**Literature Review**

Income and cost of living are important economic concepts that impact people's wellbeing and quality of life. As Campbell (2021) discusses, there is evidence that economic inequality, measured through poverty rates and income ratios, is positively associated with higher costs of living across US metropolitan areas. The study finds that a one standard deviation increase in the Gini coefficient or 90/10 income ratio predicts a 4.0-4.5 point rise in cost of living. This indicates that growth concentrated among high income groups raises housing and living costs.

Other studies corroborate connections between inequality and spatial price variation. Choi et al. (2020) show that incomes and purchasing power diverge between US cities and regions. Metropolitan areas with more advanced, high-wage industry concentrations like technology and finance tend to have far higher costs. Over the past few decades, skill-biased technological change has increased demand and returns for high-skill labour in these cities, fueling wider income gaps (Abel & Deitz, 2019). Glaeser et al. (2009) determine that about a third of differences in urban wage inequality can be explained by returns to skill. Through housing markets especially, productivity growth and demand at the top then place pressure on prices.

Research also examines specific channels through which inequality may increase living costs. Argente & Lee (2021) find that higher income households have greater ability to substitute consumption in response to prices. Poorer consumers are less mobile and flexible, so likely bear more of the amenity expenses bid up in affluent areas. Diamond (2016) and Florida & Ozimek (2021) discuss how skilled worker migration patterns shape regional costs. The ability to work remotely accelerated outflows from costly coastal cities during COVID, temporarily reducing housing demand and lowering income inequality back home. However, inflows to interior metro areas like Boise then exert local inflation.

Analyses incorporating additional socioeconomic indicators can further capture inequality's spatial footprint. Manson et al. (2020) integrate historical census data on factors like income, poverty status, and housing into a national GIS database. This enables more multidimensional study of inequality over time and space. Machine learning techniques could also help model complex relationships with living costs. Campbell (2021) uses regression analysis, but tree-based models may better handle nonlinearities and interactions.

In conclusion, a range of evidence finds that income inequality and poverty associate with higher regional living costs, compounding economic hardship for disadvantaged groups. Developing predictive models using detailed demographic data can deepen understanding of inequality dynamics. More equitable development that builds middle class jobs and wages may not only promote social justice, but also efficiency through restraining cost of living increases.

A growing body of research compares the performance of machine learning approaches on socioeconomic prediction tasks. Christopher et al. (2020) using deep learning models to predict survey-based estimates of asset wealth across approximately 20,000 African villages from publicly-available multispectral satellite imagery. They suggested that deep learning approach could be applied to the measurement of key outcomes such as consumption-based poverty metrics or other key livelihood indicators such as health outcomes. Similarly, Jean et al. (2016) develops convolutional neural nets estimating poverty from high-resolution daytime satellite imagery across five African countries. The deep learning architectures significantly outperform classic machine learning baseline models. These studies demonstrate advanced techniques like convolutional neural nets and model ensembling can better capture the intricacies of economic phenomena, including spatial inequality. Applying such methods to US income and cost data may similarly achieve higher accuracy than traditional linear regression or random forests. Carefully engineered features extracting contextual information could further improve predictive accuracy. Comparing results across different modeling paradigms can reveal new insights into the complex relationship between inequality and living costs.

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