International Journal of Economics and Financial Issues

ISSN: 2146-4138

available at http: www.econjournals.com

International Journal of Economics and Financial Issues, 2026, 16(5), 73-81.

Model Uncertainty and the Robust Determinants of World Happiness: An Extended Bayesian Model Averaging Analysis

Sagara Dewasurendra[1]*, Hee Seok Nam[2], Neil B. Sabine[2], Young Hwan You[2]

[1]Indiana University Southeast, New Albany, USA, [2]Indiana University East, Richmond, USA. *Email: sadewasu@iu.edu

Received: 13/05/2026 **Accepted:** 18/08/2026 **DOI:** https://doi.org/10.32479/ijefi.24121

ABSTRACT

This paper provides an extended analysis of the determinants of cross-country happiness using Bayesian Model Averaging (BMA). Building on the 2024 World Happiness Report dataset, we explicitly account for model uncertainty in evaluating the relative importance of economic, social, and institutional factors. The results confirm that social support, freedom to make life choices, and perceived corruption are the most robust predictors of happiness. While GDP per capita remains positively associated with well-being, its importance diminishes once model uncertainty is accounted for. These findings highlight the multidimensional nature of happiness and underscore the importance of institutional and social conditions in shaping subjective well-being.

Keywords: Happiness, Bayesian Model Averaging, Model Uncertainty, Institutions, Well-Being
JEL Classifications: B16, A12, C11, P46, Z13

1. INTRODUCTION

Understanding the determinants of happiness has become an increasingly important topic within applied economics, particularly as policymakers seek more comprehensive measures of societal progress. While Gross Domestic Product (GDP) per capita continues to serve as the dominant indicator of economic performance, a growing body of literature questions its adequacy as a holistic measure of well-being. Early contributions (Easterlin, 1974) revealed what is now known as the Easterlin Paradox: Despite sustained increases in income over time, average levels of reported happiness do not necessarily rise in parallel. The broader debate surrounding the relationship between economic growth, household welfare, and individual well-being was also developed in early contributions to the economics of growth and welfare [David, and Reder, (1974)]. Subsequent research as reinforced this view by emphasizing the role of relative income and social comparisons in shaping subjective well-being [Clark, et al., (2008)]. Together, these findings highlight a critical limitation of relying exclusively on income-based metrics and suggest that economic growth alone may not capture the full spectrum of human welfare. This perspective is further developed by [Layard, (2005)] who argues that increases in material prosperity do not automatically produce corresponding increases in happiness and emphasizes the importance of considering well-being more directly when evaluating social and economic progress.

In response, more recent research has shifted focus toward the role of non-economic factors in shaping subjective well-being. A large interdisciplinary literature highlights the importance of psychological, social, and cultural determinants of happiness [Diener, et al., (2003), Diener and Biswas, (2018)]. Empirical evidence also demonstrates that subjective economic well-being depends on more than conventional measures of income and material conditions. For example, [Hayo and Seifert, (2003)] examines subjective economic well-being in Eastern Europe and provides evidence that individual and broader socioeconomic circumstances are important for understanding differences in reported well-being. In particular, social and institutional dimensions such as social support networks, individual freedom, trust in institutions, and the quality of governance have been shown to play a central role in explaining cross-country variations in happiness (Helliwell and Putnam, 2004; Helliwell et al., 2024; Knack and Keefer, 1997).

These factors capture aspects of well-being that extend beyond material living standards, reflecting the broader social environment in which individuals operate. Moreover, institutional quality and governance structures have been identified as fundamental drivers of long-run development outcomes (Acemoglu et al., 2001), further underscoring their relevance for subjective well-being. However, empirical findings in this literature are frequently sensitive to model specification, particularly in the presence of multiple correlated explanatory variables. Conventional regression approaches typically rely on the selection of a single "best" model, thereby neglecting uncertainty surrounding variable inclusion and potentially leading to biased or overconfident inferences. This concern has been widely documented in the context of cross-country growth and macroeconomic regressions, where different model specifications often yield conflicting conclusions (Fern´andez et al., 2001; Sala-I-Martin et al., 2004).

This paper contributes to the happiness economics literature by explicitly addressing model uncertainty through the application of Bayesian Model Averaging (BMA). BMA provides a systematic framework for evaluating all possible combinations of predictors and weighting them according to their posterior probabilities (Hoeting et al., 1999; Raftery et al., 1997). Rather than conditioning inference on a single selected model, this approach incorporates uncertainty directly into the estimation process, yielding more reliable assessments of variable importance. As demonstrated by Raftery (1995), BMA helps mitigate the risks of overfitting and spurious conclusions that can arise from arbitrary model selection decisions.

Using cross-country data from the 2024 World Happiness Report, this study identifies several robust determinants of happiness. The results indicate that social support, freedom to make life choices, and perceptions of corruption consistently exhibit strong and stable relationships with subjective well-being across model specifications. These findings are consistent with previous research emphasizing the importance of social capital and institutional quality for well-being (Frey and Stutzer, 2002; Di Tella et al., 2001). In contrast, GDP per capita, while still relevant, appears to play a comparatively secondary role once these broader social and institutional factors are taken into account. Overall, the results reinforce the argument that a multidimensional perspective one that incorporates economic, social, and institutional factors is essential for understanding and promoting human well-being.

2. DATA AND VARIABLES

The dataset used in this study is drawn from the World Happiness Report 2024, which compiles cross-country data on subjective well-being and its key determinants based on the Gallup World Poll. The dataset provides a globally comparable measure of life satisfaction alongside a standardized set of economic, social, and institutional variables for a large sample of countries.

The dependent variable is the Happiness Score, which represents the national average of individuals' self-assessed life evaluations. This measure is based on the Cantril ladder, where respondents are asked to rate their current life on a scale from 0 to 10, with 0 corresponding to the worst possible life and 10 to the best possible life. This approach is widely used in the literature as a robust and comparable measure of subjective well-being across countries.

The set of explanatory variables follows the standard specification adopted in the World Happiness Report and captures multiple dimensions of well-being:

- GDP per capita (GDP): Measured in logarithmic form and adjusted for purchasing power parity (PPP), this variable captures the average level of economic prosperity in each country. It reflects material living standards and access to economic resources.
- Social support (Social): Defined as the proportion of respondents who report having relatives or friends they can rely on in times of trouble. This variable proxies the strength of social networks and community ties, which are essential for individual well-being.
- Healthy life expectancy (Life): Represents the expected number of years that individuals can live in good health. This variable captures both the quantity and quality of life, reflecting overall health conditions within a country.
- Freedom to make life choices (Freedom): Based on individuals' perceptions of their ability to make important life decisions. This variable reflects personal autonomy and the degree of control individuals feel they have over their lives.
- Generosity (Generosity): Measured using data on charitable donations, adjusted for income levels. It serves as a proxy for pro-social behavior and the willingness of individuals to contribute to others' well-being.
- Perceptions of corruption (Corruption): Captures the perceived level of corruption in government and business. Higher values indicate lower trust in institutions and weaker governance, which are expected to negatively affect life satisfaction.

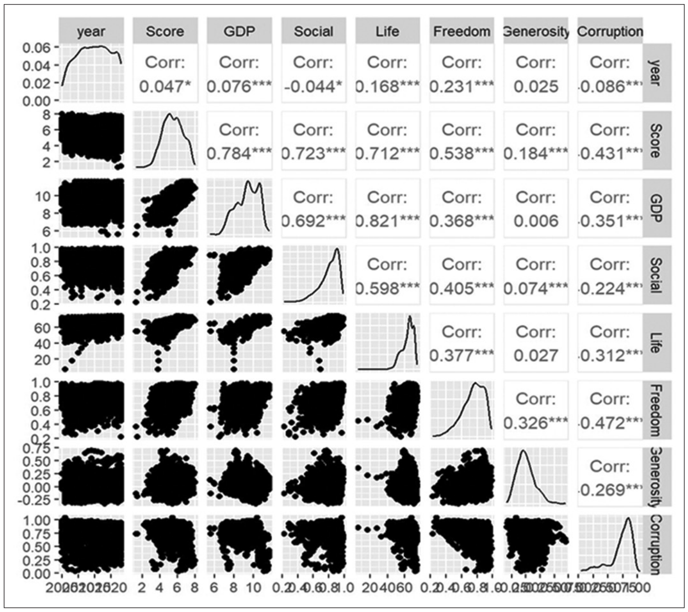
Together, these variables provide a multidimensional framework for analyzing the determinants of happiness, incorporating economic, social, health, and institutional factors. Their joint inclusion is particularly important given the potential for strong correlations among them, as highlighted by the covariance structure of the data.

2.1. Covariance Structure

To better understand the relationships among variables, Figure 1 presents the covariance (correlation) matrix.

Figure 1 presents the correlation matrix and pairwise relationships among the key variables used in the analysis. The upper triangle reports the pairwise correlation coefficients, while the lower triangle displays scatterplots that illustrate the underlying

Figure 1: Correlation matrix and pairwise relationships among happiness and its determinants. The figure highlights strong associations between happiness and key economic and social variables, as well as substantial multicollinearity among regressors



relationships between variables. The diagonal elements show the marginal distributions of each variable.

Several important patterns emerge from the matrix. First, the happiness score exhibits strong positive correlations with key explanatory variables, particularly GDP per capita (correlation 0.78), social support (0.72), and healthy life expectancy (0.71). These relationships indicate that higher levels of income, stronger social networks, and better health outcomes are all associated with higher levels of subjective well-being. In addition, freedom to make life choices also shows a substantial positive correlation with happiness (0.54), reinforcing its importance as a determinant of life satisfaction.

In contrast, perceptions of corruption are negatively correlated with happiness (−0.43), suggesting that higher levels of perceived corruption are associated with lower levels of well-being. This negative relationship is consistent with the view that weak institutional quality and lack of trust in governance reduce overall life satisfaction. The variable generosity, however, displays only a weak positive correlation with happiness (0.18), indicating that its direct relationship with subjective well-being is relatively limited.

A second key feature of the matrix is the presence of strong correlations among the explanatory variables themselves, which raises concerns about multicollinearity. In particular, GDP per capita is highly correlated with life expectancy (0.82) and social support (0.69), indicating that richer countries also tend to have better health outcomes and stronger social structures. Similarly, social support is moderately correlated with both life expectancy and freedom, suggesting that these dimensions of well-being are closely interconnected.

These interrelationships imply that the explanatory variables capture overlapping aspects of development and social conditions, which can complicate the interpretation of regression coefficients in a standard OLS framework. High multicollinearity may inflate standard errors and make it difficult to disentangle the individual contribution of each variable.

Overall, the correlation matrix highlights two key insights. First, it confirms that both economic and non-economic factors are strongly associated with happiness. Second, and more importantly, it reveals substantial correlation among the regressors, providing a strong motivation for the use of Bayesian Model Averaging. By explicitly accounting for model uncertainty and the presence of correlated predictors, BMA offers a more reliable framework for identifying robust determinants of subjective well-being.

2.2. Bayesian Model Averaging with Zellner's *g*-prior

To formally account for model uncertainty, we employ the Bayesian Model Averaging (BMA) framework. Rather than selecting a single preferred specification, BMA considers the entire model space generated by all possible combinations of candidate regressors and weights each model according to its posterior probability.

For a given model M_j, defined by a subset of the six potential explanatory variables, the happiness score for country *i* is specified as a standard linear regression:

$$y_i = \alpha + X_{ij}\beta_j + \varepsilon_i \qquad (1)$$

where y_i denotes the observed happiness score, α is the intercept term, X_{ij} is the vector of regressors included in model M_j, β_j is the corresponding vector of coefficients, and ε_i is an error term assumed to be independently and identically distributed with mean zero and variance σ_2.

A key feature of the Bayesian approach is the specification of prior distributions over the model parameters. Conditional on model M_j, we adopt Zellner's *g*-prior for the regression coefficients:

$$\beta_j \mid \sigma^2, M_j \sim \mathcal{N}\left(0, g\sigma^2 \left(X_j^{'} X_j\right)^{-1}\right) \qquad (2)$$

Where $\left(X_j^{'} X_j\right)$ represents the inverse of the information matrix associated with the regressors in model M_j. This prior is centered at zero, reflecting a conservative prior belief that, in the absence of strong evidence, coefficients are likely to be small. The scaling factor *g* controls the degree of shrinkage imposed on the coefficients.

The error variance σ^2 is assigned an inverse-gamma prior, ensuring conjugacy and analytical tractability. In this study, we set $g = n$, where *n* denotes the sample size. This choice corresponds to the so-called unit-information prior, which is commonly used in applied work as it incorporates an amount of information equivalent to a single observation. This specification balances prior influence and data-driven estimation, avoiding overly informative priors while maintaining numerical stability.

Zellner's g-prior is particularly well suited for BMA applications because it leads to closed-form expressions for the marginal likelihood of each model. This property greatly simplifies computation and allows for transparent comparison across models. Moreover, the prior is invariant to linear transformations of the regressors and automatically adapts to the scale of the data, making it a natural and robust choice in cross-country regression settings.

Given six candidate regressors, the total number of possible models is $2^6 = 64$. Excluding the null model, which contains no explanatory variables, we are left with 63 competing specifications. Following standard practice, we assume equal prior probabilities across all models, implying no a priori preference for any particular specification. Under this assumption, the posterior probability of model M_j is proportional to its marginal likelihood:

$$P(M_j|y) \propto p(y|M_j) \tag{3}$$

An important output of the BMA framework is the posterior inclusion probability (PIP), which measures the overall importance of each explanatory variable across the model space. The PIP for variable k is defined as:

$$\mathrm{PIP}_k = \sum_{j:k\in M_j} P\left(M_j \mid y\right) \tag{4}$$

that is, the sum of posterior probabilities of all models that include variable k. Variables with high PIPs are interpreted as robust determinants of the dependent variable, as they appear consistently in models with high posterior support.

In addition, BMA produces model-averaged estimates of the regression coefficients by weighting the coefficient estimates from each model by the corresponding posterior model probability:

$$\hat{\beta}_k^{\mathrm{BMA}} = \sum_j P\left(M_j \mid y\right)\hat{\beta}_{k|j} \tag{5}$$

Where $\hat{\beta}_{k|j}$ denotes the estimated coefficient of variable k conditional on model M_j, and is set to zero whenever the variable is excluded from that model. These model-averaged coefficients incorporate both parameter uncertainty and model uncertainty, providing a more reliable basis for inference than estimates derived from a single selected specification.

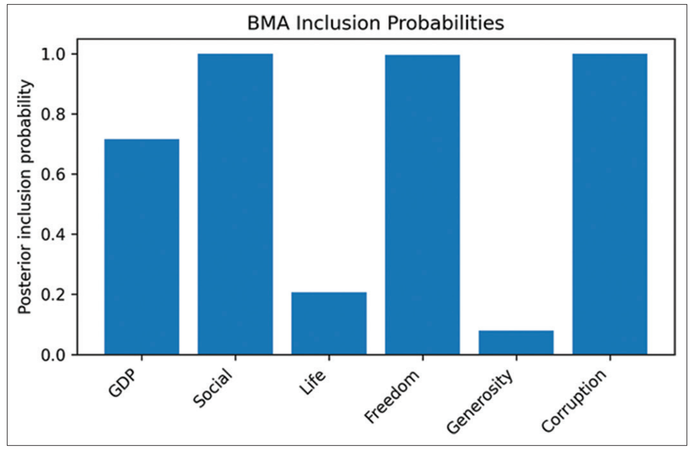
3. RESULTS

3.1. Posterior Inclusion Probabilities

The posterior inclusion probabilities display a clear ranking of determinants. Social support, freedom and corruption occupy the top tier:

- Social support: PIP = 0.9997
- Perceptions of corruption: PIP = 0.9998
- Freedom: PIP = 0.9960

Figure 2: Posterior inclusion probabilities from Bayesian model averaging



GDP per capita lies in a second tier, with a PIP of 0.7164. Healthy life expectancy at birth and generosity have low inclusion probabilities of 0.2064 and 0.0799, respectively.

Figure 2 presents the posterior inclusion probabilities (PIPs) obtained from the Bayesian Model Averaging procedure, providing a direct measure of the importance of each explanatory variable after accounting for model uncertainty. Three variables social support, freedom to make life choices, and perceived corruption stand out with inclusion probabilities effectively equal to one. This indicates that these variables are included in nearly all high-probability models and can therefore be regarded as robust determinants of happiness across alternative model specifications.

In contrast, GDP per capita exhibits a moderate inclusion probability of approximately 0.7. While this suggests that income remains a relevant factor, its role is less stable and more sensitive to the inclusion of other covariates. This finding reinforces the notion that economic prosperity alone does not fully explain cross-country differences in subjective well-being when broader social and institutional variables are taken into account.

The remaining variables, life expectancy and generosity, display relatively low inclusion probabilities, around 0.2 and below 0.1, respectively. These results indicate weak and inconsistent evidence for their contribution to explaining happiness once model uncertainty is explicitly incorporated. In particular, their low PIPs suggest that these variables are only included in a small subset of plausible models and do not exert a systematic influence on the dependent variable.

Overall, the pattern of inclusion probabilities highlights the dominance of social and governance-related factors over purely economic or demographic indicators, underscoring the value of the BMA framework in identifying robust drivers of well-being while avoiding overreliance on any single model specification.

The histograms in Figure 3 present the posterior distributions of the regression coefficients obtained from the Bayesian Model Averaging (BMA) procedure for each explanatory variable. These distributions summarize both parameter uncertainty and model uncertainty by combining estimates across all possible model specifications, weighted by their posterior probabilities.

Each histogram reflects the range of plausible values for a given coefficient, while the superimposed density curve illustrates the overall shape of the posterior distribution. The vertical dashed line indicates the posterior mean (i.e., the BMA estimate), and the spread of the distribution provides information about the precision and robustness of the effect.

A clear pattern emerges across the variables. The coefficients for social support and freedom to make life choices are tightly concentrated around relatively large positive values. Their posterior distributions are approximately symmetric and exhibit limited dispersion, indicating a high degree of certainty regarding both the magnitude and the sign of their effects. This provides strong evidence that these variables are robust and economically significant determinants of happiness.

Similarly, the coefficient for GDP per capita is centered on a positive value, suggesting that higher income levels are associated with greater life satisfaction. However, compared to social support and freedom, the distribution is wider and exhibits greater dispersion. This indicates a higher degree of uncertainty surrounding its effect, consistent with the notion that the role of income is sensitive to model specification and less robust when other variables are taken into account.

The coefficient for healthy life expectancy is also positive but relatively small in magnitude, with a distribution concentrated close to zero. This suggests that, while health may contribute to well-being, its marginal effect is modest and less precisely estimated once other factors are controlled for.

In contrast, the distribution for generosity is centered very close to zero and displays substantial overlap with both positive and negative values. This indicates that the effect of generosity is weak and not robust across model specifications, providing little evidence of a systematic relationship with happiness in the presence of other covariates.

Finally, the coefficient for perceptions of corruption is clearly centered on a negative value, with a relatively tight distribution. This implies a strong and robust negative association between corruption and subjective well-being. Countries with higher

Figure 3: Coefficients histogram obtained from the Bayesian model averaging

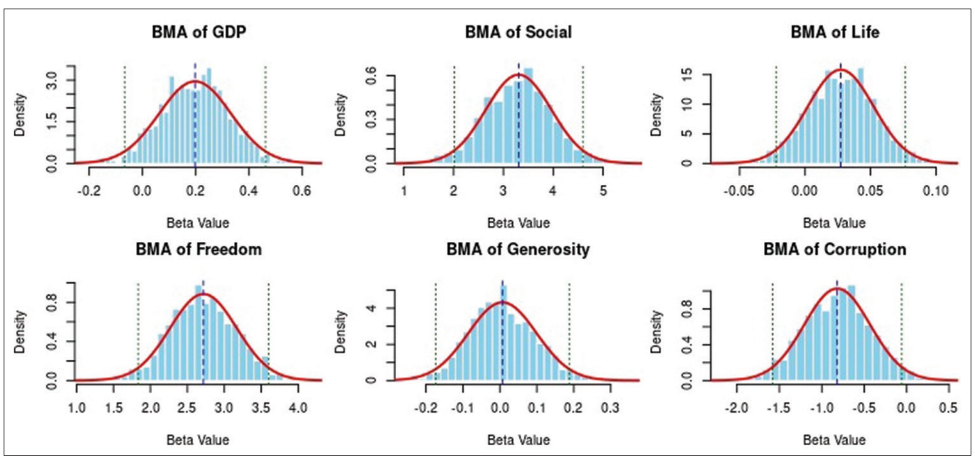
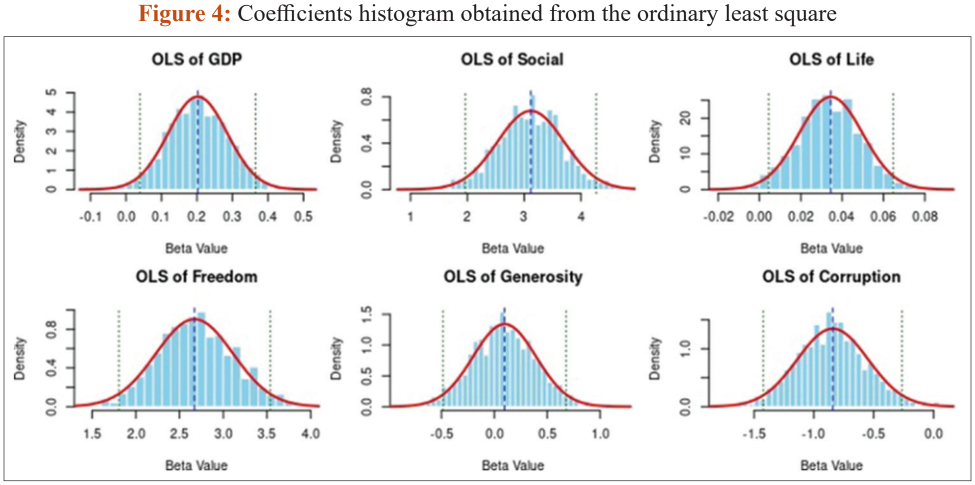


Figure 4: Coefficients histogram obtained from the ordinary least square



perceived corruption tend to report significantly lower happiness scores, and this relationship remains stable across the model space.

Overall, the BMA coefficient distributions reinforce the main findings of the analysis. Social support, freedom, and corruption emerge as the most robust determinants of happiness, characterized by stable and precisely estimated effects. In contrast, GDP per capita, life expectancy, and generosity exhibit greater uncertainty and weaker robustness. These results highlight the importance of accounting for model uncertainty when evaluating the determinants of well-being and provide further evidence in favor of a multidimensional perspective on happiness.

Figure 4 presents the distributions of the Ordinary Least Squares (OLS) coefficient estimates for each explanatory variable. These histograms illustrate the sampling variability of the estimated coefficients, typically obtained through repeated estimation (e.g., via resampling or simulation). The density curves summarize the central tendency and dispersion of the estimates, while the vertical dashed line indicates the mean coefficient value.

Across all variables, the distributions are approximately symmetric and centered around their respective point estimates, suggesting that the OLS estimators are unbiased under the maintained assumptions. However, the width of each distribution varies substantially, reflecting differences in estimation precision across regressors.

The coefficients for social support and freedom to make life choices are centered at relatively large positive values, indicating strong positive associations with happiness. While the distributions are somewhat wider than those observed under BMA, they remain clearly separated from zero, suggesting statistical significance and economic relevance. These results are consistent with the interpretation that social connections and individual autonomy are key determinants of subjective well-being.

The coefficient for GDP per capita is also positive and moderately sized, with a distribution that is relatively concentrated but wider than those for the strongest predictors. This indicates that income has a statistically significant effect on happiness, although the magnitude of this effect is smaller and estimated with less precision compared to social and institutional variables.

For healthy life expectancy, the distribution is centered on a small positive value and is tightly clustered around zero. This suggests that, although health contributes positively to well-being, its marginal effect is relatively modest in the presence of other covariates.

In contrast, the coefficient for generosity exhibits a much wider distribution, spanning both negative and positive values. This substantial dispersion indicates a high degree of uncertainty in the estimate and suggests that generosity is not a robust predictor of happiness within the OLS framework. The inclusion of zero within a large portion of the distribution further implies that the effect is not statistically distinguishable from zero in many samples.

Finally, the coefficient for perceptions of corruption is clearly centered on a negative value, with a distribution that lies predominantly below zero. This provides strong evidence of a negative relationship between corruption and happiness, indicating that higher perceived corruption is associated with lower life satisfaction.

Overall, while the OLS results identify several statistically significant relationships, the variation in the width of the distributions highlights differences in estimation uncertainty across variables. Moreover, unlike Bayesian Model Averaging, the OLS framework does not account for model uncertainty and instead conditions inference on a single selected specification. As a result, the apparent significance of some variables, particularly GDP per capita and generosity, should be interpreted with caution, as it may be sensitive to alternative model choices.

The comparison between the OLS and BMA coefficient distributions highlights important differences in both the magnitude and robustness of the estimated effects. While the OLS histograms suggest that most variables—particularly GDP per capita, social support, and freedom have statistically significant associations with happiness, these results are conditioned on a single model specification and therefore do not account for model uncertainty. In contrast, the BMA distributions incorporate uncertainty over the entire model space, leading to more conservative and reliable estimates. Notably, the coefficients for social support, freedom, and corruption remain tightly concentrated and stable under both approaches, reinforcing their role as robust determinants of well-being. However, the distributions for GDP per capita and generosity exhibit greater dispersion and shrinkage toward zero under BMA, indicating that their effects are less stable and sensitive to model selection. This divergence suggests that OLS may overstate the importance of certain variables by failing to account for alternative model specifications, whereas BMA provides a more nuanced assessment by downweighing less robust predictors. Overall, the comparison underscores the importance of accounting for model uncertainty when evaluating the determinants of happiness and supports the use of BMA as a more reliable framework for inference.

Table 1 reports the coefficient estimates from the full Ordinary Least Squares (OLS) specification alongside the corresponding Bayesian Model Averaging (BMA) estimates, allowing for a direct comparison of results across methods. The OLS estimates indicate that social support and freedom to make life choices are the most influential determinants of happiness, with large positive coefficients of 3.1171 and 2.6736, respectively. These magnitudes suggest that improvements in social networks and individual autonomy are strongly associated with higher levels of subjective well-being.

Table 1: OLS estimates of happiness determinants

Variable	OLS estimates	BMA estimates
GDP per capita	0.2016	0.2161
Social support	3.1171	3.6864
Life expectancy	0.0345	0.0104
Freedom	2.6736	2.7111
Generosity	0.0987	0.0014
Corruption	−0.8425	−0.9969

Perceived corruption, by contrast, exhibits a sizable negative coefficient (−0.8425), indicating that higher levels of corruption are associated with lower reported happiness. GDP per capita enters positively (0.2016) and is statistically significant, but its effect is considerably smaller in magnitude compared to the key social and institutional variables. This reinforces the view that economic factors, while relevant, play a more limited role once broader determinants are taken into account.

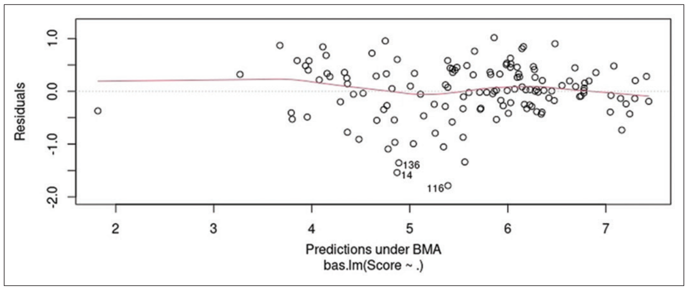
Life expectancy and generosity display relatively small coefficients (0.0345 and 0.0987, respectively), suggesting weaker associations with happiness in the full OLS model. When comparing these results to the BMA estimates, a broadly similar pattern emerges, confirming the robustness of the main findings. Social support (3.6864) and freedom (2.7111) remain strongly positive, while corruption (−0.9969) continues to exert a substantial negative effect. GDP per capita retains a modest positive coefficient (0.2161), consistent with its intermediate importance.

Notably, the BMA estimates further downweigh the effects of life expectancy (0.0104) and generosity (0.0014), aligning with their low posterior inclusion probabilities and indicating that their contributions are not robust once model uncertainty is explicitly considered. Overall, the comparison highlights that the core conclusions, namely the dominant role of social support, freedom, and corruption, are stable across estimation approaches, while the importance of other variables diminishes under a more rigorous treatment of model uncertainty.

Finally, Figure 5 presents the residuals versus fitted values obtained from the Bayesian Model Averaging (BMA) estimation. This diagnostic plot provides a useful assessment of the adequacy of the model by examining whether the residuals exhibit systematic patterns or deviations from the assumptions underlying the regression framework.

Overall, the residuals appear to be randomly scattered around zero, with no strong or systematic pattern across the range of fitted values. This suggests that the model provides a reasonably good fit to the data and that the linear specification is broadly appropriate. The absence of a clear trend in the residuals indicates that there is no obvious violation of the linearity assumption, and that the model is not omitting major nonlinear relationships between the explanatory variables and the happiness score.

Figure 5: Residuals versus fitted values from the BMA model. The plot indicates a good overall fit, with residuals randomly distributed around zero and no strong evidence of misspecification



The red smoothing curve, which represents a nonparametric fit to the residuals, remains close to zero across most of the range of fitted values. Although there is a slight curvature, particularly in the mid-range of predictions, the deviation is relatively small and does not indicate a substantial systematic bias. This suggests that any remaining nonlinearity in the relationship is limited and unlikely to materially affect the overall conclusions.

In terms of heteroskedasticity, the spread of the residuals appears relatively stable across different levels of the fitted values, although there is some mild variation in dispersion. The residuals are slightly more concentrated around the center of the distribution and somewhat more dispersed at intermediate fitted values. However, this variation is not pronounced, and there is no clear funnel-shaped pattern that would indicate severe heteroskedasticity. This supports the assumption of approximately constant variance.

The plot also reveals the presence of a few outlying observations, particularly those with large negative residuals (e.g., labeled points such as 114, 116, and 136). These observations correspond to countries whose observed happiness levels are significantly lower than predicted by the model. While these outliers may reflect unique country-specific circumstances not captured by the included variables, they do not appear to exert a disproportionate influence on the overall pattern of residuals.

Importantly, the residual distribution does not display strong asymmetry or clustering, suggesting that the model errors are approximately well-behaved. This further supports the reliability of the estimated relationships obtained from the BMA framework.

Overall, the residual diagnostics indicate that the BMA model provides an adequate representation of the data, with no major violations of the underlying regression assumptions. The relatively random dispersion of residuals, combined with the absence of strong nonlinear patterns or heteroskedasticity, reinforces the robustness of the empirical findings and supports the validity of the conclusions drawn from the analysis.

4. CONCLUSION

Using Bayesian Model Averaging (BMA) with Zellner's *g*-prior, this study reexamines the determinants of national happiness while explicitly incorporating model uncertainty into the empirical framework. By moving beyond reliance on a single selected specification, the analysis provides a more comprehensive and robust assessment of the relative importance of economic, social, and institutional factors. The results offer clear and consistent evidence that social support, freedom to make life choices, and low perceived corruption are the primary drivers of cross-country differences in subjective well-being. These variables exhibit near-unity posterior inclusion probabilities and tightly concentrated coefficient distributions, indicating that their influence is both strong and highly robust across alternative model specifications.

In contrast, GDP per capita, while positively associated with happiness, plays a comparatively secondary and less stable role once model uncertainty is taken into account. Although traditional regression approaches suggest a statistically significant relationship between income and well-being, the BMA results reveal that GDP per capita is excluded from a non-trivial share of high-probability models and displays greater dispersion in its coefficient distribution. This finding highlights that the importance of income is sensitive to model specification and may be overstated in conventional single-model analyses.

A direct comparison of the OLS and BMA coefficient distributions further reinforces these conclusions. The OLS histograms suggest that several variables, including GDP per capita and generosity, have statistically meaningful effects, as their estimated coefficients appear centered away from zero. However, these distributions reflect inference conditional on a single model and do not account for uncertainty in variable selection. In contrast, the BMA coefficient distributions incorporate both parameter and model uncertainty, leading to more conservative and reliable estimates. While the distributions for social support, freedom, and corruption remain stable and tightly concentrated under both approaches, the coefficients for GDP per capita and generosity exhibit greater dispersion and noticeable shrinkage toward zero under BMA. This divergence indicates that their effects are less robust and highly dependent on the choice of model specification.

The comparison also highlights differences in estimation precision. Under OLS, some variables appear statistically significant due to relatively narrow distributions, yet these estimates may be misleading if the underlying model is misspecified. Under BMA, the wider distributions for certain variables more accurately reflect the uncertainty surrounding their true effects. In particular, the distribution for generosity spans both positive and negative values, suggesting a lack of systematic influence on happiness once competing models are considered. These findings underscore the risk of overconfidence associated with single-model inference and illustrate how BMA provides a more nuanced and credible representation of uncertainty.

Further support for the adequacy of the BMA framework is provided by the residual diagnostics. The residuals versus fitted values plot indicates that the model captures the main structure of the data reasonably well, with residuals largely scattered randomly around zero and no strong evidence of systematic patterns. The absence of pronounced curvature or trends suggests that the linear specification is appropriate, and that important nonlinear relationships are unlikely to be omitted. Moreover, the relatively constant spread of residuals across the range of fitted values indicates that issues of heteroskedasticity are limited. While a small number of outlying observations are present, these do not appear to exert a disproportionate influence on the overall fit. Taken together, these diagnostics support the validity of the BMA estimates and reinforce the reliability of the conclusions drawn from the analysis.

More broadly, the results demonstrate that accounting for model uncertainty can materially alter the interpretation of empirical findings in the happiness literature. Variables that appear significant in a traditional regression framework may not be robust once the full model space is considered. By incorporating model uncertainty directly into the estimation process, BMA mitigates the risks of overfitting and omitted variable bias, and offers a principled framework for identifying truly robust determinants of subjective well-being.

From a policy perspective, the findings carry important implications. They suggest that strategies focused exclusively on economic growth are unlikely to generate substantial or sustained improvements in overall well-being. While income remains an important component of material living standards, it does not fully capture the broader set of factors that shape life satisfaction. Instead, the results emphasize the central role of social and institutional conditions. Policies aimed at strengthening social support networks, enhancing individual autonomy and freedom of choice, and improving institutional quality by reducing corruption are likely to be more effective in promoting long-term improvements in happiness.

Consequently, a multidimensional approach to development one that integrates economic, social, and institutional dimensions should be prioritized in the design of public policy. Future research could extend this analysis by incorporating additional determinants of well-being, exploring dynamic relationships over time, or applying alternative Bayesian frameworks to further assess the robustness of the results. Such extensions would contribute to a deeper understanding of the complex and multifaceted nature of human well-being and provide an even stronger empirical foundation for policy design.

REFERENCES

Acemoglu, D., Johnson, S., Robinson, J.A. (2001), The colonial origins of comparative development: An empirical investigation. American Economic Review, 91(5), 1369-1401.

Clark, A.E., Frijters, P., Shields, M.A. (2008), Relative income, happiness, and utility: An explanation for the Easterlin paradox other puzzles. Journal of Economic Literature, 46(1), 95-144.

David, P.A. Reder, M.W. (1974), Nations and Households in Economic Growth. New York: Academic Press. p89-125.

Diener, E., Oishi, S., Lucas, R.E. (2003), Personality, culture, and subjective well-being: Emotional and cognitive evaluations of life. Annual Review of Psychology, 129(3), 403-425.

Diener, E. Biswas-Diener, R. (2018), Happiness: A Very Short Introduction. Oxford: Oxford University Press.

Di Tella, R., MacCulloch, R.J., Oswald, A.J. (2001), Preferences over inflation and unemployment: Evidence from surveys of happiness. American Economic Review, 91(1), 335-341.

Easterlin, R.A. (1974), Does Economic Growth Improve the Human Lot? Some Empirical Evidence. New York: Academic Press.

Fern´andez, C., Ley, E., Steel, M.F.J. (2001), Model uncertainty in cross-country growth regressions. Journal of Applied Econometrics, 16(5), 563-576.

Frey, B.S. Stutzer, A. (2002), What can economists learn from happiness research? Journal of Economic Literature, 40(2), 402-435.

Hayo, B. Seifert, W. (2003), Subjective economic well-being in Eastern Europe. Journal of Economic Psychology, 24(3), 329-348.

Helliwell, J.F., Layard, R., Sachs, J.D., De Neve, J.E. (2024), World Happiness Report 2024. New York: Sustainable Development Solutions Network.

Helliwell, J.F. Putnam, R.D. (2004), The social context of well-being. Philosophical Transactions of the Royal Society B, 359(1449), 1435-1446.

Hoeting, J.A., Madigan, D., Raftery, A.E., Volinsky, C.T. (1999), Bayesian model averaging: A tutorial. Statistical Science, 14(4), 382-417.

Knack, S. Keefer, P. (1997), Does social capital have an economic payoff? A cross-country investigation. Quarterly Journal of Economics, 112(4), 1251-1288.

Layard, R. (2005), Happiness: Lessons from a New Science. London: Penguin.

Raftery, A.E. (1995), Bayesian model selection in social research. Sociological Methodology, 25, 111-163.

Raftery, A.E., Madigan, D., Hoeting, J.A. (1997), Bayesian model averaging for linear regression models. Journal of the American Statistical Association, 92(437), 179-191.

Sala-I-Martin, X., Doppelhofer, G., Miller, R.I. (2004), Determinants of long-term growth: A Bayesian averaging of classical estimates (BACE). American Economic Review, 94(4), 813-835.