect

To investigate whether an individual's unemployment affects their wellbeing, we regress our individual-level measures of wellbeing, $Happy_{ijt}$, on an indicator for whether they are unemployed or not, while controlling for a number of variables that might affect both unemployment and wellbeing. That is, we estimate the following specification as the baseline for the effect of unemployment at the individual level:

$$Happy_{ijt} = \alpha\, Unemployed_{ijt} + \Sigma\, Personal_{ijt} + \Psi\, \ln GDP_{jt} + \varepsilon_j + \lambda_t + \mu_{jit} \tag{5}$$

Here, $Unemployed_{ijt}$ is a binary indicator for whether the individual is unemployed, and $Personal_{ijt}$ is a vector of personal characteristics, the selection of which will be discussed in further detail in the next subsection. Moreover, the regression also includes country fixed effects to control for any potential national level differences in wellbeing, as well as year fixed effects to account for global trends in wellbeing. Consistent with the guidance of Wolfers & Stevenson (2008), we control for the logarithm of national real GDP to allow for positive but diminishing returns to income at the national level.

Further, we do not cluster our standard errors and instead only use Huber-White heteroskedasticity-robust standard errors. Abadie et al. (2017) provide researchers with formal guidance for when they should and shouldn't adjust standard errors for clustering. It shows that if the assignment mechanism or sampling process is clustered, then clustering the standard errors is warranted. However, if both the assignment mechanism and the sampling process is not clustered, then the researcher should not adjust the standard errors – irrespective of whether or not clustering alters the size of the standard errors. Clustering in the latter case often leads to overly conservative standard errors and therefore, poor inference on the parameters of interest. In the EVS dataset, the assignment mechanism is not clustered since each survey is nationally representative. Moreover, the sampling process is not clustered since the countries were not sampled from a sample of clusters – instead, the countries included in the EVS constitute the population of interest. Thus, following Abadie et al. (2017), we should not cluster in our specifications.

## 4.2 Control variables

The choice of control variables in this empirical design needs to balance two different concerns: on the one hand, there is the risk of " bad controls" (Angrist and Pischke, 2008), that is, the issue of controlling for variables that are also outcomes of changes in the unemployment rates, such that holding them constant would in fact be eliminating some of the variation of interest.

On the other hand, there is a concern that unemployment is endogenous with regard to wellbeing - i.e., that there are omitted variables which implicitly produce . In that case we might be able to eliminate most of the risk of unobservables causing unemployment and wellbeing jointly by controlling for all of the characteristics that might be jointly causing both wellbeing and unemployment rates.

As a result of these considerations, we chose two different ways of selecting appropriate control variables. First, we will consider a specification that includes standard variables identified in the literature on subjective wellbeing (see, e.g. Tella et al. (2003)) as affecting wellbeing and which are also plausibly not causally dependent on experienced unemployment, among the variables available in our sample. The resulting list includes the educational level, age, age squared, and sex of the respondent, as well as whether they are married, widowed, separated or divorced. Moreover, we also include separate variables for having any children at all and the total number of children, as the extensive and intensive margins of having children may have differential effects as noted for example by Aaronson et al. (2014) in the context of the fertility transition in the U.S. South.[7]

Second, given the rich set of covariates that are available in the European Values Survey, an alternative approach to selecting controls is to use the double-Lasso procedure (e.g., Belloni et al., 2014a,b). The double-Lasso procedure incorporates techniques from machine learning and takes a data-driven approach to control variable selection. Consider the following linear model where the regressor of interest, $d_i$, is plausibly exogenous after conditioning on a set of control variables, $x_i$:

$$y_i = \alpha d_i + x_i' \theta_y + r_{iy} + \varepsilon_i \tag{6}$$

where $E[\varepsilon_i | d_i, x_i, r_{iy}] = 0$ and $r_{iy}$ is an approximation error. The coefficient of interest is $\alpha$, and our problem is that we do not know which specific variables from our large set of covariates will provide us with high quality estimates of and inferences on $\alpha$. One approach in the literature has been to use Lasso for variable selection – i.e., run a Lasso regression of $y_i$ on all variables, forcing $d_i$ to remain in the model, and include selected variables in a second-stage OLS regression. However, Belloni et al. (2014a) explain that this procedure could potentially lead to substantial omitted variable bias. Any variable that is highly correlated with $d_i$ will tend to be dropped during the Lasso stage of this procedure since including it along with $d_i$ will add very little predictive power. However, if these dropped variables are also correlated with the outcome of interest, then there will be omitted variable bias in the second-stage OLS regression. As a result, Belloni et al. (2014a) propose the double-Lasso procedure: (a) run a Lasso regression of $y_i$ on $x_i$ and let $x_{yi}$ be the set of predictive variables of $y_i$ selected by this procedure; (b) run a Lasso regression of $d_i$ on $x_i$ and let $x_{di}$ be the set of predictive variables of $d_i$ selected by this procedure; (c) we then estimate $\alpha$ from an OLS regression of $y_i$ on $d_i$ and the union of $x_{di}$ and $x_{yi}$. Belloni et al. (2014b) show that this procedure is valid provided that the true, population model is "approximately sparse," meaning that regressor of interest is exogenous given a relatively small number of controls from the large set of covariates.

Due to computational constraints, we only implement this method for the aggregated wellbeing measure. To implement the double-Lasso procedure, we partition the sample into a training set (80% of observations) and hold-out set (20% of observations). We select the tuning parameter $\lambda$ by choosing the value that minimizes the out-of-sample prediction error on the hold-out set. With the selected tuning parameter, the Lasso is re-run on the full dataset and we collect the covariates that have non-zero coefficients. This process is repeated with the individual unemployment flag and the aggregated wellbeing measure as outcomes. The final set of controls is the union of the covariates with non-zero coefficients in both models.

[7] The corresponding variable names in the EVS data are the following: Education level (X025); Sex (X001); Age and Age Squared (X003); Married, Widowed, Divorced, Separated (X007); Number of Children and Any Children (X011).

## 4.3 Identifying group unemployment effects using Bartik shocks

As noted above in 2, in a framework where group-level variables may affect individual-level outcomes, we may be worried that group-level observables are endogenous with regard to unobservable shocks that also operate at the group level - and that we are therefore not identifying the true population coefficients on the group level observables. One way to overcome this issue may be to use an instrumental variable to identify the variation of the group-level observable that is plausibly uncorrelated with the error term and therefore not subject to omitted variables bias. That is, we wish to identify a group-level instrumental variable $Z$ that fulfills the exclusion restriction $E[Z \cdot G_\nu \nu] = 0$, while being a valid instrument for group-level unemployment.

One plausible instrument for unemployment consists of exogenous shocks to local labor demand. We follow a long and active literature (Bartik, 1991; Boustan, 2010; Boustan et al., 2010; Notowidigdo, 2011; Bartik, 2015; Maggio and Kermani, 2016; Diamond, 2016; Goldsmith-Pinkham et al., 2018) in instrumenting for changes in local labor demand using the variation in local industry employment due to national industry growth dynamics interacting with the pre-existing local industry structure. Due to data availability constraints, we can only construct this instrument for the 2008 survey wave.

To construct this instrument, we multiply regional industry exposure in a baseline year (either 2002 or 2006) by the national leave-one-out growth rate experienced by each industry. That is, using the 2006 baseline year example, for each geography $g$, industry $i$ and year $t$, we construct the so-called “Bartik” employment shock as

$$B_{g,t} = \sum_{i=1}^{k} \phi_{g,2006,i} \cdot \left( \frac{\nu_{-g,t,i} - \nu_{-g,t-1,i}}{\nu_{-g,t-1,i}} \right),$$

where $\phi_{g,2006,i} = \frac{e_{g,2006,i}}{e_{g,2006}}$ is the industry $i$ employment share in geography $g$ in the baseline year. Moreover, $\nu_{-g,t,i} = \frac{\sum_{c \neq g}^{n} e_{c,t,i}}{\sum_{i=1}^{k} \sum_{c \neq g}^{n} e_{c,t,i}}$ is the leave-one-out estimate - omitting region $g$ from both the numerator and the denominator - of the national employment share in industry $i$ in year $t$. Consequently, the Bartik shock input consists of the product of the importance of industry $i$ in the regional economy and the national leave-one-out growth rate of the share of employment in that industry. The Bartik shock for geography $g$ in year $t$ is then simply the sum of these national shocks, weighted by the local industry structure, across all industries. For instance, if the local industry structure remained the same as in 2006 and regional industries grew at exactly the rate of their leave-one-out equivalents at the national level, then the Bartik shock would be precisely equal to total regional employment growth in the industries contained in the sample. After computing Bartik shocks and taking into account the limited availability of the industry data, we are left with data for the last wave from 218 NUTS-2 regions to be included in the IV analysis.

## 4.4 National unemployment effects

In order to discuss the relative scale of the effect of individual unemployment on individual and aggregate social wellbeing, it is necessary to carefully define such a multiplier. Consider the following simple model. Suppose the true data generating process allows for both direct effects (own unemployment on individual happiness) and indirect effects (group average unemployment on individual happiness), as follows

$$y_ij = \beta_I U_{ij} + \beta_G \overline{U_j} + \varepsilon_{ij} \tag{7}$$

where $y_{ij}$ is an outcome measure of individual $i$ in group $j$.

The gross effect of $U_{ij}$ on $\sum_j y_{ij}$ captures the direct effect of $\beta_I$ on individual $i$, and an indirect effect of $\beta_G \times \dfrac{1}{N}$ on each member of the group. Since there are $N$ such members, the total indirect effect is thus $\beta_G$.[8] Thus the aggregate social impact is $\beta_I + \beta_G$, and the *net multiplier* is $\frac{\beta_G}{\beta_I}$. Alternately, the *gross multiplier* is $\frac{\beta_G+\beta_I}{\beta_I} = \frac{\beta_G}{\beta_I}+1$. To calculate the multiplier it is sufficient to estimate Equation 7 and construct $\frac{\hat{\beta_I}}{\hat{\beta_G}}$, which is a biased but consistent estimator of the net multiplier. Furthermore, if instead the effect of group unemployment on wellbeing is estimated without controlling for individual unemployment, this merely yields an estimate of the gross multiplier, since

$$\begin{aligned} \mathbb{E}[y_{ij}] &= \mathbb{E}[\beta_I U_{ij}] + \mathbb{E}[\beta_G \overline{U_j}] + \mathbb{E}[\varepsilon_{ij}] \\ &= \beta_I \mathbb{E}[U_{ij}] + \beta_G \mathbb{E}[\overline{U_j}] \\ \Rightarrow \frac{\partial \mathbb{E}[y_{ij}]}{\partial \mathbb{E}[U_{ij}]} &= \beta_I + \beta_G \end{aligned}$$

# 5 Results

## 5.1 Main Results

Table 1 presents our main results using the wellbeing measure constructed as a first-principal component of 16 wellbeing-related questions from the EVS.[9] Column (1) reports the impact of an individual's unemployment on their wellbeing controlling for employment status fixed effects (such that the coefficient on unemployed is relative to full-time employees) and country fixed effects. Column (2) reports the direct effect an individual's unemployment has on their wellbeing along with the indirect effect the national unemployment rate has on their wellbeing, controlling for employment status fixed effects, county fixed effects, and survey wave fixed effects. Columns (3) and (4) expand the specification of column (2) by including individual-level covariates and log national real GDP per capita.

The effect of own unemployment on wellbeing is strongly negative, reducing wellbeing by approximately 0.23-0.29 standard deviations across the specifications. In columns (2) and (3), the national unemployment rate has a large negative effect on individual wellbeing; a one percentage point increase in the national unemployment rate reduces each individual's wellbeing by approximately 0.013 standard deviations. This amounts to a *net multiplier* of 5.54 in column (3). Here, it is important to note that the national unemployment rate is the only regressor

[8]Note that if the data generating process is written as a function of individual unemployment and the mean of others' unemployment, the indirect effects are scaled by $\dfrac{1}{N-1}$ and $N-1$, so the total spillover is unaffected.

[9]See Section 4 for a discussion of the principal component analysis. Table 5 in the Appendix lists the 16 variables used.

that reflects aggregate national conditions, and thus this large coefficient estimate may reflect a substantial role of aggregate economic conditions on aggregate wellbeing. Thus, this effect may substantially attenuate if economic conditions are appropriately controlled for. Column (4) investigates this by controlling for the logarithm of national real GDP per capita, and demonstrates this to be the case. Once controlling for the level of national income, the coefficient on the national unemployment rate is in-fact positive (implying a negative multiplier). Consistent with intuition, the coefficient on national income is positive; positive economic conditions increase wellbeing.

Tables 6, 7, and 8 in the Appendix present similar estimates for our three other outcomes of interest – life satisfaction, feelings of happiness, and overall job satisfaction, respectively. The results in these tables are qualitatively similar to those in Table 1.

Table 12 in the Appendix reports results after conditioning on the set of covariates selected from the double-Lasso procedure described in Section 4. We find that the coefficients on the unemployed are attenuated toward zero are no longer statistically significant. Similarly, the coefficient on the national unemployment rate is no longer statistically significant. One possibility is that the rich set of potential covariates from the EVS contained many "bad controls". If this were the case, the double-Lasso procedure would have a high chance of selecting these variables since they would be correlated with our outcome measure. Further, as discussed in Section 4, inclusion of these "bad controls" in the final regression model could absorb some of the impact of our regressors of interest. Unfortunately, due to lack of time, we were unable to properly screen the hundreds of variables in the EVS, so it is highly likely that some "bad controls" were selected by our double-Lasso procedure. If we had more time, we believe this is an issue we could have avoided.

Table 1: Main Specification: Aggregated Wellbeing Measure

| | (1)<br>Wellbeing | (2)<br>Wellbeing | (3)<br>Wellbeing | (4)<br>Wellbeing |
|---|---|---|---|---|
| Unemployed | -0.2563*** | -0.2921*** | -0.2393*** | -0.2338*** |
| | (0.0096) | (0.0114) | (0.0158) | (0.0157) |
| National Unemployment Rate | | -1.3883*** | -1.3259*** | 1.0830*** |
| | | (0.1681) | (0.1944) | (0.2318) |
| Log National Real GDP Per Capita (PPP) | | | | 0.7251*** |
| | | | | (0.0341) |
| Employment Status FE | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes |
| Survey Wave | Yes | Yes | Yes | Yes |
| Gender FE | No | No | Yes | Yes |
| Gender x Demographics | No | No | Yes | Yes |
| R-squared | 0.1618 | 0.1724 | 0.2184 | 0.2221 |
| Observations | 162782 | 110508 | 100504 | 100504 |

* p<0.10, ** p<0.05, *** p<0.01

*Notes:* Heteroskedasticity-robust standard errors.

## 5.2 Regional Results

Table 2 presents similar results to Table 1, but now including regional levels of unemployment and income. We find that the coefficients on individual-level unemployment and national unemployment rates are very similar to the point estimates reported in Table 1. However, the coefficients on the regional results are still statistically significant. This suggests that there are regional effects above and beyond the national and individual impacts.

Table 2: Regional and National Spillovers: Aggregated Wellbeing Measure

| | (1) Wellbeing | (2) Wellbeing | (3) Wellbeing |
|---|---|---|---|
| Unemployed | -0.2863*** | -0.2340*** | -0.2377*** |
| | (0.0115) | (0.0158) | (0.0181) |
| National Unemployment Rate | -1.2617*** | -1.0804*** | 0.8082** |
| | (0.1699) | (0.1996) | (0.3414) |
| Regional Unemployment Rate | -0.2493*** | -0.2427*** | -0.0784 |
| | (0.0468) | (0.0481) | (0.0607) |
| Log National Real GDP Per Capita (PPP) | | | 0.5566*** |
| | | | (0.0529) |
| Log Regional Mean Income (PPP) | | | 0.0625*** |
| | | | (0.0159) |
| Employment Status FE | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes |
| Survey Wave | Yes | Yes | Yes |
| Gender FE | No | Yes | Yes |
| Gender x Demographics | No | Yes | Yes |
| R-squared | 0.1726 | 0.2186 | 0.2236 |
| Observations | 110504 | 100501 | 76569 |

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

*Notes:* Heteroskedasticity-robust standard errors.

Tables 9, 10, and 11 in the Appendix present similar estimates for our three other outcomes of interest – life satisfaction, feelings of happiness, and overall job satisfaction, respectively. The results in these tables are qualitatively similar to those in Table 2.

## 5.3 Country-Specific Results

Another possible interesting source of heterogeneity is at the country level. It is possible that individuals across countries respond differentially to unemployment due to different values, welfare systems, savings behavior, available jobs, etc. Figure 2 displays the country-level estimates of the impact of unemployment on an individual's wellbeing. The coefficients are estimated using a specification similar to the one used in column (1) of Table 1. From the plot, we see that there appears to be some interesting variation across Europe. We find that unemployment appears to have larger negative impacts on wellbeing in northern and central Europe while the impacts are less severe in the southwest countries. Future research could investigate these interesting trends further.

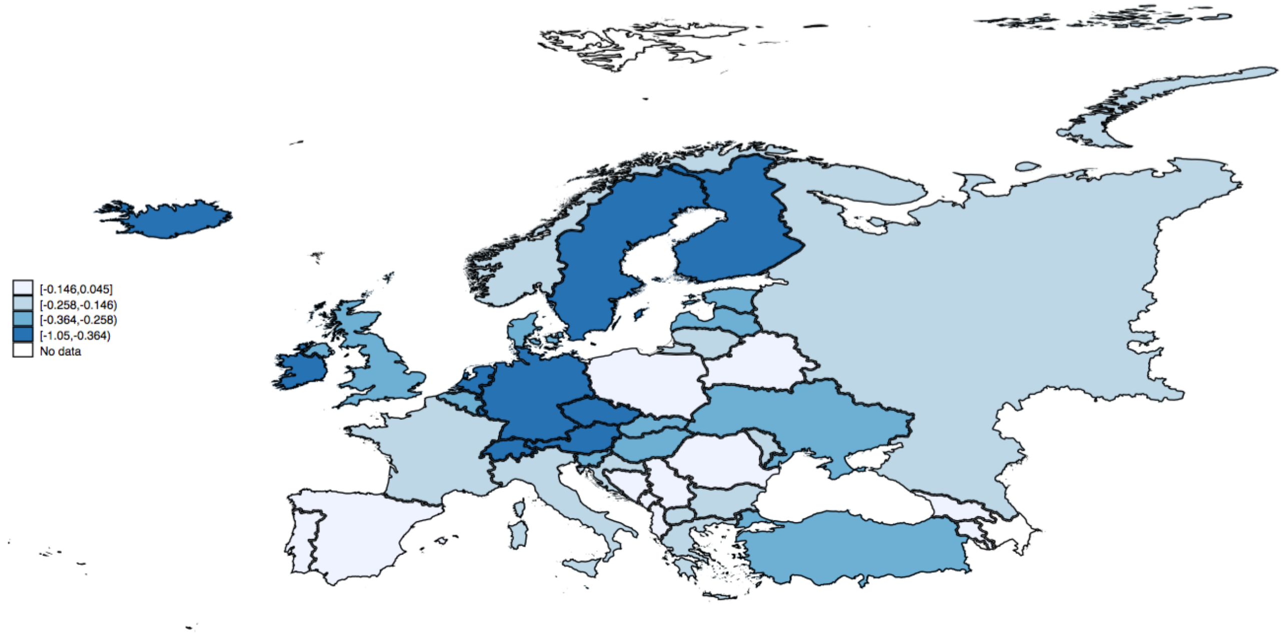


Figure 2: This figure presents the country-specific coefficients for the impact of an individual's unemployment on their wellbeing. The estimates come from a regression using a specification similar to that in column (1) of Table 1. The darker a country, the more negative the estimated impact is for that country.

### 5.4 Group-Specific Results

Table 3 summarizes how the effects of the national unemployment on subjective well-being vary by employment status. In particular, we find that national unemployment has a more negative effect on the wellbeing of those who are employed. Further, as we include a more robust set of controls, the sign of the coefficient on the national unemployment rate flips for both the employed and the unemployed. That is, a higher national unemployment rate appears to raise the subjective wellbeing for both groups. This is a surprising results but is consistent with several common arguments. For example, a rise in the unemployment rate may raise the relative social status of those that remain employed. At the same time, a rise in the unemployment rate may lower the social stigma associated with unemployment, thereby improving the subjective wellbeing of the unemployed.

Tables 13, 14, and 15 in the Appendix present similar estimates for our three other outcomes of interest – life satisfaction, feelings of happiness, and overall job satisfaction, respectively. The results in these tables are qualitatively similar to those in Table 3.

### 5.5 Bartik Shock Results

Note that we instrument for *individual* employment status using the interaction between an individual's education and the regional labor demand shock over the period 2002-2007, while regional unemployment is instrumented by the labor demand shock itself. While the constructed shift share labor demand shocks are plausibly exogenous with regard to unobserved local characteristics, they may affect wellbeing through an income channel in addition to an unemployment channel. As a result, we assign *a priori* more credibility to the estimates controlling for regional

Table 3: Differential Effects by Employment Status: Aggregated Wellbeing Measure

| | (1) Wellbeing | (2) Wellbeing |
|---|---|---|
| Unemployed | -0.3517*** | -0.3448*** |
| | (0.0246) | (0.0246) |
| Unemployed=0 × National Unemployment Rate | -1.3933*** | 1.0142*** |
| | (0.1945) | (0.2320) |
| Unemployed=1 × National Unemployment Rate | -0.4177* | 1.9786*** |
| | (0.2479) | (0.2780) |
| Log National Real GDP Per Capita (PPP) | | 0.7244*** |
| | | (0.0341) |
| Employment Status FE | Yes | Yes |
| Country FE | Yes | Yes |
| Survey Wave | Yes | Yes |
| Gender FE | Yes | Yes |
| Gender x Demographics | Yes | Yes |
| R-squared | 0.2187 | 0.2224 |
| Observations | 100504 | 100504 |

* p<0.10, ** p<0.05, *** p<0.01

*Notes:* Heteroskedasticity-robust standard errors.

income - in which case the labor demand shock can be interpreted as identifying the wellbeing effect of the variation in unemployment that goes beyond any effects of labor demand shocks on regional income.

The results in Table 4 are ambiguous: The results in column 1 and 2 confirm a negative and significant effect of individual unemployment on happiness, which is considerably larger than the estimates found in 1. Under the exclusion restriction on the instruments (which, again, is unlikely to hold without controlling for regional income), this would indicate that the *causal* local average treatment effect (LATE) identified in this case is estimated for a subset of the population that has much higher negative effects of unemployment on happiness. This finding could be explained by the fact that some unemployment observed in the data is likely an a local welfare optimum for the unemployed - an adaptation to imperfect circumstances - and therefore continuing in that state might have a lower impact on wellbeing than sudden unemployment caused by an exogenous labor demand shock. However, once we control for other individual characteristics, this individual unemployment effect becomes insignificant, even when we include regional income as a control variable. The instrumented indirect effect through regional unemployment is positive in all IV specifications, albeit only significant when controls are limited to employment status and country fixed effects.

The full specification in column 4, where all the applicable controls and regional income are included does not show any significant direct or indirect effect of unemployment on wellbeing - even though both coefficients are positive. There are two possible interpretations of this result: On the one hand, it could be the case that the true causal effect of unemployment on wellbeing is indeed not significant, casting doubt upon the non-experimental results to the contrary presented in this literature. On the other hand, the local labor demand instrument may not be able to identify the true local effect precisely once we control for income due to the reduced sample size for which the instrument and the required controls are available in our data. We cannot distinguish between these two alternatives but conservatively lean towards the latter, as the error terms on the instrumented variables increase substantially in size in column(4) of the table. Moreover, there are serious concerns that the labor demand shocks are weak instruments once we control for a larger number of observables: the first-stage F-statistics for the instruments' effect on the instrumented variables are very small in columns 3 and 4, suggesting that the labor demand shock instrument may not be valid conditional on observables.

Table 4: IV model with Bartik labor demand shocks

| *Dep. var.:* | Wellbeing (PC) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Unemployed | -5.5403*** | -6.2096*** | -7.7750 | 10.4451 |
| | (0.6558) | (0.7474) | (11.9007) | (13.6835) |
| Regional Unemployment Rate | | 6.0860*** | 5.8501 | 32.3184 |
| | | (2.0464) | (5.7793) | (64.3581) |
| Employment Status FE | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes |
| Demographics & Gender | No | No | Yes | Yes |
| Regional income | No | No | No | Yes |
| 1st-Stage F-Stat. | 50.6 No | 50.6, 366.1 1.6, 359.5 | 0.9, 0.6 | |
| Observations | 22089 | 22089 | 21548 | 16695 |

*Notes:* Heteroskedasticity-robust standard errors: * p <0.10, ** p<0.05, *** p<0.01. *Unemployed* and *Regional Unemployment Rate* are instrumented by using the interaction between an individual's education and the regional labor demand shock over the period 2002-2007, and the labor demand shock itself as instruments. Controls are included individually, without interaction terms due to the limited sample size and include: age, age squared, sex, education, employment and relationship status, number of children.

# 6 Conclusion

Using micro-data from the European Values Survey, we analyzed the effects of unemployment on subjective well-being. We find that negative indirect group effects of regional or national unemployment rates on individual wellbeing are not robust to the inclusion of controls for an alternative channel operating through income - they turn positive once income at the group level is controlled for. However, our analysis suggests that causal analysis using instrumental variables from other fields like labor economics may provide a promising avenue to resolve this debate.

While the results paint a murky picture, this paper demonstrates that there are several productive avenues for further research on happiness. In particular, we introduced several useful econometric innovations - first, we constructed an aggregated subjective wellbeing index from a variety of noisy survey responses; second, we use machine learning techniques to rigorously search for controls in a high-dimensional dataset on well-being and finally, we exploit a budding literature in labor economics on Bartik Shocks to plausibly exogenous variation in individual employment status and local unemployment rates. Taken together, the results presented above indicate that our understanding of the relationship between macroeconomic outcomes and subjective well-being is far from complete and merits further research.

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# A Additional Tables & Figures

Table 5: Variables Included in the PCA

| Variable Name | Short Description |
|---|---|
| upset | Ever felt upset because somebody criticized you |
| going your way | Ever felt that things were going your way |
| depressed | Ever felt depressed or very unhappy |
| top of the world | Ever felt on top of the world |
| bored | Ever felt bored |
| pleased | Ever felt pleased about having accomplished something |
| lonely | Ever felt very lonely or remote from other people |
| proud | Ever felt proud because someone complimented you |
| restless | Ever felt restless |
| excited | Ever felt very excited or interested |
| home sat. | Satisfaction with home life |
| health state | State of health (subjective) |
| happiness | Feeling of happiness |
| job sat. | Job satisfaction |
| fin. sat. | Satisfaction with financial situation of household |
| life sat. | Satisfaction with life |

*Notes:* This table provides a short description of the 16 variables included in the PCA. See GESIS Leibniz Institute for the Social Sciences (2015) for more details on each variable and links to sample questionnaires.

Table 6: Main Specification: Life Satisfaction

| | (1) Satisfaction | (2) Satisfaction | (3) Satisfaction | (4) Satisfaction |
|---|---|---|---|---|
| Unemployed | -0.4220*** | -0.4293*** | -0.3569*** | -0.3480*** |
| | (0.0109) | (0.0129) | (0.0181) | (0.0180) |
| National Unemployment Rate | | -2.2530*** | -2.6689*** | 1.1212*** |
| | | (0.1760) | (0.2046) | (0.2382) |
| Log National Real GDP Per Capita (PPP) | | | | 1.1413*** |
| | | | | (0.0363) |
| Employment Status FE | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes |
| Survey Wave | Yes | Yes | Yes | Yes |
| Gender FE | No | No | Yes | Yes |
| Gender x Demographics | No | No | Yes | Yes |
| R-squared | 0.1421 | 0.1495 | 0.1818 | 0.1902 |
| Observations | 161456 | 109599 | 99724 | 99724 |

* p<0.10, ** p<0.05, *** p<0.01

*Notes:* Heteroskedasticity-robust standard errors.

Table 7: Main Specification: Happiness

| | (1) Happiness | (2) Happiness | (3) Happiness | (4) Happiness |
|---|---|---|---|---|
| Unemployed | -0.3199*** | -0.3350*** | -0.2584*** | -0.2537*** |
| | (0.0105) | (0.0125) | (0.0171) | (0.0170) |
| National Unemployment Rate | | -1.1294*** | -1.1125*** | 1.0247*** |
| | | (0.1773) | (0.2058) | (0.2418) |
| Log National Real GDP Per Capita (PPP) | | | | 0.6668*** |
| | | | | (0.0352) |
| Employment Status FE | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes |
| Survey Wave | Yes | Yes | Yes | Yes |
| Gender FE | No | No | Yes | Yes |
| Gender x Demographics | No | No | Yes | Yes |
| R-squared | 0.1496 | 0.1553 | 0.1953 | 0.1982 |
| Observations | 158390 | 107649 | 98052 | 98052 |

* p<0.10, ** p<0.05, *** p<0.01

*Notes:* Heteroskedasticity-robust standard errors.

Table 8: Main Specification: Job Satisfaction

| | (1) Job Sat. | (2) Job Sat. | (3) Job Sat. | (4) Job Sat. |
|---|---|---|---|---|
| Unemployed | -0.3166*** | -0.3799*** | -0.3989*** | -0.4148*** |
| | (0.0935) | (0.0979) | (0.1344) | (0.1338) |
| National Unemployment Rate | | -1.5520*** | -1.1057*** | 1.3269*** |
| | | (0.2417) | (0.2859) | (0.3295) |
| Log National Real GDP Per Capita (PPP) | | | | 0.7153*** |
| | | | | (0.0516) |
| Employment Status FE | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes |
| Survey Wave | Yes | Yes | Yes | Yes |
| Gender FE | No | No | Yes | Yes |
| Gender x Demographics | No | No | Yes | Yes |
| R-squared | 0.0573 | 0.0568 | 0.0741 | 0.0777 |
| Observations | 85699 | 56487 | 50750 | 50750 |

* p<0.10, ** p<0.05, *** p<0.01

*Notes:* Heteroskedasticity-robust standard errors.

Table 9: Regional and National Spillovers: Life Satisfaction

| | (1) Satisfaction | (2) Satisfaction | (3) Satisfaction |
|---|---|---|---|
| Unemployed | -0.4160*** | -0.3455*** | -0.3581*** |
| | (0.0129) | (0.0181) | (0.0207) |
| National Unemployment Rate | -1.9637*** | -2.1474*** | 1.9257*** |
| | (0.1776) | (0.2103) | (0.3371) |
| Regional Unemployment Rate | -0.5681*** | -0.5168*** | -0.2939*** |
| | (0.0483) | (0.0502) | (0.0628) |
| Log National Real GDP Per Capita (PPP) | | | 1.0269*** |
| | | | (0.0545) |
| Log Regional Mean Income (PPP) | | | 0.0798*** |
| | | | (0.0163) |
| Employment Status FE | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes |
| Survey Wave | Yes | Yes | Yes |
| Gender FE | No | Yes | Yes |
| Gender x Demographics | No | Yes | Yes |
| R-squared | 0.1507 | 0.1827 | 0.1828 |
| Observations | 109595 | 99721 | 76081 |

* p<0.10, ** p<0.05, *** p<0.01

*Notes:* Heteroskedasticity-robust standard errors.

Table 10: Regional and National Spillovers: Happiness

| | (1) Happiness | (2) Happiness | (3) Happiness |
|---|---|---|---|
| Unemployed | -0.3299*** | -0.2534*** | -0.2519*** |
| | (0.0125) | (0.0171) | (0.0196) |
| National Unemployment Rate | -1.0218*** | -0.8838*** | 1.1338*** |
| | (0.1788) | (0.2106) | (0.3529) |
| Regional Unemployment Rate | -0.2228*** | -0.2316*** | -0.0858 |
| | (0.0484) | (0.0494) | (0.0616) |
| Log National Real GDP Per Capita (PPP) | | | 0.4647*** |
| | | | (0.0542) |
| Log Regional Mean Income (PPP) | | | 0.0786*** |
| | | | (0.0165) |
| Employment Status FE | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes |
| Survey Wave | Yes | Yes | Yes |
| Gender FE | No | Yes | Yes |
| Gender x Demographics | No | Yes | Yes |
| R-squared | 0.1555 | 0.1955 | 0.1978 |
| Observations | 107645 | 98049 | 75481 |

* p<0.10, ** p<0.05, *** p<0.01

*Notes:* Heteroskedasticity-robust standard errors.

Table 11: Regional and National Spillovers: Job Satisfaction

| | (1)<br>Job Sat. | (2)<br>Job Sat. | (3)<br>Job Sat. |
|---|---|---|---|
| Unemployed | -0.3787*** | -0.3977*** | -0.3090** |
| | (0.0978) | (0.1344) | (0.1531) |
| National Unemployment Rate | -1.5169*** | -0.9700*** | 1.0650** |
| | (0.2442) | (0.2943) | (0.4503) |
| Regional Unemployment Rate | -0.0876 | -0.1454* | 0.0773 |
| | (0.0721) | (0.0756) | (0.0950) |
| Log National Real GDP Per Capita (PPP) | | | 0.4584*** |
| | | | (0.0775) |
| Log Regional Mean Income (PPP) | | | 0.0954*** |
| | | | (0.0242) |
| Employment Status FE | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes |
| Survey Wave | Yes | Yes | Yes |
| Gender FE | No | Yes | Yes |
| Gender x Demographics | No | Yes | Yes |
| R-squared | 0.0568 | 0.0741 | 0.0697 |
| Observations | 56484 | 50747 | 39271 |

* p<0.10, ** p<0.05, *** p<0.01

*Notes:* Heteroskedasticity-robust standard errors.

Table 12: Controls Selected Through Double-Lasso

| | (1)<br>Wellbeing (PC) | (2)<br>Wellbeing (PC) |
|---|---|---|
| Unemployed | 0.0160 | 0.0017 |
| | (0.0128) | (0.0158) |
| National Unemployment Rate | | -10.7099 |
| | | (12.2854) |
| R-squared | 0.3813 | 0.3684 |
| Observations | 161950 | 109795 |

* p<0.10, ** p<0.05, *** p<0.01

*Notes:* This table reports coefficients from an OLS regression controlling for covariates selected using the double-Lasso procedure described in Section 4. Heteroskedasticity-robust standard errors are reported in parentheses.

Table 13: Differential Effects by Employment Status: Life Satisfaction

| | (1) Satisfaction | (2) Satisfaction |
|---|---|---|
| Unemployed | -0.5065*** | -0.4954*** |
| | (0.0288) | (0.0288) |
| Unemployed=0 × National Unemployment Rate | -2.7590*** | 1.0292*** |
| | (0.2048) | (0.2383) |
| Unemployed=1 × National Unemployment Rate | -1.4557*** | 2.3127*** |
| | (0.2764) | (0.3026) |
| Log National Real GDP Per Capita (PPP) | | 1.1403*** |
| | | (0.0363) |
| Employment Status FE | Yes | Yes |
| Country FE | Yes | Yes |
| Survey Wave | Yes | Yes |
| Gender FE | Yes | Yes |
| Gender x Demographics | Yes | Yes |
| R-squared | 0.1822 | 0.1907 |
| Observations | 99724 | 99724 |

* p<0.10, ** p<0.05, *** p<0.01

*Notes:* Heteroskedasticity-robust standard errors.

Table 14: Differential Effects by Employment Status: Happiness

| | (1) Happiness | (2) Happiness |
|---|---|---|
| Unemployed | -0.3507*** | -0.3447*** |
| | (0.0274) | (0.0273) |
| Unemployed=0 × National Unemployment Rate | -1.1680*** | 0.9682*** |
| | (0.2060) | (0.2419) |
| Unemployed=1 × National Unemployment Rate | -0.3679 | 1.7579*** |
| | (0.2708) | (0.2987) |
| Log National Real GDP Per Capita (PPP) | | 0.6663*** |
| | | (0.0352) |
| Employment Status FE | Yes | Yes |
| Country FE | Yes | Yes |
| Survey Wave | Yes | Yes |
| Gender FE | Yes | Yes |
| Gender x Demographics | Yes | Yes |
| R-squared | 0.1955 | 0.1984 |
| Observations | 98052 | 98052 |

* p<0.10, ** p<0.05, *** p<0.01

*Notes:* Heteroskedasticity-robust standard errors.

Table 15: Differential Effects by Employment Status: Job Satisfaction

| | (1)<br>Job Sat. | (2)<br>Job Sat. |
|---|---|---|
| Unemployed | -0.7122*** | -0.7326*** |
| | (0.2000) | (0.1994) |
| Unemployed=0 × National Unemployment Rate | -1.1154*** | 1.3187*** |
| | (0.2859) | (0.3295) |
| Unemployed=1 × National Unemployment Rate | 2.3745 | 4.8587*** |
| | (1.6563) | (1.6653) |
| Log National Real GDP Per Capita (PPP) | | 0.7158*** |
| | | (0.0516) |
| Employment Status FE | Yes | Yes |
| Country FE | Yes | Yes |
| Survey Wave | Yes | Yes |
| Gender FE | Yes | Yes |
| Gender x Demographics | Yes | Yes |
| R-squared | 0.0742 | 0.0779 |
| Observations | 50750 | 50750 |

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

*Notes:* Heteroskedasticity-robust standard errors.