# Income vs. Demand: Exploring Dynamics of Poverty Lines using Agent-based Modeling

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**Abstract.** More than 650 million people are living in poverty around the world. Drawing on non-linearities in empirical observations of poverty, this paper introduces an agent-based model to examine the complex demand behavior of households in the market in order to establish an initial experimental platform for advanced investigations into foundations that drive or mitigate economic growth (and by implication poverty). Exploring the model across 6800 scenarios we could reconstruct the non-linear linkage between income levels and price levels (which can lead to increased inflation and poverty). Instead, demand tends to follow an S-shaped growth pattern, especially in lower-income conditions in which needs potentially remain unsatisfied. These observations were reconciled with empirical data, suggesting that the model offers fundamental analytical value, before concluding with the discussion of future extensions (e.g., supply side, state actors, foreign investments) to more closely capture economic complexity found in the real world, and hence expand the analytical value of the model.

**Keywords:** Agent-based modeling · poverty · economic development · complexity · macro-economics

## 1 Introduction

Poverty remains an overarching theme of the 21st century, one that affects around 650 million people [19, 3] and is impacted by the ongoing climate and political crisis. Given the objective to address poverty as a central UN Sustainability Goal, it is important to understand the concept, and even before doing so, identify how it affects countries, but perhaps centrally, the patterns and phases. The primary objective of this study is to examine the correlation between income levels and poverty levels in a nation using Agent-based modeling (ABM), which remains one of the most debated topics [3, 33, 19].

## 2 Motivation and Background

Throughout history, poverty has been an ongoing topic of concern, with diverse perspectives regarding its measurement. Since the social contract [7] has started to take shape, poverty is still primarily discussed from a philosophical standpoint, since it is tied to basic human needs and rights that undergo continuous change over time [11, 31]. In the past, poverty was considered a vague concept, but in modern times, a reference point for measuring poverty levels has been established through a basket of necessary goods [3, 16, 27], linking it fundamentally to economic development. Consequently, understanding poverty, its measurement and the processes that foster it, are of utmost importance when it comes to formulating effective policies to address this societal issue.

Apart from the ethical reasons grounded in social values and assumptions about fair opportunity, from an economic perspective poverty plays a significant role in a country's development prospects, given its linkage to long-term socio-economic effects by limiting access to education and participation, and inadvertently driving unemployment in a society (hence limiting economic prospects of the country at large) (see e.g., [28]). This is particularly relevant in the context of globalization, in which economic opportunities in one country directly affect other countries, hence leveraging the opportunity to collectively facilitate poverty reduction [3, 28]. Creating opportunities for innovation and benefiting from welfare programs can lead to the growth of new ideas, ultimately resulting in greater progress for human society [14, 28]. Striving towards a reduction of poverty at large to some extent is therefore essential for the advancement of society.

Given the long-standing interest in this topic, we have seen multiple investigations carried out regarding poverty, utilizing different research inquiries and techniques such as statistical analysis [16, 26, 17, 27, 6] and AI models to support the prediction of poverty outcomes [15]. An ongoing discussion revolves around the correlation between income levels and poverty lines, as income can have an impact on inflation and the pricing of commodities. However, inasmuch as these studies highlight the linkage between poverty and GDP (or Household income levels) as a dominant metric for economic output, much lesser attention is put on the role of the actual purchasing power of individuals and households to capture the effective spending power on the individual level as an indicator of poverty experienced in society.

Poverty encompasses fundamental human necessities like food, shelter, education, and healthcare. Capturing these in a single concept, the *Poverty Line (PL)* adjusted by *Purchasing Power Parity (PPP)* draws on the concept of the basket of goods [5], which is annually updated by groups such as the World Bank and, due to its continuous maintenance, offers a reliable data basis for the analysis of poverty development over time. This basket includes commonly used goods and is adjusted for international exchange rates. It serves as a reference point for measuring poverty[3], with annual income and consumption surveys in various countries as reference data [4, 16, 26].

The PL, as documented by the World Bank's data system, holds significant importance when it comes to examining poverty lines, determining the international extreme poverty line, and predicting and designing policies. Every year, an assessment is conducted to determine the number of individuals living in poverty and corresponding initiatives are implemented to alleviate poverty.

The aim of this study is to pinpoint the PL, as well as its prospective progression over time, for a particular nation, with the intention of improving the basis to establish targeted planning efforts that best correspond to the state of current and prospective development of a particular nation. The pathway proposed in this paper is to establish a refined approximation of poverty measures; solely relying on statistical analysis (such as mean and median points) or linear regression analysis may not provide an exact representation of the causal impacts and adaptations. Complementing this effort, we propose an initial agent-based that aims at providing the opportunity to explore the causal determinants that drive a country's progression out of poverty, an aspect that statistical approaches only do not provide.

The inconsistent updates and changes in the status of the spotted *International Poverty Line* (IPL) [16] have led to limitations. One of those is the dynamic nature of the targeted IPLs and the lag in achieving the 2030 World Bank poverty vision [3, 19]. As a result, the World Bank has decided to maintain its previous estimations for the absolute minimum poverty line (initially 1.9 dollars per day [26]) instead of updating it (to 2.9 and 3.15, respectively [16, 3]). A particular limitation in recent data is the disproportionate influence of exogenous shocks such as contemporary wars and the recent epidemic on income levels [19], which caused a change in income and PPP levels. The most pronounced limitation, however, is the linear regression approach used in many of these studies, since this cannot capture distinctive behaviors of economic growth that economies undergo in different stages.

In the field of regression analysis specifically, we observe two central obstacles that researchers face: the need to simplify models (so as to establish generality) and the challenge of selecting appropriate economic growth patterns. To tackle these challenges, analysts typically employ one of two types of models – linear or nonlinear analysis. Linear analysis is a commonly used technique that involves studying how a dependent variable is affected by a set of independent variables. In this method, the mathematical form of the model is already known (i.e., it is linear), and parameters can be estimated my minimizing error terms. However, when it comes to human-based systems and associated phenomena, nonlinearity is commonly observed, which, however, can be difficult to model effectively due to constraints related to equation pattern selection (statistical model selection) and parameter value estimation.

Addressing this issue, reverse functions such as logarithmic functions are commonly employed to transform nonlinear relationships into linear ones.[16] This technique can greatly aid in parameter estimation, but it also presents a new challenge in model selection since logarithmic approaches should, in principle, only be applied to data sets in which exponential relationships are expected;

using them inappropriately can lead to technical mathematical difficulties such as scale comparison and completely new unrelated pattern recognition. Therefore, it is crucial to carefully evaluate model selection in order to avoid potential issues in the outputs. Previous studies have demonstrated the importance of taking this step, as neglecting it can have significant consequences.

This work takes an initial step at addressing both aspects, namely providing an improved statistical model fitting for a given poverty data set based on PL (adjusted by PPP 2017 [5]) information, complemented by an agent-based model that attempts to replicate the observed empirical outcomes as a starting point to explore causal scenarios that help understand processes that lead to specific poverty outcomes.

To this end, this paper initially turns to existing analyses of poverty (Section 3), before engaging in a refined fitting of different growth patterns reflecting distinct types of economies (Section 4.1). Following that, we propose an initial simple agent-based model that reproduces selected types of economic growth patterns (Section 4.1). The paper concludes with a discussion of the observed results and opportunities for future research in Section 4.2.

## 3 Statistical analysis and ABMs

The statistical analysis of poverty is a relatively recent field, with data available only since around 1960 for most countries (although some have more recent data as of 2000 [5]). One study, known as the "1.9 dollars per day" study [26], is often referenced as it gathered PL points of various nations and identified the median point as the representative of the Extreme International Poverty Line (IPL 1.9$), which closely matched the PL of poor countries in the data set. Although the study provides valuable insights into the hidden aspects of poverty, its reliance on pure statistical characteristics challenges its ability to sufficiently accurately predict future outcomes as the data may have changed over time [16]. On the policy-making side, relying solely on median and mean points could potentially lead to ineffective policy interventions.

More recent studies [16, 12, 10, 13] have explored the issue of predicting statistical characteristics and updates related to PL points. One such study examined the relationship between PL points and Household final consumption expenditures (HFCE) as the income variable. However, it was anticipated that nonlinear behavior would occur based on existing literature. To address the limitations of parameter estimation and model selection, a linear logarithmic function was applied to effectively linearize the problem. After applying the logarithm function to this dataset, the researchers expectedly observed a positive correlation between income levels and PL points, indicating an exponential relationship. This means that as a nation's income levels increase, its PL status also increases. Reviewing empirical data, however, we can quickly observe that this only captures a very specific economic configuration of developing countries (or undeveloped) at their early stages of increasing economic development. It does not, however, capture developmental patterns observed in rich countries with high salary levels, which still showcase a significant number of people living in relative poverty.

Despite some challenges associated with existing statistical analyses, its usage is growing thanks to the abundance of available data, and combination with machine learning techniques [32, 24]. However, it can only be used for predictive analysis when data is available. Simulation-based models, particularly ABMs, can also be helpful in analyzing mechanisms of actions, reactions, and causal relations, which can benefit both prediction and policy testing. The study of economic cases, and among them especially the poverty using ABMs, is not a new idea and has found quite some adoption over time [9, 25, 8, 2, 22, 21]. Many of these models focus on the analysis of very specific cases with emphasis on modeling distinct communities (e.g., [25, 2]) and particular empirical cases (such as [9, 8, 29]). Deviating from those models, the approach proposed here focuses on a macro-economic perspective, with the intent to capture distinctive empirically observed growth patterns, hence navigating the trade-off of providing sufficient precision to draw insights into the potential underlying processes, while retaining the ability to capture any observed stages of economic development (in as far as captured in the used empirical data).

In the upcoming section, we discuss the overall objective of our modeling. We will then move on to describe the specific subsystem in detail, including offering a complete conceptualization of the model employed in this study.

## 4 Method and Analysis

### 4.1 Method

The attention to agent-based modeling as a complementary technique to statistical evaluation lies in its ability to provide insight into the fundamental processes that bring about macro-level outcomes studied using empirical data. More specifically, the idea is to explore the central causal linkages that may be uniform (or variably differ) for specific countries in determining their stage of economic development and associated poverty levels.

Turning to our specific study, we aim to use an ABM to complement the established statistical model of poverty with a complex model that leverages opportunities to explore causal linkages statistical models are poorly geared to offer. As previously stated, this research aims to determine the correlation between income and the price of a basket of goods (presented as the demand level of agents), which serves as an indicator of the Poverty Lines (PL) in a given country. This requires the consideration of a market, reflecting both demand- and supply-side behavior and its influence on market prices. In this case, the specific characteristics of a country are central parameters to determine the overall outcome.

Modeling markets at large implies the consideration of numerous subsystems (such as the labor market, state influence, foreign investment, capital flow, etc.). However, as a starting point for this model – replicating observed outcomes in the statistical model – the initial emphasis lies on understanding the demand-side behavior of individuals in a society, with the initial assumptions of limitless supply and a fixed price point. Such a scenario can approximate conditions found in open economies within periods of economic stability in which price levels are constant. To simplify the simulation process, only one product, referred to as the basket of goods, is included instead of all the individual items. When the income level changes, households will react to the basket's value, which includes both the quantity and quality aspects.

Figure 1 shows a causal system diagram that reflects the demand side of the modeled economy and serves as the basis for developing the agent-based model. Agents are households, given the compatible aggregation unit with empirically reported data. In practice, this reflects the everyday purchasing decisions that shape aggregate economic demand.

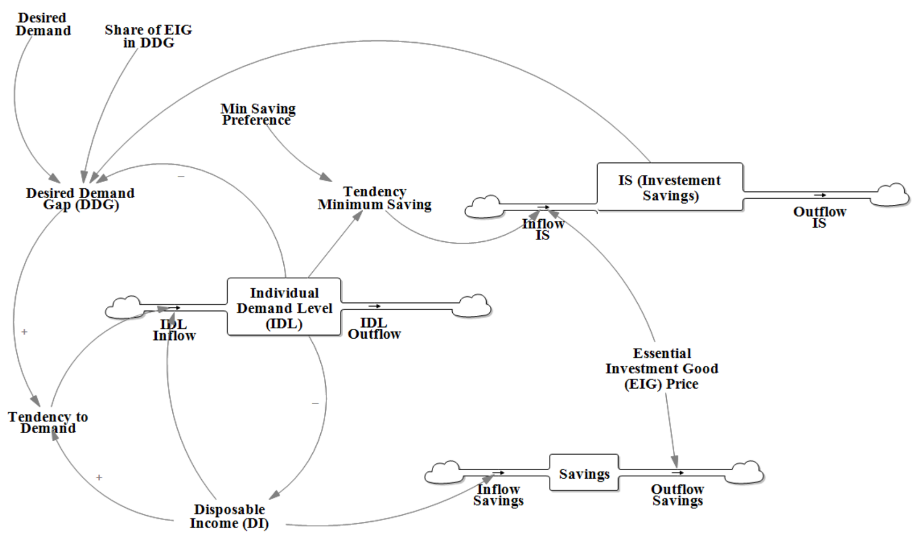


Fig. 1: Diagram of Household behavior in the system following assigned income

Reflecting the principal operation, each agent (called 'Household') is assigned an income level, which is determined by a function that calculates a mean point representing the GDP per Capita (re-scaled with factor 0.001). The income level is distributed using a standard deviation following the Gaussian distribution with a mean derived from the income function output (Figure 2 and Table 2). This process occurs at every tick (per year) for each agent. Given the absence of a complete market model at this stage, the simulation model relies on an external income function which emulates the market behavior. To capture stereotypical forms of income growth in different economics/stages of economic development, we rely on three function types, namely Linear (Equation 1), Logarithmic (Equation 2), and Exponential (Equation 3), representing different growth scenarios.

To proxy the abstracted market behavior under controlled conditions reflecting the respective economies' conditions, the stylized income functions are parameterized by assuming a value range between 0 and 200 (given the assumed default demand level of 50 (Table 2)), allowing simulation models to reach income levels of 200 at step 100. For the purpose of systematic exploration, these are modeled symmetrically (relative to the linear income function), an aspect that was established using a python package called Copatrec [18], which can be used for nonlinear model selection purposes using any data types including lookup tables. (shown in Figure 2). The function coefficients for the corresponding income function are shown below.

For the operationalization of the income function, we rely on an additional parameter referred to as *growth direction* (Table 3). This parameter determines the time step at which the direction of income growth is inverted, emulating the presence of economic shocks (i.e., a point in time at which income decreases). In this model, the income_mean can be parameterized in the range of 0-200. Combined with the *growth direction*, this can accommodate a wide range of income scenarios, reflecting stereotypical macroeconomic scenarios.

The linear function – as a baseline scenario – reflects a linear progression of income over time, with ‘a‘ being the slope of the function representing the growth rate.

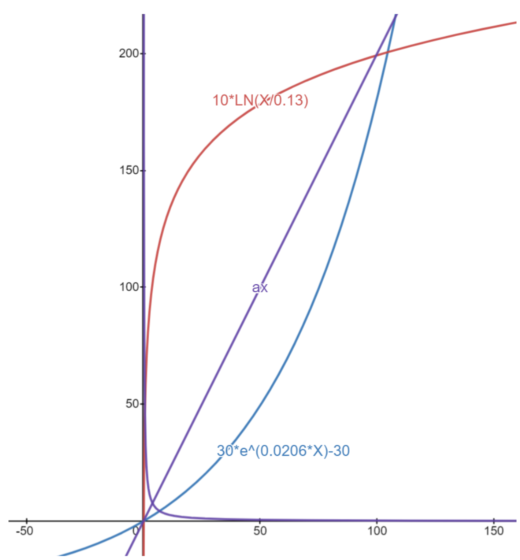


Fig. 2: Three income functions (Linear, Exponential, and Logarithmic). In the model code, at each step, the derivative of these functions has been used to update the 'incomeMean' growth.

$$Income\_Mean = a * time \tag{1}$$

The logarithmic income function shown in Equation 2, in contrast, represents economic developments of rapid growth initially that slows down over time, hence allowing households to satisfy demands swiftly during the initial levels in a short time frame (for progressions below 10 ticks, the relation between demand levels and income levels are essentially exponential), before entering a stabilizing phase in economic development.

$$Income\_Mean = 10 * LN(\frac{Time}{0.13}) \tag{2}$$

The exponential income function (see 3) showcases a smoothed initial growth; even though it has the name of exponential growth, but the growth part is activated smoother compared to the logarithmic function. This function represents economic conditions found in stable economies, but with an event that activates and rapidly progressing growth (such as newly identified natural resources, and industrialization), leading to different demand-side behavior due to the high level of demand satisfaction present in the society prior to the growth event.

$$Income\_Mean = 30 * e^{0.0206*Time} - 30 \tag{3}$$

For all income function types, the parameters for the corresponding function are noted in Table 3 (*income_growth*). To generate income functions, a package called Copatrec [18] is hired, which suggests mathematical models (linear and nonlinear) based on the given data. To generate these equations, a hypothetical lookup table is used as input.

Returning to the agent model, each agent has a preferred level of demand (50) that they aim to meet. This desired demand (Table 2) is based on the value of the basket of goods (PL) and is considered a constant parameter since it is assumed that there is an unlimited supply and constant price in the market (Table 2).

To determine the demand level based on income and desired demand, the difference between both is referred to as the *demand gap*. We use this to calculate a tendency toward increasing or lowering demand at each step. The tendency toward demand (*demand inflow*) is based on the minimum value between the disposable income (the remaining income after allocating to the current demand level) and the current gap.

The agent spends money until its demand level is met and then starts to save any income in excess of its (satisfied) demand. The model recognizes two types of savings: *regular savings* (for instance, in the form of equity) and *essential investment savings (IS)*. Essential investment savings refer to goods that the agent may choose to save for instead of purchasing in the market, as they will cover part of their current demand and also provide long-term savings. A typical example of such goods is houses (via the pay-off of which is the presumed long-term reduction in rent payments (reduction of immediate demands), alongside the capital value bound in the investment).

**Algorithm 1** Household Behavior

```
Relevant Model Level Variables:
income_mean ← f(time)
income_std ← Parameter
citizen_desired_demand ← Parameter
citizen_required_demand ← citizen_desired_demand / 2
Behavior:
Initialization:
income ← 1
current_demand_level ← 0
Execution Cycle:
income ← Gaussian(μ = income_mean, σ = income_std)
disposable_income ← MAX(income − current_demand_level, 0)
if has an EIG then
   update EIG_Share_desired_demand
end if
demand_gap ← f(disposable_income, current_demand_level, EIG_Share_desired_demand)
demand_inflow = Min(disposable_income, demand_gap)
demand_outflow = f(income, current_demand_level, citizen_required_demand)
current_demand_level =+ demand_inflow − demand_outflow
savings_inflow = income − current_demand_level
savings_outflow = f(investment_savings_inflow, citizen_required_demand)
savings =+savings_inflow − savings_outflow
investment_savings_state ← f(investment_savings_inflow)
```

The operational difference between both forms of saving is that for *essential investment goods (EIG)* savings, the equivalent costs presenting in their desired demand are updated in each round and with increasing satisfaction of demand, resulting in an adjusted (lowered) future demand. For regular savings, in contrast, the savings will continuously increase for income values above the desired demand level, unless income declines over time and can no longer satisfy the demand. Following the market development (i.e., change in income and reaction to adjusted demand – increasing demand in case of falling income, reducing demand in the case of increasing income), the household can decide to either use the saving or even sell the EIG at the current price in the market (which is modelled as the ration between EIG and income, tagged *eig_ to_ income_ ratio*).

The entire behavior of households, including initial parameterization, relevant global model parameters, as well as the operational execution cycle, is shown in Algorithm 1.

Table 1 describes all variables, including auxiliary ones, such as emergency savings, regular savings in accounts, the share of EIG in the basket of goods, and the price of EIG [30, 23].

As previously discussed, with the exception of the income function (depends on time) and the EIG price (depends on the median income level), the supply subsystem and government rely on external processes that are not included in this model (and hence abstracted). Both variables are updated at the Model level at the of each tick and made available to Household agents that do not show any other form of direct interaction. Table 2 provides details on the parameters and variables operating at the model level.

To populate the model, we use rescaled GDPPC data (GDPPC/1000) and unscaled PL original data, with GDPPC proxying for income mean and PL for desired demand. A sensitivity analysis is performed to investigate how different parameters affect the relationship between income and demand levels reported in Table 3. This serves as the basis to parameterize different nations with distinctive configurations of income growth (such as slowly growing nations, fast-growing

Table 1: Household Attributes

| Name | Type | Value | Description |
|---|---|---|---|
| citizen_desired_demand | Constant | 50 | For model inputs Table 2 |
| citizen_required_demand | Constant | $\frac{citizen\_desired\_demand}{2}$ | For model inputs Table 2 |
| income_mean | Variable | Income Functions, Figure 2 | For model inputs Table 2 |
| income_std | Constant | 10 | For model inputs Table 2 |
| income | Variable | Gaussian(income_mean, income_std) | For inputs Table 2 |
| eig_to_income_ratio | Constant | 0.25 | For inputs, Table 2 |
| median_income_level | Variable | Median point of all incomes | |
| EIG_Price | Variable | $median\_income\_level * eig\_to\_income\_ratio$ | EIG: Essential Investment Goods, For inputs Table 2 |
| demand_gap | Variable | $citizen\_desired\_demand - current\_demand\_level$ | |
| disposable_income | Variable | $income - current\_demand\_level$ | The remaining income after consumption |
| demand_inflow | Variable | $Min(disposable\_income, demand\_gap)$ | |
| demand_outflow | Variable | f(income, current_demand_level, citizen_required_demand) | |
| current_demand_level | State Variable | $f(demand\_inflow, demand\_outflow)$ | |
| savings | State Variable | $+= saving\_inflow - savings\_outflow$ | |
| saving_inflow | Variable | $f(income - current\_demand\_level)$ | |
| savings_outflow | Variable | f(income, current_demand_level, citizen_required_demand) | |
| emergency_savings | Variable | A multiplication of some months of income | The minimum amount of equity savings in which citizen prefers to have in the account. |
| investment_saving_state | State Variable | =+ investment_saving_inflow | |
| investment_saving_inflow | Variable | f(savings, EIG_Price, emergency_savings) | If the savings is above the price of investment good and emergency savings, then they will do an investment saving. |

nations, etc.). The initial setup of the model parameters can be found in Table 3.

Based on the initial parameters, we ran the following different combinations of parameter values (with ranges and step sizes reported in Table 3) over 6800

Table 2: Model Level Parameters and Variables

| Name | Type | Value | Description |
|---|---|---|---|
| Steps | Variable | Time | Unit of time of the model is years (i.e., one year per step/tick). |
| citizen_desired_demand | Constant | 50 | Extracted based on the top 10% observed PPP |
| citizen_required_demand | Constant | $citizen\_desired\_demand/2$ | The minimum amount of basket which is needed for survival. |
| income_mean | Variable | Income Functions, Figure 2 | |
| income_std | Constant | 10 | Different values have been explored in Sensitivity Analysis (see Table 3 for details) |
| income_dir_change_step | Constant | 200 | income pattern turn over step. Different values have been explored in Sensitivity Analysis (see Table 3 for details) |
| growth_direction | Constant | 1 or -1 | indicates the current direction of the income growth. Different values have been explored in Sensitivity Analysis (see Table 3 for details) |
| n_citizen | Constant | 100 | Number of citizens. |
| emergency_savings_preference | Constant | 5 | How many salaries are meant to be saved in savings? |
| eig_to_income_ratio | Constant | 4 | How much of the annual income is needed to buy a property?[30] |
| share_eig_in_demands | Constant | 0.3 | What is the portion of rents in the basket of goods?[23] |
| median_income_level | Variable | Median point of all incomes | |
| EIG_Price | Variable | $median\_income\_level * eig\_to\_income\_ratio$ | EIG: Essential Investment Goods |

runs (reflecting all possible parameter combinations), with a maximum number of rounds of 100 steps per simulation, a parameterization that is based on the initial experimental observation that showcased convergence under any condition within this number of steps.

Table 3: Parameter setup for sensitivity analyses

| Name | Type | Range | Description |
|---|---|---|---|
| income_mean | Variable | (Linear, Logarithmic, and Exponential) | Three different functions have been selected. It is discussed further in the content. |
| income_std | Constant | [1,6,11,...30] | This is mostly used for the Linear income function in the second setup of runs. |
| income_growth | Constant | [0.1, 0.2, 0.3, ..., 1.9] | This item is also in the scope for the linear function. |
| income_dir_change_step | Constant | [10, 20, 30, ..., 90] | |

### 4.2 Results

Reviewing the results of all simulation runs, a set of specific behaviors observed as the results will be highlighted. Figure 3 illustrates the different combinations of time-series results for income and demand levels (representing PL) using three different functions.

Figures 4 showcase selected comparable results for each of the income functions (with four plot sets, each of which consists of two vertically oriented diagrams, with the top one reflecting the mean demand level, and the bottom ones representing the mean income). Each simulation is parameterized to show a direction change in income at time step 60. Given the differentiated growth rate parameter for linear distributions (unlike the other functions), two versions of the linear function are included (the top left and top right sets), with the initial showcasing of income growth rate equal to 0.5 (low slope) and the second being parameterized with the value 2 (high slope). The remaining functions are the logarithmic one (bottom left) and exponential income growth function (bottom right).

Reviewing the two top left diagrams (Linear function, std = 11 and growth rate = 0.5, which means multiply by 1.5), the income essentially never manages to satisfy the desired demand level. Thus, the demand level follows the income. This means if the income vs. demand level curve is plotted, a positive linear correlation should be observed. This can be representative of a nation in which the income levels are low, an aspect that supports the analysis reported in [16]. The same behavior is observed similarly in the bottom right set of curves in which the income levels grow exponentially; it manages to satisfy the demand level, and retains stability for some time, before decaying. However, in this exponential scenario and the other two (top-right and bottom-left) figures, the stability of the demand level after the desired demand is satisfied can not show a positive correlation. This means, in these convergence points, the growth of the income level doesn't affect the demand level any further. To demonstrate this, a set of

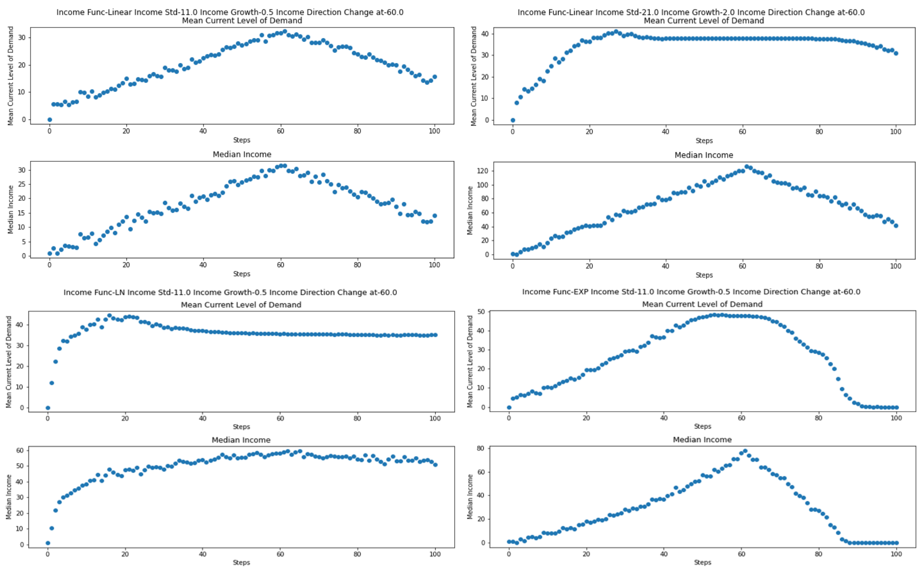


Fig. 3: Selective time series results of income and demand levels

different combinations of income vs. demand levels with different scenarios is plotted in Figure 4.

Observing the combined output in Figure 4, considering each run representative of a stylized economy (i.e., country), across all instances, we can observe an S-shape behavior for which the demand levels are growing to a point (with different initial performance) corresponding to their gap and income levels. To investigate the distinctive patterns in greater detail, a selected subset of series are plotted in Figure 5.

For some scenarios with lower income levels (e.g., ID 365), a positive correlation can be observed. However, this does not imply a different pattern compared to other scenarios but rather points to the fact that this scenario never experienced the economic conditions of the fully developed cases (i.e., ID 2606). If so, this scenario would likewise showcase the identified S-shape behavior found in other countries. This is likewise valid for other cases that are in the early developing phase (i.e., ID 401) and approximate the desired demand level but retain a positive relation. In short, looking at the scenarios at large, the developmental trajectory for any country follows an S-shape behavior in the ideal case, but subject to the current stage of economic development (proxied via income level), only specific stages can be recreated in the simulation setting – an aspect that is best reflected when comparing the generated outcomes to empirical data, both to establish a sense of the ability of the model to recreate real patterns, but also to substantiate the observed simulation outcomes by comparing specific scenarios.

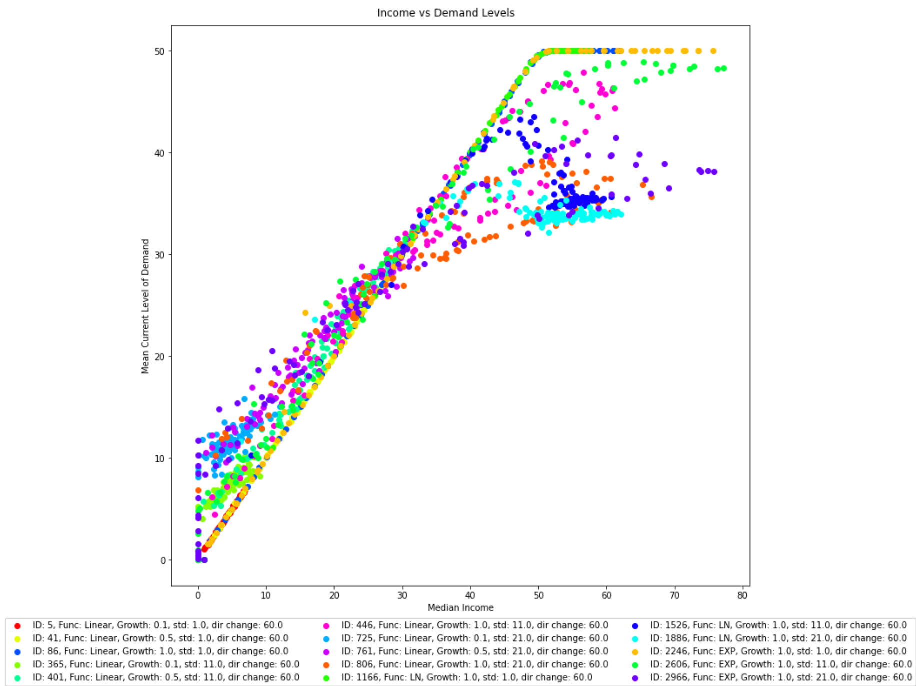


Fig. 4: Income vs. demand levels 15 scenarios

### 4.3 Validation

To afford the validation, we draw on the GDPPC [4] and poverty lines (PL) [5] data referenced earlier. While GDPPC data is based on 2015 values, the employed PLs are adjusted based on 2017 PPP values which are based on either consumption or income surveys at the national level for the included. For the sake of facilitating the alignment with the cases observed in the simulation output, the empirical data have been clustered using k-means [20] with parameter k set to 4, given that the observed S-shape behavior can have four different sections (based on the respective derivates), ranging from exponential growth to transition to linear growth, and toward convergence. The results of this clustered empirical is shown in Figure 6.

Recalling the developing economy labeled ID 365 in 5 as part of the simulation outcomes, and comparing it to real-world economies (identified in red color in Figure 6), we can observe aligned patterns that reflect correspondence of actual low-income economies. On the other hand, other clusters of countries, such as the second, green cluster in Figure 6 is representative of scenarios similar to ID 401 in the simulation run (Figure 5), which are reflecting economies that entered a development phase. The purple cluster in Figure 6 aligns with observations captured as IDs 2606, 446, and 1526 in the simulation runs. Here, they reflect economies that are moving toward convergence based on the inher-

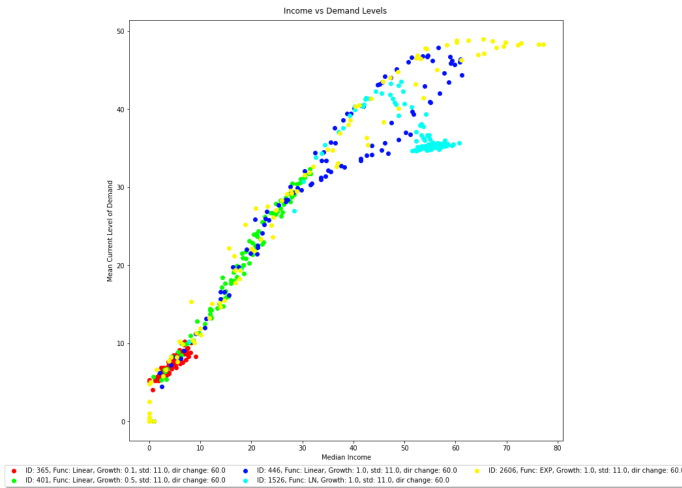


Fig. 5: Income vs. demand levels for 5 scenarios

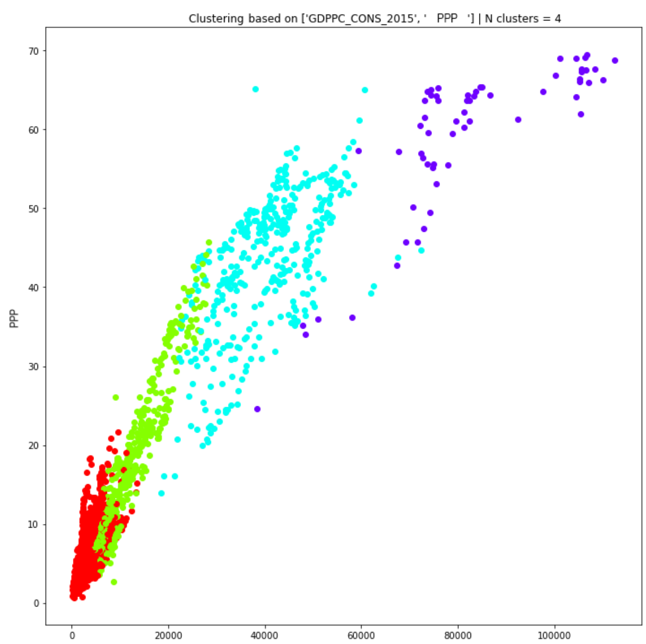


Fig. 6: GDPPC vs. Poverty Lines

ent demand satisfaction. To support the analysis in terms of real-world data, the names of actual countries and their relevant data points are provided in Figure 7 (Appendix A.1).

## 5 Conclusion

In this work, we took an initial step toward affording a more accurate reflection of macro-economic outcomes with respect to economic growth and associated household-level income, with the intent to showcase the interaction between economic development and demand-side behavior, driven by the original intent to grow the variable economic constellations that real-world countries operate in, and that represent the environmental conditions that foster, or variably reduced poverty. To this end, we initially introduced existing work in the area of political economy, before turning to agent-based modeling as a technique to reconstruct the outcomes observed in empirical data. Building on stylized income functions and a simplified market model (with a demand-side focus), we were able to replicate specific economic scenarios. Integrating the results enabled the identification of real-world patterns, suggesting that this initial model is able to provide a starting point for further refinement in order to better capture the complexity that makes macro-economic conditions come about, and serve as an explanatory tool or basis to explore alternative hypotheses.

Turning to the overall outcomes, we noted that a distinct S-shaped pattern emerged, which could only be captured by integrating the distinctive scenarios (based on specific income functions). The general pattern, however, appears stable: as income levels increase to a certain point (i.e., a state in which the vast majority of individuals earn an income that meets or exceeds the desired demand), consumption stabilizes in line with the desired demand.

This scenario mirrors empirical data of impoverished countries that have since experienced growth and achieved stability over time. However, such countries are few, and, given issues related to data quality and completeness makes conclusive analyses challenging. What we can learn, however, is that during the initial stages of growth, nations may experience significant fluctuations in demand levels due to high consumption and inflation. Yet, once the nation begins to address its consumption habits, prices stabilize, and inflation rates decrease. This pattern aligns with studies that aim to understand the Marginal Propensity to Consume (MPC) [1].

Although the S-shape is a common pattern, it may not always be observed in all scenarios. However, this does not necessarily indicate a different relationship. One such case is when a nation is unable to meet the demand levels, resulting in only the growing part of the S-shape being observed. Depending on income growth rates, this could manifest as either linear or exponential growth. Another scenario not captured with this approach is based on an immediate change in income levels based on exogenous shocks in which a bell shape behavior (one positive and one negative S-shape).

Returning to the main research question, even though it is indicated that the increase in income levels can cause an increase in price levels, inflation, and thus the poverty line, it should be asked and indicated exactly in which scenario and under which circumstances, an aspect the results of the simulation illustrate (and which is supported by empirical data). Even though there is a positive relation between income levels and demand levels (representing poverty lines) in poor countries, poverty conditions may already be controlled and satisfied when incomes reach above the desired demand and are satisfied. This highlights the immediate need to consider policies as an important mediating factor (e.g., social policy related to welfare, market regulation with direct or indirect impact on price levels) to establish a clear assessment of poverty, and providing the basis for an informed investigation.

The work presented focuses on the demand sub-system of the market, which appears to be relevant to reproduce the behavior of interest. However, to capture a more complete representation of economic activity further improvements are needed. Those include the integration of the supply sub-systems and exploring scenarios of economic openness (e.g., domestic production, importing that enables the mechanism of market pricing following market balance and would be the result of agents' communication). However, even at this stage, the developed model offers a starting point to develop a better understanding of the conditions that mitigate economic growth, and, by implication, poverty.

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# A Appendixes

## A.1 Country information related to Figure 6

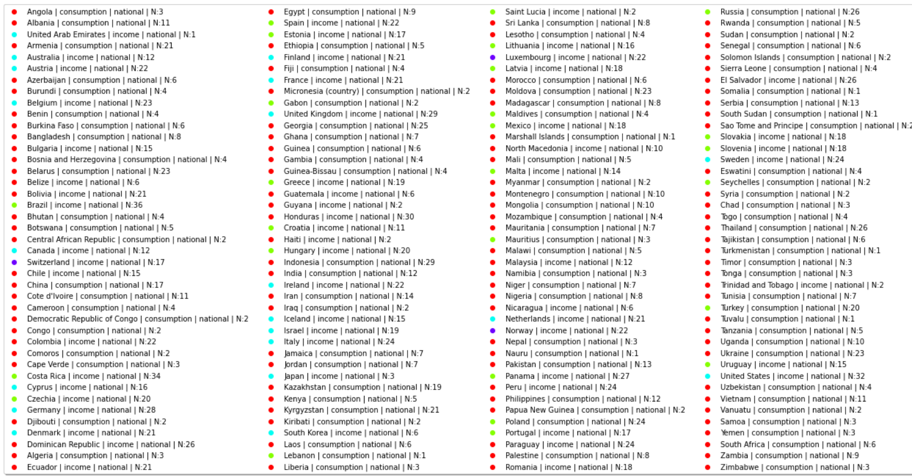


Fig. 7: Legend of country information related to Figure 6