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RESEARCH ARTICLE

REGIONAL VARIATIONS IN CRIME ACROSS THE US STATES

Fadime İrem DOĞAN*

Abstract

The economics of crime encompasses a broad framework, highlighting the impact of unemployment, poverty, and inequality on criminal behavior. Addressing these issues requires a comprehensive approach that considers not only individuals' rational choices but also systemic factors contributing to inequality and their potential impact on crime rates. Effective solutions necessitate a thorough understanding of these interrelated factors to enhance social well-being and create environments that mitigate the conditions fostering criminal behavior. This study employs the Spatial Durbin Model (SDM) to examine spatial variations in property crime across US states in 2022. Findings indicate that GDP, minimum wage, and the demographic composition of the prison population significantly influence property crime and are, in turn, shaped by socioeconomic conditions in neighboring states.
Keywords: Crime, Spatial Analysis, Regional Economics, Spatial Durbin Model, Unemployment
JEL classification: J01, J1, J6, K13

1. Introduction

Crime is a significant issue that requires careful examination. Since Becker (1968), numerous scholars have attempted to explore its complexities, each contributing new insights to the literature. The investigation of crime and its relationship with different parameters reveals a complicated interplay between economic, social, and individual factors. The search for solutions aims to include a complete understanding of these interconnected phenomena to foster social well-being and create environments that mitigate the conditions encouraging to criminal behavior. The literature on the economics of crime, focusing on the determinants of crime, is vast. Several studies explore the relationship between crime and macroeconomic and institutional variables such as unemployment, unemployment benefits, education and income inequality. A strong link between unemployment and crime has been widely documented. Jawadi et al. (2021) established a robust connection between unemployment and crime, focusing on both violent and non-violent crimes by using a time-varying VAR model. They find that significant positive effects of unemployment shocks on crime rates. Schleimer et al. (2022) explore the association between unemployment and violent crime during the COVID-19 pandemic in the US between

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2018-2020. They observe that increases in unemployment are correlated with higher firearm violence and homicide rates. Juárez et al. (2022) examine the relationship between youth bulges, unemployment, and violent crime in Mexico from 1997 to 2010. The study suggests high youth unemployment in the low-education strata correlates with increased violent crime rates and large cohorts of young men may facilitate the recruitment of criminal organizations.

Another crucial component is the link between income inequality, education and crime. Sugiharti et al. (2023) examine the relationship between income inequality, poverty, and crime rates across 34 Indonesian provinces. The findings indicate that higher income levels and wider income inequality correlate with higher crime rates. Non-food expenditure significantly affects crime rates more than food expenditure and the Gini ratio. The research suggests leveraging education and investment to minimize crime rates in Indonesia. According to van de Weijer et al. (2024), the causal effects of educational attainment on criminal offending using a discordant sibling design and data from the Netherlands. Their research emphasizes that higher education may reduce the risk of delinquency and crime. There are also some studies focus on institutional factors like unemployment insurance benefits to understand crime patterns. NoghaniBehambari and Maden (2021) explore how unemployment insurance (UI) benefits effect crime rates in the US. They conclude that one standard deviation increase in UI benefits correlates with reduced property and violent crime rates. In another study by Britto et al. (2022), the role of unemployment benefits is observed to increase the crime probability by 23% for displaced workers, particularly among young and low-tenure individuals in Brazil. Unemployment benefits offset the potential crime increases, but the effects vanish after benefit expiration.

Research on the economics of crime examines both the linear and spatial dimensions. The seminal study of Andresen (2006) investigates the spatial aspect of criminal activity in Vancouver using social disorganization and routine activity theories. The author compares crime counts and rates with residential and ambient populations as denominators and finds strong support for the routine activity theory and the use of ambient populations in crime rate calculations. Another spatial study by Quick et al. (2018) examine spatial crime patterns using Bayesian multivariate spatial models for burglary, robbery, vehicle, and violent crimes in Greater London. They identify shared components that explain the correlations between crime types and their underlying crime-general patterns. In their study, ToppiReddy et al. (2018) address crime prediction using advanced systems and machine-learning algorithms to improve crime analytics and community protection by employing visualization techniques to analyze crime data and reveal patterns and trends for law enforcement . Leiva et al. (2020) analyze the relationship between immigration and crime in Chile from 2005 to 2015 using a dynamic Spatial Durbin Model (SDM). Their study reveals a negative relationship between immigrants and crime for one of the eight crime types analyzed.

I believe this study contributes to the literature in two key ways. First, it extends beyond a single set of variables by incorporating socioeconomic, institutional, and demographic factors that may impact property crime. Second, it reexamines the determinants of property crime from a

spatial perspective across the US states using cross-sectional data for 2022, a period that allows for post-pandemic analysis. By applying Spatial Durbin Model (SDM), it explores both the direct and spillover effects. The purpose of this study is to spatially explore the regional variations in crime in the US. By revisiting the determinants of crime, such as unemployment rate, educational attainment, GDP growth, minimum wage rate, and prison population based on gender and race, SDM is employed. The results suggest that the GDP, minimum wage, and demographic composition of the prison population have a significant impact on property crime. Additionally, findings confirm that determinants of property crime are also influenced by neighboring states.

The remainder of this paper is organized as follows. Section 2 presents the data and empirical methodology, along with stylized facts. Section 3 presents the empirical results of the study. Finally, Section 4 concludes the study.

2. Data and Empirical Strategy

This study aims to spatially and empirically investigate regional variations in crime across US states. This study uses property crime rates at the state level, and the data is compiled from the Federal Bureau of Investigation (FBI). The study period is 2022, including 45 states [1] in the US. Crime is affected by many factors such as unemployment, education, gender, age, and poverty. Reduced unemployment results in a decreased opportunity cost for persons to engage in criminal activities (Becker, 1968; Melick, 2003). Moreover, higher education is expected to reduce crime rates, as it results in a more trained workforce and increased pay (Lochner and Moretti, 2004; Lochner, 2010). Gender and age influence criminal behavior, with males exhibiting a higher propensity for criminal activity (Wilson and Hernstein, 1985). Poverty, associated with inadequate nutrition and living conditions, is also correlated with criminal activity (Philips 1991). Rapid socioeconomic changes, and crime prevention are crucial elements that contribute to an increase in crime rates (Quetelet, 1835). Economic inequality, which impacts the living standards of both rich and poor individuals, increases the probability of criminal engagement (Merton, 1938; Shaw and McKay, 1942; Becker, 1968). Rapid socioeconomic changes such as industrialization and urbanization generate increased opportunities for criminal activity, as individuals are often resistant to adopting new norms and values (Tsushima, 1996). Crime prevention requires moderating the risk factors associated with individuals, including the financial implications of punishment and the effectiveness of public policy (Becker 1968). By comprehending these factors, society can more effectively tackle and avoid crime. Therefore, we incorporate determinants of crime such as (high school) educational attainment, GDP growth rate, unemployment rate, hourly minimum wage, and prison population based on gender and race, and include them in the model (Zavodny 2000; Elsby et al. 2013; Altonji et al. 2016; Fanfani 2023). Data for the control variables are obtained from the Bureau of Labor Statistics (BLS) and the National Center for Education Statistics.

1 Alaska, Connecticut, Delaware, Hawaii, Rhode Island, and Vermont are not included in the analyses due to data availability. District of Columbia is included.

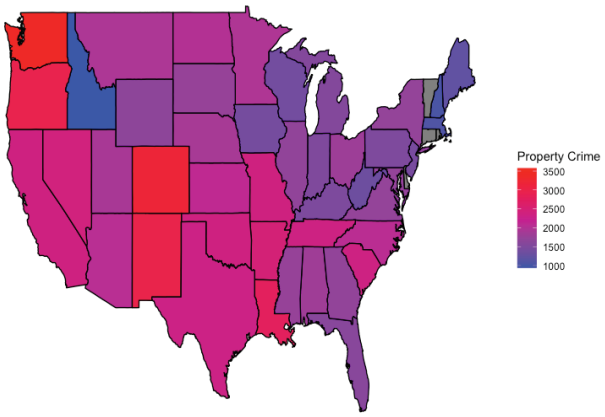

Figure 1. Property Crime Rate in the US (per 100,000)

Source: FBI, Author's own calculation.

Figure 1 presents maps of property crime for 2022, demonstrating how different regions spatially experience changes in property crime rates. In Washington, Oregon, Colorado, New Mexico, and Louisiana, we observe higher levels of property crimes that may reflect higher population density, inequality, urbanization, and more opportunities, that is, theft. The high levels of substance use in these states also reflect higher crime rates. As we move to states such as Idaho, New Hampshire, and Massachusetts, we observe lower crime rates that may be due to low population density and greater economic stability, reducing opportunities for property crime.

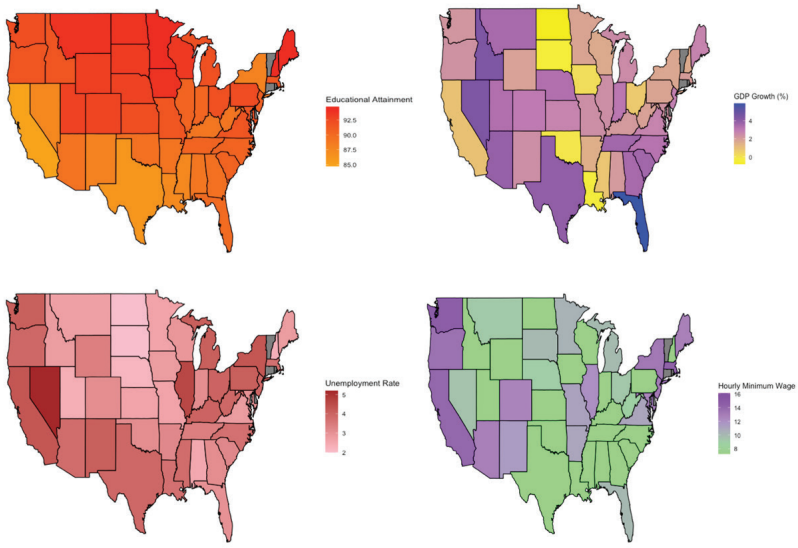

Figure 2. Economic and Labor Market Indicators

Source: Bureau of Labor Statistics (BLS), National Center for Education Statistics, Author's own calculation.

Figure 2 represents the socioeconomic factors in the US States in 2022. The map on the top left presents high school educational attainment, and Northern States such as Minnesota, North Dakota, New England have the highest level, while we see lower rates for the southern states. The map on the top right shows the GDP growth rate across states, and we observe that some of the Midwest states show higher GDP along with Florida, while yellow shaded states indicate lower GDP growth. Regarding the unemployment rate, a higher unemployment rate appears in the Midwest and Southern states such as Nevada, while the Northern states reflect a lower unemployment rate. Finally, the map on the bottom right represents the hourly minimum wage across states, and higher wage levels are seen in West and Northeastern states, such as California and Washington. This reflects the differences in state policies and cost of living adjustments.

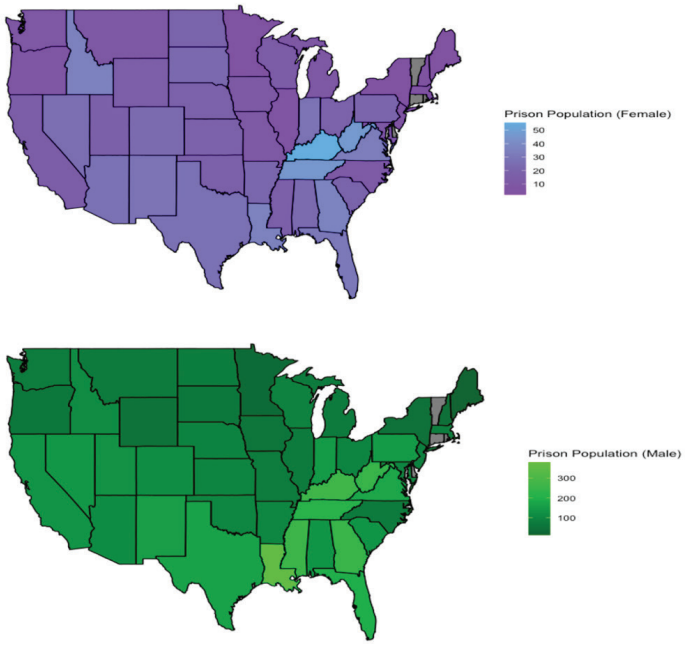

Figure 3. Prison Population Based on Gender

Source: Annual Survey of Jails, Author's own calculation.

The prison population for men and women is higher in states such as Kentucky, Tennessee, Idaho, West Virginia, Georgia, and Louisiana as depicted in Figure 3. Strict criminal justice policies, high drug use rates, and economic conditions reflect the higher prison population in these states. Additionally, Louisiana has a very large private prison industry in the US However, overall, the prison population is six times higher for men, revealing the importance of the gender aspect of the criminal justice system.

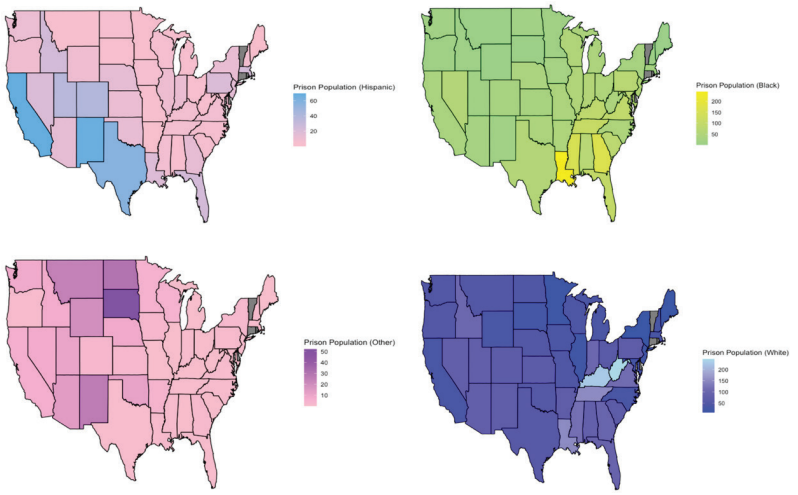

Figure 4: Prison Population Based on Race
Source: Annual Survey of Jails, Author's own calculation.

The prison population based on race showed different outcomes across states, as shown in Figure 4. The Hispanic prison population is mostly higher in Southern Western states (California, New Mexico, Texas), which are neighbors of Mexico. When we look at the black individuals' prison population, we see that Louisiana and Georgia have the highest rates, which could be explained by the high number of private prisons in these states. The prison population for white individuals is mostly higher in Kentucky and West Virginia, while the rate is higher for others in the Northern states.

The Spatial Durbin Model (SDM) extends the Spatial Lag Model (SLM) by including spatial lags of the independent variables. This allows the model to capture both direct effects (the impact of independent variables on the dependent variable within a region) and spillover effects (the impact of independent variables from neighboring regions).

The general form of SDM is:

$$y = \rho W_y + X\beta + WX\theta + \varepsilon$$

where y is the N×1 vector of the dependent variable property crime, p is the spatial autoregressive parameter, capturing the dependence of y on neighboring values through the spatial weight matrix W. W_y is the spatially lagged dependent variable, which introduces spatial feedback effects and $WX\theta$ is the spatially lagged control variables. X is the N×K matrix of control variables. And ε is the error term.

3. Results

To scrutinize the spatial dependence of crime rates across US states, we employ spatial models, including the Spatial Lag Model (SLM), Spatial Error Model (SEM), and Spatial Durbin Model

(SDM). These models are selected to account for potential spatial autocorrelation in the data, ensuring robust estimation. We first estimate the SLM, which incorporates spatial dependence in the dependent variable by including a spatially lagged term. Next, we run the SEM, which accounts for spatial dependence in the error term. Finally, we estimate the SDM, which extends the SLM by including spatially lagged explanatory variables. One must consider two key criteria when determining the most appropriate model. The first criterion is the Akaike Information Criterion (AIC), in which a lower AIC value indicates a better model fit [2]. Second is Moran's I test of residuals. Moran's I [3] is to assess whether spatial autocorrelation remains in the residuals after model estimation. Given that SDM had the lowest AIC and shows no significant spatial autocorrelation in the residuals, we selected it as the preferred model for our analysis. SDM not only provides a better fit, but also effectively accounts for spatial spillover effects by incorporating both spatially lagged dependent and independent variables.

Table 1 presents the results of the spatial models of property crimes. The Spatial Durbin Model (SDM), which includes spatially lagged independent variables to capture both direct and spillover effects, indicates significant spatial dependence (p = 0.073293). Unlike the Spatial Lag Model (SLM), SDM accounts for these dependencies and provides a more comprehensive analysis. Among the key determinants of property crime, GDP growth is statistically significant with a negative coefficient, aligning with the general expectation that better economic conditions reduce economically motivated crimes. This may stem from improved job prospects and stronger social cohesion. The coefficient of minimum wage indicates a positive and significant relationship with property crime, which may be explained by adjustments in the labor market, since minimum wage is determined at the federal level. This may reflect an adjustment period in which businesses reduce employment opportunities, or a cost-of-living effect.

Regarding demographic variables, a negative coefficient for the male prison population suggests that higher incarceration rates are associated with lower property crime, consistent with deterrence or incapacitation effects. The prison populations of Black, Hispanic, and White are positively associated with property crime, whereas the prison populations of other individuals show no significant relationship with property crime.

Table 1. Spatial Durbin Model (SDM) Estimates

	Property Crime
Educational Attainment	0.031
	(0.025)
Unemployment Rate	-0.009
	(0.022)

2 AIC for the SLM is – 47.48917, SEM is – 49.82004, and finally SDM is – 57.76281. Therefore, SDM is a better fit, and results are reported for SDM. Results for SLM and SEM are available upon request.

3 Additionally, we conducted Moran's I test on the residuals to evaluate the presence of spatial dependence. The test results indicated no significant spatial autocorrelation in all models (for SLM p = 0.2965, for SEM p= 0.5295 and for SDM p= 0.4485 residuals).

GDP growth	-0.038*
	(0.019)
Log_minimum wage	0.031*
	(0.017)
Prison Population (male)	-0.802*
	(0.386)
Prison Population (female)	-0.059
	(0.063)
Prison Population (white)	0.471*
	(0.259)
Prison Population (black)	0.568**
	(0.264)
Prison Population (Hispanic)	0.248**
	(0.096)
Prison Population (other)	0.079
	(0.056)
L.Educational Attainment	-0.053
	(0.048)
L.Unemployment Rate	-0.013
	(0.049)
L. GDP growth	-0.095**
	(0.040)
L.log_minimum wage	-0.072
	(0.063)
L. Prison Population (male)	-2.625*
	(1.351)
L. Prison Population (female)	-0.090
	(0.219)
L. Prison Population (white)	1.537*
	(0.904)
L. Prison Population (black)	1.772*
	(0.925)
L. Prison Population (Hispanic)	0.748**
	(0.325)
L. Prison Population (other)	0.208
	(0.168)
Intercept	3.015***
	(0.657)
Rho	0.073
Moran's I	-0.011
Log-Likelihood	51.881
AIC	-57.763
LM	0.081332

Note: ***p < 0.01; **p < 0.05; *p < 0.1. L refers to the lagged value. Author's own calculation.

To measure spillover effects, we examine the statistically significant lagged independent variables, as they exhibit cross-state influences on property crime. These spillover effects would allow us to distinguish the direct and indirect impacts. By measuring these influences, one can understand how economic and social circumstances in one state would spread across state borders that shape crime dynamics beyond local factors. A positive coefficient reveals that higher values in neighboring states are linked with an increase in the property crime in the local region, highlighting spillover effect. On the other hand, a negative coefficient shows that higher values in neighbor states stand for a decrease in the local property crime rate, reflecting a deterrent spillover effect. Specifically, lagged GDP growth indicates that higher GDP in neighboring states is associated with local crime rates, potentially due to improved economic opportunities. Regarding the prison population, the findings suggest that higher male incarceration in neighboring states reduces property crime. However, higher incarceration rates among different racial groups in neighboring states are linked to increased property crimes, possibly due to economic distress spillovers or migration patterns. Gunadi (2021) analyzes the pace at which 11 million illegal immigrants in the US have become part of the institutional system, as well as the impact of their presence on crime rates. The rate of institutionalization is higher among younger newcomers. Stuart and Taylor (2021) investigate the influence of social connectivity on crime rates in the US cities between 1970 and 2009. The findings indicate that higher levels of social connectedness have a substantial effect in lowering crime rates, especially among teenagers and young adults engaged in gang – and drug-related behaviors. Furthermore, demographic structures in neighboring states play a crucial role in shaping local crime dynamics. These findings highlight the importance of considering regional interactions, economic opportunities, and disparities in law enforcement when analyzing crime patterns.

4. Conclusion

This study aims to empirically investigate regional variations in crime across the US states. We used cross-sectional data for the US states for the year 2022. Literature on the economics of crime indicates that various factors affect crime rates in a society (Becker, 1968; Freeman, 1999; Melick, 2003; Imrohoroglu et al., 2006). Consequently, we empirically investigate this issue by conducting spatial analysis. Our approach moves beyond the standardization of crime determinants and introduces a novel methodological framework that incorporates neighborhood effects to analyze the factors influencing crime. SDM provides the most comprehensive understanding of spatial crime dynamics by capturing both direct and spillover effects. The results underscore the significance of GDP, minimum wage, and demographic composition in explaining crime patterns, while also emphasizing the role of neighboring states' socioeconomic and institutional conditions on local crime rates. Finally, our results reveal that crime is not merely a local phenomenon but is strongly influenced by the socioeconomic and demographic conditions of neighboring states.

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RESEARCH ARTICLE

DUAL DYNAMICS OF SAVINGS IN GLOBAL CONSUMPTION DISPARITIES

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Abstract

This paper examines global consumption inequality through empirical and theoretical approaches. To provide a clear perspective on the magnitude of consumption inequality globally, the study utilizes the Penn World Tables 10.01 dataset covering the period from 1960 to 2019. The categorization of countries into five consumption groups reveals a remarkably stable distribution, with the majority of the global population persistently concentrated in the lowest and highest consumption groups. Over the past six decades, the proportion of the worldwide population of the lowest consumption group has remained strikingly high, highlighting global inequality's entrenched and severe nature. This paper refines the theoretical framework by examining how savings rates influence economic disparities among countries, drawing on Solow's (1956) and Pasinetti's (1962) perspectives. While the Solow-Swan model highlights the role of higher savings in fostering economic growth and decreasing economic inequalities, this study incorporates Pasinetti's (1962) perspective, which argues that increased savings among lower-income groups may disproportionately benefit wealthier groups, potentially intensifying inequality. Using Gillman's (2011) general equilibrium model, the paper bridges these theoretical insights to examine how class-based economic differences shape the outcomes of savings behavior. Empirical results derived from the theoretical model show that the impact of savings rates on global consumption patterns varies significantly depending on the economic structures of different countries. This analysis underscores the importance of designing economic policies sensitive to each country's unique characteristics and structural realities rather than applying uniform, one-size-fits-all solutions.
Keywords: Consumption-Saving, Solow Growth Model, Demand-led Growth Models, Dynamic Panel Data Models.
JEL codes: E21, O47, C21

Introduction

Understanding and explaining the mechanism behind the distribution of economic inequality – both within and across countries – has a solemn place in economics. Within countries, the primary concern about inequality is how wealth, income, and consumption are distributed among individuals or social groups. In contrast, inequality across countries focuses on the disparities in economic performance and living standards across sovereign nations. Inequality within and across countries intersects

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through common economic behaviors, such as savings habits, which influence long-term economic trajectories at both the individual and national levels. Besides, national and individual savings rates also play a critical role in shaping long-term macroeconomic outcomes and economic growth paths.

There are different approaches in the economic literature to explain the relationship between savings behavior and economic inequality, with various schools of thought offering distinct perspectives on how savings influence growth trajectories and distributional outcomes. Neo-classical and demand-led or neo-Keynesian models recognize the critical role of savings in shaping economic development and inequality (Solow, 1956; Kaldor, 1957; Lewis, 1954; Pasinetti, 1962). The Solow (1956) model, a cornerstone of the neo-classical approach, highlights the importance of savings rates in driving long-term economic growth and convergence across countries. However, demand-led growth models suggest that increasing savings without considering the social structure can exacerbate income inequality within a country. Pasinetti (1962) argues that higher savings rates among the poor may disproportionately benefit the wealthy, worsening income inequality. Therefore, while increased savings are essential for economic growth, it is equally important to consider their impact on income distribution to ensure equitable growth (Pasinetti, 1962). The comparison of Solow's (1956) neo-classical model and Pasinetti's (1962) demand-led model provides valuable insights into the complex dynamics of savings behavior and economic inequality.

The theoretical motivation of this study stems from an integration of the class-based savings theory of Pasinetti (1962) with the long-run growth dynamics presented by Solow (1956). Pasinetti (1962) emphasizes the heterogeneity in savings behavior across different social classes, arguing that capital owners tend to save more while wage earners exhibit higher consumption tendencies. This class-based perspective suggests that differences in savings behaviors across social groups are critical in shaping economic inequality. On the other hand, Solow's (1956) model assumes a homogeneous savings impact across all countries, disregarding the differences in savings behaviors and their implications for inequality. While Pasinetti's (1962) analysis focuses on within-country inequality, this study extends his class-based approach to the global context by categorizing countries into distinct economic classes based on their consumption levels. In this adaptation, high-income countries function as capital owners, accumulating and reinvesting savings, while low-income countries function as wage earners, relying more on consumption. By applying Pasinetti's (1962) insights to the international level, this study provides a framework for understanding how differences in national savings behaviors contribute to global consumption inequality.

The impact of savings rates on inequality is not uniform; it varies depending on where these savings are concentrated and which economic class or country group is primarily responsible for the savings. In this context, the analysis presented here examines the differential effects of savings behaviors across distinct economic classes of countries. Specifically, this study investigates how the savings practices of high-income countries, which tend to have higher savings rates and more capital-intensive economies, contribute to consumption inequality compared to the savings behaviors of lower-income countries. By combining Pasinetti's (1962) insights on class-based savings with Solow's (1956) emphasis on long-term growth dynamics, this research offers a more nuanced

understanding of how global consumption inequality is influenced by country-specific savings patterns. This approach also addresses a critical gap in the existing literature by showing that global economic inequality cannot be fully understood through aggregate savings rates alone. Instead, it is essential to account for the heterogeneity in savings behaviors across different economic classes of countries, as these behaviors play a pivotal role in shaping global inequality dynamics.

The measure of inequality that best represents overall economic disparities remains a subject of academic debate, as studies suggest that differences between income inequality and consumption inequality may be driven by increasing savings gaps favoring high-income households. As Aguiar and Bils (2015) point out, if consumption inequality appears less severe than income inequality, this discrepancy is mainly due to higher savings rates among wealthier households, which can obscure the long-term effects of economic disparities if the gap between the two measures is overlooked. Therefore, it is essential to approach consumption-based inequality measures cautiously, as they may underestimate future disparities in living standards. However, noteworthy arguments in the literature highlight the importance of consumption inequality as a metric for understanding current living standards, particularly in cases where income and wealth data may fail to reflect everyday economic realities due to short-term fluctuations and the influence of policy changes. In contrast, consumption patterns are generally more stable over time, providing a more reliable indicator of household welfare (Johnson and Ship, 1991; Cutler and Katz, 1991; Krueger and Perri, 2006; Blundell and Preston, 1998; Slesnick, 1993). Furthermore, some scholars consider consumption inequality the final stage of economic inequality, capturing the combined effects of disparities in income, wealth, and resource access (Atkinson, 2015).

Before delving into the technical parts of the article, it is helpful to remind readers about the word inequality: This word is used throughout this article to express "economic inequality." However, this generalizing style should be approached cautiously because it is concerned in the literature that inequality is reduced to economic or even income inequality (Sen, 1999). This is why we work on the final stage, where inequality will manifest itself, namely consumption.

While poverty reduction has been a primary focus of global development policies, whether inequality or poverty should be the central concern remains a topic of debate in the literature. Feldstein (1999) argues that policies should focus on reducing poverty rather than addressing inequality, whereas Bourguignon (2004) emphasizes that reducing poverty requires tackling inequality, as the two issues are inherently linked. Similarly, Basu (2006) highlights that if there is a trade-off between reducing poverty and reducing inequality, absolute poverty should take precedence, even if it means tolerating a certain level of inequality. Despite these differences, these perspectives prioritize poverty reduction as the primary objective of development efforts.

Historical evidence shows that global poverty rates have declined significantly over the past two centuries. For instance, Angus Maddison's (1995) historical GDP estimates reveal that in 1820, approximately 84% of the global population lived in extreme poverty, which fell to 24% by 1992 (Bourguignon and Morrisson, 2002). Despite these gains in poverty reduction, consumption

disparities have proven far more resilient. As this study demonstrates, countries with low per capita consumption levels tend to remain in the same consumption class for decades, indicating the presence of a global caste system in consumption. This persistence of inequality raises critical questions about the underlying dynamics of economic development and the extent to which savings behavior can facilitate upward mobility in global consumption rankings.

Following Tümer (2019) and Kane (2016), Table 1 categorizes countries into five consumption groups based on their per capita consumption levels relative to the global average consumption ($\bar{c}_t$). These thresholds provide a framework for assessing global consumption inequality by illustrating which countries fall into high, middle, and low consumption categories over time:

Table 1: Consumption Group Classification by Threshold Levels

Consumption Group	Threshold Consumption Level
The Top Class	$2 * \bar{c}_t \leq X_{it}$
The Upper-Middle Class	$1.5 * \bar{c}_t \leq X_{it} < 2 * \bar{c}_t$
The Middle-Class	$\bar{c}_t \leq X_{it} < 1.5 * \bar{c}_t$
The Lower-Middle Class	$0.5 * \bar{c}_t \leq X_{it} < \bar{c}_t$
The Lowest Class	$X_{it} < 0.5 * \bar{c}_t$

Note: X_{it} represents the per capita real consumption level of the country *i* in year *t*, $\bar{c}_t$ denotes the average global consumption level for the same year.

To further explore the dynamics of global consumption inequality, this study analyzes annual shifts in population shares across different consumption groups between 1960 and 2019. Drawing on data from the Penn World Tables (PWT 10.01), the analysis tracks how countries have transitioned—or remained stagnant—within these consumption classes over time. The following figure illustrates these movement patterns, providing valuable insights into the persistence of global consumption disparities.

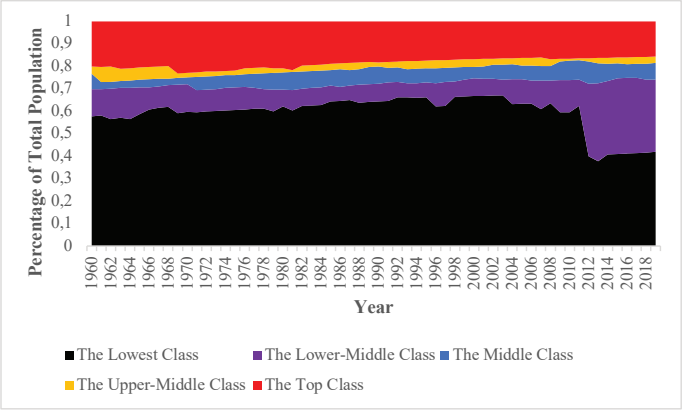

Figure 1: Global Population Distribution by Consumption Class (1960-2018)

Source: Penn World Table 10.01.

The construction of Figure 1 follows the approach outlined by Mankiw et al. (1992). Countries with a population of less than 1 million in 2019 were excluded from the Penn World Table (PWT) dataset, as were major oil-exporting countries. After these exclusions, countries with complete data across all variables were included in the analysis, resulting in a sample of 100 countries. [1]

Figure 1 illustrates the annual distribution of the global population across five consumption classes from 1960 to 2019, highlighting the persistence of global consumption inequality over time. The classes are categorized as the lowest, lower-middle, middle, upper-middle, and top class based on their per capita consumption relative to the global average. Throughout the period, much of the global population was concentrated in the lowest class (black area), indicating persistent consumption inequality. This group represents countries with less than half the global average per capita consumption. The size of this class remains relatively stable until the early 2000s, reflecting limited upward mobility for countries in this category. A notable decline in the size of the lowest class is observed starting from the early 2000s, particularly after 2012, when China transitioned into the lower-middle class category. This shift underscores the significant impact of China's economic growth on global consumption patterns. As one of the most populous countries in the world, China's upward movement reduced the global share of the lowest consumption class and expanded the lower-middle class (purple area). The lower-middle class (purple area) has gradually grown over time, especially after 2012, when China's economic advancement accelerated its transition from the lowest to the lower-middle class. The top class (red area), representing countries with per capita consumption at least double the global average, remains relatively stable throughout the period. This stability suggests that high-consumption countries consistently maintain their privileged position. The upper-middle class (yellow area) and middle class (blue area) show minimal fluctuations over time, indicating that countries in these classes tend to maintain their consumption levels without significant movement between classes. However, as noted in a previous study by the author, while these groups – the upper-middle and middle class – appear stable in the aggregate, they exhibit considerable internal mobility, with countries frequently shifting positions within their bands (Elcin, 2024). When China is excluded, a similar pattern can be observed in the lower-middle class (purple area), indicating that upward or downward mobility across broader consumption categories is rare, but internal mobility within these three classes is more common. As a result, Figure 1 reveals that global consumption inequality is persistent, with low-income countries struggling to ascend into higher consumption classes. The "global caste system" in consumption is evident, as high-consumption countries consistently retain their top position, while lower-consumption countries face significant barriers to upward mobility.

1 Countries with a population of less than 1 million that were excluded from the analysis are as follows: Anguilla, Antigua and Barbuda, Aruba, The Bahamas, Barbados, Belize, Bermuda, Bhutan, British Virgin Islands, Brunei Darussalam, Cabo Verde, Cayman Islands, Macau, Comoros, Curaçao, Cyprus, Djibouti, Dominica, Fiji, Grenada, Guyana, Iceland, Luxembourg, Maldives, Malta, Montenegro, Montserrat, Saint Kitts and Nevis, Saint Lucia, São Tomé and Príncipe, Seychelles, Sint Maarten, Saint Vincent and the Grenadines, Suriname, and Turks and Caicos Islands. *The excluded oil-exporting countries* are Bahrain, Gabon, Iran, Iraq, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates.

As previously mentioned, this study builds on the theoretical insights of Solow (1956) and Pasinetti (1962) to explore how national savings behaviors influence global consumption inequality. While Solow's (1956) growth model highlights the importance of savings rates for long-term economic growth, Pasinetti's (1962) class-based perspective emphasizes that the distribution of savings across social groups matters for income distribution. Extending this framework to the country level, this study investigates how differences in national savings rates across high-income and lower-income (or developed and developing) countries shape persistent global consumption disparities.

As part of the theoretical framework, this study employs the general equilibrium model proposed by Gillman (2011), which models the macroeconomic process of converting savings into investment. The consumption function derived from this model is used to explore the relationship between savings behaviors and global consumption disparities. Following the approach of Jones and Vollrath (2013), who manipulated the steady-state output in the Solow-Swan model using the ratio of $\frac{y_i}{y_{US}}$, where y_i and y_{US} represent output per worker in the country i and the United States, respectively, this study applies a similar method to Gillman's (2011) consumption function. Instead of output, the ratio $\frac{c_t}{c_t^*}$ is used, where c_t represents the higher per capita consumption level in a benchmark country and c_t^* represents the per capita consumption level in another country with a lower per capita consumption level. This ratio captures consumption inequality across countries as c_t exceeds c_t^*, indicating disparities in consumption levels.

To empirically examine the relationship between national savings behaviors and global consumption inequality, this study utilizes an unbalanced panel dataset covering multiple countries from 1960 to 2019, primarily sourced from the Penn World Tables (PWT 10.01). The analysis focuses on how differences in savings rates across high-income and lower-income countries affect per capita consumption disparities, using the United States as a benchmark due to its historically high consumption levels. The key regression model employs the $\frac{c_{US}}{c_i}$ ratio, where c_{US} represents per capita consumption in the United States and c_i represents per capita consumption in the country i, as the dependent variable. The primary explanatory variables include gross capital formation (as a proxy for savings) and an interaction term between savings rates and a high-income dummy variable, with real GDP per capita and GDP share of government consumption included as control variables. This empirical framework allows the study to test the hypothesis that higher savings in wealthier countries contribute to persistent global consumption disparities.

The empirical analysis uses a high-income dummy variable based on the World Bank's income classification. Countries classified as high-income by the World Bank are assigned a value of 1, and all others are assigned 0. The sample includes 139 countries, excluding small countries (population below 1 million) and oil-exporting countries. Unlike the Figure 1 analysis, which uses a balanced dataset, the empirical analysis employs an unbalanced dataset to maximize observations. [2]

2 The classification used in Figure 1 differs from the high-income and low-income discrimination applied in the empirical analysis. The approach in Figure 1 enables the study to observe annual changes in consumption inequality

The findings highlight the heterogeneous impact of savings rates on global consumption inequality. The interaction term with the high-income dummy shows that while general savings rates reduce inequality, savings in high-income countries have the opposite effect, suggesting that capital accumulation in wealthier countries reinforces long-term consumption disparities.

The structure of this paper is as follows: Section 2 presents the theoretical framework, which provides the foundation for defining consumption inequality using the general equilibrium model of Gillman (2011) and the approach proposed by Jones and Vollrath (2013). This section describes how these theoretical insights were applied to Pasinetti's (1962) class-based savings approach to cross-country consumption inequality. Section 3 discusses the data, methodology, and empirical analysis, detailing the construction of the dataset and the regression model used to test the relationship between savings rates and consumption inequality. Finally, Section 4 provides the conclusion, summarizing the key findings and their implications for global consumption inequality.

2. Theoretical Framework

This section outlines the theoretical framework underpinning this study, focusing on the interplay between savings behavior and consumption inequality in a cross-country context. The analysis draws on the Solow (1956) and Pasinetti (1962) models to highlight how different savings patterns can shape income distribution and economic growth. Building on this foundation, the study adopts Gillman's (2011) general equilibrium model, combined with the approach of Jones and Vollrath (2013), to define consumption inequality. This framework provides a basis for understanding how savings rates across different income groups influence global consumption disparities.

The general equilibrium model proposed by Gillman (2011) incorporates a recursive utility function, which reflects the consumer's decision-making process regarding consumption, leisure, and savings. The unique aspect of Gillman's (2011) model is that individual consumers cannot directly save their income; instead, they must use a financial intermediary, such as a bank, to convert their savings into investments. The efficiency of this financial intermediary is crucial — any imperfections in the financial market can cause savings to be lost or partially transformed into investment, leading to inefficiencies in capital accumulation.

The recursive utility function is expressed as follows:

$$V(k_t^s) = \underset{c_t^d,\, x_t,\, l_t^s,\, k_{t+1}^s}{\text{Max}} \; u(c_t^d,\, x_t) + \beta V(k_{t+1}^s)$$

In above equation $V(k_t^s)$ describes the maximum utility that can be obtained given the state of capital investment at the time t. c_t^d represents the consumer's demand for consumption goods.

across income groups, which is not possible using the static World Bank classifications.

x_t denotes leisure, reflecting the consumer's choice between work and free time. l_t^s represents the labor supply to the financial intermediary and firm. β is the discount factor reflecting the weight given to future utility compared to current utility. It captures time preference, where higher values indicate greater importance for future utility. k_{t+1}^s describes the future state of capital investment.

The recursive utility function presented in its generic form captures the consumer's decision-making process regarding consumption, leisure, savings, and investment. In the logarithmic specification in equation (1), the utility function is transformed to account for the role of financial intermediaries and time allocation decisions. Unlike in traditional models, where consumers directly invest in capital, investment in this model takes the form of choosing d_{t+1}, which represents the new deposits made for the next period. Consumers receive a return on these deposits in the form of $d_t(1 + R_t^d)$, which includes both the principal and interest. The state variable, therefore, becomes d_t, representing the consumer's current deposits instead of k_t^s, the traditional capital stock. Additionally, consumers allocate time spent working in the bank l_{Ft}^s, reflecting the unique structure of this general equilibrium framework in which financial intermediaries play an active role in the economy.

$$V(d_t) = \max_{c_t^d,\, x_t,\, l_t^s,\, l_{Ft}^s,\, d_{t+1}} \ln c_t^d + \alpha \ln x_t + \beta V(d_{t+1}) \tag{1}$$

The utility function consists of three components, $\ln c_t^d$, $\alpha \ln x_t$ and $\beta V(d_{t+1})$ and representing the utility derived from consumption, leisure, and discounted future utility. The parameters and denote the relative weight of leisure in utility and – as stated earlier – the discount factor applied to future utility respectively.

To enhance the realism of the model, a government sector is introduced, imposing a tax on labor income, represented by $\tau_l (\tau_l \in [0,1])$. The government collects an amount of $\tau_l w_t (l_t^s + l_{Ft}^s)$ as revenue, where l_t^s represents the labor supplied to the firm and l_{Ft}^s denotes the labor supplied to the financial intermediary. The collected revenue is then used to provide public goods for the benefit of consumers, denoted by G_t. This can be expressed through the following equation:

$$G_t = \tau_l w_t (l_t^s + l_{Ft}^s)$$

The consumer's income consists of labor income and interest income from deposits, represented by $R_t^d d_t$. The amount reinvested in deposits, expressed as $d_{t+1} - d_t$, is subtracted from income to determine the net investment. The resulting budget constraint shows that consumption is equal to total income minus net investment and can be expressed as:

$$c_t = w_t(1 - \tau_l)(l_t^s + l_{Ft}^s) + R_t^d d_t + G_t - (d_{t+1} - d_t) \tag{2}$$

Consumers allocate their available time between working at the bank, working for the firm, and engaging in leisure activities.

$$l_t^s + l_{Ft}^s + x_t = 1$$

Based on these pieces of information, rearranging equation (2) yields the following equation.

$$c_t = w_t(1-\tau_l)(1- x_t) - d_{t+1} + G_t + d_t(1+R_t^d)$$

Using the above equation allows us to obtain the following recursive utility function:

$$V(d_t) = \underset{x_t}{\text{Max}} \ln[w_t(1-\tau_l)(1- x_t) - d_{t+1} + G_t + d_t(1+R_t^d)] + \alpha \ln x_t + \beta V(d_{t+1}) \quad (3)$$

The first-order conditions for leisure yields:

$$w_t = \frac{\alpha c_t}{x_t(1-\tau_l)} \quad (4)$$

The consumer earns wage income by maximizing utility with respect to leisure.

To further enhance the model's realism, the tax collection and redistribution assumption is relaxed by incorporating a voter-driven government policy framework, following the approach of Meltzer and Richard (1981) and Elgin et al. (2013). In this framework, the government collects taxes based on individuals' current wages and redistributes these funds based on the average wage level in the economy. Since the average income exceeds the median income in an unequal society, the decisive voter—whose preferences influence tax policy—seeks to maximize utility by supporting a tax rate that ensures redistributive benefits outweigh personal tax contributions. As a result, the consumption function for the decisive voter can be expressed as follows:

$$c_t^d = w_t^d(1-\tau_l)(1- x_t) - d_{t+1} + \tau_l \bar{w}_t(1- x_t) + d_t(1+R_t^d) \quad (5)$$

In an economy characterized by economic inequality (that is: $M = \frac{\bar{w}_t}{w_t^d}$ and, $M > 1$), the median/decisive individual will choose the tax rate that maximizes their utility, as the government, according to the assumption, cannot ignore the demands of those adversely affected by economic inequality.

Equation (5) can be rewritten in the following form:

$$c_t^d = (1- x_t)(w_t^d(1-\tau_l) + \tau_l \bar{w}_t) + d_t(R_t^d - g)$$

Where (economy's growth rate) is calculated as:

$$g = \frac{d_{t+1} - d_t}{d_t}$$

In equilibrium, the capital stock k_t equals the amount of the deposit d_t, this leads to the following equation:

$$k_t = d_t$$

From the consumer's intertemporal margin, we also have [3]:

$$R_t^d - g = \rho(1+g)$$

Therefore, the consumption demand can be expressed in a more familiar format as:

$$c_t^d = (1 - x_t)(w_t^d(1-\tau_l) + \tau_l \overline{w}_t) + \rho(1+g)k_t$$

And equation (4) implies that:

$$x_t = \frac{\alpha c_t^d}{w_t^d(1-\tau_l)}$$

After substituting x_t to the above consumption equation, the consumption function can be expressed by the following equation.

$$c_t^d = [w_t^d(1-\tau_l) + \tau_l \overline{w}_t + \rho(1+g)k_t]\left[\frac{w_t^d(1-\tau_l)}{w_t^d(1-\tau_l)(1+\alpha)+\alpha\tau_l\overline{w}_t}\right] \quad (6)$$

To define consumption inequality in a comparable manner across countries, let us assume that a country's per capita consumption level c_t exceeds another country's per capita consumption level $c_t{}^*$, indicating that the first country (with c_t) enjoys a higher standard of living than the second (with $c_t{}^*$). This inequality can be expressed through the ratio $\frac{c_t}{c_t{}^*}$ where a higher ratio indicates greater relative consumption. Similar to the approach of Jones and Vollrath (2013), this metric allows us to capture disparities in consumption levels across countries and over time.

Assuming that $c_t > c_t{}^*$, consumption inequality can be expressed by the following equation:

$$\frac{c_t}{c_t{}^*} = \frac{\frac{\left[w_t^d\left[(1-\tau_l)^2+\tau_l M(1-\tau_l)\right]+\rho k_t(1-\tau_l)\right]}{(1-\tau_l)(1+\alpha)+\alpha\tau_l M}}{\frac{\left[w_t^{d^*}\left[\left(1-\tau_l^*\right)^2+\tau_l{}^* M^*\left(1-\tau_l^*\right)\right]+\rho k_t^*\left(1-\tau_l^*\right)\right]}{\left(1-\tau_l^*\right)(1+\alpha)+\alpha\tau_l^* M^*}}$$

Letting $\frac{c_t}{c_t{}^*} = \hat{c}_t$, the following equation shows the consumption inequality across countries.

$$\hat{c}_t = \frac{\left[w_t^d[(1-\tau_l)^2+\tau_l M(1-\tau_l)]+\rho k_t(1-\tau_l)\right]}{\left[w_t^{d^*}\left[\left(1-\tau_l^*\right)^2+\tau_l{}^* M^*\left(1-\tau_l^*\right)\right]+\rho k_t^*\left(1-\tau_l^*\right)\right]}\frac{\left[\left(1-\tau_l^*\right)(1+\alpha)+\alpha\tau_l^* M^*\right]}{\left[(1-\tau_l)(1+\alpha)+\alpha\tau_l M\right]} \quad (7)$$

In equation (7), the parameters and variables marked with stars represent the country with lower consumption level that is $c_t{}^*$.Pasinetti's (1962) perspective can be applied to equation (7) to examine how the savings behaviors and capital accumulation patterns of countries in different income groups influence consumption inequality. [4] By deriving the first-order conditions of

3 This condition follows the Ramsey (1928) equilibrium condition for the case of zero growth, as outlined in Gillman (2011). ρ represents the subjective rate of discount ($\frac{1}{1+\rho} \equiv \beta$), and the full derivation of this condition is provided in Gillman (2011).

4 This adaptation allows the study to examine how different national savings rates influence global consumption

equation (7) with respect to k_t and k_t^*, it becomes possible to identify the differential effects of capital accumulation across country classes, highlighting that countries wi th varying savings rates contribute to consumption inequality in distinct ways.

$$\frac{\partial \hat{c}_t}{\partial k_t} = \frac{\rho(1-\tau_l)}{\left[w_t^{d^*}\left[(1-\tau_l^*)^2+\tau_l{}^* M^*(1-\tau_l^*)\right]+\rho k_t^*(1-\tau_l^*)\right]} \frac{\left[(1-\tau_l^*)(1+\alpha)+\alpha\tau_l^* M^*\right]}{\left[(1-\tau_l)(1+\alpha)+\alpha\tau_l M\right]} > 0 \tag{8}$$

$$\frac{\partial \hat{c}_t}{\partial k_t^*} = -\left[w_t^{d^*}[(1-\tau_l^*)^2+\tau_l{}^* M^*(1-\tau_l^*)]+\rho k_t^*(1-\tau_l^*)\right]^{-2}\rho(1-\tau_l^*)[w_t^d[(1-\tau_l)^2+\tau_l M(1-\tau_l)]+\rho k_t(1-\tau_l)]\frac{\left[(1-\tau_l^*)(1+\alpha)+\alpha\tau_l^* M^*\right]}{\left[(1-\tau_l)(1+\alpha)+\alpha\tau_l M\right]} < 0 \tag{9}$$

Inequality (8) implies that higher capital accumulation in wealthier countries widens consumption inequality. In contrast, inequality (9) shows that increased capital accumulation in poorer countries can help reduce consumption inequality across countries.

As previously discussed, Pasinetti (1962) argued that increased savings by lower-income groups would ultimately exacerbate inequality. However, the situation presented here does not fully align with Pasinetti's (1962) approach, as increased savings in poorer countries appear to reduce consumption inequality across countries. At first glance, this may suggest a policy recommendation that wealthier countries should reduce their savings rates while poorer countries should increase theirs. However, such a recommendation would be detached from economic realities and oversimplify the complexities of global inequality. Therefore, the validity or limitations of Pasinetti's (1962) argument will be discussed in greater detail after the empirical results are presented.

3. Data, Methodology, and Empirical Results

This section presents the data, methodology, and empirical results to examine the relationship between savings behavior and consumption inequality across countries. The analysis is based on unbalanced panel data from the Penn World Table (PWT) version 10.01, covering a wide range of countries from 1960 to 2019. As mentioned, the dataset comprises 139 countries, with small countries (populations under 1 million) and oil-exporting countries excluded from the analysis. [5] The methodology includes Pooled OLS, Fixed Effects (FE), and the Two-Step System Generalized Method of Moments (GMM)

inequality. In line with the Solow-Swan growth model, this study assumes that savings are transformed into investment, which in turn adds to the capital stock. While savings is a flow variable representing the portion of income not consumed within a period, capital *k* is a stock variable that accumulates over time through investment *i*. Following this framework, the Gillman (2011) model incorporates the role of savings in shaping consumption patterns, which is further explored in this study through the $\hat{c}_t$ ratio to understand how national savings behaviors influence global consumption disparities.

5 Refer to Footnote 2 for the list of excluded countries.

estimator to address endogeneity concerns and ensure robust and reliable results. The findings emphasize the differential impacts of savings rates in high-income and low-income countries on global consumption inequality, following the theoretical framework outlined in the previous section.

The theoretical framework presented in this study highlights the role of savings behavior and capital accumulation in shaping consumption inequality. Building on the work of Gillman (2011), the theoretical model suggests that savings decisions made by different economic agents can lead to diverging consumption patterns over time. The following empirical model translates these theoretical insights into an empirical framework by examining how savings rates and capital accumulation impact global consumption inequality.

$$\ln\left(\frac{C_{US}}{C_i}\right) = \alpha + \beta_1 \ln(K_i) + \beta_2 \ln(K_i).D_R + \beta_3 Z_i + \varepsilon_i \quad (10)$$

In particular, the theoretical model emphasizes that the marginal effect of savings on consumption inequality depends on the economic class or country group in question. This idea is captured in the empirical model through the inclusion of an interaction term between capital accumulation and a high-income dummy variable, allowing us to test whether savings behavior in high-income countries differs in its impact on consumption inequality.

$$D_r = \begin{cases} 1 \; if \; C_i = High \; Income \\ 0 \; if \; C_i \neq High \; Income \end{cases}$$

The empirical model used in this study examines the relationship between savings rates and consumption inequality across countries. The dependent variable, $\ln\left(\frac{C_{US}}{C_i}\right)$, represents the log of the ratio between per capita consumption in a benchmark country and per capita consumption in the country. The key explanatory variable is $\ln(K_i)$, which measures the capital accumulation in the country. The term D_R is a dummy variable that takes 1 for high-income countries and 0 otherwise. The interaction term $\ln(K_i).D_R$ captures the differential impact of savings rates on consumption inequality between high-income and non-high-income countries. Additionally, Z_i represents a set of control variables while ε_i is the error term.

Table 2 presents a detailed description of the variables used in the empirical analysis, including their definitions, transformations, and data sources. The primary focus of this study is to investigate the relationship between savings behavior and global consumption inequality, using a dynamic panel data model estimated through the Two-Step System GMM approach. The variables in the table are carefully selected to capture key theoretical insights from the consumption function discussed in the theoretical framework.

Table 2: Description of Variables and Data Sources Used in the Empirical Analysis

Variable Name		Description	Source
Dependent Variable			

Consumption Inequality	*ln (CI)*	Consumption inequality is measured as the ratio of per capita consumption in the U.S. to per capita consumption in country *i*, and the natural logarithm of this ratio is then calculated.	PWT 10.01
Independent Variables			
Natural Log of Savings Rate	*ln (SR)*	Natural logarithm of the share of Gross Capital Formation (GCF) in GDP at current PPPs.	PWT 10.01
Savings Rate (High-Income Dummy Interaction)	*ln (SR).*D_r	The interaction term between the natural logarithm of GCF and a dummy variable D_r that equals 1 for high-income countries, capturing how savings behavior differs between high-income countries and other countries.	PWT 10.01
Natural Log of Real GDP per Capita	*ln (GDPpc)*	The natural logarithm of real GDP per capita is adjusted for purchasing power parity (PPP). This variable reflects the standard of living in each country.	PWT 10.01
Natural Log of Government's Share	*ln (GS)*	The natural logarithm of the government's share of GDP reflects the total output allocated to government consumption expenditures, including public services, infrastructure, and welfare programs.	PWT 10.01
Instrumental Variables			
Natural Log of Latitude	*ln(L)*	Latitude is a geographic variable that measures a country's distance from the equator.	DSPL*
British Legal Origin Dummies	*LO*	British legal origin dummy variable indicates whether a country's legal system is based on British common law traditions. It takes 1 for countries with a British legal origin and 0 otherwise.	LaPorta et al. (1999)

Note*: The DataSet Publishing Language (DSPL) is a format for structuring data and metadata for interactive visualizations.

Consumption inequality as a key metric in this study follows the existing literature highlighting its importance in assessing long-term well-being (Krueger and Perri, 2006; Meyer and Sullivan, 2013; Attanasio and Pistaferri, 2016). In the theoretical framework, consumption inequality was defined through the $\frac{c_t}{c_t^*}$. In the empirical analysis, the U.S. per capita consumption level is used as the benchmark, a choice that aligns with the approach taken by Jones and Vollrath (2013). The U.S. has consistently ranked among the top two countries in per capita consumption from 1960 to 2019. Therefore, $\frac{c_{US}}{c_i}$ is used as a proxy for consumption inequality in the empirical analysis to capture cross-country disparities in living standards.

In this study, gross capital formation (GCF) is used as a proxy for savings behavior, a common approach in the literature where GCF is often used as a substitute for investment (Rao, 1980; Akinola and Omodale, 2013). The interaction term between GCF and the high-income dummy is based on Pasinetti's (1962) class-based savings theory, which suggests that savings behavior differs across income groups. Previous studies have shown that wealthier economic agents – whether individuals or countries – tend to have higher savings rates, driven by differences in income levels and wealth accumulation (Carroll, 2000; Deaton, 1999; Fisher et al., 2020). This study investigates whether such differences in savings behavior contribute to consumption inequality across countries.

Real GDP per capita is included to account for economic differences across countries, a control variable widely used in growth and inequality studies (Hall and Jones, 1999; Mankiw et al., 1992;

Barro, 1991). This variable reflects the overall development level of a country and is essential for understanding disparities in consumption levels. The share of government consumption in GDP captures the redistributive role of government policies, which has been shown to influence inequality across countries (Alesina and Rodrik, 1994; Acemoglu et al., 2019). Government consumption can reduce inequality through public services and welfare programs.

Latitude is included as a proxy for geographic and climatic differences that influence economic development. Previous studies have shown that latitude correlates with institutional quality and historical development paths (Acemoglu et al., 2002). Furthermore, Jauch and Watzka (2016) use latitude as an instrumental variable for financial development while estimating the financial Kuznets curve. Finally, legal origin is included to account for institutional differences across countries. It has been used as an instrumental variable in various studies to capture the impact of historical legal traditions on economic outcomes. For example, Elgin et al. (2013) use legal origin as an instrument for religiosity in their analysis of the informal economy.

Before delving into the core analysis, the descriptive statistics and correlation matrix are presented to provide a foundational understanding of the key variables, distributions, and relationships. Table 3 presents the descriptive statistics of the key variables used in the empirical analysis. The table shows the number of observations, mean values, standard deviations, and the minimum and maximum values for each variable.

Table 3: Descriptive Statistics of Key Variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
C_{us}/C_i	7,509	11.66	14.07	0.84	203.72
GCF*	7,509	0.20	0.10	0.01	0.95
Real GDP pc	7,509	10608.35	12752.32	244.6	102354
Gov. Share	7,509	0.19	0.10	0.01	0.82
Latitude	8,335	20.25	25.35	-40.9	61.92

Note*: Five observations with negative or zero values in the gross capital formation (GCF) variable were excluded to facilitate the logarithmic transformation applied in the regression analysis.

Including summary statistics provides a general overview of the distribution and variability of the variables used in the regression models. Given the necessity of transforming some variables into their natural logarithmic form, special attention was paid to ensuring that all variables used in the analysis meet the requirements for such transformations. As noted, negative or zero values in the gross capital formation variable (GCF) were excluded from the sample to ensure accurate logarithmic calculations.

Table 4: Pairwise Correlation Matrix of Variables Used in the Empirical Analysis

	C_{us}/C_i	GCF	Real GDP pc	Gov. Share	Latitude	Legal O. D.
C_{us}/C_i	1					
GCF	-0.28***	1				

Real GDP pc	-0.45***	0.39***	1			
Gov. Share	-0.06***	-0.13***	-0.08***	1		
Latitude	-0.27***	0.22***	0.40***	0.12***	1	
Legal O. D.	0.02*	0.04***	0.02*	-0.14***	-0.32***	1

Note: The correlation coefficients are shown with significance levels indicated by stars. ***, **, and * indicate that the coefficient is significant at 1%, 5%, and 10%, respectively.

The correlation matrix reveals notable relationships between the dependent variable, C_{us}/C_i, and key independent variables. Gross capital formation (GCF) shows a negative correlation with consumption inequality, suggesting that savings behavior may reduce disparities across countries. However, the correlation matrix does not account for differences across country groups. This concern will be further investigated by including the interaction term in the upcoming regression analysis. Additionally, real GDP per capita shows a negative correlation, supporting the expectation that wealthier countries experience lower consumption inequality. Government share in GDP and latitude display negative correlations with consumption inequality, aligning with theories that associate institutional and geographic factors with inequality. The correlation coefficient between British legal origin and consumption inequality is significant. This positive but weak correlation suggests that countries with British legal origins tend to have slightly higher cross-country consumption inequality compared to countries with other legal systems.

Table 5: Regression Results

Dependent Variable: Consumption Inequality (*ln (CI)*)							
	POLS	POLS	POLS	FE	FE	FE	GMM
L. ln (CI)							0.999***
							(0.044)
ln (SR)	-0.814***	-0.467***	0.040***	-0.049	-0.034	0.018	-0.062**
	(0.019)	(0.016)	(0.010)	(0.042)	(0.045)	(0.023)	(0.031)
ln (SR). Dr		1.011***	0.113***		-0.171	-0.038	0.102*
		(0.014)	(0.010)		(0.105)	(0.044)	(0.054)
ln (GDPpc)			-0.859***			-0.628***	-0.006
			(0.007)			(0.040)	(0.030)
ln (GS)			-0.014			-0.020	-0.010
			(0.011)			(0.033)	(0.050)
Constant	0.174*	1.305***	8.732***	1.704***	1.660***	7.581***	
	(0.093)	(0.084)	(0.081)	(0.084)	(0.083)	(0.357)	
Obs.	7,509	7,509	7,509	7,509	7,509	7,509	5,485
R-squared	0.20	0.53	0.87	0.10	0.10	0.66	
Sargan							0.78
AB AR(1)							0.00
AB AR(2)							0.21

p values				
# of Countries	139	139	139	108

Notes: ***, **, and * indicate that the coefficient is significant at 1%, 5%, and 10%, respectively. Standard errors in parentheses. All estimations with time dummies and robust standard errors. Values in parentheses indicate standard errors.

The regression results highlight the complex relationship between savings behavior and consumption inequality across countries. The Pooled OLS models reveal substantial findings. In the first and second Pooled OLS models, savings rates *ln (SR)* alone appear negatively correlated with consumption inequality. However, in the second model when the interaction term *ln (SR).* D_r is included, and the combined marginal effect becomes positive, indicating that higher savings rates increase inequality across countries. In the third Pooled OLS model, both *ln (SR)* and the interaction term *ln (SR).*D_r are positive and significant, suggesting savings behavior reinforces consumption disparities rather than reducing them. In the Fixed Effects (FE) models, only *ln (GDPpc)* is statistically significant in the third model, showing a negative coefficient that suggests economic growth reduces consumption inequality. Other variables, including savings rates and their interaction term, are insignificant in the Fixed Effects models. The Two-Step System GMM model addresses endogeneity concerns and shows that the savings variables remain significant, whereas the control variables become insignificant. While one might interpret this as evidence that higher savings reduce inequality, this would ignore the heterogeneity across different economic classes like the second Pooled OLS model. The findings demonstrate that the effect of savings on consumption inequality varies significantly by country group, underscoring the importance of accounting for class-based differences in savings behavior, as emphasized in Pasinetti's (1962) theory. Overall, the results suggest that increasing savings rates without considering the economic class of countries can exacerbate consumption inequality across the globe.

It is necessary to assess the share of government consumption in GDP separately. Despite its lack of statistical significance in the models, its inclusion is warranted by the theoretical framework. The inclusion of the government in the theoretical model enhances its realism. Given that the theoretical model serves as the foundation for the empirical analysis, excluding the government from the empirical model would be unjustifiable.

4. Conclusion

This study builds upon insights from earlier research, where we explore the role of savings in explaining cross-country consumption dynamics (Elcin, 2024). Inspired by Chang's (2002) argument that a one-size-fits-all growth strategy is unsuitable for all nations, this study delves deeper into how savings behaviors impact global consumption inequality, particularly across countries with varying economic statuses. While Solow's (1956) model highlights the importance of savings in explaining economic disparities, my earlier work demonstrated that savings also play a crucial role in shaping consumption disparities. Integrating Pasinetti's (1962) class-based perspective further

underscores the necessity of considering heterogeneity in economic agents' behaviors. By bridging these theoretical insights, this study emphasizes the importance of tailoring economic strategies to account for the diverse savings behaviors of different country groups.

This study contributes to the literature by extending Pasinetti's (1962) class-based perspective on inequality to the context of cross-country consumption disparities. Pasinetti's (1962) approach, which assumes heterogeneity in individual savings behaviors within a country, is here adapted to analyze how heterogeneity in national savings behaviors affects global consumption inequality. Although the presented theoretical model and the empirical findings do not explicitly confirm Pasinetti's (1962) theoretical argument that savings by disadvantaged individuals increase inequality, his emphasis on distinguishing the effects of savings across different income groups remains highly relevant. The study underscores the importance of considering how savings behavior varies across economic classes and its implications for inequality dynamics. Applying this framework to countries instead of individuals demonstrates that assuming uniform savings behavior across nations is as unrealistic as expecting homogeneity in savings behaviors within a single country. The classification method used in Figure 1 plays a critical role in this adaptation. One striking observation from the calculations is that, between 1960 and 2019, countries in the top class exhibited an average GCF (a proxy for savings) of 0.28, while this figure was only 0.16 for the lowest-class countries. This gap in savings behaviors lays the foundation for analysis and highlights that policies aimed at reducing consumption inequality cannot rely on a 'one-size-fits-all' approach. Because increasing savings in lower-income countries may reduce global consumption inequality, the same cannot be said for wealthier countries, where higher savings exacerbate consumption disparities. The theoretical approach and the empirical findings confirm this divergence. The interaction term in the dynamic regression model shows that savings increases in wealthy countries have a statistically significant positive impact on consumption inequality, reinforcing existing disparities. This raises the critical question of whether savings should be discouraged in affluent nations. As the literature suggests, however, higher marginal propensities to save among the wealthy are well-documented (Carroll, 2000; Deaton, 1999; Alvarez and Vilalta, 2018; Fisher et al., 2020). While expecting wealthy nations to curb their savings is impractical, our findings suggest that global consumption inequality is likely to persist as long as savings behavior remains concentrated among these countries.

In formulating economic policies, ignoring the heterogeneity of economic agents and nations can lead to misguided outcomes. Each country possesses unique historical, cultural, and geographical contexts, and this diversity extends to economic agents and institutions. For instance, expecting a fish to climb a tree is as unrealistic as expecting a country or an individual to conform to a standard economic model without considering their unique circumstances. Therefore, economic policies must be flexible and context-specific, taking into account the heterogeneity of agents. Policies sensitive to differences can enhance the sustainability of economic growth and reduce inequalities. In this regard, the discipline of economics must adopt more inclusive approaches, placing heterogeneity at the core of both theoretical frameworks and practical applications.

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RESEARCH ARTICLE

THE IMPACT OF REGIONAL TAX INCENTIVES ON HOUSEHOLD INCOMES IN TÜRKİYE

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Abstract

This study analyzes the effects of regional tax incentives on household incomes in Türkiye by using difference-in-differences regression methodology. In Türkiye, a comprehensive regional tax incentive law was introduced in 2009 and it was reorganized in 2012. This new tax incentive law includes additional incentives for investments to be made in the Southeastern Anatolia region. This paper analyzes the effects of these tax incentives on household incomes mainly in the Southeastern Anatolia region of Türkiye. The households of the Southeastern Anatolia region were considered as the treatment group, whereas the households of the neighboring regions were considered as the control group. We estimated household incomes in the regions using the Income and Living Conditions Surveys conducted by Turkstat from 2006 to 2018. In conclusion, it is estimated that incomes of households especially living in Southeastern Anatolia region have increased significantly higher than the household incomes of neighboring regions after 2012. When the analysis is repeated for households whose main income source is entrepreneurial incomes there is no significant effect of the tax incentives on entrepreneurial incomes.

Keywords: Household Income, Tax Incentives, Region
JEL Codes: H31, I38, R11

1. Introduction

Developing countries implement various incentive policies in order to increase employment in underdeveloped regions, reduce regional development differences within the country, attract foreign capital investments and facilitate the adoption of new technologies (Schalk & Gerhard, 2000; Tung & Cho, 2001; Karakurt, 2010; Akdeve & Karagöl, 2013). These incentive policies aim to increase employment by attracting domestic and foreign investments to underdeveloped regions through tools such as regional tax rate incentives, import duty exemptions and tax

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holidays (Bondonio & Greenbaum, 2006; Klemm & Van Parys, 2012; Simay-Karaalp, 2014). There are many studies in the literature that examine whether tax incentives are successful in attracting foreign capital investments to the host country (Tung & Cho, 2001; Klemm & Van Parys, 2012; Lodhi, 2017; Munongo & Ribinson, 2017).

Tax incentives act as a motivational tool for manufacturing companies to direct their production facilities to rural areas. Holland & Vann (1998) argue that regional development is a common objective for the use of tax incentives. Porsse et al. (2007) evaluate the success of the regional tax incentive schemes implemented in Brazil in the second half of the 1990s in attracting investments using a generalized equilibrium model. The implementation of such incentive schemes has positive effects on employment and household welfare. However, due to the specialized nature of regional production, the impact on real GDP does not follow the same path (Porsse et al., 2007). Lodhi (2017) underlines that tax incentives need to be considered holistically as a component of the overall economic policy in order to achieve overall economic development in the country. This effect is empirically analyzed for Ghana using time series data and it is found that tax incentives have a positive significant effect on regional economic growth (Amankwaah et al., 2022).

This research attempts to find out the impact of regional tax incentives on household welfare in Türkiye using household level data. Various tax incentive regulations have been implemented in Türkiye, varying in scope, types, and regions of application. The most prominent of these policy instruments are the incentives introduced by the 2009 Incentive Law and expanded by the 2012 Incentive Law, targeting general, regional, large-scale, and strategic investments in the production of products with high import dependency. This research examines whether the tax incentives introduced by the 2012 Incentive Law, which predominantly benefit the Northeastern, Middle-Eastern Anatolia, and Southeastern Anatolia regions, have led to an increase in household incomes in these regions compared to other regions. The data for the study were obtained from microdata of annual surveys that is called as Income Conditions and Living Survey from 2006 to 2018 conducted by Turkstat. We apply the difference-in-differences methodology to measure the impact of the 2012 Incentive Law on household incomes. The difference-in-differences econometric methodology is commonly used in the literature to measure the effects of policy changes (Angrist & Pischke, 2008; Bondonio & Greenbaum, 2006).

In 2009, a nationwide law divided Türkiye into four investment regions, adjusting the level of incentives based on the development status of each region. The aim of these investment incentives is to direct savings towards high value-added investments and to reduce regional development disparities by increasing production and employment in economically underdeveloped regions. In 2012, a new incentive law was enacted that grouped Türkiye's provinces into six investment regions based on their development levels. This law also introduced two additional preferential incentive measures specifically for investments directed to the Southeastern Anatolia Region. Since these incentives include legal regulations prioritizing and promoting investments in underdeveloped regions, there are expectations that investments will concentrate in these areas, positively impact household incomes through their job creation potential, and help reduce

income disparities among regions. To assess the effectiveness of the currently implemented regional incentive instruments becomes important in order to reduce regional inequality and to provide policy recommendations. For this reason, we test the effect of the incentive law that started to be implemented in 2012.

This paper has the following sections. The following section summarizes the literature review. The section 3 explains detail the tax incentives implemented in Türkiye. The data and methodology of the paper is seen at section 4. Section 5 presents results of the regression analysis. The final section concludes the paper.

2. Literature Review

In the literature, the effects of incentives on the economy are mostly examined empirically through their capacity to create employment (Schalk & Gerhard 2000; Gabe & Kraybill 2002; Hoyt et al., 2008; Bondonio & Greenbaum, 2007). According to some studies, regional investment incentives have positive effects on investment demand and employment targets (Schalk & Gerhard, 2000). The business incentives in the structural fund "target 2", a specific one of the European regional development funds have shown positive employment growth effects in targeted areas in northern and central Italy (Bondonio & Greenbaum, 2006). Bondonio & Greenbaum (2007) analyze the effects of geographically targeted tax incentives on local economic growth in entrepreneurial regions in the U.S. and find that these incentives positively affect employment, sales, and capital expenditures. On the other hand, a study examining how manufacturing and other businesses in the state of Ohio are affected by government economic development incentives finds that the effect on actual employment is weak or even negative, while the impact on projected employment is significant. This finding suggests that businesses may have misrepresented their hiring plans to secure larger incentives from the government (Gabe & Kraybill, 2002). Similarly, according to an analysis by Hoyt et al. (2008) on regions in the state of Kentucky, educational incentives have a strong and positive impact on economic activity, while tax incentives have a comparatively lower positive effect. Porsse et al. (2007) find that implementing regional tax incentive programs in Brazil has positive effects on employment and household welfare for consumers. In research searching the relationship between tax incentives and firm performance in Nigeria using the survey responses finds a significant relationship between tax incentives and firm performance (Oyerogba et al., 2024).

One of the studies that empirically analyzed the effects of public incentives in Türkiye, Karaçay-Çakmak & Erden (2004), examine the impact of three major public support policies "grouped as public investments, loans, and incentives" on private sector industrial investments across regions. They find that public investments negatively affect private sector investments in developed regions, while positively influencing them in less developed regions. Akan & Arslan (2008) conclude that there is a linear relationship between incentive investments and employment in the Eastern Anatolia region of Türkiye during the 1980-2006 period, and that these investments

create new job opportunities. Yavuz (2010) find that the number of incentive certificates, fixed investment and machinery and equipment investment variables have a positive effect on the employment variable. Selim et al. (2014) conclude that the number of investment incentive certificates and fixed investment amounts issued in 81 provinces between 2001 and 2012 have an effect on employment.

Regional tax incentives aim to increase the welfare level of households in underdeveloped regions by supporting investments in these regions. Şahin & Uysal (2011) state that the share of total incentives received by underdeveloped regions in Türkiye between 2002 and 2009 is insufficient, both in terms of investment amount and job creation. Ulusoy & Akarsu (2012) emphasize SMEs and observe that employment increases as the number of investment incentive certificates and the amount of credit increase. Aydıner (2015) finds that an increase in investment with incentive certificates leads to higher employment covering the provinces of Aydın, Denizli, and Muğla for the period 2002-2014. He also adds that it generates more employment in labor-intensive sectors. Whereas Hosono et al. (2023) find that the tax incentive does not on average increase the capital investment but it improves labor productivity of Japanese SMEs using firm-level panel data.

There are studies in the literature that test the claim that public incentives lead to economic growth by increasing regional investments and income using data from Türkiye. Ay (2005) concludes that, during the period 1980-2003, investment incentives, national income, and imports positively affect fixed capital investments, while treasury bonds and interest rates have negative impact. In another study, Yavan (2011) finds that the number of investment incentives in provinces increases GDP by using the cross-sectional data of 81 provinces for the year 2000. Simay-Karaalp (2014) examines the impact of various variables on private sector employment in 81 provinces during the 2002-2011 period. The study concludes that the amount of public infrastructure investment and public education investment positively affects employment. In the study by Recepoğlu & Değer (2016), the relationship between investment incentives and economic growth is analyzed for Nuts-2 regions during the period 2004-2011. The study finds a long-term positive and significant relationship between investment incentives and regional value added; and concludes that the growth effect of incentives in less developed regions is weak in the short run.

3. Tax Incentives Implemented in Türkiye

The most commonly used tool for regional development in Türkiye is a differentiated incentive system based on sectors and regions. This system has historically been applied at varying rates depending on the development levels of the provinces. The aim of the incentive systems implemented in 2004 and 2006 was to increase investments and employment opportunities by providing tax and social security premium incentives in some provinces, offering energy support, and supplying free land and real estate for investments (Arslan, 2005; Acar & Çağlar, 2012). The first comprehensive national incentive program in Türkiye was implemented with

the incentive law of 2009. The 2009 incentive law includes seven items: VAT exemption, customs duty exemption, interest support, employer social security premium support, tax reduction, investment location allocation, and relocation support. Karakurt (2010) notes that the sectoral-regional and large project-based new incentive system is essentially a three-pillar structure that employs a wide range of incentive tools. With the tax incentives arrangement in this incentive system, a new concept not previously included in the tax legislation, "investment contribution rate or amount," has been introduced and implemented.

A significant development in the incentive system after 2009 was the incentive law that came into effect in 2012. The law covers VAT exemption, tax refunds, tax reductions, interest support, allocation of investment locations, employer social security premium support, social security premium support, and income tax withholding practices. Ersungur & Takım (2018) criticize the fragmented nature of the 2012 incentive system's institutional structure, arguing that this fragmentation weakens the effectiveness of the incentive system. Akdeve & Karagöl (2013) state that the new incentive system designed in 2012, considering the needs and demands of investors, includes four main investment incentives: general incentive applications, regional incentive applications, large-scale investment incentives, and strategic investment incentives. They note that due to its many features, this incentive law is the most extensive and comprehensive incentive system ever implemented to date. According to Akdeve & Karagöl (2013), as in the old incentive system, the support provided in the new incentive system varies depending on the region where the investments are located and the scale of the investment. The new incentive system includes measures aimed at reducing regional development disparities at the provincial level as well as reflecting technological transformation in the production structure.

In the 2009 law covering Türkiye as a whole, the country was divided into four investment regions, with adjustments in the level of incentives made according to the development level of each region. In the new incentive law introduced in 2012, Türkiye's provinces were grouped into six investment regions based on their level of development. The aim of these investment incentives is to redirect savings towards high value-added investments and to reduce regional development disparities by increasing production and employment in economically underdeveloped regions. Today, investment incentives have been expanded to include the promotion of international direct investments and to enhance international competitiveness, with a focus on high research and development content, regional and large-scale investments, as well as strategic investments. Accordingly, in 2017 and 2018, small adjustments were made to the sectoral scope and financial support amounts outlined in the incentive law enacted in 2012.

Public incentives are applied at different rates to selected sectors, strategic investments in research and development, and the six distinct regional groups specified in the law according to their development levels (see Appendix, Figure A.1). Among these types of support are "customs duty exemption," "VAT exemption," "employer social security premium support," "allocation of investment locations," and "interest support" (for investments in the 3rd, 4th, 5th, and 6th regions). The 2012 incentive law includes two specific provisions for the 6th Region, which is

covered by comprehensive incentives, that differ from the other five regions grouped in the law. These are "social security premium support covering the employee's share" (whereas the support for the employer's share of social security premiums is applicable to other regions as well) and "income tax withholding discount." This situation provides an opportunity to measure the policy impact on investments in the 6th Region. The "employee's share of social security premium support" involves covering the portion of the social security premium payable by the employer, equivalent to the minimum wage, from the Ministry's Budget for ten years for large-scale and strategic investments in the 6th Region. The "income tax withholding discount" involves deducting the income tax calculated on the portion of employees' wages equivalent to the minimum wage, provided for additional employment created by investments in the 6th Region, from the tax assessed on the tax return over a period of ten years.

4. Data and Methodology

The data used in this research comes from household survey microdata called as the Surveys of Income and Living Conditions (SILC) conducted by TURKSTAT. These surveys were first conducted in 2006 and provide detailed data on a wide range of variables at the household and individual level, including demographic variables, income, living conditions, employment status, working conditions, material deprivation indicators, and indebtedness. In this study, "SILC data" produced for each year from 2006 as the starting year to 2018 as the final year. Since the income-related variables in these surveys refer to the previous year's income, the research period is set as 2005-2017. The sufficiently large sample size of these surveys allows for estimations at the NUTS1 division (12 regions) (see Appendix, Figure A.2).

In examining the impact of regional incentives on household incomes, the data from the SILC cross-sectional individual, and/or household datasets were aggregated to create variables for household income, wage income, and entrepreneurial income. These household incomes were converted to real incomes using the Consumer Price Index (CPI).

The positive effects of the 2012 Incentive Law through investments in the relevant regions are expected to create economic externalities in those areas. This situation is expected to increase the incomes of households living in the regions. In this study, the difference-in-differences analysis methodology (Angrist & Pischke, 2008) is used to test whether the tax incentives have an effect on regional household incomes. In the literature, the difference-in-differences method has been used to examine the employment effects of business incentives using firm-level data from Northern and Central Italy (Bondonio & Greenbaum, 2006).

In the 2012 Incentive Law, Region 6 is the region that benefits from the incentive policy at the highest rate since it includes two separate regulations different from the incentives applied to other regions. The regional definitions in the 2012 incentive law differ from those in the SILC, which defines 12 regions, as the law includes six regions grouped according to their level of development. Therefore, the regional boundaries in the SILC do not overlap with the regional

boundaries defined in the law. The highest degree of overlap is observed for the provinces in the Southeastern Anatolia Region. The provinces in the 6th Region defined by the law (a total of 15 provinces) cover 62.5% of the provinces in Nuts1 regions 10, 11, and 12 (a total of 24 provinces) (see Appendix, Figure A.1 and Figure A.2).

In this study, the "treatment group" consists of the provinces in the 6th Region of the incentive law, which are the provinces in Nuts1 regions 10, 11, and 12, namely the North Eastern Anatolia, Middle Eastern Anatolia, and Southeastern Anatolia regions. Initially, provinces outside these regions were selected as the "control group" for the analysis. However, the presence of provinces with significant income variability within this set poses issues for the homogeneity of the control group in the difference-in-differences analysis. Therefore, for the difference-in-differences analysis methodology, the first six Nuts1 regions (Istanbul, Western Marmara, Aegean, Eastern Marmara, Western Anatolia, Mediterranean) were not included in the control group. Instead, households living in the provinces of regions 7, 8, and 9, which are close neighboring regions to the "treatment group" in Nuts1, are selected as the "control" group.

In this study, data covering the years 2005-2017 were aggregated to form a pool data, and the following model is estimated. This model analyzes whether the two tax incentive tools applied to the 6th Region create a significant difference in the household incomes in the 6th Region.

$$Y_{ijt} = \beta_1 + \beta_2 D_j + \beta_3 TI_t + \beta_4 (D_j * TI_t) + \beta' \boldsymbol{X} + \varepsilon_{ijt} \quad (1)$$

In this regression model (equation 1), *Y* represents household disposable income. *D* is a dummy variable that takes a value of 1 for households in the treatment group (households in the 6th Region, which includes the North Eastern Anatolia, Central Eastern Aanatolia, and Southeastern Anatolia regions) and 0 for households in other regions geographically neighborhood to the treatment group (households in Nuts1 regions 7, 8, and 9). *TI* is a dummy variable that takes a value of 1 for years after 2012, when tax incentives were introduced under the 2012 incentive law, and 0 for the years 2012 and prior. *D*□*TI* is the "difference-in-differences" variable, which takes a value of 1 when both the treatment region and the incentive period are 1, and 0 otherwise. The group of variables represented by ***X*** includes variables that affect household income, such as the age, education, gender, sector, occupation, and employment status of the household head, as well as household size.

The coefficient β_1 represents the disposable income per household in the regions 7,8 and 9 for the years 2012 and prior; $\beta_1 + \beta_2$ represents the disposable income per household in the regions 10,11 and 12 for the years 2012 and prior; $\beta_1 + \beta_3$ represents the disposable income per household in the regions 7, 8 and 9 for the years after 2012 and finally $\beta_1 + \beta_2 + \beta_3 + \beta_4$ represents the disposable income per household in the regions 10, 11 and 12 for the years after 2012 (Table 1).

Table 1. Regression Coefficients of Difference-in-Differences Methodology

	Control Group (7.,8.,9. Region)	*Treatment Group (10.,11.,12. Region)*	*Difference*
2012 and prior	β_1	$\beta_1 + \beta_2$	β_2
After 2012	$\beta_1 + \beta_3$	$\beta_1 + \beta_2 + \beta_3 + \beta_4$	$\beta_2 + \beta_4$
Difference	β_3	$\beta_3 + \beta_4$	β_4

The difference in differences (DID) methodology involves some assumptions that need to be evaluated for the model we estimate (Angrist & Pischke, 2008; Murray & Bardaka, 2022). The first one of them is that the methodology needs to observe parallel trends in the outcome variable between the treated and control groups before the program's implementation (Tonetto et al., 2023; Kim et al., 2023). In our model disposable household income trends would be the same in both regions (5th region and 6th region defined by the law) in the absence of treatment. Figure 1 is prepared to look at the validity of this assumption. It plots the trend in average disposable household incomes of the control group households (in Nuts 1 regions 7, 8 and 9) and the treatment group households (in Nuts 1 regions 10, 11 and 12). The outcome variable namely household disposable income follows parallel trends between the control and the treated regions before the tax incentive law implementation.

The second assumption of the methodology is about that treatment assignment independency from the potential outcomes (Murray & Bardaka, 2022). To provide this assumption we have made the following corrections. We add a number of control variables such as sector, occupation, and employment status of the household head. Households living in regions 7, 8, and 9, which are neighboring areas to the treatment group regions and share similar economic potential and socioeconomic characteristics with the treatment groups, have been carefully selected as the control group.

The third assumption of the DID methodology is the Stable Unit Treatment Value Assumption (SUTVA), which is usually made in casual inference (Murray & Bardaka, 2022). According to this assumption one unit's treatment status does not have any effect on the outcomes of another unit. In our model, this assumption remains valid since treatment and control group units are located in geographically different regions and certain tax incentives are explicitly provided by law to Region 6.

5. Results

To analyze the impact of incentive laws on household incomes, first, household incomes for the Nuts1 regions of Türkiye are calculated from the SILC surveys and converted in 2005 constant prices using the CPI. To observe the effects of the incentive laws, the time series plots of the

averages of real household incomes for the "control" and "treatment" group regions for the period 2005-2017 are presented in Figure 1.

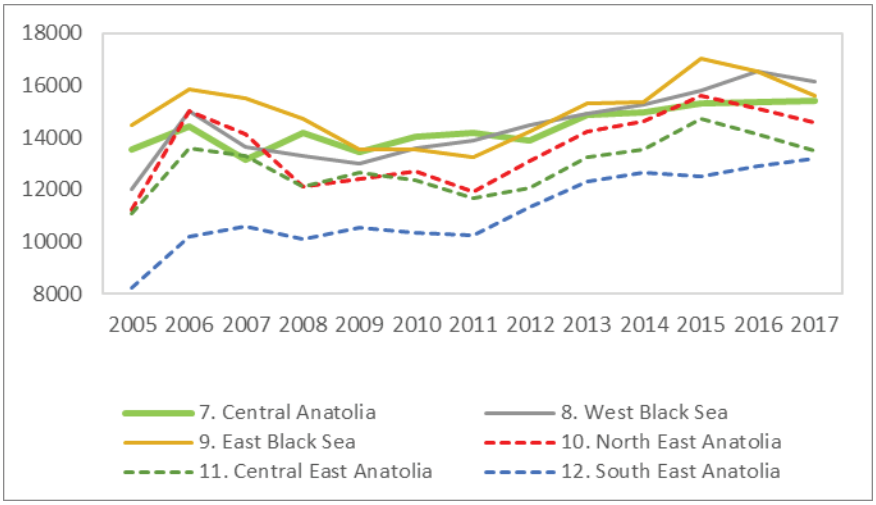

Figure 1. The Regional Disposable Income per Household (2005 Constant Prices, TL)

Among these six regions, the Southeastern Anatolia Region has the lowest average household disposable income. However, after 2011, we observe that the real household incomes in the Southeastern Anatolia Region increase more rapidly compared to the control group regions, as well as the treatment regions of the North Eastern Anatolia and Middle Eastern Anatolia regions. This increase in real household disposable income averages continued until 2015, after which real incomes declined in regions other than Southeastern Anatolia during the 2015-2017 period.

Since the primary components of household income are earnings income and entrepreneurial income, Figures 2 and 3 are prepared to also show the development of these income types over the same period. Households that reported receiving earnings income are selected from the survey data, and the total earnings income for each of these households is calculated. This income is then converted to 2005 constant prices using the CPI price index. Figure 2 presents the development over time of the average household earnings income for each region. Among these regions, the Southeastern Anatolia Region has the lowest average earnings income. Real wage income averages generally show an upward trend from 2009 to 2015. After 2009, average earnings income increased in the Middle Anatolia and Western Black Sea regions. In the Eastern Black Sea, North Eastern Anatolia, Middle Eastern Anatolia, and Southeastern Anatolia regions, an increasing trend in wage income is observed starting from 2012.

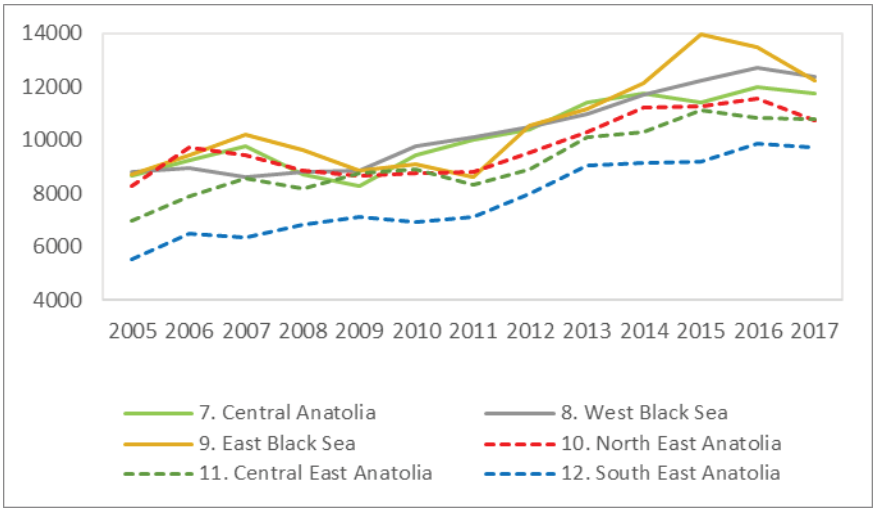

Figure 2. The Regional Earnings Income per Household (2005 Constant Prices, TL)

When investigating the source of the increase in household earning income during this period, one might first examine the developments in the minimum wage. How did the minimum wage change during the period when real increases in household earnings income were observed? During the period when the incentive law was implemented, the nominal minimum wage increased by 4.5% in 2013, 15.3% in 2014, and 22.2% in 2015. The highest increase in minimum wage occurred in 2016, at 30%, followed by an 8% increase in 2017. During this period, the annual inflation rates were 7.40% in 2013, and subsequently 8.17%, 8.81%, 8.53%, and 11.92% in the following years. Adjusted for inflation, the average annual real growth rate of the minimum wage over these five years was 6.13%.

Another factor that could contribute to the increase in household earnings income is the addition of new wage earners who have completed their education and started working, or the rise of the added worker effect due to economic difficulties within the household. To investigate this, the average number of wage earners per household in the SILC microdata was calculated for each year. The number of wage earners per household shows an increasing trend in both the treatment and control group regions up to 2015; however, no such increase is observed after 2015. The similarity of this trend with that shown in Figure 2 indicates that the development in wages per household is influenced by changes in the number of wage earners.

Another source of income affected by the incentive law is entrepreneurial income. Household data with entrepreneurial income were selected from the survey, and these incomes were converted into real terms using the Consumer Price Index (CPI). Figure 3 shows that entrepreneurial real incomes exhibit fluctuating movements over the period. Between 2006 and 2009, there is a downward trend in the average entrepreneurial incomes of households in both the control and

treatment regions. Although there was some improvement after 2009, some regions exhibited movements contrary to the overall trend in subsequent periods.

The tax incentives analyzed in the study, such as social security premium support covering the employee's share, primarily target large-scale and strategic investments in Region 6. Therefore, their impact on entrepreneurial incomes is expected to be weaker and more indirect compared to their effect on earnings incomes.

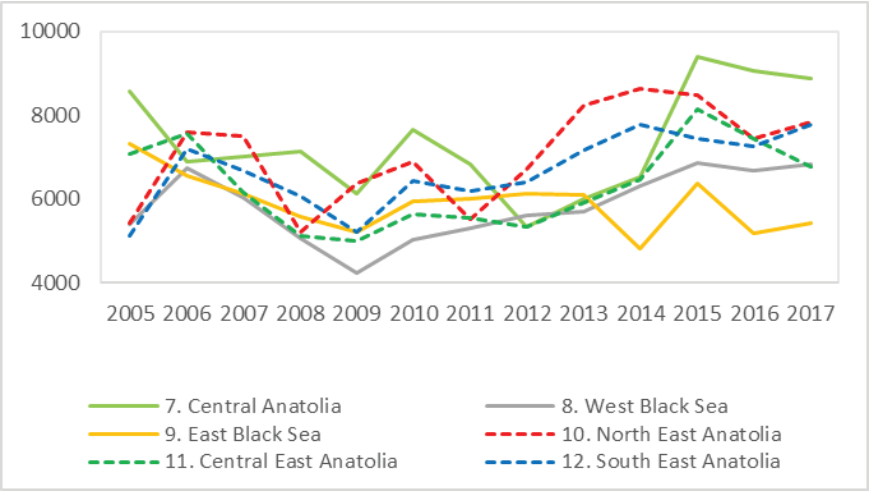

Figure 3. The Regional Entrepreneurial Income per Household (2005 Constant Prices, TL)

To measure whether the benefits of the incentive law implemented in 2012 have been reflected in the incomes of the 6th Region, the difference-in-differences regression equation estimated from the pooled data presented in Table 2 has been used. In the equation, the dependent variable is the natural logarithm of household income, as household income is log-normally distributed. The variable Dum_D represents a dummy variable that takes the value of 0 for Regions 7, 8, and 9, and 1 for Regions 10, 11, and 12. The variable Dum_2013 is a dummy variable that takes the value of 0 for the year 2012 and earlier, and 1 for the year 2013 and later. The variable Dum_D*Dum_2013 is the interaction term of these two dummy variables and its coefficient is estimated as the difference-in-differences coefficient. Several control variables affecting household income have been included in the equation. The first is the household size variable, where an increase in household size is expected to lead to an increase in disposable income. Since the primary source of household income is the household head, demographic characteristics of the household head, such as age, gender, and education level, have been included as dummy variables in the model. Additionally, dummy variables representing the employment status, occupation, and sector of the household head have been included as other control variables in the model.

According to the regression results, the average income of the treatment group regions is 17.10% lower than the average income of the control group regions. The average incomes in 2013 and

later, following the year when the incentive law started to be implemented, are 13.61 per cent higher than the average incomes before 2013. Household incomes in the treatment region grew 2.22 per cent faster than in the control region for the period after 2013. Since the difference-in-differences coefficient is statistically significant at the 1% significance level, it indicates that the household incomes in the treatment group differed significantly from those in the control group during the period when the policy change was implemented.

Table 2. The Regression Equation of Difference-in Differences for Household Disposable Incomes

Dependent Variable: The natural logarithm of household disposable income	Coefficients	Probability	Interpretations of Coefficients (%)
Dum_D	-0.1870***	0.000	-17.10
Dum_2013	0.1276***	0.000	13.61
Dum_D*Dum_2013	0.0220***	0.010	2.22
Household size	0.0518***	0.000	
Gender	-0.0257**	0.028	
Age Groups	Yes		
Education Levels	Yes		
Employment Status	Yes		
Occupation	Yes		
Sector	Yes		
Constant	8.6620***	0.000	
R^2	0.4044	0.000	
N	54481		

Note: (***) and (**) denote 0.01 and 0.05 significance levels, successively. D represents the treatment region. Dummy variable coefficient is interpreted by taking the inverse logarithm of the estimated dummy variable coefficient (according to base e) and subtracting it from 1.

To examine the impact of the tax incentive law on the regression equation, sensitivity analyses were performed by creating separate dummy variables for the years before and after the period 2013 and onward (2009-2015) instead of using a single dummy variable for the period 2013 and later. The model estimation was then repeated. Table 3 presents the results of these regression equation estimates, showing only the difference-in-differences coefficient (β_4).

The difference-in-differences coefficient for the model estimated for the period from 2009 onward is not statistically significant. Similarly, the difference-in-differences coefficients in the models tested for 2010, 2011, and 2012 are also not significant at the 5% level. However, this coefficient is found to be significant in the regression models tested for the period from 2013 onward. This finding indicates that, in the post-2013 period, household incomes in the treatment group significantly differed from those in the control group.

Table 3. Sensitivity Analysis: The Regression Coefficient of Difference-in Differences

Difference-in Difference Variable	Regression Coefficients	Probability	Interpretations of Coefficients (%)
Dum_D*Dum2009	-0.0129	0.281	-
Dum_D*Dum2010	-0.0201*	0.058	-
Dum_D*Dum2011	-0.0165*	0.085	-
Dum_D*Dum2012	0.0076	0.394	-
Dum_D*Dum2013	0.0220***	0.010	2.22
Dum_D*Dum2014	0.0301***	0.001	3.06
Dum_D*Dum2015	0.0254***	0.006	2.57

Note: (***), (**) and (*) denote 0.01, 0.05 and 0.10 significance levels, successively. D represents the treatment region.

6. Conclusion

In this project, the tax incentives by the 2012 Incentive Law have been examined, and the effects of these incentives on regional incomes have been evaluated. The analysis of the impact of public investment incentives on household disposable incomes contributes to the literature by testing the statistical significance of the difference in household incomes between regions that received more intensive incentives and those that received fewer incentives.

According to the 2012 Incentive Law, the four provinces in the Northeast Anatolia Region (Ağrı, Kars, Iğdır, and Ardahan), the five provinces in the Eastern Anatolia Region (Bingöl, Van, Muş, Bitlis, and Hakkari), and the six provinces in the Southeastern Anatolia Region (Şanlıurfa, Diyarbakır, Mardin, Batman, Şırnak, and Siirt) are designated as the sixth region. The extra preferential incentives provided to these provinces include "social insurance premium support including the employee's share" and "income tax withholding discount" for investments in these areas. It is expected that the implementation of these incentives will benefit the increase in investments and the improvement in regional development levels. Our research examines whether this policy implementation has impacted household incomes in the sixth region. The study seeks to answer whether there is a significant difference between the sixth region, which benefits from the incentives, and the fifth region, which benefits less and does not have the aforementioned two incentives. Estimates obtained using the difference-in-differences regression analysis methodology reveal that, following the implementation of the law, household incomes in the sixth region grew significantly faster compared to those in the fifth region. The research results indicate that the incentive law and the associated policy change created a significant difference up to 2015, after 2012. The success of the incentive applications demonstrates that such policy measures are effective in reducing regional income disparities. Additionally, it is necessary to empirically investigate the impact of incentive laws on employment levels in different sectors.

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Appendix

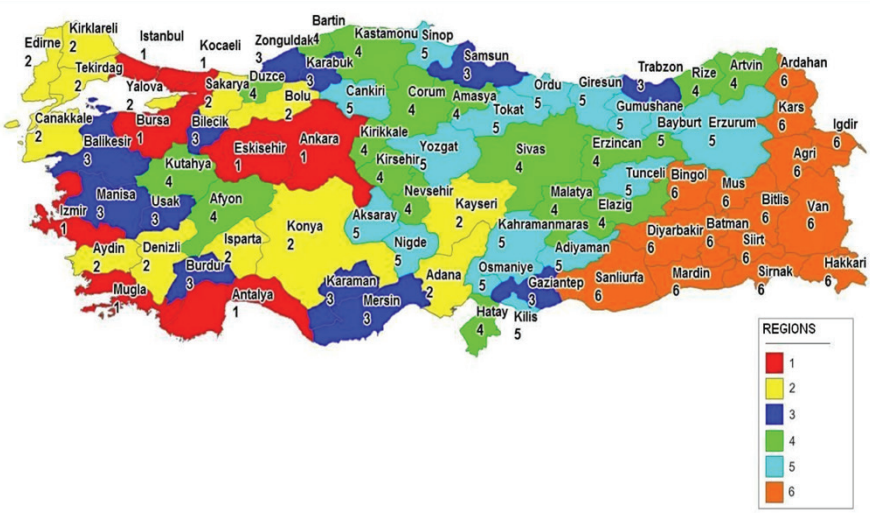

Figure A.1: Tax Incentive Law Provinces Grouped According to Development Level

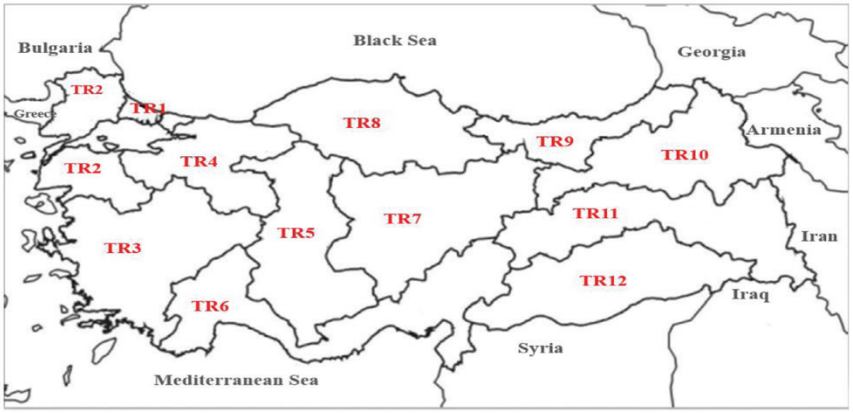

Figure A.2: Regions according to Nomenclature of Territorial Units for Statistics (NUTS) 1 Classification in Türkiye (Altuntas, et al., 2022).

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RESEARCH ARTICLE

DOES AIR POLLUTION IMPACT CONSUMER SENTIMENT IN PAKISTAN: A CITY-LEVEL ANALYSIS*

Syed Zulqernain HUSSAIN**

Abstract

Over the past few years, air pollution has been a rising concern in Pakistan. Apart from a direct bearing on the health of households and a significant risk to the environment, it is hypothesized that poor air quality has an impact on consumer sentiment in Pakistan. In this study, the impact of air quality on consumer sentiment is estimated for major cities in Pakistan. A consumer confidence survey conducted by the State Bank of Pakistan is a leading indicator of economic activity. This survey primarily reflects consumers' perceptions of the current and expected economic conditions. Consumer sentiment is measured by the diffusion index, whereas the air quality index is used to capture the magnitude of air pollution. Using the city fixed effects model on balanced panel data of ten cities and 36 time periods, the findings suggest that air pollution has a negative impact on consumer sentiment in Pakistan. The coefficient of air pollution is statistically significant and consistent in all specifications, reflecting that air pollution impacts consumer sentiment. The reverse causality test confirms that consumer sentiment does not impact air pollution. Control variables, such as dummies for floods, terrorist attacks, and household characteristics for each city, are included in this study to gain an improved model fit. The Pakistani government needs to acknowledge the severity of air pollution and its impact on consumer sentiment, which is a leading indicator of economic activity

Keywords: Air Pollution, Consumer Sentiment, Diffusion Index, Balanced Panel, Environment
JEL Codes: Q53 P46 C23 F64

1. Introduction

Being categorized as an emerging financial market – an economy transitioning into a developed market economy–Pakistan's economy is the 24th largest based on GDP using purchasing power

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parity (PPP). [1] Pakistan holds the position of the fifth most populous country in the world. [2] A surge in urbanization, along with a proportional increase in vehicular loads, has adverse consequences (Anjum, et al., 2021). Pakistan is ranked second in the world in terms of pollution (Figure 1.1). Persistent poor air quality reduces life expectancy by almost 4 years in Pakistan (The Air Quality Life Index, 2023). In Pakistan, outdoor air pollution leads to twenty-five deaths per 100,000 people, while indoor air pollution is responsible for almost 30 deaths per 100,000 people. [3]

Air pollution is considered a key environmental issue since the 1970s (The World Bank, 2019). The main causes of air pollution are fossil fuel burning, industrial processes, transportation, and agricultural activities. Furthermore, anthropogenically generated climate change increases the threat of exposure to air pollutants (Ministry of Finance, 2022). There are frequent episodes of hazardous levels of air quality emanating from crop burning stubbles, deforestation, and industrial and vehicle emissions (IQAir, 2023). The worsening situation compels the government to impose strict restrictions such as closure of public places and restriction of unnecessary movement (Bukhari & Shahid, 2024).

The consequences of pollution are not only limited to the environment, chronic diseases, and depression, but also has an impact on macroeconomic indicators, such as high government expenditures and surges in housing prices in areas with better air quality. The hypothesis that air quality impacts consumer sentiment is formulated and tested in this study. Consumer sentiment about the current and expected economic conditions of a country is a reflection and leading indicator of economic activity. In this study, the year-on-year growth of the confidence index is used to examine the impact of air pollution on consumer sentiment.

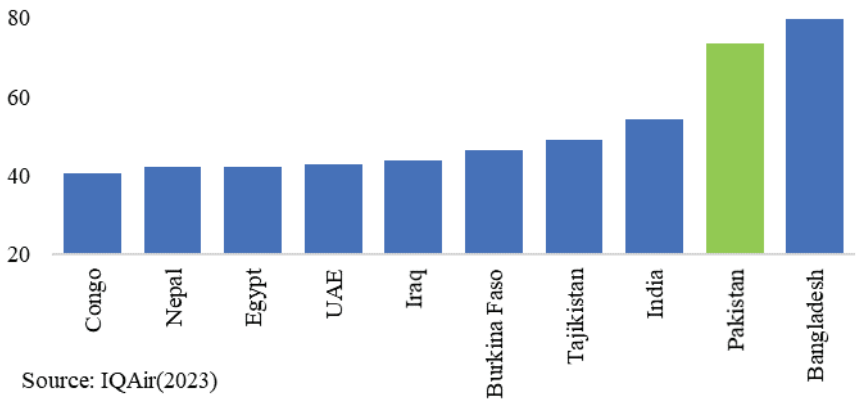

Figure 1. 2023 Country Ranking Population weighted PM 2.5 concentration

1 DAWN News. https://www.dawn.com/news/1704774. Retrieved on 1st December 2024.

2 UN Women. https://asiapacific.unwomen.org/en/countries/pakistan/about. Retrieved on 5th December 2024.

3 World Health Organization. https://www.emro.who.int/pak/programmes/environmental-health.html. Retrieved on 1st December 2024.

2. Literature Review

Air pollution is a byproduct of urbanization and industrial development over the past few decades. Air pollution is a serious environmental issue in cities, particularly in developing economies (Mayer, 1999). Tagged as the greatest environmental threat, air pollution is responsible for roughly 7 million deaths worldwide every year. Air pollution adversely impacts child growth and development (Balietti et al., 2022). The harm caused by air pollution extends to both physical and mental health (Xue et al., 2021). Air pollution further impedes consumer choice (He et al., 2022). The credibility of local government is also compromised due to air pollution (Yao et al., 2022). In some cases, air pollution may lead to social conflicts, aggressive behaviour, and violent crimes (Li and Meng, 2023). Sleeplessness is another implication of air pollution (Heyes and Zhu, 2019).

The consequences of air pollution on health seems clear, and several studies have estimated the association between air pollution and health issues. A study of six cities in the United States of America (US) reveals that long-term exposure to air pollution leads to respiratory diseases, and air pollution and mortality are highly correlated (Dockery et al., 1993). Air pollution contributes in the development lung cancer (Loomis et al., 2013). Air pollution has an adverse impact on children's health. Premature birth, low birth weight, and developmental disorders are also a consequence of bad air quality (Perera, 2008). Another major consequences of climate change is the high extinction of specific species and the possible loss of biodiversity (Bellard et al., 2012).

The macroeconomic challenges related to air pollution are alarming. The foremost macroeconomic cost to economies worldwide is health-related expenditures. Air pollution-related costs alone account for over US$ 5 trillion globally (The World Bank, 2016). The adverse impact of air pollution is substantial in the airline industry. A study in China showed higher PM2.5 concentration levels and a high probability of flight delays and/or cancellations (Chen et al., 2023). The migration to areas with cleaner air is also an outcome of pollution (Pan, 2023).

Another macroeconomic implication of air pollution is the loss of labor productivity. A study conducted at two industrial locations in China reveals that the output per worker is reduced in proportion to severe air pollution (He et al., 2019). Environmental protection must be treated as an investment in human capital because ozone pollution leads to a loss in agricultural worker productivity (Zivin and Neidell, 2012). The link between air pollution and mental health is well established. Air pollution is one of the contributing factors to mental health disorders, and high exposure to PM2.5, is associated with a high risk of depression (Power et al., 2016). Lim et al., (2012) emphasize that high levels of and exposure to air pollution are correlated with a high suicide rate. A meta-analysis reveals that exposure to air pollution negatively impacts mental health, mood swings, anxiety, and depression. Air pollution also limits consumer choices, and its impact of air pollution is disproportionate in different economic sectors. Air pollution leads to a slowdown in movie theater market sales in China (He et al., 2022). Brain drain and loss of firm productivity is one of the consequences of air pollution (Xue et al., 2021).

Air pollution affects mental health. The important question is whether the impact also affects consumers' decision-making. There are a number of studies emphasizing that air pollution influences

consumer behavior, including preferences, spending habits, and lifestyle choices. Air pollution reduces recreational activities, which hampers overall demand in the economy (Zivin and Neidell, 2009). Consumer spending patterns change due to air pollution. Consumers can swap outdoor activities and expenses related to indoor activities. Subjective well-being is also influenced by air pollution (Welsch, 2006). Dynamics of the housing market changes due to air pollution. Areas with clean and high-quality air have high demand, and property prices rise in such areas (Chay & Greenstone, 2005).

The impact of air pollution on health, infrastructure, and the overall economy in Pakistan has been estimated to some extent. However, we find no study previosuly which directly assesses the impact of air pollution on consumer sentiments in Pakistan. This study fills this gap by analyzing the impact of air quality on ten major cities in Pakistan from January 2018 to December 2023. At least one city is selected from each province (state) of Pakistan. [4]

3. Methodology

The hypothesis formulated and tested in this study is as follows:

H_0 : There is no impact of air pollution on consumer sentiment in Pakistan

H_a : There is an impact of air pollution on consumer sentiment in Pakistan

In this study, panel linear fixed effects models are employed to test the null hypothesis for 10 cities and 36 time periods. Panel variable is city, and it is strongly balanced.

$$CS_{it} = \beta_0 + \beta_1 AQI_{it} + \alpha_i + \mu_{it} \qquad (1)$$

CS = Consumer Sentiment measured by diffusion index

AQI = Air quality index

α_i = city fixed effects

i= 10

t = 36

In equation (1), *i* is cross sectional units, *t* is time units, consumer sentiment (CS) is the dependent variable, and the air quality index (AQI) is the main explanatory variable that varies over time. The year-on-year growth of consumer sentiment and air quality index is used in the estimations to avoid any seasonality. β_0 is the intercept that may differ for each period. As mentioned earlier, city fixed effects are employed in this specification. The two terms α_i and μ_{it} (the error term) behave somewhat differently. There is a different μ_{it} for each city at each point in time, but α_i only varies across cities and not over time (Allison, 2009). However, μ represents purely random variation at each point in time.

The State Bank of Pakistan (SBP), in collaboration with the Institute of Business Administration (IBA), organizes the Consumer Confidence Survey. The responses received through this survey are

4 These cities are Abbottabad, Faisalabad, Gujranwala, Islamabad, Karachi, Lahore, Mirpur Khas, Rawalpindi, Peshawar and Quetta

used to construct (i) current economic conditions, (ii) expected economic conditions, and (iii) the consumer confidence index. For the data on air quality, Air Quality Index (AQI) by IQAir is used. [5]

In addition, several control variables (Z) for the robustness check are included in equation (2). These control variables are (i) *Education* – the average level of education of the respondents in a city, (ii) *income*–the average level of income of the respondents in a city, (iii) dummy for *Floods* in a city, (iv) *household size* – number of people in a house and (v) dummy for *Terror incidents* in a city.

$$CS_{it} = \beta_0 + \beta_1 AQI_{it} + \beta_2 Z_{it} + \alpha_i + \mu_{it} \quad (2)$$

For robustness, the time fixed effect is also added to the above specification. The inclusion or exclusion of the time-fixed effect does not significantly impact the results. Moreover, previous consumer sentiment is included as a control variable to check whether lagged sentiment influences current consumer sentiment.

Clustered (by city) standard errors are used in all specifications. Clustered standard errors, such as normal or robust standard errors, are not underestimated and they provide unbiased standard error estimates.

4. Data Description

Consumer sentiment is the leading indicator of economic activity. The perception of economic indicators such as inflation, interest rates, and employment are important for an emerging economy such as Pakistan, in which forward-looking policy formulation is followed. The SBP, in partnership with IBA conducts the Consumer Confidence Survey largely following the University of Michigan Consumer Sentiment Survey. [6] Each wave of this survey roughly covers about 1800 households contacted through fixed line telephone across Pakistan starting from January 2012 on a bi-monthly frequency, but from January 2023, it is conducted monthly. It covers all regions of Pakistan. The questionnaire is administered in different regional languages to ensure maximum outreach. The population of Pakistan is divided into 59 strata, and each stratum is represented in the sample according to its population.

In addition, household characteristics such as the number of households, age, income, occupation, and qualification of the respondents are also part of the survey. These household characteristics are used as the control variables in this study. The SBP reports the results of this survey in the form of a Diffusion Index (DI). The DI reflects the overall trend in respondents' perspectives on a specific aspect of a given survey. The questionnaire offers five options to the respondents for each question.

Very positive= Increase/improve significantly.

Positive = Increase/improve.

5 This index constitutes 120 major cities worldwide. The figure presented for each major city represents the average AQI calculated from all monitoring stations within that city at the specified time. Focusing on major cities rather than an extensive list of all cities allows for a clear, insightful, and impactful comparison of air quality in urban centers across the globe (IQAir, 2023).

6 State Bank of Pakistan. http://www.sbp.org.pk/research/CCS.asp. Accessed 15 May 2024.

E = Unchanged/neutral.

Negative = decline /deteriorate and

Very negative= decline/deteriorate significantly.

The Diffusion Index is then computed as follows:

Step 1: Net Response (NR) is computed as below:

NR = (1.00*PP) + (0.50 × P) + (-0.50 × N) + (-1.00*NN).

Step 2: Diffusion Index (DI) is calculated as follows: DI = (100 + NR) / 2

Where DI ranges from 0 to 100; interpretation of which is as follows:

DI > 50 indicates that Positive views are more than Negative views.

DI = 50 indicates that Positive views and Negative views are equal.

DI < 50 indicates that Positive views are less than the Negative views.

Table 1. Summary Statistics of Consumer Sentiment and Air Quality Index

Variable	Mean	Min	Max	*s.d*
Consumer Confidence Index	37.43	17.0	58.0	*4.11*
Current Economic Conditions Index	34.23	16.0	61.0	*4.85*
Expected Economic Conditions Index	40.66	19.0	61.0	*4.75*
Education	Graduate	Primary	Post-Graduate	-
Income	300-500$	100-200$	1000-2000$	-
Household size	7	2	12	*1.1*
Air Quality Index	64.98	14.1	261	*48.1*

Source: Author's Calculations

The Consumer Confidence Survey (CCS) data used in this study covers the period from January 2018 to December 2023. Due to the limited available data on the Air Quality Index, ten major cities of Pakistan – at least one from each province (state)–are analysed in this study. Thirty-six surveys, comprising almost 100,000 households, are included in the analysis.

Summary statistics related to consumer sentiment and air pollution are provided in Table 4.1.

Table 2. Air Quality Index – Categories

Category	AQI level	PM 2.5 (ug/m^3)	Recommendation
Good	0-50	0-9.0	Air quality is satisfactory.
Moderate	51-100	9.1-35.4	Outdoor activities to be avoided by sensitive individuals.
Unhealthy for sensitive groups	101-150	35.5-55.4	General public and sensitive individuals face risk to experience irritation and respiratory problems.
Unhealthy	151-200	55.5-125.4	Increased likelihood of adverse effects and aggravation to the heart and lungs among general public.
Very unhealthy	201-300	125.5-225.4	General public will be noticeably affected. Sensitive groups should restrict outdoor activities.
Hazardous	301+	225.5+	General public at high risk of experiencing strong irritations and adverse health effects.

Air pollution is proxied by the AQI. The AQI quantifies the concentration of air pollutants in the surrounding environment and the related health risks (IQAir, 2023). This index assigns a

numerical value corresponding to different air quality categories. As pollutant levels increase within each category, the associated health risks also rise accordingly. The air quality index ranges from 0 to 500, although air quality can be indexed beyond 500 when there are high levels of hazardous air pollution. Good air quality ranges from 0 to 50, whereas measurements over 300 m are considered hazardous. Table 4.2 provides information on the different categories of AQI.

5. Results and Discussion

Table 5.1 provides the result of the air quality index and overall consumer confidence index. The coefficient of the air quality index is statistically significant with a negative sign in all specifications, which intuitively makes sense. If the air quality index rises (implying more air pollution), consumer sentiment is likely to deteriorate. This coefficient of the air quality index is approximately equal to one-half of the standard deviation of the dependent variable (consumer confidence index), which implies that a considerable amount of variation in consumer sentiment is influenced by air quality.

Table 3. Impact of Air Quality Index on Consumer Confidence Index

	(1)	(2)	(3)	(4)
AQI[a]	-0.06**	-0.09**	-0.100**	-0.09**
	(0.027)	*(0.028)*	*(0.024)*	*(0.033)*
Control Variables				
Education		0.044	0.045	0.043
Income		0.142**	0.156**	0.133**
Household size		0.032	0.031	0.033
Floods			-0.210**	-0.231**
Terror incidents			-0.126**	-0.123**
Lag of Sentiment			0.002	0.001
City Fixed Effect	***Yes***	***Yes***	***Yes***	***Yes***
Time Fixed Effect	No	No	No	***Yes***
Observations	360	360	360	360
Number of cities	10	10	10	10
R-squared	0.64	0.67	0.72	0.72

Notes: Clustered (by city) standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

a: Year-on-year growth rate of air quality index.

In Column (2) of Table 5.1, several control variables are added for robustness purposes. The results show that the higher the level of income, the response of consumer gets stronger (more optimistic). However, the coefficient of education level is not statistically significant. Even when these two control variables are added, the coefficient of our main explanatory variable remained statistically significant. Regarding the size of the coefficient, it is still equal to half the standard deviation of the dependent variable (consumer sentiment).

In the last two columns of Table 5.1, additional control variables such as a dummy for floods and a dummy for terrorist incidents in a city are added. In addition, the time dummy variable is included; the result of this specification makes our main variable of interest significant. Hence, all specifications are consistent, and we reject our null hypothesis that air pollution has no impact on consumer sentiment.

The results validate the hypothesis that cities with higher air pollution levels tend to have more pessimistic sentiments. In columns 3-4, the lag value of the dependent variable (consumer sentiment in the previous period) is also used as a predictor for the current value of the dependent variable (current sentiment), and the results indicate that previous sentiment does not impact current sentiment.

Table 4. Impact of Air Quality Index on Current Economic Conditions Index

	(1)	(2)	(3)	(4)
AQI[a]	-0.07**	-0.10**	-0.11**	-0.09**
	(0.025)	*(0.026)*	*(0.023)*	*(0.031)*
Control Variables				
Education		0.040	0.042	0.042
Income		0.120**	0.119**	0.125**
Household size		0.030	0.029	0.031
Floods			-0.210**	-0.201**
Terror incidents			-0.130**	-0.125**
Lag of Sentiment			0.002	0.001
City Fixed Effect	***Yes***	***Yes***	***Yes***	***Yes***
Time Fixed Effect	No	No	No	***Yes***
Observations	360	360	360	360
Number of cities	10	10	10	10
R-squared	0.63	0.66	0.71	0.73

*** p<0.01, ** p<0.05, * p<0.1

a: Year-on-year growth rate of air quality index.

Table 5.2 and Table 5.3 provide the result of the air quality index on the current economic condition index and expected economic condition indices, respectively. These results are consistent with the overall consumer confidence index. The coefficient of air quality index is statistically significant, with a negative sign in all specifications. The Wooldridge test for autocorrelation is used to detect serial correlations. The p-value is greater than 0.05, which implies that the null hypothesis of no serial correlation is not rejected, i.e., errors are not serially correlated. It is also important to highlight that clustered standard errors are used at the panel level, which is a common fix for autocorrelation.

One possibility is that air pollution itself is due to high economic activity in Pakistan. To verify this, the reverse causality test is also estimated. The reverse causality results indicate that consumer sentiment does not impact air pollution in Pakistan. Even during the COVID-pandemic period, when smart lockdowns are imposed and the industrial sector is completely shut down, air quality in Pakistan remained poor. It appears, and to some extent, validated by the reverse causality test, that air pollution is largely exogenous and probably due to global climate change.

Results of this study are consistent with previous empirical studies mentioned in the section on literature review. Air pollution has a negative impact on consumer sentiment which effects households spending behaviour, individual's recreational activities etc.

Table 5. Impact of Air Quality Index on Expected Economic Conditions Index

	(1)	(2)	(3)	(4)
AQI[a]	-0.06**	-0.09**	-0.10**	-0.09**
	(0.026)	*(0.027)*	*(0.024)*	*(0.030)*
Control Variables				
Education		0.039	0.036	0.039
Income		0.122**	0.121**	0.127**
Household size		0.031	0.030	0.033
Floods			-0.200**	-0.213**
Terror incidents			-0.128**	-0.126**
Lag of Sentiment			0.003	0.002
City Fixed Effect	***Yes***	***Yes***	***Yes***	***Yes***
Time Fixed Effect	No	No	No	***Yes***
Observations	360	360	360	360
Number of cities	10	10	10	10
R-squared	0.65	0.66	0.72	0.72

a: Year-on-year growth rate of air quality index.

6. Conclusion

Pakistan is facing problems such as premature death, respiratory diseases, and a reduction in life expectancy due to air pollution. Agricultural productivity also suffers as crops become damaged owing to pollutant exposure. A visible fall in tourism is also a byproduct of pollution. As pointed out in previous studies, air pollution can lead to depression and anxiety. Another possible impact of air pollution on consumer sentiment related to current and expected economic conditions is estimated in this study. Consumer sentiment is a leading indicator of economic activity, and the consumer confidence index is treated as an important variable during monetary policy formulation. Using the city fixed effects model on balanced panel data of ten cities and 36 time periods, the main findings indicate that air pollution has an adverse impact on consumer sentiment. The impact is significant for all three indices used in this study. The coefficient of the air quality index is roughly equal to one standard deviation of the consumer confidence index. The reverse causality test shows that consumer sentiment or economic activity does not impact air pollution, and this relationship is only one-way. Control variables such as dummies for floods, terrorist attacks, average level of education, and average level of income for each city are included in this study to gain an improved model fit. The results are consistent for all the specifications. Given the significant impact of air pollution on consumer sentiment – a leading indicator of economic activity–stakeholders, particularly the government of Pakistan, need to tackle the surging issue of air pollution.

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Ethical compliance: This study does not require ethical approval because it does not involve human participants and is based on secondary data analysis.

Declaration: I hereby declare that the ideas, concepts, and research presented in this work are entirely my own. I used AI tools solely for purposes of enhancing articulation, grammar, and rephrasing, ensuring clarity and coherence. The original intellectual content, analysis, and findings remain the product of my independent effort.

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