sustainability

MDPI

Article

Examination of the Effects of COVID-19 on Happiness in Different Geographical Regions with Piecewise Linear Panel Data Models

Elif Tuna, Atıf Ahmet Evren, Zehra Zeynep Şahinbaşoğlu * and Mert Veznikli

Department of Statistics, Faculty of Sciences and Literature, Yildiz Technical University, Davutpasa, Esenler, 34210 Istanbul, Turkey; eozturk@yildiz.edu.tr (E.T.); aevren@yildiz.edu.tr (A.A.E.)

* Correspondence: zeynepsahinbasoglu@gmail.com; Tel.: +90-532-212-33-11

Abstract: The COVID-19 pandemic has recently caused the loss of millions of lives, and billions of others have been deeply affected. This crisis has changed the way people live, think about life, and perceive happiness. The aim of this study is to reveal differences between geographical regions by investigating the effect of the happiness variable on different countries during the international COVID-19 pandemic. The primary purpose is to demonstrate how such a pandemic may affect different countries in terms of happiness at the individual level and to identify possible strategies for the future. With this aim, both static and dynamic panel data models were used while applying fixed effects, random effects, and the generalized method of moments (GMM). A basic assumption in panel data models is that the coefficients do not change over time. This assumption is unlikely to hold, however, especially during major devastating events like COVID-19. Therefore, the piecewise linear panel data model was applied in this study. As a result of empirical analysis, pre- and post-COVID differences were seen between different geographical regions. Based on analysis conducted for three distinct geographical regions with piecewise linear models, it was determined that the piecewise random effects model was appropriate for European and Central Asian countries, the piecewise FGLS model for Latin American and Caribbean countries, and the piecewise linear GMM model for South Asian countries. According to the results, there are many variables that affect happiness, which vary according to different geographical conditions and societies with different cultural values.

Keywords: piecewise linear panel data models; happiness; COVID-19; Pandemics; quality of life; disasters; well-being

check for updates

Citation: Tuna, E.; Evren, A.A.; Şahinbaşoğlu, Z.Z.; Veznikli, M. Examination of the Effects of COVID-19 on Happiness in Different Geographical Regions with Piecewise Linear Panel Data Models. *Sustainability* **2023**, *15*, 8569. https://doi.org/10.3390/su15118569

Academic Editors: Luigi Aldieri, Amlan Haque, Huong Le and Nadeera Ranabahu

Received: 20 March 2023
Revised: 9 May 2023
Accepted: 18 May 2023
Published: 25 May 2023

1. Introduction

The disease now known as COVID-19 was first identified in Wuhan, China, in December 2019. The first case outside of China was diagnosed in Thailand in mid-January 2020, after which the disease rapidly spread globally. On 30 January, the World Health Organization (WHO) declared it a public health emergency of international concern and subsequently named it COVID-19 on February 11. The disease was then classified as a pandemic on March 11. The total number of confirmed cases of COVID-19 worldwide continued increasing at an unprecedented rate, surpassing 6.2 million by the end of May 2020 [1].

Happiness is a crucial human disposition that denotes a construct characterizing positive feelings in individuals and overall well-being. It can be perceived as a relatively stable state linked to diverse facets of an individual's life and distinguishes itself from more transient emotions like joy or sadness. The comprehension of happiness holds significant importance in philosophical, psychological, scholarly, narrative, and governmental spheres, but conclusive agreement regarding the factors that genuinely engender happiness remains elusive [2].

Happiness is "commonly understood as how much one likes the life one lives" [3]. While the meaning and attainment of happiness may differ from person to person, levels of happiness also often fluctuate from one day to the next, and a pandemic such as COVID-19 is likely to change the dynamics of existing happiness [4].

The variable of happiness has exhibited nonlinearity across different time periods and different countries with significant changes due to the impact of the pandemic. Therefore, a linear model is inadequate to explain this phenomenon. We employed piecewise linear panel data models in this study with that concern in mind.

Building upon previous studies in the literature, we conducted modeling of happiness across three distinct geographical regions while employing a comparative approach that utilized static and dynamic panel data models to account for the pre- and post-COVID-19 periods.

The structure of this paper is as follows: This introductory section has provided an overview of the research. Section 2 offers a review of the relevant literature. Section 3 includes a description of the data and definitions of the variables. Section 4 outlines the applied methods and analyses. Finally, in Section 5, we present and interpret the results comparatively.

2. Literature Review

When the literature is examined, descriptions of happiness include the following five important elements: (i) happiness encompasses positive emotions, good emotions, experiences, and life pleasures without negative emotions such as anxiety and depression; (ii) achieving happiness is the basic human desire and the most important goal of humans; (iii) achieving happiness is a difficult goal for some and it is not always attainable; (iv) happiness has different meanings and entails different life goals for different people, there are different ways to be happy, and happiness cannot be transferred from one person to another; and (v) happiness entails satisfaction, success, and the achievement of wishes and desires [5].

There are several reasons to consider happiness from an academic perspective. Experimental evidence shows that happiness plays a key role in achieving success. It is a positive affective experience and happy individuals are more prone to approaching new people and events, which helps to enhance their mental, social, and physical development. Happiness studies show that happier people are more educated, are better paid, live longer, are healthier, get married more often, get divorced less often, have more friends, find jobs they enjoy more easily, and are happier in their marriages. Another reason for studying happiness on an academic basis is that, along with quality of life, it has become a common public policy goal. The growing interest in measuring happiness is a result of a decline in gross domestic product (GDP) per capita, which reflects human development over the course of many years [6].

In this study, the effects of several variables on happiness during the COVID-19 pandemic are examined based on geographical regions. These variables are GDP per capita, social support, life expectancy at birth, freedom, generosity, corruption, and confidence in the government. The definitions of these variables are provided in Appendix A.

2.1. *Impact of GDP on Happiness*

Many studies have explored the relationship between happiness and GDP per capita, and the consensus is that there is a positive relationship between these two variables. A higher GDP per capita typically correlates with higher levels of happiness, at least up to a certain point.

A study of data from more than 100 countries found that GDP per capita was positively associated with happiness. That study concluded that this relationship was partially mediated by factors such as income inequality and social capital [7].

Similarly, according to a study from 2006, individuals in countries with higher GDP levels tend to report higher levels of happiness compared to those in countries with lower

GDP levels. However, GDP is not the only determinant of happiness; other factors such as social support, personal freedoms, and cultural values also play roles in determining happiness levels [8].

Kahneman and Deaton found that when a country's GDP per capita reaches about USD 25,000, further increases in GDP per capita do not lead to significant increases in happiness. Their study was based on Gallup World Survey data obtained from more than 450,000 respondents in 155 countries and their findings suggest that the relationship between income and happiness weakens beyond a certain income threshold. The authors suggested that other factors, such as social support, freedom, and health, become more important determinants of well-being as individuals reach higher income levels [9].

While there is a positive relationship between GDP per capita and happiness, the relationship is not always straightforward and there are important moderating factors, such as income inequality, that must be taken into account.

2.2. Impact of Social Support on Happiness

Social support refers to the resources that individuals receive from their social networks, such as emotional support, practical assistance, and companionship. There is a growing body of research examining the relationship between social support and happiness.

Nettle suggested that happiness can be considered on three levels. The first of these includes instant feelings such as joy and pleasure. The second level entails general contentment and satisfaction, while the third level involves individual self-actualization [10]. Within this framework, it can be said that individuals with sufficient social support experience the first or second level of happiness. Social support from different sources ensures that an individual is not alone and feels stronger and more valuable. Therefore, social support positively affects the happiness of an individual.

According to Diener and Seligman, very happy people are more social and have stronger relationships. They are more likely to get married, have wider social networks, and receive more emotional support from others [11].

2.3. Impact of Happiness on Life Expectancy at Birth

There is a significant positive relationship between happiness and life expectancy at birth according to several studies. For example, according to Veenhoven's extensive survey, people who consider themselves relatively happy within a country tend to live 7–10 years longer than those who describe themselves as unhappy [12]. Levy, Slade, Kunkel, and Kasl reported a similar result for a sample of Americans aged 50 or older, even after controlling for the participants' baseline levels of health. Their research suggests that happy Americans tend to live 7 years longer than those who are less happy, even at an age when people have established most of their fundamental habits [13].

In the early stages of economic development, even small economic advances yield substantial returns in various areas including calorie intake, clothing, housing, medical care, and ultimately life expectancy. However, when a society exceeds a certain development threshold, it reaches a point where further economic growth results in only marginal increases in both life expectancy and happiness. This nonlinear relationship between income and life expectancy is known as the Preston curve in honor of Samuel H. Preston, who first described it in 1975 [14,15].

Pandemics are not only a medical phenomenon; they are also a social phenomenon that affects individuals and society on many different levels. A few months after the outbreak of the COVID-19 virus, many countries went into "lockdown" in response to the rapid spread of the virus and thousands of deaths [16]. These lockdowns often closed businesses, making it necessary for individuals to stay home and/or work from home and avoid physical contact with others. Thus, the consequences of the virus have not only been physical (such as illness and hospitalization) and financial (such as redundancy, financial insecurity, and unemployment) [17] but also possibly psychological, with impacts including fear and loneliness [18].

2.4. Impact of the Freedom to Make Life Choices on Happiness

The freedom to make one's own life choices (FMLC) is often described as an important component of individual well-being and happiness. Several studies have examined the relationship between happiness and FMLC.

Inglehart et al. explored the relationship between happiness and economic development, as well as the role of freedom in contributing to happiness. They found that increases in FMLC were positively associated with higher levels of happiness [19].

According to Brulé and Veenhoven, the variations in average happiness among wealthy nations can be attributed largely to differences in freedom. This includes not only perceived freedom but also actual freedom, and particularly psychological freedom. The reason why Finns are happier than the French, for instance, is that they feel freer and are freer. This increased actual freedom is not simply due to less restrictive policies in Finnish society but also to a greater willingness to pursue personal freedom [20].

2.5. Impact of Generosity on Happiness

Generosity can be defined as the willingness to give time, money, or other resources to others without expecting anything in return. Research suggests that there is a positive relationship between happiness and generosity.

Aknin, Proulx, and Dunn conducted a study in which they gave participants money and instructed them to either spend it on themselves or on others. They found that participants who spent the money on others reported higher levels of happiness than those who spent the money on themselves [21].

Nelson, Layous, Cole, and Lyubomirsky conducted a study in which they instructed participants to perform five acts of kindness over the course of a day. They found that participants who performed those acts of kindness reported increased happiness compared to a control group [22].

In parallel with these studies, Diener and Seligman suggested that very happy people are more altruistic and engage in more prosocial behavior. They are more likely to volunteer, donate to charity, and help others in need [11].

2.6. Impact of the Perception of Corruption on Happiness

The perception of corruption can be defined as the degree to which individuals perceive corruption to be prevalent in their society. Research suggests that there is a negative relationship between happiness and the perception of corruption. Corruption is often seen as a barrier to social and economic progress and it undermines social trust and cooperation, which can negatively impact well-being.

According to Ma et al. [23], perceptions of official corruption are negatively related to subjective well-being. Corruption tends to lower income and it is one of the most important generators of poverty [24]. On the micro level, personal experiences of corruption can influence an individual's happiness. Experiences of corruption have detrimental effects on individuals' mental health. Thus, corruption can undermine citizens' happiness, but governments can remedy those negative impacts by improving government performance [23].

2.7. Impact of Confidence in the National Government on Happiness

Confidence in the national government can be defined as the degree to which individuals have trust and confidence in their country's government and political institutions. Several studies have shown a positive correlation between happiness and confidence in the national government. In other words, people who have higher levels of trust in their government tend to report higher levels of happiness and life satisfaction.

For example, a study conducted by Inglehart and Klingemann in 2000 analyzed data from the World Values Survey and found that people who trusted their national government were more likely to be happy than those who did not [19]. Similarly, Helliwell and Huang analyzed data from the World Values Survey and found that confidence in government was positively associated with happiness, even upon controlling for other factors such as income and social support [25].

Another study by Oishi and Schimmack used data from the Gallup World Poll to examine the relationship between trust in government and subjective well-being in 129 countries. The authors found that trust in government was positively related to life satisfaction and emotional well-being, and this relationship was consistent across different cultures and economic systems [26].

In another previous study, the relationships between respondents' subjective well-being and confidence in six institutions were assessed in ten South American countries. Confidence in national institutions was significantly positively associated with both types of life satisfaction and the relationships persisted after controlling for sociodemographic and macroeconomic factors [27].

Overall, these studies suggest that confidence in the national government is an important predictor of happiness and well-being at both individual and societal levels.

2.8. Impact of COVID-19 on Happiness and Other Variables

Most of the studies in the literature to date have focused on the economic effects of COVID-19. The pandemic has generated processes that affect economic factors such as stock prices and government bonds [28,29]. While the negative impact of the pandemic on GDP was experienced at the highest level, there were also significant losses in national welfare. In past years, GDP was used to measure a nation's happiness, but the GDP cannot measure qualities such as family and friendship, moral values, happiness, or life purpose. Therefore, there is an increasing trend of using subjective measures of happiness beyond the classical income-based approach [30].

Taking into account different psychological definitions, scholars have generally developed research to consider personal psychological and emotional happiness or effects of the restrictions applied for COVID-19. People's mental health can be severely affected by isolation. While there were significant increases in online searches for the words "loneliness", "worry", and "sadness" according to Google Trends, there were decreases in searches related to stress, suicide, and divorce [31]. Hamermesh also ran simulations and used Google Trends data to predict the life satisfaction of married and unmarried people under government-ordered quarantine and found that single people were less satisfied with their lives than married people [32]. When 24 of 3166 relevant articles were evaluated, it was seen that the studies primarily focused on the psychological effects of quarantine [33]. Most studies have emphasized the existence of negative psychological effects such as confusion and anger, and among the variables that constituted emotional stress factors, long quarantine periods, fear of infection, boredom, anxiety about not being able to access information, exclusion due to financial loss, and illness were listed. Greyling et al. [15] studied the causal effects of quarantine on happiness in a cross-sectional study using OLS. They found that quarantine had a negative impact on happiness regardless of different country characteristics and the duration and type of quarantines and restrictions. They also provided a comprehensively arranged table of the methods used in the literature and the results found in studies to date, and they showed that stricter prohibition rules correlated with higher costs of happiness. As a result, they concluded that quarantine has a significant and negative impact on happiness. Sibley et al. [18] investigated the impact of bans in New Zealand on institutional trust, attitudes, health, and happiness using survey data collected over two periods. They showed a small increase in people's sense of community and trust with the pandemic. However, they noted an increase in post-quarantine anxiety and depression, which could pose longer-term challenges to people's mental health. Li et al. [34] used big data in their analysis of the Chinese social media platform Weibo. They found that negative emotions such as depression, anxiety, and anger and susceptibility to social risks increased under the influence of COVID-19 and negatively impacted mental health. In contrast, positive emotions such as "Oxford happiness" and life satisfaction were reduced.

According to another study, people were more concerned about their health and family and less concerned about fun and friends in this period [35].

3. Variables and Data

In this report, the primary data source utilized is the Gallup World Poll, which entails asking individuals to evaluate their current lives using the Cantril ladder. The Cantril ladder is a scale that ranges from 0 (worst possible life) to 10 (best possible life). With this method, responses are typically gathered from approximately 1000 individuals annually from each country, and population-representative national averages for each year in each country are constructed using weighted averages. The usual happiness rankings are based on a three-year average to increase the sample size and provide more accurate estimations. However, for this year's report, the focus is on the effects of COVID-19.

Using randomly selected samples, the Gallup World Poll continuously surveys residents of more than 140 countries, representing 95% of the world's adult population. In some regions, alternative questions are asked in addition to the basic questions. In many countries, the survey is conducted once a year and the fieldwork is usually completed in two to four weeks.

Although World Happiness Reports are based on a wide variety of data, the Gallup World Poll has been the most important source of information on this topic. Using the Gallup World Poll, Gallup measures degrees of life satisfaction and emotional well-being and tries to capture how people feel about what is happening in their lives, which GDP cannot explain. Gallup data were therefore used to model happiness. The modeling considers the effects of six factors, which are family, GDP per capita, health, freedom, generosity, and trust. The happiness scores used in this work were taken from the Gallup World Poll publication of 18 February 2022, which covers the years from 2006 to 2021. Subjects were asked to respond to life assessments on a scale of 1 to 10 with 1 representing the worst possible life and 10 representing the best possible life.

Throughout this article, abbreviations will be used for some variables to make it easier for readers to follow the text. These variables are as follows: The variable of happiness is denoted by H in this article and it represents the average of the answers given. The GDP variable represents GDP in purchasing power parity, assuming constant 2017 international dollar prices. The SSP variable reflects social support and represents the national average of the binary responses to the following question: "Do you have relatives or friends you can trust if you are in trouble?" The HLEB variable represents healthy life expectancy at birth and is based on data from the WHO Global Health Observatory Data Repository. Data from that source are available for the years 2000, 2010, 2015, and 2019. Interpolation and extrapolation were used to fit the sample period of the present study (2005–2021). The FMLC variable represents the national average of the binary responses (0 or 1) to the Gallup World Poll question of "Are you satisfied or dissatisfied with your freedom to choose what to do with your life?" The variable G represents generosity, reflected by national average answers to the Gallup World Poll question of "Have you donated to a charity in the last month?" The PC variable represents the perception of corruption, measured by the national average answers to two questions of the Gallup World Poll: "Is corruption prevalent across government?" and "Is corruption common in businesses?" These overall perceptions are measured as binary responses of 0 or 1. According to Gallup, if there is no perception of corruption within the government, the general perception of corruption among businesses is used. The CNG variable, or confidence in the national government, represents institutional trust. Institutional trust is a basic combination of five items: trust in the national government, trust in the judiciary and courts, trust in the integrity of elections, trust in the local police force, and perceived corruption in business [36]. Detailed definitions of these variables can be found in Appendix A. Positive effects are denoted by the abbreviation PE.

Closer geographical areas may harbor some similarities, such as similarities among cultures or climate, to a greater extent than random distant countries. This means that neighboring societies are often more similar in terms of social development and cultural environment than other more distant countries. In general, countries from a common geographical region also show some heterogeneity, but they are not as diverse on average as countries from different regions. Social development and cultures in a given geographical region are much closer than those from different geographical regions. Therefore, the evaluations of happiness by respondents from the same geographical region, the satisfaction of their wants and needs, and the ways in which these participants respond to the questions may yield similar values. In the present study, we aimed to examine the effect of the COVID-19 pandemic according to geographical regions. Regions were considered based on the World Bank's classification as follows: East Asia and the Pacific, Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa, North America, South Asia, and Sub-Saharan Africa. Following the elimination of some countries due to lack of data from among the regions considered according to this World Bank classification, the countries to be examined in regional groups in the period of 2006–2021 were as follows:

East Asian and Pacific countries: Australia, Indonesia, Japan, New Zealand, Philippines, and Thailand.

Europe and Central Asia: Austria, Bosnia and Herzegovina, Croatia, Cyprus, Denmark, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Ireland, Italy, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, the Netherlands, Poland, Portugal, Romania, Russia, Serbia, Slovenia, Spain, Sweden, Turkey, Ukraine, and the United Kingdom.

Latin America and the Caribbean: Argentina, Brazil, Chile, Colombia, Costa Rica, the Dominican Republic, Ecuador, El Salvador, Mexico, Nicaragua, Paraguay, Peru, Uruguay, and Venezuela.

Middle East and North Africa: Iran, Iraq, and Israel.

North America: Canada and the United States.

Sub-Saharan Africa: Burkina Faso, Cameroon, Ghana, Kenya, Mali, Nigeria, Senegal, South Africa, Tanzania, Uganda, Zambia, and Zimbabwe.

South Asia: Nepal, Pakistan, and Sri Lanka.

4. Results

The foundation of the piecewise linear model is predicated on the idea that the regression function ought to be modeled in "pieces" if the data exhibit distinct linear trends at varying intervals. The model's graphical representation comprises two or more straight line segments with a predetermined number of breakpoints. The key aspect of the model entails identifying the appropriate breakpoints and subsequently estimating the coefficients for each segment. At the structural break, the slope changes, but the lines remain continuous. Consequently, the model offers the advantage of allowing for a broader range of shapes for the curve, instead of solely being limited to linearity, squareness, or cubicity. The piecewise linear model implies that happiness may differ at different times in different geographical regions. In the reduced form, for the European and Central Asian countries, the model can be presented as follows (static random effects model):

$$H_{it} = \alpha_0 + \beta_1 \ln GDP_{it} + \beta_2 SSP_{it} + \beta_3 FMLC_{it} + \beta_4 CNG_{it} + \beta_{k.c} X^{c}_{k.it} + \alpha_i + \nu_{it} \quad (1)$$

$$D = \begin{cases} 0 & t < 2000 \\ 1 & t \geq 2000 \end{cases} \quad (2)$$

Here, H_{it} is the mean happiness score for country i in year t, and GDP_{it} is the gross domestic product per capita for country i in year t. The error term ε_{it} has two orthogonal components. One of them, α_i, is the country random effect to control for unobserved time-invariant heterogeneity resulting from factors such as geographical differences. The other one, ν_{it}, represents idiosyncratic shocks. α_0 is a constant, and $X^{c}_{k.it}$ represents the k_{th} variable that changed after COVID-19 in the relevant geographical region. $\beta_{k.c}$ represents the coefficient of the variable that changed after COVID-19. Variables with coefficients that vary after COVID-19 differ according to the geographical regions discussed. For example, while the coefficient of the $FMLC$ variable differed in some regions after the pandemic, the coefficient of the SSP variable differed in some other regions. $FMLC^c_{it}$ represents the variable $FMLC_{it}$ measured in the post-COVID-19 period.

$$X^c_{k.it} = X_{k.it}.D$$

We hypothesize that happiness will decrease linearly after the pandemic, with different slopes obtained for the periods before and after. We assume that each region has a two-piece linear spline. In piecewise linear equations the slope is assumed to change from β_k to $\beta_k \pm \beta_{k.c}$ with the COVID-19 pandemic.

Panel data should not contain unit roots in order to avoid the spurious regression problem in piecewise linear panel data models. Therefore, unit root tests were applied for the geographical region groups in this section. If there is a correlation between the units in the panel data, the asymptotic properties of the tests may be affected. For this reason, different unit root tests have been developed according to the existence of cross-sectional dependence. In the literature, unit root tests developed for situations where there is no correlation between units are called first-generation tests, while tests used in the presence of inter-unit correlation are referred to as second-generation tests. The Breusch–Pagan LM test for cross-sectional dependence was applied when N < T, and when N > T, the Pesaran CD test was applied. In these tests, the null hypothesis is that there is no cross-sectional dependence. There are two main types of panel data, with static panels and dynamic panels. Static panels can be classified into models with fixed or random effects, depending on how they consider the individual effects. In this context, the Hausman test is used in panel data models to distinguish between fixed effects (FE) and random effects (RE). For European and Central Asian countries, the Hausman χ^2 test statistic was found to be 6.43 (Pr = 0.1693). Therefore, it was decided that the random effects model was appropriate for this group of countries.

In the Levene Brown–Forsythe test, the null hypothesis established is that the variances are equal. According to the results, the null hypothesis is rejected and there is varying variance (W0 = 4.7164576, df (30, 465), Pr > F = 0.0000). When we tested whether there was autocorrelation in the RE model with the Durbin–Watson test as proposed by Bhargava, Franzini, and Narendranathan, DW = 0.9397. Since this value of DW is much smaller than 2, the random effects model also has a serious autocorrelation problem. The Pesaran CD (cross-sectional dependence) test is used to test whether residuals are correlated across entities. Cross-sectional dependence can lead to bias in tests results. The null hypothesis is that the residuals are not correlated. When the Pesaran CD test is applied, we see that there is no cross-sectional dependence problem between European and Central Asian countries (CD = 1.141, Pr = 0.2539). Since there is no cross-sectional dependency, first-generation panel unit root tests can be applied. The ADF test has been widely used to test the unit roots of series. Fisher-type ADF unit root tests can be applied for different lag lengths related to the individual ADF regression and so these tests were applied for this region. Based on the p-values of individual unit root tests, Fisher's test assumes that all series are non-stationary under the null hypothesis (random walk process (RW)) against the alternative that at least one series in the panel is stationary. The results of unit root tests for European and central Asian countries can be seen in Table 1:

Table 1. Unit root tests for European and Central Asian countries.

	Variable	Fisher ADF	p Value
H	Pure R.W.	81.8298	0.0466
	R.W. with Trend	81.7755	0.0470
	R.W. with Drift	183.5686	0.0000
GDP	Pure R.W.	48.9820	0.8852
	R.W. with Trend	69.0905	0.2504
	R.W. with Drift	80.9863	0.06173
$\ln(GDP)$	Pure R.W.	49.5763	0.8727
	R.W. with Trend	69.5664	0.02379
	R.W. with Drift	133.4957	0.0000
SSP	Pure R.W.	142.9903	0.0000
	R.W. with Trend	131.4878	0.0000
	R.W. with Drift	247.6513	0.0000
$FMLC$	Pure R.W.	109.5911	0.0002
	R.W. with Trend	102.3474	0.0010
	R.W. with Drift	210.2400	0.0000
CNG	Pure R.W.	88.7584	0.0145
	R.W. with Trend	115.8312	0.0000
	R.W. with Drift	243.3572	0.0000

In the European and Central Asian countries, since the GDP variable is not stationary, it is used by taking the natural logarithm ("ln"). It can be seen in Table 2 that the other variables have no unit roots and are stationary.

Table 2. Estimated models for European and Central Asian countries.

Variable	Random Effect	GMM
$L.H$		0.3848 ***
$LGDP$	9.3346 ***	6.9007 ***
SSP	1.7301 ***	2.5524 ***
$FMLC$	0.9954 **	0.4296 *
CNG	0.8191 ***	0.5320 ***
$FMLC^c$	0.6254 *	0.2898
CNG^c	−0.9062 *	0.5062
Constant	−18.2483 ***	−15.0814 ***
N	496	434
R^2	0.74	0.86

legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. X^c represents the k_{th} variable that changed after COVID-19.

The most common problems encountered in panel data modeling are heteroskedasticity, cross-sectional dependence, and autocorrelation problems. In this respect, it has been shown that the Arellano–Bond GMM estimator should be preferred if the unit size is larger than the time dimension in order to solve the autocorrelation, heteroskedasticity, and cross-sectional dependence problems encountered in panel data. The random effects model that we discuss is estimated with robust standard errors developed by Arellano, Froot, and Rogers, which they used when residuals were correlated within the unit and uncorrelated between the units. Consequently, for European and Central Asian countries, we used both static and dynamic panel estimators by applying random effects and the difference generalized method of moments (GMM) methods with the aim of obtaining robust empirical results. In the modeling phase, we evaluated the static and dynamic model predictions with interaction variables that represent the break in the COVID period. However, the post-COVID coefficients were not significant in the dynamic model. This may be due to the fact that the effect of the pandemic is included in the model due to the model's dynamic nature.

Dynamic panel data models are useful when the dependent variable depends on its own past realizations. Therefore, in dynamic regression equations, the lagged dependent variable is included as one of the regressors to control for the problem of endogeneity. The difference GMM method starts by transforming all regressors, usually by differencing, and uses the GMM.

$$H_{it} = \alpha_0 + \gamma_1 H_{i(t-1)} + \beta_1 \ln GDP_{it} + \beta_2 SSP_{it} + \beta_3 FMLC_{it} + \beta_4 CNG_{it} + \beta_{k.c} X^c_{k.it} + \varepsilon_{it} \quad (3)$$

Here, the definition of each expression is as given for the random effects model. The only difference is the $H_{i(t-1)}$ expression on the right side of the model. The $t-1$ lagged value of the dependent variable is used as a GMM instrument. $H_{i(t-1)}$ represents the one-period lagged value of the dependent variable.

The alternative models of (4) (random effect) and (5) (difference GMM) are created, respectively, for the European and Central Asian countries as follows:

$$H_{it} = -18.25 + 9.33 \ln GDP_{it} + 1.73 SSP_{it} + 1.62 FMLC_{it} - 0.09 CNG_{it} + \varepsilon_{it} \quad (4)$$

$$H_{it} = -15.08 + 0.38 H_{i(t-1)} + 6.9 \ln GDP_{it} + 2.55 SSP_{it} + 0.43 FMLC_{it} + 0.53 CNG_{it} + \varepsilon_{it} \quad (5)$$

When the change in the coefficient of the CNG variable, which represents trust in the state, police, and so on, is examined, it is seen that the coefficient became negative with the pandemic ($0.8191 - 0.9062 = -0.0871$). This finding reveals that as confidence increases happiness decreases with the effect of the pandemic. It is also seen that the coefficient of the FMLC variable increased from 0.99 to 1.62 after the pandemic. The coefficients of the SSP and CNG variables for the happiness variable in the GMM model are higher than those in the random effects model, while the coefficient of the FMLC variable is lower. Meanwhile, when viewed from the perspective of R^2 values, it is seen that the dynamic model has the largest R^2 value. However, since the post-pandemic coefficients in the GMM model were not significant in that model, it was concluded that the robust random effects model was appropriate.

If there are one or more endogenous variables, the number of instruments increases even more as each regressor is instrumentalized by all the differences and levels with the GMM. This causes overidentification of the model, mainly when the number of degrees of freedom is small, or when there are fewer individuals. Therefore, as the panel grows in periods and the number of individuals decreases, the probability of overidentification increases.

In Table 3, the Sargan test and the test for autocorrelation of the residuals were conducted to evaluate the specification of the model and the validity of the instruments as shown below.

Table 3. Model specification tests for European and Central Asian countries.

Sargan Test	Chi-Square	Probability Value	Conclusion
	43.54299	0.1812	Fit/Homoskedasticity
	Autocorrelation/Arellano–Bond Test		
	z	Probability Value	Conclusion
lag1	−1.4868	0.1371	No Autocorrelation
lag2	−1.14	0.2543	

We used the Sargan test with the null hypothesis that overidentification restrictions are valid. The higher the *p*-value of the Sargan statistic, the better. However, according to [37] the Sargan *p*-value should be greater than 0.25. To identify whether or not autocorrelation exists, the Arellano–Bond test is used. The null hypothesis for this test is that autocorrelation does not exist. The test for autocorrelation presented no evidence of model misspecification.

The two tests specified above with the model specifications can also be used to test classical assumptions. The Sargan test can be used for heteroscedasticity, while the Arellano–Bond test is used for autocorrelation.

For Latin American and Caribbean countries, the Hausman χ^2 test statistic was found to be 1.11 (Pr = 0.9532). Therefore, it was decided that the random effects model was appropriate for this group of countries. After the Levene Brown–Forsythe test, the null hypothesis was rejected, which means that there is a heteroskedasticity problem (W0 = 1.7983076, df(13, 210), Pr > F = 0.04493042). The result of the Durbin–Watson test proposed by Bhargava, Franzini, and Narendranathan was DW = 1.3628. Since this DW value is smaller than 2, the random effects model also has an autocorrelation problem. In the case of N < T, one of the tests developed to test for cross-sectional dependence is the Breusch–Pagan LM test (LM = 242.752, Pr = 0.0000). Since there is cross-sectional dependency, second-generation panel unit root tests can be applied. Peseran (2003) suggested a *t*-test for unit roots in heterogenous panels with cross-sectional dependence. It is based on the mean of the individual DF (or ADF) t-statistics of each unit in the panel. The null hypothesis assumes that all series are non-stationary. To eliminate the cross-dependence, the standard DF (or ADF) regressions are augmented with the cross-sectional averages of lagged levels and first differences of the individual series (CADF statistics). Unit root test results are as follows (Table 4):

Table 4. Unit root tests for Latin American and Caribbean countries.

	Variable	Peseran CADF	*p* Value
ΔH	R.W. with Trend + Drift	−3.352	0.000
	R.W. with Drift	−3.421	0.000
$\Delta \ln(GDP)$	R.W. with Trend + Drift	−4.209	0.000
	R.W. with Drift	−3.303	0.000
ΔSSP	R.W. with Trend + Drift	−3.367	0.000
	R.W. with Drift	−3.053	0.000
ΔPC	R.W. with Trend + Drift	−2.881	0.018
	R.W. with Drift	−2.871	0.000
$\Delta FMLC$	R.W. with Trend + Drift	−3.674	0.000
	R.W. with Drift	−3.659	0.000

Since the variables discussed here have unit roots at the level, first difference series are studied, and it is shown in the table above that the series are I(1).

Since there is heteroskedasticity, cross-sectional dependence, and unit-specific AR(1) correlation in the random effects model applied for Latin American and Caribbean countries, feasible generalized least squares regression (FGLS) was estimated. The results were compared with the dynamic GMM model as shown below (Table 5).

Table 5. Estimated models for Latin American and Caribbean countries.

Variable	FGLS	GMM
$L.H$		1.0872
$\Delta LGDP$	1.1811 ***	2.0277
ΔSSP	1.9228 ***	2.9138
ΔPC	−0.7404 ***	−2.4748 *
$\Delta FMLC$	1.6787 ***	1.7581
$\Delta FMLC^c$	−0.2325 **	−0.3268 **
Constant	0.9677 *	−1.0872
N	224	196
R^2	0.74	0.41

legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. X^c represents the k_{th} variable that changed after COVID-19.

In the dynamic model, most coefficients were found to be insignificant. In addition, determination rate R^2 of the model was lower compared to the FGLS model. Therefore, the FGLS model was preferred. The model with its first differenced variables is as follows:

$$H_{it} = 0.96 + 1.18 \ln GDP_{it} + 1.92SSP_{it} - 0.74PC_{it} + 1.45FMLC_{it} + \varepsilon_{it} \tag{6}$$

The coefficient of the FMLC variable decreased from 1.67 to 1.45 after the pandemic. The coefficient of lnGDP is approximately 9 times smaller compared to the European and Central Asian countries. The coefficient of PC is significant compared to the European and Central Asian countries, while the coefficient of CNG was found to be insignificant.

For South Asian countries, the Hausman χ^2 test statistic was found to be 26.25 (Pr = 0.0001). Therefore, it was decided that the fixed effects model was appropriate for this group of countries. With the modified Wald test, the null hypothesis was accepted, which means that there is no heteroskedasticity problem (χ^2 = 5.00, df = 3, Pr > χ^2 = 0.1721). The test statistic of the autocorrelation test proposed by Wooldridge was found to be F = 3.312 with Pr > F = 0.2104. In this case, we can say that there is no autocorrelation. In the case of N < T, one of the tests developed to test for cross-sectional dependence is the Breusch–Pagan LM test (LM = 3.524, Pr = 0.3176). The result indicated no cross-sectional dependence, so first-generation panel unit root tests could be applied. Fisher-type ADF unit root tests were applied for the South Asian countries as shown in Table 6.

Table 6. Unit root tests for South Asian countries.

	Variable	Fisher ADF	*p* Value
H	Pure R.W.	16.5610	0.0110
	R.W. with Trend	12.0044	0.0619
	R.W. with Drift	28.5890	0.0001
$\ln(GDP)$	Pure R.W.	4.7597	0.5750
	R.W. with Trend	0.7398	0.9936
	R.W. with Drift	17.1854	0.0086
SSP	Pure R.W.	16.6423	0.0107
	R.W. with Trend	11.8678	0.0650
	R.W. with Drift	27.9394	0.0001
$FMLC$	Pure R.W.	5.0271	0.5403
	R.W. with Trend	14.1868	0.0276
	R.W. with Drift	14.6393	0.0233
$HLEB$	Pure R.W.	8.7074	0.1907
	R.W. with Trend	72.0971	0.0000
	R.W. with Drift	11.9706	0.0626

In the modeling phase, both static and dynamic panel estimators are compared by applying fixed effects and GMM methods as shown in the Table 7 below.

The Sargan test and the test for autocorrelation of the residuals were conducted to evaluate the specification of the model and the validity of the instruments for the dynamic model as shown in Table 8 below.

The results indicate that overidentifying restrictions are valid and there is no autocorrelation problem in the dynamic model.

It is seen in both of the models that the coefficient of the HLEB variable, which represents life expectancy, is significant in this geographical region, unlike other geographical regions. Interaction terms representing the post-COVID-19 period were added to the SSP and HLEB variables, which were revealed in trials where the coefficient changed with COVID-19. These interaction terms were found to be significant in both of the models.

Table 7. Estimated models for South Asian countries.

Variable	FGLS	GMM
$L.H$		0.0997 *
$LGDP$	23.6017 ***	21.8824 ***
SSP	4.1563 ***	4.5905 ***
$HLEB$	−0.3400 ***	−0.3355 ***
SSP^c	8.5546 ***	7.7661 **
$HLEB^c$	−0.0976 **	−0.0882 **
Constant	−28.3266 *	−25.7028
N	48	42
R^2	0.54	0.63

legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. X^c represents the k_{th} variable that changed after COVID-19.

Table 8. Model specification tests for South Asian countries.

Sargan Test	Chi-Square 43.54299	Probability Value 0.1812	Conclusion Fit/Homoskedasticity
Autocorrelation/Arellano–Bond Test			
	z	Probability Value	Conclusion
lag1	−1.4868	0.1371	No Autocorrelation
lag2	−1.14	0.2543	

The fixed effects and difference GMM dynamic panel models for the South Asian countries are as follows, respectively:

$$H_{it} = -28.33 + 23.607 \ln GDP_{it} + 12.71 SSP_{it} - 0.44 HLEB_{it} + \varepsilon_{it} \quad (7)$$

$$H_{it} = -25.70 + 0.11 H_{i(t-1)} + 21.88 \ln GDP_{it} + 12.26 SSP_{it} - 0.42 HLEB_{it} + \varepsilon_{it} \quad (8)$$

When the change in the coefficient of the SSP variable, which represents trust in the state, police, and so on, was examined in both models, it was seen that the coefficient increased by nearly 3 times due to the effect of the pandemic (for fixed model: 4.1563 + 8.5546 = 12.7109; for GMM model: 4.5905 + 7.6661 = 12.2566). This result shows that as social support increases happiness is affected three times more than it was before the pandemic.

Both predicted models gave approximate results for South Asian countries. For both models, the assumptions were tested, and no serious problems were found. If the dataset consists of observations of a large population and it is desired to draw conclusions for the entire population, it is more appropriate to use the dynamic GMM model.

For North American countries, since N < T for testing cross-sectional dependency, the Breusch–Pagan LM test was used (LM = 1.767, Pr = 0.1837). Since there was no cross-sectional dependency, first-generation panel unit root tests could be applied. As can be seen in Appendix B, according to the unit root test results, it was decided to use the I(1) difference series for the static and dynamic models. However, when the I(1) series was used, no significant relationship was found in terms of the variables considered.

As a result, when we evaluated the findings according to geographical regions, it was determined that piecewise linear panel data models were not suitable for East Asian and Pacific countries, Middle Eastern and North African countries, or Sub-Saharan African countries. For the remaining geographical regions, the parameters related to happiness were evaluated before and after the pandemic. For North American countries it was decided to use the I(1) difference series for the static and dynamic models. However, when the I(1) series was used, no significant relationship was found in terms of the variables considered. The remaining geographical country groups that showed piecewise linear relationships that changed with the pandemic are listed in the Table 9.

Table 9. Geographical country groups with piecewise linear relationships after the pandemic.

Geographic Regions	Chosen Model	Variables That Affect Happiness	Variables That Changed After COVID-19
European and Central Asian Countries	Piecewise Random Effects	lnGDP, FMLC, SSP, CNG	FMLC, CNG
Latin American and Caribbean Countries	Piecewise FGLS	ΔLGDP, ΔSSP, ΔPC, ΔFMLC	ΔFMLC
South Asian Countries	Piecewise GMM	L.H, LGDP, SSP, FMLC, HLEB	SSP, HLEB

Since there is no cross-sectional dependency in the European and Central Asian countries, first-generation panel unit root tests were applied.

5. Conclusions

Panel data methodology is widely employed for quantitative analysis in the social sciences, particularly in the fields of economics and business. It facilitates the simultaneous examination of individual effects, multiple time periods, and the endogeneity of the model or independent regressors. By analyzing panel data, researchers can control for unobserved heterogeneity across individuals and time periods, estimate fixed or random effects models, and explore dynamic relationships between variables over time. This approach enables a more comprehensive understanding of individual behavior, as well as the effects of policy interventions or changes in economic conditions.

This study investigated the influence of GDP, FMLC, SSP, HLEB, PC, and CNG on happiness in three geographic regions from 2006 to 2021 by employing a piecewise linear fixed effects model, piecewise linear random effects model, and difference GMM model.

According to the findings, it would not be correct to represent the series containing the pre- and post-COVID-19 periods with a single line, and modeling the relations with the piecewise linear model would yield more meaningful and consistent results.

One of the results of this study indicated that when we evaluated the data according to geographical regions, piecewise linear panel data models were not suitable for East Asian and Pacific, Middle Eastern and North African, North American, or Sub-Saharan African countries. For the remaining geographical regions, parameters related to happiness before and after the pandemic were evaluated.

The examined results demonstrated that GDP has a positive and significant impact on happiness in the three considered geographical regions. Compared to European and Central Asian countries, the impact of GDP on happiness is much higher in South Asian countries. The FMLC variable, which represents freedom in making choices, was also found to have a significant effect on happiness in the European and Central Asian countries. Unlike other country groups, in Latin American and Caribbean countries, the PC variable has a significant negative effect on happiness. Similarly, the HLEB variable, which represents life expectancy at birth, was found to have a significant effect on happiness only in South Asian countries. Since the countries in the South Asian country group are the underdeveloped countries such as Nepal, Pakistan, and Sri Lanka, the HLEB variable was found to be significant in this country group, unlike other groups. This result is in line with what was expected for this group of countries, which is in the first stage of the Preston curve representing low income.

It was seen that the SSP variable, which represents social support, has a significant and positive effect on happiness in all three considered geographical regions. This effect only varied in the South Asian countries in the post-COVID period. The coefficient of the FMLC variable changed after COVID in the European and Central Asian countries and the Latin American and Caribbean countries. This variable did not change after COVID in the South Asian countries, and when other variables are considered, it is seen that the variables affecting happiness in the South Asian countries before and after COVID differ from those of the other two country groups. For South Asian countries, the coefficient of the HLEB variable is significant, unlike in other regions. It was demonstrated by experiments that the coefficients of the SSP and HLEB variables changed with COVID-19, and after the pandemic effect, a 2-fold increase was observed, especially for the social support coefficient. For European and Central Asian countries, it was seen that the coefficients of the FMLC and CNG variables changed with COVID-19. Thus, it was concluded that the effects of freedom and confidence on happiness increased with the pandemic.

Unlike European and Central Asian countries, the coefficient and sign of the PC variable, which represents corruption, were found to be significant in Latin American and Caribbean countries. Thus, the assumption that happiness decreases as corruption increases was supported. For the FMLC variable, it was observed that the coefficient of the variable decreased in the post-COVID-19 period and the coefficient of freedom was negatively affected by the effect of the pandemic.

This study emphasizes the importance of viewing the concept of happiness as a changing outcome before and after the pandemic, taking into account important emotional variables such as social support, trust, and freedom as well as GDP. According to the literature, while money is considered the primary motivation for happiness, money is not sufficient for ensuring happiness and personal satisfaction in isolation from other factors.

Research on happiness indicates that individuals who report higher levels of happiness tend to be more educated, receive higher wages, have longer life expectancies, enjoy better health, be married, experience lower rates of divorce, possess more social connections, secure employment more readily, and exhibit greater levels of satisfaction within their marital relationships. In the words of the philosopher Plato, “People are happy when they have what is good for them.” Consequently, promoting happiness has gained increasing recognition as a public policy objective alongside quality of life measures.

Author Contributions: Formal analysis, E.T., A.A.E., Z.Z.Ş. and M.V.; data curation, E.T., A.A.E., Z.Z.Ş. and M.V.; writing—original draft E.T., A.A.E., Z.Z.Ş. and M.V.; writing—review and editing, E.T., A.A.E., Z.Z.Ş. and M.V. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data link is given within the manuscript.

Acknowledgments: Thanks to Mehmet Şamil Güneş from Yildiz Technical University for help in editing the format.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The variables used in the article and their explanations are shown in detail in the table below.

Table A1. Definitions of variables.

Variable	Definition
H	Happiness: The state of being proud of achieving all aspirations completely and continuously, prosperous, blessed, blissful.
GDP	Gross Domestic Product: The monetary value of final goods and services—that is, those that are bought by the final user—produced in a country in a given period of time such as a quarter or a year.
SSP	Social Support: The share of people who report having friends or relatives whom they can count on in times of trouble.
HLEB	Healthy Life Expectancy at Birth: Defined as how long, on average, a newborn can expect to live if current death rates do not change.

Table A1. *Cont.*

Variable	Definition
FMLC	Freedom to Make One's Own Life Choices: The national average of the binary responses (0 or 1) to the GWP question of "Are you satisfied or dissatisfied with your freedom to choose what to do with your life?"
G	Generosity: The national average response to the GWP question of "Did you donate to a charity last month?"
PC	Perception of Corruption: The national average of survey responses to the two GWP questions of "Is corruption prevalent across government?" and "Is corruption common in businesses?"
CNG	Confidence in the National Government: A combination of trust in the national government, trust in the judiciary and courts, trust in the integrity of elections, trust in the local police force, and perceived corruption in the business world.
PE	Positive Effect: The average of the three positive impact measures of "laughing, having fun, and doing interesting things" in the GWP.
NE	Negative Effect: The average of the three negative impact measures of "anxiety, sadness, and anger" in the GWP.

Appendix B

Table A2. Fisher-type ADF unit root tests applied for North American countries.

	Variable	Fisher ADF	p Value
H	Pure R.W.	16.5610	0.0110
	R.W. with Trend	12.0044	0.0619
	R.W. with Drift	28.5890	0.0001
ΔH	Pure R.W.	4.7597	0.5750
	R.W. with Trend	0.7398	0.9936
	R.W. with Drift	17.1854	0.0086
$\ln(GDP)$	Pure R.W.	16.6423	0.0107
	R.W. with Trend	11.8678	0.0650
	R.W. with Drift	27.9394	0.0001
SSP	Pure R.W.	5.0271	0.5403
	R.W. with Trend	14.1868	0.0276
	R.W. with Drift	14.6393	0.0233
ΔSSP	Pure R.W.	8.7074	0.1907
	R.W. with Trend	72.0971	0.0000
	R.W. with Drift	11.9706	0.0626
G	Pure R.W.	6.7307	0.1508
	R.W. with Trend	10.6298	0.0311
	R.W. with Drift	14.4221	0.0061
ΔG	Pure R.W.	52.8521	0.0000
	R.W. with Trend	42.3959	0.0000
	R.W. with Drift	34.4089	0.0000

References

1. Ding, W.; Levine, R.; Lin, C.; Xie, W. Corporate immunity to the COVID-19 pandemic. *J. Financ. Econ.* **2021**, *141*, 802–830. [CrossRef] [PubMed]
2. Freedman, J.L. *Happy People: What Happiness Is, Who Has It, and Why*; Harcourt Brace Jovanovich: San Diego, CA, USA, 1978.
3. Veenhoven, R. World database of happiness: Continuous register of research on subjective appreciation of life. In *Challenges for Quality of Life in the Contemporary World: Advances in Quality-of-Life Studies, Theory and Research*; Springer: Dordrecht, The Netherlands, 2004; pp. 75–89.
4. Greyling, T.; Rossouw, S.; AFSTEREO (Pty) Ltd. Gross National Happiness Index. Available online: http://gnh.today (accessed on 21 September 2022).

5. Gyeltshen, K. *Happiness in the Eyes of Nurses Working in the Second Happiest District in Eastern Region of Bhutan*; Burapha Unıversity: Saen Suk, Thailand, 2012.
6. Petrovič, F.; Murgaš, F.; Králik, R. Happiness in Czechia during the COVID-19 Pandemic. *Sustainability* **2021**, *13*, 10826. [CrossRef]
7. Easterlin, R.A.; McVey, L.A.; Switek, M.; Sawangfa, O.; Zweig, J.S. The happiness–income paradox revisited. *Proc. Natl. Acad. Sci. USA* **2010**, *107*, 22463–22468. [CrossRef]
8. Tella, R.D.; MacCulloch, R. Some uses of happiness data in economics. *J. Econ. Perspect.* **2006**, *20*, 25–46. [CrossRef]
9. Kahneman, D.; Deaton, A. High income improves evaluation of life but not emotional well-being. *Proc. Natl. Acad. Sci. USA* **2010**, *107*, 16489–16493. [CrossRef]
10. Nettle, D. *Happiness: The Science behind Your Smile*; OUP Oxford: Oxford, UK, 2005.
11. Diener, E.; Seligman, M.E. Very happy people. *Psychol. Sci.* **2002**, *13*, 81–84. [CrossRef] [PubMed]
12. Veenhoven, R. Healthy happiness: Effects of happiness on physical health and the consequences for preventive health care. *J. Happiness Stud.* **2008**, *9*, 449–469. [CrossRef]
13. Levy, B.R.; Slade, M.D.; Kunkel, S.R.; Kasl, S.V. Longevity increased by positive self-perceptions of aging. *J. Personal. Soc. Psychol.* **2002**, *83*, 261. [CrossRef]
14. Preston, S.H. The changing relation between mortality and level of economic development. *Popul. Stud.* **1975**, *29*, 231–248. [CrossRef]
15. Preston, S.H. The changing relation between mortality and level of economic development. Population Studies, Vol. 29, No. 2, July 1975. *Int. J. Epidemiol.* **2007**, *36*, 484–490. [CrossRef]
16. Frank, A.; Grady, C. Phone Booths, Parades, and 10-Minute Test Kits: How Countries Worldwide Are Fighting COVID-19. Available online: https://www.vox.com/science-and-health/2020/3/22/21189889/coronavirus-COVID-19-pandemic-response-south-korea-phillipines-italy-nicaragua-senegal-hong-kong (accessed on 15 May 2020).
17. McKibbin, W.; Fernando, R. The global macroeconomic impacts of COVID-19: Seven scenarios. *Asian Econ. Pap.* **2021**, *20*, 1–30. [CrossRef]
18. Sibley, C.G.; Greaves, L.M.; Satherley, N.; Wilson, M.S.; Overall, N.C.; Lee, C.H.; Milojev, P.; Bulbulia, J.; Osborne, D.; Milfont, T.L. Effects of the COVID-19 pandemic and nationwide lockdown on trust, attitudes toward government, and well-being. *Am. Psychol.* **2020**, *75*, 618. [CrossRef] [PubMed]
19. Inglehart, R.; Klingemann, H. Genes, Culture, Democracy, and Happiness. In *Culture and Subjective Well-Being*; Diener, E., Suh, E., Eds.; Mit Press: Cambridge, MA, USA, 2000.
20. Brulé, G.; Veenhoven, R. Freedom and happiness in nations: Why the Finns are happier than the French. *Psychol. Well-Being* **2014**, *4*, 17. [CrossRef]
21. Aknin, L.B.; Hamlin, J.K.; Dunn, E.W. Giving leads to happiness in young children. *PLoS ONE* **2012**, *7*, e39211. [CrossRef] [PubMed]
22. Nelson, S.K.; Layous, K.; Cole, S.W.; Lyubomirsky, S. Do unto others or treat yourself? The effects of prosocial and self-focused behavior on psychological flourishing. *Emotion* **2016**, *16*, 850. [CrossRef]
23. Ma, J.; Guo, B.; Yu, Y. Perception of Official Corruption, Satisfaction With Government Performance, and Subjective Wellbeing—An Empirical Study From China. *Front. Psychol.* **2022**, *13*, 748704. [CrossRef]
24. Satrovic, E.; Cetiner, O.; Muslija, A. Whether control of corruption matters for happiness: Evidence from panel data analysis. *Press. Procedia* **2018**, *7*, 381–387. [CrossRef]
25. Helliwell, J.F.; Huang, H. How's your government? International evidence linking good government and well-being. *Br. J. Political Sci.* **2008**, *38*, 595–619. [CrossRef]
26. Oishi, S.; Diener, E.; Kahneman, D.; Helliwell, J. 343 Culture and Well-Being: Conceptual and Methodological Issues. In *International Differences in Well-Being*; Oxford University Press: Oxford, UK, 2010. [CrossRef]
27. Macchia, L.; Plagnol, A.C. Life satisfaction and confidence in national institutions: Evidence from South America. *Appl. Res. Qual. Life* **2019**, *14*, 721–736. [CrossRef]
28. Yilanci, V.; Pata, U.K. COVID-19, stock prices, exchange rates and sovereign bonds: A wavelet-based analysis for Brazil and India. *Int. J. Emerg. Mark.* **2022**. [CrossRef]
29. Huang, S.; Liu, H. Impact of COVID-19 on stock price crash risk: Evidence from Chinese energy firms. *Energy Econ.* **2021**, *101*, 105431. [CrossRef]
30. Algan, Y.; Murtin, F.; Beasley, E.; Higa, K.; Senik, C. Well-being through the lens of the internet. *PLoS ONE* **2019**, *14*, e0209562. [CrossRef] [PubMed]
31. Brodeur, A.; Clark, A.E.; Fleche, S.; Powdthavee, N. Assessing the impact of the coronavirus lockdown on unhappiness, loneliness, and boredom using Google Trends. *arXiv* **2020**, arXiv:2004.12129.
32. Hamermesh, D.S. *Lock-downs, Loneliness and Life Satisfaction*; National Bureau of Economic Research: Cambridge, MA, USA, 2020.
33. Brooks, S.K.; Webster, R.K.; Smith, L.E.; Woodland, L.; Wessely, S.; Greenberg, N.; Rubin, G.J. The psychological impact of quarantine and how to reduce it: Rapid review of the evidence. *Lancet* **2020**, *395*, 912–920. [CrossRef]
34. Li, J.; Dong, W.; Meng, D. Grouped gene selection of cancer via adaptive sparse group lasso based on conditional mutual information. *IEEE/ACM Trans. Comput. Biol. Bioinform.* **2017**, *15*, 2028–2038. [CrossRef] [PubMed]
35. Li, S.; Wang, Y.; Xue, J.; Zhao, N.; Zhu, T. The Impact of COVID-19 Epidemic Declaration on Psychological Consequences: A Study on Active Weibo Users. *Int. J. Environ. Res. Public Health* **2020**, *17*, 2032. [CrossRef]

36. Helliwell, J.F.; Layard, R.; Sachs, J.D.; Neve, J.-E.D. *World Happiness Report 2021*; Sustainable Development Solutions Network: New York, NY, USA, 2021.
37. Roodman, D. How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata J.* **2009**, *9*, 86–136. [CrossRef]