the critical role of state-supported education in debt minimization. The exclusion of income and poverty variables in favor of unemployment rates suggests that for this specification, labor market tightness was a more distinct predictor of debt variance than general household wealth.

Discussion The major-mix model explains additional variance but does not account for demographic composition or aid distribution. Residual patterns indicate systematic differences by population structure. Approach 4 tests demographic and aid variables as moderators of borrowing outcomes.

Approach 4: Equity, Aid, and Demographic Composition

This approach examines how state-level affordability, aid intensity, and demographic composition relate to median student loan debt among completers, using a panel of U.S. states from 2011–2020 and focusing on equity-relevant differences across populations.

Model development The modeling sequence begins with an initial full-sample specification (Model 1), estimated on all available state–year observations. Influence diagnostics for Model 1 revealed several observations with disproportionately large Cook's distances. To assess sensitivity, a second specification (Model 2) was estimated after removing all state–years with Cook's $D > 4/n$, which eliminated 28 observations across several states and improved overall fit at the cost of reduced geographic coverage. Inspection of the influence patterns showed that three states—New Hampshire, West Virginia, and Wyoming—accounted for most high-Cook observations across multiple years. A third specification (Model 3) was therefore estimated excluding only these three states in all years. Model 3 retains nearly the full sample while improving residual behavior and explanatory power, and is adopted as the baseline specification.

The baseline model is written compactly as

$$grad\_debt\_mdn\_w_{st} = \beta_0 + \sum_{k=1}^{14} \beta_k \, z(X_{k,st}) + \gamma_t + \varepsilon_{st}, \tag{1}$$

where $grad\_debt\_mdn\_w_{st}$ is the weighted median loan balance among completers in state s and year t, $z(\cdot)$ denotes standardization, and γ_t captures year effects. The predictors $X_{k,st}$ are:

X_1: *state_pell_share*	X_8: *median_hh_income_real*
X_2: *state_net_price*	X_9: *pct_ba_plus*
X_3: *pct_male*	X_{10}: *pct_poverty_lt100*
X_4: *pct_black*	X_{11}: *sector_private_np_share*
X_5: *pct_hispanic*	X_{12}: *sector_forprofit_share*
X_6: *pct_white*	X_{13}: *pct_25_34*
X_7: *pct_asian*	X_{14}: *fafsa_apps_total*

Diagnostics For each specification, residual-versus-fitted plots were inspected for linearity and homoskedasticity; Q–Q plots were used to assess approximate normality; Variance Inflation Factors were computed to check for multicollinearity; and Cook's distance was examined to detect influential observations. Relative to the full-sample model, Model 3 shows reduced heteroskedasticity and fewer extreme influence points, while maintaining strong overall fit (Adjusted $R^2 \approx 0.899$).

Results In Model 3, several standardized coefficients are large and statistically significant. State net price is the strongest positive predictor: a one-SD increase in net price is associated with roughly \$2,000 higher median debt, holding other factors constant. Pell Grant share exhibits a robust negative association, with a one-SD increase linked to a reduction of approximately \$560 in median debt. FAFSA application volume has a positive, marginally significant association with debt.

Demographic covariates also contribute: states with higher Hispanic shares tend to have lower debt, while those with higher White shares have higher debt, conditional on cost and income; Black and Asian shares have smaller, more mixed effects. Higher median household income is associated with lower debt, and a larger private non-profit sector share is associated with higher debt relative to public institutions.

To assess heterogeneity in these effects, the baseline specification was extended with single interaction terms: Pell × NetPrice (Model 4), Pell × %Black (Model 5), Pell × %Hispanic (Model 6), Pell × FAFSA (Model 7), NetPrice × FAFSA (Model 8), NetPrice × %Black (Model 9), NetPrice × %Hispanic (Model 10).

Model comparison using Adjusted R^2, AIC, BIC, and nested ANOVA indicates that the cost–race interactions provide the most substantive improvements over the baseline. In particular, the Net Price × Hispanic Share specification (Model 10) achieves the best overall fit (Adjusted $R^2 \approx 0.901$) and represents a statistically significant improvement over Model 3 (ANOVA $p \approx 0.002$). The Net Price × Black Share specification (Model 9) also improves model fit, though more modestly (ANOVA $p \approx 0.023$), reinforcing the conclusion that allowing the net-price effect to vary with racial composition yields meaningful gains in explanatory power.

These patterns are summarized in the coefficient plot in Figure 3. The coefficient plot comparing the baseline model (Model 3) with the interaction models (Models 6, 9, and 10) shows that the core financial drivers are highly stable, while the cost effect is clearly race-dependent. Across all specifications, net price remains the largest positive predictor (on the order of \$2,000 per standard deviation) and Pell share remains a sizable negative predictor (roughly $600 per standard deviation in the opposite direction), confirming that higher costs increase debt and greater aid intensity reduces it. When the Net Price × % Hispanic interaction is added in Model 10, the main-effect coefficient on net price decreases from about $2,037 to $1,880, indicating that the impact of higher prices on debt is attenuated in states with larger Hispanic populations. At the same time, the main effects for % Black (positive) and % Hispanic (negative) remain directionally distinct and statistically relevant. Taken together, these patterns make Model 10 the most informative specification: median student debt is strongly driven by cost, but the magnitude of that relationship is systematically conditioned by state racial composition, especially the Hispanic share.

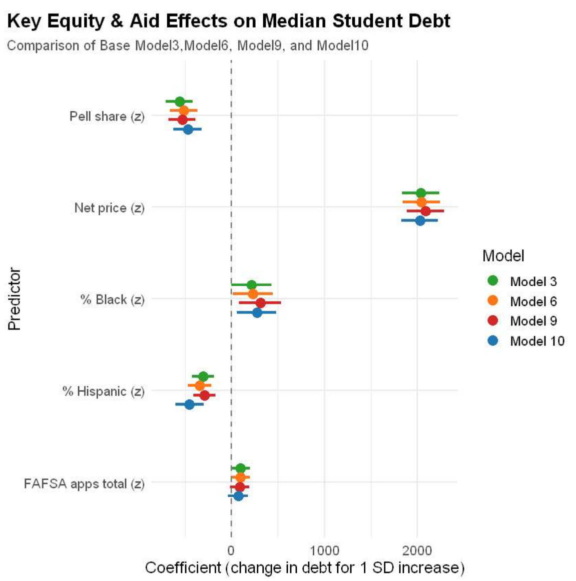

Figure 3: *Approach 4: Cross-Model Coefficient Comparison*

Discussion Taken together, the models indicate that cost and aid intensity are the primary drivers of state-level student debt, with net price exerting a strong positive effect and Pell share acting as a protective factor. These relationships are highly stable across alternative specifications, suggesting that the core associations are robust to the treatment of influential observations and to the inclusion of interaction terms. The interaction results reveal that the effect of net price is not homogeneous across states: the marginal impact of higher net price is attenuated in states with larger Hispanic populations and shows moderate heterogeneity with respect to Black population share. Demographic main effects remain substantively relevant even after controlling for cost, income, and sector mix, indicating that population composition shapes both baseline debt levels and the sensitivity of debt to price. Overall, the evidence suggests that student debt burdens are generated by the joint influence of cost, aid, and demographic structure rather than by financial variables alone.

The demographic-aid model completes the set of structural drivers. The Conclusion integrates results from all four approaches.

Explanation of Changes

Approach 1: Socioeconomic and Price Determinants. The final Approach 1 specification differs from the original analysis plan based on empirical results from the cleaned dataset. Percent BA attainment (pct_ba_plus) was moved into the core model after demonstrating consistent significance and direct relevance to affordability. Variables such as FAFSA volumes, enrollment counts, sticker-price tuition, and sector shares were removed because they introduced noise or redundancy without improving explanatory structure. HC3 robust standard errors were incorporated after initial diagnostics indicated heterogeneous variance across states and years. The partial regression plot for net price was retained as the primary visualization because it directly illustrates the adjusted effect of the key affordability variable. Other diagnostics were performed during analysis but are omitted here to maintain consistency with the scope and structure used in the other approaches.

Approach 2: Institutional Pricing and Structural Factors. One of the datasets we had planned to use in the Analysis Plan (Federal Student Aid Portfolio) ended up not having a viable path to join with the other data. As a result, we selected another dataset from the Free Application for Federal Student Aid, and aggregated it into state/year data. This changed some of the variables we had access to with the regression analysis, but the majority level of institutional level factors came from the College Scorecard dataset.

Approach 3: College Majors and Local Employment Factor. The final analysis deviated from the preliminary analysis plan regarding independent variables. The original plan included Median Household Income and Poverty Rate as socioeconomic controls. However, the stepwise regression procedure removed these variables, likely due to their correlation with general economic health indicators; the Unemployment Rate provided sufficient signal regarding the local economic environment without redundancy. Additionally, while the plan discussed potential noise in measuring STEM shares, the model successfully utilized the aggregated `state_stem_share` variable without significant noise, identifying it as the most potent positive predictor in the model.

Approach 4: Equity, Aid, and Demographic Composition. Several adjustments were made relative to the original analysis plan. First, although a log transformation of median debt was initially proposed, Box–Cox analysis yielded $\lambda \approx 0.78$, close to linear; modeling the outcome on the original dollar scale was therefore preferred for interpretability with little loss of fit. Second, planned inclusion of federal portfolio variables (such as income-driven repayment participation) was not feasible due to inconsistent merging at the state–year level; FAFSA application volume was adopted instead as a proxy for aid demand. Third, demographic controls were expanded to include additional race and gender categories in order to avoid treating any group as an implicit residual. Fourth, detection of NH, WV, and WY as influential states motivated the development of Models 2 and 3; Model 3 was ultimately selected as the baseline because it balanced robustness with sample retention. Finally, empirical results indicated that cost–race interactions were more informative than the initially emphasized Pell-centric interactions, leading to a focus on Models 6, 9, and 10 in the final comparison.

Conclusions

Our analysis demonstrates the varied factors impacting student loan debt; no one single factor can be said to be the primary driver of increased debt at graduation. Rather, a multitude of factors that span across social, demographic, and institutional dimensions affect student loan debt. Some of these include cost, institutional structure, academic program mix, demographics, and aid environments.

Across all four approaches, some consistent findings were that higher net price and lower real household income consistently predict higher median debt. States that steer students into more expensive STEM programs, rely heavily on private nonprofit institutions, or charge high net prices without sufficient aid tend to generate the highest debt burdens. Demographic composition also affects debt outcomes; even after controlling for cost and income, states with larger White shares typically show higher debt, while those with larger Hispanic shares show lower debt and a weaker marginal effect of price. These patterns suggest that student debt is a complex outcome of the socioeconomic and education landscape, impacted heavily by how states finance higher education, who their institutions serve, and what kinds of degrees students pursue.

Successes Among the four methods, the equity–aid–demography framework in Approach 4 yielded the strongest overall performance. Explaining around 90% of the variance in the response variable, Approach 4 utilized demographic data and impactful interaction terms (such as between Net Price and Hispanic Share). This resulted in slightly improved fit while preserving interpretability. This method was perhaps the most successful because it utilized the key cost variables that Approaches 1-3 found to be significant (net price, income, sector mix, STEM concentration), but also modeled how financial aid and racial composition modified their effects. It showed that the debt impact of a given price level is smaller in states with higher Pell Grant coverage and larger Hispanic populations, and larger in states with higher White shares and a greater private-nonprofit presence. This highlights the complex interaction between public and private money in education, and how different states can respond differently to the same amount of aid. This finding could pave the way for policy decisions and further studies that analyze how to allocate aid where it will be most impactful, and how to improve its efficacy in states where outcomes are less significant for the same level of aid.

The other approaches arrive at and support many of the same conclusions as Approach 4. Approach 1 established that net price and income alone form a robust affordability baseline around which to structure analysis, even adjusting for demographics and time effects. Approach 2 demonstrated that institutional sector mix (public vs. private vs. for-profit) adds substantial explanatory power and that STEM-heavy educational landscapes tend to result in higher debt. Approach 3 showed that academic specialization and labor-market conditions meaningfully shape borrowing, with high STEM shares and smaller public sectors associated with higher debt. Together, these methods lend support to each other's findings and show that the most successful modeling strategy is one that layers cost, institutional, education, and demographic factors into a single integrated framework.

Limitations

Several limitations exist, primarily pertaining to the datasets used. Due to dataset mismatches regarding granularity and for efficient joining, the data primarily consisted of aggregated data at the temporal/spatial resolution of per state and per year. While this allows for analysis of broad patterns across higher education in the United States, it necessarily prevents analysis of within-state or even within-institution factors that could have significant impacts on student debt outcomes. Factors at the individual level also must be ignored; while median household income per state was an effective predictor, it also hides patterns that could exist due to aggregation. A state's distribution of income, income inequality, geographic distribution of income; all of these are factors that could heavily affect student loan debt outcomes which cannot be modeled with aggregated data.

Another limitation pertains to the response variable being median debt at graduation, which does not capture the total impact of student loan. For one, this approach omits students who did not graduate but still must repay loans, which could constitute a significant portion of the student population. Indeed, due to lack of completion, these students could very well face significantly poorer financial outcomes compared to those students that were captured within the study, and will necessarily interact with the student aid landscape differently.

Additionally, this approach and does not capture repayment trajectories, as the total sum of debt at graduation only reflects a snapshot in time of a factor that could impact students' lives for years or even decades. Longitudinal studies would likely be required to assess the impact of student loan debt outcomes over the course of the full repayment.

Finally, the relationship between private aid and scholarships cannot be captured by this study, despite these making up a significant part of the aid landscape. Data collection will necessarily be more difficult, as private aid is by nature not centralized. We used proxies for student aid (such as FAFSA application volume) that are imperfect measures and do not capture the fine details of the aid landscape.

Next Steps and Future Work

Future work could address these limitations in several ways. A natural next step is to utilize broader and more fine-resolution datasets to evaluate student debt outcomes at the sub-state or institutional level, perhaps using individual-level data to capture the finer nuances.

Another avenue to build on this work is through analysis of a longitudinal study that tracked how student loan repayment affected students over time, which would allow us to have a better picture of the true outcomes of student loans. Experimental design could be utilized for causal inference, which could be much more easily used to guide policy-making decisions for both educational institutions and state or federal student aid. Finally, extending our framework to simulate policy scenarios (e.g., increasing Pell generosity, expanding public-sector capacity, or capping net price growth) would provide concrete guidance to states and institutions seeking to reduce debt burdens while preserving access.