

The Relationship Between National Income and Mental Health: Analyzing GNI and Depressive Disorders Across Nations

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Abstract: This study explores the intricate relationship between economic inequality and the prevalence of depressive disorders across countries from 1990 to 2021. Gross National Income (GNI) per capita is used as an economic measure, and its association with mental health outcomes, particularly depressive disorders, is analyzed. By employing advanced predictive models, including Random Forest, ARIMA, and ETS, we estimate future mental health trends, providing a comprehensive picture of how economic factors shape mental health disparities globally. The datasets are sourced from the World Bank and WHO, ensuring robustness in the study's conclusions. According to the forecasts generated by the ARIMA model, depressive disorder rates might escalate to exceed 6,000 cases per 100,000 people by 2030 in the absence of specific interventions. This underscores the pressing necessity for policymakers in high-income nations to tackle both income disparities and enhance mental health facilities. Both the ARIMA and ETS models delivered forecasts that closely aligned with actual rates, where the ARIMA model exhibited an RMSE of 927.97, while the ETS model demonstrated a slightly better performance with an RMSE of 573.65. These findings underscore the significance of economic factors in forecasting depressive disorder rates.

Keywords: national income, depressive disorders, GNI per capita, machine learning models, ARIMA predictions.

1. Introduction

Economic inequality is a persistent global challenge that not only affects economic indicators but also has profound implications for mental health [1, 2]. While considerable attention has been devoted to understanding its impact on physical health, the potential links between inequality and mental health, especially depressive disorders, remain underexplored. Depression, now recognized as one of the leading contributors to global disability, warrants a closer examination within the framework of economic disparities [3, 4].

Our hypothesis posits that nations with higher levels of national income, as measured by the GNI per capita, will demonstrate elevated rates of depressive disorders. This is expected to be especially pronounced in high-income regions, where the mental health impact of relative deprivation may be more acute [5, 6]. The aim of this study is to explore these patterns across diverse income categories and national contexts.

2. Methods and Results

2.1. Data Sources

The data for this analysis was retrieved from credible sources, including the World Bank's World Development Indicators [7] and the WHO Global Burden of Disease Study [8]. These datasets offer a longitudinal view of GNI per capita, and the incidence of depressive disorders, covering a diverse range of countries from 1990 to 2021. Our sample includes high-income countries like the United States and Germany, alongside low-income nations such as Somalia, providing a wide spectrum of economic contexts.

2.2. Modeling Approach

To explore the correlation between GNI and depressive disorders, we applied several statistical and machine learning models to capture the complexity of the data.

- Random Forest Regression: This non-parametric model identifies intricate relationships between economic and health variables by considering various input features without presupposing linearity [9].
- ARIMA (AutoRegressive Integrated Moving Average): A robust time-series forecasting model used for predicting depressive disorder trends based on past values, taking into account the autocorrelations in the data [10].
- ETS (Error, Trend, Seasonal): A decomposition-based method that models the seasonality and trends in depressive disorder rates, accounting for any irregularities in the data [11].

We employed Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) metrics to evaluate model performance. A rigorous 80-20 data split was applied for training and testing purposes, with cross-validation used to avoid overfitting (Figure 1).

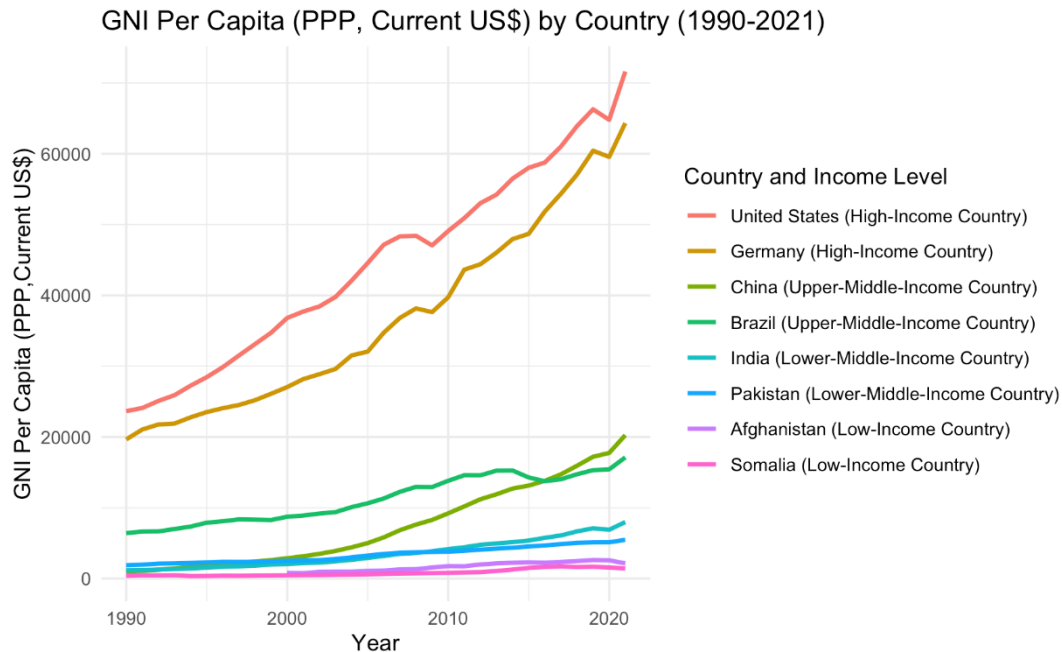


Figure 1: GNI Per Capita (PPP, Current US\$) by Country (1990-2021). (Picture Credit: Original)

2.3. Visualizations

Data visualizations play a crucial role in understanding economic inequality trends and their potential links to mental health outcomes. Figure 1 shows GNI per capita trajectories across selected countries over the period from 1990 to 2021.

Similarly, Figure 2 highlights the depressive disorder rates in various countries during the same time frame, illustrating significant mental health disparities.

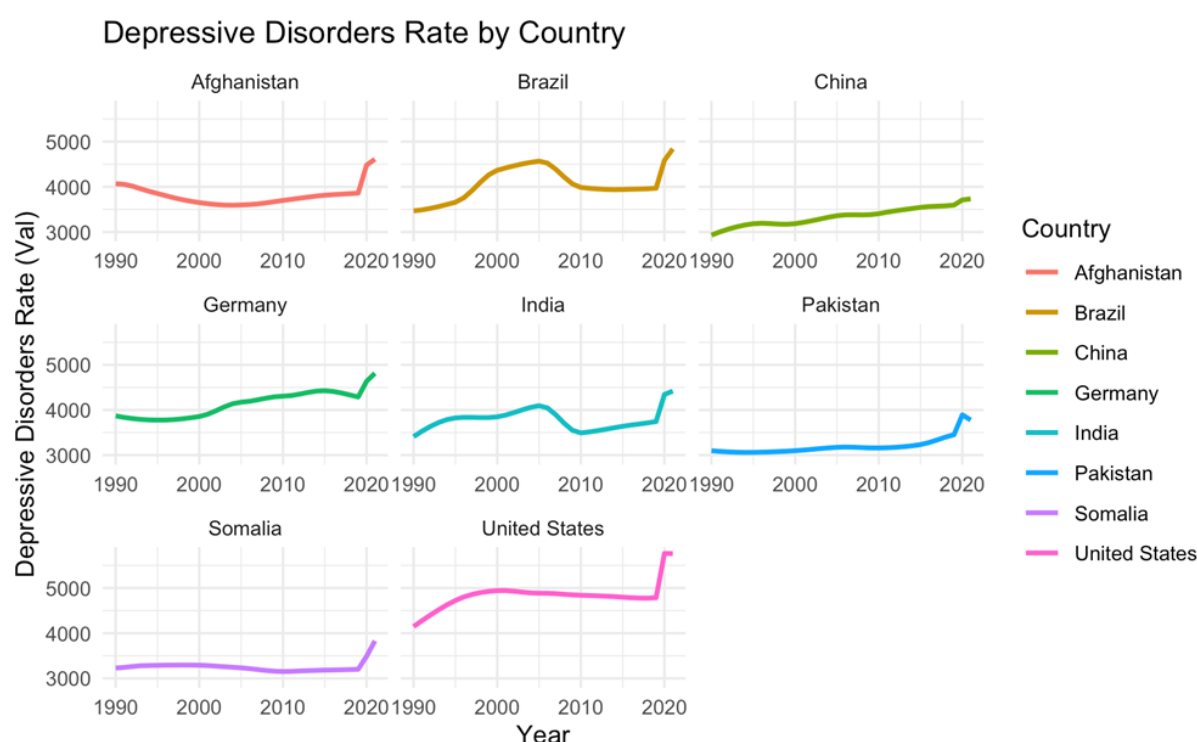


Figure 2: Depressive Disorders Rate by Country (1990-2021). (Picture Credit: Original)

2.4. Correlation Analysis Results

In high-income countries, there is a significant positive correlation between GNI and depressive disorder rates. For example, Germany (Corr: 0.93) and the United States (Corr: 0.61) demonstrate strong correlations, indicating that as GNI increases, the prevalence of depressive disorders also tends to rise. This finding aligns with the “status anxiety” theory, which suggests that in wealthier nations, social comparison and psychological stress become more pronounced as economic inequality grows, leading to higher rates of depression.

In middle-income countries, the relationship between GNI and depressive disorders exhibits a more varied pattern. For instance, China (Corr: 0.96) shows a strong correlation, while Brazil (Corr: 0.36) demonstrates a relatively weaker relationship. This suggests that even with rapid GNI growth, the increase in depressive disorders is not always proportional. The variation could be due to differences in social safety nets, cultural factors, or the effectiveness of mental health interventions in these countries.

In low-income nations, the correlation between GNI and depressive disorder rates is notably weaker. Somalia (Corr: 0.07) and Afghanistan (Corr: 0.62) show relatively low correlations, with Somalia’s correlation being nearly insignificant. This implies that in these regions, factors such as political instability, lack of healthcare resources, and education levels play a more critical role in determining depression rates than economic growth alone. While high-income countries show a

strong positive relationship between GNI and depressive disorders, the correlation weakens in low-income countries. This suggests that depression in these regions is influenced by a complex set of socio-economic factors beyond mere economic growth. It is essential to acknowledge these nuances in the analysis rather than attributing depressive disorders solely to income inequality (Figure 3).

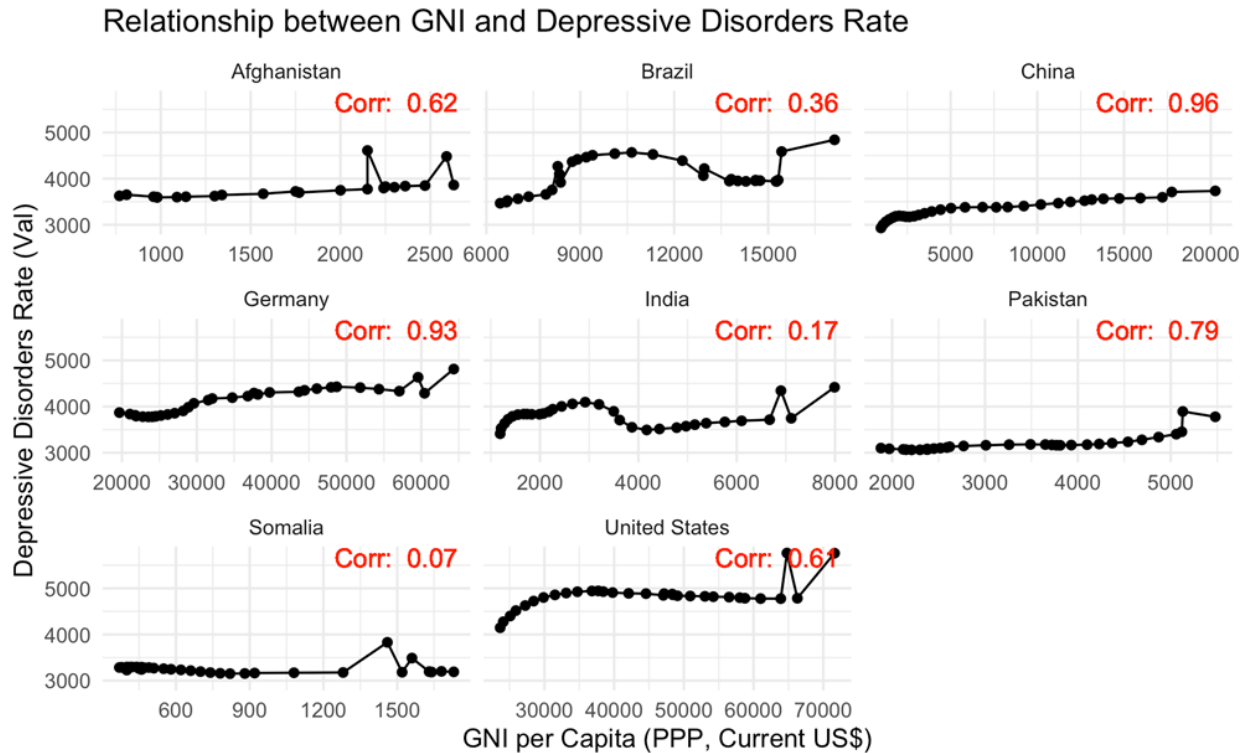


Figure 3: Depressive Disorders Rate by Country (1990-2021). (Picture Credit: Original)

2.5. United States Forecasting with ARIMA

Given the significant correlation observed in the United States, we extended the analysis by applying an ARIMA (1,1,1) model to forecast future trends in depressive disorder rates. The ARIMA model is well-suited for time-series analysis as it incorporates historical patterns, accounting for both trend and seasonal components.

In the forecast, the depressive disorder rate in the U.S. is projected to increase significantly over the next decade, following a similar upward trajectory observed in the past. The prediction emphasizes the continuous impact of income inequality and associated factors on mental health outcomes. The model's performance metrics include an RMSE of 927.97 and an MAE of 830.07, indicating a high level of accuracy in capturing trends from the historical data.

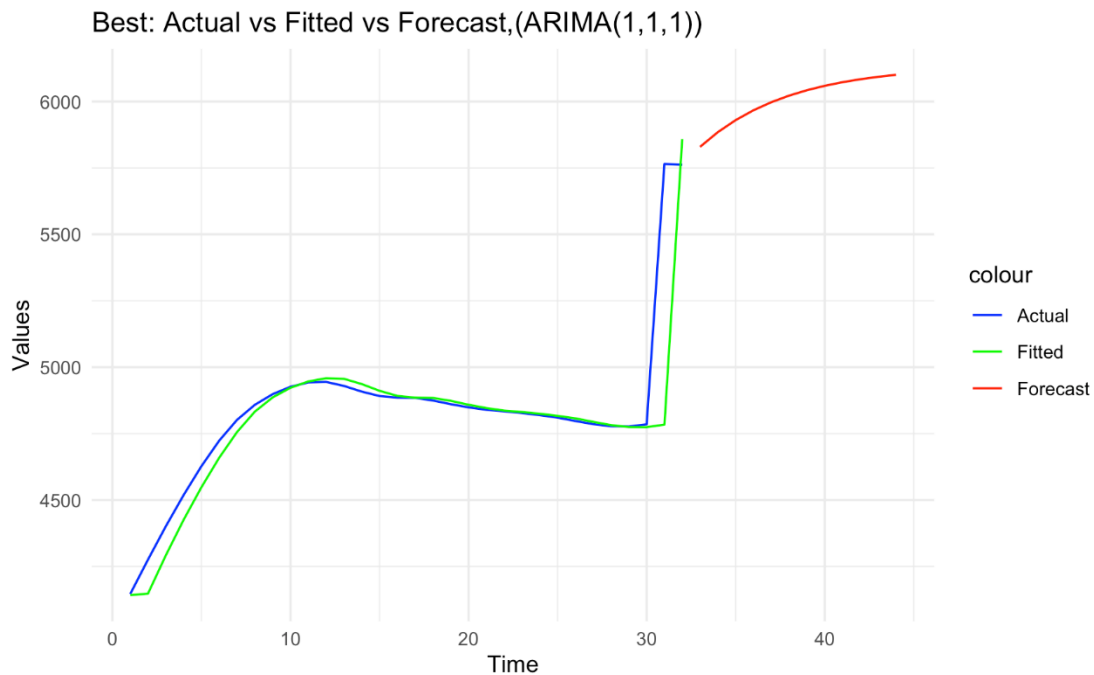


Figure 4: ARIMA Forecast of Depressive Disorder Rates in the United States (2021-2030). (Picture Credit: Original)

The ARIMA model forecasts suggest that, without targeted interventions, depressive disorder rates could rise to over 6,000 per 100,000 individuals by 2030. This highlights an urgent need for policymakers to address both income inequality and mental health infrastructure in high-income countries (Figure 4).

2.6. Model Performance

The Random Forest model accounted for approximately 41.22% of the variance in depressive disorder rates, with an RMSE of 387.69 and an MAE of 316.37. ARIMA and ETS models provided forecasts that closely matched actual rates, with the ARIMA model yielding an RMSE of 927.97 and the ETS model showing a slightly lower RMSE of 573.65. These results emphasize the importance of economic variables in predicting depressive disorder rates.

2.7. Discussion

Our analysis demonstrates that in wealthier countries, higher GNI per capita is closely linked to an increase in depressive disorder rates. This aligns with theories like the “status anxiety” hypothesis, which suggests that individuals in highly unequal societies are more likely to suffer from mental health issues due to social comparisons [5, 1].

In contrast, the lack of a strong correlation in lower-income nations suggests that mental health challenges in these contexts may be driven more by factors such as healthcare access, social infrastructure, and political stability [12]. These results underline the need for multifaceted approaches in addressing mental health crises globally.

2.8. Policy Implications

The findings of this study emphasize the urgent need for targeted policy interventions, especially in high-income countries where the correlation between GNI per capita and depressive disorders is the

strongest. Governments could consider integrating mental health initiatives into broader economic policies, recognizing that while income growth is beneficial in many ways, it can also worsen mental health disparities if not paired with adequate social support measures.

One of the key areas for intervention is improving access to affordable and comprehensive mental public health services, which includes both preventative care and treatment for existing mental health conditions. Expanding the availability of these services can help alleviate the mental health challenges associated with economic inequality. In addition, enhancing social safety nets, such as unemployment benefits and welfare programs, could ease the psychological stress caused by economic instability and inequality. By providing a stronger financial cushion, these programs can reduce the risk of depression among vulnerable populations.

Another crucial policy approach is promoting mental health awareness through public campaigns focused on improving mental health literacy, encouraging early intervention, and reducing the stigma associated with mental health issues. These initiatives can help individuals cope more effectively with socio-economic pressures and reduce the adverse effects of “status anxiety” observed in more unequal societies. Over the long term, addressing income inequality itself through policies like progressive taxation and wage subsidies could contribute to alleviating the underlying economic drivers of mental health disparities. By implementing such policies, governments can create a more equitable environment that fosters both economic and mental well-being.

3. Conclusion

This study underscores the strong association between GNI per capita and depressive disorder rates, particularly in high-income countries. The findings suggest that as national income rises, so too does the prevalence of depressive disorders, supporting theories such as status anxiety that link economic inequality to mental health challenges. However, the analysis also shows that in lower-income countries, this relationship is much weaker, indicating that factors beyond economic growth—such as political stability and healthcare access—are more influential in determining mental health outcomes. The implications for policymakers are clear: while economic growth is important, it must be accompanied by robust mental health services and social safety nets to mitigate the negative effects of inequality on mental well-being. Expanding access to mental health care, promoting public awareness, and addressing income inequality through redistributive policies are all essential strategies for reducing the mental health disparities highlighted in this study. Future research should continue to explore the complex dynamics between national income and mental health, incorporating additional socio-economic factors and examining the long-term impact of different policy interventions. By doing so, we can move towards a more comprehensive understanding of how to address mental health challenges in an increasingly unequal world.

References

- [1] Kate E. Pickett and Richard G. Wilkinson (2015). *Income inequality and health: A causal review*. *Social Science & Medicine*, 128, 316-326.
- [2] Richard Layte (2012). *The association between income inequality and mental health: Testing status anxiety, social capital, and neo-materialist explanations*. *European Sociological Review*, 28(4), 498-511.
- [3] Raj Chetty, Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron, and David Cutler (2016). *The association between income and life expectancy in the United States, 2001-2014*. *JAMA*, 315(16), 1750-1766.
- [4] Anne Case and Angus Deaton (2015). *Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century*. *Proceedings of the National Academy of Sciences*, 112(49), 15078-15083.
- [5] Richard G. Wilkinson and Kate E. Pickett (2006). *Income inequality and population health: A review and explanation of the evidence*. *Social Science & Medicine*, 62(7), 1768-1784.

- [6] Steven H. Woolf, Heidi Schoomaker, and Jessica Green (2021). *The widening gap in life expectancy among socioeconomic groups in the United States: Implications for health equity*. *JAMA*, 325(3), 1607-1615.
- [7] World Bank (2022). *World Development Indicators*. Retrieved from <https://databank.worldbank.org/source/world-development-indicators>.
- [8] World Health Organization (2023). *Global Burden of Disease Study 2019*. IHME, University of Washington.
- [9] Andy Liaw and Matthew Wiener (2002). *Classification and regression by randomForest*. *R News*, 2(3), 18-22.
- [10] George E.P. Box, Gwilym M. Jenkins, Gregory C. Reinsel, and Greta M. Ljung (1970). *Time Series Analysis: Forecasting and Control*. John Wiley & Sons.
- [11] Rob J. Hyndman and George Athanasopoulos (2008). *Forecasting with Exponential Smoothing: The State Space Approach*. Springer.
- [12] Kakoli Patel, Iain Buchan, Raymond M. Agius, and Noor Soomro (2021). *Mental health during the COVID-19 pandemic in the United States: Online survey*. *BMJ Open*, 11(5), e042297.