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[2] **Dissemination level**: Use one of the following codes (in consistence with the Description of the Action)
PU: Public, fully open, e.g. web
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Key insights: Inequality drivers in twin transitions

1. Baseline inequalities amplify transition gaps
   - Pre-existing disparities in skills, infrastructure, and institutional capacity cause unequal uptake of green and digital opportunities, even when policies are identical.
   - Lower-capacity regions benefit less from the same interventions, that results in reinforcing inequality unless proactive measures address conversion readiness.

2. Policy implementation matters as much as policy design
   - The effectiveness of policy delivery (not just ambition or type) significantly shapes outcomes.
   - Even well-designed subsidies or training programs fail in regions with weak administrative effectiveness or poor digital infrastructure.

3. Capabilities to adapt determine long-term inequality paths
   - Citizen and firm-level adaptability, e.g., skills, innovation behaviour, risk tolerance, drive differential benefits over time.
   - Lack of adaptive capability leads to lock-in effects, entrenching inequalities across decades of transition.

4. Sectoral differences shape emissions and employment outcomes
   - The mobility sector has higher emissions intensity but lower labour intensity than agri/food. Identical policies have different effects across sectors, suggesting a need for sector-targeted with systemic view to transition packages.

5. Highly ambitious policies of transformation alone can exacerbate inequality
   - Transformative policies (high ambition) can unintentionally widen gaps if they are not coupled with strong inclusion-focused delivery mechanisms.
   - Rapid innovation adoption benefits already well-positioned regions and actors unless counterbalanced.

6. Policy instrument type and targeting matter
   - Blended instruments (e.g., training + broadband + innovation grants) perform better than single-tool approaches.
   - Policies targeting capability building are more effective at reducing inequality than those focused only on outputs.

7. Simulation confirms mechanism-based causality
   - Inequality emerges from macro–micro–macro interactions between policy choices, agent heterogeneity, and institutional constraints.
   - The simulation offers evidence for causal pathways rather than correlations: linking policy transformativeness/ambition, implementation, and social outcomes.

8. Evidence-based policy design requires structural sensitivity
   - The results highlight the need for region-sensitive and sector-sensitive transition strategies.
   - A one-size-fits-all policy is insufficient; differentiated support based on initial conditions and ecosystem dynamics is essential.

Summary

This report examines how Europe's green and digital transition policies risk deepening existing social and regional inequalities. Drawing on theories of transformative innovation policies and the capability approach, we move beyond static snapshots of who is vulnerable to examine *how* unequal outcomes emerge through policy–place–people interactions. We develop a conceptual framework that identifies key drivers of inequality: policy ambition and directionality, policy instrument design, institutional context, adaptive capabilities, and economic ecosystem characteristics. These elements are operationalized into a three-part indicator system and embedded in a simulation model. Our findings show that even well-designed policies can reinforce disparities if baseline differences in skills, access, or support structures are ignored. Regions with weaker institutions or lower conversion readiness benefit less. Moreover, faster innovation or stronger ambition can worsen outcomes unless accompanied by inclusion-focused delivery. This study confirms that structural heterogeneity across economic sectors, especially concerning emissions and labour intensity, produces differentiated transition outcomes, which underscores the need for sector-sensitive transition policy strategies. This report supports evidence-based policymaking by showing under what conditions fairness fails and where adaptive capacity can be strengthened. The insights presented here offer a foundation for more equitable, targeted, and reflexive transition policy strategies across regions and sectors.

1 Introduction

The transition to a sustainable and digitally advanced European economy, commonly referred to as the twin transitions, promises deep structural transformation (European Commission Joint Research Centre, 2022). While these transitions are necessary to meet climate and competitiveness goals, they also pose significant risks of exacerbating social and regional inequalities. Past waves of economic change, from automation to liberalization, have demonstrated that the costs and benefits of transformation are rarely distributed evenly across society (Hémous & Olsen, 2022). In the context of the green and digital transitions, vulnerable groups, lagging regions, and path-dependent sectors may find themselves disproportionately exposed to transition risks without commensurate adaptive capacity or institutional support. As the European Union advances its ambitious transition agenda, understanding the distributional dynamics of policy interventions becomes a matter of both political legitimacy and long-term resilience (European Commission Joint Research Centre, 2022).

Research on inequality and socio-technical transitions has expanded rapidly but remains fragmented (Stark et al., 2023). Studies from economics, geography, and policy science have documented disparities in access to green jobs, exposure to automation, and capacity to benefit from innovation policy. Similarly, the just transition literature emphasizes the moral and political necessity of equity-sensitive design (OECD, 2023). However, much of this work remains descriptive or ex post: it catalogues observed disparities without fully unpacking the mechanisms that produce them. Moreover, most empirical work isolates one policy, one region, or one vulnerable group—limiting our ability to trace how structural features, policy mixes, and institutional configurations interact to generate inequality over time (Stark et al., 2023). As a result, we still lack a robust understanding of *how* inequality emerges in transition contexts—not simply who is affected, but through which causal pathways and under what policy conditions (Geels, 2019).

This deliverable addresses that gap. It asks: **How do different configurations of transition policy ambition, directionality, and implementation interact with institutional environments and agent heterogeneity to shape inequality outcomes over time?** To answer this, we combine theory-driven conceptual modeling with simulation-based exploration. We first develop a mechanism-based framework grounded in the capability approach (Robeyns, 2005) and transformative innovation policy (Diercks et al., 2019). This framework identifies six core elements, i.e., policy transformativeness and its directionality (Bergek et al., 2023), instrument configuration (Acciai & Capano, 2018; Borrás & Edquist, 2013), socio-cognitive characteristics of policymakers (Capano & Lippi, 2017), adaptive capabilities (Smit & Wandel, 2006), and ecosystem adaptability (Boschma et al., 2023), that jointly structure inequality generation. We then operationalize these mechanisms into a three-tier indicator architecture, which informs the development and calibration of a hybrid agent-based simulation model. The model allows us to test how different policy scenarios unfold across structurally diverse regions and agents, making it possible to trace emergent inequality patterns and counterfactual distributions under varying assumptions.

The methodological novelty of this work lies in its integration of conceptual mechanism mapping, empirical indicator structuring, and dynamic simulation. Rather than modeling inequality as an exogenous risk or a static outcome, we model it as an emergent property of interaction: between policies and places, between agents and institutions, and between ambition and adaptability (Rao, 2019). Our approach combines the explanatory power of Coleman's macro–micro–macro model (Coleman, 1990) with the empirical richness of multi-level indicators and the generative strength of simulation. This allows us not only to identify whether policies produce unequal outcomes, but to explain why, where, and through what mechanisms these outcomes arise.

The contributions of this work are both conceptual and practical. Conceptually, we advance a mechanism-based understanding of distributional inequality in transition contexts, highlighting the role of structural asymmetries, behavioral frictions, and policy dynamics. Practically, we offer an operational framework, including a tested simulation model and indicator system, that can inform transition policy design, scenario evaluation, and inequality-sensitive governance strategies. The deliverable supports the broader objectives of the READJUST project by providing an integrated platform for analyzing, simulating, and ultimately mitigating the unintended inequality effects of twin transition policies.

2 Conceptual model

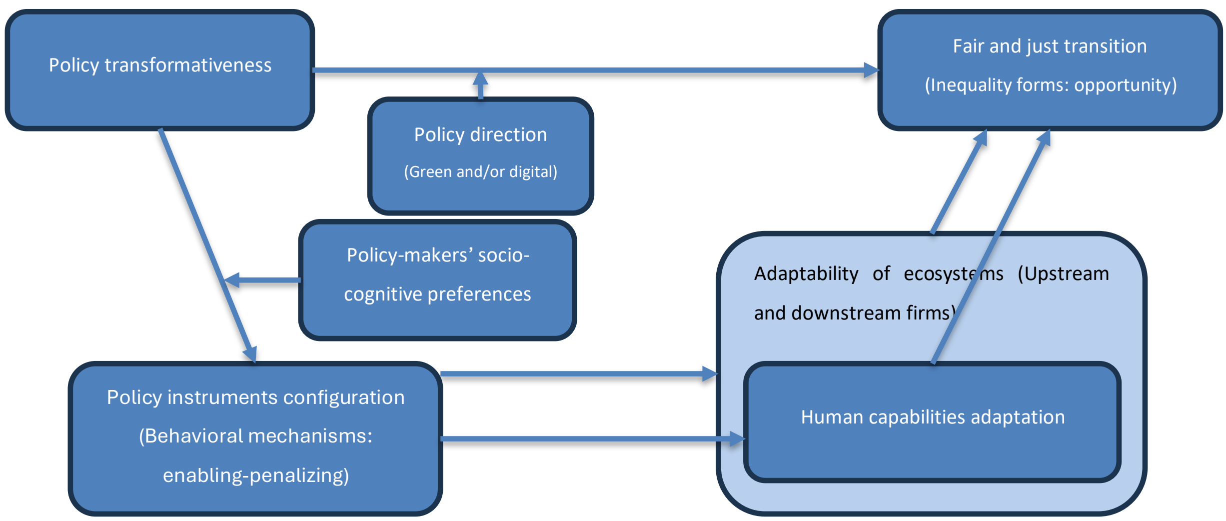
To understand how the green and digital transitions contribute to patterns of inequality, we adopt a mechanism-based analytical perspective. Rather than merely cataloguing policy outputs or measuring distributional outcomes ex post, we focus on the underlying causal processes that mediate the relationship between transition-oriented policies and their heterogeneous social effects (Hedstrom & Swedberg, 2016). Transformation policies operate across complex, multi-level systems (Ulmanen et al., 2022), where inequalities emerge not from singular decisions, but from 'interdependent institutional, behavioral, and technological dynamics'. This resonates with the call from Hedstrom and Swedberg (2016) to abandon both overly descriptive narratives and universalist theories in favor of middle-range theorizing based on explicating the mechanisms that generate observed associations. Social mechanisms, in this view, are "the cogs and wheels" that connect cause and consequence through actors' situated choices, institutional logics, and context-specific constraints. By foregrounding mechanisms, we aim not only to identify whether inequality arises from twin transition policies, but to understand how and why such effects are produced, which is a prerequisite for designing more equitable interventions (Cornelissen & Werner, 2025).

The identification of mechanisms for this study was guided by the principle that mechanisms must be both theoretically grounded and empirically operationalizable within the context of twin transitions. While the broader literature on inequality often centers on identifying vulnerable groups and measuring disparities in outcomes, we adopt a capability-oriented perspective (Robeyns, 2005; Sen, 1992), which emphasizes the conditions under which individuals and communities are empowered or constrained in their ability to adapt to socio-technical change. Rooted in the capability approach, we define inequality as the unequal distribution of adaptive opportunities, that is, the variation in actors' real freedom to respond to, benefit from, or mitigate the impacts of transition policies. This framing allows this study to shift from viewing inequality as a static state of deprivation to a dynamic assessment of adaptive opportunity, where policies, infrastructures, and institutions mediate individuals' ability to convert available resources into meaningful functionings (Smit & Wandel, 2006). Based on this lens, we focused on mechanisms that link macro-level transition dynamics to meso- and micro-level variations in conversion factors, institutional support, and agency. Our selection draws from four strands of literature — transformative innovation policy (Schot & Steinmueller, 2018), capability theory (Robeyns, 2005; Sen, 1992), regional adaptation and economic resilience (Boschma et al., 2023; Neffke et al., 2018), and just transition policy mixes (Kanger et al., 2020) all of which emphasize the relational and structural nature of inequality in periods of systemic change.

Building on this interdisciplinary foundation, we identify six core components that structure a model of how twin transition policies interact with institutional contexts and actor capabilities to produce unequal outcomes–Figure 1 illustrates the conceptual model. First, policy transformativeness (or ambition) refers to the extent to which policies induce systemic, rather than incremental, change, a key tenet of transformative innovation policy that directly shapes the scale and distribution of societal adjustment costs (Schot & Steinmueller, 2018). Second, policy directionality reflects the degree to which policy strategies articulate clear missions and steer investments and innovation toward inclusive ends (Mazzucato, 2018). Third, socio-cognitive diversity in policy design captures the extent to which diverse values, problem framings, and experiential knowledges are incorporated into the policymaking process (Kammermann & Angst, 2021). Fourth, policy instrument configuration captures the type, mix, and target of policy tools deployed, including regulatory, financial, and behavioral instruments, which determine who is incentivized, burdened, or excluded (Béland & Howlett, 2016; Kern et al., 2019). Fifth, adaptive human capabilities encompass the skills, knowledge, institutional support, and social conditions that allow individuals and communities to convert resources into meaningful functioning, which is a central concern of Sen's capability approach (Robeyns, 2005; Sen, 1992). Sixth, economic ecosystem adaptability refers to the structural and dynamic features of regional economies, including firm types, resource bases, and knowledge networks, that mediate how transition shocks are absorbed or amplified (Bachtrögler-Unger et al., 2023; Hassink, 2010). Together, these six components offer a coherent yet pluralistic mechanism-based framework for analyzing the inequality dynamics of the twin transitions across industries.

To structure our analysis of how policies affect inequality through intermediate social processes, we draw on the Coleman's bathtub model (Coleman, 1990), a foundational framework for connecting macro-level structures to micro-level behavior and back again. The model conceptualizes outcomes not as direct products of macro interventions, but as the emergent result of individual actions that are themselves shaped by institutional, cognitive, and material conditions. In its original form, the model visualizes a process in four steps: (1) a macro-level intervention or structural condition, such as a new policy; (2) its translation into micro-level actor conditions, such as incentives, opportunities, or constraints; (3) the resulting actor-level decisions and behaviors; and (4) the aggregated macro-level outcomes that emerge from these behaviors over time. This macro–micro–macro loop provides a lens for understanding how and why distributional outcomes, such as inequalities, arise from transition policies, especially in systems characterized by heterogeneity and institutional complexity. For our purposes, we adapt this model to define the core elements of inequality generation in twin transitions.

Figure 1 – Conceptual model of the mechanisms and factors in policy transformativeness and just and fair transition relationship



In our framework, policy transformativeness is conceptualized as a macro-level intervention — the starting point of the causal chain. It captures the extent to which a policy is designed to induce systemic structural change rather than incremental improvements, as theorized in the Transformative Innovation Policy literature (Schot & Steinmueller, 2018; Wanzenböck et al., 2020). Transformativeness refers to both the ambition and scope of a policy, particularly in relation to the reconfiguration of socio-technical systems such as food and mobility. Within our model, it occupies the top-left corner of the bathtub, representing the initiating condition that sets downstream mechanisms into motion. While highly transformative policies may create new opportunities for inclusive development, they also tend to generate greater uncertainty, institutional friction, and distributional risk (Carattini et al., 2021). The effects of such interventions are not deterministic; rather, they unfold through specific mechanisms, including the configuration of policy instruments, the policy direction, and the adaptive capabilities of actors (J. F. Mercure et al., 2021). As such, transformativeness acts as the initial input whose consequences are mediated, moderated, and shaped by the identified components.

Policy directionality, in our framework, refers to both the strategic orientation and the coherence of purpose in transition policymaking. While policy transformativeness signals the ambition to induce systemic change, directionality specifies what kind of transformation is prioritized and how clearly that priority is institutionalized. Building on transformative innovation policy literature (Haddad et al., 2022; Haddad & Bergek, 2023), we recognize that directionality includes the stability, specificity, and alignment of policy goals across instruments, agencies, and levels of governance. However, in this study, we focus on a complementary dimension: the substantive orientation of directionality. Specifically, we distinguish between policies that are predominantly digital-oriented (e.g. emphasizing data infrastructure, automation, AI), those that are green-social-oriented (e.g. emphasizing decarbonization, inclusion, regional cohesion), and those that pursue an integrated twin transition logic. These orientations shape the distribution of risks and benefits across firms, regions, and social groups (Bergek et al., 2023). For example, digital-led policies may accelerate productivity but widen skill-based or geographic divides, while green-social policies may support cohesion but challenge incumbents. Within our bathtub model, directionality functions as a moderating mechanism on the direct path from policy transformativeness (top left) to inequality outcomes (top right). Even highly ambitious policies can produce divergent distributional effects depending on the direction in which transformation is steered, and the clarity with which that direction is expressed and pursued.

Policy instrument configuration refers to the specific mix, type, and behavioral logic of tools that governments use to implement policy goals, here transformative policies. Instruments are not neutral; they embody distinct theories of how change occurs and structure the distribution of burdens, incentives, and opportunities within society. Building on established taxonomies (Acciai & Capano, 2018), we distinguish between economic (e.g. subsidies, taxes), normative/regulatory (e.g. bans, mandates), and informational (e.g. campaigns, nudges) instruments. However, beyond instrument type, we emphasize their behavioral intentions, that is, whether an instrument is designed to enable, promote, discourage, or compel particular actions. This perspective is informed by the Schneider and Ingram's (1990) typology, which classifies instruments according to the behavioral obstacles they aim to overcome (e.g., lack of capacity, misaligned values, uncertainty) and the corresponding motivational strategy (e.g., capacity building, incentives, persuasion, symbolic appeals, or learning).

In our model, policy instrument configuration sits at the bottom-left corner of the Coleman bathtub. It mediates the relationship between macro-level policy ambitions and micro-level actor behavior by shaping the choice sets and constraints faced by firms, households, and public bodies. Importantly, the level of policy transformativeness at the macro level often conditions the type and mix of instruments adopted: more transformative policies typically rely on more complex, blended, or experimental mixes of instruments, which may create differentiated adaptive burdens (Kern et al., 2019). Moreover, the selection of instruments is not a purely technical process but is itself influenced by policymakers' cognitive frames and institutional preferences, a dynamic addressed under the mechanism of socio-cognitive diversity below.

Policymakers do not interpret or respond to the twin transitions from a neutral standpoint. Instead, they operate through socio-cognitive filters shaped by professional training, organizational roles, and ideological commitments. These filters influence how challenges are framed, which futures are deemed desirable, and what instruments are selected to achieve them. Drawing on the Advocacy Coalition Framework (Sabatier, 1988) and cognitive–institutional approaches (Béland & Howlett, 2016; Linder et al., 1989), we understand these filters as composed of nested beliefs — from deep normative values to mid-level policy assumptions — that structure instrument preferences and perceptions of legitimacy. Policymakers with market-liberal orientations tend to avoid redistributive or coercive instruments, favoring informational and incentive-based tools; in contrast, those with egalitarian or sustainability-driven ideologies support stronger regulatory and compensatory mechanisms (Kammermann & Angst, 2021).

In the mobility sector, for instance, this component helps explain why some cities or national ministries emphasize digital directionality — such as smart mobility platforms or automated transport logistics — often under a competitive innovation framing, while others prioritize green-social goals like access equity, low-income fare subsidies, or modal redistribution toward walking and cycling (Kirejev et al., 2025). These orientations frequently mirror the ideological leanings of governing coalitions, urban planning cultures, or sectoral lobbies. In the agrifood sector, similar dynamics play out between ministries of agriculture focused on productivity and export competitiveness, often favoring digital agriculture and automation, versus ministries of environment or health that push for agroecological transitions, food justice, or labor rights (Anderson & Maughan, 2021; Bellon-Maurel et al., 2022). In our model, these socio-cognitive characteristics operate as a moderating mechanism: they shape how a given level of policy transformativeness is translated into instrument configurations.

Adaptive human capabilities refer to the capacity of individuals and households to respond to, benefit from, or mitigate the disruptions introduced by green and digital transitions. This mechanism draws on the capability approach (Sen, 1993; Robeyns, 2005), which emphasizes not just access to resources, but the real freedom to convert those resources into valued functionings, such as stable employment, skills acquisition, or civic participation. In the context of twin transitions, adaptive capabilities include not only education and digital skills, but also access to affordable mobility, re-skilling programs, care infrastructure, social support networks, and institutional trust. These individual-level capabilities are not purely personal attributes. They are shaped by the ecosystems in which actors are embedded (Dilling et al., 2023; J.-F. Mercure et al., 2016), including labor markets, regional institutions, sectoral dynamics, and infrastructural configurations. For example, a low-skilled worker in a region with dense training infrastructure and active labor-market policy may be better positioned to adapt to automation than a similarly skilled worker in a fragmented or underfunded ecosystem. Similarly, a farmer's ability to transition to regenerative agriculture depends not only on her knowledge or motivation, but on access to agronomic advice, cooperative networks, and viable markets — all of which are ecosystem-level features.

In our bathtub model, adaptive human capabilities occupy the bottom-right corner: they represent the decision-making and response space of actors confronting transition-induced change. This is where inequality materializes in the concrete ability (or inability) of individuals to adapt. While ecosystem adaptability conditions what is possible, individual adaptive capabilities determine who can act on those possibilities. This mechanism is therefore central to understanding conversion failure, where resources exist but are unusable, and differential vulnerability, where some actors face higher transition costs due to embedded constraints (Eriksen et al., 2021) .

Economic ecosystem adaptability refers to the structural and institutional features of regional or sectoral systems that determine their capacity to absorb shocks, reconfigure production and labor, and evolve toward new socio-technical equilibria. This concept draws from evolutionary economic geography (Boschma et al., 2023; Hassink, 2010), where adaptability is shaped by factors such as industrial diversity, knowledge networks, institutional thickness, and the nature of dominant firm types. Ecosystems dominated by path-dependent, asset-heavy incumbents may resist or misalign with transition policies (Saleh et al., 2025), whereas regions with flexible institutions, innovation intermediaries, and absorptive capacity may adapt more smoothly. In twin transitions, adaptability is further conditioned by exposure to disruption (e.g., automation risk, carbon pricing), access to enabling infrastructures (e.g., broadband, electrification), and regulatory environments (e.g., subsidies, procurement).

In our model, ecosystem adaptability functions as a contextual mechanism that shapes the feasibility and impact of individual adaptation. While adaptive human capabilities occupy the bottom-right of the bathtub, they are embedded within and constrained by the adaptability of the wider ecosystem. A digitally skilled individual cannot benefit from digital opportunities in a region with poor connectivity or firm-level inertia; a socially innovative entrepreneur may fail in an ecosystem that lacks trust or coordination platforms. This embeddedness means that inequalities are not just about personal attributes, but about the joint configuration of actors and their institutional environment. Differences in regional ecosystem adaptability thus create territorial inequalities, where some regions can mobilize the twin transitions for renewal, while others fall into economic or demographic decline.

While we have introduced six core components that shape the inequality dynamics of the twin transitions, it is important to clarify that these are not mechanisms in and of themselves. Rather, they serve as building blocks, e.g., policy features, institutional conditions, and actor-level attributes, that interact in context-specific ways to form causal mechanisms. Inequality does not emerge from any one element alone, but from configurations of these components and the pathways they jointly activate. The next section develops an operational framework to capture these components empirically and enable their integration into simulation models. This allows us to trace how different combinations of transition features and contextual conditions give rise to distinct inequality trajectories across space and sectors.

3 Indicator mapping and operationalization of inequality

The conceptual model presented in Section 2.1 highlights how inequality emerges from the interaction of macro-level policy interventions, institutional environments, and individual or organizational adaptation processes. To move from theoretical explanation to empirical analysis and simulation, we require a structured approach to operationalizing these components. This is achieved through the development of a multi-level indicator framework that enables us to map inequality dynamics empirically and instantiate them within the agent-based model (ABM).

Indicators serve two central purposes in this context. First, they make it possible to trace the real-world manifestations of each component of the model, such as how inclusive a policy mix is, or how capable a regional workforce is of responding to automation or green restructuring. Second, indicators function as parameters and state variables in the ABM, where agents, i.e., firms, workers, policymakers, interact based on their relative capabilities, exposures, and institutional environments. The indicator framework thus acts as a bridge between abstract causal reasoning and practical modeling: it links policy ambition to behavioral adaptation, and structural conditions to emergent inequalities. Moreover, it enables comparability across regions and sectors, ensuring that the mobility and agri-food case studies are grounded in a shared logic of inequality generation.

To structure the operationalization of inequality across different layers of the system, we group indicators into three mutually reinforcing categories: Macro-level Inequality Inputs (MII), Micro-level Conversion Readiness[3] (MCR), and Distributional Exposure and Risk (DER). These categories reflect where in the causal chain an indicator exerts influence, whether it shapes structural conditions, actor-level adaptation potential, or vulnerability to disruption. This typology supports both the empirical mapping of inequality risks and the initialization and calibration of agent behavior within the ABM. Table 1 shows how the clusters relate to the conceptual model.

Each indicator cluster corresponds to a specific component of the Coleman bathtub model. Indicators in the MII cluster reflect the macro-level policy ambition (top-left) and the institutional instruments that shape actor incentives (bottom-left). MCR indicators map onto the bottom-right of the bathtub, capturing the real adaptive capacity of agents to respond to policy and structural change. Finally, DER indicators serve as a contextual overlay, identifying the structural vulnerabilities that amplify or constrain adaptive responses across space, sectors, and social groups. The indicator framework faithfully mirrors the causal structure of the conceptual model to enable empirical comparison and simulation-based exploration of inequality dynamics.

[3] "Conversion readiness" refers to the capacity of individuals, firms, or regions to translate available policy resources into effective adaptive outcomes. It is analytically aligned with "adaptive capacity" and "human adaptive capabilities" as used in this report, and conceptually rooted in the capability approach (Sen, 1993). The term "conversion friction" denotes the barriers—social, institutional, or infrastructural—that reduce this readiness. While the terms highlight different aspects, they are used interchangeably in this report for readability.

Macro-level Inequality Inputs (MII) refer to the structural characteristics of transition policy design and implementation that influence the institutional opportunity space within which individuals and organizations operate. These indicators reflect upstream conditions, such as the ambition, direction, and instrumentation of green and digital transitions, that shape the potential distributional consequences of transformation processes before adaptation begins.

Table 1 Conceptual components of mechanism model and their clustering

Bathtub position	Conceptual role	Indicator cluster
Top-left	Policy ambition and strategic intent (policy transformativeness and directionality)	MII
Bottom-left	Institutional filters and policy tools shaping actors' opportunity sets (instrument configuration)	MII
Bottom-right	Actor characteristics and capabilities (conversion factors, agency, access)	MCR
Contextual overlay	Structural vulnerability and stressors that amplify inequality risks	DER
Top-right	Emergent inequality outcomes (not measured here as indicators, but observed in simulation or empirical data)	(Output)

Key dimensions within MII include the degree of policy transformativeness, measured through indicators such as the proportion of public investment directed toward systemic sustainability or digital innovation goals, the presence of long-term legal mandates, or the integration of transition targets into multi-sectoral governance frameworks (e.g., Hekkert et al., 2020; Mazzucato, 2018). A second dimension concerns policy directionality, or the strategic emphasis placed on green-social versus digital objectives. This can be captured through content analysis of national recovery plans, allocation of EU structural funds, or the thematic composition of industrial or innovation strategies. Directionality determines whether policy ambition is translated into inclusive outcomes or remains narrowly technocratic. A third component involves the configuration of policy instruments, including their type (e.g., regulatory, financial, informational), behavioral intention (e.g., incentivize, compel), and target populations. These aspects influence the accessibility and adaptability of support structures across regions and sectors (Schneider & Ingram, 1990; Howlett, 2011; Rogge & Reichardt, 2016).

Taken together, MII indicators form the systemic baseline conditions that moderate how the other two indicator clusters, conversion readiness and exposure risk, materialize across space and sectors. In the ABM, these indicators define the policy environment and institutional constraints under which agents (e.g., policymakers, firms, citizens) formulate decisions and respond to change.

Micro-level Conversion Readiness (MCR) captures the extent to which individuals, households, or firms possess the actual capacity to convert policy support and structural conditions into meaningful adaptive outcomes. Rooted in the capability approach (Sen, 1993; Robeyns, 2005), this indicator cluster focuses on conversion factors, such as the material, institutional, and personal conditions that influence an actor's real freedom to choose and act in response to transition-induced disruptions or opportunities. In the Coleman bathtub, these indicators correspond to the bottom-right corner, where micro-level agency is enacted in response to macro-level interventions and policy filters.

MCR indicators are operationalized through measures of education, digital literacy, access to reskilling programs, and affordability of transport or housing, all of which shape whether individuals can adapt to evolving labor markets, technology regimes, and ecological norms. For households, this includes indicators like income sufficiency, care responsibilities, and social network embeddedness; for firms, it encompasses absorptive capacity, workforce diversity, and managerial openness to change. These indicators reflect not just resources, but also the presence of enabling environments that support adaptive choice. For example, a worker may be willing to retrain but unable to access programs due to distance, language barriers, or financial constraints. In simulation terms, these factors influence agent decision rules, such as whether a firm automates or reskills, or whether a worker adapts or exits the labor market.

By focusing on the variation in conversion readiness rather than static resource endowments, the MCR cluster makes it possible to trace how inequality emerges from differentiated capacities to act. It also highlights how similar policy instruments can have unequal effects when applied across socially or spatially differentiated populations. This provides critical insights for designing inclusive transition strategies.

Distributional Exposure and Risk (DER) relates to the structural vulnerabilities and external stressors that condition how severely different actors are affected by transition dynamics. Unlike the MCR cluster, which captures agents' internal capabilities to act, DER indicators focus on external risk factors—that is, features of the socio-economic or environmental context that amplify the disruptive effects of green and digital transitions. These include both legacy inequalities (e.g., labor market precarity, infrastructural deficits) and emerging exposure risks (e.g., automation threats, ecological volatility, fossil fuel dependency). DER indicators function as a contextual overlay to the Coleman bathtub model, shaping the baseline probability of harm or exclusion that different agents face, regardless of their adaptive capacities.

Examples of DER indicators include the share of employment in high-automation-risk sectors, regional fossil fuel dependency, ecological vulnerability (e.g., drought, heat stress), or housing insecurity. In the agri-food sector, exposure may stem from climate shocks or declining land productivity; in mobility, it may arise from car dependency or digital exclusion. Such exposures are not evenly distributed, but clustered along lines of class, geography, and sector, reinforcing pre-existing disparities. In the ABM, DER indicators influence how shocks are allocated across agents and how risks cascade through labor markets, value chains, and spatial networks.

The DER cluster complements MCR's focus on adaptive capacity by capturing the differential exposure of regions and groups to transition-related stress. Together, they provide a dual lens: who can adapt, and who is most at risk. This duality facilitates understanding the uneven terrain on which twin transitions unfold. It is also useful for designing policy responses that are transformative and just.

These indicators are used for empirical mapping and to form the basis for the ABM developed within the READJUST project to explore how policy design and contextual conditions jointly shape inequality trajectories over time. The ABM relies on the indicator architecture not only for initialization, but also for structuring the behavioral rules, constraints, and interaction patterns that drive system dynamics. Each of the three indicator clusters—MII, MCR, and DER—plays a distinct role in the simulation architecture, contributing to different dimensions of model behavior and inequality emergence.

MII indicators serve as model-level parameters that define the structural policy environment within which all agents operate. These indicators condition the model's scenario space by varying the ambition (transformativeness) and orientation (directionality) of transition strategies, as well as the distribution and type of policy instruments deployed. For example, a scenario with high digital directionality and coercive instrument mixes will influence both which firms automate and how workers respond to displacement. In practice, MII data is embedded in the ABM as scenario settings, policy levers, and institutional rules.

MCR indicators define the attributes of individual and organizational agents, including their capacity to act, adapt, or resist change. Citizen agents are initialized with characteristics such as education level, digital skills, income sufficiency, and social capital, while firm agents are assigned capabilities such as absorptive capacity or investment readiness. These attributes affect agents' response thresholds and decision logic, determining whether an agent adapts, stagnates, or exits under various transition pressures. The heterogeneity across agents in MCR variables is key to simulating differential outcomes across social groups and regions.

DER indicators act as contextual stressors that influence how susceptible agents are to shocks and structural transformations. These can be modeled as exogenous shocks (e.g., sudden increases in automation risk or climate vulnerability) or as spatial overlays (e.g., heat maps of transition sensitivity). In some cases, DER indicators are used to adjust probabilities in agent decision trees—such as increasing the likelihood of displacement or firm closure in high-exposure contexts.

The ABM does not hard-code inequality outcomes but accounts for their emergence dynamically from the interaction between policy, agents, and structures. This design enables exploration of not just whether a policy is effective overall, but for whom, under what conditions, and with what distributional trade-offs. The result is a modeling environment that mirrors the logic of the conceptual framework: inequality is not the outcome of isolated factors, but of configurations, where structural inputs, individual agency, and institutional context interact over time.

Our approach to inequality measurement is grounded in the capability-based definition introduced in Section 2.1: inequality is not limited to disparities in income or wealth, but refers to differential access to adaptive opportunities and the varying ability to convert resources into meaningful functionings.

To capture this multidimensional understanding, we distinguish between three types of inequality outcomes:

Conversion inequality: Variation across individuals or households in their ability to convert available resources (e.g., training access, digital tools) into adaptive outcomes (e.g., employment, mobility access). In the ABM, this is measured by tracking agents' realized functionings relative to their endowments and scenario constraints. Empirically, this can be proxied using differences in re-skilling participation rates, modal shift behaviors, or employment outcomes after policy shocks.

Distributional inequality: Unequal distribution of burdens (e.g., job loss, relocation, cost of technology upgrades) and benefits (e.g., access to green subsidies, mobility infrastructure) across social groups, firms, or regions. In the ABM, this is tracked through outcome variation between agent groups (e.g., low- vs. high-capability agents, urban vs. rural regions). Empirically, GINI coefficients, employment elasticity, or sectoral benefit uptake can serve as indicators.

Spatial and sectoral disparities: Territorial or sectoral concentration of inequality outcomes, such as digital divides, uneven automation impacts, or regional stagnation. In the simulation, this is observed through geographic clustering of negative transitions (e.g., firm exits, labor market dropouts).

We track inequality at each simulation step using summary statistics (e.g., distribution tails, interquartile gaps, agent-level entropy) and compare these under different policy configurations. This allows us to identify where inequality increases or decreases, and which combinations of MII, MCR, and DER are responsible. Such outputs provide insights into mechanism-sensitive analysis.

4 Simulation: Integrating mechanisms into a dynamic policy space

Understanding how inequality emerges from the twin transitions requires more than identifying statistical associations or evaluating policy outcomes ex post. Transition dynamics are inherently complex, involving multi-level interactions between institutions, technologies, and heterogeneous agents operating under uncertainty. In such settings, inequality is not the linear result of isolated variables, but the emergent property of interdependent mechanisms — shaped by policy ambition, institutional filters, adaptive capacities, and environmental stressors over time. To capture this complexity, the READJUST project employs a hybrid agent-based model that simulates the interaction of three core agent types, citizens, firms, and government policymakers, over a 50-year timeline, divided into annual simulation ticks. Each agent is initialized with attributes drawn from the MII, MCR, and DER indicator clusters defined in the previous sections. These attributes evolve endogenously over time based on scenario-specific policies and interaction effects, allowing inequality to emerge dynamically rather than being predefined.

The ABM is designed to go beyond average treatment effects and static analysis. It provides a virtual laboratory for exploring how different configurations of policy ambition (transformativeness), policy design (instrument mixes), and policy directionality (green, digital, or twin) influence inequality trajectories across space, sectors, and social groups. Agents interact through labor markets, technology adoption decisions, access to training or subsidies, and exposure to structural risks (e.g., automation, climate stress), producing feedback loops that simulate real-world complexity. Key outputs from the simulation include agent-level trajectories (e.g., capability gains, employment status, adaptation failure), regional inequality scores (e.g., GINI, conversion gaps), and aggregate transition outcomes (e.g., firm innovation, citizen wellbeing). By logging key performance indicators (KPIs) over time, the model supports comparison of counterfactual policy pathways and trade-offs that are difficult to observe empirically.

In other words, the ABM helps to move from the question “Does this policy reduce inequality?” to “Which mechanisms produce unequal outcomes, under what conditions, and for whom?” It operationalizes the conceptual model in a dynamic environment where policy design, institutional context, and agent behavior co-evolve based on links between theory, simulation, and policymaking.

4.1 Simulation architecture

The simulation architecture developed for READJUST is structured to reflect the complexity and asymmetry of transition processes. It centres on a tri-agent model that distinguishes between three classes of actors, i.e., citizens, firms, and policymakers, whose interactions unfold over a fifty-year horizon. Each year is represented as a simulation tick, to model gradual shifts in capabilities, market structures, and institutional contexts. This way, the slow-moving cumulative effects of transition policies on inequality is captured.

Citizen agents represent individuals or households embedded in spatially differentiated contexts. They are endowed with heterogeneous attributes drawn from the MCR indicator set: education level, digital and green skills, income sufficiency, access to care infrastructure, and social capital. These attributes shape their response space, i.e., what opportunities they can recognize, what risks they can buffer, and which adaptation strategies are feasible. A worker with low skills and limited mobility in a remote region may experience transition policies quite differently from a highly educated urban resident with stable access to retraining options. This approach keeps the simulation open to model such variation to express itself dynamically.

Firms are represented as productive actors situated in either the agri-food or mobility sectors. They vary in size, capital intensity, degree of digitalization, and exposure to regulatory or market shifts. Their behavioral logic is informed by DER and MCR indicators: some firms may aggressively pursue automation or green restructuring, while others may resist adaptation due to sunk costs, strategic uncertainty, or workforce limitations. These decisions are shaped by their local ecosystem’s adaptability, which can either buffer or amplify transition shocks.

Policymakers, in contrast, do not act as autonomous agents within the model. Rather, they structure the simulation environment through predefined scenario settings. These include combinations of policy transformativeness, strategic directionality (green, digital, or integrated), and instrument configurations (e.g., subsidies, mandates, informational tools). The role of policymakers is to define the institutional context under which firms and citizens interact, establishing the rules of the game, but not adjusting them in real time.

Each simulation tick proceeds through a set sequence: the policy context is updated, agents evaluate their circumstances, behavioral rules are activated, and outcomes are recorded. What make this model distinct are the heterogeneity of agent attributes and the way adaptation is shaped by feedback loops. A firm that automates may shed labor, which affects regional employment, which in turn shapes household decisions about retraining or migration. These second-order effects accumulate, creating emergent inequality patterns not visible at the point of intervention.

The model is spatially aware. Regions differ in institutional density, connectivity, exposure risk, and economic base. A uniform policy may play out quite differently in high-capacity versus low-capacity settings. This design makes it possible to simulate key concerns in debates about just transition namely the diffusion of opportunities and the concentration of vulnerabilities.

At the end, key outcomes are tracked through a set of performance indicators: adaptation success or failure, firm exits or growth, regional convergence or divergence, and agent-level functionings. These metrics are logged at each step and allow us to compare the consequences of different policy mixes over time, not just in terms of average effects, but in terms of distributional impacts across social and geographic groups. This architecture enables us to examine how policy interacts with structure and agency, not as abstract categories, but as mutually conditioning forces unfolding over time. It offers a simulation space where inequality is not an input, but a pattern that emerges through the interaction of differentiated actors within dynamic institutional settings.

4.1.1 Data sources and parameter validation

The parameterization of the agent-based simulation model in Task 1.3 was informed by a structured combination of empirical data, consortium knowledge, and established theoretical frameworks. Rather than relying on a single dataset, the model draws on triangulated sources to ensure plausibility and analytical robustness.

Empirical grounding was provided by European institutional datasets such as Eurostat (e.g., emissions intensity, Gini coefficients), OECD regional indicators (e.g., broadband access, education levels), the EU Labour Force Survey (e.g., participation, reskilling), the DESI Index (e.g., digital infrastructure), and the European Environment Agency (e.g., sectoral emissions). These sources supported the initialization of agent attributes and contextual overlays, such as digital skills distribution or exposure to automation risks. Policy-relevant parameters were aligned with strategic EU-level documents including the European Green Deal, the Digital Decade Policy Programme, the Just Transition Mechanism guidance, and national energy and climate plans (NECPs). While not all policy features were quantitatively extracted, these documents informed the structure and content of scenario designs and policy mixes. Where empirical data was unavailable or insufficiently granular, the model relied on qualitative insights generated within the READJUST consortium. This included policy mapping from Task 1.2 and stakeholder feedback from Task 1.1. Such inputs guided the selection of parameter ranges, e.g., for administrative effectiveness, ecosystem adaptability, and agent responsiveness.

Finally, parameter defaults and behavioral rules were benchmarked using values and ranges derived from peer-reviewed literature in the fields of transformative innovation policy, agent-based economic modeling, and regional adaptation. Sensitivity testing and expert reviews were conducted iteratively to assess output stability and ensure internal model consistency.

A detailed specification of parameter values, sources, justification logic, and validation protocols is provided in the Appendix 4: Specification of data sources and variable validation.

4.2 Mechanism-to-model translation

Building on the mechanism-based framework introduced in Section 2.1, the agent-based simulation model translates the six core components into a computational environment structured around scenario variation, agent heterogeneity, and institutional context. Rather than restating conceptual definitions, this section explains how these mechanisms are embedded in the model architecture and drive emergent inequality patterns over time.

Policy transformativeness and directionality are treated as scenario-defining parameters. Each simulation scenario specifies the ambition level (low, moderate, or high) and strategic orientation (digital, green-social, or integrated twin transition). These inputs determine the intensity and scope of structural change that agents face, and thereby influence both the opportunity space and pressure to adapt. Transformativeness shapes the degree of systemic reconfiguration; directionality influences which groups, sectors, or regions are exposed to disruption or positioned to benefit.

Policy instrument configuration is encoded through policy mix profiles within each scenario. These profiles specify the type (e.g., regulatory, financial, informational) and reach (percentage of agent access) of instruments. Instruments also vary in their behavioral logic (e.g., enabling, penalizing, incentivizing), which determines how agents respond when exposed to policy stimuli. While all agents are subject to the same policy environment in a given run, their responses differ based on underlying attributes and contextual fit.

Socio-cognitive characteristics of policymakers are not directly represented through agent behavior in this model iteration. However, they are implicitly captured through the structure of scenarios—particularly in the choice of directionality and instrument mix. For instance, a scenario reflecting a market-liberal orientation may emphasize digital tools and incentives, while one based on egalitarian logics may combine regulatory mandates with inclusion-oriented financial instruments. This abstraction allows exploration of how ideologically driven governance designs affect inequality outcomes, even without simulating policymakers as active agents.

Human adaptive capabilities are encoded at the agent level. Citizen agents are initialized with a bundle of attributes—education, digital skills, care responsibilities, social capital, and income sufficiency—that shape their ability to recognize and respond to adaptive opportunities. Firms similarly vary in absorptive capacity, investment readiness, and path dependence. These characteristics influence decisions such as whether to upskill, exit the labor market, adopt green technology, or pursue innovation. Importantly, capability thresholds are scenario-sensitive: the same policy may enable adaptation in one context but fail in another.

Ecosystem adaptability is represented through regional overlays and sectoral differentiation. Regions differ in institutional density, exposure to transition risks, and infrastructural readiness. Sectors (agri-food vs. mobility) are initialized with distinct structural properties—labor intensity, emissions profiles, capital requirements—which affect how transition pressures are absorbed. These contextual layers influence how agent-level capabilities translate into actual adaptation outcomes, and how localized feedback loops shape macro-level inequality patterns.

The simulation does not treat these mechanisms as isolated levers. Instead, it allows for interaction effects across dimensions: e.g., policy ambition interacts with ecosystem adaptability to determine whether firms reconfigure or retrench; policy reach interacts with conversion readiness to shape agent uptake. This approach preserves the configurational logic of the conceptual model while grounding it in empirically informed simulation dynamics.

4.3 Simulation outputs and tracked outcomes

The simulation model developed in READJUST produces a structured set of output indicators at each time step to monitor macro-level system dynamics and emerging inequality patterns under varying transition scenarios. These outputs serve a dual purpose: they enable comparative analysis across policy configurations, and they support interpretation of the causal relationships that link policy ambition, agent adaptation, and structural transformation.

Each simulation run spans a 50-year timeline, with outcomes recorded at annual intervals. Core output indicators are exported in structured .csv files and logged through integrated dashboards. These include both economic performance measures and inequality-relevant indicators. Specifically, the model tracks (1) macroeconomic indicators (real GDP, price levels, wages, and employment), (2) social indicators (Gini coefficient for income inequality, unemployment rate, and access to work or training), (3) environmental indicators (emissions, emissions intensity, and green technology adoption rates), (4) technological transition indicators (share of green and digital technology in firm portfolios, and (5) government indicators (fiscal balance and the relative weight of redistributive spending).

These indicators are generated by aggregating agent-level behaviors, such as firm investment choices, worker transitions into or out of employment, and household consumption patterns, into macro-level outcomes. For instance, the Gini coefficient is calculated from the income distribution of all active citizen agents at each time step. Similarly, emissions intensity is derived from sector-specific activity, weighted by green technology uptake. All indicators are structured to facilitate longitudinal analysis and comparative evaluation between scenarios.

To explore how different policy configurations shape these outcomes, a series of targeted simulation experiments were conducted. These include: (1) examining how regional disparities in skills and administrative capacity affect aggregate performance and inequality; (2) assessing how the timing and quality of policy implementation influence adaptation trajectories; and (3) analyzing how differences in dynamic capabilities among agents shape long-term distributional outcomes. Each experiment was executed over 30 simulation years with 100 bootstrapped repetitions per scenario. Output data includes both means and standard deviations of key performance indicators, enabling analysis of volatility and systemic sensitivity under different settings.

Importantly, the simulation does not impose fixed outcome targets. Instead, results emerge dynamically from the interaction between agent heterogeneity, scenario parameters, and structural context. This allows for tracing causal pathways and understanding unintended consequences — such as how a digital-forward policy may improve productivity while simultaneously deepening regional inequality. The model's design allows policy makers and researchers to investigate not only whether an intervention is effective, but for whom, in which regions, and under what exposure conditions it may exacerbate or mitigate inequality.

By linking scenario architecture, agent behavior, and system-level outcomes through a traceable output logic, the simulation environment provides a robust empirical platform for testing alternative transition pathways and analyzing their social and economic consequences.

4.4 Illustrative findings from simulation experiments

To explore how different configurations of policy ambition, agent capabilities, and structural context affect inequality, we designed four targeted simulation experiments. These are not intended as comprehensive scenario sweeps, but as controlled demonstrations of the model's ability to express theoretically grounded mechanisms under varying contextual inputs. In other words, the experiments aim to illustrate how core dynamics, such as the amplification effect of baseline disparities or the role of instrument reach, manifest in a dynamic simulation space. This also serves to empirically ground our mechanism-based framework using emergent patterns from agent-level interactions.

The experiments test the implications of:

1. Conversion readiness differentials (Experiment 1)
2. Implementation reach, i.e., policy access (Experiment 2)
3. Variation in dynamic capabilities (Experiment 3)
4. Sector-specific structure and asymmetries (Experiment 4)

Each simulation spans 30 years and outputs indicators such as Gini coefficient, employment, and skill acquisition, logged annually. Below, we integrate results into the discussion to illustrate their empirical behavior and their theoretical significance.

Scope of simulation experiments

While the overarching goal of the simulation model is to enable systematic exploration of how policy ambition, directionality, and instrument design interact to shape inequality outcomes, the current set of experiments represents a first-stage diagnostic implementation. The purpose of these initial scenarios is to test whether the model expresses known distributional dynamics consistent with theoretical expectations and empirical literature. Accordingly, each experiment isolates a single mechanism (e.g., conversion readiness, policy reach, sectoral asymmetries) to ensure interpretive clarity and avoid confounding effects. Full factorial exploration of interacting policy parameters is planned in subsequent extensions of the model, including integration into the scenario co-design activities of WP3 and WP4. These future applications will systematically vary ambition, directionality, and policy mix to identify robust configurations and transition pathways with equitable outcomes across diverse contexts.

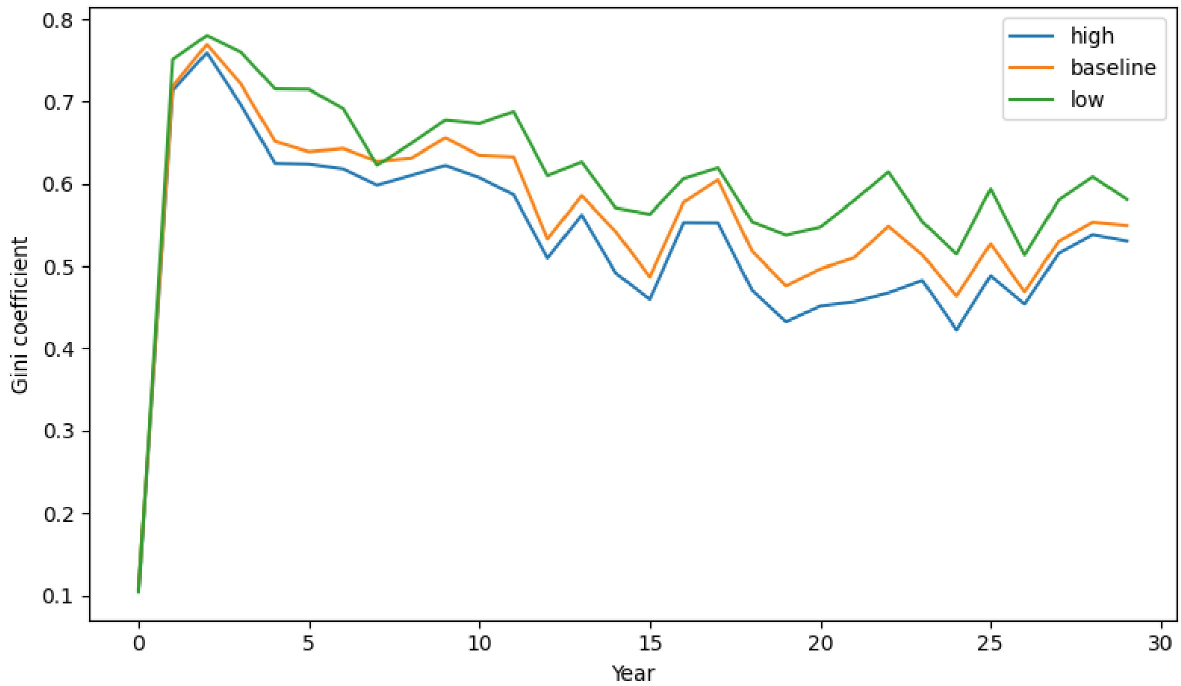
Experiment 1: Regional skill levels and administrative capacity

This experiment tests how different levels of regional conversion readiness—defined by education levels, reskilling infrastructure, and institutional capacity—shape the evolution of inequality over time under identical transition policies. The goal is to demonstrate how variation in adaptive capacity acts as a generative mechanism of inequality. This experiment operationalizes two components of the conceptual model: *Mechanism component 5 (Human adaptive capabilities)* and, to a lesser extent, *Mechanism component 6 (Ecosystem adaptability)*.

We simulated three regional clusters: one with high conversion readiness (e.g., strong training infrastructure, educated workforce), one with baseline capacity, and one with low readiness (e.g., weak institutions, limited skills). All three regions were exposed to the same policy scenario: moderately transformative and balanced in green–digital orientation.

The results show marked divergence in inequality outcomes, as reflected in the Gini coefficient trajectory over 30 simulation years (see Figure 2 below). All regions experience an initial rise in inequality due to transition shocks, but over time, their trajectories split. The high-readiness region sees a steady decline in inequality, stabilizing at a significantly lower Gini value (≈0.53) than the other regions. The baseline scenario follows a more volatile path with modest improvement. In contrast, the low-readiness region exhibits persistently higher inequality, peaking above 0.75 and remaining elevated even after 30 years.

Figure 2 - Experiment 1: Gini coefficient over time across conversion readiness levels



These dynamics confirm that pre-existing disparities in conversion readiness are not neutral background conditions but powerful amplifiers of distributional outcomes. The same policy environment yields diverging inequality patterns because agents' ability to adapt—via upskilling, occupational switching, or technology absorption—is unevenly distributed. This supports the report's core claim that inequality in twin transitions is not merely a reflection of resource gaps, but an emergent property of conversion friction and adaptive asymmetry *(Mechanism component 5: Human adaptive capabilities)*.

This finding also reinforces the relevance of the capability approach within the simulation: functionings are not guaranteed by formal access alone. Adaptive outcomes depend on whether regions can mobilize the institutional, cognitive, and infrastructural support required to convert opportunities into realized gains. In this way, the experiment demonstrates how regional variation in capabilities shapes the relationship between policy interventions and inequality.

Experiment 2: Implementation efficiency and inequality outcomes

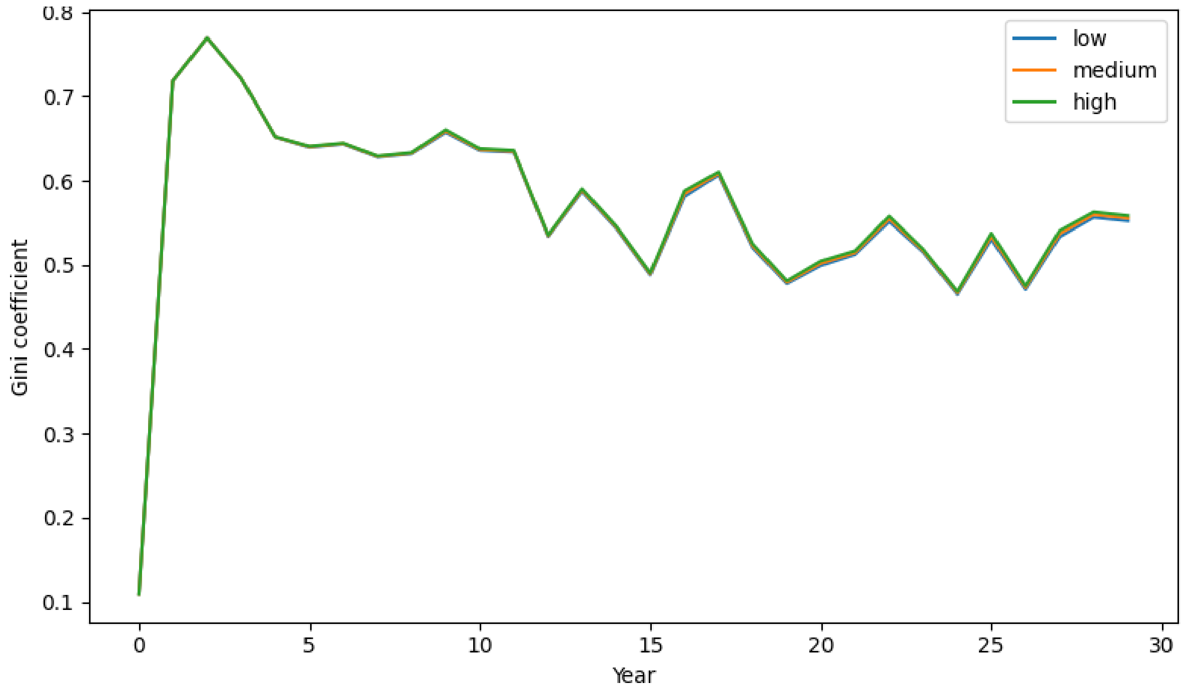
his experiment was designed to test whether implementation efficiency, operationalized as the share of agents accessing policy support, affects inequality under otherwise identical conditions. The hypothesis was that more inclusive implementation would produce more equitable outcomes. This experiment isolates the impact of implementation reach, corresponding to *Mechanism component 3 (Instrument configuration)* in the conceptual model, while holding policy ambition and agent heterogeneity constant.

We simulated three levels of implementation efficiency:

- *Low*: marked by leakage, bureaucratic delay, and uneven access.
- *Medium*: moderate performance with some gaps in reach.
- *High*: streamlined, universal delivery with minimal friction.

The results reveal minimal divergence in inequality outcomes across these scenarios (see Figure 3). All three trajectories follow a near-identical path, with the Gini coefficient peaking early due to systemic transition shocks and stabilizing around 0.55 after 30 years. The marginal improvements in the high-efficiency scenario are not substantial enough to meaningfully alter inequality dynamics. This counterintuitive finding suggests that implementation efficiency alone is not sufficient to overcome structural inequality drivers embedded in conversion readiness and agent heterogeneity. Even highly effective policy delivery systems struggle to reduce inequality if the recipients lack the absorptive capacity to act on the opportunities provided. In other words, reach without readiness does little to close inequality gaps.

Figure 3 - Experiment 2: Gini coefficient over time under varying implementation efficiency



While Experiment 2 operationalizes policy access through implementation efficiency, this dimension also indirectly reflects *Mechanism component 4 (Policymaker socio-cognitive characteristics)*. The design and targeting of policy instruments are shaped by how policymakers interpret the causes of inequality and the appropriate levers of change. Cognitive framings—such as whether inequality is viewed as structural, behavioral, or temporary—inform choices about delivery channels, eligibility, and follow-up mechanisms. Thus, access effectiveness is not merely technical, but deeply tied to the social and cognitive filters that influence policy design.

Theoretically, this supports the simulation's emphasis on interaction effects: efficient implementation is necessary but not sufficient. It must be coupled with tailored interventions that enhance adaptive capabilities (as explored in Experiment 1) for it to be distributionally transformative. Although implementation efficiency determines how widely a policy can be delivered, its transformative impact depends on how well it aligns with structural enablers like absorptive capacity and conversion readiness. These findings reinforce the importance of *Mechanism component 3 (Instrument configuration)* and its interaction with *Mechanism component 5 (Human adaptive capabilities)* and highlight that effective policy mixes must be co-designed with the underlying capacity landscape in mind.

Experiment 3: Dynamic capabilities and the limits of learning

This experiment investigates whether improving agents' dynamic capabilities—particularly their speed and flexibility in learning, retraining, and technology adaptation—can reduce inequality over time. The scenario reflects a capability-enhancing policy context, with supportive infrastructure for upskilling and organizational innovation. All other structural and institutional parameters were held constant to isolate the effect of dynamic capability growth. This experiment operationalizes *Mechanism component 5 (Human adaptive capabilities)* and *Mechanism component 6 (Ecosystem adaptability)* in the conceptual model.

Figure 4 - Experiment 3: Gini coefficient over time with enhanced dynamic capabilities

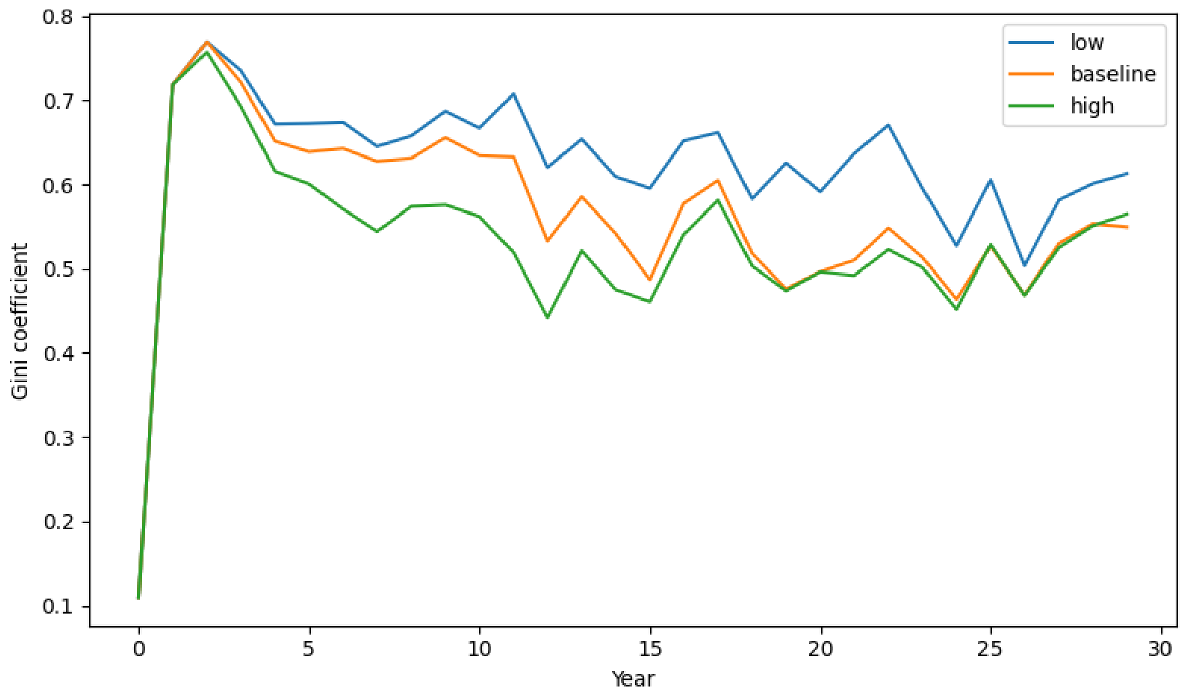


Figure 4 shows the trajectory of the Gini coefficient over 30 simulation years under this enhanced capability regime. The Gini peaks early, in response to transition shocks, and then declines modestly before plateauing. Importantly, inequality persists throughout the simulation, stabilizing above 0.5 despite the widespread uptake of skills and technology across the agent population.

The data indicate that greater learning and adaptation capacity is not sufficient to generate inclusive outcomes. While aggregate productivity and innovation improve under this scenario, these benefits accrue unevenly: agents with already favorable conditions (e.g., institutional support, digital access, sectoral alignment) adapt faster and gain more. By contrast, structurally disadvantaged agents—especially those located in fragile ecosystems or with constrained mobility—continue to lag behind.

This result highlights that conversion readiness interacts with capability deployment. Simply accelerating learning is not enough. Without corresponding improvements in exposure mitigation, social infrastructure, and support mechanisms, enhanced dynamic capabilities risk reinforcing existing divides. This reinforces the need for policy mixes that combine capability-building with structural equalization measures, aligning with the dual relevance of *Mechanism component 5 (Human adaptive capabilities)* and *Mechanism component 6 (Ecosystem adaptability)* in shaping inequality dynamics.

Experiment 4: Sectoral structure and diverging transition dynamics

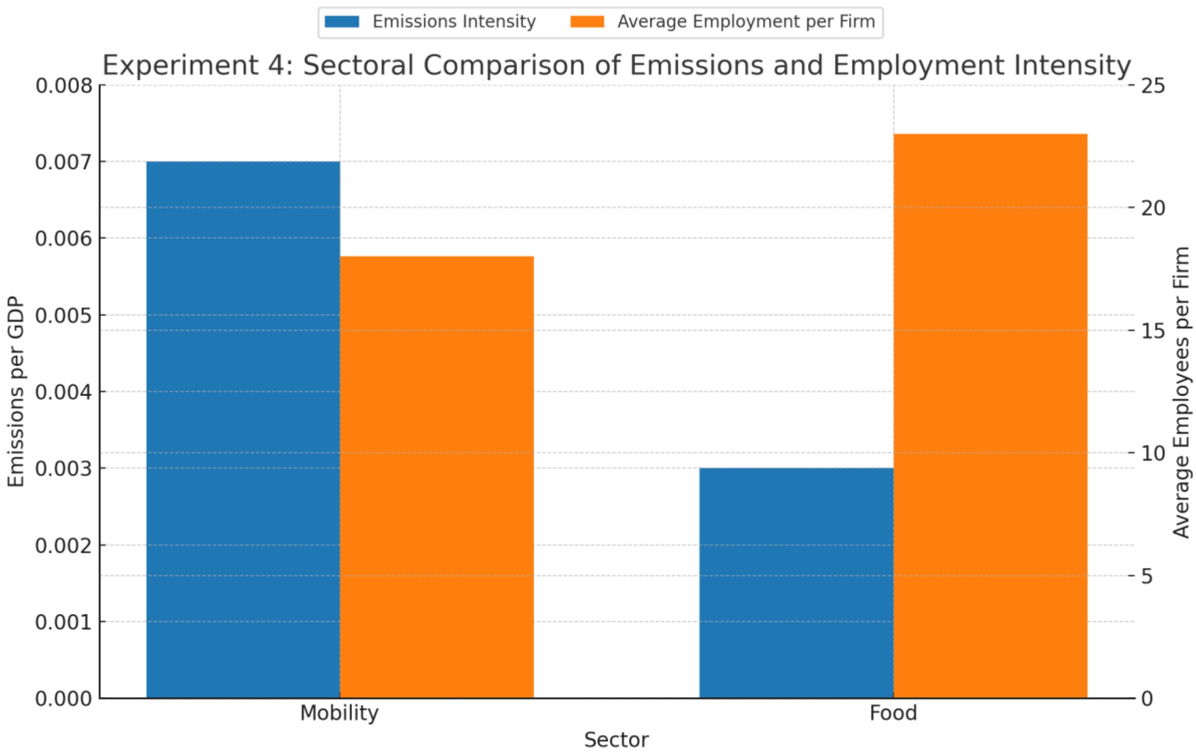
To explore whether structural differences between sectors affect transition trajectories and inequality dynamics, a fourth experiment compared stylized representations of the mobility and agri-food sectors (Figure 5). Initial runs using the baseline model—where firms differed only in emissions and adoption speed—produced nearly identical labour-market and distributional outcomes across sectors. This suggested that meaningful divergence required deeper structural differentiation. The model was therefore extended to include sector-specific firm attributes, using new parameters to reflect capital intensity, emissions profiles, and labour demand elasticities.

Mobility firms were initialized with higher emissions intensity, greater capital intensity, and slightly faster initial technology uptake. In contrast, agri-food firms were modelled as more labour-intensive, with lower emissions per output and slower technology adoption. These sectoral distinctions yielded divergent results over a 30-year simulation horizon, repeated across 30 runs. While both sectors converged to full green and digital adoption by year 30, structural contrasts produced persistent asymmetries. Mobility firms consistently exhibited more than double the emissions intensity (≈0.007

vs. 0.003) and employed fewer workers per unit of capital (≈20 vs. ≈24). Aggregate GDP remained similar across sectors due to offsetting productivity dynamics.

The experiment underscores that sector-specific structural features—particularly those related to emissions and labour intensity—meaningfully shape the outcomes of transition pathways. While technology diffusion trends may converge, emissions and employment patterns diverge. These results suggest the need for differentiated policy mixes: stronger decarbonization levers for mobility, and more robust skills and employment supports for agri-food. Structural heterogeneity across sectors thus interacts with transition dynamics in ways not captured by uniform policy modelling, reinforcing the importance of sector-sensitive transition design.

Figure 5 - Experiment 4: Sectoral comparison of emission and employment intensity in the mobility and food sectors



Although both the agri-food and mobility sectors were exposed to the same policy mix, their responses diverged due to underlying sectoral profiles. Mobility firms, with higher emissions intensity and greater capital intensity, responded more rapidly to digital subsidies and green mandates but did so primarily through labor-reducing automation. In contrast, agri-food firms—being more labor-intensive and slower to adopt new technologies—exhibited delayed adjustment patterns, often absorbing shocks through employment volatility rather than productivity gains.

This outcome illustrates how *Mechanism component 6 (Ecosystem adaptability)* mediates policy impact: structurally distinct sectors process identical policy stimuli in fundamentally different ways. It also reflects the partial influence of *Mechanism component 5 (Human adaptive capabilities)*, as sectoral labor structures condition how agents respond to change. When capital intensity and automation pathways dominate, inequality effects emerge differently than in labor-intensive settings with weaker uptake dynamics. These findings affirm that transition policies must be aligned not only with environmental targets, but also with sectoral absorption capacity and structural differentiation.

Further considerations

The simulation experiments described above were designed to explore how different structural and institutional configurations affect the relationship between transition policies and inequality. Each experiment selectively activates one or more of the six conceptual mechanism components defined in Section 2. Table 2 below maps the alignment between each experiment and these mechanisms.

Although scenario parameters include transformativeness and directionality, these were held constant across experiments 1–4 to isolate the effects of other mechanisms. Future model extensions may explore these dimensions more systematically. Their effects are thus treated as contextual constants. *Mechanism component 4 (Policymaker socio-cognitive characteristics)* is not explicitly modeled but is partially reflected in how policy access and targeting are conceptualized in Experiment 2. The reach and inclusiveness of implementation, as shaped by underlying assumptions about who policies are for, and what barriers matter, are informed by cognitive framings held by policymakers. In this sense, the experiment indirectly captures how policymaker beliefs and biases may influence distributional outcomes through design and delivery logic.

Table 2 - Mapping of simulation experiments to conceptual mechanisms

Conceptual Mechanism	Experiment 1 (Regional readiness)	Experiment 2 (Implementation efficiency)	Experiment 3 (Dynamic capabilities)	Experiment 4 (Sectoral structure)
1. Policy transformativeness	✓	✓	✓	✓
2. Policy directionality	✓	✓	✓	✓
3. Instrument configuration	—	✓✓	—	✓
4. Policymaker socio-cognitive characteristics	—	✓	—	—
5. Human adaptive capabilities	✓✓	✓	✓✓	✓
6. Ecosystem adaptability	✓	✓	✓✓	✓✓

Legend:

✓✓ = Mechanism is explicitly operationalized and tested

✓ = Mechanism is embedded in the scenario design or interpretation, but not experimentally varied

— = Mechanism is not substantively engaged

This mapping confirms that the simulation framework engages most of the theoretical concepts introduced in Section 2, while leaving room for future expansions to endogenize policy ambition, directionality, and cognitive biases more directly.

In addition to reinforcing theoretical expectations from the capability approach, several findings reveal emergent patterns not easily anticipated ex ante. Experiment 2 further demonstrates that expanding access to policy instruments is insufficient unless accompanied by readiness-enhancing investments. This nuance is often overlooked in policy design, which tends to assume that more efficient delivery will automatically yield equitable outcomes. In Experiment 3, agents with strong dynamic capabilities did not uniformly benefit: structural positioning and ecosystem feedback still produced divergence. This highlights the importance of coupling agent-focused interventions with context-aware ecosystem design.

A more nuanced insight emerges from Experiment 3, where dynamic capabilities, the ability of agents to learn, adapt, and reconfigure in response to shocks, were enhanced across the board. While this led to improvements in aggregate performance (e.g., skill levels, productivity), it did not uniformly reduce inequality. Instead, the benefits of adaptability were captured disproportionately by agents already embedded in more favorable ecosystems (those with better access to networks, infrastructure, and demand-side opportunities). This indicates that enhancing capabilities alone is insufficient if structural asymmetries persist. Without coordinated interventions at the ecosystem level (e.g., improving institutional density or reducing geographic skill mismatches), policy efforts to boost dynamic capabilities risk reinforcing rather than mitigating inequality.

Taken together, the experiments show that inequality in the twin transition is not a passive reflection of conditions. It emerges from the interaction of cognitive, institutional, and spatial factors that evolve over time. These experiments, for instance, demonstrate that inequality in the twin transitions does not result solely from macro-level policy ambition or instrument type, but emerges through the interplay between structural readiness, agent heterogeneity, and policy reach. Even ambitious and well-designed policies can generate regressive outcomes when implementation falters or when baseline disparities are not addressed.

5 Discussion: Mechanisms, dynamics, and implications

The simulation results empirically demonstrate the systemic conditions under which inequality emerges and persists during twin transitions: inequality is not merely a passive outcome of macroeconomic restructuring but is actively shaped by interacting mechanisms that govern how individuals, firms, and regions respond to policy-induced change. Rather than functioning as linear causal chains, these mechanisms configure into dynamic, path-dependent systems in which small differences in capability, access, or institutional density can compound over time into significant disparities in adaptation outcomes. While the mechanisms themselves are theoretically grounded in the capability approach and policy instrumentation literature, the simulation exercises give them empirical specificity that reveals how they play out under different assumptions about digital and green transitions, and in structurally distinct sectors such as agri-food and mobility.

Conversion readiness and implementation effectiveness

The first set of findings highlights the central role of conversion readiness (as an indicator of ecosystem adaptability and human adaptive capability), defined as the capacity of individuals and firms to translate policy access into meaningful adaptation, in shaping long-term inequality trajectories. As shown in Experiment 1 (Section 4.3), regional differences in conversion readiness, which reflect variation in education levels, reskilling infrastructure, and institutional capacity, lead to sharply divergent Gini trajectories under identical transition scenarios. This result illustrates how human adaptive capabilities (Mechanism component 5) operate as generative rather than merely moderating factors in inequality dynamics. The same formal access to policy tools yielded unequal outcomes because agents' ability to convert opportunity into adaptation varied systematically.

Moreover, implementation efficiency alone does not compensate for low conversion readiness. Even in simulations where policy instruments reached a broad share of the population (e.g., 90% agent reach), inequality remained high when conversion capacity was low. This reveals a vulnerability in current transition strategies: extending policy access alone does not ensure equitable outcomes without addressing baseline conversion capacities. Distributional equity depends not only on how far a policy travels, but on what agents are able to do once they receive it. This finding carries direct implications for how funding, training, and institutional reforms should be sequenced across sectors and regions.

Emergent inequality and the logic of simulation

The simulation approach enables the modeling of emergent inequality dynamics that arise from decentralized adaptation behaviors under heterogeneous conditions. In our experiments, inequality emerges not as a static input or exogenous condition, but as a dynamic outcome shaped by the interplay of learning, competition, mobility, and structural opportunity sets. Even when all agents are formally exposed to the same policies, those starting from more favorable positions (be it in terms of skills, connectivity, or ecosystem support) accumulate advantages more quickly, reinforcing the distributional asymmetries over time.

This emergent logic is particularly salient in the context of the *twin transition*, where policy domains and technological change processes are deeply interdependent.

Digital transformation, for example, can accelerate access to training and market platforms, but may also increase productivity in capital-intensive sectors faster than in labor-intensive ones, thereby driving sectoral wage gaps. Green transition policies may generate high adjustment costs in some regions or industries (e.g., meat and dairy in agri-food), while benefiting others (e.g., EV infrastructure in urban mobility) more immediately. These interplays are not always visible in traditional policy evaluation models, but become analytically accessible through simulation.

By modeling how inequality is not simply a residual, but a *system-level emergent outcome*, the simulation foregrounds the need for transition governance strategies that anticipate and intervene in cumulative dynamics—before path dependency locks in undesirable distributions of risk, burden, or benefit.

Sectoral and twin transition-specific implications

While the simulation model captures general mechanisms of inequality emergence, the findings also reveal important sector-specific and twin transition-specific patterns. In particular, the agri-food and mobility sectors respond differently to identical policy stimuli due to inherent structural asymmetries, for instance, differences in capital intensity, labor absorption, and baseline emissions. Green-oriented policies tend to generate more inclusive employment effects in labor-intensive sectors like agri-food, but risk slower technological uptake. In contrast, digital-oriented or twin-transition policies accelerate innovation in mobility systems but may exacerbate inequality unless accompanied by inclusive design and targeted capability investments. These divergences underscore the need for *sector-sensitive policy calibration within twin transition strategies. One-size-fits-all* approaches of transition policies counter the idea of “*leaving no one behind*” and are likely to reinforce structural divides, for example in cases where labor-market structures and ecosystem adaptability differ sharply across regions and sectors.

These modeled dynamics mirror structural realities in EU sectoral governance. The agri-food sector is shaped by the Common Agricultural Policy (CAP), which provides direct payments and rural development subsidies but often struggles to incentivize structural green and digital shifts due to persistent labor-intensity and low margins. In contrast, the urban mobility sector is governed through transport and infrastructure policy instruments (e.g., TEN-T, Urban Mobility Packages) that more easily support capital-intensive transitions like electrification, automation, and modal integration. The simulation findings reflect these asymmetries: green-oriented policies lead to more inclusive outcomes in agri-food but require sustained support to overcome inertia, while digital strategies in mobility catalyze faster transformation yet risk polarizing outcomes without targeted capability reinforcement. This suggests that sector-specific policy sequencing and differentiated support mechanisms are essential for fair twin transitions.

Static design, dynamic conditions: Limits of one-time interventions

Another critical insight that emerges from the simulation is the *inadequacy of static, one-time policy designs* in the face of dynamic and uneven transition processes. Even relatively well-targeted policies, such as inclusive subsidies or reskilling initiative, lose effectiveness over time if they are not adapted to changes in ecosystem structure, agent learning, or shifting technological trajectories. The simulated experiments suggest that interventions designed as front-loaded boosts tend to have *diminishing distributional returns*, particularly when the environment they operate in evolves faster than the policies themselves.

This limitation is especially relevant when comparing structurally different sectors. In the *mobility sector*, where firms are more capital-intensive and transitions toward electrification or smart logistics may occur rapidly, static support policies can be absorbed quickly and may temporarily reduce inequality but without adaptive recalibration, their effects taper off. In contrast, the *agri-food sector* exhibits slower, path-dependent change, with tight margins, fragmented ownership structures, and persistent skills bottlenecks. Here, static policies are more likely to be either underutilized or captured by early movers, leading to entrenched inequality over time.

Moreover, the *interplay between digital and green dimensions* introduces additional timing mismatches. For example, rapid digital adoption may accelerate firm adaptation and labor substitution before green transition benefits (e.g., emission reductions, circular practices) are fully realized. Without feedback-responsive policies, such asymmetries can produce *transitional inequalities* and long-term structural divides.

Together, these findings reinforce the need for **adaptive policy architectures** that are capable of learning from transition dynamics, updating instruments in response to emergent patterns, and differentiating their timing and scope across sectors.

Green–digital divergence in inequality effects

The simulation results also suggest that green and digital transition policies affect inequality through distinct but interacting pathways. In the mobility sector, policies emphasizing digital innovation accelerate firm-level transformation but risk exacerbating inequality via skill mismatches and labor market polarization—particularly when training systems lag behind automation. Conversely, green subsidies in the agri-food sector tend to preserve employment but reveal sharp regional disparities in uptake, especially in areas with limited institutional capacity or innovation infrastructure. These sectoral asymmetries reflect the need for a twin transition policy mix that goes beyond uniform incentives and incorporates adaptive support mechanisms tailored to each sector's structure, workforce profile, and absorptive context.

Note on Technical Appendices

Full technical documentation of the simulation model is provided in Appendices 2, 3, and 4. Appendix 2 lists the complete parameter manifest, including value ranges, categories, and empirical sources used for model calibration. Appendix 3 offers a detailed user guide to the model architecture, configuration logic, and code implementation. Appendix 4 addresses specifically concerns about the data sources and validation of the simulation model. These appendices ensure transparency, reproducibility, and alignment with Horizon Europe's FAIR data principles, to support other researchers and consortium members in replicating or adapting the simulation framework.

5.1 Scope and Opportunities for Further Development

The simulation model developed for the READJUST project is explicitly designed as a mechanism-oriented tool: its primary purpose is to explore how inequalities emerge from the interaction of structural conditions, policy choices, and heterogeneous agent capabilities. In this respect, the model is deliberately calibrated to enable causal tracing and configuration testing across stylized policy scenarios. As with any mechanism-based model, certain boundaries have been drawn to maintain analytical transparency, reproducibility, and interpretive clarity.

One such boundary is the decision to treat policy parameters — including the ambition, directionality, and instrument mix — as fixed within each scenario. This approach ensures comparability between governance configurations and allows us to isolate the effects of specific strategic designs on inequality trajectories. While real-world policymaking is often iterative and reactive, incorporating endogenous policy feedback would introduce additional complexity and reduce the traceability of causal pathways. Future extensions may explore dynamic policy regimes, but the current structure reflects a conscious choice to foreground mechanism identification.

A second design principle has been to rely on structured agent heterogeneity rather than fully individualized behavioral modeling. Agents are initialized using empirically grounded indicators — capturing variation in education, skills, infrastructure access, and exposure risk — and their decisions follow threshold-based rules derived from real-world policy contexts. This structure allows the model to simulate patterned adaptation and inequality outcomes without overfitting to case-specific behaviors. While behavioral realism could be enhanced in future iterations, the current focus is on representing key systemic asymmetries in capability and context, which are well documented in transition literature.

In terms of spatial and sectoral representation, the model introduces regional and sectoral overlays to simulate differentiated institutional environments and exposure levels. While it does not operate at the level of formal administrative regions or detailed supply chains, the model architecture enables robust simulation of relative disparities, path dependencies, and cascading effects across economic ecosystems. These stylized spatial distinctions allow us to draw generalizable insights while maintaining computational and conceptual tractability.

One mechanism component (the socio-cognitive characteristics of policymakers) is only partially operationalized in the current model version. While the policy scenarios reflect ideologically embedded assumptions (e.g., about inclusion, green priority, digital acceleration), policymakers are not yet modeled as agents with distinct framing logics or adaptive behavior. Future model extensions may explore this mechanism more directly by embedding decision heuristics, institutional behavior rules, or scenario updates triggered by emergent social or political feedback.

Next, while the simulation does not currently include political responses, social mobilization, or real-time institutional change, it generates insights that are highly relevant for these dynamics. By tracing how inequality patterns unfold under different transition designs, the model can inform anticipatory governance, equity-sensitive policy mixes, and early-warning signals for system stress.

Finally, the insights generated by the simulation model hold several implications for the broader READJUST project. First, they offer a causal diagnostic perspective that can complement and inform the construction of the *inequality self-assessment tool in WP2,* especially by identifying which structural conversion factors are likely to amplify disparities under green and digital transitions. For WP2, the simulation insights provide diagnostic input for identifying where implementation frictions are most likely to generate inequality due to capability gaps or policy misalignment. Second, the findings provide concrete points of reference for the *co-creation activities in WP3*, where policymakers and stakeholders will need to tailor interventions to sectoral and regional contexts. The demonstration that identical policies produce divergent distributional outcomes depending on readiness, reach, and timing can help guide these actor-led refinements. For WP3, the simulation insights serve as a reference point for stakeholder engagement and co-creation processes, enabling regionally grounded reflection on which mechanisms drive exclusion or opportunity. Third, the model sets a foundation for scenario-based exploration and policy pathway design in *WP4*, particularly by highlighting the risks of relying on static implementation strategies in dynamic, path-dependent environments. In WP4, the model supports scenario-based policy sandboxing by highlighting key leverage points (such as adaptive policy timing or conversion factor targeting) for designing inclusive transitions. By embedding these mechanism-based insights into the wider project architecture, READJUST can offer more actionable, context-sensitive guidance on how to govern twin transitions in an inclusive and anticipatory way.

The simulation model is fit-for-purpose: it is grounded in robust theory, built on empirically anchored indicators, and structured to reveal distributional mechanisms that are often hidden in conventional evaluation approaches. Its modular design provides a strong foundation for future expansion while already delivering critical insights into how policy strategy and structural context interact to shape inequality in the twin transitions.

6 Conclusion

This deliverable has developed a mechanism-oriented framework to understand how inequalities emerge—and can potentially be reduced—within the green and digital transitions. Rather than focusing on end-state disparities or pre-defined vulnerable groups, our approach explains inequality as the result of interacting structures: policy design, institutional context, agent capabilities, and regional exposure. Three elements distinguish the work. First, the use of Coleman's bathtub model and the capability approach enables a systemic and actor-sensitive understanding of transition dynamics. Second, the custom-built simulation operationalizes these mechanisms across heterogeneous agents, structured policy scenarios, and stylized regional contexts—making distributional consequences visible over time. Third, the MII–MCR–DER indicator framework provides a replicable link between theory and empirical calibration. The outputs offer insights for policymakers by showing how and when different transition strategies may inadvertently deepen or reduce inequality. They also lay the foundation for more interactive and reflexive environments in the next phases of the READJUST project. Future work will extend this foundation by incorporating co-design with stakeholders, and dynamic policy learning mechanisms that reflect real-world governance challenges.

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Appendix 1: Diagnostic companion of Section 2.2

This appendix summarizes how the conceptual mechanisms outlined in Section 2 were operationalized into measurable constructs and linked to empirical indicators. The goal was to assess empirical visibility—i.e., whether a given mechanism is observable in existing data—and to inform the initialization of simulation agents, scenario parameters, and contextual overlays.

The mapping followed a three-step procedure: (1) mechanism components were derived from transformative innovation policy, capability theory, and just transition frameworks; (2) each component was translated into operational constructs using keyword sets; and (3) these constructs were matched to data sources such as Eurostat, OECD STIP, SES-WOA, and EU policy documents. Constructs were then coded by level of empirical visibility: directly measurable, indirectly visible (through discourse or proxy), or currently missing.

Table A1 summarizes the mapping across the six mechanisms—transformativeness, directionality, instrument configuration, socio-cognitive framing, adaptive capabilities, and ecosystem adaptability—and their alignment with the MII, MCR, and DER indicator clusters. This mapping supported two main functions: transparent simulation design and highlighted empirical gaps where theoretical dynamics had to be implemented via stylized assumptions.

A1.1 Summary of visibility assessment

Tables A1.1 and A1.2 summarize the results of this assessment. They indicate which mechanisms are most empirically grounded, and which require theoretical modeling due to visibility gaps.

Table A1.1 – Component visibility across indicator clusters

Conceptual components	Indicator cluster	Empirical visibility	Example indicators / sources	Simulation role
Policy Transformativeness	MII	Moderate	STIP Compass, Green Growth Indicators	Scenario ambition setting
Policy Directionality	MII	Weak	EU Recovery Plans, Structural Fund Allocation	Scenario orientation parameter
Instrument Configuration	MII	Strong	OECD STIP, Eurostat, regulatory burden indices	Policy mix configuration
Policymaker Socio-Cognitive Characteristics	—	Low	Policy culture surveys, AC frameworks (qualitative)	Moderating logic (non-empirical)
Adaptive Human Capabilities	MCR	Strong	SES-WOA, SIM Europe, Eurostat digital skills	Citizen agent capability initialization
Ecosystem Adaptability	DER / MCR	Partial	Regional Competitiveness Index, Smart Specialisation	Regional overlay and firm heterogeneity
Fair and Just Transition Framing	—	Low	Doenvermogens-toets, policy narratives	Output interpretation (not input)

Table A1.2 – Visibility classification by indicator cluster

Indicator cluster	High visibility	Moderate visibility	Low visibility / gaps
MII	Instrument types (regulatory, financial)	Policy ambition (mission targeting)	Directionality clarity, behavioral logic
MCR	Skills, income sufficiency, digital literacy	Conversion frictions, care burden	Embedded agency, social networks
DER	Fossil dependency, industrial mix	Sectoral automation risk	Climate exposure, housing precarity

A1.2 Conceptual component translation examples

To link abstract mechanism components to specific indicators, we developed keyword sets and translation matrices. Table A1.3 illustrates sample mappings between conceptual mechanisms, search terms, and corresponding datasets. This translation process helped us ensure alignment between theoretical mechanisms and real-world monitoring practices, even when direct indicators were lacking. Table A1.3 shows examples of how mechanisms were translated into search terms and mapped to specific data sources.

Table A1.3 – Construct translation examples

Conceptual components	Construct	Keywords Used in Mapping	Example Sources / Datasets
Adaptive Capabilities	Digital readiness	digital literacy, ICT skills	Eurostat ICT surveys
Policy Instruments	Behavioral logic	nudge, incentive, subsidy, mandate	OECD STIP Compass
Ecosystem Adaptability	Innovation density	R&D intensity, patent activity	Regional Innovation Scoreboard

Fair Transition	Participation metrics	community engagement, co-design	EU Urban Agenda reports

A1.3 Concepts-to-Simulation linkage

The mapped indicators were used to initialize agent attributes, build scenario parameters, and define regional stress overlays. Table A1.4 outlines how each mechanism component informed simulation design, specifying the empirical anchors and encoding method. Table A1.4 summarizes how each mechanism was encoded in the agent-based simulation, indicating whether the linkage relied on direct data or stylized assumptions.

Table A1.4 – Mechanism-to-simulation linkage summary

Conceptual components	Empirical anchor	Simulation encoding	Model role
Transformativeness	STIP investment share	Scenario ambition tag	Structural pressure
Directionality	Green/digital budget share	Scenario orientation tag	Strategic path
Instruments	Instrument type mix	Policy package rule	Agent response triggers
Capabilities	Skills, reskilling access	Agent capability score	Adaptation threshold
Exposure	Automation risk index	Regional stress overlay	Probability of harm

A1.4 Implications and gaps

This mapping exercise revealed asymmetries in current data ecosystems. Individual-level adaptive capacity is relatively well captured through education, income, and digital access data. In contrast, directional clarity, behavioral logics of instruments, and socio-cognitive diversity in policymaking remain under-measured. These gaps justify why some mechanisms are implemented through stylized logic in the model rather than empirical calibration. By grounding what we can and theorizing what we must, the model balances realism and explanatory power in simulating inequality trajectories.

Appendix 2: Simulation parameter manifest

This appendix summarizes a curated subset of parameters from the full simulation manifest that directly relate to policy design, adaptive capacity, inequality pathways, and support mechanisms. The selected parameters, presented in Table A2-1 are used to shape scenario architecture, agent behavior thresholds, and contextual stressors within the agent-based simulation model. The JSON file of the parameters manifest is attached to this report.

Table A2.1 – Simulation parameters

Parameter Name	Category	Unit	Description
Default R&D Tax Credit (Chi)	Policy Levers - Defaults	rate (0-1)	Default R&D tax credit rate if not set by policy. This is the rate firms use in R&D calculations if not overridden by a specific policy signal. Applied to gross R&D expenditure.
Adoption Beta (Subsidy)	Firm Behavior - Tech Adoption	logit unit per subsidy rate unit	Sensitivity of adoption utility to technology subsidy rates. Higher value means subsidies are more effective.
Default Carbon Tax Rate (€/tCO2)	Policy Levers - Defaults	€ per tCO2	Default carbon tax rate applied to firm emissions if not set by policy. `carbonTaxRate` from PolicyTweaker overrides this. Used for A1 lever.
Default Green Adoption Subsidy Rate	Policy Levers - Defaults	rate (0-1)	Default subsidy for green tech adoption if not set by policy. Used by firms if not overridden by `policySignals`.
Default Digital Adoption Subsidy Rate	Policy Levers - Defaults	rate (0-1)	Default subsidy for digital tech adoption if not set by policy. Used by firms if not overridden by `policySignals`.

Govt Base Green CAPEX Subsidy Rate	Government Agent - Policy	rate (0-1)	Base subsidy rate for green capital expenditure by firms, if not overridden by PolicyTweaker.
Govt Base Digital CAPEX Subsidy Rate	Government Agent - Policy	rate (0-1)	Base subsidy rate for digital capital expenditure by firms, if not overridden by PolicyTweaker.
Carbon Dividend Share (F1) - Default	Policy Levers - Defaults	share (0-1)	Default value for the 'Carbon Dividend Share (F1)' policy lever. Share of carbon tax revenue redistributed.
Digital Infra Grant/Region (B1) - Default	Policy Levers - Defaults	€ per tick per region	Default value for the 'Digital Infrastructure Grant per Region (B1)' policy lever. Specifies grant amount (€) per tick to eligible regions for broadband.
R&D Matching Grant Rate (C1) - Default	Policy Levers - Defaults	rate (0-1)	Default value for the 'R&D Matching Grant Rate (C1)' policy lever. Government's matching rate for firm R&D.
Emission Standard (D1) - Default	Policy Levers - Defaults	kg CO2eq / € VA	Default value for the 'Emission Standard (D1)' policy lever. Max allowed emission intensity for firms.
Reskilling Voucher Value (E1) - Default	Policy Levers - Defaults	€ per eligible worker	Default value for the 'Reskilling Voucher Value (E1)' policy lever. Value (€) of a voucher for eligible workers.

Table A2.2 lists the sector-specific simulation parameters used to initialize distinct structural conditions for the mobility and agri-food sectors in Experiment 4. These parameters enable comparative analysis of emissions intensity, labour demand, and technology uptake trajectories.

Table A2.2 – Sector specific simulation parameters (experiment 4)

Parameter Name	Category	Unit	Description
SECTOR_SPLIT	Structural Config	Ratio	Proportion of firms allocated to "mobility" and "food/agri" sectors
MOBILITY_EMISSIONS	Emissions Factor	tCO_2/output	Initial emissions intensity for mobility firms
FOOD_EMISSIONS	Emissions Factor	tCO_2/output	Initial emissions intensity for agri-food firms
MOBILITY_LABOUR_RATIO	Labour Demand	Workers/unit capital	Employment intensity in mobility sector
FOOD_LABOUR_RATIO	Labour Demand	Workers/unit capital	Employment intensity in agri-food sector
TECH_START_MOB	Technology Config	Share	Initial green and digital tech shares in mobility firms
TECH_START_FOOD	Technology Config	Share	Initial green and digital tech shares in agri-food firms

Appendix 3: Simulation framework documentation and user guide

This appendix provides a comprehensive guide to the agent-based model (ABM) developed within the READJUST project. It explains the purpose of the model, its main components, how policies are represented and adjusted, how to configure and run simulations, and how to interpret the outputs. The aim is to make the tool accessible to both technical users and policymakers who do not write code.

A3.1 Purpose of the Model

The ABM offers a virtual laboratory for exploring how Europe's green and digital ("twin") transitions affect economic growth, employment, income inequality, emissions and public finances over multiple decades. By representing individual firms, citizens and a government agent, it captures feedback loops and heterogeneity that are absent from equilibrium-based models. The model is intentionally modular so that new behaviours, sectors or policies can be added as the project evolves.

A3.2 Structure of the Codebase

The project is organised into a folder named abm_model with three main subdirectories:

- **config/** – stores scenario files and parameter files in human-readable JSON format. For example:
    - baseline_params.json lists baseline values for all 97 parameters (see Appendix A for definitions).
    - scenario_baseline.json specifies the simulation horizon and references the parameter file.
- **src/** – contains the model implementation:
    - agents.py defines the behaviour of firms, citizens and the government.
    - model.py orchestrates the simulation loop, price and wage formation, labour allocation and key performance indicator (KPI) logging.
    - utils.py provides helper functions, such as computing the Gini coefficient.

- run_experiment.py is a command-line entry point to run scenarios and export results as CSV files.

- **results/** – this directory is created automatically when simulations are run. It holds CSV files containing one row per simulation tick (year) with the recorded KPIs.

A3.3 Agents and Behaviour

A3.3.1 Firms

Firms produce goods, invest in green and digital technologies, hire workers, pay wages, generate emissions and pay taxes. Key attributes include:

- **Capital stock**: initial capital is drawn from a distribution and grows when profits are reinvested.

- **Innovation capacity**: determines a firm's propensity to adopt new technologies.

- **Green and digital tech shares**: represent the fraction of production reliant on green or digital technologies. These increase through investment decisions influenced by subsidies and profitability.

- **Emission intensity**: emissions per unit of output decrease as green tech share increases.

- **Hiring decisions**: labour demand scales with capital and technology adoption.

A3.3.2 Citizens

Citizens supply labour, earn wages, consume goods, acquire skills and pay income taxes. They are heterogeneous in initial income and skill levels. Behavioural features include:

- **Income and consumption**: citizens receive wages from their employer (with a one-tick lag) and spend a fixed proportion of their disposable income on goods.

- **Skill dynamics**: skills can improve via reskilling vouchers or decay over time. Higher skill levels increase the probability of employment.

- **Employment decisions**: citizens decide whether to seek work each year based on their skills and the prevalence of green jobs in the economy.

A3.3.3 Government

The government collects income and corporate taxes, pays subsidies and vouchers, and manages a budget. In the enhanced version of the model, it also **adapts its policies dynamically** based on socio-economic indicators observed in the previous year. Adaptive rules include:

- **Reskilling vouchers** increase by 10 % (capped at 10 000 €) when unemployment exceeds a target level (default 10 %).
- **Income tax rates** rise incrementally if the Gini coefficient exceeds a target (default 0.35).
- **Subsidies** for digital and green capital expenditures decrease if the government runs a deficit.
- **Carbon tax** rates increase gradually if emissions intensity (emissions per unit of GDP) exceeds a target level (default 0.005).

These adjustments are stored in the parameter dictionary and take effect immediately in the following year, allowing the model to simulate responsive policy regimes.

A3.4 Simulation Loop and Market Mechanisms

Each tick (year) follows eight logical steps:

1. **Policy Update** – the government applies dynamic adjustments as described above.
2. **Citizen Actions** – citizens receive last year's wages, adapt their skills (accept vouchers or experience decay), consume goods and decide whether to seek employment.
3. **Labour Market Clearing** – citizens willing to work form a labour pool; firms request workers based on their capital and technology; available workers are assigned sequentially to requesting firms.
4. **Firm Actions** – firms invest in technology, produce goods using capital and labour, pay wages, generate emissions and pay corporate taxes on profits.

5. **Price and Wage Formation** – the model calculates a market price by comparing aggregate demand (citizen consumption) and aggregate supply (firm output) and adjusts wages based on the unemployment rate.

6. **Government Accounting** – tax revenues and expenditures are tallied, and the government budget balance is updated.

7. **KPI Logging** – key indicators are recorded, including GDP, emissions, Gini coefficient, unemployment rate, government budget balance, average wage and price, and **new metrics**: average green and digital technology shares across firms and emissions intensity.

8. **Tick Advance** – the simulation moves to the next year and repeats the loop.

A3.5 Parameters and Configuration

All behavioural and policy levers are configured through the parameter JSON files. The baseline parameter file includes 97 entries, covering areas such as taxation, subsidies, skills policies, adoption costs and behavioural elasticities. Additional policy-adaptation targets can be specified via the parameters:

- UNEMPLOYMENT_TARGET – unemployment threshold triggering increased reskilling vouchers (default 0.1).
- GINI_TARGET – inequality threshold triggering income tax increases (default 0.35).
- EMISSIONS_INTENSITY_TARGET – emissions-per-GDP threshold triggering carbon tax increases (default 0.005).

Users can edit these targets or any other parameter values directly in the JSON files using a plain-text editor. Appendix A provides a full description of each parameter and its plausible range.

A3.6 Running a Simulation

To run the model, you need Python 3 on your computer. No additional packages are required. Follow these steps:

1. **Extract the code archive** to a working directory.

2. **Open a terminal or command prompt** and navigate into the extracted folder.

3. **Execute the simulation** using the provided script. For the baseline scenario:

```
python -m abm_model.src.run_experiment --scenario config/scenario_baseline.json
```

The model will run for the number of years (`horizon`) specified in the scenario file. Upon completion, it will write a CSV file in the `abm_model/results/` directory containing one row per tick with all logged KPIs.

4. **Examine the results** using any spreadsheet or data visualisation tool. Policymakers may wish to focus on trends in the Gini coefficient, unemployment, emissions intensity and government budget balance.

A3.7 Designing and Testing Scenarios

To explore the effects of different policies or assumptions:

1. **Create a new parameter file** by copying `baseline_params.json` and changing the values of interest. For example, increasing `GOVT_SUBSIDY_RATE_DIGITAL_CAPEX` simulates larger digital infrastructure grants, while raising `POLICY_CONSTANT_RESKILL_VOUCHER` provides more generous training support.

2. **Create a scenario file** by copying `scenario_baseline.json`. Modify the `parameter_file` field to point to your new parameter file and adjust the `horizon` if needed.

3. **Run the scenario** with `run_experiment.py` and compare its results to the baseline.

4. **Use the adaptive policy** by leaving the dynamic parameters enabled (default). If you wish to fix policies over time, set the targets very high or adjust the adaptive rules in `GovernmentAgent.step()`.

A3.8 Interpreting the Output

The output CSV contains the following columns:

Column	Description
tick	Simulation year (starting at 0).
GDP	Total revenue of all firms. This is a proxy for economic output.
Emissions	Aggregate greenhouse-gas emissions from firms.
Gini	Income inequality measure among citizens (0 = perfect equality, 1 = maximum inequality).
UnemploymentRate	Proportion of citizens without a job in that year.
GovtBudgetBalance	Tax revenues minus expenditures; positive values indicate a surplus.
AverageWage	Wage per employed citizen.
AveragePrice	Market price of goods, reflecting demand–supply balance.
AverageGreenShare	Mean green technology adoption rate across firms.
AverageDigitalShare	Mean digital technology adoption rate across firms.
EmissionsIntensity	Emissions divided by GDP; lower values indicate greener growth.

By plotting these indicators over time or comparing them across scenarios, you can identify trade-offs and synergies between policy levers. For instance, you might observe that increasing digital subsidies accelerates digital adoption (higher AverageDigitalShare) but could widen inequality if not accompanied by training support.

A3.9 Extending the Model

The code has been designed with extensibility in mind. It can be enhanced further by:

- **Adding sectors or regions**: define new firm types or replicate the model across multiple geographic areas to capture sector-specific or regional dynamics.

- **Introducing additional agent heterogeneity**: extend `FirmAgent` and `CitizenAgent` to include attributes such as sector, size, age or education and adapt decision rules accordingly.
- **Refining market mechanisms**: replace the simple price and wage formulas with supply–demand curves, wage bargaining or credit markets.
- **Integrating empirical calibration**: adjust parameters based on real data (e.g. Eurostat, EU-SILC) to align the baseline simulation with observed GDP, inequality and unemployment levels.
- **Conducting formal sensitivity analyses**: embed functions that draw parameter sets from their plausible ranges, run multiple simulations and compute global sensitivity measures to identify the most influential factors.

3.10 Mechanisms-to-model translation (Overview)

The agent-based simulation model developed in READJUST translates the conceptual mechanism components outlined in Section 2 into a dynamic, computational environment. Rather than treating inequality as a static outcome, the model embeds mechanism components such as policy ambition, directionality, instrument configuration, adaptive capabilities, and structural exposure into agent behavior and institutional settings.

Each mechanism component is encoded through one or more of the following channels: scenario-level parameters, agent-level attributes, or regional overlays. These components interact over time, allowing inequality patterns to emerge from feedback loops, adaptive decisions, and spatial variation.

To avoid fragmentation and repetition, we present the full technical encoding—including scenario structure, agent heterogeneity, spatial dynamics, and calibration logic—in Section 4.2.

3.11 Scenario design, parameter encoding, and calibration

3.11.1 Scenario structure and policy configuration

Scenarios in the simulation model represent stylized policy regimes defined by three interacting components: policy ambition (transformativeness), strategic orientation (directionality), and policy instruments (configuration and delivery logic). These are exogenously set and remain constant throughout the 50-year simulation period.

Transformativeness reflects the extent of systemic change required. High-transformativeness scenarios increase the demand for adaptation across agents and elevate the risk of exclusion for those unable to keep pace. Directionality defines whether the scenario prioritizes green, digital, or integrated transitions. Each mode redistributes adaptation incentives differently across social groups, sectors, and regions. Instrument mix is built from MII indicators and defines whether policies rely more heavily on financial subsidies, regulatory mandates, or informational nudges. These influence the behavioral thresholds for agent decision-making, such as whether to invest, retrain, or exit. Policy ambition (transformativeness) and directionality (digital, green-social, twin) are encoded as scenario-level parameters. While these features are explicitly defined in the architecture and can be varied in future experiments, the current simulation exercises hold them constant across most scenarios for comparability. Table 2 reflects this by marking them as embedded but not manipulated in the present run design.

Scenario logic is implemented using structured parameter files that control policy levers, institutional rules, and baseline redistribution schemes.

3.11.2 Agent initialization and capability heterogeneity

Agents are initialized using data-derived attributes from the MCR and DER indicator clusters. These define each agent's capability to recognize, evaluate, and act on transition opportunities.

Citizen agents are characterized by education, digital skills, income sufficiency, care responsibilities, and access to mobility or infrastructure. Their conversion friction scores reflect structural barriers to adaptation. Firm agents are assigned absorptive capacity, investment readiness, and exposure to disruption. These attributes influence technology adoption, innovation strategies, and employment dynamics. Agents are heterogeneous by design, and their behavior is governed by threshold-based rules. For example, a firm may invest in digital tools if its absorptive capacity is high and subsidies lower the adaptation threshold. A worker may exit the labor force if their skill level falls below the employment viability cutoff in a digitizing region.

3.11.3 Regional overlays and institutional context

Agents are embedded in spatially differentiated ecosystems that shape the availability and effectiveness of policy support. The model does not simulate real administrative regions but uses stylized overlays to reflect regional variation in:

- Institutional density (e.g. training systems, governance capacity)
- Infrastructure (e.g. broadband access, transport)
- Risk exposure (e.g. climate vulnerability, automation shock intensity)

These overlays modify the conversion friction of agents and the effective reach of policy instruments. For example, a subsidy may be available across all regions, but only effective in areas where administrative capacity allows uptake.

Sectoral dynamics are similarly embedded. Firms operate in agri-food or mobility ecosystems with differing supply chain interdependencies, transition risks, and regulatory exposure.

3.11.4 Sectoral initialization

For Experiment 4, the agent-based simulation model was extended to include a sectoral initialization layer. At simulation start, each firm is randomly assigned to either a 'mobility' or 'agri-food' sector, with a 50/50 split. This designation determines the firm's starting emissions intensity, labour demand coefficient, and technology adoption baseline. These sectoral attributes are loaded from the SECTOR_PARAMS and SECTOR_SPLIT configuration entries in the simulation parameter manifest. By encoding structural differences directly into the firm initialization logic, the model allows for the analysis of how emissions, labour market behavior, and inequality dynamics diverge across sectors even under uniform policy scenarios.

3.11.5 Calibration logic and model realism

The model adopts a pattern-oriented calibration strategy. Rather than fitting to historical outcome trajectories, it uses real-world indicator distributions to assign starting conditions and constrain model dynamics. Scenario parameters are derived from empirical transition strategies (e.g. EU recovery plans, national sustainability goals). Agent attributes reflect regional and sectoral conditions using Eurostat, OECD, and SES-WOA data. Spatial stressors such as ecological vulnerability or fossil dependency are implemented as environmental overlays.

While not predictive, this approach ensures plausible futures grounded in real heterogeneity and structural asymmetry. The goal is to explore mechanism sensitivity—not forecast accuracy. This approach aligns with best practices in complexity modeling for policy (e.g., Hammond et al., 2015; Wallace et al., 2015).

Appendix 4: Specification of data sources and variable validation

This appendix outlines the methodological rigor underlying the parameterization and validation of the agent-based simulation model developed as part of Task 1.3 within the READJUST project. The purpose of the simulation is to explore how different policy mixes influence inequality dynamics across Europe's twin transitions, with a particular focus on the food and mobility sectors. To ensure robustness, transparency, and empirical grounding, all simulation variables were defined, structured, and tested based on an integrated set of data sources, institutional references, and literature-based assumptions.

A4.1 Parameterization structure

All simulation inputs are defined in a central, version-controlled parameter manifest file (`PolicyPilot_Parameter_Manifest.json`). Each parameter object is described using the following fields:

- `id` (unique identifier)
- `baselineValue` (default value used in the model)
- `plausibleLow` and `plausibleHigh` (used for sensitivity analysis)
- `unit` (measurement unit, where applicable)
- `type` (parameter class)
- `description` (concise explanation of model function)
- `dataSourceNotes` (empirical or theoretical justification)

The manifest currently contains 97 parameters, systematically grouped into thematic categories. These include policy levers, firm and citizen behavioural dynamics, institutional capacities, sectoral baselines, and socio-technical characteristics. Parameters are loaded at runtime from a separate configuration file (`simulation_config.json`), enabling fully modular and scenario-driven execution.

A4.2 Sources of empirical data and theoretical justification

The parameter values were informed by a triangulation of empirical data, consortium research, EU policy documentation, and relevant academic literature.

A4.2.1 Institutional and statistical data

Wherever possible, parameter values are based on authoritative datasets, including:

- Eurostat: Regional GDP, Gini coefficients, unemployment, emissions intensity
- OECD Regional Statistics: Broadband access, education levels, innovation capacity
- European Environment Agency (EEA): Sectoral greenhouse gas emissions, decarbonisation benchmarks
- DESI (Digital Economy and Society Index): Digital infrastructure, connectivity gaps, public sector digitisation
- EU Labour Force Survey (EU-LFS): Labour market participation, reskilling patterns, skills mismatch

These sources were used to inform initial conditions (e.g., digital access), sectoral heterogeneity (e.g., emissions per GDP), and behavioural responsiveness (e.g., labour mobility or price elasticity).

A4.2.2 Policy and strategic documents

Policy levers and institutional capacity variables were aligned with the following EU strategies and programming documents: European Green Deal, Digital Decade Policy Programme, Just Transition Mechanism Guidance, National Energy and Climate Plans (NECPs), and European Commission Joint Research Centre (JRC) Reports. This approach is the bases for the model to reflect the actual policy landscape within which transitions are unfolding, while allowing for ex-ante exploration of plausible alternative configurations.

A4.2.3 Consortium-derived inputs

Inputs were also derived from qualitative research conducted by project partners:

- Stakeholder interviews and workshops (Task 1.1)
- Policy mapping and institutional diagnostics (Task 1.2)

These findings were used to inform variable ranges and structural assumptions, particularly concerning regional implementation constraints, administrative capacity, and variation in citizen adaptability.

A4.2.4 Academic literature and theoretical frameworks

For variables not directly observed, the model draws on well-established literature in:

- Transformative innovation policy (Schot & Steinmueller, 2018; Diercks et al., 2019)
- The capability approach (Sen, 1992; Robeyns, 2005)
- Regional adaptation and resilience (Boschma et al., 2023; Hassink, 2010)
- Agent-based economic modelling (Mercure et al., 2019; Farmer et al., 2015)

Behavioural parameters such as price elasticity, green technology adoption thresholds, and learning curves were benchmarked using published values from peer-reviewed sources and sensitivity ranges validated through bootstrapped testing.

A4.3 Validation and testing procedures

The simulation architecture includes multiple layers of verification and testing to ensure methodological integrity.

A4.3.1 Scenario configuration and execution

All scenario experiments are defined through structured JSON files referencing the validated parameter manifest. With this approach we maintain traceability, consistency, and reproducibility across experiments.

A4.3.2 Sensitivity analysis

Parameters include `plausibleLow` and `plausibleHigh` values to support univariate and multivariate sensitivity analyses, Monte Carlo and bootstrapped experimental runs, and robustness testing under high- and low-stress scenarios. This is particularly important for assessing distributional outcomes under uncertain implementation conditions and across diverse regional baselines.

A4.3.3 Empirical benchmarking

Model outputs (e.g., GDP, employment, emissions, Gini coefficient) were benchmarked against historical EU trends. While the model is not predictive, it is calibrated to reflect plausible trajectories across time, to be able to explore counterfactual policy configurations.

A4.3.4 Expert review and face validation

Simulation mechanisms, parameter definitions, and early-stage outputs are reviewed by domain experts, consortium partners, and external advisors. Feedback was incorporated into parameter tuning and behavioural rule adjustments which are reflected in this report and simulation documentation.

4A.4 Data transparency and FAIR compliance

The simulation framework adheres to the FAIR principles:

Principle	Implementation details
Findable	Parameters, configurations, and outputs are clearly labelled and stored in a structured repository.
Accessible	Simulation input and output files are available in open formats (JSON, CSV).
Interoperable	Standardised formats ensure compatibility with Python, Excel, Power BI, and institutional databases.
Reusable	All parameters include full descriptions, units, source notes, and ranges, enabling replication and future extension.

All simulation results are stored in structured directories with metadata, and a formal documentation annex (Appendix 3) describes the model architecture and codebase in detail.

A4.5 Conclusion

The simulation model supporting Task 1.3 is underpinned by a transparent, empirically informed, and rigorously tested parameter framework. It integrates multiple data sources—ranging from institutional statistics to stakeholder insights—and employs well-established validation protocols. This ensures that the model's outputs can meaningfully inform policy recommendations related to the fairness, effectiveness, and sectoral implications of Europe's twin transitions.