About Me



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TITLE

Clinical Associate Professor,
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4

RESEARCH FOCUS AREAS

- Time Series Analysis
- Simulation
- Pre-Trained Deep Learning Models for Forecasting
- Economic Impacts of AI Especially on Labor Markets
- Value-at-Risk (VaR) Models

Adjusting Wealth Inequality to Make a Substantial Majority of the World Economically Better Off

Country	Top 1%	Top 10%	Middle 40%	Bottom 50%	Country	Top 1%	Top 10%	Middle 40%	Bottom 50%
Algeria	24.8%	57.0%	37.1%	5.9%	**Japan**	24.5%	57.8%	36.5%	5.8%
Argentina	25.7%	58.2%	36.1%	5.7%	**Mexico**	46.9%	78.7%	21.5%	-0.2%
Australia	23.7%	56.2%	37.7%	6.1%	**Morocco**	30.4%	63.2%	32.3%	4.5%
Brazil	48.9%	79.8%	20.6%	-0.4%	**Nigeria**	25.2%	58.1%	36.2%	5.7%
Canada	25.0%	57.7%	36.5%	5.8%	**Poland**	30.3%	61.8%	38.9%	-0.7%
Chile	49.6%	80.4%	20.1%	-0.6%	**Russia**	47.7%	74.1%	22.8%	3.1%
China	30.5%	67.8%	25.8%	6.4%	**S Africa**	55.0%	85.7%	16.8%	-2.4%
France	27.0%	59.5%	35.6%	4.9%	**S Korea**	25.4%	58.5%	35.9%	5.6%
Germany	29.7%	59.6%	37.1%	3.4%	**Spain**	24.2%	57.6%	35.8%	6.7%
India	33.0%	64.6%	29.5%	5.9%	**Sweden**	27.3%	58.0%	36.2%	5.8%
Indonesia	29.4%	60.2%	34.3%	5.5%	**Turkey**	36.9%	67.5%	28.9%	3.7%
Israel	31.1%	62.3%	32.7%	5.0%	**UK**	21.3%	57.1%	38.2%	4.6%
Italy	18.0%	47.7%	42.4%	10.0%	**USA**	34.9%	70.7%	27.8%	1.5%
World	**38.0%**	**76.0%**	**22.0%**	**2.0%**					

Table 1. Wealth distribution in selected countries and the world, 2022

	Top 0.001%	Top 0.01%	Top 0.1%	Top 1%	Top 10%	Bottom 50%	Bottom 20%	Bottom 10%	Bottom 1%
Canada	1,451,415,077	282,035,973	54,728,260	10,561,149	2,209,207	103,324	77,349	65,376	17,897
China	487,578,512	91,493,082	13,541,607	2,412,203	539,634	10,025	2,154	-1,690	-21,701
India	261,256,364	34,622,075	4,626,469	625,486	101,315	2,000	429	-209	-4,234
Iran	55,114,761	11,125,844	2,405,416	568,548	133,497	1,975	-985	-2,556	-10,747
Israel	2,743,846,201	380,265,860	61,780,055	11,831,003	2,448,105	30,177	-16,809	-42,971	-192,617
New Zealand	762,216,050	159,441,238	36,136,775	9,175,993	2,310,542	40,130	-17,818	-47,624	-185,412
Norway	1,363,086,527	237,261,692	43,807,744	8,375,673	1,880,767	25,549	-53,730	-98,891	-219,461
RussianFed	844,516,571	127,680,236	18,842,800	2,866,072	444,859	3,139	-658	-2,290	-14,928
Saudi Arabia	751,383,170	140,643,130	28,463,128	6,054,432	1,291,604	14,964	-9,803	-24,600	-118,648
Singapore	2,900,016,070	396,741,574	64,382,403	12,774,307	2,769,038	38,927	-19,120	-49,761	-207,132
UK	620,050,396	95,225,408	19,206,769	5,910,148	1,585,207	25,743	-2,748	-7,016	-37,365
USA	2,584,330,483	495,973,233	93,970,067	17,777,874	3,554,412	9,764	-19,775	-34,749	-49,238
Venezuela	60,171,480	9,652,209	1,760,804	350,466	71,912	784	-540	-1,347	-6,620
World	**520,412,998**	**90,610,967**	**15,616,699**	**3,022,431**	**612,068**	**3,728**	**-2,947**	**-7,272**	**-48,247**

Table 2. Average wealth in selected countries and the world by percentile

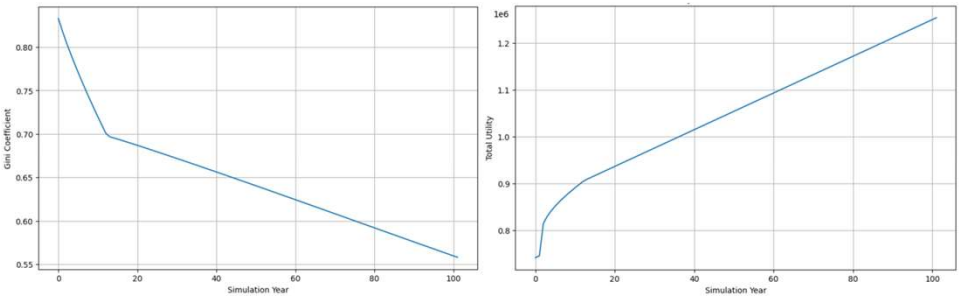
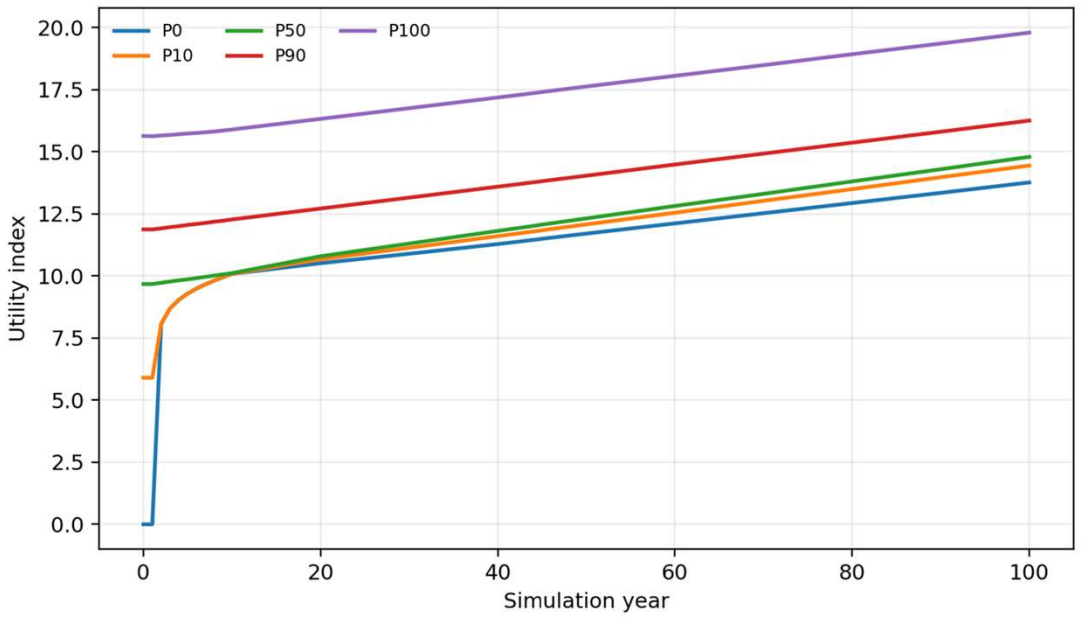


Figure 2. Trajectory of Gini coefficient and Total Utility series.

Adjusting Wealth Inequality to Make a Substantial Majority of the World Economically Better Off



Country	10/1	10/2.5	5/1	5/2.5	Country	10/1	10/2.5	5/1	5/2.5
World	2 - 8	1 - 4	2 - 9	1 – 5	Mozambique	3 - 43	2 - 36	4 - 45	2 - 38
Argentina	2 - 16	1 - 11	3 - 25	1 – 13	New Zealand	3 - 4	1 - 2	3 - 4	2 - 2
Bangladesh	3 - 17	1 - 14	3 - 22	2 – 16	Norway	6 - 8	3 - 3	8 - 11	4 - 5
Canada	1 - 1	1 - 1	1 - 1	1 – 1	Pakistan	3 - 35	1 - 26	3 - 39	2 - 29
China	1 - 4	1 - 3	1 - 6	1 – 3	Palestine	2 - 40	1 - 28	3 - 43	1 - 31
Egypt	2 - 34	1 - 25	3 - 36	1 – 28	Panama	2 - 9	1 - 5	3 - 11	1 - 6
Germany	1 - 3	1 - 2	1 - 3	1 – 2	Peru	3 - 18	1 - 11	3 - 20	2 - 12
Greece	18 - 25	8 - 11	25 - 34	10 – 15	Russian Fed	1 - 12	1 - 7	1 - 13	1 - 7
India	1 - 20	1 - 15	1 - 21	1 – 16	Saudi Arabia	2 - 5	1 - 2	3 - 6	1 - 3
Indonesia	2 - 21	1 - 14	3 - 24	1 – 16	Singapore	2 - 3	1 - 2	3 - 4	1 - 2
Iran	2 - 28	1 - 18	3 - 32	2 – 21	Spain	1 - 4	1 - 2	1 - 5	1 - 2
Israel	2 - 3	1 - 2	3 - 4	1 – 2	Sudan	2 - na	1 - na	3 - na	2 - na
Jamaica	2 - 27	1 - 13	3 - 32	1 – 17	Switzerland	1 - 1	1 - 1	1 - 1	1 - 1
Japan	2 - 6	1 - 3	3 - 7	2 – 3	Turkey	2 - 9	1 - 5	3 - 10	1 - 5
Kazakhstan	2 - 12	1 - 7	3 - 14	1 – 8	Turkmenistan	2 - 10	1 - 6	3 - 12	1 - 7
Kenya	2 - 32	1 - 24	3 - 36	1 – 27	UK	1 - 3	1 - 2	1 - 4	1 - 2
Korea	1 - 4	1 - 2	1 - 5	1 – 3	USA	2 - 3	1 - 1	2 - 3	1 - 2
Malaysia	2 - 15	1 - 9	3 - 17	1 – 11	Venezuela	2 - na	1 - na	3 - na	1 - na
Mexico	2 – 18	1 - 9	3 - 21	2 - 11	Zimbabwe	3 - na	1 - na	3 - na	2 - na

Table 7. Years for the poorest to attain positive wealth (left of hyphen in cells) and to cross $16,000

Technological Displacement and Macroeconomic Divergence: A General Equilibrium Model of AI-Driven Unemployment

The representative household maximizes expected lifetime utility: $\max \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\sigma}}{1-\sigma} - \chi \frac{N_t^{1+\phi}}{1+\phi} \right]$

where C_t is aggregate consumption, N_t is aggregate labor supply, $\beta \in (0,1)$ is the discount factor, $\sigma > 1$ represents the coefficient of relative risk aversion, and $\phi > 0$ is the inverse Frisch elasticity of labor supply.

The household budget constraint in real terms is given by: $C_t + I_t + B_t + T_t \leq (1-\tau_w) W_t N_t + (1-\tau_k)(R_t - \delta) K_t + (1 + r_{t-1}) B_{t-1} + \Pi_t$

where W_t is the real wage, R_t is the rental rate of capital K_t, I_t is investment, δ is the depreciation rate, B_t denotes risk-free government bonds yielding real interest rate r_t, Π_t represents firm profits, and τ_w and τ_k are tax rates on labor and capital income, respectively.

Aggregate output Y_t is produced by combining a continuum of intermediate tasks $i \in [N_{t-1}, N_t]$ aggregated via a Cobb-Douglas or Constant Elasticity of Substitution (CES) production function with elasticity $\epsilon > 0$: $Y_t = \left(\int_0^1 Y_t(i)^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}}$

Each task i can be produced either by human labor (L) or by AI-capital (K_a):

$$Y_t(i) = \begin{cases} A_l(i) l_t(i) & \text{if performed by labor} \\ A_k(i) k_t(i) & \text{if performed by AI−capital} \end{cases}$$

where $A_l(i)$ and $A_k(i)$ denote task-specific factor productivities. Let $I_a \in [0,1]$ denote the threshold index of tasks automated by AI. Tasks $i \in [0, I_a]$ are performed by AI-capital, while tasks $i \in (I_a, 1]$ are performed by human labor.

The cost minimization condition dictates that a task is automated if and only if the unit cost of production using AI is less than that using labor:

$$\frac{R_{a,t}}{A_k(i)} < \frac{W_t}{A_l(i)}$$

where $R_{a,t}$ is the user cost of AI-capital, incorporating specialized computing hardware and software depreciation.

Let aggregate labor demand L_d be determined by the span of non-automated tasks: $L_d(W_t, R_{a,t}) = \int_{I_a}^1 y_t(i) \left(\frac{W_t}{A_l(i)} \right)^{-\epsilon} di$

We introduce labor market frictions via a matching function or search-and-matching framework where structural unemployment U_t is defined as: $U_t = 1 - \frac{N_t}{L_s}$

When the AI automation frontier I_a expands rapidly due to exogenous efficiency jumps in machine learning architectures (e.g., Transformer-based systems), labor demand contracts faster than wages can adjust downward due to nominal rigidities or efficiency wage floors ($\underline{W}$). Consequently, structural unemployment rises.

DEEP LEARNING ARCHITECTURE

Pre-Trained Transformer Models for Time Series

Universal zero-shot forecasting across domains without task-specific retraining.

Predict Any Dataset Instantaneously

By translating continuous time steps into sequence tokens, pre-trained transformers transfer foundation model power directly to temporal data.

BENCHMARK IMPACT
Zero-Shot Accuracy

1. Patch Tokenization

Groups sub-series time steps into dense input embeddings.

2. Pre-Trained Scale

Learns deep temporal dynamics across millions of public series.

3. Universal Inference

Executes immediate predictions on unseen domains and frequencies.

Key Advantage: Eliminates costly model training pipelines for new time-series channels.

✓ Finance ✓ Energy ✓ IoT & Supply Chain