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Panel data regression modelling for crime against children's data

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Abstract
In India, crimes against children have emerged as a substantial challenge, with a surge in cases of abuse, exploitation, and trafficking. Reports indicate a 67% rise in child abuse cases in the past decade, with poverty, illiteracy, and social stigma in vulnerable communities exacerbating the issue. Children are often forced to work in hazardous conditions; many fall prey to sexual exploitation and trafficking. These crimes severely impact children, causing physical and mental trauma that leaves long-lasting scars. This study employed panel data regression to assess the Total Crime Rate (TCR) trend for children in India. It concluded that the fixed-effect model was appropriate for the analysis. The study further predicted an increase in TCR in the forthcoming years.

Keywords: Regression modelling, crime against, children's data

1. Introduction

1.1 Background of the study: Crime against children is one of India's most heinous and disturbing issues. Children are the future of any country, and they deserve a safe and secure environment to grow and develop. However, the reality is that children in India are vulnerable to various forms of crimes, such as sexual abuse, physical abuse, child labor, child trafficking, and child marriage, to name a few. The consequences of these crimes can be devastating and long-lasting, affecting the child's physical, emotional, and psychological well-being.

According to NCRB, overall, 1,49,404 cases relating to crime against children were registered in 2021 against 1,28,531 cases in 2020, a 16.2 percent rise.

Crime against children in India remains a serious concern that requires urgent attention and action from all stakeholders. Despite some progress in recent years, incidents of child abuse, exploitation, and trafficking continue to be reported across the country, often due to socioeconomic and cultural factors such as poverty, lack of education, and gender inequality.

A comprehensive approach is needed to address this issue to improve the legal and policy framework for child protection, strengthen law enforcement and justice systems, and promote greater awareness and education about children's rights and safety. Additionally, it is essential to address the underlying causes of crime against children, such as poverty and discrimination, by improving social and economic conditions and promoting gender equality. Ultimately, the safety and well-being of children should be a top priority for all members of society, and concerted efforts are needed to ensure that children are protected from harm and given the opportunity to grow and thrive. By working together, we can create a safer and more secure environment for children in India and build a brighter future for future generations.

1.2 Types of crimes against children in India

The following are the few crimes against children in India.

1.2.1 Sexual abuse

Sexual abuse of children is one of the most prevalent and disturbing crimes in India. It can take many forms, including molestation, rape, and sexual exploitation. According to the National Crime Records Bureau (NCRB), there has been a steady increase in cases of sexual abuse against children in India in recent years. Many of these cases go unreported due to social stigma, fear, and lack of awareness.

1.2.2 Physical abuse
Physical abuse is another crime against children in India. It can take many forms, including beating, slapping, and even torture. Physical abuse can cause severe injuries and psychological trauma, affecting the child's physical and mental health.

1.2.3 Child labour
Child labor is another significant issue in India, where children are forced to work in hazardous conditions. Many children in India work in factories, mines, and other dangerous environments, which can cause physical and mental harm.

1.2.4 Child trafficking
Child trafficking is a severe crime in India, where children are kidnapped or sold for forced labor, prostitution, or organ harvesting. According to the UN, India is a source, destination, and transit country for human trafficking.

1.2.5 Child marriage
Child marriage is also a prevalent issue in India, where children, especially girls, are married off at a young age. Child marriage can lead to early pregnancy, health complications, and a lack of education, affecting the child's prospects.

1.3 Causes of crimes against children in India
There are several reasons behind the rising cases of crimes against children in India. Poverty, illiteracy, and a lack of awareness about child rights are some primary reasons. Children from economically weaker sections of society are more vulnerable to exploitation and abuse. Social stigma and fear of reprisals also prevent victims from reporting the crimes.
Another significant cause is the patriarchal mindset prevalent in Indian society, where children, especially girls, are seen as inferior and are often subjected to discrimination and abuse. The lack of proper law enforcement and a weak judicial system also contribute to the problem, as perpetrators are usually not held accountable for their actions.

1.4 Preventive measures
To prevent crimes against children in India, various measures can be taken. These include:

1.4.1 Awareness and Education
There is a need to create awareness and educate people about child rights and the consequences of child abuse. Children should be taught about their rights and how to report any abuse.

1.4.2 Strengthening laws
The government must strengthen and implement child protection laws effectively. The judicial system should be maintained to ensure that perpetrators are held accountable for their actions.

1.4.3 Protection and Support
Children who are abuse victims should be provided with protection and support, including medical and psychological care. NGOs and other organizations can play a significant role in supporting these children.

1.4.4 Economic empowerment
The government should reduce poverty and provide economic opportunities to families, especially those from economically weaker sections of society. This will reduce the vulnerability of children to exploitation and abuse.

1.5 Objectives of the present study
The main objective of the present study is to find the best model to study the trends in the number of crimes against children using the panel regression model, i.e., whether the number of crimes against children decreased or increased. The impact of the crime against children in all the states and union territories (cross-sections) was investigated using panel data models. There are 28 states, and 6 Union territories were taken into this study.

2. Materials and Methods
2.1 Materials
The Crime against Children data set was collected from National Crime Records Bureau (NCRB) India's website www.ncrb.gov.in. The data contains the number of crimes against children from 2011 to 2021 for the twenty-eight states and six union territories in India. EViews Ver. 11 was used for the model estimation.

2.2 Methods
2.2.1 Panel data
Panel data are a type of data that contain observations of multiple phenomena collected over different periods for the same group of individuals, units, or entities. In short, econometric panel data are multidimensional data collected over a given period. A simple panel data regression model is specified as

$$y_{it} = \alpha + \beta\, x_{it} + v_{it}$$

where v_{ij} is the estimated residuals from the panel regression analysis, Y is the dependent variable, X is the independent or explanatory variable, α, and β is the intercept and slope, i is the i^{th} cross-sectional unit, t is the t^{th} month, and X is assumed to be non-stochastic and the error term to follow classical assumptions, identically, independently normally distributed with mean zero and constant variance σ^2
In this study, i, the number of cross-sections is 4 (i = 1, 2, 3, 4) and t = 1, 2, 3…, 31.
Detailed discussions of panel data modeling can be found in *viz*., Hsiao (2003) [10], Baltagi (2001) [2] and Gujarati *et al*. (2017) [7].
By combining time series of cross-sections of observations, panel data provide "more informative data, more variability, less colinearity among variables, more degrees of freedom and more efficiency".

2.2.2 Unit root test
The validity of many time series models and panel data models requires that the underlying data is stationary. As such, reliable unit root testing is an essential step of any time series analysis or panel data analysis.
Unit roots for the panel data can be tested using either the Leuin-Llin-Chu test (Levin *et al*., 2002) [13] or the Hadri LM stationary test (Hadri, 2000) [8]. The null hypothesis is that panels contain unit roots, and the alternative hypothesis is that panels are stationary. If the p-value is less than 0.05, then one

can reject the null hypothesis and accept the alternative hypothesis. Similarly, the unit root for the first difference can also be tested using a similar method.

2.2.3 Panel Least Squares

Panel least squares (PLS) is a straightforward method used to estimate the coefficients of a linear regression model in panel data. It is also known as pooled OLS, as it pools all the data across individuals and time periods to estimate the model's coefficients. The advantage of PLS is that it is simple to implement and provides unbiased estimates of the coefficients, assuming that the error term is uncorrelated with the explanatory variables and that there is no unobserved heterogeneity across individuals or time periods.

However, PLS ignores individual heterogeneity and treats all individuals as having the same coefficients. This may not be appropriate when significant individual heterogeneity affects the outcome variable.

2.2.4 Panel Fixed Effects

Panel fixed effects (PFE) is a method used to estimate the coefficients of a linear regression model in panel data by controlling for individual-specific heterogeneity. PFE assumes that the unobserved heterogeneity across individuals is time-invariant and captures it through a set of dummy variables representing each individual in the regression equation. By including individual fixed effects, PFE allows for estimating the within-individual variation in the outcome variable over time. This method is useful when heterogeneity is significant and one wants to control for unobserved factors that may correlate with the explanatory variables.

One of the advantages of PFE is that it controls for unobserved time-invariant heterogeneity, such as differences in individual ability or personality traits. This is important when analysing outcomes such as wages, where unobserved individual heterogeneity may be a significant factor. However, PFE assumes that the effect of the explanatory variables is the same for all individuals, which may not be true. Also, PFE cannot estimate the impact of time-invariant variables.

The model is given by:

$$Y_{it} = X_{it}\beta + c_i + \epsilon_{it}$$

where Y_{it} is the dependent variable for individual i at time t, X_{it} is a vector of independent variables for individual i at the time t, β is a vector of coefficient, c_i is a fixed effect for individual i, and ϵ_{it} is the error term.

The fixed effect c_i captures the unobserved heterogeneity specific to each individual and does not vary over time. By including this fixed effect, we can control for this heterogeneity and estimate the effect of the independent variables on the dependent variable.

2.2.5 Redundant Fixed Effects Model

The redundant fixed effects model (RFEM) is used when there is a high degree of multicollinearity among the explanatory variables in the panel data. When there is high multicollinearity, the fixed effects in the PFE model are no longer identified, and RFEM is used to estimate the coefficients by exploiting the within-variation of the explanatory variables. RFEM assumes that the explanatory variables are time-invariant and that the within-variation is informative about the relationship between the outcome and explanatory variables. In other words, RFEM estimates the model's coefficients by using only the variation within individuals over time.

One of the advantages of RFEM is that it is robust to multicollinearity and can estimate the coefficients of the model even when there is a high correlation among the explanatory variables. However, RFEM assumes that the explanatory variables are time-invariant and that there is no time-varying correlation between the explanatory variables and the unobserved heterogeneity. If these assumptions are violated, the estimates of the coefficients may be biased.

A redundant fixed effect model is a case of the panel fixed effect model where the fixed effects are perfectly collinear with the independent variables. In this case, the model becomes:

$$Y_{it} = \alpha_i + \epsilon_{it}$$

where α_i is a fixed effect model for individual i and ϵ_{it} is the error term. If the fixed effect is perfectly collinear with the independent variables, it cannot be estimated separately. Therefore, it is redundant and can be dropped from the model.

2.2.6 Random-effect model

The Random Effect (RE) model assumes that individual-specific effects α_i are random, and one should include α_i them in the error term. Each cross-section has the same slope parameters and a composite error term. So model (1) become Random-Effect Model (REM):

$$y_{it} = x_{it}\beta + (\alpha + v_{it})$$

Let:

$$\varepsilon_{it} = \alpha_i + v_{it}$$

Here, ε_{it}, α_i, and v_i are normally distributed with zero means and constant variances. σ_ε^2, σ_α^2 and σ_v^2 respectively.

Hence

$$\text{Var}(\varepsilon_{it}) = \sigma_\alpha^2 + \sigma_v^2$$

$$\text{Cov}(\varepsilon_{it}, \varepsilon_{is}) = \sigma_\alpha^2$$

Therefore

$$\rho_\varepsilon = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\varepsilon^2}$$

Rho is the interclass correlation of the error or the fraction of the variance in the error term due to individual-specific effects. These variables approach 1 if individual effects dominate the idiosyncratic error.

2.2.7 Hausman test

The null hypothesis of the Hausman test (Hausman, 1978) [9] is that the preferred model includes random and not fixed effects. This test determines whether the unique error (α_i) is correlated with the regressor, and the null hypothesis is that they are not correlated. The random-effects estimator is highly efficient and should be used if the Hausman test supports it. The Hausman test statistic can be calculated only for time-varying regressors and is given as follows:

$$H = (\widehat{\beta_{RE}} - \widehat{\beta_{FE}})(V(\widehat{\beta_{RE}}) - V(\widehat{\beta_{FE}})(\widehat{\beta_{RE}} - \widehat{\beta_{FE}})$$

Here, $\widehat{\beta_{RE}}$ and $\widehat{\beta_{FE}}$ are the vector of random and fixed effects parameter estimates, respectively. Under the null hypothesis, this statistic has asymptotically the chi-squared distribution with the number of degrees of freedom equal to the rank of the matrix:

$$(V(\widehat{\beta_{RE}}) - V(\widehat{\beta_{FE}}))$$

3. Results and Discussion

3.1 Descriptive Statistics

The results presented in Table 1 reveal that the number of reported crimes against children in India has increased over the years. Specifically 2011, there were 33,098 reported crimes against children, which grew to 150,030 cases in 2021. Moreover, the mean crime rate against children increased from 973.471 in 2011 to 4412.65 in 2021. This suggests that the overall risk of crimes against children has risen over time.
The year 2011 had the minimum crime rate against children with only 3 reported cases, while the maximum crime rate was recorded in 2018 with 19936 cases. However, it is worth noting that the standard error has increased from 1447 in 2011 to 5301.67 in 2021, indicating that the precision of the estimate of the mean crime rate is declining over time. The year-wise crime rate against children exhibits a fluctuating pattern, with some years indicating a rise in crime rates compared to the previous year while others show a decline. For instance, there was a substantial increase in the crime rate from 2012 to 2013, followed by a decrease from 2019 to 2020, and a gradual increase in the crime rate in 2021. These findings suggest a need for greater attention and action to address the crimes against children in India.

Table 1: Descriptive summary of the year-wise crime against children

Year	Sum	Mean	Std. Err	Maxi.	Mini.
2011	33098	973.471	1447.04	5500.0	3.0
2012	38172	1122.71	1585.93	6033.0	8.0
2013	58274	1713.94	2564.29	9857.0	8.0
2014	90189	2652.62	3885.5	15085.0	7.0
2015	94170	2769.71	3789.43	13921.0	28.0
2016	106953	3145.68	4286.81	16079.0	21.0
2017	129028	3794.94	5220.45	19121.0	24.0
2018	141856	4172.24	5483.9	19936.0	34.0
2019	148160	4357.65	5531.68	19592.0	50.0
2020	128587	3781.97	4628.07	17008.0	31.0
2021	150030	4412.65	5301.67	19713.0	51.0

Table 2 presents descriptive statistics for each state, including the sum, mean, standard error, minimum, and maximum measures. Notably, Uttar Pradesh stands out with the highest state-wise crime rates (153857) against children from 2011-2021. This is evidenced by its highest mean crime rate (13987), highest maximum crime rate (19936), and standard error (5102.66). Furthermore, Uttar Pradesh has reported the highest number of cases and overall crime rate, highlighting a worrying trend in child safety in this state over the past decade.
Following Uttar Pradesh, Madhya Pradesh, and Maharashtra have the second and third highest state-wise crime rates, 153267 and 136957, respectively, against children from 2011-2021. Madhya Pradesh stands out with the second-highest mean crime rate (13933.4) and the third-highest maximum crime rate (15330) among all the states in the dataset. Conversely, Maharashtra has the third-highest mean crime rate (12450) and the second-highest maximum crime rate (19592). Both states also have relatively high standard errors (5686.4 & 6049.58). These findings indicate that child safety remains a significant concern in these states.
From the descriptive statistics table, it can be deduced that Daman and Diu and D-N Haveli have comparatively lower crime rates (436 & 416) against children than other states in the dataset. The mean crime rate (37.8182 & 39.6364) is lower, indicating fewer reported crimes against children on average in these states. The standard error of the mean crime rate against children in Daman and Diu and D-N Haveli is (35.4734 & 34.3694), representing the precision of the population mean crime rate estimate based on the sample data. The minimum values (3 & 8) indicate that Daman, Diu, and D-N Haveli have the lowest crime rate against children among the states considered. Furthermore, the maximum value (104 & 104) shows that even the highest crime rate observed in these states is relatively low compared to others.
The descriptive statistics of crime rates against children in all states from 2011-2021 provide valuable insights into states with a higher or lower risk of crimes against children. This information can be instrumental in developing effective policies and interventions to prevent and address crimes against children in India.

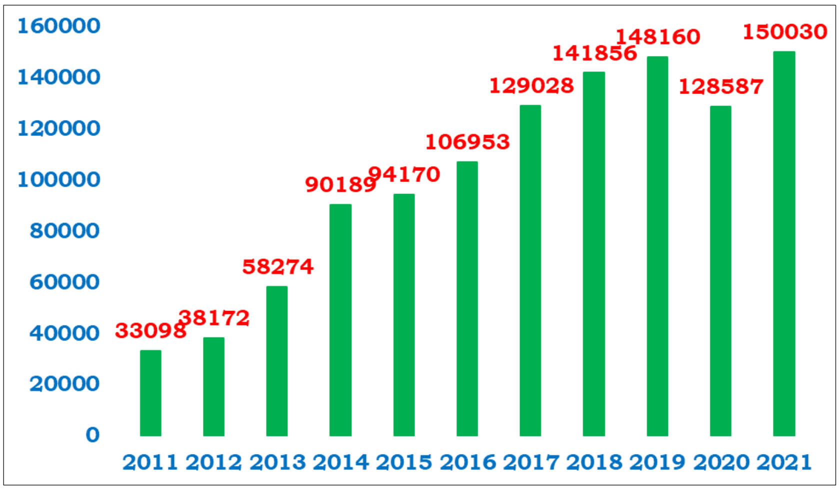

Fig 1: Year wise Total Crime Rate in India

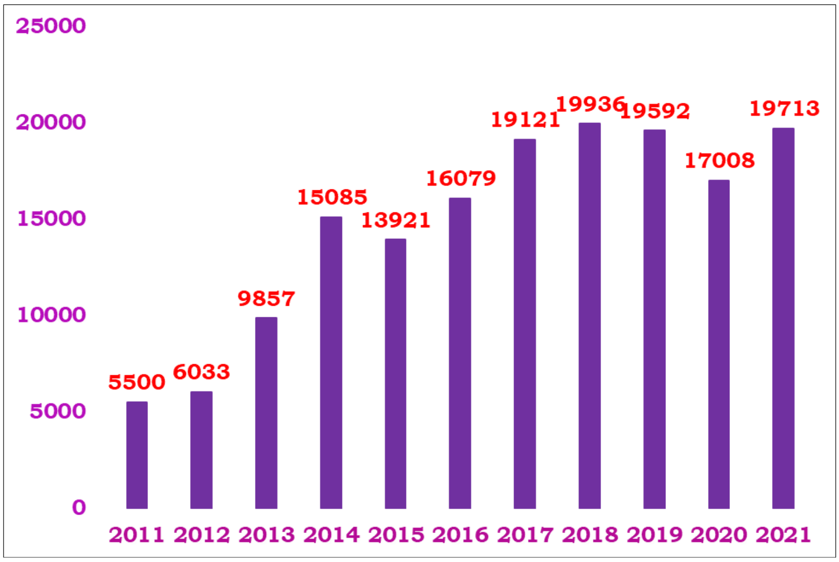

Fig 2: Year wise Maximum Crime Rate in India

Table 2: Descriptive statistics for state-wise crime rate against children during the year 2011-2021

District	Sum	Mean	Std. Err	Maxi.	Mini
Andhra Pradesh	55580	5052.73	2044.14	8336	2213.0
Arunachal Pradesh	1336	121.455	49.6334	181	35.0
Assam	36240	3294.55	2320.83	6608	236.0
Bihar	50342	4576.55	2653.33	9320	1580.0
Chhattisgarh	51187	4683.36	1686.58	6924	1782.0
Goa	2090	190.0	73.8431	330	75.0
Gujarat	37172	3379.27	1316.38	4929	1131.0
Haryana	36031	3275.55	1762.76	5700	280.0
Himachal Pradesh	5789	526.273	180.284	772	260.0
Jammu & Kashmir	3634	330.364	255.098	845	25.0
Jharkhand	9935	903.182	719.293	1867	85.0
Karnataka	45452	4132.0	2385.15	7261	334.0
Kerala	33353	3032.09	1242.06	4754	1324.0
Madhya Pradesh	153267	13933.4	5686.4	15330	4383.0
Maharashtra	136957	12450.0	6049.58	19592	3362.0
Manipur	1348	122.545	18.4139	148	87.0
Meghalaya	3127	284.273	131.063	481	91.0
Mizoram	1586	144.182	54.0866	220	54.0
Nagaland	509	46.2727	28.4643	93	8.0
Odisha	39543	3594.82	2656.35	7899	315.0
Punjab	20019	1819.91	646.475	2625	622.0
Rajasthan	49737	4521.55	2088.9	7653	1491.0
Sikkim	1235	112.273	66.9105	221	29.0
Tamil Nadu	33201	3018.27	1616.07	6064	925.0
Tripura	2474	224.909	105.012	369	20.0
Uttar Pradesh	153857	13987.0	5102.66	19936	5500.0
Uttarakhand	7897	717.909	453.723	1306.0	83.0
West Bengal	61361	5578.27	2887.53	10248.0	1450.0
A &N island	1096	99.6364	44.4956	162.0	28.0
Chandigarh	2354	214.0	69.9971	288.0	74.0
D&N Haveli	436	39.6364	34.3694	104.0	8.0
Daman &Diu	416	37.8182	35.4734	104.0	3.0
Delhi UT	79289	7208.09	1796.13	9489.0	4250.0
Puducherry	667	60.6364	29.5915	122.0	15.0

3.2 Unit root tests
The stationary of the variable under study must be determined before estimating the panel data regression model. The unit root test result in Table 3 revealed that the Levin, Lin, and Chu t statistics value -3.83458 is significant at the 1% significance level since the p-value is 0.0001. The p-value is less than 0.05, the null hypothesis of the unit root is rejected, and it is concluded that the variable under study is found to be stationary.

Table 3: Characteristics of Unit Root Test

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-3.83458	0.0001

3.3. Panel least squares
Table 4 shows that the independent variable X explained 0.04% variations in TCR (adjusted R-squared is 0.000404). The R-squared value (0.003084) is low, which means the predictor variable is weak in explaining the response variable.

The situation in TCR revealed a solid but negative and statistically insignificant contribution by X (t-statistics -2.228767and p-value 0.2841which is more significant than 0.05). The implication is that the contributions made by X in explaining TCR in different States or UT are statistically insignificant. The low Durbin-Watson stat value indicates that the successive error terms are positively correlated.

Table 4: Characteristics of panel least squares test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3408.581	449.5348	7.582462	0.0000
X	-2.228767	2.077698	-1.072710	0.2841
Root MSE	4326.466	R-squared %		0.003084
Mean dependent var	2990.687	Adjusted R-squared %		0.000404
S.D. dependent var	4338.957	S.E. of regression		4338.081
Akaike info criterion	19.59359	Sum squared resid		7.00E+09
Schwarz criterion	19.61457	Log-likelihood		-3662.000
Hannan-Quinn criter.	19.60192	F-statistic		1.150706
Durbin-Watson stat	0.071355	Prob(F-statistic)		0.284097

3.4. Panel Fixed Effect Model

The results presented in Table - 5 reveal that the fixed effect model explains that 85% of the variation in the dependent variable or R-squared value is higher and successful for predicting the model. The model is highly significant at the 1% level of significance. The coefficient value of X indicates that as the independent variable (X) increases, the mean of the dependent variable (TCR) also tends to increase. The root means the square error is 1670.273with the SE of regression is 1754.38. The Prob(F-statistic) value 0.00 is smaller, and it can say that all the variables jointly in the model significantly affect the dependent variable at a given significance level.

Table 5: Characteristics of Fixed Effect Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-64898.85	5379.607	-12.06387	0.0000
X	362.0775	28.68716	12.62159	0.0000
Effects Specification				
Cross-section fixed (dummy variables)				
Root MSE	1670.273	R-squared		85%
Mean dependent var	2990.687	Adjusted R-squared		84%
S.D. dependent var	4338.957	S.E. of regression		1754.38
Akaike info criterion	17.86653	Sum squared residual		1.04E+09
Schwarz criterion	18.23377	Log-likelihood		-3306.041
Hannan-Quinn criter.	18.01234	F-statistic		57.13429
Durbin-Watson stat	0.436053	Prob(F-statistic)		0.000000

3.5 Redundant Fixed Effects Tests

The redundant fixed effect test was carried out to confirm the presence of the fixed effect, and the results are presented in Table 6. The test results reveal that the Cross-section F and Chi-square statistics values are significant at the 1% significance level, indicating that the presence of fixed effects differs from one state to another.

Table 6: Characteristics of redundant fixed effects tests

Effects Test	Statistic	D.F.	Prob.
Cross-section F	58.652422	(33,339)	0.0000
Cross-section Chi-square	711.919690	33	0.0000

3.6. Random Effect Model

The random-effect model is estimated, and the results are presented in Table 6. The results reveal that the model is not significant at the 1% level of significance with an R-squared value of 0.003084 with an SE of regression 4338.081, Root MSE, 4326.466. Hence, the very low R-squared implies that the model is unsuccessful in predicting.

Table 6: Characteristics of the random effect model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	360.5978	1330.773	0.270969	0.7866
X	14.02714	6.115222	2.293808	0.0224
Effects Specification				
			S.D.	**Rho**
Cross-section random			3902.932	0.8319
Idiosyncratic random			1754.378	0.1681
Root MSE	2078.993	R-squared		0.009919
Mean dependent var	401.6562	Adjusted R-squared		0.007257
S.D. dependent var	2092.180	S.E. of regression		2084.575
Sum squared resid	1.62E+09	F-statistic		3.726710
Durbin-Watson stat	0.306483	Prob(F-statistic)		0.054309

3.7 Hausman Test

The Hausman test result presented in Table 7 reveals as probability = 0.00 < 0.05, H_0 hypothesis is rejected, which means the model will be estimated through the fixed effect. So, among the other panel models, the Panel Fixed Effect model emerged as the appropriate statistical model to study the TCR.

Table 7: Characteristics of Hausman's test

Test Summary		Chi-Sq. Statistic	Chi-Sq. D.F.	Prob.
Cross-section random		154.207884	1	0.0000
Cross-section random effects test comparisons				
Variable	**Fixed**	**Random**	**Var (Diff.)**	**Prob.**
X	362.077540	14.027143	785.556973	0.0000

4. Conclusion

In this study, the panel data regression was suitable for assessing the trend of TCR in India for children. The fixed effect model was found to be suitable for studying the trend. TCR is predicted to increase in the coming years, according to the study.

To prevent this alarming trend, the government, law enforcement agencies, and civil society organizations must work together to address the root causes of these crimes and implement effective measures to protect children from harm. This includes increasing awareness and education about child safety, strengthening child protection laws, providing support and services to victims, and improving vulnerable communities' overall social and economic conditions. We can create a safer and more secure environment for our children in India through concerted efforts and sustained action.

It is essential to ensure that children are protected, and their rights are safeguarded to grow up in a safe and nurturing environment. The government, civil society, and individuals all have a role to play in creating a safer society for children, and we must take action now to prevent the TCR for children's crime from increasing any further. Therefore, the government must take proactive steps to address this issue and ensure a safer and better future for the youth of India.

References

1. Al-Rousan N, Al-Najjar H. Data Analysis of Coronavirus COVID-19 Epidemic in South Korea Based on Recovered and Death Cases. Journal of Medical Virology, 92, 1603-1608.
2. Baltagi BH. Econometric Analysis of Panel Data. Wiley, New York, NY; c2001.
3. Breusch TS, Pagan AR. A Simple Test for Heteroscedasticity and Random Coefficient Variation. Econometrica. 1979;47:1287-1294.
4. Chatterjee A, Gerdes MW, Martinez SG. Statistical Explorations and Univariate Time-series Analysis on COVID-19 Data Sets to Understand the Trend of Disease Spreading and Death. Sensors (Basel). 2020;20:3089.
5. Godfrey LG. Testing Against General Autoregressive and Moving Average Error Models when the Regressors Include Lagged Dependent Variables. Econometrica. 1978;46:1293-1301.
6. Gondauri D, Mikautadze E, Batiashvili M. Research on COVID-19 Virus Spreading Statistics based on the Examples of Cases from Different Countries. Electron Journal of General Medicine. 2020;17:1-4.
7. Gujarati DN, Porter DC, Sangeetha G. Basic Econometrics, 5th edition. McGraw Hill Education, New York, NY.; c2017.
8. Hadri K. Testing for Units Roots in Heterogeneous Panel Data. Econometrics Journal. 2000;3:148-161.
9. Hausman JA. Specification Tests in Econometrics. Econometrica. 1978;46:1251-1271.
10. Hsiao C. Analysis of Panel Data. Cambridge University Press, Cambridge; c2003.
11. Jiang X, Zhao B, Cao J. Statistical Analysis on COVID-19. Bio-medical Journal of Scientific & Technical Research. 2020;26:19716-19727.
12. Kumar A, Roy RR. Application of Mathematical Modeling in Public Health Decision Making Pertaining to control of COVID-19 pandemic in India. Epidemiology International. 2020;5(2):23-26.
13. Levin A, Lin CF, Chu CSJ. Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties. Journal of Econometrics. 2002;108:1-24.
14. Mittal S. An exploratory Data Analysis of COVID-19 in India. International Journal of Engineering Research & Technology. 2020;9(4):580-584.
15. Nesteruk I. Statistical-Based predictions of coronavirus Epidemic Spreading in Mainland China. Innov. Biosyst. Bioeng. 2020;4(1):13-18.
16. Ogundokun RO, Lukman AF, Kibri GBM, Awotunde JB, Aladeitan BB. Predictive modelling of COVID-19 confirmed cases in Nigeria. Infections Disease Modelling. 2020;5:543-548.
17. Rajarathinam A, Tamilselvan P. Autoregressive Distributed Lag Model of COVID-19 Cases and Deaths, Appl. Math. Inf. Sci (in press); c2021.
18. Rajarathinam A, Tamilselvan P. Vector error correction modeling of covid-19 infected cases and deaths, Journal of Statistics Applications & Probability (in press); c2021.
19. Takele R. Stochastic modeling for predicting COVID-19 prevalence in East Africa Countries. Infectious Disease Modelling. 2020;5:598-607.
20. Wald A. Tests of Statistical hypotheses concerning several parameters When the Number of Observations is Large. Transactions of the American Mathematical Society. 1943;54:426-482.