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Fiscal Capacity under Devolution: Households, Livestock & Fishing Activities in Kenya's County Governments

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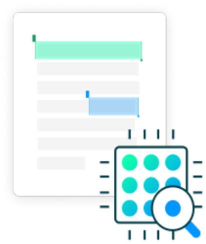

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Fiscal Capacity under Devolution: Households, Livestock & Fishing Activities in Kenya's County Governments

Abstract

Decentralized revenue collection performance is shaped by geographical, technological, and institutional conditions. Kenya's 47 county governments have persistently under-performed in mobilizing own source revenue (OSR) relative to their estimated potential. This study examines the determinants of cross-county variation in OSR by analyzing the roles of household scale and specific agrarian sub-sectors. The analysis employs an Ordinary Least Squares (OLS) regression model with a log-linear specification of OSR and diagnostic tests are conducted to verify compliance with classical linear regression assumptions. The results show that the model provides a statistically robust explanation of OSR variation across counties. Household scale exhibits a positive and highly significant association with OSR. Livestock abundance is positively associated with revenue generation, whereas reliance on Fishing is negatively related to OSR performance. These findings offer empirical insights into the structural opportunities and constraints facing county revenue mobilization and inform policy debates on sub-national fiscal capacity in devolved systems.

Keywords: Devolved governments, Own-source revenue, Counties, Kenya

Introduction

Decentralization is one of the approaches encouraged to realize global development (Rugeiyamu & Msendo, 2025). A sustainable and effective sub-national governance requires a robust revenue collection mechanism for the purpose of local development and service delivery. Kenya's devolved system of governance grants counties a mandate to generate Own Source Revenue (OSR) inline with the Sustainable Development Goal 17.1 which explicitly calls for strengthening domestic resource mobilization to reduce aid dependency (Boex & Kelly, 2011).

Historically, the global discussions on devolution and intergovernmental finance and revenue mobilisation have evolved overtime. Traditional fiscal theory, often grounded in the political economy of the "Rentier State," posits that intergovernmental transfers create a disincentive for local mobilization—a phenomenon known as the "dependency syndrome" or "crowding-out" effect. In Nigeria, for instance, (Salami, 2011) argues that the centralized control of oil revenues has crippled the administrative will of state governments to tax their own economies, effectively rendering them passive recipients of federal handouts. This view is supported by (Mogues & Benin, 2012) in Ghana, who observed that local officials often find it politically expedient to rely on transfers rather than enforce unpopular local taxes. However, more recent empirical evidence from Africa has begun to challenge this pessimistic consensus. In a landmark study of communes in Benin, (Caldeira & Rota-Graziosi, 2014) identified a "crowding-in" effect, where unconditional grants actually improved local revenue collection. They argued that in resource-constrained environments, central transfers provide the necessary liquidity to fund the fixed costs of tax administration—such as vehicles, offices, and computers—which poor local governments could otherwise not afford. This suggests that the relationship between central support and local autonomy is not binary but depends heavily on how those resources are deployed to build administrative capacity.

Kenya provides a compelling case for examining these dynamics. Following the adoption of the 2010 Constitution, Kenya embarked on an ambitious decentralization reform that established 47 county governments with constitutionally guaranteed transfers and assigned revenue powers (Boex & Kelly, 2011). Yet, despite this strong legal foundation, counties have consistently underperformed in own-source revenue collection relative to potential (Khadondi, 2016). This sparked a debate on whether the causes are structural (immutable geographic factors) or administrative (managerial efficiency). (Khadondi, 2016) provides compelling evidence that physical size (land area) is statistically insignificant for revenue potential, whereas urbanization and economic density are paramount. Conversely, (Nyanjom, 2014) and (Onyango et al., 2015) argue that the current revenue-sharing formula may inadvertently penalize counties with lower urbanization rates, trapping them in a cycle of low capacity. county-level studies emphasise the role of managerial strategies—such as digitization, automation, enforcement, and diversification—in improving revenue performance (Mulinge et al., 2025); (Munguti et al., 2022)

The existing evidence suggests a need for an integrated perspective that accounts for capacity constraints, institutional design, governance quality, and policy implementation trade-offs. Several existing limitations include heavy reliance on cross-sectional data, limiting causal inference (Khadondi, 2016); (Mulinge et al., 2025), single-country or single-county focus, constraining generalizability (Nyanjom, 2014), limited integration of institutional quality and political economy variables (Salami, 2011). This shared limitation signals a broader evidence gap in longitudinal and comparative fiscal decentralization research.

This study, therefore, seeks to understand the structural and economic factors affecting own source revenue (OSR) in Kenyan counties. OSR is modeled using an OLS regression with households, livestock, and fishing as key explanatory variables. A log transformation of OSR is applied to improve model fit. Diagnostic tests confirm that the main OLS assumptions are satisfied.

The remainder of the paper is organized as follows. Section 2 reviews the theoretical and empirical literature on OSR. Section 3 describes the data and econometric methodology. Section 4 presents and discusses empirical results. Section 5 concludes with policy implications and directions for future research.

Literature Review

Structural determinants of revenue capacity (e.g. urbanisation, poverty, economic base), administrative mechanisms (e.g. internal controls, governance, monitoring, automation) and intergovernmental fiscal arrangements (e.g. grants, revenue allocation formulas, fiscal autonomy) are identified as the determinants of Own Source Revenue (OSR) performance and bridge the gap between fiscal potential and actual collection as shared by (Khadondi, 2016)(Mulinge et al., 2025), cross-country decentralization analyses by (Caldeira & Rota-Graziosi, 2014), and policy-oriented fiscal federalism work by (Salami, 2011); (Boex & Kelly, 2011). The collective aim is to diagnose administrative inefficiencies and propose strategies—specifically digitization and internal controls—to reduce dependency on central government transfers (Boex & Kelly, 2011); (Salami, 2011); (Munguti et al., 2022). The majority of researchers utilized descriptive survey designs or explanatory designs, relying on primary data collected via questionnaires from revenue officers and finance staff (Oluoch et al., 2021); (Ayieko & Cherono, 2024); (Edmond et al., 2023); (Thyaka & Kavale, 2021); (Kipkirui & Makori, 2023); (Henry et al., 2018); (Mulinge et al., 2025). This primary data is frequently triangulated with secondary financial reports (e.g., Controller of Budget, Auditor General reports) to perform regression analyses (OLS, binary logistic, or multiple regression), establishing statistical significance between independent variables (technology, controls, structure) and the dependent variable (revenue growth) (Khadondi, 2016); (Munguti et al., 2022); (Mulinge et al., 2025). Revenue mobilisation capacity varies structurally across sub-national units, driven by: Urbanisation and economic concentration (Khadondi, 2016); (Nyanjom, 2014), poverty levels that constrain taxable economic activity (Khadondi, 2016) and historical and geographic disadvantages (Nyanjom, 2014) demonstrating that OSR underperformance is not solely an administrative failure, but reflects unequal starting conditions.

Two competing narratives emerge, one narrative argues that structural economic capacity—such as urbanisation levels, poverty, and economic base—largely determines sub-national revenue performance ((Khadondi, 2016); (Nyanjom, 2014)). Another strand emphasises the role of institutional design and administrative systems, including governance frameworks, internal controls, and revenue technologies, as levers through which governments can overcome structural constraints and enhance revenue outcomes (Henry et al., 2018); (Mulinge et al., 2025). The assumption that reforms uniformly translate into improved revenue performance has been recently challenged. Empirical findings increasingly reveal heterogeneous outcomes, particularly with respect to technology-driven reforms and governance interventions. While several studies report statistically significant positive relationships between automation, digitization, and revenue growth (Henry et al., 2018); (Ayieko & Cherono, 2024); (Mulinge et al., 2025), others demonstrate that technology alone may fail to generate substantive revenue gains in the absence of complementary institutional and behavioural reforms (Adu et al., 2019). Similarly, in Ethiopia, (Mascagni et al., 2021) found that while Electronic Billing Machines (EBMs) increased reported sales, businesses adjusted by inflating their costs to offset tax liabilities, thereby neutralizing the net revenue gain. Technology, therefore, appears to be a necessary but insufficient condition for revenue growth, contingent on the strength of the underlying "hardware" of internal controls and risk management (Thyaka & Kavale, 2021); (Kipkirui & Makori, 2023). Corporate governance reforms may enhance effectiveness without proportionate efficiency gains (Juma & Kinyamjui, 2025).

While the literature largely agrees on the benefits of digitization and control, significant divergences exist regarding the impact of central grants, the reliability of technology, and the structural drivers of revenue potential. These contradictions highlight that revenue mobilization is not a "one-size-fits-all" science but is deeply context-dependent. For example, the "crowding-out" effect as reviewed by (Mogues & Benin, 2012) in Ghana and (Boex & Kelly, 2011) versus "crowding-in" effect as reviewed by (Caldeira & Rota-Graziosi, 2014) in Benin and Masaki (2018) in Tanzania. Studies like (Munguti et al., 2022) and (Henry et al., 2018) present automation as a linear driver of success, finding that digital systems (e-billing, mobile money) account for nearly 50% of revenue variance in counties like Nakuru and Machakos. Conversely, (Heeks, 2003) and (Mascagni et al., 2021) introduce the concept of "partial failure." In Ethiopia, (Mascagni et al., 2021) found that while Electronic Billing Machines (EBMs) increased reported sales, businesses responded by artificially inflating their costs to offset the tax liability, muting the net revenue gain. Similarly, (Adu et al., 2019) in Ghana found that technology is often undermined by "human interference" and sabotage by officials who lose bribe opportunities, suggesting that without cultural change, tech is ineffective. (Khadondi, 2016) explicitly tested the variable of "land area" in Kenya and found it to be statistically insignificant for revenue mobilization. This challenges the administrative assumption that larger counties have a broader rateable base. In contrast to the land argument, (Nyanjom, 2014) and (Onyango et al., 2015) emphasize that urbanization and population density are the only true structural predictors of fiscal health.

This divergence suggests that revenue policies based on "territorial size" (often used in allocation formulas) may be fundamentally flawed compared to those based on economic density creating a geographical literature gap. While enforcement strategies significantly relate to OSR growth (Mulinge et al., 2025), (Munguti et al., 2022), aggressive enforcement can marginalize informal-sector or low-capacity taxpayers (Mulinge et al., 2025); (Munguti et al., 2022).

Data methodology

Descriptive Analysis

Table 1 below presents the descriptive statistics for OSR and the key explanatory variables used in the regression analysis.

Table 1: Descriptive Statistics (OSR Model Variables)

Summary Statistics				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
OSR	857,549,641.32	1,624,197,058.62	60,123,112.00	10,248,425,385.00
Households	258,381.13	234,455.19	37,963.00	1,506,888.00
Livestock	100,623.15	54,339.14	8,749.00	235,264.00
Fishing	2,332.77	3,281.02	209.00	17,770.00

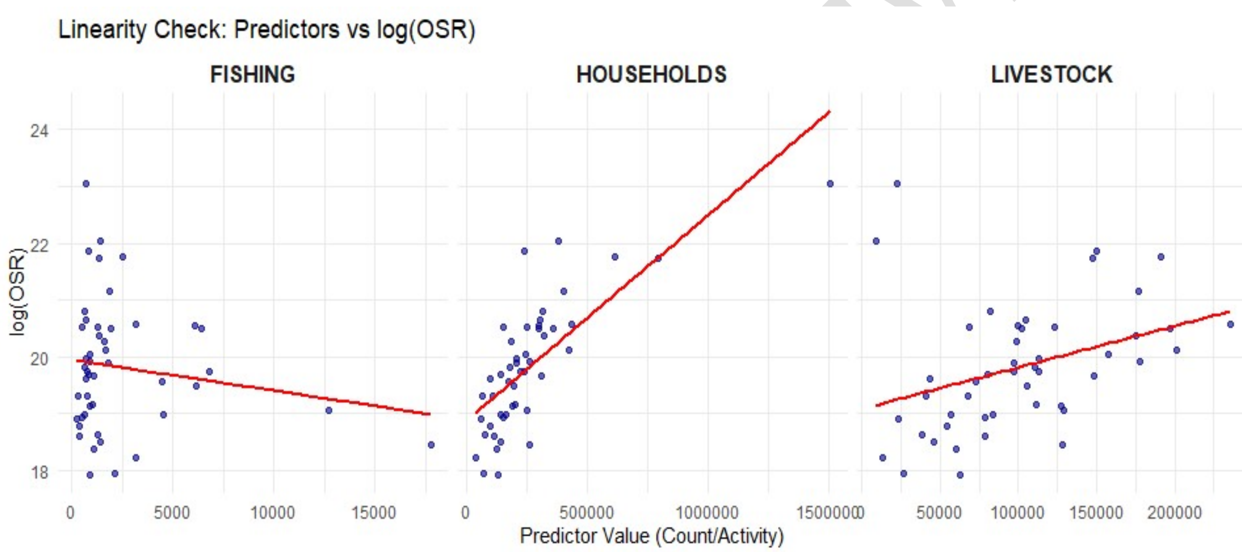
The descriptive statistics reveal substantial cross-sectional heterogeneity in OSR, household scale, and specific agricultural sub-sectors. This variability supports the use of regression analysis to examine how differences in the number of households, livestock rearing, and fishing activity are associated with variations in OSR across units.

Correlation Analysis

Table 2: Correlation Matrix of OSR Model Variables

Pairwise Correlation Coefficients				
	OSR	**Households**	**Livestock**	**Fishing**
OSR	1.000	0.898	-0.055	-0.120
HOUSEHOLDS	0.898	1.000	0.239	0.010
LIVESTOCK	-0.055	0.239	1.000	0.145
FISHING	-0.120	0.010	0.145	1.000

Graphical Visualization



The combined plots of log(OSR) against the selected predictors visually reinforce the regression results. Log(OSR) displays a clear and strong positive relationship with the number of households, with observations closely following an upward trend. A positive association is also observable for livestock, consistent with its significant contribution to revenue. In contrast, the relationship between log(OSR) and fishing exhibits a downward trend, aligning with the negative coefficient observed in the model. Visual inspection confirms that these variables capture distinct economic dimensions, with no evidence of problematic multicollinearity among the predictors.

Causal Analysis

This study employs an ordinary least squares (OLS) regression framework to examine the determinants of OSR. The dependent variable is OSR, and the primary explanatory variables are the number of households, livestock, and fishing activity. To improve model fit and address potential skewness, the analysis is conducted using a log-linear specification of OSR.

Model specification

The specified regression model is expressed as follows:

$$\log(\mathrm{OSR}_i) = \beta_0 + \beta_1\,\mathrm{HOUSEHOLDS}_i + \beta_2\,\mathrm{LIVESTOCK}_i + \beta_3\,\mathrm{FISHING}_i + \varepsilon_i$$

where: * $\log(\mathrm{OSR}_i)$ represents the natural logarithm of Own Source Revenue for county i. * β_0 is the intercept (constant). * β_1, β_2,and β_3 are the coefficients estimating the effect of Households, Livestock, and Fishing, respectively. * ε_i is the error term assumed to be normally distributed.

Model estimation is carried out using OLS. Standard diagnostic tests are performed to assess the validity of the classical linear regression assumptions, including tests for normality of residuals (Shapiro–Wilk), homoscedasticity (Breusch–Pagan), and serial correlation (Durbin–Watson and Breusch–Godfrey). The results indicate that the model satisfies the key OLS assumptions, supporting the reliability of statistical inference.

Estimated results

Table 3: Significant Predictors of log(OSR) (OLS Regression)

Dependent variable: log(OSR)					
Independent Variable	**Estimate**	**Std. Error**	**t-Stat**	**P-Value**	**Sig.**
Constant	1.865e+01	2.362e-01	78.96	0.0000	***
Households	3.379e-06	4.603e-07	7.34	0.0000	***
Livestock	4.416e-06	2.007e-06	2.20	0.0332	*
Fishing	-6.708e-05	3.228e-05	-2.08	0.0437	*

Dependent variable: log(OSR)					
Independent Variable	**Estimate**	**Std. Error**	**t-Stat**	**P-Value**	**Sig.**

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

Interpretation

Households (Positive Driver): This variable remains highly significant ($p < 0.001$). In this log-linear specification, the relationship implies a percentage growth in revenue rather than a fixed unit increase. The results indicate a strong positive elasticity, confirming that population density and urbanization are the primary drivers of Own Source Revenue.

Livestock (Positive Driver): Unlike the general "Farming" variable used previously, Livestock is statistically significant ($p < 0.05$) and carries a positive coefficient. This suggests that counties with significant livestock economies (e.g., organized meat production or pastoralist markets) tend to generate higher revenue, contradicting the assumption that all agricultural sectors dampen OSR.

Fishing (Negative Driver): This variable is statistically significant ($p < 0.05$) with a negative coefficient. An increase in fishing activity is associated with a decrease in OSR performance. This indicates that counties heavily reliant on the fishing sub-sector face structural challenges in revenue mobilization compared to those with industrial, commercial, or livestock-based economies.

Diagnostic Tests

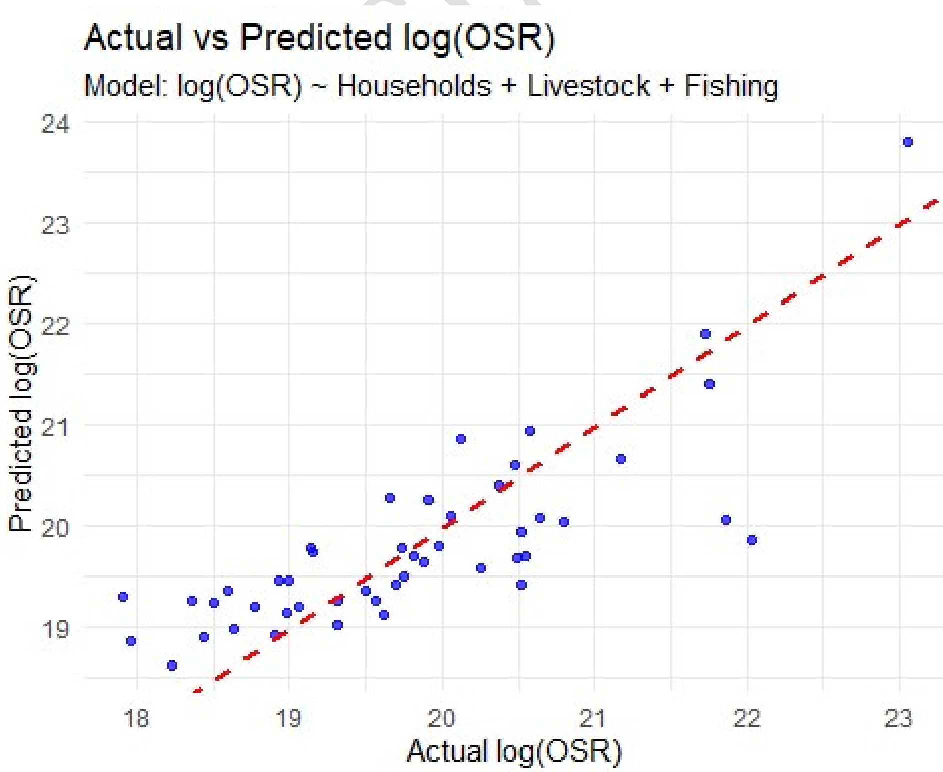
Table 4: Residual Diagnostic Tests

Model Assumptions Check				
Diagnostic Test	**Test Stat**	**P-Value**	**Status**	**Conclusion**
Shapiro-Wilk (Normality)	0.955	0.0653	Pass (Non-Significant)	Residuals approximately normal

Model Assumptions Check				
Diagnostic Test	**Test Stat**	**P-Value**	**Status**	**Conclusion**
Breusch-Pagan (Homoscedasticity)	3.191	0.3631	Pass (Non-Significant)	Constant variance (homoscedastic)
Durbin-Watson (Autocorrelation)	2.247	0.8109	Pass (Non-Significant)	No autocorrelation detected
Breusch-Godfrey (Serial Correlation)	5.036	0.2837	Pass (Non-Significant)	No serial correlation detected

The diagnostic tests indicate that all key OLS assumptions are satisfied. The Shapiro–Wilk test fails to reject normality of the residuals, while the Breusch–Pagan test provides no evidence of heteroskedasticity. In addition, both the Durbin–Watson and Breusch–Godfrey tests suggest the absence of autocorrelation and serial correlation. Overall, the model appears well specified, and the OLS estimates are reliable.

Goodness of Fit Plot



The blue data points (counties) are clustered closely around the red dashed line, indicating a strong model fit. The pattern is clearly linear, confirming that the relationship between your predictors (Households, Livestock, and Fishing) and Revenue (log scale) is consistent across small and large counties. There is no obvious curve (U-shape), which aligns with the passing diagnostic tests. The Red Dashed Line represents perfect prediction (where Actual Revenue equals Predicted Revenue). The closer the points are to this line, the more accurate your model is. This graph helps identify over- and under-performing counties relative to their household size and specific sector activities (livestock and fishing). Deviations from the line are relatively small and appear random, suggesting no systematic over- or under-prediction.

Discussion

To investigate the determinants of Own Source Revenue (OSR) across counties, an Ordinary Least Squares (OLS) regression was conducted. The dependent variable was transformed into its natural logarithm (log_OSR) to address issues of non-normality and skewness inherent in revenue data. The final model retained three statistically significant independent variables: Households, Livestock, and Fishing. The goodness-of-fit tests indicate a robust model. The coefficient of determination (R^2) suggests that the independent variables explain approximately 63% of the variance in the log of Own Source Revenue. The F-statistic is highly significant ($p < 0.001$), confirming that the model is statistically valid and effectively predicts revenue generation capacity based on these structural economic factors.

Interpretation of Predictors

All three independent variables included in the final model were statistically significant, though they exhibit distinct effects on revenue:

Households (Positive Driver): The analysis reveals a strong, highly significant ($p < 0.001$) positive correlation between the number of households and OSR. This variable serves as a proxy for urbanization, market size, and the taxable base. As the number of households increases, the demand for county services (parking, permits, land rates) and the volume of trade are likely to increase, thereby expanding the revenue base.

Livestock (Positive Driver): Livestock activity shows a significant positive relationship ($p < 0.05$) with OSR. Unlike general farming, which often correlates negatively with revenue, this finding suggests that the livestock sub-sector—likely through organized meat production, sale yards, and cess fees—contributes meaningfully to the county fiscal base.

Fishing (Negative Driver): In contrast, fishing activity exhibits a significant negative relationship ($p < 0.05$) with OSR. This finding implies structural difficulties in mobilizing revenue from this sub-sector. Counties heavily reliant on fishing may face challenges related to informality, lower commercial value chains compared to other sectors, or specific difficulties in enforcing collection within the fisheries industry.

The validity of these findings was confirmed through a series of diagnostic tests on the model residuals. The log-linear specification successfully satisfied all key OLS assumptions. The graphical analysis of Actual vs. Predicted OSR supports these statistical findings, showing a strong linear alignment along the line of perfect fit. Deviations from this line offer actionable policy insights.

Conclusion

In conclusion, the analysis demonstrates that urbanization (Households) is the primary driver of revenue accumulation. However, the agricultural landscape is not uniform in its impact: while Livestock economies contribute positively to the fiscal base, high reliance on the Fishing sub-sector is structurally associated with lower revenue performance. The model is statistically sound and provides a reliable framework for forecasting county revenue potentials based on these distinct economic activities.

Policy recommendations

The significant negative relationship between fishing activity and OSR signals that current revenue models for this sub-sector are structurally inefficient or counterproductive. Rather than aggressively taxing primary production (which may face high resistance and low yield), counties with large fishing communities should consider value-chain taxation. This involves shifting the tax point from the catch landing sites to market centers, processing hubs, and cold storage facilities where value is added and transactions are more formal.

Conversely, the positive contribution of livestock suggests that existing mechanisms in this sector (e.g., sale yard fees and movement permits) are relatively more effective and could be further optimized. Finally, the disparity in revenue potential between urbanized economies and those reliant on specific agrarian sub-sectors implies that national revenue allocation formulas should be re-evaluated. This would better compensate counties that lack lucrative urban tax bases, ensuring fiscal equity for regions dependent on lower-yielding economic activities.

Future studies

Longitudinal panel studies are needed to examine how changes in household dynamics, urbanization, and specific sectoral shifts—such as the growth of livestock markets or fluctuations in fishing output—affect OSR performance over time. This approach would allow for stronger causal inference regarding the distinct economic impacts of these agricultural sub-sectors than is possible with cross-sectional models.

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