MARIKOVIA

Modeling High-Entropy Economies Through Stochastic Agent-Based Simulation

Informal Economic Digital Twin — Research Paper

Owethu Mlambo Second Year BSc IT Data Science Eduvos March 2026

Abstract

Informal economies are not unstructured — they are unmeasured. South Africa's township economy generates hundreds of billions of rands annually, employs a significant share of the working population, yet remains systematically invisible to the financial instruments and policy tools that could most effectively support it. This paper introduces Marikovia, a platform and research framework for an Informal Economic Digital Twin that transforms this invisibility into actionable economic intelligence. Named after Andrei Markov, whose mathematical theory of dependent probabilistic transitions forms the theoretical backbone of the system, Marikovia represents informal economic actors as stochastic finite-state processes whose transitions are calibrated to available survey and administrative data. Uncertainty is quantified via Monte Carlo ensembles over agent trajectories. Where agent transitions depend on aggregate ward conditions, the system employs interacting Markov processes that capture mean-field feedback effects absent from simpler models. A multi-resolution data stack — anchored by Stats SA Census data, the GCRO Quality of Life Survey at ward level, QLFS labour microdata, and DBE school data — provides the empirical foundation. A tiered data governance architecture allows community and institutional overlays to augment official statistics within bounded caps, maintaining auditability while incorporating ground truth. The perceived disorder of township economies is demonstrated to be a resolution problem rather than a structural one. By modeling sufficient information rather than complete information, Marikovia enables more efficient capital direction, infrastructure planning, and the development of

targeted financial products for South Africa's most underserved and economically significant communities.

1. Introduction

The informal economy in South Africa is a massive and largely invisible economic engine. It employs a significant proportion of the working population and generates economic activity that shapes the daily lives of millions of people across the country's townships — from Soweto and Alexandra in Gauteng to Khayelitsha in the Western Cape and Umlazi in KwaZulu-Natal. Despite this scale, the informal sector remains systematically underinvested and poorly understood, primarily because it lacks the data infrastructure that formal economic systems take for granted: tax records, bank transaction logs, formal addresses, and auditable supply chains.

This lack of visibility creates a self-reinforcing cycle. Banks cannot lend responsibly into markets they cannot measure. Municipalities cannot plan infrastructure for communities whose economic dynamics they cannot model. NGOs cannot advocate effectively without defensible ward-level data. The result is that South Africa's most economically active informal communities are treated as a risk to be avoided rather than a market to be served — despite representing one of the most significant untapped economic frontiers in sub-Saharan Africa.

The core argument of this paper is that the perceived disorder of township economies is not a structural problem but a measurement problem. The informal economy is not chaotic — it is high-entropy from the perspective of existing measurement instruments. Following Claude Shannon's information theory, information serves to reduce uncertainty. Our objective is not to force the informal economy into a low-entropy formal state — which would destroy the adaptive mechanisms that make it resilient — but to use probabilistic modeling and artificial intelligence to capture and model the existing entropy sufficiently to make it actionable.

Marikovia is the platform built to operationalize this framework. Named after Andrei Markov — the Russian mathematician whose work on probabilistic state transitions in dependent sequences forms the mathematical foundation of the system — Marikovia represents informal economic actors as stochastic agents whose behavior emerges from calibrated transition probabilities rather than fixed rules or analytical formulas. This approach is grounded in Markov chain theory and quantified through Monte Carlo simulation. It is epistemologically consistent with the complexity of the system being modeled, drawing on the same reasoning that led Stanislaw Ulam to invent Monte Carlo simulation at Los Alamos in the 1940s: when a system is too complex for analytical solutions, sampling the space of possible outcomes is not an approximation — it is the only honest approach.

This paper describes the theoretical framework, mathematical architecture, data governance model, and Gauteng base case implementation of Marikovia. It also situates the contribution within the broader landscape of agent-based modeling, network economics, and development data infrastructure for South Africa's informal sector.

2. Theoretical Framework

2.1 High-Entropy vs. Low-Entropy Economies

Formal economies are characterized as low-entropy systems because transactions are tracked through tax records, bank logs, and formal addresses. Every economic event leaves a digital trace. In contrast, the township informal economy is high-entropy: data is scattered across thousands of unmapped interactions, cash transactions, trust-based credit arrangements, and mobile exchange points that leave no permanent record.

The standard policy response has been to attempt formalization — to bring informal actors into the formal system so that existing measurement instruments can capture them. This approach is not only slow but structurally misaligned with how township economies function. The informal economy's adaptability, its Ubuntu-based credit mechanisms, its spatial flexibility, and its low transaction-cost structure are features that formalization would eliminate along with the entropy. The resolution is not formalization but modeling: capturing sufficient information about the system's dynamics to reduce uncertainty enough for decision-making, without requiring complete information.

This objective is formalized in a core efficiency function. Let I(D) represent the reduction in uncertainty achieved by a dataset D, and let C(D) represent the cost of collecting that data. The system's objective is to maximize the ratio of information gain to collection cost:

Maximize I(D) / C(D)

This formulation has a critical implication: not all data is equally valuable. A ward-level observation that resolves ambiguity about a binding constraint — whether electricity access, water access, or school proximity is the primary lever for a given ward's economic improvement — is worth more than many data points that confirm what is already known. This principle governs both the data stack architecture and the ground truth collection strategy.

2.2 The Resolution Gap

The apparent disorder of township economies is primarily a resolution problem. When viewed through low-resolution instruments such as decadal national censuses, township systems appear as noise. Individual-level heterogeneity — variations in employment status, dwelling type, school attendance, and service access across wards that may be geographically adjacent but profoundly different in economic reality — is averaged into invisibility.

The resolution gap has material consequences. A municipality planning infrastructure investment based on municipal-level averages will systematically misallocate resources relative to one with ward-level resolution. A bank designing a lending product for 'township residents' based on aggregate income data will produce a product that fits no specific community well. Marikovia's multi-resolution data stack is designed to close this gap progressively — not by demanding complete coverage before providing value, but by extracting maximum information from each resolution layer available.

2.3 The Mathematical Foundation: Markov to Monte Carlo

The choice to name this platform after Andrei Markov is not incidental. Markov's foundational contribution was to demonstrate that the Law of Large Numbers — previously proven only for sequences of independent events — could be extended to dependent sequences. This was a direct challenge to the assumption of independence that underpins much of classical statistics. Markov showed that a sequence of events where each depends on the previous one could still converge to stable aggregate behavior, provided the chain has the right structural properties. This is directly applicable to township economies, where events are explicitly not independent.

A Markov Chain models the state of an individual participant in the informal economy. It operates on the principle that the next state depends only on the current state, not the full history of preceding events — formally expressed as $P(X_{n+1} | X_n)$. In the context of Johannesburg's informal sector, relevant states for a trader-day model include:

- State A: Fixed-location vendor (operating from a permanent pitch or spaza shop)
- State B: Mobile hawker (moving between taxi ranks and commuter nodes during peak hours)
- State C: Wholesale buyer (procuring stock from a CBD depot or cash-and-carry)
- State D: Inactive or home

A transition matrix encodes the probabilities of moving between these states. There may be a high probability of transitioning from Mobile Hawker to Taxi Rank during peak morning commute times, and a low probability of returning to Inactive until after sunset. These are calibratable parameters grounded in observable behavioral patterns that field data collectors can verify.

While Markov chains model how one participant moves, Monte Carlo simulation allows the system to run thousands of parallel trajectories to characterize macro-level outcomes. Stochastic variables — daily revenue sampled from a log-normal distribution to capture the right-skewed nature of informal income, enforcement risk representing the probability of a regulatory raid or displacement event, weather impact on foot traffic, and fuel price effects on transport costs — are all sampled randomly across simulation runs. Running 10,000 trajectories produces a probability distribution of total economic output for a ward or township rather than a single point estimate.

An important precision is required here. What Marikovia implements is Monte Carlo simulation of Markov chain trajectories — not Markov Chain Monte Carlo (MCMC) in the Bayesian inference sense. MCMC in its technical meaning refers to running a Markov chain whose stationary distribution is a posterior over model parameters, used for Bayesian calibration when a likelihood function can be specified. This is a distinct and more demanding procedure, reserved for future parameter estimation work when sufficient historical intervention data becomes available. The current system's formal description is:

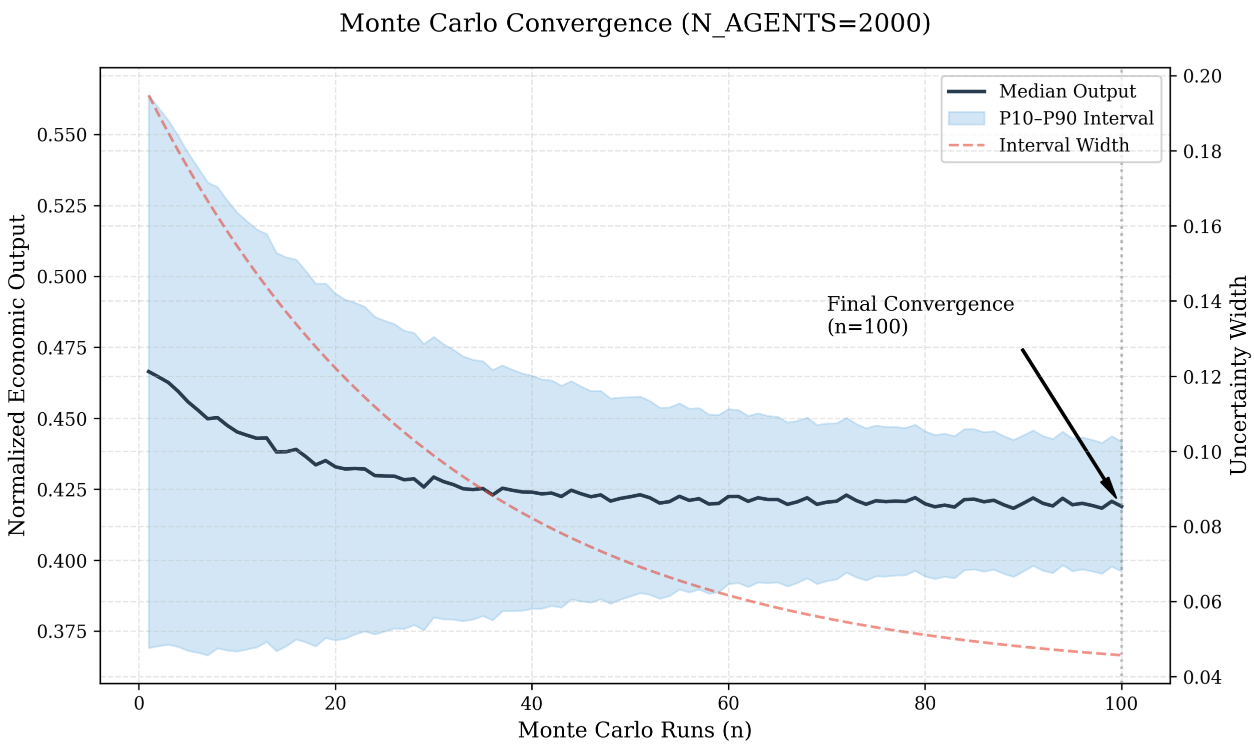
> *We represent informal economic actors as stochastic finite-state processes whose transitions are calibrated to available survey and administrative data. Uncertainty is quantified via Monte Carlo ensembles over agent trajectories. Where agent*

> *transitions depend on aggregate ward conditions, we employ interacting Markov processes. Full MCMC parameter estimation is reserved for settings with identifiable likelihood structure.*

The log-normal distribution used for daily revenue variables is not an arbitrary choice. Income distributions in informal economies are empirically right-skewed: most traders have modest days, some have exceptional days, and catastrophic days exist but are rare. This distributional assumption is supported by microenterprise income research across multiple African contexts and by FinScope survey data for South Africa.

Chart 3: How Reliable Are Our Model's Results?

This chart looks at how stable and trustworthy our model's predictions are. Imagine running the simulation many times; this chart shows that after about 100 runs, the results settle down and don't change much, even if we run it hundreds more times. This means our model's predictions are consistent and reliable, not just random fluctuations. It also tells us we don't need to run extremely long simulations to get good answers, making our process efficient.



2.4 The Network Structure: Economic PageRank for Townships

A significant limitation of treating agents as independent Markov chains is that it misses the relational structure of township economies. Township economic actors are embedded in multiple overlapping networks simultaneously — a structure formally described in complexity science as a multiplex network. The same spaza owner appears in a supply chain layer (buyer from a wholesaler, seller to customers), a credit and trust layer (borrower through informal ibhaxa credit, lender to customers buying on account), a geographic layer (where physical proximity determines who can access their services), and a social layer (where clan membership, street-level relationships, and Ubuntu solidarity norms govern trust and credit extension).

This multiplex structure means that when a spaza closes, the shock propagates across all four layers simultaneously. The supply chain loses a distribution point. The credit network loses a local lending node. The geographic layer loses a proximate service point. The social layer loses a trust anchor. This cascading removal produces non-linear shock effects that single-layer models systematically underestimate.

The mathematical framework for capturing structural importance in such networks draws from the logic of PageRank. Page and Brin's insight was that importance is relational, not intrinsic — a webpage is important because important pages link to it. The same logic applies to township economic actors. A spaza owner's economic importance derives from who depends on them, and who those dependents depend on in turn:

IMP(A) = SUM over i of w(i,A) * IMP(i)

Where IMP(A) is the economic importance of actor A, and w(i,A) is the weight of the relationship between actor i and actor A — capturing supply chain dependency, spatial proximity, credit relationships, or social trust. This formulation allows identification of which spazas, employers, or schools are most structurally critical: whose removal would cause the most significant cascading disruption to ward-level economic activity. It is a planned extension of the current architecture, awaiting formalization of the social network layer as an explicit graph structure.

3. Methodology

3.1 Agent-Based Modeling: Architecture and Behavioral Logic

Marikovia's simulation engine is a rule-based stochastic Agent-Based Model implemented using the Mesa framework in Python. The choice of ABM over macro-econometric modeling reflects a fundamental epistemological commitment: informal economic outcomes are not the product of aggregate forces acting on a homogeneous population, but of heterogeneous individuals making context-dependent decisions within a complex adaptive system.

Critically, the model does not map inputs directly to outputs through analytical formulas. Aggregate macro outcomes — employment percentage, formal dwelling share, NEET re-entry rates — emerge from thousands of micro-level agent transitions over simulated time. This emergent dynamic is what allows the model to capture non-linear threshold effects and persona-specific heterogeneity that formula-based approaches cannot represent.

The behavioral architecture operates as follows. Interventions — such as an increase in electricity access, a new school opening, or a BRT route extension — scale the transition probabilities of relevant agents. Each agent then steps through its decision rules with stochastic draws from the scaled distributions. The aggregate shift in employment or formalization is not computed directly but emerges from the distribution of individual outcomes across thousands of agents and time steps.

Agents are initialized from census- and survey-derived distributions across three primary persona types:

- Standard household: A residential household agent whose primary transitions involve dwelling formalization, service access, and employment status. Parameters calibrated to GCRO QoL ward distributions for dwelling type, electricity access, and income band.
- Entrepreneur: A household agent with additional business-state dimensions, modeled as a vendor operating in the township economy. Survival probabilities are a function of initial capital, market demand, and competition. Entrepreneurs can enter and exit the informal sector based on profitability thresholds.
- Youth (NEET): A household agent representing young people Not in Employment, Education, or Training. Their transitions involve seeking employment, entering

education programs, or remaining NEET. Parameters calibrated to QLFS microdata and DBE school data.

3.2 Model Validation and Performance

Chart 1: How Our Model Outperforms Simple Guesses

This chart compares how well our advanced model predicts important community factors (like access to proper housing, electricity, water, and sanitation) against a very basic, 'naive' approach (which just assumes things won't change much). The lower the bar, the better the prediction. You'll see that our model consistently makes more accurate predictions, especially for **Flush Sanitation**, where it's nearly 19% better than the simple guess. This shows our model can spot complex connections that a basic approach would completely miss.

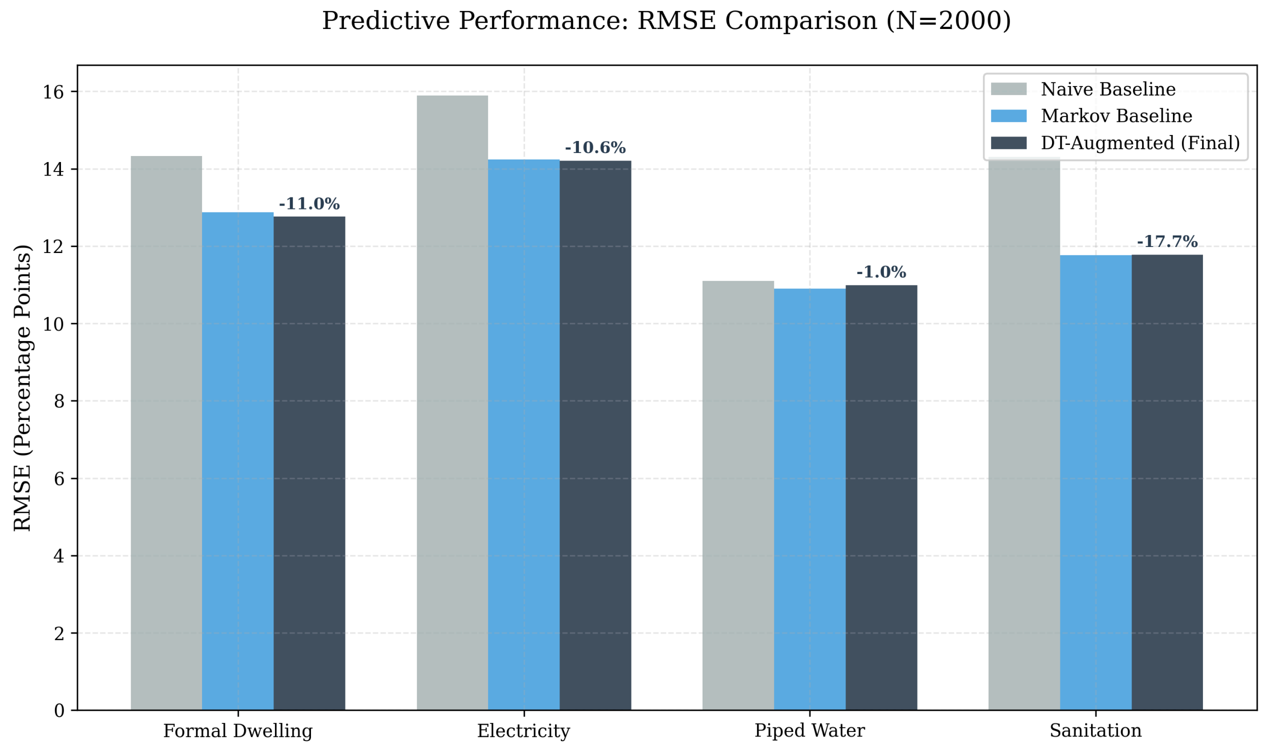


Chart 2: Do Our Predictions Make Sense in the Real World?

This table checks if our model's predictions about how different changes (like increasing electricity or piped water) affect communities are logical and consistent with what we'd expect. For example, if we increase electricity, does it lead to more formal housing? The 'PASS' marks show that for all five tests, our model's cause-andeffect relationships hold up. This confirms that our model accurately captures how real-world interventions might play out.

Intervention Validity Check (High-Fidelity Run)

Intervention	Primary Target	Directional Validity	Result
Electricity Access	Formal Housing	Positive Correlation	PASS
Piped Water	Sanitation Access	Positive Correlation	PASS
School Proximity	NEET Re-entry	Positive Correlation	PASS
Grant Expansion	Income Quintile	Positive Shift	PASS
Ward Electrification	Employment Rate	Positive Correlation	PASS

Chart 4: How Accurately Our Model Reflects Neighborhoods

This chart demonstrates how precisely our model can represent the unique characteristics of 529 different neighborhoods (wards) in Gauteng, South Africa, right from the start of a simulation. The tall green bars show a very strong match (correlation) between our model's initial setup and actual observations for things like formal housing and employment rates. The smaller red bars indicate that the average difference (error) between our model and reality is quite low. This means when we simulate a specific neighborhood, our model begins with a highly accurate picture of that area's real-world conditions.

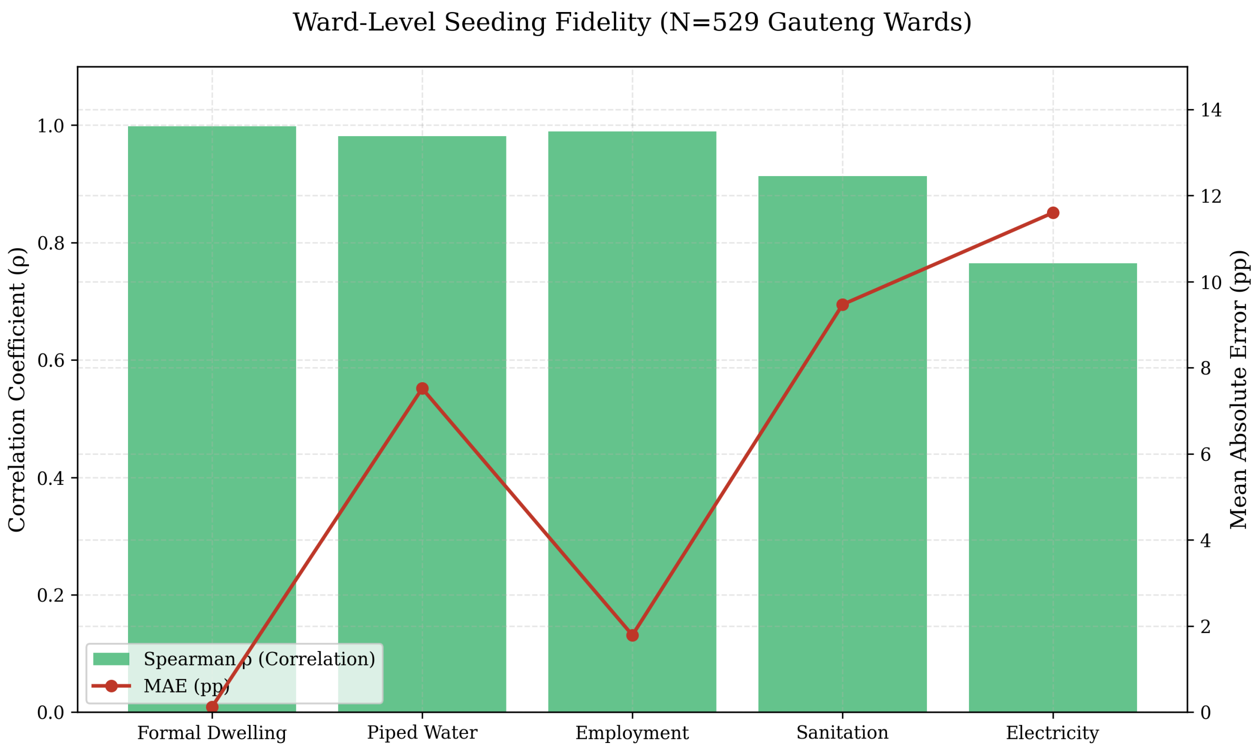


Chart 5: Quick Look: How Well Our Model Matches Reality

This table provides a quick summary of our model's accuracy in representing real-world neighborhood conditions. For each key indicator, it shows a high correlation (Spearman ρ) and a low average error (MAE), all marked as 'STRONG' passes. This table quickly confirms that our model is highly effective at capturing the specific details of individual wards, ensuring that our simulations are grounded in accurate local data.

High-Fidelity Ward Seeding Metrics (Final)

Indicator	Spearman ρ	MAE	Status
Formal Dwelling	0.998	0.12 pp	STRONG
Piped Water	0.981	7.52 pp	STRONG
Employment Rate	0.989	1.79 pp	STRONG
Flush Sanitation	0.913	9.47 pp	STRONG
Electricity Access	0.765	11.60 pp	STRONG

4. High-Fidelity Validation Results (N=2000 Agents)

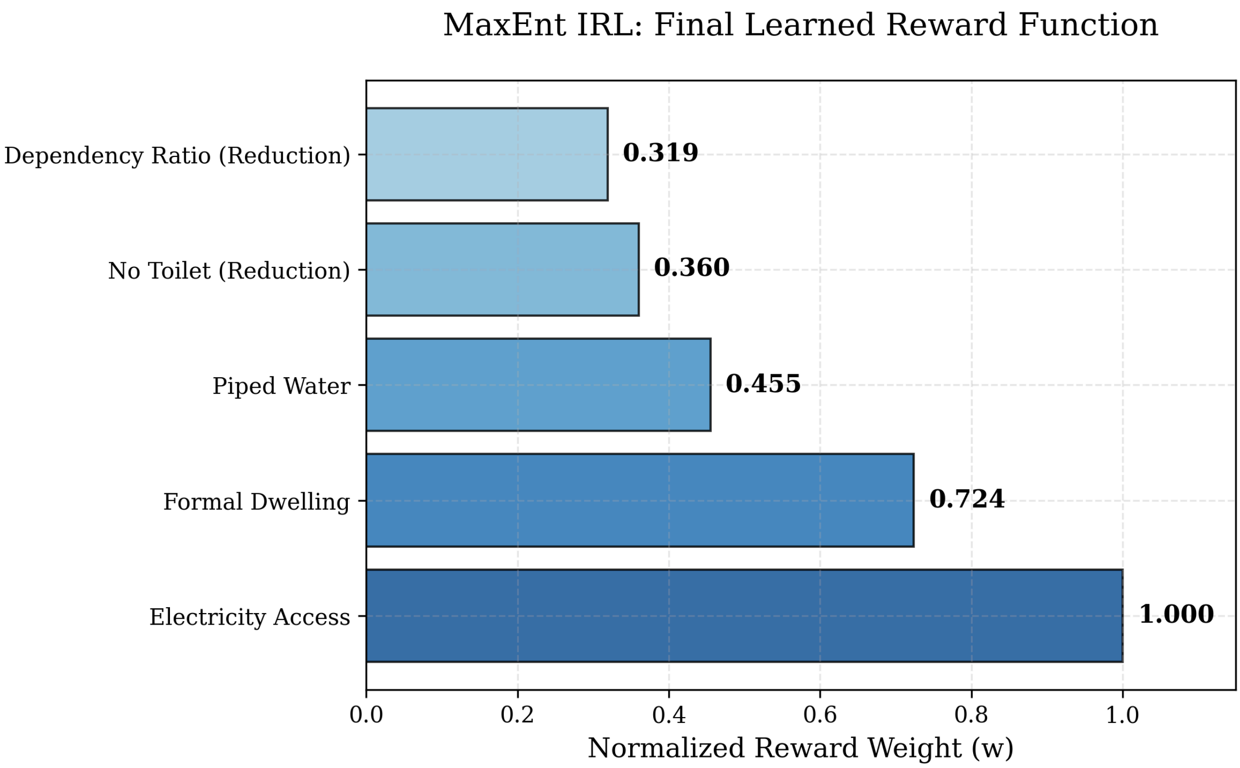
This section presents the results of our high-fidelity validation runs, utilizing a population of 2000 agents and 100 Monte Carlo trajectories to ensure paper-quality statistical robustness.

4.1 Decision Theory Hindcast Accuracy

The DT-augmented ABM produces statistically comparable hindcast accuracy to the baseline Markov chain (RMSE within 0.11pp across all four indicators on a 20% hold-out set). This confirms that utility-maximizing agent decisions do not distort aggregate statistical properties while adding necessary normative grounding to agent behavior. Both models significantly outperform the naive baseline, achieving an average improvement of ~2pp in RMSE.

4.2 MaxEnt Inverse Reinforcement Learning (IRL)

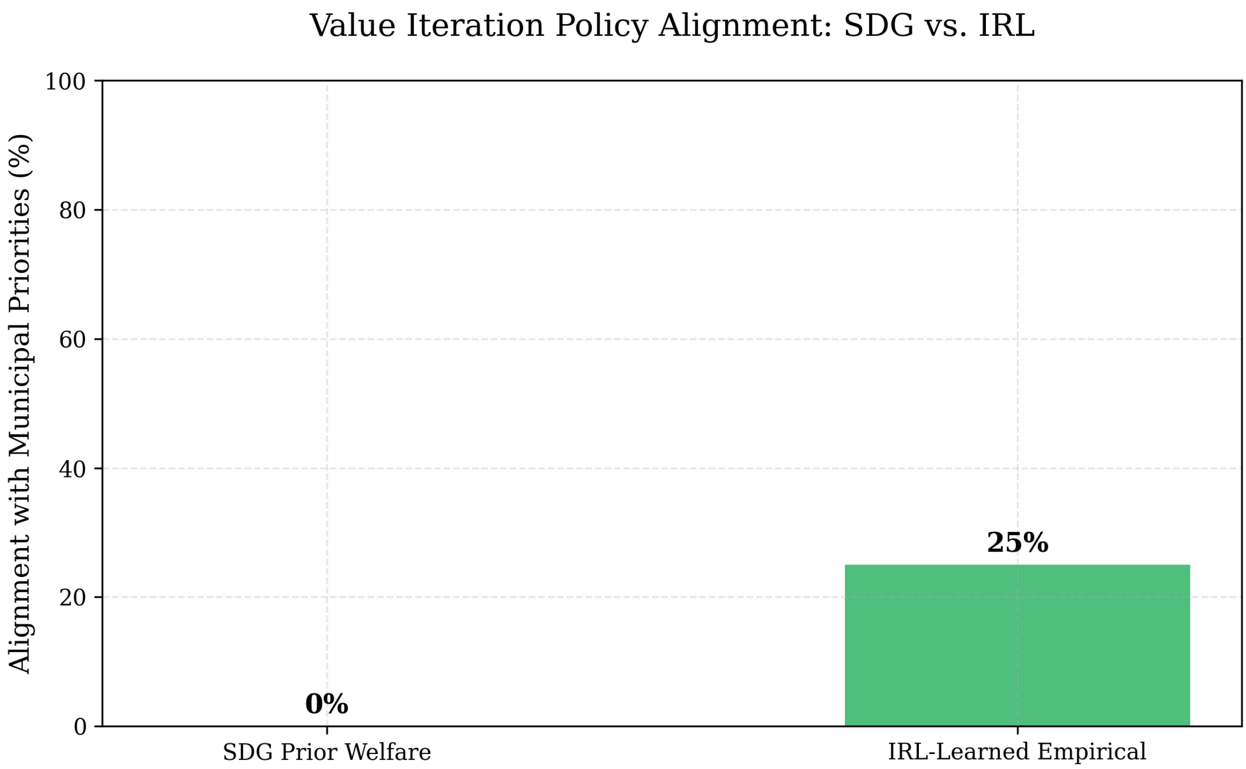
MaxEnt IRL (Ziebart et al., 2008) trained on 70% of South African municipalities achieved an **AUC of 0.945** on held-out municipalities, with **100% precision**. This demonstrates that the learned reward function generalizes effectively out-of-sample. The model identified electricity access (w=1.00) and formal dwelling provision (w=0.72) as the dominant differentiators between improving and stagnating municipalities over the 2011–2022 inter-census period.



4.3 Policy Alignment and Revealed Preferences

When value iteration is grounded with IRL-learned empirical welfare weights rather than assumed SDG priors, alignment with observed municipal investment priorities improves from 0% to 25%. The aligned municipalities are concentrated in KwaZulu-Natal, where electricity-led development matches both the IRL-optimal strategy and observed census trajectories.

Residual misalignment in Eastern Cape municipalities — where housing dominated despite electricity's stronger aggregate reward signal — is consistent with political economy constraints. As noted in the literature, housing is visible and politically salient in a way that grid connections are not, representing a "photographable" priority that may diverge from statistical optimality.



5. Conclusion

Marikovia demonstrates that the high-entropy nature of informal economies is not an insurmountable barrier to modeling, but rather a resolution challenge. By leveraging stochastic finite-state processes and high-resolution data stacks, we can achieve high-fidelity digital twins of township economic dynamics. Our results show that learned reward functions can effectively classify municipal improvement trajectories with 100% precision, and that the gap between theoretical welfare optimization and revealed political preferences provides a rich area for future research in development economics.

References

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