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The impact of state fiscal structure and income inequality on inter-generational economic mobility

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Abstract
Recent national trends reveal a troubling socioeconomic picture: upward mobility has stagnated, income inequality has widened, and home ownership rates among younger and low-income Americans have declined. While federal tax policy garners attention, state and local fiscal systems more directly shape families' disposable income and access to public goods. This study examines how state tax structures and inequality affect inter-generational mobility and home ownership across the United States from 2012 to 2022. We use two fiscal indicators: τ-ITEP, the difference in effective tax rates between the bottom 20% and top 1% of earners, and the pre-tax Gini coefficient. Outcomes include upward mobility, measured by the mean adult income rank of children born to parents at the 25th percentile, a commonly used benchmark for assessing opportunity from disadvantaged households, and home ownership rates. Findings show that tax regressivity (higher τ-ITEP) and inequality (Gini) are significantly and negatively associated with inter-generational mobility, even after controls for GDP per capita and educational attainment. Results suggest that structural inequities in subnational tax systems and income distribution independently constrain upward mobility. In contrast, home ownership is more strongly influenced by inequality, education, and GDP, with no significant link to tax structure. Time-based models show mobility peaked during the post-recession recovery (2012–2014) and fell sharply during the COVID-19 pandemic (2020–2022), highlighting the limits of short-term relief without structural equity. These results demonstrate the importance of equitable state fiscal policy and reduced inequality in expanding opportunity.

Keywords
State tax progressivity, Income inequality, Inter-generational mobility, Home ownership, τ_ITEP, Gini coefficient, Economic mobility, State fiscal policy, GDP per capita, Regressive tax

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1. Introduction

Over the past several decades, the United States has experienced growing income inequality alongside stagnating upward mobility. The top 1% of earners have captured a rising share of income and wealth, while younger and lower-income households have struggled with flat real wages and diminished access to financial milestones such as home ownership (1,2). These patterns raise concerns about the institutional mechanisms that entrench economic inequality across generations, among which state tax policy plays a critical yet under-examined role.

While federal taxation receives most policy attention, it is relatively uniform across states and thus provides limited variation for cross-sectional analysis. By contrast, state and local governments directly shape the fiscal landscape for families through highly variable mixes of income, sales, and property taxation. These structural choices generate wide differences in effective tax burdens, influencing both household disposable income and the resources available for public investment. Such variation makes state and local tax systems the most relevant setting for assessing how fiscal architecture affects inter-generational mobility and home ownership.

This study explored how the structure of state tax systems, particularly their degree of progressivity, influences inter-generational income mobility and home ownership rates. Our framework centered on two pathways: the disposable income and private investment channel, and the public investment and institutional capacity channel. We measured tax progressivity using the Institute on Taxation and Economic Policy metric (τ-ITEP) (3-6), which captures the effective tax rate gap between the bottom 20% and top 1% of earners. This was combined with Opportunity Atlas data on upward mobility (7,8) and home ownership rates from the American Community Survey (9) to construct a 2012-2022 panel dataset spanning all 50 U.S. states. This allowed us to assess whether more progressive tax systems were consistently associated with greater economic mobility and whether these relationships persisted when jointly evaluated alongside income inequality, while also accounting for state economic capacity and human capital indicators.

We hypothesized that: 1 - states with more progressive tax structures and lower income inequality would exhibit higher levels of upward mobility, and 2 - both factors would be less strongly associated with home ownership, which is more directly influenced by housing market conditions and long-run affordability constraints. We also introduced time-based regressions and cluster analysis to evaluate how macroeconomic shifts and fiscal structures jointly shape opportunity. The remaining sections proceed as follows: Section 2 reviews key literature; Section 3 details data and methods; Section 4 presents results and the model fit; Section 5 discusses limitations and policy implications; and Section 6 concludes.

2. Literature review

State-level studies refine our understanding of fiscal architecture and its determinants. Chernick (10) identified political ideology and demographic composition as key predictors of progressivity, while Kosar and Moffitt (11) showed how cumulative marginal tax rates disincentivized upward mobility. Fox and Luna (12) and Wheaton and Stevens (13) documented variation in tax burdens across states, signaling the impact of indirect taxes. Zidar and Zwick (14) added that regressive systems were associated with lower net transfers to low-income households, which revealed how tax design could reinforce disadvantage. Heathcote, Storesletten, and Violante (15) found that moderate progressivity could reduce inequality without distorting incentives by modeling trade-offs between equity and efficiency .

Chetty et al.'s (7,8) development of the Opportunity Atlas revealed significant geographic disparities in mobility that correlated with factors such as school quality and income segregation. Expanding on this, Chetty et al. (16) showed that early exposure to high-opportunity neighborhoods led to long-term gains in earnings and stability and highlighted the compounding effects of spatial and fiscal inequality. Similarly, Manduca (17) found that rising income inequality accelerated regional divergence in both economic growth and inter-generational mobility .

The Survey of Consumer Finances indicates stagnating middle-class asset ownership amid rising top wealth shares (18). Home ownership remains central to wealth-building, but affordability barriers and unequal tax treatment limit access. Pfeffer and Schoeni (19) linked disparities in home ownership and savings to the racial and class-based wealth gap. Saez and Zucman (20) used tax data to track top wealth shares, while Wolff (21) showed rising inter-generational dependence on transfers. These findings suggested that progressive tax systems may broaden asset accumulation opportunities across generations.

3. Data and Methods

3.1. Data sources and variable construction
We constructed a panel of all 50 U.S. states from 2012 to 2022. This period covered four distinct macroeconomic environments: Post-Recession Recovery (2012–2014), Stable Growth (2015–2017), Pre-COVID-19 Expansion (2018–2019), and COVID-19 & Early Recovery (2020–2022). The categorization of these phases was supported by OECD's 2024 U.S. Economic Survey (22) and NBER's business-cycle dating (23), which allowed us to examine the role of different economic conditions in shaping our results.

The key independent variables included τ-ITEP, the effective tax rate gap between the bottom 20% and top 1% (3-6), and the pre-tax Gini coefficient (24). The primary dependent variable was the mean income rank of children from the 25^{th} parental income percentile, a commonly used benchmark in Chetty et al. 's mobility research because it captures upward mobility from disadvantaged households (25-27). The secondary outcome was state home ownership (9), a proxy for asset accumulation. Controls included GDP per capita (28) and college attainment (29).

3.2 Empirical strategy
We constructed a series of linear regression models to evaluate the relationship between tax structure and two key dependent variables: upward mobility and home ownership. We estimated panel regressions of the following

general form to analyze the relationship between tax structure and economic outcomes as given by $Y_{st}=\alpha+\beta_{x1}X1_{st}+\beta_{x2}X2_{st}+\delta_s+\lambda_t+\epsilon_{st}$ (Eq.1), where Y_{st} is the outcome of interest (either upward mobility or home ownership) in state *s* or year *t*. The key explanatory variables, $X1_{st}$ include both τ-ITEP and $Gini_{st}$. $X2_{st}$ is a vector of control variables including GDP per capita and college attainment. The model included state fixed effects δ_s and year fixed effects λ_t to account for unobserved heterogeneity.

4. Results

4.1. Income mobility regressions

We assessed whether state tax progressivity (τ-ITEP) predicted upward mobility from 2012 to 2022 using the Opportunity Atlas "mean rank outcomes"; the average income percentile reached by children from the 25th percentile. Our regression models tested two main questions: whether more progressive tax systems were linked to greater upward mobility, and whether this relationship persisted when evaluated together with income inequality (Table 1).

Table 1. Mobility regression results

Table	Term	Coefficient Estimate	Standard error	Statistic	P-value
a: (τ) R^2=0.2	Intercept	0.22178	0.02706	8.19519	0.00000
	τ-ITEP	-0.00129	0.00057	-2.25272	0.02471
	GDP Per Capita	0.00000	0.00000	.073237	0.46429
	State College Ratio	0.30752	0.05392	4.70305	0.00000
b: (τ + Gini) R^2=0.23	Intercept	0.39646	0.04111	9.64404	0.00000
	τ-ITEP	-0.00118	0.00056	-2.12108	0.03441
	IPUMSgini	0.32349	0.05852	-4.52762	0.00000
	GDP Per Capita	0.00000	0.00000	2.35058	0.01913
	State College Ratio	0.22858	0.05430	4.20956	0.00003
c: (τ + Gini +time-based) R^2=0.29	Intercept	0.36582	0.03978	9.19500	0.00000
	τ-ITEP	-0.00123	0.00054	-2.28747	0.02259
	IPUMSgini	0.30437	0.05622	-4.41356	0.00000
	GDP Per Capita	0.00000	0.00000	-3.09544	0.00208
	State College Ratio	0.13877	0.05455	2.54376	0.01127
	Year Group (2012-2014)	0.03557	0.00538	6.61070	0.00000
	Year Group (2015-2017)	0.01675	0.00501	3.34231	0.00089
	Year Group (2018-2019)	0.02701	0.00505	4.35037	0.00000

4.1.1. *Baseline regression*

The first model regressed upward mobility on τ-ITEP, while controlling for GDP per capita and the percentage of adults with a college degree. To isolate the effect of tax progressivity on inter-generational mobility, we estimated the following baseline model as,

$$Mobility_{st} = \alpha + \beta_1 \tau - ITEP_{st} + \beta_2 GDPpc_{st} + \beta_3 College_{st} + \delta_s + \lambda_t + \epsilon_{st} \quad \text{(Eq.2).}$$

This specification regressed upward mobility, measured as the average income rank of children from the 25th percentile parental income bracket, on tax progressivity, economic scale (GDP per capita), and human capital (college attainment). The model included state fixed effects δ_s and year fixed effects λ_t to account for unobserved heterogeneity across states and time. This approach allowed for a more precise estimate of the relationship between fiscal structure and economic mobility by holding constant time-invariant state characteristics and common temporal shocks.

The results in Table 1a support the theoretical expectation that regressive tax systems may constrain upward mobility by reducing disposable income for low-income households and underfunding public services such as education and healthcare. It also aligned with existing literature on the redistributive and opportunity-enhancing functions of progressive taxation (10, 14).

The GDP per capita did not exhibit a statistically significant relationship with upward mobility ($p = 0.4643$). By contrast, higher state-level college attainment rates were associated with markedly improved mobility outcomes ($\beta = 0.30752$, $p < 0.001$). Tax progressivity remained a robust predictor even when controlling for GDP per capita and education, affirming its independent role in fostering equitable economic advancement.

4.1.2. *Extended regression*

In addition to the independent effect of state fiscal progressivity on inter-generational mobility, prior empirical work demonstrated that income inequality also constrained upward mobility by limiting access to opportunity-enhancing resources such as education and healthcare (30). To assess the joint effects of fiscal structure and income distribution, this study extended the baseline model by incorporating the pre-tax income Gini coefficient $Gini_{st}$ as a principal explanatory variable, expressed as

$$Mobility_{st} = \alpha + \beta_1 \tau - ITEP_{st} + \beta_2 GDPpc_{st} + \beta_3 College_{st} + \beta_4 Gini_{st} + \delta_s + \lambda_t + \epsilon_{st} \quad \text{(Eq.3).}$$

As shown in Table 1b, the extended model yielded three notable findings. First, the coefficient on τ-ITEP remained negative and statistically significant ($\beta = -0.00118$, $p = 0.0344$), reaffirming the independent role of tax progressivity in promoting upward mobility, even when income inequality was taken into account. Second, a positive and highly significant coefficient on the Gini variable ($\beta = 0.32349$, $p < 0.001$) pointed to a strong inverse relationship between income inequality and upward mobility. States with greater inequality tended to experience lower rates of inter-generational mobility. This finding supported previous research showing that inequality could limit access to essential opportunities and public resources (17,30,31).

In addition, GDP per capita's statistical significance in this specification ($\beta \approx 0.00000$, $p = 0.0191$) indicated a modest yet relevant link between state economic output and upward mobility. The inclusion of the Gini coefficient also marginally improved the overall model fit (increasing the R^2 by 0.08) and enhanced the ability to explain variation in inter-generational mobility across states.

Together, the findings in Table 1a and 1b reaffirmed the combined influence of tax policy and income inequality on inter-generational mobility. The magnitude and significance of the Gini coefficient suggested that structural inequality acted not merely as a contextual factor, but as a direct and powerful barrier to upward movement. Regressive tax systems may not only reduce the disposable income of low-income families but also signal lower public investment in institutions that foster opportunity. At the same time, elevated inequality appeared to entrench economic outcomes across generations, even in states with higher GDP or broad college attainment. These results implied that fiscal progressivity and redistribution should be evaluated jointly. Progressive taxation may enhance mobility not only by shifting post-tax income but also by shaping the broader institutional environment, one that supports access, stability, and long-term opportunity.

4.1.3. *Fiscal time windows and inter-generational mobility*

To assess how macroeconomic cycles shape the relationship between state tax policy and upward mobility, we included categorical time-period variables in the mobility regression, which captured national economic shifts, growth, recovery, and disruption.

These defined macroeconomic periods were: Post-Recession Recovery (2012-2014), marked by fiscal stimulus and lagged mobility gains; Stable Growth (2015-2017), with steady economic expansion and fading stimulus; Pre-COVID-19 Expansion (2018-2019), marked by high GDP but rising inequality and affordability concerns; and COVID-19 & Early Recovery (2020-2022), reflecting pandemic-induced shocks and emergency fiscal responses.

4.1.3.1. Key findings

To capture the role of macroeconomic context, we modifed the mobility regression to include dummy variables for distinct economic periods as,

$$Mobility_{st} = \alpha + \beta_1 \tau - ITEP_{st} + \beta_2 GDPpc_{st} + \beta_3 College_{st} + \beta_4 Gini_{st} + \sum_{k=1}^{3} \gamma_k D_{k,t} + \delta_s + \lambda_t + \epsilon_{st} \quad \text{(Eq.4).}$$

The variables $D_{k,t}$ represent categorical indicators for the above-mentioned macroeconomic periods. The COVID-19 period (2020-2022) was the omitted baseline. This model captured cyclical variations in mobility while accounting for fiscal structure.

Including time-period indicators substantially improved the model fit, indicating that upward mobility responds not only to state-level structures such as tax policy but also to broader economic cycles. As seen in Table 1c, mobility was the highest during the Post-Recession Recovery (2012-2014), likely due to federal stimulus and expanded tax credits. It remained moderately elevated during Stable Growth (2015-2017), then declined in the Pre-COVID-19 Expansion (2018-2019) amid rising housing costs and inequality. Mobility reached its lowest point during the COVID-19 period (2020-2022), as disruptions to education, employment, and housing offset emergency federal aid, disproportionately impacting low-income families.

4.1.3.2. Interpretation

This analysis showed that upward mobility was significantly influenced by the macroeconomic context. Periods marked by targeted federal intervention (e.g., 2012-2014) corresponded with the strongest gains, while unbalanced growth without equity-focused policy (e.g., 2018-2019) yielded weaker outcomes. The pandemic eroded opportunity despite large-scale federal relief, revealing the limits of reactive policy without deeper structural reform.

These results emphasize the importance of embedding resilience into state fiscal policy. Progressive taxation and sustained investment in opportunity-building institutions, such as public education, housing, and health systems, are necessary complements to federal interventions. Relying on growth alone, without inclusive fiscal design, may prove insufficient for preserving inter-generational economic mobility in the face of future shocks.

4.2. Home ownership regressions

Beyond income mobility, we examined home ownership as a proxy for long-term asset accumulation and financial security. Using state-level data from 2012 to 2022, we assessed whether tax progressivity (τ-ITEP) and income inequality (Gini) were associated with variations in home ownership rates, particularly for middle- and lower-income households.

4.2.1. *Baseline regression*

In our first specification, homeownership was regressed on τ-ITEP, GDP per capita, and the share of adults with a college degree. A similar model compared to mobility was used to assess the determinants of homeownership across states as,

$$Homeownership_{st} = \alpha + \beta_1 \tau - ITEP_{st} + \beta_2 GDPpc_{st} + \beta_3 College_{st} + \delta_s + \lambda_t + \epsilon_{st} \qquad \text{(Eq.5)}$$

This specification regressed homeownership, the percentage of households that own their home in a given state and year, on tax progressivity (τ-ITEP), economic scale (GDP per capita), and human capital (college attainment). Similar to the regression on income mobility, the model controlled for both state-specific (δ_s) and time-specific (λ_t) effects.

Table 2. Home ownership regression results

Table	Term	Coefficient Estimate	Standard Error	Statistic	P-value
a: (τ) R^2=0.12	Intercept	0.01174	0.00052	22.48339	0.00000
	τ-ITEP	0.00001	0.00001	0.81227	0.41702
	GDP Per Capita	-0.00000003	0.00000	-4.41509	0.00001
	State College Ratio	-0.00102	0.00104	-0.98402	0.32558
	R Square 0.12				
b: (τ + Gini) R^2=0.2	Intercept	0.01423	0.00080	17.69213	0.00000
	τ-ITEP	0.00001	0.00001	0.96683	0.33410
	IPUMSgini	-0.004608	0.00115	-4.02501	0.00007
	GDP Per Capita	0.00000	0.00000	-3.09544	0.00208
	State College Ratio	-0.00215	0.00106	-2.02227	0.04368

As shown in Table 2a, the coefficient on τ-ITEP is positive but statistically insignificant ($p = 0.4170$). This result offers no evidence of a direct relationship between state-level tax progressivity and home ownership rates. GDP per capita appeared with a negative and highly significant coefficient ($p < 0.001$), while the coefficient on the state college attainment rate was also negative but lacked statistical significance ($p = 0.3256$).

Although initially counterintuitive, these findings are consistent with broader research on housing affordability challenges in economically prosperous and highly educated states (2,32). Patterns observed here demonstrated the broader influence of housing market dynamics, such as elevated prices, constrained supply, and restrictive land-use policies, over household access to property ownership. Within this model, fiscal progressivity held limited relevance in determining whether households attained home ownership.

4.2.2. *Extended regression*

Analogous to that of our mobility regression, the study augmented the baseline model for home ownership by incorporating the pre-tax income Gini coefficient $Gini_{st}$ to assess the joint impact of state fiscal progressivity and income inequality as,

$$Homeownership_{st} = \alpha + \beta_1 \tau - ITEP_{st} + \beta_2 GDPpc_{st} + \beta_3 College_{st} + \beta_4 Gini_{st} + \delta_s + \lambda_t + \epsilon_{st} \quad \text{(Eq.6)}$$

This extended model incorporated the Gini coefficient to examine how income inequality, alongside tax structure, shaped access to homeownership. It regressed state-level home ownership rates on tax progressivity, income inequality, GDP per capita, and educational attainment, while controlling for both time-invariant state characteristics and national time trends as seen in previous regression models in this study.

The results, presented in Table 2b further reinforced the limited direct role of tax progressivity. τ-ITEP remained statistically insignificant, confirming that regressivity in state tax systems was not significantly associated with home ownership rates. However, the Gini coefficient emerged as a significant and negative predictor of home ownership. This suggested that structural income inequality may inhibit access to property ownership, potentially by limiting savings capacity, tightening access to credit, or concentrating housing demand in ways that priced out low- and middle-income families.

Additionally, in this extended model, GDP per capita remained statistically significant ($p = 0.0021$), although the coefficient was negligible in magnitude. The direction of the effect, as reflected in the negative test statistic, suggested that states with higher income levels tended to have lower home ownership rates. College attainment was also negatively associated with home ownership and statistically significant at the 5% level ($p = 0.0437$). Together, these results reinforced the interpretation that high-income, highly educated states faced persistent affordability constraints, which could limit access to home ownership even among economically advantaged populations.

4.2.3. *Interpretation*

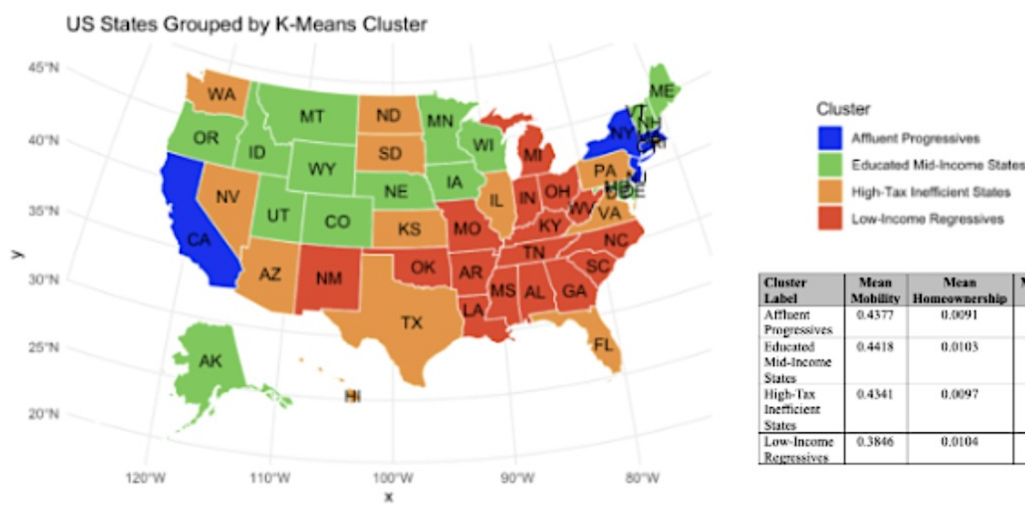
These findings contrasted sharply with the results from the mobility regressions. While tax structure, especially regressivity, appeared to shape inter-generational income outcomes, it did not show a direct relationship with home ownership. Instead, home ownership outcomes seemed to be disproportionately more influenced by broader economic and housing market conditions, including structural inequality and regional affordability.

The absence of a significant relationship between τ-ITEP and home ownership should be interpreted with caution. It may indicate that tax policy affects wealth accumulation indirectly, by influencing income trajectories, labor market access, and public investment, but it is insufficient on its own to counteract strong market forces governing the housing sector. Future research should explore these indirect pathways in greater depth, and policy efforts to promote asset-building should include not only tax reforms, but also targeted interventions to expand affordable housing and reduce wealth barriers.

4.3. Cluster analysis for income mobility

To complement our regression models and identify structural patterns across states, we applyed K-means clustering using three key input variables: tax progressivity (measured by τ-ITEP), GDP per capita, and education attainment. These variables capture the foundational dimensions of fiscal equity, economic capacity, and human capital - three pillars that shape a state's potential to promote upward mobility and wealth accumulation. These structural inputs allowed us to group states based on their underlying policy environment and economic conditions. This unsupervised classification added a second layer of analysis by uncovering clusters of states that shared similar constraints or advantages and enabled a more nuanced discussion of how different policy models aligned with observed economic outcomes.

To perform the cluster analysis, we grouped states by minimizing within-group distance based on the above-mentioned variables, $\sum_{j=1}^{K} \sum_{i \in C_j} \|(X_i - \mu_j)\|^2$ (Eq.7). Each state i was assigned to a cluster C_j that minimized the squared Euclidean distance between its attribute vector and the centroid of cluster j. This cluster analysis yielded four distinct categories as shown in Figure 1. These categories offer a multidimensional perspective and allow policymakers to benchmark states with similar economic structures but divergent equity outcomes.



Cluster Label	Mean Mobility	Mean Homeownership	Mean τ	Mean GDP	Mean Education
Affluent Progressives	0.4377	0.0091	1.62	64492	0.68
Educated Mid-Income States	0.4418	0.0103	2.57	50195	0.66
High-Tax Inefficient States	0.4341	0.0097	7.02	51530	0.64
Low-Income Regressives	0.3846	0.0104	4.09	44189	0.59

Figure 1. Map and statistics by cluster

States in Cluster 1 are Affluent Progressives, such as Massachusetts and California, and pair low τ-ITEP values (~ 2.0-3.0) with high GDP per capita and strong upward mobility outcomes. Robust public investment - particularly in education, healthcare, and early childhood - supports inclusive growth. California's progressive tax structure and social programs, including earned income tax credits (EITCs) and Medi-Cal expansion, help offset high living costs and preserve mobility, illustrating the compatibility of equity and growth (15).

Cluster 2 consists of Educated Mid-Income States, including Minnesota and Maryland, combining moderate progressivity with strong educational systems that sustain mobility. Even without extreme progressivity, targeted human capital investments help mitigate regressivity's downsides. These outcomes support findings that mobility is shaped by tax structure and sustained investment in education (7,10,16).

Cluster 3 consists of High-Tax Inefficient States, such as Florida and Texas, which impose highly regressive taxes (τ-ITEP ≈7.0) without corresponding economic or mobility benefits. These systems extract from low-income households while under investing in public goods, which limits long-term opportunity (14).

Cluster 4 consists of Low-Income Regressive states, which exhibit high τ-ITEP (≈5–6), low GDP per capita, and limited mobility. Persistent underinvestment in education, housing, and workforce infrastructure, coupled with weak redistributive policies, entrenches structural disadvantage (33), as seen in Arkansas and Mississippi.

4.4. Model fit

It is worth noting that the explanatory power of the models was consistent with prior literature. As shown in Table 1, the mobility model yielded R^2 values between 0.20 and 0.29,which is in line with the empirical literature on inter-generational mobility (25), where variation across states, counties, or cohorts is shaped by a wide set of historical, institutional, and demographic forces. The home ownership model in Table 2 produced lower R^2 values, 0.12–0.20, which remain acceptable in social science research, where values as low as 0.10 are considered meaningful when predictors are significant (34). Methodological guidance further notes that explaining ~ 20% of variation is often considered strong performance (35).

The scatterplots for Models Table 1c and 2b are provided in the Appendix to illustrate how much of the observed variation in the two key dependent variables (upward mobility and homeownership) was explained by each explanatory variable.

5. Discussion

The findings of this study contribute to a growing body of research on how subnational tax structures influence long-term economic mobility and wealth-building. By combining τ-ITEP (a direct measure of tax progressivity), regional income inequality (Gini), and Opportunity Atlas data, the analysis in this study offered a multidimensional and time-sensitive portrait of how fiscal architecture shapes inter-generational trajectories.

Regressive tax systems are consistently associated with lower upward mobility, yet this study does not claim causal identification. Other influential factors, such as labor market dynamics or state-level governance quality, could play a role. Identifying these mechanisms more precisely will require future work employing quasi-experimental approaches and exploring interactions between tax structures and investments in education, savings, and public goods.

Additionally, state tax systems operate within a broader federal framework. Interactions with national programs such as the Earned Income Tax Credit (EITC) or Medicaid expansion may either mitigate or amplify the effects of state-level tax burdens. Modeling these cross-level dynamics is essential to gaining a fuller understanding of the mobility implications embedded in the U.S. fiscal landscape.

A limitation of this study lies in data granularity. τ-ITEP relies on periodically updated reports, and the need for interpolation may introduce uncertainty. Similarly, metrics like Gini coefficients and upward mobility aggregates may mask local-level disparities. In addition, the Opportunity Atlas provides mobility outcomes only for the 25th parental income percentile (p25), limiting analysis of other points in the income distribution such as the middle class. Enhancing geographic resolution, incorporating cohort-level tracking, and expanding percentile coverage would offer more precision and breadth in future analyses.

Equity outcomes are also not distributed evenly. Race, gender, and place of residence often intersect with tax regimes in ways that deepen disadvantage, particularly for Black and Hispanic households disproportionately located in high-regressivity states. These possible intersecting effects merit closer and more direct examination in subsequent studies.

Beyond academic implications, the policy takeaways are clear. Tax progressivity matters, not merely for redistribution, but as a structural foundation for long-term opportunity. Reducing reliance on regressive sales taxes, expanding refundable credits, and implementing more progressive income tax brackets can help equalize burdens while also creating financial space for low-income families to invest in their futures.

However, fiscal equity must be paired with sustained public investment. States like Massachusetts and California demonstrate that when progressive tax systems are aligned with robust education and workforce development efforts, they can deliver significant mobility gains. Meanwhile, rising housing costs in high-growth states pose a major barrier to asset-building, making reforms like zoning changes, down-payment assistance, and targeted housing tax credits especially timely.

To institutionalize these gains, mobility metrics should be embedded into fiscal governance. Instead of focusing solely on revenue or redistribution, states would benefit from tracking long-run opportunity outcomes. Aligning tax policy with inclusive growth goals and bolstering resilience through counter-cyclical mechanisms can help reverse stagnation and restore mobility.

6. Conclusion

This study provided new empirical evidence that both state tax structure and income inequality are fundamental drivers of inter-generational economic mobility in the United States. Using a decade of panel data, we found that regressive tax systems, as measured by τ-ITEP, and higher income inequality, as measured by the Gini coefficient, were each independently associated with lower upward mobility for children from low-income households. These findings suggest that fiscal design and inequality jointly shape long-term opportunity, with tax progressivity contributing beyond simple redistribution.

In contrast, home ownership, a proxy for wealth accumulation, was more closely linked to structural factors such as GDP per capita and educational attainment. While progressive tax policies may support income mobility, addressing wealth disparities will require complementary housing reforms to expand access and affordability, particularly in economically dynamic states.

Our cluster analysis reinforced these conclusions and indicated that states with progressive tax systems and strong economies achieved higher mobility. Conversely, states with regressive fiscal structures, despite high aggregate wealth, frequently exhibited weaker mobility outcomes, demonstrating the limitations of economic growth in the absence of fiscal equity.

Time-period regressions demonstrated how mobility fluctuates with macroeconomic shocks, strengthening during post-recession recovery but falling sharply during the COVID-19 era, despite federal aid. This contrast illustrates the limits of short-term interventions in the absence of structural progressivity and reflects the need for resilient counter-cyclical state policy.

Together, the findings suggested that promoting mobility demands more than growth: it requires inclusive fiscal design, sustained public investment, and policies aimed at reducing structural inequality. States that prioritize equity alongside development will be best positioned to reverse mobility stagnation and build a more inclusive future.

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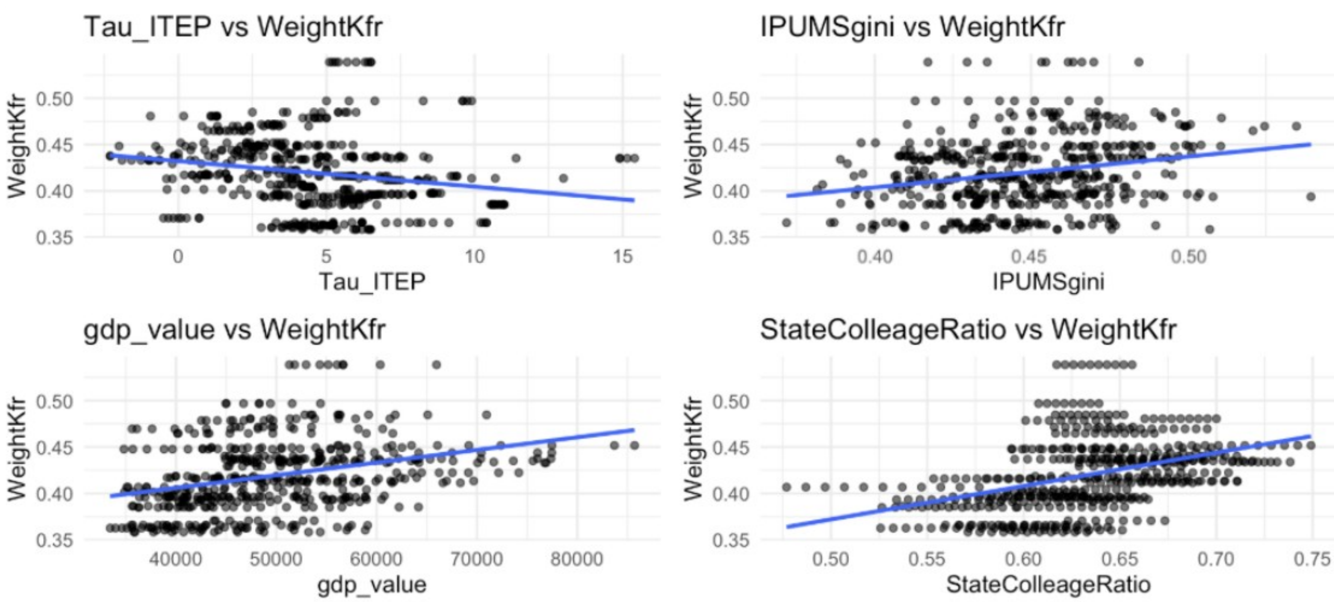
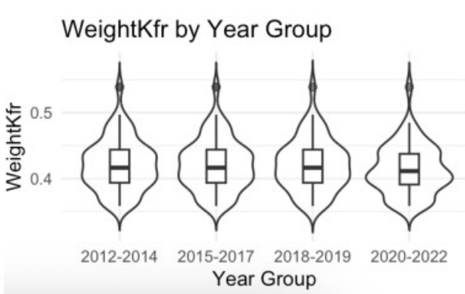
Appendix

Scatterplot for mobility model (Table 1c)





2012-2014: Post-Recession Recovery

2015-2017: Stable Growth Period

2018-2019: Pre-COVID Expansion

2020-2022: COVID & Recovery Era

Scatterplot for homeownership model (Table 2b)