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Revisiting the American Dream: Social Mobility and Poverty in the United States

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Abstract

Nowadays, a growing number of Americans are losing faith in or questioning the matter-of-factness of the American Dream. A major culprit of this situation is the pernicious effect of poverty that has been lingering, while mostly remaining intractable over time. This paper endeavors to explore another avenue of solutions to address poverty through social mobility.

Using a time series dataset within a vector error correction model (VECM), it has been uncovered that the pursuit of social mobility exerts depressing effects on poverty. Based upon these findings, this investigation argues for the implementation of diligent economic policies to promote the human development index (HDI) in the US, especially by furthering efforts to prop up outcomes in education and healthcare. Moreover, revitalizing, reinforcing, and expanding social overhead capital, to improve the current C letter grade on America's infrastructure Report Card, will provide a comprehensive solution to making lasting inroads in both the fight against poverty and the enhancement of social mobility.

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Keywords: *Poverty, Social Overhead Capital, Social Mobility, VECM.*

1. Introduction

The concept of *American Dream* has always been more than a mantra, it's an ideal. Specifically, it's an American ideal that was incepted by James Truslow Adams in 1931 and gained traction during the Great Depression. It generally encapsulates the idea that everyone can achieve social, economic, and financial success for a better life and reach their full potential regardless of their background.

The unabating trajectory of poverty in the past decades has eroded the firm belief in this dream. As a matter fact, despite dozens of billions of dollars spent yearly, poverty has not notably retreated,

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and it has been accompanied by rising income disparities. According to the US Census Bureau, from 1980 to 2022, average poverty rates at \$1.75 and \$2.00 a day were 27.2% and 39.1% of the population, respectively.

This situation has pushed away the dream and made it elusive for a growing number of people. Overcoming poverty remains the biggest economic policy challenge in the US. The seemingly intractable nature of poverty is not due to a lack of initiative. The US has indeed established a myriad of welfare programs destined to counter poverty. Notwithstanding the fact that these programs are generously funded, results remain meager at best in many instances, suggesting some inefficiencies in the current approach. This stylized fact has fueled new reflections among scholars and decision-makers to scout other avenues for comprehensive and effective solutions to dealing with a long-standing problem. This study draws its relevance from that background by exploring how social mobility can help tangibly attenuate poverty. Additionally, it aims at expanding the literature, which remains relatively limited on the topic for the US.

According to the Organization for Economic Co-operation and Development (OECD), social mobility is about how a person's socio-economic situation improves or declines relative to that of their parents or throughout their lifetime. Moreover, the Archbridge Institute defines social mobility as the opportunity to better oneself and those around them. It commonly refers to a person's ability to climb the income ladder and outearn the previous generation.

The existence of a high social mobility in society can, therefore, appear as a viable option to restore or reinvigorate the dream for all. The guarantee that any person can climb up any ladder to reach any level of income or their full potential is also the guarantee that this person can achieve the *American Dream*. In essence, the paper specifically endeavors to examine the impacts of social mobility upon poverty in the US. The behavior of poverty in the face of social mobility will either boost optimism and confidence in this ideal across society or label it as simply a myth.

As this paper proceeds with addressing its main research question, it is organized as follows. Part II surveys the literature for relevant scholarly works. Part III presents the methodological foundations of empirical estimations, while Part IV discusses results and policy implications. Lastly, some concluding remarks are made in Part V.

2. Literature Review

In any society, people's view about social mobility is oftentimes a corollary of their perception about contemporary circumstances or conditions. Alesina et al. (2018) attempt to figure out whether that perception, which is influenced by beliefs held about the presence of intergenerational mobility, affects the way people feel about income redistribution. They focus on five countries– namely, France, Italy, Sweden, the United Kingdom, and the United States– and find out that Europeans typically appear more pessimistic about mobility, whereas Americans remain optimistic. It is further uncovered using randomized treatments that pessimists favor redistributive and equity policies. Optimists, on the other hand, are inclined to resist such policies because they view government intervention as a nonfactor in addressing societal inequalities.

There has also been some scholarly interest in understanding the relationship between social mobility and inequality both in the United States and beyond. Specifically, Hertel & Groh-Samberg (2019) investigate the link between mobility and between-class economic inequality. Using 39 countries, they find that mobility is reduced or slowed when there is a larger gap of resources between classes. This finding is evidenced in three areas–education, wages, and income–along with a composite measure.

Moreover, three papers by Jannson (2015), Mareeva et al. (2022), and Sun et al. (2020) have examined a similar relationship in Sweden, Russia, and China, respectively. In the first paper, the author explores intergenerational income mobility in Gothernburg, Sweden, from 1925 to 1958, before the rise of the welfare state. With two distinct definitions of mobility, namely, income mobility and socioeconomic mobility, she comes across strong evidence regarding the existence of intergenerational mobility in Sweden even before the advent of the welfare state.

The second paper scrutinizes the interrelationship between social mobility and the support level in the population for efforts, or programs, designed to reduce income inequalities in Russia. The authors consider different metrics for social mobility over varying time horizons, including actual and expected mobility. With data sourced from the Russian subsets of the International Social Survey Programme's (ISSP) surveys, results point out that the impact of past mobility and expected mobility on public support for such efforts is not significant in the medium-term. However, significance of this impact is detected with expected mobility in the short-term.

The third paper is concerned with inquiring about the nature of the sources of conflicting results about the presence or not of income mobility and class mobility in China. Empirical findings are derived through smooth estimates of trends in social class mobility and income mobility. No consistency is established for both forms of mobility in the country.

3. Methodology and Data

3.1 Methodology

Toward its goal of understanding the potential impacts of social mobility upon poverty in the United States (US), this paper resorts to the widely used econometric technique of vector error correction model (VECM). The relevance of this technique is its ability to capture both long and short-run dynamics in the interactions between variables. A summary of this approach is presented as follows.[1] Let's start by considering a vector auto-regression (VAR) of order q, VAR(q):

$$z_t = b_1 z_{t-1} + b_2 z_{t-2} + \ldots + b_q z_{t-q} + \omega_t \quad (1),$$

where z is a (1x h)' matrix of h endogenous variables; b is a (h x h) matrix of coefficients; ω is a (1 x h)' matrix of h residuals, and t is the time subscript. ω follows a normal distribution with mean 0 and variance Ω, i.e., $\omega \sim N(0, \Omega)$. Using equation (1), the VECM form is extracted:

$$\Delta z_t = \Pi z_{t-1} + \textstyle\sum_{v=1}^{q-1} \Lambda_v \Delta z_{t-v} + \omega_t \quad (2)$$

where Π is a coefficient matrix of cointegrating relationships and $\Pi = -(I_r - b_1 - b_2 - \ldots - b_q)$; Λ_v is a coefficient matrix of the lags of differenced variables of z and $\Lambda_v = -(b_{v+1} + \ldots + b_q)$. Π can be transformed and expressed as $\Pi = \alpha\beta'$, where α and β are (h x r)

[1] For further developments of this technique, see Engle and Granger (1987), Lütkepohl (1991), Lütkepohl (2005), Brüggemann et al. (2006), and Juselius (2006), among others.

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matrices of rank r, with $0 \leq r \leq h$.[2] The error correction term (ECM) is $\alpha\beta' z_{t-1}$, and α represents the speed of convergence of the dependent variable to its equilibrium value.

In practice, this study alternatively uses h = 4, h = 5, or h = 6 variables to describe the baseline model. They include metrics for (i) poverty (POV), (ii) social mobility (SOCMOB), (iii) social overhead capital (SOC), (iv) business cycle (BC), (v) a trend, and (vi) an interaction term, as needed. In particular, SOC proves to be important, as the quantity and quality of infrastructure have the potential to determine both the availability and growth of economic activities and opportunities, which, in turn, affect social mobility.[3]

3.2 Data

Data range from 2000 to 2024 and are collected from the *World Bank Group*'s World Development Indicators (WDI) and the *United Nations Development Programme*'s Human Development Reports. Overall, five sets of data are considered as proxies for all variables included in the model.[4] POV is measured by *Poverty gap at $2.15 a day (% of population) (POVG2_15)*, or *Poverty headcount ratio at societal poverty line (% of population) (POVSPL)*. SOCMOB is accounted for by the *Human Development Index (HDI)*. We argue for the relevance of HDI with two rationales. First, time series data on social mobility are hardly available, if at all, for countries in general and the United States in particular. Second, based upon the definition of social mobility provided, HDI accurately parallels movements in this variable. At the core of the concept of social mobility, one notes the ability to improve or not an individual's socio-economic situation over their lifetime, and comparatively to previous generations.

SOC and BC are, respectively, staked out on a per capita basis with *Gross fixed capital formation (GFCFPC)*[5] and *real gross domestic product (RGDPPC)*.

4. Results and Policy Implications

4.1 Results

This section discusses results and policy implications in three steps. Firstly, the paper surveys some descriptive statistics along with correlation patterns. On the one hand, Table 1 indicates that the data set is a combination of series with normal and non-normal distributions. Case in point, RGDPPC, GFCFPC, and HDI are normally distributed, while POVG2_15 and POVSPL are not.[6]

On the other hand, the correlation matrix (Table 2) shows correlation pairs among series. One important element to pay attention to is the high positive correlation between RGDPPC and GFCFPC at about 0.94. This is to be expected because capital formation and output growth have mutually reinforcing effects over time, as explained by economic theory.

In the next step, unit roots and cointegration tests are completed. The former reveals that series are all I(1), while the latter highlights the presence of at least one cointegrating relation regardless of techniques considered (Tables 3, 4, and 5).

With cointegrating relations, a VECM is appropriate to fully capture and understand short-term dynamics of an observed long-term relationship.

Table 1. Descriptive Statistics

	RGDPPC	GFCFPC	HDI	POVG2_15	POVSPL
Mean	56000.84	11539.37	0.919336	0.74	19.1536
Median	54152.83	11365.25	0.921	0.8	19.2
Maximum	68160.46	14684.8	0.942393	1	19.7
Minimum	48597.42	9357.004	0.895	0.2	16.7
Std. Dev.	5463.895	1498.114	0.013447	0.202073	0.637581
Skewness	0.597869	0.530507	-0.29171	-1.39772	-2.44646
Kurtosis	2.47847	2.313279	2.119141	4.928155	9.900307
Jarque-Bera	1.772692	1.663893	1.162793	12.01279	74.53625
Probability	0.412159	0.435201	0.559117	0.002463	0
Observations	25	25	25	25	25

Table 2. Correlation Matrix

	RGDPPC	GFCFPC	HDI	POVG2_15	POVSPL
RGDPPC	1	0.935135	0.883374	0.219074	-0.16745
GFCFPC	0.935135	1	0.714507	0.144438	-0.19974
HDI	0.883374	0.714507	1	0.386158	0.056196
POVG2_15	0.219074	0.144438	0.386158	1	0.698028
POVSPL	-0.16745	-0.19974	0.056196	0.698028	1

Table 3. Unit Root Tests, Ho: Unit Root (Level)[7]

	Intercept		Trend and Intercept	
	Statistics	Prob.	Statistics	Prob.
Fisher-ADF (AIC)	12.1686	0.2739	11.8627	0.2944
Fisher-ADF (SIC)	19.3962	0.0355	11.8627	0.2944
IPS (AIC)	1.20844	0.8866	-0.27067	0.3933
IPS (SIC)	-0.03456	0.4862	-0.27067	0.3933
Fisher-PP	12.8788	0.2305	9.44072	0.4908

Results are tackled in two broad phases in the third step. This precaution is taken to ensure the robustness of findings, as multilayered regressions are performed with two distinct proxies of poverty. Each phase includes four variants of the baseline model.[8]

[2] Π is of rank r. In practice, $r > 0$. If $r = 0$, there are no cointegrating relations, as no linear combinations of z_t are I(0). That also means $\Pi = 0$.

[3] Special attention is paid to both SOC and BC, which may appear highly correlated. In that case, appropriate actions will be followed to mitigate such impacts on results.

[4] The trend variable is separately entered in the model, as needed.

[5] Computed in real terms.

[6] At the 1% significance level.

[7] ADF, IPS, PP, AIC, and SIC stand for Augmented Dickey-Fuller; Im, Pesaran, and Shin; Phillips-Perron; Akaike Information Criteria; and Schwarz Information Criteria, respectively.

[8] One lag is considered for all estimates, and log forms of variables are introduced, except for POVG2_15, POVSPL, HDI and TREND. Moreover, t-statistics are in brackets.

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Table 4. Unit Root Tests, Ho: Unit Root (First Difference)[9]

	Intercept		Trend and Intercept	
	Statistics	Prob.	Statistics	Prob.
Fisher-ADF (AIC)	60.2576	0	48.1639	0
Fisher-ADF (SIC)	60.2576	0	48.1639	0
IPS (AIC)	-6.80655	0	-5.8954	0
IPS (SIC)	-6.80655	0	-5.8954	0
Fisher-PP	65.5942	0	50.4798	0

Table 5. Cointegration Tests[10]

Test Type	Method 1[11]	Method 2[12]	Method 3[13]	Method 4[14]
Trace	1	1	1	2
Max-Eigen	1	1	1	1

Tables 6 and 7 report the first batch of results, which point to interesting empirical facts. It comes out that improvements in HDI reduce poverty as measured by POVG2_15, and these impacts consistently carry a negative sign that remains significant in all variants (I, I', II, and II'). In variants I, I', and II', RGDPPC bears an unexpected positive sign, but it is insignificant. It carries the expected negative sign in variant II, but it still is insignificant. On the other hand, GFCFPC displays a negative sign as expected, excepting in variant II only where it is positive. In any case, these impacts are insignificant.

Table 6. Cointegrating Estimation Results with POVG2_15

Variables	I	I'	II	II'
HDI	-10.38932**	-11.87766**	-15.00393***	-19.1226***
	[-2.67675]	[-2.41876]	[-4.30060]	[-4.61281]
log(RGDPPC)	1.377707	3.310897	-0.65686	11.95627
	[1.40708]	[0.13678]	[-0.46268]	[0.60032]
log(GFCFPC)	-0.330706	-0.19767	0.089927	-1.292341
	[-0.72940]	[-0.07880]	[0.19530]	[-0.62825]
log(RGDPPC*GFCFPC)		-0.19767		-1.292341
		[-0.07880]		[-0.62825]
TREND			0.027959**	0.029628**
			[2.19508]	[2.44599]
C	0.020833	-22.1976	19.03424	-113.0897

The second batch of results are displayed in tables 8 and 9. When the second metric of poverty–namely, POVSPL–is considered, HDI showcases the expected negative sign in all variants (I, I', II, and II'). However, it remains significant only in variants II and II'. RGDPPC unexpectedly exhibits a positive but insignificant sign in variants I, I', and II'. In variant II, however, the expected negative sign is in order, and it is significant. In other words, when the trend in the series is accounted for, any increase in HDI reduces poverty.

Table 7. VEC Estimation Results with POVG2_15

d(HDI)	0.006211	0.006559	0.008405*	0.009962*
	[1.43845]	[1.52644]	[1.75088]	[2.05300]
d(log(GDPPC))	-0.01643	-0.0179	-0.00533	-0.005775
	[-0.72787]	[-0.79447]	[-0.20589]	[-0.21578]
d(log(GFCFPC))	-0.03325	-0.03718	-0.0114	-0.015712
	[-0.60500]	[-0.67763]	[-0.18143]	[-0.24208]
d(log(GDPPC*GFCFPC))		-0.58227		-0.234135
		[-0.74296]		[-0.25209]
TREND			-4.21E-30	1.39E-28
			[-1.4e-14]	[4.4e-13]
R-squared	0.160025	0.141741	0.13332	0.095077
Adj. R-squared	0.121845	0.102729	0.093926	0.053944
F-statistic	4.19127	3.633277	3.384236	2.311448
Log likelihood	6.179726	5.921309	5.804153	5.285981

Furthermore, GFCFPC has no significant impact on poverty according to variants I, I', and II'. Nonetheless, variant II indicates a sign that is unexpectedly positive and significant. This finding, although out of the box, suggests that increasing capital formation–that is, improving physical infrastructure such as roads, bridges, power grids, airports, ports, etc.–worsens poverty. The economic rationale behind this outcome would be that the bulk of these improvements remain concentrated in certain areas of the country.

Table 8. Cointegrating Estimation Results with POVSPL

Variables	I	I'	II	II'
HDI	-15.7488	-47.1483	-50.77636***	-74.03225***
	[-0.62958]	[-1.57647]	[-2.87967]	[-3.99992]
log(RGDPPC)	5.323599	134.9991	-21.99198***	126.0492
	[0.84363]	[0.91573]	[-3.06497]	[1.41756]
log(GFCFPC)	-2.61952	145.9865	*4.241275	-14.6098
	[-0.89645]	[0.88090]	[1.82252]	[-1.59078]
log(RGDPPC*GFCFPC)		-13.6584		-14.6098
		[-0.89399]		[-1.59078]
@TREND			0.318228***	0.249368***
			[4.94339]	[4.61114]
C	0.038998	-1420.38	224.086	-1344.199

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[9] Idem.

[10] Rank selected at 0.05 level using critical values from MacKinnon-Haug-Michelis (1999).

[11] Method 1- Johansen-Hendry-Juselius: Cointegrating relationship includes a constant.

[12] Method 2- Johansen-Hendry-Juselius: Cointegrating relationship includes a constant and trend.

[13] Method 3- Cointegrating relationship includes a trend.

[14] Method 4- Johansen-Hendry-Juselius: Both the cointegrating relationship and short-run dynamics include a constant and trend.

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This may not come as a surprise considering that infrastructure quality across states varies in the US, suggesting therefore an uneven distribution of capital formation.

Table 9. VEC Estimation Results with POVSPL

d(HDI)	-0.00133	-0.00078	-0.002194	-0.001967
	[-1.05359]	[-0.68136]	[-1.44573]	[-1.15937]
d(log(GDPPC)	-0.00958	-0.009321*	0.002639	-0.001635
	[-1.53729]	[-1.710]	[0.32937]	[-0.18515]
d(log(GFCFPC))	-0.01554	-0.01804	*0.005431	-0.001301
	[-0.99910]	[-1.33050]	[1.82252]	[-0.06070]
d(log(GDPPC*GFCFPC))		-0.28878		-0.033542
		[-1.50320]		[-0.10933]
d(TREND)			-4.17E-29	1.84E-28
			[-4.4e-13]	[1.7e-12]
R-squared	0.298079	0.199159	0.525412	4.97E-01
Adj. R-squared	0.266174	0.162757	0.503839	4.74E-01
F-statistic	9.342575	5.471114	24.35595	2.18E+01
Log likelihood	-22.3575	-23.9396	-17.66106	-1.84E+01

4.2 Policy Implications

Overall, the takeaway of this paper is the discovery of empirical evidence pertaining to the depressing impacts over time of social mobility upon poverty in the US. As noted, poverty has been a lasting societal scourge despite hundreds of billions spent over time on a myriad of programs both at the state and federal levels to resorb or contain it. The policy implications of such an outcome deserve attention on two major grounds. Firstly, an avenue of effective solution for a notable reduction in poverty could be to focus on improving the HDI. As a matter of fact, recent data reveal that the HDI in the US was 0.938 in 2023. Notwithstanding the fact that this score is high, it hasn't experienced any notable upward movements for about two decades. That stagnation has either weighed down or stalled social mobility, which in turn has contributed to increasing the hardship in achieving the *American Dream*.

Moreover, compared to peer developed nations, the US ranks 17th for HDI with a substantially higher output and income per capita. For instance, the United Kingdom, Germany, and Australia, among others, rank higher with lower total output and income per capita. This indicates that these countries outclass the US in the other metrics of the index as far as education and healthcare are concerned.[15] It also points to weaknesses in the cost-effectiveness of the US model with respect to education and healthcare financing for given outcomes.

Secondly, the other implication emanating from the study alludes to the potential role of physical infrastructure in combating poverty. Economic theory teaches that social overhead capital creates an environment that fosters growth in economic activities. Through that channel, when evenly completed nationwide, riches are created nationwide with benefits felt by the average individual living in every corner. Granted! Variant II of regression with POVSPL suggests otherwise. However, a closer look helps understand the root cause of this finding.

Case in point, infrastructure in the US earns a letter grade of C according to the 2025 Report Card for America's Infrastructure by the American Society of Civil Engineers (ASCE).[16] This is the tip of the iceberg regarding the dire state of infrastructure in the US for two reasons. On the one hand, grades go as low as D+ for infrastructure in categories like aviation, dams, energy, levees, roads, schools, stormwater, and wastewater. These troubling facts should suffice in calling out decision-makers in the federal and state governments to resolutely adjust priorities toward infrastructure for the sustenance and growth of economic activities. On the other hand, the development of social overhead capital is unevenly distributed across the country. For instance, infrastructures were rated D+ in Hawaii (in 2019), South Carolina (in 2021), Louisiana (in 2017), while West Viginia earned a grade of D in 2020. There is a list of some other states that earned a C- including, but not limited to, Kentucky (in 2019), California (in 2019), Pennsylvania (in 2022), Illinois (in 2022), and Michigan (2023).

In a nutshell, this paper argues that a readjustment of economic policies prioritizing infrastructure across the country coupled with a broad and even distribution of investment across states would help make inroads in the US longstanding fight against poverty through an improvement in social mobility.

5. Conclusion

Chances of reaching the *American Dream* have been dwindling for many Americans owing to the lingering and pernicious effects of poverty, which has been weathering down social mobility. This empirical work has explored and found out that improving social mobility can be a lasting solution to containing and reducing poverty. In that regard, pursuing economic policies that boost HDI in the US, especially addressing weaknesses and inefficiencies in education and healthcare, and prioritize substantial investments to prop up America's Report Card on infrastructure can synergistically provide a comprehensive solution. A noteworthy expansion of this work that accounts for inequalities in both income distribution and physical infrastructure investment will add to the current literature.

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[15] Broadly speaking, three factors are considered in the HDI, namely, income (per capita), health, and education.

[16] Retrieved on August 12, 2025, https://www.asce.org/ and https://infrastructurereportcard.org/

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