Research Article

Economic Drivers and Impacts of Interstate Migration: The California to Texas Exodus

David Qian

St. John's School, 2401 Claremont Lane, Houston, TX 77019, United States

ABSTRACT

This paper examines the economic determinants behind the recently observed migration flow from California to Texas. This paper is motivated by the recent rapid increase in migration from California to Texas, a trend that has sparked significant debate among politicians and media members and raised questions about the underlying economic factors driving this shift. While interstate migration has been broadly studied, few analyses have focused specifically on the recent California-to-Texas migration flow. By analyzing key economic indicators between 2010 and 2020, including outflow migration, unemployment, housing costs, crime rates, median household income, and labor participation—this study employs data on these factors in a two-way fixed effects regression model to uncover the factors that drive relocation decisions. Notably, the findings of the model suggest that median household income is a critical predictor, with higher income levels associated with a reduction in outflow migration, while other variables, such as housing costs and unemployment, exhibited limited statistical significance as predictors in the model. The results highlight the differences in economic environments in California and Texas in issues like housing affordability and income disparities. Limitations of the study include a relatively small dataset and potential model misspecification, suggesting the need for further research incorporating additional variables and possibly a more specialized model.

Keywords: Interstate Migration; Financial Security; California; Texas; Migration Indicators

INTRODUCTION

Relocation is an important economic decision. This decision can be based on several reasons, including income differentials, job opportunities, cost of living, and the environment. Literature is abundant on these reasons, analyzing how each factor influences one's migration decisions.

Although overall interstate migration in the U.S. has declined in recent years, migration from California to Texas has remained high, with the 102,000 movers making it the most significant state-to-state migration flow in 2022 (5). California's climate and cultural amenities are often cited as a strong attraction, with good weather year-round, big cities, tourist attractions, and a strong, diverse culture. However, California is experiencing high levels of net outmigration, while Texas, a state with extremely hot weather and a more average environment, is experiencing

Corresponding author: David Qian, E-mail: davidyqian@gmail.com.

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the opposite.

Some political analysts attribute this trend to California's regulatory environment that California's policies, most of which are out of the scope of this paper, are to blame. This paper will not examine the political differences, but rather the economic differences that may or may not result from differing policies.

While many may see this as a political talking point, this issue's relevance runs deeper. Today, migration is low, and with new phenomena such as super-commuters appearing in our new digital age (1). Migration in the US has always been an indicator of economic success. At the same time, this issue concerns what factors matter more to individuals considering migration, environment, or economy. This paper focuses specifically on economic trends, such as income, housing, and employment, to assess their role in recent migration flows. This study sets out to understand what economic factors have caused this recent wave of migration from California to Texas. Thus, this paper hypothesizes that median household income, crime rates, housing prices, and unemployment rates are primary drivers of migration from California to Texas.

LITERATURE REVIEW

Interstate migration has been a longstanding focus of economic research, given its impact on regional labor markets and economic growth. Many studies have examined which dynamics motivate migration, including financial, geographic, and political factors. This paper synthesizes prior research on interstate migration theory with data gathered by various government agencies to address the specific case of migration flows from California to Texas in recent years. Several prominent studies have explored interstate migration's causes, highlighting both economic and non-economic factors.

Bayer and Juessen (1) developed a dynamic structural model to analyze migration decisions based on costs. The study estimates that the cost of migrating between U.S. states is approximately two-thirds of the average household's annual income. Their study addresses the endogeneity of location choice by measuring expected income changes over time. It also accounts for income persistence using an auto-regressive model and demonstrates that ignoring it can lead to biased estimates of migration costs. Although such a sophisticated model provides a detailed explanation for the cost-based decisions behind migration, it focuses on aggregate migration patterns from throughout the country rather than specific state-to-state migration flows, such as the one this paper will focus on, in particular between California and Texas.

Cebula and Alexander (3) focused on factors influencing state migration rates during the early 2000s. By using regression analysis, they found that higher median family income, employment rates, and warmer climates encourage in-migration, while high costs of living, pollution, and high state income taxes deter migration. The study's findings reveal key factors causing the migration from California to Texas.

Bright and Thomas (2) build on Stouffer's theory of intervening opportunities, which hypothesizes that migration is influenced by the availability of opportunities rather than the distance to the destination. They found that people are more likely to migrate if fewer intervening opportunities exist. While the paper provides essential theory, it is outdated and would benefit from re-evaluation using modern data to assess its relevance to contemporary trends.

Kaplan and Schulhofer-Wohl (4) analyze the decline in U.S. interstate migration between 1991 and 2011. They attribute this trend to, reduced geographic specificity of jobs and greater access to information. They argue that these factors cause income to become more uniform across regions and knowledge of new places to become easily accessible, thus decreasing the desire for migration. While the study provides a theory on the reasons behind long-term national migration trends, it does not focus on recent data and specific cases such as California and Texas, which will be discussed in this paper.

The existing literature uses models and data analysis to analyze the theory behind patterns and observations of migration patterns. They provide statistics to back up reasons positively and negatively correlated with in-migration. However, few studies have explicitly focused on migration from California to Texas, a high-volume state-to-state migration flow that remains underexplored in recent empirical research. Unlike previous research, this paper analyzes recent government data and focuses on migration from California to Texas. Focusing on a specific migration flow, the study addresses a gap in the literature: the lack of studies on high-volume state-to-state migration routes in modern America.

While most existing literature uses complex models such as Bayer and Juessen (1), who use a dynamic structural model, this study takes a simpler approach using recent migration data from government sources accessible online. Similarly, while Kaplan and Schulhofer-Wohl (4) utilize calibrated models to explain declining migration trends, this paper will use existing theory to define specific data trends in the California-to-Texas migration flow.

These sources provide essential background knowledge about how migration tends to be motivated at a national level. These sources also show how the existing literature is focused on national levels of migration flow, while this paper specifically examines migration patterns between California and Texas.

METHODS AND MATERIALS

This study examines the economic and social factors influencing migration patterns between California and Texas from 2010 to 2020. Data on housing prices, crime rates, median household incomes, and more were collected from publicly available sources to analyze these trends. The data was processed, visualized, and compared to identify patterns and potential correlations with net migration.

First, data was collected from government sources, various Fed locations, Texas and California comptrollers, Zillow, the Census Bureau, and the Bureau of Labor Statistics. The data included net migration between California and Texas, economic indicators such as unemployment rates, median household income, job growth rates, GDP per capita, housing costs, consumer price index (CPI), state tax rates, crime rates, education rankings, wage growth, and labor force participation. This data was collected only between 2010 and 2020 due to inconsistencies following the COVID-19 pandemic. Even after narrowing the time frame down, some data was still missing. Missing values were imputed using a three-year moving average to reduce temporal noise and maintain continuity. This was most notably used for crime levels in 2010 and net migration in 2020.

After collecting data, the statistics of the independent variables were narrowed down based on their usefulness. Statistics like CPI and GDP per capita were excluded because data was only available for large metropolitan areas and not for the whole state, while statistics like tax rates were excluded because of the nature of the variable. Strong economic indicators like unemployment, housing price index (HPI), crime rates (crimes per 100k), median household income, and labor participation at the state level were plotted in Figure 1 as a correlation matrix. As shown by the matrix, housing costs and labor participation exhibit a high correlation, which may introduce multicollinearity into the model. To preserve predictor reliability, labor participation was excluded. Labor participation and unemployment also seem to be redundant, so labor participation was excluded from the model.

After determining the variables to be used in the model (predictors: unemployment, housing price index (HPI), crime rates (crimes per 100k), median household income, and response variable: net migration between the two states), the model was implemented in Python using the linearmodels package, enabling estimation of fixed effects while also controlling for unobserved heterogeneity. We apply the following two-way fixed effects model to understand the relationships between the predictors and the response variable.

Equation 1: Dual Panel Regression Model Equation

$$Y_{it} = \beta_1 X_{1,it} + \beta_2 X_{2,it} + \beta_3 X_{3,it} + \beta_4 X_{4,it} + \alpha_i + \tau_t + \epsilon_{it}$$

where Y_{it} is net migration from state i to the other state at year t, representing the net outflow from California to Texas (where a positive number represents a net outflow from California to Texas), the X_{it}'s are the different independent variables (i.e., unemployment, housing price index, crime rates, median household income), α_i is the entity fixed effect, τ_t is the year fixed effect; ϵ_{it} is the error term assumed to be normally distributed with mean 0 and variance σ^2. We chose to apply a two-way fixed effects model rather than a simple linear regression because the two-way fixed effects model accounts for both unobserved, time-invariant state-level characteristics (α_i) and year-

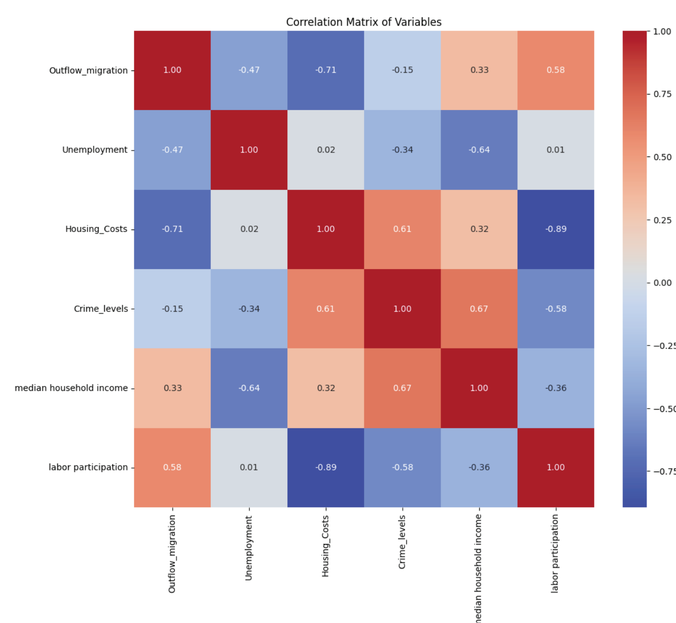

Figure 1. Correlation Matrix.

specific variations (τ_t) that could bias our estimates. In this model, the "entity" refers to each state, California and Texas. The α_i term accounts for factors unique to each entity (e.g., baseline differences in geography), while τ_t captures macroeconomic events or national trends affecting all states in a given year. This model ensures that the relationships observed between independent variables and migration are not biased by these persistent or cyclical influences. For example, the COVID-19 Pandemic or the housing crisis could cause such state or time-level effects.

RESULTS

We report the summary statistics for California in Table 1. The data for California shows moderate variability across several indicators. Outflow migration between California and Texas has a mean of approximately 38,544, with a standard deviation of about 2,914, indicating that while migration figures vary from year to year (ranging between 32,290 and 43,005), the fluctuations remain relatively similar. The unemployment rate shows a mean of 7.88% with a standard deviation of 3.10, suggesting that some years experienced significant job market fluctuations, with rates oscillating from a low of 4.10% to a high of 12.50%. Housing costs are notably high, averaging an HPI of 523.63, and the standard deviation of 109.87 reflects considerable variation in the housing market, with values spanning from 387.38 to 683.16. In contrast, crime levels remain more stable with a mean of 427.17 and a low standard deviation of 20.14, while median household income has a mean of $64,775 and a standard deviation of $8,622, highlighting moderate income disparities across regions. Labor participation is the most consistent indicator, with a mean of 62.57% and a very narrow standard deviation of 0.89, showing the stability of workforce engagement in California through the decade.

We report the summary statistics for Texas in Table 2. Texas shows greater variation in migration figures and unemployment, while metrics such as crime and labor participation remain more stable. The mean outflow migration is substantially higher at approximately 69,185, with a standard deviation of 8,437, indicating a broader spread in migration (from 58,992 to 86,164) compared to California. The unemployment rate is lower, with a mean of 5.73% and a standard deviation of 1.72, which suggests a more consistent employment environment with rates ranging between 3.50% and 8.19%. Housing costs in Texas are considerably more affordable, with a mean HPI of 274.97 and a standard deviation of 50.59, reflecting less dramatic fluctuations (values from 219.18 to 355.97) than seen in California. Crime levels average 418.98 crimes per 100k with a standard deviation of 13.98, signaling relatively minor variability in public safety. Median household income is recorded at a mean of $68,045 with a standard deviation of\$5,414, indicating less income

Table 1. Summary Statistics for California

	State to State Outflow migration	Unemployment	Housing Costs	Crime levels	Median household income	Labor participation
mean	38544.273	7.878	523.627	427.173	64774.545	62.572
std	2914.399	3.104	109.874	20.140	8621.695	0.887
min	32290.000	4.100	387.375	396.400	53370.000	60.908
max	43005.000	12.500	683.162	453.300	78110.000	64.375

Table 2. Summary Statistics for Texas

	State to State Outflow migration	Unemployment	Housing Costs	Crime levels	Median household income	Labor participation
mean	69185.364	5.727	274.973	418.980	68045.455	64.511
std	8437.459	1.720	50.588	13.983	5413.935	1.001
min	58992.000	3.500	219.180	406.700	61680.000	62.975
max	86164.000	8.192	355.968	446.500	77110.000	66.025

disparity across the state, and labor participation shows a stable mean of 64.51% with a standard deviation of 1.00, further emphasizing the consistency in Texas's workforce engagement through the decade.

Figure 2 compares Texas and California's Housing Price Index (HPI) from 2010 to 2020. Both states show an upward trend in housing prices, but California's is consistently higher than Texas's. In 2010, California's HPI began above 400, while Texas's HPI was slightly above 200. Both California and Texas see a gradual increase in HPI throughout the decade. However, California demonstrates a higher average rate of increase, causing the gap between the two states to widen over time, with California surpassing 600 by 2020, while Texas remains at around 300. This could be a result of the housing market in California's high demand, stricter zoning laws, and a supply shortage, leading to more significant price increases. With more available land and fewer restrictions, Texas experiences a steadier and more moderate rise in housing costs. Rapidly rising housing costs in California could indicate affordability challenges for residents, while Texas's slower rise suggests a more stable and accessible housing market.

In Figure 3, the median household income in Texas and California between 2010 to 2020. Both states exhibit a general increase in median household income over time. Texas initially had a higher median household income than California, but by 2020, the two states converged at nearly the same income level. This could be due to increasingly advanced information spreading technology homogenizing opportunities across the country (2). In 2010, Texas began with a median income above $60,000, while California is slightly lower, around $55,000. By 2020, both states reached approximately $80,000, indicating significant income growth over the decade. California's steady increase could be due to economic growth in high-income industries such as technology and entertainment. Texas's fluctuations might be influenced by variations in energy sector performance and other economic factors. The increase in median household income is a positive economic indicator, suggesting improved financial well-being in both states. However, considering the earlier housing price index graph, the rising income in California may not necessarily translate to greater affordability, given the higher cost of living. Also, the lack of a state income tax in Texas compared to a steep income tax in California means that the converging median household income can be misleading.

Figure 4 demonstrates the migration from California to Texas in blue and from Texas to California in red. Migration from California to Texas seems to be about two times higher than the other way around, resulting

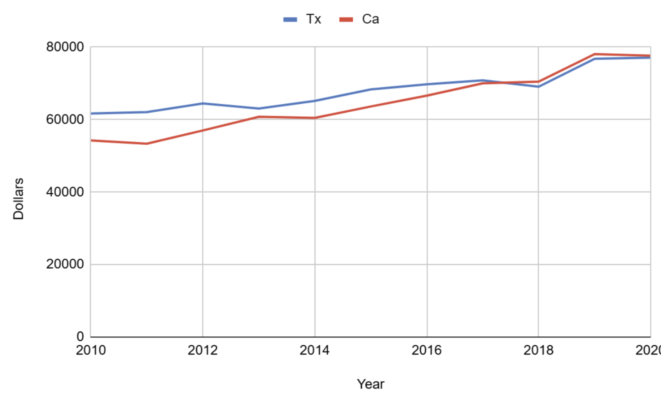

Figure 3. Median Household Income Trends between California and Texas (Dollars).

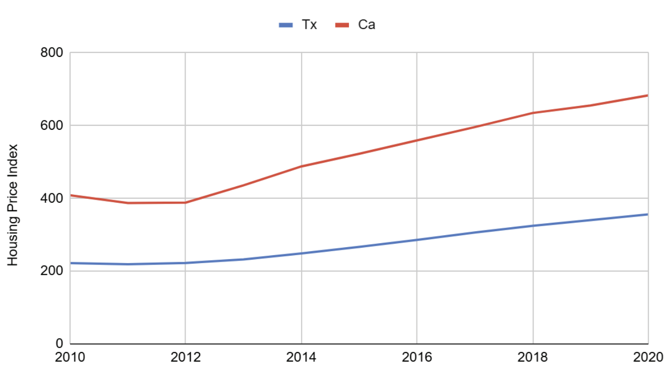

Figure 2. Housing Cost Trends between California and Texas (HPI).

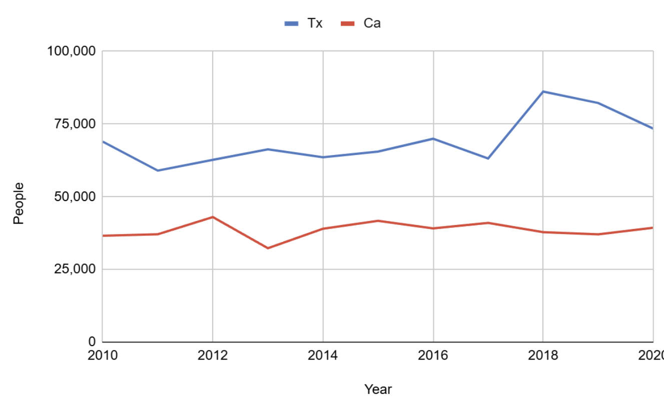

Figure 4. Migration Trends between California and Texas (Number of Migrants Entering from the Other State).

in a net inflow of migrants to Texas and a net outflow of migrants from California over the decade. The migration trend is primarily stable until 2017, with a sharp increase in California-to-Texas migration, which peaked at around 85,000 in 2018. The causes for this trend are this paper's primary topic of discussion. This could be linked to higher costs of living in California, increasing job opportunities in Texas with large companies like Tesla moving there, lack of income tax in Texas, less regulation on businesses in Texas, or overall differences in the environment.

Figure 5 demonstrates the crime rate per 100,000 people in Texas and California between 2010 to 2020. Crime rates in both states fluctuate between 400 and 450 crimes per 100,000 people over the decade. From 2010 to 2020 both states experienced a slight increase in crime, although California's crime rate has been slightly higher for most of the decade. Fluctuations could be due to changes in law enforcement policies, economic conditions, or social factors affecting crime rates. The rise in crime rates after 2015 may be linked to broader national trends in large cities. The closely aligned crime rate between the two states could indicate that the crime rate is not a key factor in driving interstate migration in the case of California and Texas.

The resulting linear regression model is very informative, with coefficients and P-values shown in Table 3 but Model diagnostics reveal signs of potential misspecification, notably negative R-squared values and heteroskedastic residuals, which limit interpretability. The model shows outflow migration as the dependent variable, and uses two-way fixed effects with entity and time effects included, with 2 entities (CA and TX) observed over 11 time periods (22 total observations).

The first aspect that must be addressed is model fit.

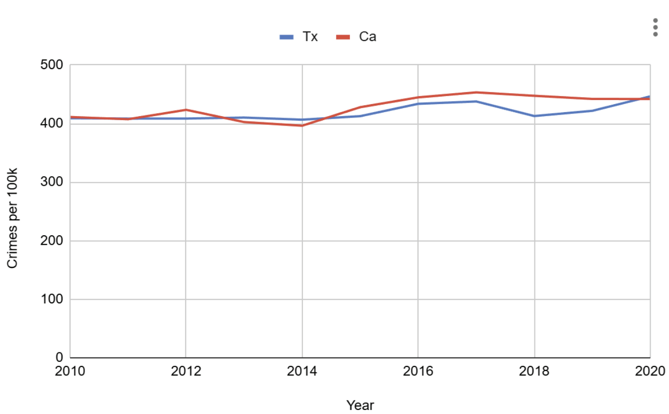

Figure 5. Crime Trends between California and Texas (Crimes per 100,000 Residents).

The overall R-squared is -2.03, indicating the model performs worse than a simple intercept-only model for "overall" variation. This is unusual and suggests potential misspecification or that predictors explain less variance than noise. The R-squared (Within) is -11.09 (Negative), implying poor fit for within-entity variation, most notably changes over time within the same state. Finally, the R-squared (Between) -0.63, shows a poor fit for between-entity variation. However, a strong F-statistic of 5.43 (p=0.034), which is significant at the 5% level, suggests the model, when accounting for heteroskedasticity, still has some explanatory power. The model successfully explains a meaningful part of the relationship between variables, and the results are unlikely to be due to random chance. The negative R-squared could be due to a variety of reasons. It is possible that key variables were not accounted for and that more data is needed due to the small dataset. For example, the model could be improved by incorporating variables such as education quality (e.g., high school graduation rates or average test scores), cost of living indices (to adjust for real income differences), state-level welfare benefit levels (to understand social support differences), or environmental indicators (such as pollution or natural disaster frequency). These omitted factors may have a significant impact on migration decisions, especially for families, low-income groups, or retirees. Incorporating these variables in future analyses could improve accuracy and provide a more comprehensive understanding of migration drivers.

DISCUSSION

Of the four coefficients, Median Household Income demonstrates a statistically significant negative effect (-3.16, p=0.007), meaning that holding other variables constant, a 1-unit increase in income is associated with a 3.16-unit decrease in outflow migration from California to Texas. However, given the negative R^2 values, small sample size, and possible omitted variables, this finding should be interpreted as exploratory. Further research with

Table 3. Coefficients and P-values from Two-Way Fixed Effects Regression

	Coefficient (β)	**P-value**
Housing Costs	32.106	0.618
Crime Levels	-248.740	0.244
Median Household Income	-3.160	0.007
Unemployment	-3602.700	0.366

broader datasets and additional predictors is needed before drawing firm causal conclusions. The other independent variables, Unemployment, Housing Costs, and Crime Levels, have statistically insignificant p-values (p>0.05), thus showing no statistically meaningful relationship with migration.

The key takeaway from this model is the negative R-squared values, which are highly unusual. This could indicate that the model is misspecified or that fixed effects absorb too much variation, especially because there are only entities. Only using 2 entities over 11 years limits generalizability and increases sensitivity to outliers. Results should be interpreted cautiously due to the limited sample size and potential omitted variable bias. Results should be validated with further data across a wider range of variables.

However, another key finding from this model is that median household income is still a driver of migration. We can see from the data that Texas experienced an inflow of migrants from California throughout the decade. From our model, median household income is the statistically significant factor in this dataset, with a 1-unit increase in income being associated with a 3.16 unit decrease in outflow migration from California to Texas. Income appears to be associated with migration patterns in this dataset, though the relationship should be interpreted with caution. First, higher income may reflect "aspirational migration. High-income households have more resources at their disposal for an interstate move. Migration often requires heavy costs (transportation, housing deposits, job search), which wealthier individuals can afford more easily. Also, this could be reflected further in accounted-for variables, especially environmental or child-related reasons. Parents' most significant motivator is often their children, so a family with a high income may be more able to make a move for their children's sake, often for schooling. Median household income may capture some of this effect, but this only reveals a hole in our model. Due to unreliable school ranking data, we were unable to incorporate these statistics into our model, although school ranking may have provided an interesting correlation with migration, especially in high-income families with children.

On the other hand, Unemployment is an unreliable predictor of migration. Unemployment rates might not reflect job quality, low unemployment could mean low wages or unstable jobs. Also, unemployed individuals might lack the financial means to move, leading to "trapped populations." For example, California's large homeless population may lack the financial resources to move to Texas. Homeless and unemployed people also receive more welfare benefits in California. These factors lead to a "snowball effect" of unemployment where more and more unemployed people are incentivized to stay rather than move to high-employment areas. Unemployment is only a measure of employment as a percentage, so some regions with low unemployment might still lack upward mobility or have a shrinking labor force, for example, aging populations, or limited high-skill industries. However, median household income is a more complete predictor, with places with higher median incomes often having dynamic, growing economies that attract skilled migrants. A pertinent example is the growing industry in Austin, Texas. Large tech companies like Tesla have moved from California to Austin in recent years, reflecting this migration trend. While unemployment is a crucial economic indicator, Median household income may be a more consistent correlate of migration in this dataset because it reflects overall economic opportunity and quality of life rather than just job availability.

The relationship between income, education, and stability likely creates a more comprehensive pull for migrants than unemployment alone. Still, though, within this model, the whole story is not told. In future analysis, it would be pertinent to include variables like education (high median income often correlates with a more educated workforce), cost of living (high cost of living deters lower-income migrants), social networks (migrants often follow established communities or trends), or environment (migrants often seek better environmental conditions like weather).

From the residual plot, ideally, all points should be scattered randomly around the red line at zero. In the plot for our model, Figure 6, the residuals do not follow any clear pattern, however, the results seem more dispersed at

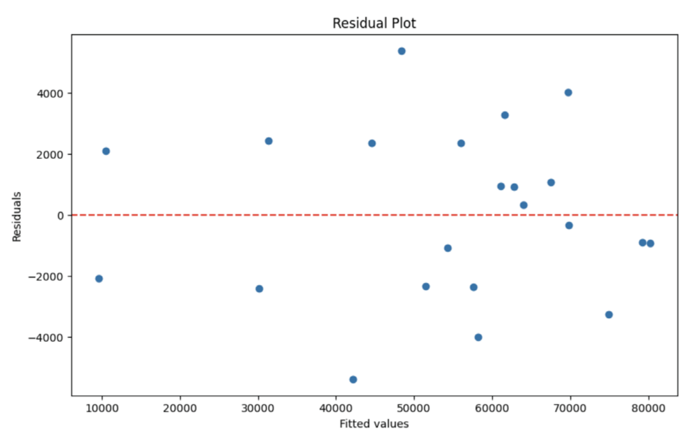

Figure 6. Residual Plot.

higher fitted values. Ideally, a residual plot should exhibit homoskedasticity and constant variance across fitted values, but we can see this is not the case. The spread increases as fitted values increase, suggesting heteroskedasticity in our dataset. This means the variability in residuals might depend on the level of fitted values, which can affect standard error estimates. The lack of an apparent curve in the residual plot suggests that the relationship between predictors and the outcome is roughly linear. However, the spread at higher fitted values might indicate that nonlinear relationships must be explored further. We can also see a few residuals significantly over 4000 or -4000. These points may indicate potential outliers or leverage points influencing the model. These facts indicate potential missing predictors or an inappropriate functional form. In addition to the negative R-squared, this suggests that the model does not explain much of the variance in migration. Future research may consider adding additional predictors or trying a different modeling approach.

CONCLUSION

This paper explored the forces behind the recently noticed migration flow from California to Texas. It aims to fill a gap in the literature by focusing on this specific state-to-state dynamic rather than broader, past trends. By leveraging a range of economic indicators, such as median household income, housing costs, unemployment rates, and crime levels, the analysis sought to determine which factors most strongly influence migration decisions.

Median household income was the only factor to reach statistical significance in this dataset, though the limited model fit and sample size mean this should be mostly treated as an exploratory result without further study. The negative relationship between income and outflow migration suggests that higher household income correlates with reduced migration pressure, possibly reflecting the greater capacity for affluent households to absorb relocation costs or the pull of localized economic opportunities. In contrast, variables such as unemployment, housing costs, and crime levels did not demonstrate statistically significant impacts in this model.

From a policy perspective, these results, if confirmed in future research, suggest that addressing economic disparities, particularly in income and associated opportunities, could be central to managing interstate migration flows. Future state-level policy efforts may focus on improving income mobility and affordability in high-cost states to slow outbound migration. Encouraging the opening or relocation of companies and businesses into states and promoting high-paying jobs and competition could help to achieve this. Governments could also reduce regulation in business and home sectors and increase competition to encourage higher wages and economic dynamism, while addressing the affordability challenges that drive residents away.

However, there are several limitations and constraints to these conclusions. The small dataset and limited available data to be collected, limited to two states over only a decade for a relatively new phenomenon, and the resulting negative R-squared values hint at potential model misspecification or omitted variable bias. These issues underscore the need for more robust data and the inclusion of additional factors, such as education quality, cost of living, and social networks, in future analyses.

Overall, this paper contributes to understanding the economic drivers behind recent migration from California to Texas. This also paper contributes to the literature by applying a two-way fixed effects model to a specific, high-profile migration stream, using recent data. Future research should expand the dataset and explore alternative modeling approaches, including more advanced methods to better capture the complex nature of migration decisions in a rapidly changing economic landscape.

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DECLARATION OF CONFLICT OF INTERESTS

The author declares that there are no conflicts of interest regarding the publication of this article.

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