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Place-Based Prosperity or Poverty? Investigating Economic Well-being in California

**Introduction**

California has continued to strengthen as an economic powerhouse for the United States. Silicon Valley leads the world in technological advancements, spurring new innovations annually and generating over $275 billion in economic output, greater than the output of Finland (Bureau of Economic Analysis), along with California's Agricultural exports being 12.1% of total U.S. agricultural exports in 2021, and over 75% of the country's fruits and nuts being grown in California (California Department of Food and Agriculture); it is evident that California has some of the strongest economic industries in the country and even in the world.

However, with this trend of expansive and accelerated economic growth, there is an increasing inequality of regions in California experiencing this growth. According to a report by California 100, there is a drastic difference in the jobs and wages available in California, with coastal metropolitan areas having a higher concentration of high-wage jobs, and the inland empire with low-wage jobs (Brady et al.). This affects quality of living and income, with personal income in the Inland Empire being two-thirds less per capita than Orange County (Emmerson et al.). Thus, this paper aims to explore regional economic disparities in California,

specifically: how does land development contribute to labor opportunity in California? And how does labor opportunity affect income inequality in California?

With this framework, I aim to explore the relationship between labor market opportunity (measured by economic growth) and income inequality. In spite of California experiencing strong economic growth, it experiences equally high levels of income inequality. Thus, conducting a regression analysis of economic growth on income inequality, with a scatter plot to determine the correlation between the two would be useful to not only understand the layered meaning of economic 'well-being' but also for policymakers to be aware of when establishing initiatives to promote sustainable regional economic development.

**Significance of this Issue**

If California were a country, it would be the fifth largest economy in the world. In 2022, California's GDP was $3.6 trillion dollars - making 14.6% of total U.S GDP (Hughes). With such a productive economy, it is important to examine the geographic and labor landscape of different regions in the state to see which regions are contributing to the state's GDP the most.

Not only is California economically diverse, the level of land development, specifically farmland being converted to urban use varies drastically across this state. This is an important facet to consider while policymakers continue to introduce initiatives that promote regional economic development, as the level of urban industrialized land varies county by county and this inhibits the type of job available in certain regions over others, and the industry composition is controlled by the level of land development in an area.

Another facet to consider is that while California has experienced tremendous economic growth, it has also experienced an imbalance in its type of job growth. Since 1979, California has seen an increase in the number of jobs available by 174% (California 100), however this increase

pertains to creating more ‘high-quality’ jobs, which are jobs with higher wages stemming from the technology industry or technology-adjacent industries. With 70% of job growth in the state coming from the Bay Area, San Diego, and Los Angeles (Regions Rise Together). Such jobs require workers to have skills acquired from higher education. Consequently, this has created a skill inequality gap, with educational attainment affecting the level of skills acquired by individuals in certain regions of the state. Higher educational attainment (bachelor’s degree) is seen more in the Bay area, coastal and higher income counties compared to lower income and rural counties - for instance, 13% in Lassen County to 60% in Marin County (Perez et al.). Thus, the lack of education attainment in some regions of California also affects its regional economic outcomes.

However, one of the most pressing issues affecting California is income inequality. As a result of imbalanced economic growth, Californian families in the top 10th income percentile searned 11 times more than the bottom 90th percentile with $291,000 vs $26,000 respectively in 2021 (Thorman et al., 2023). This inequality is also a result of the skill inequality gap that certain regions of California have, with families of college graduates earning $2.24 for every $1 a family without college graduates earns (Thorman et al.).

\Thus, by examining the regions and counties in which income inequality is most prevalent in California, policymakers can implement more nuanced policies that can help address region-specific income and educational inequalities promoting more equity in regions of California that require it and more economic growth in regions that do not have it.

**Background**

To better understand the relationship between income inequality and economic growth in California, we need to look more closely at the terms. Income is defined as the household

disposable income in a particular year, consisting of earnings, self-employment, and public cash transfers (Organization for Economic Cooperation and Development). As for income inequality, the Gini coefficient is used to measure it. The Gini coefficient measures the comparison of cumulative proportions of the population and the cumulative proportions of income these populations receive, hence, a Gini coefficient of zero corresponds to perfect equality, whereas a Gini coefficient of 1 is perfect inequality (OECD).

Meanwhile economic growth is often measured by gross domestic product (GDP) which is the monetary value of final goods and services produced in a region in a given period of time. (International Monetary Fund).

Initial literature on the relationship between income inequality and economic growth determine the relationship between the two to be positively correlated (Aghion et al.). This is attributed to the efficiency versus equity argument wherein in order to be more efficient in producing goods and services, equitable outcomes for business and individuals in a region are disregarded, increasing the social and income inequality in the region.

Additionally, literature examining regional economic growth and income distribution in California found that regional income divergence in California could be attributed to the changing composition of the population and the increasing importance of education and training (Woods). The literature also explores research by Williamson (1965) which supports the theoretical model of the inverted ‘U-shape’ relationship between income inequality and growth. Williamson applies this analysis to regions and identifies that unequal natural resource endowments across regions contribute to unbalanced growth during the initial stages of economic development, and during this development skilled labor will migrate to urban areas and away from rural areas.Applying this to the contemporary landscape of California, there

exists a divergence in the level of skill and education attained between the rural and urban counties of California, and this skill inequality gap persistently contributes to regional income inequalities in California. The initial distinction between rural and urban counties also corresponds to the unequal employment of natural resources and land, and now with the overlay of rapid technological advancement in certain regions of California over others - the unequal regional economic development is exacerbated further.

The state legislature is becoming increasingly aware of this issue hence they have invested $600 million in the new Community Economic Resilience Fund (CERF) which aims to support regional collaboratives among businesses, labor, community organizations, local government and other stakeholders as they create and strategize new initiatives for inclusive development (Emmerson et al). This initiative has risen from Senate Bill 162 which aims to improve California's workforce investment system and better match California's workforce to the needs of the 21st century economy and workforce (California Legislative Information). This initiative takes a step toward understanding the regional economic disparities present in California, and attempting to equalize it by promoting sustainable growth on a more local level. However, it is in only the very early stages of implementation, with CERF pilot projects only expected to be executed in the latter half of 2023.

**Theory and Argument**

I hypothesize that an increase in land development increases labor opportunity and reduces the unemployment rate in a county. The causal mechanism here is that more urban counties, such as the Bay Area or coastal counties, have employed more natural resources and land over other rural counties, resulting in greater economic development and more

technologically-advanced markets, which has contributed to more diverse labor markets and greater opportunity of jobs available for these urban counties.

The independent variable *x* I will use to measure this is the percentage of farmland converted to urban use in 43 counties in California. The reason there are only 43 counties in my analysis and not all 58 is due to data limitations, data was not available for all 58 counties. I expect to see more urbanized counties such as the Bay area counties, and coastal counties to have a higher percentage of farmland converted to urban use. The dependent variable *y* I will be measuring is the average unemployment rate present in all 43 counties from the time period 2014-2016. I expect more urbanized counties to have to lower unemployment rates, due to greater opportunities for job availability.

My second conceptual hypothesis is that with an increase in labor market diversity, there is an increase in economic growth. However, with this increase in economic growth there is an increase in income inequality. Put shortly, I hypothesize that an increase in economic growth, increases the income inequality in a county. The independent variable *x* I would use to measure this is the economic growth, or gross domestic product (GDP) in each county. Since labor market diversity helps increase productivity in a certain county or region, GDP can be used as a proxy to measure the labor productivity stemming from each county in California. The dependent variable *y* I would be measuring is the income inequality present in each county. I would use the Gini Coefficient Index to compare the varying degrees of income inequality present in the counties. I will use these two variable measures to evaluate the relationship between economic growth (as a proxy for labor market diversity and productivity) and income inequality.

The causal mechanism here is that with more diverse labor markets, especially technologically-driven markets, income accumulates much faster at higher-income brackets, than

lower income brackets due to systemic barriers in specific urban settings - in this case counties, even if the county seems to be economically 'successful' i.e has a higher GDP. Potential confounding variables that also affect income inequality are socioeconomic status, race and ethnicity, and gender. Hence, by expanding my scope to 43 counties, I hope to control for these confounding variables with different counties from different regions having similar demographics which would help provide a more balanced composition.

In spite of trying to account for intervening variables such as socioeconomic status, ethnicity, gender etc, there are many other confounding variables that could affect income inequality. One of the notable variables being level of education attainment across school districts in a neighborhood or county. Since education greatly contributes to skill accumulation, which affects the quality of job an individual receives, it might be difficult to control for such granular differences in data, potentially biasing the level of income inequality (the dependent variable $y$) which is a limitation to be aware of when analyzing my findings. Other confounding variables to be aware of include social safety net programs available by county, and level of housing insecurity or homelessness, and minimum wage differences.

**Research Design and Data**

The research design for this project is a large-n cross-sectional analysis of 43 counties in California from 2014 to 2016. Only 43 of 58 counties were analyzed as the remaining counties had no data on urban land conversion - the independent variable measure of my first hypothesis. In the Farmland Conversion Report it was mentioned that unavailable county data was due to the fact the county had large public land holdings that were not covered by modern soil surveys. This is an important limitation to consider while analyzing these findings as more counties to the north of the Inland Empire were missing, which could potentially skew the results.

In addition to this, this cross-sectional analysis is only from 2014 to 2016 as this is the most recent publicly available data on urban land conversion. This is another limitation to account for while analyzing findings and validity, as more contemporary data would allow for a stronger analysis on the relationship between economic growth and income inequality post the COVID-19 pandemic as well.

For the first hypothesis, the independent variable, land development, was measured using the urban and built-up land data per county. This data was extracted from the Farmland Conversion Reports that the California Department of Conservation produces every two years. In this report, they collected data on 'important farmland', 'grazing land', 'agricultural land', 'urban and built-up land', 'water area', and 'total county area', and measured this data in acres. Thus, to measure land development in a county, I used 'urban and built-up land' data as a percentage of total county area to control for the differences in acreage from county to county.

For the dependent variable, labor opportunity was measured using the average unemployment rate in a county from 2014 to 2016. Conceptually, the lower the unemployment rate in a county, the greater the job opportunity a county has as a result of the use of natural resources like land, thus the unemployment rate was used as the measure for labor opportunity (the dependent variable). This unemployment rate data was acquired from the California Employment Development Department. Their website had monthly statistics on the unemployment rate for each county. The dependent variable measure was then created by averaging all monthly unemployment rates for the 43 counties of interest to create a single average unemployment rate for each county. This was done to mitigate yearly and even monthly fluctuations in the unemployment rate for a county.

With data for both the independent and dependent variable measures, I reorganized this data into a spreadsheet to export into a csv file.

For my second hypothesis, the independent variable of interest is economic growth, as a proxy for labor opportunity. Economic growth was chosen to be a viable proxy for labor opportunity, as labor productivity strongly contributes to GDP, the main measure of economic growth. GDP data was collected from the Bureau of Economic Analysis using their interactive graphic tool from the years 2014 to 2016. GDP was measured as a percent change from the previous year, compounded annually. While GDP per capita could have also been a viable measure controlling for population, previous literature has used percent change for GDP growth. To remain in line with previous literature, and also better understand if certain counties and regions in California experienced faster GDP growth than others during this time period, GDP growth as a percent change, compounded annually was used.

For the dependent variable, income inequality was measured using the Gini coefficient index, whereby a score of 0 corresponds to perfect equality and a score of 1 corresponds to perfect inequality. Values can take on a continuous range between 0 and 1 for their Gini coefficient. Data was extracted from the Gini index collated by the U.S. Census Bureau, American Community Survey for the years 2014 to 2016. Averages were taken for these values to mitigate any yearly fluctuations. The scope of the analysis for both the independent and dependent variable measures for this hypothesis were also the same 43 counties to uniformly analyze findings across both hypotheses. The data for the independent and dependent variable measures were compiled into a spreadsheet and exported to a csv file to be analyzed.

To better examine the direction of the relationship and correlation of economic growth and income inequality, education levels and percent of people of color by county were controlled

for. This data was acquired from the U.S Census Bureau, American Community Survey and percentages of ‘Education level: any college degree or higher’ were used to ascertain the level of education per county, while racial demographics were taken from the Decennial Survey conducted . Although there are many other confounders *z* that could also affect income inequality, education and ethnicity are by far the largest confounding variable affecting income inequality, primarily due to the skill inequality gap that rises from varying levels of education; and systemic racism that disproportionately affected people of color, preventing them from gaining access to capital and other economic indicators of success like homeownership.

Limitations with the data and research design were briefly mentioned earlier, the largest drawback being the lack of land data available for all 58 counties. This gives rise to generalizability issues as, although populations are controlled for by using percentages, the counties that data has been collected for might have varying racial, ethnic, and gender demographics that might not be able to be accounted for. Thus, while analyzing the results of my findings, a general impression of how land development affects labor opportunity, and how economic growth affects income inequality in California can be recognized for different regions in California but cannot be generalized to the entire state.

Another limitation that was also previously mentioned was the outdated nature of the data, as the most publicly available data for all independent and dependent variable measures is from 2014 to 2016, which is close to 7 to 9 years ago. While this may call for another re-evaluation of the hypotheses once more recent data is released, the results from running regression models on land development and labor opportunity, and economic growth and income inequality, may allow for recognizing trends in the differences of economic opportunity and well-being in California; and how these variables have interacted with each other in the past and

serve as indicator for the future while California policymakers continue to promote regional economic development.

Apart from this, the independent variable measure used for land development: urban land percentages by county might not be the strongest or only measure of land development; as urban land, in this context, is only in relation to farmland and other agricultural land. Therefore, it is important to acknowledge that other measures of land development exist such as infrastructural development in a county which could be used to determine the effect of land development on labor opportunity.

The same holds for the other dependent variable measure in my hypothesis. Labor opportunity could also be measured by the labor force participation rate in a county, and the industry compositions per county. However, the average unemployment rate better captures the state of the working population than some of the other measures listed previously, and were easier to standardize. Industry composition would have also  been difficult to encapsulate in a regression analysis as there exist many types of industries which would be difficult to characterize quantitatively.

To analyze the effect of land development on labor opportunity, and economic growth on income inequality, I will be running two linear regression models to assess the direction and correlation of the relationship between my two hypotheses. To consider my findings statistically significant I would need to obtain a p-value less than or equal to 0.05. However, given the limitation of endogeneity with my regressions, and being unable to control for all confounding factors that also affect land development and income inequality (DVs), if my p value is statistically different from zero, I would be able to suggest that there is some correlation between both land development and labor opportunity, and economic growth and income inequality.

**Findings and Analysis**

In order to capture which regions and counties have a more dense concentration of land development, a map was created detailing each county's percentage of land development from 2014 -2016. The total counties outlined in the map were the 43 used for the rest of the data analysis.

***Figure 1*** below suggests that there is a trend that remains in line with the hypothesis that more urban counties, such as Bay area counties, and coastal counties have a higher percentage of farmland converted to urban land. Counties such as Orange county and San Diego county had percentages of land development as high as 91.4% and 66.9% respectively, compared to the inland county of San Bernardino and northern county of Siskiyou which had percentages as low as 4.1% and 2.9% respectively. This does support the notion that coastal counties, during 2014 to 2016, were more developed than their inland or northern counterparts.


***Figure 1: Land Development Trends in California (2014-2016)***

Additionally, looking more closely at the San Joaquin Valley counties, all except Kern had among the lowest percentages in land development ranging between 6% to 16%, meanwhile their agricultural land subtotal as a percentage of total county area was close to 57.1% and 81.2% in counties such as Fresno and San Joaquin respectively (CA Department of Conservation). This is expected as San Joaquin Valley counties contribute significantly towards agricultural output for California and the United States. As for Kern, this county is an outlier with 47.5% of urban land developed. This outlier might exist due to the time period it was captured in, between 2014 to 2016, where it might have experienced greater development than other inland counties. However it is difficult to ascertain the factors for the level of land development without a closer look into land development policy in Kern at the time, and other external factors like population changes which may have warranted a change in land development.

To test my hypothesis of whether an increase in land development contributes to a decrease in unemployment rates per county, a linear regression analysis was conducted with unemployment rates per county (2014 to 2016) as the *y* regressor and percentage of urban land development per county (2014-2016) as the *x* regressor.

***Figure 2*** below captures the slightly negative relationship between urban land development and unemployment rates that was found. These are statistically suggestive findings with a p-value of 0.0515. Thus, given the scope of the data, there is very little support for my hypothesis that with an increase in urban land development, there is a decrease in unemployment rates across counties in California during this time period.


***Figure 2: Correlation between Land Development and Unemployment (2014-2016)***

| | *P-Value* | *Standard Error* | *R-Squared* |
|---|---|---|---|
| *$H_1$: Land Development on Unemployment Rates (2014-2016)* | 0.0515*<br>*: Statistically significant at the 10% level | 1.199 | 0.07832 |
| *$H_2$: Economic Growth on Income Inequality (2014-2016)* | 0.7874 | 0.02387 | 0.02641 |

***Table 1: Regression Findings for Hypothesis 1 and Hypothesis 2***

As shown in ***Table 1***, the standard error of the unemployment rate per county is 1.199, suggesting that since this is a relatively smaller standard error of the regression coefficient, the

observations fall somewhat close to the line of best fit. However, while looking at the R-squared value of 0.07832, there is close to no correlation between urban land development and unemployment rates per county in California. This suggests that perhaps there are better predictors or measures of land development, or other independent variables altogether which may better explain the variation in unemployment rates per county in california. While specifically thinking of land development as an independent variable, potentially looking at the level of infrastructure developed in a county is a closer measure towards understanding how unemployment rates are affected.

While looking at the relationship between urban land development and unemployment rates per county in California, I found no support for my hypothesis that an increase in urban land development would result in a decrease in unemployment rates. Most counties were clustered around 15% to 40% of urban land development, and counties experienced between 4% to 8% of unemployment on average. Indicating that there was not too much variation in land development trends across counties in California at the time, as well as unemployment rates. Extrapolating this further, this is several years after the great recession, suggesting that counties were able to adapt to the high levels of unemployment and fluctuations by this time period, and the state of California adopted policies to stabilize the economy.

While testing for the relationship between economic growth, as a proxy for labor opportunity, and income inequality, I was not able to find support for my hypothesis that an increase in economic growth leads to an increase in income inequality. ***Figure 3*** below captures the scatterplot between economic growth and income inequality, and each county is populated by the percentage of people of color within that county. This was done to ascertain whether there was an underlying relationship between ethnicity, economic growth, and income inequality.

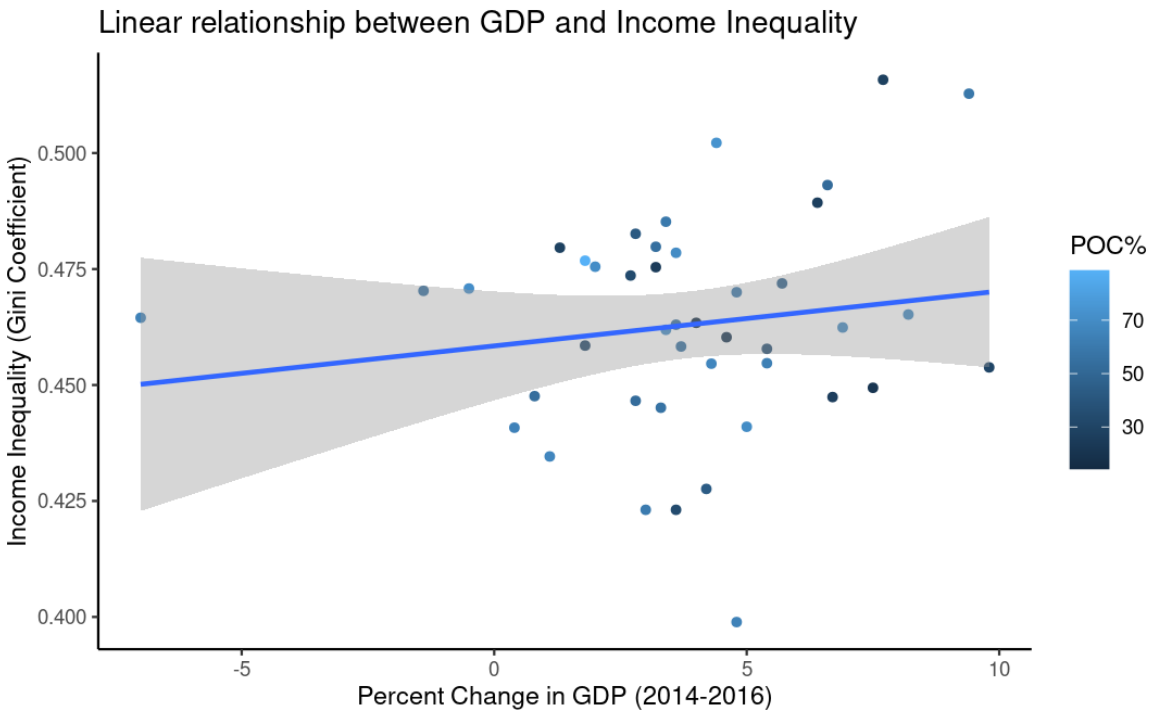


***Figure 3: Correlation between Economic Growth and Income Inequality (2014-2016)***

Although the findings of this regression were not statistically significant (p-value = 0.7874), on average, counties with more people of color had higher levels of income inequality. This has implications for how people of color, especially those within black and latino communities, have been historically denied access to capital and homeownership; two large indicators of economic and financial success causing pockets of wealth and capital concentration in whiter communities. While wealth and income are two different measures, they are inextricably linked with income contributing to an individual's wealth accumulation. Thus, it is important to examine how certain communities of color are disproportionately affected by income inequality and economic well-being when concerned with policymaking that aims to provide more equitable solutions to regional economic development.

When looking at the relationship between economic growth and income inequality and controlling for education levels by county and ethnicity, I found no support for my hypothesis. Although the findings were statistically insignificant and with an R-squared value of 0.02641, suggesting no correlation between the two variables, ***Figure 3*** shows the slightest positive relationship between the two variables suggesting that in the presence of control variables like education and ethnicity no discernible predictive relationship between GDP and income inequality can be found, however these variables still move together, and it is worth investigating what forces contribute this movement.

**Further Research and Research Implications**

While I was unable to gather support from my hypotheses, it is crucial to examine the relationship between economic growth and income inequality to ensure that equitable outcomes are achieved while designing policies to increase development. Thus, these research questions on land and labor development, and the effect of this on economic growth and income inequality, should be revisited once more recent data is available on these measures. Since no discernable correlations were found between my independent and dependent variables, perhaps finding stronger measures for each would result in more statistically significant findings. Such as infrastructure development for land development as the IV, and labor force participation rate for labor market opportunity as the DV.

Additionally, as mentioned earlier in the paper, the data collected for my measures was several years after the great recession, a potentially interesting research objective could be to investigate how the great recession affected income inequality and economic growth and doing a time-series analysis comparing the state of counties prior to the economic shock and after the shock and perhaps using a regression discontinuity design to evaluate this. This would be

interesting to explore, as the same could be simulated with more recent data on income inequality and economic growth using the COVID-19 pandemic as the shock. By conducting such analysis policymakers would be able to better understand how to deal with economic shocks and the path to equitable and healthy economic recovery, with the pandemic and great recession as examples to learn from.

As for research implications, initiatives like the Community Economic Resilience Fund (CERF) are currently being implemented to promote regional economic development in California. A stronger understanding of the potential positive relationship between economic growth and income inequality can allow for more nuanced policies targeted towards development, ensuring equitable growth practices in regions of California that need it the most. Not finding a correlation between income inequality and economic growth could suggest that the controls incorporated into the regression such as education and ethnicity have a greater impact on income inequality than GDP itself. Perhaps running separate regressions with each of the variables as the independent variable might reveal significant correlations between ethnicity or education on income inequality, requiring policymakers to be more aware of certain collaterals when implementing policies specifically geared toward economic development.

Additionally, the lack of correlation could also be due to the fact that running a simple OLS regression may not have the statistical power to capture the effects of a concept as layered as economic growth on income inequality. Further research on this topic might require a multivariate regression allowing for more dimensionality with the inclusion of more independent variables, and more robust findings as a result.

**Conclusion**

When looking at regional economic development in California, economic growth and income inequality are two facets policymakers cannot afford to overlook in the policymaking process. This paper aims to look at economic 'well-being' more holistically and examine relationships between income inequality and economic growth to determine whether there is a relationship that policymakers are not looking at more closely. It aimed to ask why some of the most economically successful counties like the Silicon Valley saw increases in income inequality by 5% while the state of California and the rest of the nation saw decreases by 1% and 3% respectively in 2021 (Cal Matters). While my findings did not support my hypothesis of a positive relationship between income inequality and economic growth, there is still similar directional movement between the two variables. This, in of itself, warrants further research into what forces are causing such movement and whether there are systemic or institutional policies disproportionately affecting communities of color increasing income inequality for these communities at a higher rate than their white counterparts.

Evidently, studying economic well-being is a challenging and multi-faceted task, with several dimensions such as ethnicity, education, income inequality, land development, and economic growth at play with one another. However, by examining each dimension individually, and then in conjunction, public policymakers and economists can better understand what constitutes a successful and well-run Californian economy, one that is not measured solely by economic growth, and one that is not viewed as a monolith; rather one that recognizes regional economic and social differences within the counties of California and uses this knowledge to create more nuanced policies that target sustainable and equitable regional economic development.

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