Navigating complexity: agent-based simulations for climate-resilient economies

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Navigating complexity: agent-based simulations for climate-resilient economies

Navigating complexity: agent-based simulations for climate-resilient economies

Proefschrift

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Two magnificently dressed young women sit upright on their chairs, calmly facing each other. Yet neither takes notice of the other. Fortuna, the fickle, wheel-toting goddess of chance, sits blindfolded on the left while human figures desperately climb, cling to, or tumble off the wheel in her hand. Sapienta, as reason personified, the calculating and vain deity of science, gazes into a hand-mirror, lost in admiration of herself. Sapientia's most exceptional power and greatest threat is her own capacity for self-recognition and self-admiration – endless capacity for pride – presuming omniscience. That is why she is looking into the mirror. Sapientia has good reason for self-admiration. With science's development of Probability Theory, Sapientia has shrunk Fortuna's domain. We seek to use the knife in the art of measurements to determine if we are facing Fortuna or Sapientia.

Risk literacy: woodblock on Fate & Wisdom.

Contents

Summary

Amid the Anthropocene, the escalating threat of flooding, driven by extreme rainfall and sea-level rise, challenges societies worldwide. In the last two decades, floods have impacted billions and inflicted colossal economic losses. Concurrently, the global trend towards urbanization predicts that by 2050, about 70% of the global population will inhabit urban areas. This demographic trend, heavily influenced by agglomeration forces, further underscores the vulnerability of these urban centers, many of which are precariously situated in flood-prone areas. Given the confluence of escalating climate risks and the surge in populations settling in vulnerable zones, a pressing question emerges: How will rapidly urbanizing coastal societies adapt to intensifying flood risks in the face of escalating climate-induced shocks and changing regional economic landscapes?

To address this multifaceted issue, this dissertation delves into the complex nexus between climate shocks, regional economic dynamics, and societal responses. Central to this exploration is the creation of innovative simulation tools tailored to incorporate the autonomous adaptation strategies of various actors within a regional economic framework. This thesis stands at the forefront of a new wave of computational models that encompass risk and embed resilience into complex adaptive systems.

I commence by examining the current advancements and gaps in employing Agent-Based Models to unravel the dynamics of flood risk and adaptation assessments. In this exploration, I underscore the pivotal role of human actions in shaping risks and resilience within flood-prone urban settings.

Building on this foundation, I introduce the Climate-Economy Regional Agent-Based (CRAB) model. The CRAB model employs an evolutionary perspective to provide a comprehensive view of the balances struck between the driving forces of economic agglomeration and the counteracting pressures of climate hazards. It focuses on the decision-making of heterogeneous agents, representing households and firms, as they navigate the choice of relocation between safer inland regions and hazard-exposed coastal zones.

Venturing further, I enhance the CRAB model to embody autonomous household adaptation behaviors, drawing from empirical data. Here, I challenge the traditional reliance on rational agents in sustainability models, unveiling a notable adaptation deficit when juxtaposed against boundedly-rational choices gleaned from real-world surveys. This nuanced exploration uncovers how varied adaptive capacities can potentially accentuate inequality and impede resilience.

Subsequently, I include in the CRAB model a layered risk strategy that encompasses an array of climate change adaptation measures. This refined model, enriched by extensive behavioral and flood data, bridges existing gaps in the current understanding of feedback loops and cascading effects triggered by flood shocks within a socio-economic system of boundedly-rational agents.

In conclusion, this dissertation pioneers a unique trajectory in understanding societal responses to the specter of flooding, offering invaluable insights and frameworks for devising future climate-resilient strategies.

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Alessandro
Delft, September 2023

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Introduction

1.1 Navigating the Storm: addressing climate change challenges in coastal agglomeration economies

As we navigate through the Anthropocene, the realities of climate change pose increasingly stark challenges to societies worldwide. The Intergovernmental Panel on Climate Change (IPCC) unequivocally reports that the climate system is warming, and many of the observed changes are unprecedented throughout millennia (IPCC, 2022b). Among numerous climate-related adverse impacts, flooding presents an immediate and severe threat, which frequency and intensity, fueled by extreme rainfall events and sea-level rise, have been steadily increasing (Coronese et al., 2019; Tripathi, 2014).

The devastation caused by floods is far-reaching and catastrophic, making it the costliest climate-induced hazard worldwide United Nations Office for Disaster Risk Reduction (2018). The United Nations Office for Disaster Risk Reduction (UNDRR) reported that between 1998 and 2017, flood-related disasters comprised 43.4% of all weather-related disasters, affecting 2.3 billion individuals and causing an estimated $662 billion in damages United Nations Office for Disaster Risk Reduction (2018). This substantial impact extends beyond immediate physical damage. Flooding can also lead to long-term economic disruption, impacting labor productivity, damaging infrastructure, and stalling regional development. According to a World Bank study, the global annual cost of fluvial floods alone was approximately $104 billion in 2018, with residential properties bearing the brunt of these costs World Bank (2020). A report from the European Environment Agency (EEA) further emphasized that the occurrence of severe floods requiring disaster relief assistance in Europe more than doubled over the 1990s and early 2000s, linking this increase in frequency and intensity to both climate change and socio-economic factors such as land use change (European Environment Agency, 2016). Furthermore, the International Organization for Migration (IOM) also reported that in 2019, floods accounted for 40% of the displacements associated with disasters, underscoring the significant contribution of flooding to the global crisis of forced displacement International Organization for Migration (2020). Regrettably, these figures have only escalated in recent years, with climate change fueling more intense rainfall and sea-level rise, which further exacerbate flood risks (IPCC, 2022b).

The impending threat of future damages is intensified as escalating climate conditions coincide with unprecedented urbanization and other human-induced factors. Global projections anticipate that cities will encapsulate around 70% of the global populace by 2050, significantly reshaping demographic patterns and spatially redistributing economic assets (United Nations, 2018). The driving force behind this urbanization trend lies in the magnetic pull of agglomeration forces. These forces, defined as the self-reinforcing economic and social benefits stemming from the clustering of populations and economic activities in specific areas (Thisse, 2010), foster economies of scale and provide firms with spatial-specific comparative advantages (Fujita et al., 1999). These advantages encompass both tangible and intangible benefits. Tangible advantages include access to larger local labor and consumption markets, while intangible ones are exemplified by “localized knowledge spillovers” that act as Marshallian externalities (Breschi and Lissoni, 2001; Krugman, 1998). Historical evidence highlights the pivotal role of geographical factors in amplifying these forces, particularly in coastal areas and cities located near waterways. Such regions benefit from easier trade access, abundant natural resources, and amenities that fuel their growth more rapidly than their inland counterparts (Glaeser, 2010; Krugman, 1992).

However, the strategic positioning of these cities along coastlines and river deltas also exposes them to exacerbating climate risks. Many of the world's largest urban areas find themselves in low-lying regions that are directly in the potential pathway of flood hazards and sea-level rise (Barragán and de Andrés, 2015; Nicholls et al., 2021). As these risks amplify, the scientific community is confronted with a pivotal challenge: How will coastal societies, particularly those undergoing rapid urban growth, navigate and adapt to the increasing threats of climate-related flooding? To enhance our understanding of this, this dissertation delves into the complex interplay between climate shocks, shifts in regional economies, and societal response.

Flood risk, as defined in the literature, encompasses the potential damage a flood event can inflict multiplied by its probability, taking into account both the direct and indirect consequences they impose (IPCC, 2022b).

Direct damages are immediate and tangible, encompassing physical destruction such as ruined buildings, damaged infrastructure, and the obliteration of natural habitats. These damages can often be evaluated quantitatively by assessing the cost of restoration, repair, or replacement (Hallegatte et al., 2013; Merz et al., 2004). The consequences are visible immediately following the flood, leaving a clear trail of wreckage in its wake. Conversely, indirect damages are more elusive, typically arising as a series of socio-economic disturbances rippling through time. A primary example is unemployment, which can surge following a flood event due to disruptions in local businesses and industries. Floods may render places of work inoperable or even entirely destroyed, leading to layoffs or business failures (Hallegatte, 2008a). Furthermore, ongoing safety concerns in flood-affected areas might drive outmigration, leading to population decline and the associated socio-economic effects on community vitality and local economies (Deryugina et al., 2018).

These indirect consequences can extend far beyond the immediate area of the flood, creating knock-on effects at regional, national, and even global levels. For instance, the disruption of local industries can have cascading impacts on global supply chains, particularly in our increasingly interconnected world economy. For instance, a local flood in a key manufacturing area could disrupt production and deliveries, affecting businesses and consumers thousands of miles away (Rose, 2004). This necessitates a broader, macro-level comprehension of flood risks and impacts (Koks et al., 2015, 2019).

The degree and intensity of flood risks are significantly shaped by climate change adaptation (CCA) strategies implemented by either public or private entities (Adger et al., 2011; Fankhauser et al., 1999; Mendelsohn, 2000). Such strategies are specifically designed to mitigate the harm caused by climate hazards and broadly fall into two primary categories: incremental and transformational adaptations (Kates et al., 2012; Wilson et al., 2020).

Incremental adaptation refers to modifications that improve efficiency within existing systems to cope with expected changes in climate (Biesbroek et al., 2017). These changes can include structural adjustments, such as a public intervention to improve the sewage system or gradually increase strengths of flood defenses, and private households replacing the ground floor with water-resistant material or installing door water barriers, both of which fit within existing technological, governance, and value systems.

In contrast, transformational adaptation involves a fundamental shift that alters the core attributes of a system in response to climate change and its impacts (Kates et al., 2012).

These changes can include large-scale or intense actions, the introduction of new structures or systems, or reimagining existing systems innovatively (Desai et al., 2021; Fedele et al., 2019). An example of such adaptation is relocation, which represents a profound changes in lifestyle and may lead to the abandonment of previously established structures. Relocation can manifest autonomously, initiated by households themselves, or be induced/forced through governmental directives (Haasnoot et al., 2021). The choice between incremental and transformational adaptations often depends on the specific context, such as the severity of the climate change impacts, the capacity for adaptation, and the overarching goals of the actors involved (Wilson et al., 2020). Importantly, both incremental and transformational strategies unfold at different scales, weaving together top-down government initiatives and bottom-up actions by private individuals (Kahn, 2016). Crucially, even incremental actions smaller in scale can become transformative when adopted widely across communities, cities, or nations (Wilson et al., 2020). Thus, a crucial step to addressing rising flood threat lies in understanding what drives national adaptation (Noll et al., 2022b; van Valkengoed and Steg, 2019) and managing the interactions across scales - individual, community, regional, and global - of different CCA strategies as actions or inactions at one level can profoundly affect outcomes at others, sometimes in unexpected ways (Adger et al., 2005; Collenteur et al., 2015).

1.2 Adaptation strategies for a changing climate

The quantitative methods for analyzing public CCA primarily adopt an economic lens. This approach typically involves conducting cost-benefit analyses (CBA) to assess public CCA policies, by comparing the costs of their implementation and maintenance against the aggregate damages they could potentially prevent (Vousdoukas et al., 2020). The methods used were often based on Computable General Equilibrium (CGE) models, aiming to capture the economic interdependencies and sectoral impacts of climate change (Bosello et al., 2010; Stern, 2016). The focus was largely on top-down public protective measures—planned government-led adaptation embarking on large-scale infrastructural projects like erecting sea walls (Kondrup et al., 2022). These actions, consisting primarily of engineering solutions, have been regarded as the front line of defense against the escalating onslaught of climate-related events (Mechler et al., 2014).

In light of the dynamic and uncertain nature of climate change and its effects, adaptive policy pathways have been introduced as an addition to those methodologies. Adaptive pathways provide a flexible framework that considers multiple plausible future scenarios and allows for iterative decision-making and adjustment of adaptation strategies over time (Haasnoot et al., 2013).

However, as the understanding of climate change deepened, so did the realization that CCA is not merely an economic or engineering problem. It's a complex societal challenge with deep roots in human behavior, societal norms, and institutional structures (Noll et al., 2020; van Valkengoed and Steg, 2019; Wilson et al., 2020). Consequently, the scientific community has advanced in significant ways to better understand and address this complexity (Fedele et al., 2019).

For instance, the acknowledgment of the far-reaching consequences of our actions, has led scholars to an intensified exploration of feedback loops and potential maladaptation. An example is the “levee effect,” where the introduction of flood protection measures, like levees, paradoxically leads to increased development in flood-prone areas, thus potentially amplifying the risk and consequences of future floods (Di Baldassarre et al., 2013, 2015). This realization underscores the need for a systemic view of adaptation, acknowledging that actions at one point can have unintended consequences elsewhere, demanding an integrated, whole-systems approach to CCA.

Furthermore, an important progression in CCA research is the shift towards "autonomous adaptation," emphasizing individual actions. Using surveys and game experiments, researchers have explored how individuals respond to climate adversities (Hudson et al., 2019; Noll et al., 2020). This bottom-up perspective complements top-down interventions, offering a comprehensive view of societal responses to climate change. However, a significant gap exists: many models assessing autonomous CCA uptake don't adequately account for the rich behavioral complexity. Factors like risk perception, social norms, and cognitive biases deeply influence decision-making (Berrang-Ford et al., 2021). Thus, moving away from oversimplified assumptions of perfect rationality and including empirical-grounded behavioral theories for adaptation actions is essential.

Another notable challenge lies in the distributional impacts of adaptation. Specific adaptation measures can have varying impacts on different groups, raising questions about social equity and justice(Walsh and Hallegatte, 2022). Climate change does not affect all members of a community in the same way, nor do they all have the same resources and capacities to adapt (Field et al., 2012). Unpacking these nuances is critical to ensuring that CCA strategies do not inadvertently exacerbate existing social inequalities.

In general, a research gap still persists in providing an integrated understanding of the complex interactions between climate change, economic forces, and societal responses. Climate change not only influences our physical world but also interweaves with social and economic structures at all levels. Our understanding of these interconnections and their implications remains incomplete. A more comprehensive analysis, considering the interconnected nature of climate change, societal behavior, and economic systems, is crucial. Such a comprehensive and interdisciplinary approach could enhance our understanding of the intricate dynamics of climate adaptation, ultimately contributing to more resilient and sustainable societies.

1.3 State of the art in the economics of climate change adaptation

1.3.1 Economic approach for flood damages estimation

In light of escalating climate change conditions, the frequency and intensity of flood-induced damages are projected to rise. Researchers typically classify these damages into two main categories to encapsulate the overall economic impact of floods.

- Direct damages: These encompass losses inflicted upon humans, property, assets, and other elements within areas physically affected by the flood. Estimation of these damages generally involves employing a hydrological model overlayed with a land-use model, with the extent of the damages contingent upon factors such as water depth, salinity, speed, and the flood damage curve - a measure reflecting the percentage of losses in relation to the severity of the flood (commonly approximated by water levels) (Di Baldassarre et al., 2013; Merz et al., 2004).

- Indirect damages: These losses, which can occur both within and outside the flooded area, stem from direct costs and business interruptions triggering a cascade of "upstream" and "downstream" economic reactions impacting suppliers and customers. These ripple effects disrupt economic flows, transmitted via the interconnected channels within the economic system. It's crucial to note that these indirect damages can outweigh direct damages, underlining their significance in the overall impact assessment of flood events (Hallegatte, 2008a; Hallegatte et al., 2022; Koks et al., 2019).

The scientific community utilizes various methods to estimate damages, including statistical/econometric techniques, CGE models, and I-O models (Botzen et al., 2019). Surveys and econometric models provide accurate estimates when quality post-event data is available. However, only I-O and CGE models can trace effects across the economic spectrum (Koks et al., 2019). I-O models depict industry relationships but are constrained by their linearity and price insensitivity (Botzen et al., 2019; Galbusera and Giannopoulos, 2018). Conversely, CGE models are non-linear, price-responsive, and account for disaster-specific dynamics, relying on relationships among various goods and services to trace shocks (Botzen et al., 2019; Carrera et al., 2015). Both methodologies require a two-step analysis, focusing first on direct damages and then on their ripple effects throughout the economy. However, such an aggregate approach can overlook details on the heterogeneity of impacts, ripple effects stemming from individual interactions or private CCA strategies, highlighting the need for refined models to better understand flood damages and their socio-economic implications (Jongman et al., 2012; Walsh and Hallegatte, 2022).

1.3.2 Spatial Economics, agglomeration forces and climate change

The extent of damages from natural hazards is heavily connected to the total amount of people and assets at risk in the affected location, also defined in the literature as exposure (IPCC, 2022b). Notably, the latter is deeply connected to the choices made by households and firms concerning where to consume and produce, and the interactions that subsequently occur, topics that traditionally have been somewhat overlooked by economists. This changed around 1990 with the emergence of "New Economic Geography" (NEG), which became a significant aspect of economic theory (Thisse, 2010). NEG asserts that households and firms select locations relative to each other, creating spatial externalities and spillover effects that can either stimulate or undermine the economy (Mossay and Picard, 2020).

NEG emerges from a modeling framework introduced by Dixit and Stiglitz in 1977, which is known for its applications to trade theory (Krugman, 1998). The resulting models assume a general equilibrium across multiple markets (including labor, resources, and land) with economic agents - firms and households - seeking to maximize their profits or utility within budget constraints related to both finances and resources. The NEG frameworks describes a cumulative process where market size and cost-of-living effects operate in a way that promotes the agglomeration of industry in a specific region. As this region grows, the market expands, attracting more industry and qualified labor - an effect known as *market access* (Behrens et al., 2014). Moreover, as the market expands, more differentiated varieties are produced, leading to a decrease in the regional price, which in turn increases real wages, known as the *price index effect* (Fujita and Thisse, 2013). These forward and backward linkages generate an agglomeration, or centripetal, force (Thisse, 2010). The agglomeration process, however, yields more than just the centralization of industries and labor. It gives rise to Marshallian externalities from firms sharing a pool of resources and specialized labor as well as inter-firm learning that amplifies innovation due to knowledge spillovers (Breschi and Lissoni, 2001; Thisse, 2010). On the contrary, a more concentrated market can enhance price competition, acting as a dispersion or centrifugal force, referred to as a *market crowding effect* (Krugman, 1998).

Nonetheless, as trade barriers decrease, the largest country's export hurdles also decrease because firms can take greater advantage of scale economies, promoting agglomeration and discouraging dispersion. Thus, the level of transportation costs is a key determinant of industry spatial distribution. Therefore, unlike the neoclassical model predicting only spatial convergence, NEG accounts for both convergence and divergence, indicating a circular two-way feedback between individual agents' location choices and the spatial landscape (Head and Mayer, 2019).

Significant advancements have been made following Krugman's landmark Nobel-prize winning work, which considered two symmetric regions and two industries (Krugman, 1991). Subsequent developments involved a new interpretation of the Von Thunen model, in which the existence of a central city was derived endogenously rather than merely assumed (Fujita and Krugman, 1995). The same model was used to investigate the emergence of new cities in a one-dimensional space economy with a gradually increasing population (Fujita and Mori, 1996a). Adding to this, multiple manufacturing industries with varying scale economies and transport costs were introduced to showcase the spontaneous development of central places (Fujita et al., 1999). Notably, further work highlighted the significance of ports or other types of transportation nodes in triggering agglomeration forces and hence the emergence of major cities along coastline and delta rivers (Barragán and de Andrés, 2015; Fujita and Mori, 1996a).

While the contributions of NEG to our understanding of spatial economics and agglomeration forces are substantial, its applications to contemporary challenges such as climate change remain limited. As we transition into the "new normal," the interplay between agglomeration dynamics and climate change, as seen in coastal urbanization phenomena, underscores the need to elucidate how these two aspects mutually influence one another (Kim et al., 2021).

However, the traditional NEG models, rooted in general equilibrium dynamics, face a formidable challenge when grappling with the non-linear and inherently unpredictable characteristics of climate phenomena. Their analytical elegance, while valuable for tractability, often entails a simplification of the world's complexity that may not fully capture the realities of a rapidly changing climate and the resulting economic implications.

It is, therefore, crucial to develop modeling approaches capable of navigating out-of-equilibrium conditions and comprehensively accounting for the uncertainty of the changing climate, even in situations characterized by imperfect or incomplete information (Commendatore, 2015). Such models would offer a more precise depiction of the complexities involved in the intersection of climate change, CCA, and agglomeration forces, paving the way for a more profound understanding of these multifaceted relationships.

1.3.3 Autonomous climate change adaptation

Nearly three decades ago in 1990, the IPCC prepared the first comprehensive report on climate change. A critical aspect of this report highlighted the role of autonomous adaptation (individual actions) as a necessary supplement to public adaptation (governmental actions and policies) (Berrang-Ford et al., 2021). Misunderstanding individual responses can result in counterproductive government policies (Di Baldassarre et al., 2015; Mechler et al., 2014), and conversely, misinformed decisions by individuals can amply existing risks. Nevertheless, with an accurate understanding of individual perceptions, actions, and motivations, the combination of private and public adaptation measures can create positive externalities that enhance systemic resilience (Adger et al., 2005).

Recent developments in the field of disaster-risk and climate-change adaptation have spotlighted the significant roles that autonomous adaptation and social vulnerability play in determining disaster risk and its impacts (Field et al., 2012). These areas have previously been overlooked, largely due to the intricate nature of human behavior and risk perception, and the inherent challenges in quantifying these elements for numerical assessments.

One key advancement in this realm is the exploration of household-level autonomous adaptation measures. Households exhibit a range of strategies, acting independently from governmental interventions, to mitigate their exposure or vulnerability to flood risks. These measures, can be categorized into distinct types, each representing a specific approach to flood risk reduction. The categories include:

- *Structural Measures:* These measures involve modifications to the physical structure of the home or property to reduce the risk of flooding. Structural measures can be further classified into:

  - *Dry-proofing:* This refers to measures that prevent floodwater from entering the building. Techniques may include sealing walls and floors, installing flood shields or barriers, and using waterproof coatings.
  - *Wet-proofing:* These are measures that allow floodwater to enter the building but aim to minimize the damage. This can be achieved through the use of flood-resistant materials, installation of drainage systems, and creation of flood vents.
  - *Elevation:* This entails raising the building above the flood level to prevent floodwater from entering. Methods include elevating the foundation, building on stilts, or using raised platforms.

- *Non-structural Measures:* These measures do not involve modifications to the physical structure of the home or property, yet they aim to reduce the risk of flooding. Actions in this category might include creating an emergency plan, monitoring weather forecasts, and participating in community flood planning.

- *Insurance:* This involves purchasing flood insurance to protect against the financial impacts of flooding.

- *Relocation:* This involves moving to a safer area to reduce exposure to flood hazards. Actions under this category include managed retreat, where communities relocate to safer areas, and buyouts, where property owners are compensated for relocating.

Notably, researchers employ various methods to understand individual-level behavior, including surveys, experiments, ethnographic fieldwork, and games. Resulting empirical evidence significantly reveals that household CCA actions are not purely guided by rational economic reasoning (Duijndam et al., 2023; Noll et al., 2022b; van Valkengoed and Steg, 2019). Many households tend to under-invest in measures that protect their property from floods, even when these adaptations would be economically beneficial (Bubeck et al., 2012). This finding challenges the conventional assumption of perfect rationality of Expected Utility theory that is widely adopted in models simulating households' CCA actions. As such, the empirical evidence suggests that these models, and their resulting outcomes, may need to be reconsidered in light of this more nuanced, bounded rational behavior.

Conversely, researchers highlighted the importance of various socio-behavioral drivers that affect household decision-making processes. These drivers, often more influential than cost-effectiveness analyses, are mainly drawn from the field of environmental psychology (Noll et al., 2022b):

- *Risk Perception*:
  - *Perceived Probability*: How likely individuals believe a flood event might occur.
  - *Perceived Damages*: The extent of damage individuals believe a flood might inflict on their property or community.
  - *Worry*: Concern or worry about the potential impacts of flooding and climate change can motivate households to take adaptation measures.
- *Self-Efficacy*: The belief in one's ability to successfully implement adaptation measures can drive households to take action to protect themselves from flooding.
- *Response Efficacy*: This relates to individuals' beliefs that the measures they take will effectively reduce the threat or mitigate the impact of the flood.
- *Perceived Costs*: The perceived financial costs associated with adaptation measures can impact households' decisions to undertake specific actions.
- *Social Influence*: The influence of social networks, neighbors, and community norms can play a significant role in shaping household adaptation to flooding.
- *Climate Change Beliefs*: The beliefs and perceptions that households hold about climate change and its connection to flooding can influence their adaptation decisions.
- *Trust in Government*: Confidence in public entities and their CCA initiatives.

These factors offer insight into the "soft limits" of CCA and improve our understanding of adaptation constraints. One relevant theory that incorporates these elements is the Protection Motivation Theory (PMT). It studies risky choices as a two-stage procedure – risk appraisal and coping appraisal – and acknowledges multiple factors affecting risk perception, influencing the decision-making process (Rogers, 1975). Research employing PMT in flood-risk management (Bamberg et al., 2017a; Botzen et al., 2020; Bubeck et al., 2012; van Valkengoed and Steg, 2019) indicates that individuals implement adaptation measures if they perceive a high threat from the hazard (threat appraisal) and believe that the available protective measures are effective (response efficacy), easy (self-efficacy), and affordable (response costs). Also, individuals' risk perception is influenced by their interactions with both natural (flood experience) and social (social networks) environments (Noll et al., 2022b).

Recent advances in autonomous CCA research have illuminated the intricate web of factors influencing individual and household adaptation behaviors. It has become increasingly apparent that such complexity must be mirrored in models used to evaluate the impact of CCA strategies. Incorporating these multifaceted aspects allows for a more nuanced understanding and realistic representation of real-world adaptation behaviors and their outcomes. Meanwhile, the exploration of other significant actors, such as firms and their relationships with households, remains largely uncharted territory. Through a comprehensive understanding of these dynamics, we can devise more effective, context-specific adaptation strategies. Ultimately, this deeper insight will contribute to enhancing societal resilience, better preparing communities for the uncertainties and challenges posed by climate change.

1.3.4 Socio-economic Resilience

The Resilience Alliance defines resilience as *"the capacity of a social-ecological system to absorb or withstand perturbations and other stressors such that the system remains within the same regime, essentially maintaining its structure and functions. It describes the degree to which the system is capable of self-organization, learning and adaptation"* (Holling, 1973; Holling and Gunderson, 2002; Walker et al., 2004). Similarly, viewed from the perspective of complex adaptive systems (CAS), signifies the *capability to absorb a shock, cope with it, learn, adapt, and self-organize during recovery to maintain long-term development despite adversities* (Folke, 2006; Mochizuki et al., 2018). This perspective encompasses the traditional risk framework focused on coping and the evolution of projected damages through adjustments in probability, exposure, and vulnerability. Nevertheless, resilience goes beyond this by considering the long-term consequences on the socio-economic system, the distribution of risks across different actors, and how these factors elicit their behavioral responses. Stakeholders can learn and adapt, changing their behavior incrementally or drastically, possibly leading to a collective reorganization of societal institutions. This dynamic results in varied paths and speeds of recovery.

Notably, the resilience of a SES is a flexible concept that continues to evolve in line with ongoing research as highlighted by the 2014 definition given by the Zurich Flood Alliance which defines it as *"the ability of a community, system, or society to pursue its development and growth objectives while managing flood risk over time in a mutually reinforcing way"* (Khamis, 2018; Linkov et al., 2014).

More than a hundred studies attempt to operationalize resilience, but only a few of these have empirically verified it (Crowe et al., 2016). Most are based on indices that they believe serve as good proxies for measuring resilience from different perspectives. Alternatively, resilience can be defined as a latent property that is only revealed ex-post after a baseline is established and impossible to define ex-ante (Keating et al., 2017). With a vast body of work already done in creating numerous categories and indicators, cross-scale empirical testing is the next step in validating the credibility of many of these indices (Bakkensen et al., 2017).

Risk assessments are frequently employed to test resilience indicators. Traditional components of risk assessments (hazard, exposure, and vulnerability) might not sufficiently elucidate the capacity of affected populations to cope with and recover from a disaster. To address this, a fourth component, socio-economic resilience, has been introduced to measure how asset losses affect well-being losses (Walsh and Hallegatte, 2019). The World Bank defines well-being losses such that "$1 of well-being losses affects a rich and a poor individual equally" and simulation results in the Philippines shows that the well-being losses following a disaster would be US$3.9 billion, 170% more than asset losses (US$1.4 billion). This is a crucial step in understanding how the risk burden is distributed among different actors. For example, households with different socioeconomic statuses will be impacted differently by the same asset losses. In the aftermath of a disaster, wealthier households will have access to savings or other sources of income, while poorer households may have to reduce their consumption or their basic needs to cope with losses (i.e., repair costs). It's critical for disaster risk strategies and budgets to consider this difference to prevent the most vulnerable populations from bearing a disproportionate share of flood-induced risks.

Resilience is often strongly associated with two other terms: vulnerability and adaptive capacity. While vulnerability underscores the exposure and difficulty experienced by individuals, families, communities, and countries in handling shocks, risks, and other contingencies, adaptive capacity stands as a counterpoint, representing the resources and skills that these entities possess to respond to changes (IPCC, 2022b). Adaptive capacity, in the context of climate change, refers to the ability of a system, region, or community to adjust to the effects or impacts of climate change (Brooks and Adger, 2005). It serves as a gauge of potential resources, encapsulating financial capacity, human capital, and available adaptation options that can be harnessed to tackle environmental and socio-economic shifts (Adger and Vincent, 2005). Importantly, the strength of adaptive capacity can vary between different risks and sectors. For instance, a region adept at handling floods may struggle when confronted with heatwaves (Cinner et al., 2018). Assessing adaptive capacity involves a range of socio-economic indicators including income levels (e.g., GDP), educational attainment, availability of impact data, emergency response capabilities, business continuity plans, and the overall adaptation strategies in place. This holistic evaluation provides a readiness overview of a system, community, or region in adjusting to the impacts of climate change (Brooks and Adger, 2005; Cinner et al., 2018). Building and enhancing adaptive capacity is pivotal in the face of climate change. It facilitates the development of resources and assets that can be used to adapt to future circumstances, and, along with hazard, exposure, and vulnerability, contributes significantly to the overall risk associated with climate change. Therefore, bolstering adaptive capacity is not just about overcoming current challenges but also about preparing for future uncertainties.

1

1.3.5 Complexity methods to capture adaptation in an economy

Traditional literature on flood risk and CCA has largely adopted the neoclassical economic framework. This paradigm posits representative agents that are perfectly rational and equipped with complete information. However, these assumptions fall short of effectively encapsulating the complexities of behavioral change, biases, risk perception, and adaptation actions that empirical research has shown to affect human behavior under risk. The models derived from this neoclassical perspective tend to struggle when dealing with heterogeneity and interactions among agents and addressing the evolutionary dynamics of temporal phenomena. This limitation underscores the need for a more nuanced approach capable of capturing the intricacies of real-world decision-making and the evolutionary nature of socio-economic systems.

In this context, Agent-Based Models (ABMs) have emerged as the key methodology for tackling these challenges (Arthur, 2021; Axtell and Farmer, 2022; Tesfatsion and Judd, 2006). ABMs are computer simulations that model the behavior of individual agents and their interactions with each other and their environment (Axtell and Farmer, 2022). They have proven instrumental in probing the complexities of environmental, social, and economic systems for several reasons:

- *Bounded Rationality*: ABMs effectively incorporate the concept of boundedly-rational behavior into their modeling of human responses to environmental risks. Moving away from traditional models that assume perfect rationality, ABMs instead capture more realistic decision-making processes that take into account the behavioral biases derived from theories in environmental psychology. This inclusion of boundedly-rational behavior enhances the precision and real-world applicability of simulations, thereby bridging the gaps identified in conventional damage assessments and climate change adaptation strategies (Schwarz et al., 2020; Stern, 2016).

- *Heterogeneity and interactions*: ABMs excel in simulating heterogeneity among and within classes of stakeholders, capturing unique perspectives and behaviors in response to flood risks. The models accommodate not just a variety of stakeholders, but also recognize behavioral differences within the same group. They account for diverse risk tolerances, adaptive capacities, and social influences. Moreover, ABMs integrate intricate social interactions including aspects of competition, cooperation, influence, and learning. Alongside, they reflect agent-environment interactions, which capture dynamics like responses to changing conditions and feedbacks (Axtell and Farmer, 2022; Filatova et al., 2013). This multi-faceted approach provides a nuanced understanding of flood risk scenarios, enriching the uniformity of traditional models.

- *Learning and adaptation behavior*: In the absence of perfect information about the future and the actions of others, agents form expectations and make decisions with imperfect sometimes asymmetric information, learn on a go as the simulation unfolds and consequently adapt their behavior (Axtell and Farmer, 2022; Farmer et al., 2015; Filatova et al., 2013).

- *Path dependency and non-linearities*: ABMs are able to capture evolutionary intertemporal and path-dependent phenomena (Bell et al., 2012), as well as non-linear dynamics that can lead to system tipping points (Abdulkareem et al., 2018; Filatova et al., 2016), aspects that traditional models often ignore or inadequately represent. Given that decisions on relocation, building adaptations, or mitigation strategies have long-term implications, are often influenced by past experiences, and can result in non-linear responses (Balint et al., 2017).

- *Empirical data*: ABMs are particularly well suited to be calibrated with individual data such as surveys. This characteristic allows ABMs to be anchored in empirical evidence, applying observed patterns to theories and models. It offers a significant advantage over traditional models, enhancing the practical applicability and accuracy of the simulations (Coronese et al., 2022; Monti et al., 2023; Troost et al., 2023).

- *Macro-level impact from micro-level decisions*: ABMs uniquely bridge the micro-macro gap (Tesfatsion and Judd, 2006), for example by aggregating individual autonomous adaptation choices and simulating the resultant macro-level effects. This provides insights into how individual actions cumulatively impact systemic resilience against flood risks, a pivotal feature that traditional models often fall short of addressing .

Given the multifaceted nature of flood risks and the critical role of accurate simulations of individual behaviors and societal dynamics, ABMs present the best suited and relevant framework for understanding climate-induced systemic vulnerabilities, and formulating effective related climate change adaptation strategies (Aerts et al., 2018; Taberna et al., 2020).

1.3.6 State of the Art in ABMs

The use of ABMs has become increasingly pervasive in academic research concerning complex socio-economic and environmental phenomena (Coronese et al., 2022; Filatova et al., 2013). These studies, often characterized by their interdisciplinary nature, can simultaneously contribute to multiple research areas. In this section, I delineate the state of the art in ABMs, focusing on the central topics of this thesis: climate and spatial economics, resilience, and climate change adaptation. It's worth noting that many of these works could be assigned to multiple domains, reflecting the interconnectedness of these fields.

climate economics

Given the inherent complexities and path-dependencies associated with climate phenomena, conventional economic models frequently exhibit limitations. This has led to the escalating application of ABMs in the realm of climate damage assessments over recent years. Illustrating this, ABMs have been increasingly used as innovative instruments to probe climate change mitigation strategies, underscoring their capacity to encompass non-linear dynamics traditionally excluded from conventional models (Lamperti et al., 2018, 2019b).

While studies incorporating sector-specific climate damages into ABMs exist, focusing on areas such as stranded assets, policy risks in the financial sector, and impacts on housing markets in flood prone areas and on agriculture (Coronese et al., 2021; Filatova, 2015; Gawith et al., 2020a; Monasterolo et al., 2019), the full potential of ABMs remains underexplored. Still, a broader investigation is essential to develop a thorough understanding of the economics of climate damage assessments. This inquiry must account for the significant heterogeneity both within and across sectors, given its profound influence on the scale and nature of climate damages (Coronese et al., 2022).

Spatial Economics

ABMs have become an integral part of the field of spatial economics. Simulation models have been successful in replicating the outcomes of landmark urban models like Alonso, Mills, and Muth, but in a dynamic framework (Lemoy et al., 2010). Subsequently, these models have advanced the state-of-the-art by adding features not analytically tractable such as multi-job centers and multi-worker households or specific location characteristics such as the relationship between amenities and disamenities with land cost or flood risk (Filatova, 2015; Filatova et al., 2009; Lemoy et al., 2017; Olner et al., 2015).

The application of ABMs in spatial economics is not limited to these aspects; they also extend to simulating urban land growth. Examples include accurate representation of China's urban-rural migration structure (Fu and Hao, 2018), and residential expansion (Li et al., 2019).

Moreover, ABMs have served to capture interactions among heterogeneous agents, a key element often overlooked in new economic geography (Ottaviano, 2011). Such models are consistent with the evolutionary economic geography tradition (Boschma and Frenken, 2006; Frenken and Boschma, 2007; Martin and Sunley, 2007), demonstrating how stochastic exchanges of knowledge and innovation can generate new market opportunities and catalyze agglomeration.

Yet, there remains a noticeable gap in representing firms' and households' dynamic location choices within a complex spatial environment, suggesting the need for future research (Fowler, 2007).

Climate Change Adaptation

The ability of ABMs to incorporate spatial data has made them very suitable for combining flood hydrological models into socio-technical systems, allowing for a nuanced understanding of the relationship between natural processes and socio-economic adaptation dynamics (Aerts, 2020; de Ruig et al., 2019).

Furthermore, ABMs have pioneered an approach that includes individual adaptation actions in conjunction with traditional top-down interventions. This innovative focus has specifically allowed for the integration of household-level responses to flood risks, shedding light on the dynamic interplay between individual actions and overarching intervention measures (Haer et al., 2020; Michaelis et al., 2020a).

In the context of housing markets, ABMs have facilitated a deeper understanding of the interplay between flood risks, relocation dynamics, and house prices uncovering intricate feedback loops that highlight risks of gentrification and provide valuable insights for policy development (de Koning and Filatova, 2019; Filatova, 2015). Nonetheless, despite these advancements, there is still significant room for further exploration and refinement of ABMs within the field of climate change adaptation, especially when examining the integration and interaction of various stakeholders' adaptation strategies within broader socio-economic systems.

Resilience

In the field of resilience, ABMs have made substantial contributions, advancing our understanding of complex, adaptive systems and their responses to shocks. Particularly, this line of work centered around the ability of socio-economic systems to recover from disturbances, whether economic, environmental, or otherwise.

For example, simulation models have been employed to study the vulnerability of households to flooding, highlighting individuals' ability to cope with damages and rebuild their assets as crucial factors for socio-economic resilience (Walsh and Hallegatte, 2019, 2022). Furthermore, learning capacity and adaptation behavior have also been underscored as critical to enhance systemic resilience against disturbances (Janssen and Ostrom, 2006). Additionally, another stream of research using ABMs focuses on the role of system connectivity in the resilience of socio-ecological systems, providing insights on how system components' interconnections affect its shock-absorbing capacity (Baggio et al., 2016). However, the multifaceted and elusive nature of resilience remains, indicating the need for continued exploration in this field.

1.4 Research gaps

In recent years, the scientific community has experienced a surge in the application of ABMs for studying various aspects of flood risks, incorporating the simulation of diverse boundedly-rational agents. However, transitioning from a representative rational actor, typical in climate policy models, to behaviorally-rich agents that interact, learn, and adapt, presents a complex challenge (Stern, 2016).

Despite this proliferation, a gap exists in the form of a comprehensive **systematic review** that evaluates the advancements and shortcomings in employing **ABMs** to probe the dynamics of **flood risk** and adaptation assessments. An in-depth review would be instrumental in establishing the current state of the art in ABMs for flood risk and identifying future directions in the literature.

One of the critical points emerging from the current state-of-the-art of flood-ABMs is that a computation model able to capture the **agglomeration/dispersion** forces outlined by NEG in an **out-of-equilibrium** fashion is lacking (Boschma and Martin, 2007; Boschma and Frenken, 2006; Ottaviano, 2011). Current ABM research focuses on household location decisions under climate change and flood risks (Filatova, 2015; Hassani-Mahmooei and Parris, 2012). However, a similar investigation into firm behaviors, which are critical constituents of regional economies, is missing. Firms' responses to flood risks, such as adaptation investment decisions and location choices, can significantly influence the spatial distribution of economic losses and post-disaster recovery rates (Hallegatte et al., 2013; Surminski et al., 2018).

Furthermore, current ABMs often use **simplified**, ad hoc **decision-making** processes that inadequately reflect the complex nature of **human responses** to flood risks. This simplicity can overlook critical constraints in adaptation strategies, both hard (technical and financial limitations) and soft (institutional, socio-cultural factors) (Thomas et al., 2021). Emerging empirical findings from fields such as environmental psychology and behavioral economics reveal human responses to flood risks to be multifaceted, influenced by a wide spectrum of factors like affect (worry), social pressure, and perceived coping capacity (Noll et al., 2022b; van Valkengoed and Steg, 2019). Furthermore, the calibration of agent behavior in ABMs is typically based on expert judgments, despite the growing availability of primary data from surveys and other empirical sources (World Bank poll; 2021). The integration of such data would offer a more realistic depiction of human behavior and enhance simulation validity (Filatova et al., 2013).

Notably, comprehensive flood risk management involves not only individual CCA actions, but also large-scale, top-down interventions such as the construction of levees and dams, floodplain zoning, and financial aid schemes like subsidies or insurance. Although some computational models are gradually incorporating these interventions, their integrated, multi-scaled interaction is still not adequately represented. These interventions significantly shape the risk environment and influence stakeholder decisions, and their interplay across different scales can lead to complex outcomes. For instance, the implementation of flood defense infrastructure at a macro level may influence micro-level perceptions of flood risk and discourage individual protective actions (Kousky, 2017). Similarly, the availability of financial aid or subsidies could incentivize or disincentivize adaptation behaviors at different levels (Hudson et al., 2019). However, the complex web of **feedback loops** that arise from the interactions of these actions across different societal levels is currently underrepresented in ABMs. Therefore, a more inclusive and interaction-focused approach is needed to properly reflect the micro-macro dynamics in flood risk management.

Building on these considerations, a new generation of simulation tools can be unlocked through a comprehensive complex adaptive systems resilience approach. This approach needs to be firmly rooted in empirically backed social science theories and behavioral data. It must encompass a diverse array of stakeholders, and effectively map the heterogeneity of risk distribution and damages. Moreover, it needs to account for the dynamic behavior and institutional factors that drive the emergence of transformational climate change adaptation. Such an approach transcends the traditional risk framework that merely focuses on expected damages. Conversely, it should consider the consequences to the socio-economic system in the long run and how such consequences reflects agents' behavior. It acknowledges that actors can learn and adapt by changing their behavior incrementally or drastically, possibly by collectively reorganizing entire social institutions, leading to different pathways and speeds of recovery. This shift towards a resilience-centered perspective provides us with our best chance at fostering societies that develop and thrive despite the pressing challenges posed by climate change.

1.5 Thesis goal and research questions

The principal objective of this dissertation is to enhance the scientific comprehension of the intricate interplay among climate change shocks, regional economic dynamics, and societal responses including adaptation across scales. To achieve this, I propose the construction of innovative simulation tools capable of integrating the autonomous adaptation strategies of heterogeneous individuals within a regional economy. This work contributes to the emerging new generation of computational models that encapsulate risk and apply a resilience perspective to complex adaptive systems, and it is a crucial step in the direction of shaping robust and adaptation strategies to confront climate change, thereby fostering resilient societies.

To address the overarching goal of this thesis, I pose the following research questions:

1. What the advancements and gaps in employing ABMs to explore the dynamics of (flood) risk and adaptation assessments? What are the future literature directions?
2. How do agglomeration forces and technological change shape the evolution of economic centers in coastal regions? How do climate shocks of varying severity and probability interplay with such dynamics?
3. How does the interaction of financial constraints, socio-behavioral factors, and households' adaptive capacity shape regional patterns of adaptation diffusion and distributional economic impacts of hazards?
4. How do private CCA strategies and governmental subsidies affect regional development, fiscal stability, and CCA uptake under extreme flooding events?

1.6 Structure of this Thesis

Chapter 2 conducts an extensive review of the current state of the art in ABMs for flood risk, laying particular emphasis on the critical role human actors play in altering the risks and resilience in flood-prone urban environments. It explores the paradigm shift in climate risk assessments that has triggered a growing demand for computational models that explicitly portray societal dynamics and behavioral changes. Recognizing the complexities of substituting the traditional single representative rational actor with diverse, behaviorally-rich agents that learn, adapt, and interact in response to risks, the chapter explores how such dynamics are embedded into ABMs. In doing so, it reveals a heavy emphasis on households, while other influential entities such as the government, insurance bodies, urban developers, and firms - fundamental to regional resilience - are often oversimplified or entirely overlooked. The chapter further distinguishes between literature stemming from economics and social sciences and that from hydrology, each showing differential approaches to modeling bounded rationality. The chapter concludes by advocating for a complex adaptive system perspective centered on resilience as the way forward to improve our understanding of societal adaptation to climate-driven risks.

In **Chapter 3**, the theoretical foundation of the Climate-Economy Regional Agent-Based (CRAB) model is introduced. The CRAB model, which encapsulates an evolutionary agent-based approach, is designed to scrutinize the trade-offs between the economic benefits of urban agglomeration and the mounting risks induced by climate change, particularly coastal flooding and sea level rise. The model, representing heterogeneous, boundedly-rational economic agents, factors in their adaptive learning within a shifting environment. These agents, symbolizing both households and firms, make relocation decisions between safer Inland regions and hazard-exposed Coastal regions. The influence of variables such as transport costs and flood-induced damages to Coastal firms are carefully evaluated. The chapter explores five distinct flood scenarios with different frequencies and severities to analyze the complex interplay between climate hazards and agglomeration patterns, and their impact on the macroeconomic performance. The findings reveal the potential for severe economic downturns in situations where economic activities are locked in hazard-prone areas due to sudden escalations in flood hazards.

Chapter 4 illustrates a novel version of the CRAB model, introducing autonomous household adaptation behaviors parameterized using surveys data from Miami, USA. The work in this chapter challenges the prevailing dominance of the representative rational agent in sustainability science models, highlighting the significant adaptation deficit when assuming rationality compared to the boundedly-rational choices revealed in surveys. It underscores that this discrepancy is driven by economic heterogeneity and, in particular, by alternative decision heuristics that account for behavioral diversity and social influences. The analysis illustrates how varied adaptive capacity and uneven adaptation uptake can exacerbate inequality and undermine resilience. Particularly, it emphasizes that households with low capacity and less effective adaptations experience extended recovery periods following floods. The exploration of uncertainty indicates that behavioral assumptions significantly influence the importance of physical factors like exposure and the effectiveness of flood-proofing measures.Ultimately, the chapter demonstrates the utility of integrating agent-based and exploratory modeling for assessing the cumulative and distributional effects of boundedly-rational behavior, which is crucial for climate change adaptation and for ensuring equitable sustainability transitions.

In **Chapter 5**, a new version of the CRAB model is introduced, featuring a risk layering strategy that includes a variety of CCA measures from individual risk reduction to insurance and subsidies. The enhanced model, richly informed by extensive behavioral data, bridges the gap in flood risk modeling by addressing both direct and indirect damages, such as business interruption and diminished tax revenues. The CRAB model depicts a dynamic and rapidly expanding economy with interacting households and firms, subjected to extreme flood events. This framework allows for the delineation of feedback loops and cascading effects caused by flood shocks within a socio-economic system of boundedly-rational agents. Loosely calibrated to the context of Shanghai, China, the work in this chapter shows the effectiveness of synergistic adaptation actions at all levels in combating the increasing climate threat. The integration of localized risk management with top-down strategies in the model provides crucial insights into creating climate-resilient societies by addressing direct and indirect risks effectively.

Chapter 6 encapsulates the key findings from Chapter 2-5. It provides a synthesis of these findings, discusses their implications for climate change adaptation policies and practices, and reflects on the evolution of the CRAB model and its potential future developments. The chapter concludes with suggestions for future research and a final reflection on the significance of this research in the context of global climate change.

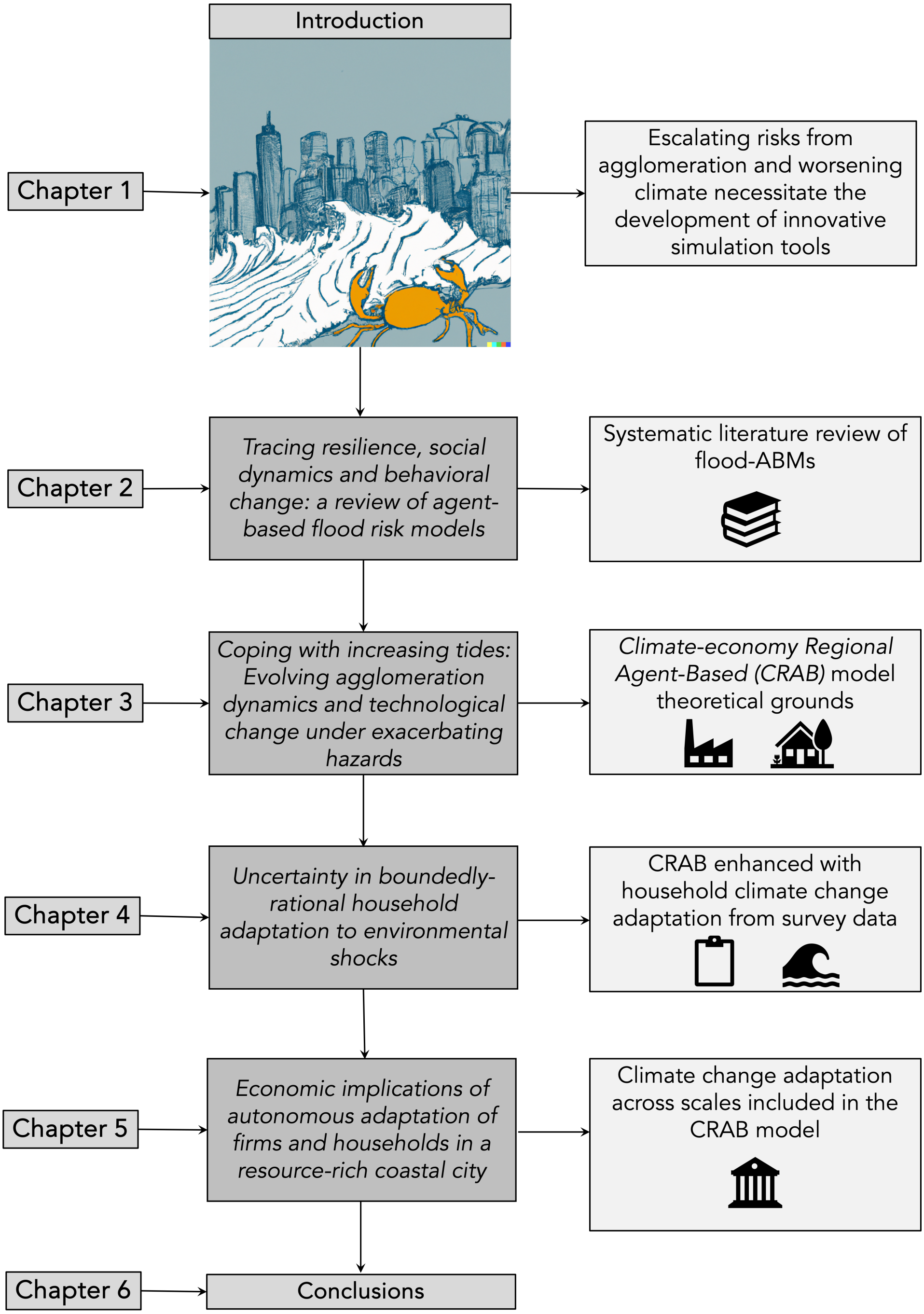

Figure 1.1: The visual representation of this dissertation.

2

Tracing resilience, social dynamics and behavioral change: a review of agent-based flood risk models

Climate change and rapid urbanization exacerbate flood risks worldwide. Recognizing the crucial role that human actors play in altering risks and resilience in flood-prone cities has triggered a paradigm shift in climate risk assessments. This shift has driven the proliferation of computational models with explicit representation of societal dynamics and behavioral change, which increasingly simulate adaptation, learning, recovery and reorganization essential for tracing the evolution of resilience rather than only risks. Yet, replacing a single representative rational actor, dominant in climate policy models with various behaviorally-rich agents that interact, learn, and adapt, is not a straightforward feat. Focusing on the costliest climate hazard, flooding, we review computational agent-based models that include behavioral change and societal dynamics. We distinguish between two literature streams: one stemming from economics & behavioral sciences and the other from hydrology. Our findings show that most studies focus on households while representing other agents (government, insurance, urban developers) simplistically and entirely overlooking firms' choices in the face of risks; a key to a resilient regional development. The two streams vary in the extent they ground the agents' design in social theories and behavioral data when modeling bounded rationality, a core component in computing adaptation and learning decisions. While both streams aspire to trace feedbacks that agents collectively instigate, they employ different learning mechanisms and, therefore, dissimilar interactions when computing societal dynamics in the face of climate risks. In both streams, the dynamics of hazard, exposure, and vulnerability components of flood risks driven by incremental adaptation of agents are well represented, in contrast to transformational adaptation and reorganization. We highlight that applying a

complex adaptive system perspective to trace the evolution of resilience can lead to a better understanding of societal adaptation to climate-driven risks. The methodological advances in computational models with heterogeneous behaviorally-rich adaptive agents are relevant for adaptation to different climate-driven hazards beyond flooding.

2

This chapter is based on *Taberna, A., Filatova, T., Roy, D., & Noll, B. (2020). Tracing resilience, social dynamics and behavioral change: a review of agent-based flood risk models. Socio-Environmental Systems Modelling.* (Taberna et al., 2020).

2.1 Introduction

Rapid urbanization and climate change exacerbate natural hazard risks worldwide. As the costliest climate-induced hazard, floods impose billions of property damage globally, disrupt millions of livelihoods, and take thousands of lives annually. Individuals and institutions have adapted to floods with varying degrees of success. Since the 1950', top-down governmental and public planned climate change adaptation (CCA) – such as dikes strengthening, beach nourishments and zoning has been the dominant societal response to flooding. Yet, coordinated anticipatory actions involving stakeholders across all social levels are required to address rising flood risks (Adger and Vincent, 2005). CCA acknowledges adaptation by private actors as essential and complementary to public actions (Fankhauser et al., 1999; Mendelsohn, 2000). The increasing knowledge about "behavioral climate change adaption" derives from the extensive use of surveys and other empirical studies that study factors triggering private adaptation for different people, behavioral biases, and the role of peer influence (Bamberg et al., 2017b; Noll et al., 2020; Steg and Vlek, 2009). It highlights the necessity to overcome the rational optimizing behavior used in traditional flood risk assessments and corresponding models by accommodating the complexity of behavioral heterogeneity and social interactions. Moreover, the increasing uncertainty, frequency, and severity of natural hazards challenge the risk reduction paradigm in managing climate change impacts on human societies (Bayer et al., 2014; Wilson et al., 2020). Therefore, policymakers have increasingly embraced resilience thinking as a response to climate change (Field and Barros, 2014). Resilience in the view of complex adaptive systems (CAS) is defined as the ability to withstand a shock and cope, learn, adapt, and (self)-reorganize during a recovery to continue long-term development despite adversities (Folke, 2006; Mochizuki et al., 2018). It encompasses the traditional risk framework focused on coping and based on the evolution of expected damages, either through probability, exposure, and vulnerability adjustments. Yet, resilience goes further by considering the consequences to the socio-economic system in the long run, the distribution of risks across various actors, and how these factors contribute to their behavioral responses. Actors can learn and adapt by changing their behavior incrementally or drastically, possibly by collectively reorganizing entire social institutions, which leads to different pathways and speed of recovery.

The recognition of the crucial role of human actors in altering these risks and resilience in hazard-prone cities calls for developing behaviorally rich models that couple social and environmental dynamics in flood risk assessments (Aerts et al., 2018). Agent-based models (ABMs) are designed to study individual decisions and social institutions' dynamics in computational models, especially when these societal dynamics are to be coupled with the environment (Filatova et al., 2013). For flood risk assessments, ABMs are uniquely positioned to quantify the cumulative effects of actions of various stakeholders, considering the influence of behavioral biases, social interactions, and cross-scale feedbacks that may magnify existing flood risks. In the past years, the scientific community has witnessed a proliferation of ABMs applied to study various aspects of flood risks that explicitly simulate diverse boundedly-rational agents. Yet, replacing a representative rational actor dominant in climate policy models with various behaviorally-rich agents that interact, learn, and adapt is not a straightforward process(Stern, 2016).

This article presents a systematic review of the first generation of computational models

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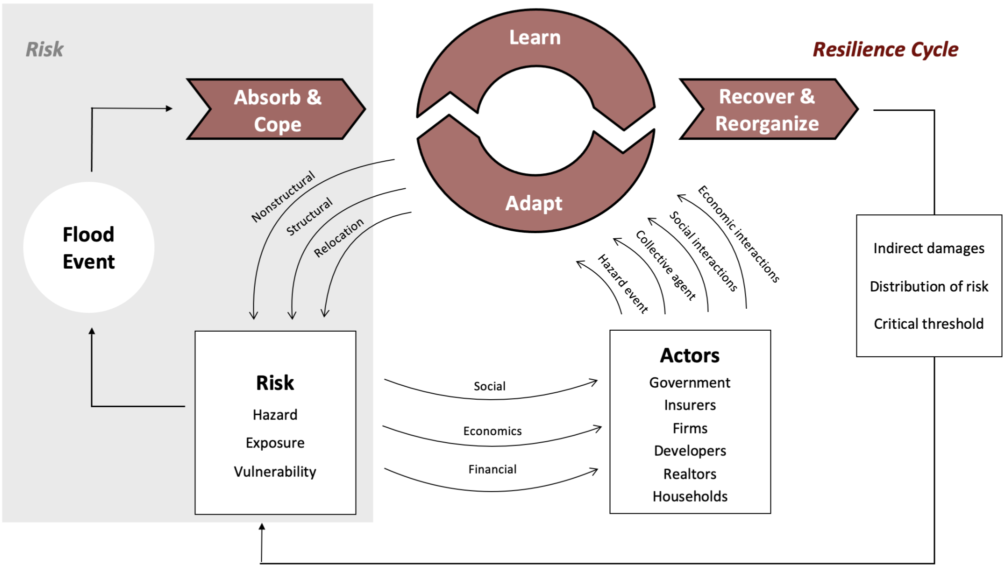

Figure 2.1: Capturing resilience in complex adaptive systems and CAS models.

that include behavioral change and social dynamics in flood risk assessments. We focus on peer-review articles that study the mid- to long-term flood risk and resilience in urban areas in light of climate change. Hence, papers reporting simulations to explore evacuation and a short-term reconstruction (days and months after a hazard event, usually less than one year) are outside the scope. Our review centers around the CAS perspective (Martin-Breen and Anderies, 2011; Wilson et al., 2020). At first, we take the three traditional components of risk hazard, exposure and vulnerability – that predefine how well a socio-environmental system is able to cope with a shock. Furthermore, we advance the coping element of resilience to encompass the adaptive behavior, learning, and long-term recovery and reorganization (Figure 2.1).

In this article, we demonstrate how our understanding of resilience can be advanced through the use of ABMs from different disciplines. From the CAS perspective, adapting and learning are the key elements shaping resilience (Folke, 2006). When discussing the learn-adapt cycle (2.1), we focus on how various stakeholders in CCA are represented in computational models, on the type of actions and interactions they pursue, and on how they learn when making decisions under risk and uncertainty. We examine social science theories and data that lay the foundation of such a learn-adapt cycle for boundedly rational agents in flood-ABMs. Furthermore, we deliberate on feedbacks between socio-economic and environmental systems and the capacity of such CAS to recover and to reorganize (2.1). Flooding is a multi-faceted problem. It is, therefore, unsurprising that different disciplines adopt varying approaches. Among behaviorally-rich computational models of social dynamics in the face of floods we distinguish between two strands of literature: one focusing mainly on relocations and exposure, which we call further Market

& Relocation, and another focusing on hazard and vulnerability modeling stemming from Socio-Hydrology. Our review covers both groups and discusses how their disciplinary views represent various elements of the CAS resilience framework (Figure 2.1)) and its components –“cope”, “adapt”, “learn” and “recover & reorganize” –in agent-based flood models.

The article first describes our search strategy and the review criteria. We then explain how risk components, spatial and temporal scales have been modeled in the context of resilience. Next, we discuss the type of actors, theoretical and empirical micro-foundations of their decisions, feedback, and recovery; we highlight differences in disciplinary approaches that were evident. Further, we discuss how resilience-thinking can reconcile current efforts from social and environmental sides by learning from each other. Finally, we summarize gaps and challenges for future research, focusing on features that a new generation of complex adaptive systems models integrating interdisciplinary research traditions in flood resilience assessments should encompass.

2.2 Methods

2.2.1 Scope and search strategy

We systematically review ABMs that explore mid-term (1 to 3 years after an event) and long-term (longer than three years) reactions of the socio-economic system threatened by flood hazards in urban areas (hereafter flood-ABMs). While floods impact societies on various fronts, including farmland and natural ecosystems, most of the damage and disruption occurs in urban areas, which serve as dense clusters of population and infrastructure (Jha et al., 2011). Rapid urbanization in flood-prone areas is a primary threat to pursue the Sustainable Development Goal 11. Hence, our review focuses on the socio-economic impacts of urban floods and responses, particularly the adaptation behavior of different actors and resilience against floods in the face of climate change.

We implemented an extensive search using the SCOPUS database to retrieve relevant flood-ABMs papers (Figure 2.2). Confined to papers written in English and published in peer-reviewed journals, our search returned 348 results (as of the 10th of May 2020). We then further refine the search by screening titles, abstracts, and eventually full-texts to filter-out the articles that:

- belong to fields outside our research domain (Veterinary, Astronomy, Microbiology);
- mention river or coast (often concerning the geographical location of a case-study) but did not present an ABM to study the socio-economic impacts of flooding. These articles often include ABMs that explore urban expansion (land-use), water-use and management, tourism, or non-human dynamics (biology, ecology, chemistry, archeology). Also, those ABMs that model responses to other natural hazards such as Tornado or Earthquake are excluded;
- model flooding unrelated to urban areas (farmers, villages, rural areas). Albeit similar, these papers look at CCA from a different perspective on natural hazards and human actions. The former includes mainly droughts, a primary concern among farmers. The latter follow crop growth models and their time scales, aiming to maximize harvest productivity despite adversities;

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- focus on the short-term operational response to floods (evacuation, emergency management, immediate recovery).

Using the above-mentioned criteria, we collected 28 articles published between 2009-2020 to form the core of our analysis[1] (Figure 2.2). Some of the comprehensive papers that look at societal dynamics and floods are outside the scope because they prioritize different processes such as the immediate evacuation response (Dawson et al., 2011) or a short-term recovery in the first few months (Coates et al., 2019). Alternatively, some articles use cellular models (McNamara and Werner, 2008; Werner and McNamara, 2007) or are not peer-reviewed (Sobiech, 2011; Walsh and Hallegatte, 2019).

2.2.2 Review criteria

Several aspects, including flood resilience, ABMs, and contemporary modeling challenges, are relevant when considering CAS resilience. Hence, we rely on the recent review articles from these domains to develop the criteria and align them with the keeping the CAS resilience framework (Figure 2.1).

From the view of ABMs (Filatova et al., 2013; Groeneveld et al., 2017), the clarity on empirical and theoretical foundations guiding agents' behavior and the presence of explicit feedbacks between human and environment systems are essential. They also form the basis of agents' adaptive behavior and learning that strengthen resilience. From the flood perspective, (Aerts et al., 2018) argue for the importance of including dynamic vulnerability – human adaptive behavior and risk perception – into flood risk assessments, calling for modeling different risk components (hazard, exposure, and vulnerability). Stressing the paradigm shift from risk to resilience, (McClymont et al., 2019) stand with the proposition of (Tempels and Hartmann, 2014) that a co-evolution between social and natural-physical systems across scales is a pathway to improve the resilience of complex adaptive socio-environmental systems. Concerning the latter, (Elsawah et al., 2020) review grand challenges in socio-environmental systems modeling and stress that integrating the human dimension, including the behavior of different stakeholders, is a top priority. They note that caveats deal with scales, systemic changes (transformational vs. incremental CCA in case of floods), matching models with data, among other aspects.

- **Criterion 1. Coping with flood risk:**

    1. How do the 3 risk components – hazard, exposure and vulnerability – enter an agent-based model? How do they link to socio-economic agents?

[1]While an ABM developed by a team of authors constantly evolves adding new elements to address unique research questions in each article, the comparison of published versions of the same family of ABMs is hindered due to irregular reporting on code modifications. To assure the consistency and reproducibility of this review, we compare published articles rather than models.

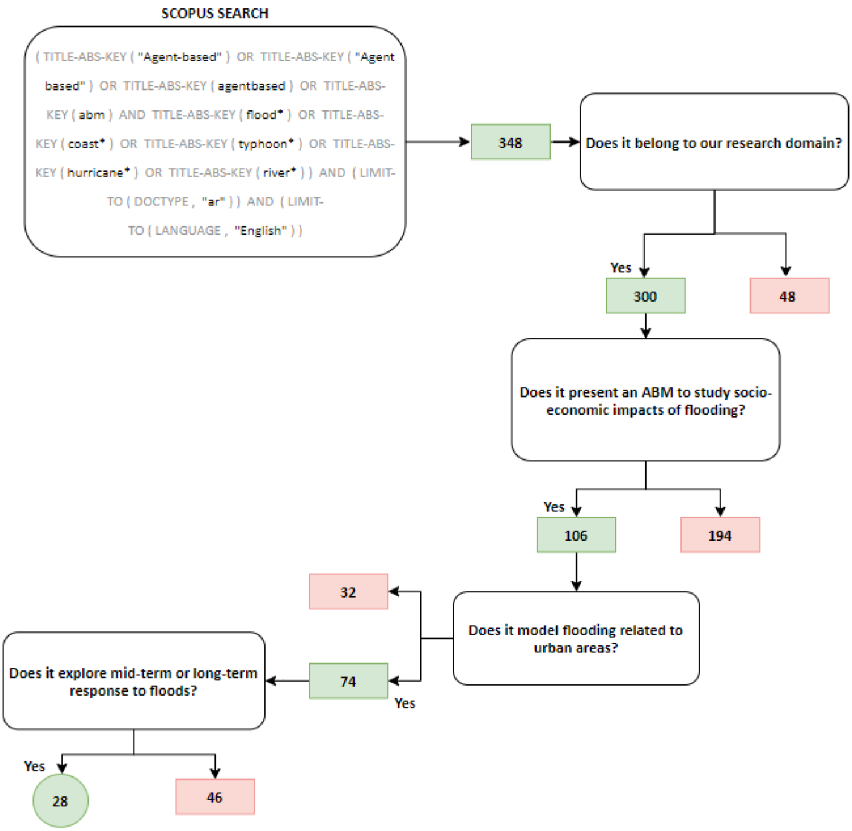

Figure 2.2: Search and filtering process to select articles for the review.

2. What spatial & temporal scales are appropriate to capture societal resilience to floods?

- **Criterion 2. Learn-adapt cycle in flood-ABMs:**
  1. Which actors are modeled? How do they interact?
  2. Which actions drive agents' behavior? Do they evolve through learning?
  3. What are the theoretical micro-foundations of these decisions? What socio-economic or behavioral data is employed?
- **Criterion 3. Recovery and reorganization in flood-ABMs:**
  1. How is the CAS capacity to recover and self-organize modeled?

This review does not focus on other relevant agent-based modeling aspects such as model transparency, uncertainty exploration, and validation extensively discussed elsewhere (Kremmydas et al., 2018; O'Sullivan et al., 2016). An adequate overview of these criteria would require significant space and dilute this paper's focus, namely Flood-ABMs within the CAS resilience framework.

2.3 Results and discussion

Articles that report ABM analysis of mid- and long-term flood impacts on human societies share many commonalities. However, managing flood risks and building urban resilience is a complex topic; thus, different disciplines have approached the issue differently. We identify two broad categories of flood-ABMs:

1. Those developed principally by environmental scientists and hydrologists, which traditionally focus on changes in hazard, vulnerability, and expected annual damage (EAD), hereafter *Socio-Hydrology (SH)* group;
2. Those developed by economists and geographers focus on exposure, land use, and market dynamics that affect values at risk, hereafter *Markets & Relocation (MR)* group.

The two strands of literature vary in the types of research questions, objectives, critical characteristics of agents and their decisions, and the model output. The flood-ABMs in the SH group usually analyze how flood risks and EAD change over time. Starting from 2013, the SH community has adopted the ABM method in the quantitative flood risk assessments driven by the ambition to include human behavior (McNamara and Keeler, 2013) and to explore natural-human interactions quantitatively (Di Baldassarre et al., 2013; Sivapalan et al., 2012). The SH group advances flood risk modeling by tracing endogenous vulnerability changes, yet assuming exogenous or inexistent changes in people and assets at risk (exposure). The articles assigned to this group (65% of our review) distinguish themselves for their output measures, focus on quantifying changes in direct EAD, with just two articles reporting the diffusion of CCA actions (Erdlenbruch and Bonté, 2018; Haer et al., 2016). The first flood-ABM in the MR group dates back to 2009, focusing on both direct and indirect flood impacts in urban areas, and the exposure component of risk. The MR flood-ABMs' output is different from the SH group and typically aims to

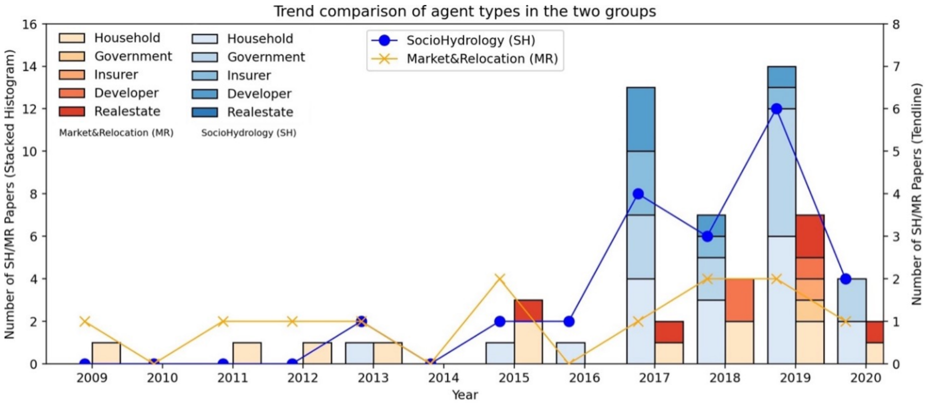

Figure 2.3: Temporal trends in the number of published articles reporting flood-ABMs that originate from *Socio-Hydrology (SH)* versus those that focus on *Markets & Relocation (MR)*. The histogram illustrates the type of stakeholders being modeled within each group. Please note that 2020 includes only articles before the 10th of May.

trace the effects of flood risks on location choices, house prices, and overall changes in the urbanization patterns and economic value at stake (Filatova, 2015; Walls et al., 2018). Therefore, this group advances flood risk modeling by replacing the assumption of the static value at risk with the endogenous housing market and relocation dynamics, usually grounded in urban economics. The MR group also explicitly considers migration due to floods and focuses on the number of people at risk (Hassani-Mahmooei and Parris, 2012).

There are examples of flood-ABMs that bridge the two groups by measuring both the endogenous changes in housing prices that shape values at risk and estimating EAD with related vulnerability (Chandra-Putra et al., 2015; McNamara and Keeler, 2013)[2]. Further, there are examples of MR articles that link vulnerability elements, namely insurance uptake (Magliocca and Walls, 2018) and insurance claims (Chandra-Putra and Andrews, 2019) as a form of validation of agents' decision-making process. Such structural realism tests the ability of a model to replicate new patterns that were not explicitly included in its initial design (Grimm and Berger, 2016; Latombe et al., 2011). Notably, all flood-ABMs model Household agents and use their spatial location to link natural and human subsystems, further reinforcing the connection between SH and MR groups.

2.3.1 Coping with flood risk

Risk components in Flood-ABMs

Flood-ABMs actively model how natural factors and human actions shape the level of risk, defined as hazard * exposure * vulnerability (Porter, 2014), over time. Thus, the ability of a socio-economic system to cope with flooding is well represented. Furthermore, we identify that the two groups mainly focus on risk components differently. The SH group exploits more in detail the hazard and vulnerability components, while the MR group centers on exposure (Table 2).

[2]Therefore, we count these two articles as overarching and belonging to both groups.

Hazard refers to the probability that the socio-economic system under study has to cope with a flood of a certain magnitude. In flood-ABMs, scholars use four alternatives to estimate such probability. The MR group uses non-linear distant-dependent functions from the coast or river as a proxy of hazard probability (Filatova et al., 2011; Magliocca and Walls, 2018; Walls et al., 2018). Second, flooding probabilities can be determined through statistical methods that sample historical values (Chandra-Putra et al., 2015; Han and Peng, 2019; Tonn and Guikema, 2018; Tonn et al., 2019). Alternatively, location-specific fixed flood maps (Dubbelboer et al., 2017; Haer et al., 2017) are used for different return periods, for example, 1:100 flood. Finally, the SH group employs advanced hydrologic models (Abebe et al., 2019b; Haer et al., 2019, 2020; Löwe et al., 2017; McNamara and Keeler, 2013; Michaelis et al., 2020a). Despite the increased complexity of coupling engineering and socio-economic models, hydrologic models' presence establishes two-way feedback between human and natural systems. Specifically, human actions such as land-use affect overall surface imperviousness (Abebe et al., 2019a,b) or rain drainage (Löwe et al., 2017). These changes are inputs in the hydrologic models that, in return, provide dynamic flood maps for a given return period. With a two-way linkage, hazard affects human actions, but social activities have consequences on future floods.

Moreover, flood probabilities might evolve with climate change and human actions. The latter entail governmental CCA actions -such as building dikes or performing sand nourishments (see 2.3.2)- that decrease such probabilities. The former, although we have not experienced it yet, it is an additional factor of risk included in flood-ABMs through various forms. In the most simplistic, it enters as repetitive floods to proxy increasing future frequency (De Koning and Filatova, 2020). A more advanced way to include climate change into flood-ABMs is to use sea-level rise as an input to the hazard sub-model either via statistical methods (Han and Peng, 2019; Hassani-Mahmooei and Parris, 2012), flood maps (Haer et al., 2017) or hydraulic models (McNamara and Keeler, 2013). Finally, flood-ABMs directly increase hazard probability (Magliocca and Walls, 2018; Walls et al., 2018) or the floodwater levels (Tonn and Guikema, 2018) under different climate scenarios, linking greenhouse gas emissions levels with changing flood maps (Dubbelboer et al., 2017; Haer et al., 2017, 2020).

Yet, almost half of the articles (15:28) treat the natural hazard component of risk as constant, based on empirical evidence. Only 4:12 of the MR group models dynamic climate conditions compared to 10:18 of the SH group. This is related to the temporal horizon of a flood-ABM, typically shorter in the MR group (Table 2.1)

Vulnerability determines the amount of damages that a defined amount of people and assets suffers in case of a flood. The SH group employs empirical water-depth damage functions, often for specific building (Dubbelboer et al., 2017; Haer et al., 2020; Han and Peng, 2019). The MR ABMs treat vulnerability simplistically, for example, calculating damages as a fixed percent of property value average for the whole floodplain (de Koning et al., 2017, 2019). Moreover, in flood-ABMs, agents can decrease their vulnerability undertaking structural CCA actions such as elevating a house or installing flood barriers, which is the focus in the SH literature (17:18 papers) (see 2.3.2, Table 2.2)

Exposure indicates the total amount of people and assets directly damaged in case of a flood. On the one hand, the amount of people can change following households relocation, core of MR group (100% paper) or zoning policies undertaken by Government

(See 3.2.2). On the other hand, the amount of assets is estimated through land-value maps. When a housing market is modeled explicitly (11:12 MR, 5:18 SH), the land-value evolves endogenously as a product of households relocation decisions, leading to price differentials between flood-prone and safe zones. Alternatively, the dynamic land value might change through exogenous GDP projections (Haer et al., 2019), though not differentiating values between flood-prone vs. safe areas.

Spatial and temporal scales

Spatial scale is directly correlated with the amount of people and assets at risk -exposure-. In flood-ABMs the spatial dimension ranges from a town up to a macro area such as regions or nation-states. Likewise, depending on the scope of the paper, the representation of space itself differs from a stylized landscape (McNamara and Keeler, 2013; Walls et al., 2018) to raster (Mustafa et al., 2018) and vector-based maps (Filatova, 2015).

Within the MR group, 11:12 of articles focus on a city with flood-prone areas, with some models comparing two cities (Chandra-Putra and Andrews, 2019; De Koning and Filatova, 2020). Flood-ABMs from the SH community work at a variety of scales: from urban neighborhoods (Dubbelboer et al., 2017) to counties (Han and Peng, 2019), to islands Abebe et al. (2019a,b), to provincial regions (Mustafa et al., 2018) up to the entire European Union (Haer et al., 2019, 2020). The latter are the first attempts to scale-up these models to continental macro-areas, still maintaining a high spatial resolution.

The majority of articles (25:28) use data or are based on empirical case-studies in developed countries such as Europe (13:28) or the US (11:28). Only three articles examine case studies of dies (Abebe et al., 2019a,b; Hassani-Mahmooei and Parris, 2012). This bias is likely due to data limitations in developing countries, especially regarding data on behavior and social interactions.

Risk propagates through time. Moreover, resilience encompasses the risk framework and the system ability to cope with a shock considering its capacity to learn, adapt, recover and self-organize. Therefore, the temporal dimension is crucial to capture critical transitions happening in such system.

Temporal scales in flood-ABMs vary between 25 (MR) – 43 (SH) years of simulations on average and up to 100 years (Haer et al., 2017). Instead of a fixed temporal horizon, some flood-ABMs establish it endogenously, for example, via market outcomes (Filatova et al., 2009; McNamara and Keeler, 2013). The length of each time step is typically one year in 17 and 4 of the SH and MR groups respectively (Table 1). Alternatively, time steps can be semi-annual (De Koning and Filatova, 2020; de Koning et al., 2017), monthly (Filatova, 2015; Haer et al., 2017; Hassani-Mahmooei and Parris, 2012), or daily (Chandra-Putra and Andrews, 2019). Thus, each group employs a scale that fits the phenomena of interest. The SH flood-ABMs focus on environmental processes that require longer time horizon and annual resolution. The MR group uses shorter time horizon and resolution (Table 1) to emphasizes social dynamics. Moreover, while it is useful to develop models to match the temporal horizon of 50-100 years of physical flood models (Haer et al., 2019, 2017; McNamara and Keeler, 2013; Mustafa et al., 2018), it raises a question about the escalating uncertainty of the socio-economic forecasts. In particular, relevant factors such as Households' behavior, flood risk perceptions, preferences, and technological progress will likely change dramatically.

Table 2.1: Temporal scale in flood-ABMs. The numbers within the orange boxes represent the count of *Market & Relocation (MR)* papers, while the numbers in the light-blue boxes indicate the count of *Socio-Hydrology (SH)* articles.

Time step	Daily 1 0	Monthly 4 1	Semi-annual 3 0	Yearly 4 17
Time horizon (Years)	Endogenous 3 0	< 30 4 2	30-60 4 12	60 < 1 4

2.3.2 Learn-adapt cycle in flood-ABMs

The learn-adapt cycle (Figure 2.1) covers the actor modeled endogenously (Figure 2.3), how they interact, the CCA actions they pursue, and how these actions might change over time through learning. Hence, it plays a central role in connecting incremental to transformative adaption, a crucial process to achieve CAS resilience (Wilson et al., 2020).

Actors in flood-risk management and their interactions

Households' micro-level behavior is the core component of flood-ABMs. Both SH and MR groups employ Households' interactions to explore the potential of modeling societies from the bottom-up. The Household agents are heterogeneous in income, preferences, risk perception, and sometimes behavioral strategies. However, there is a clear distinction between SH and MR groups in how Households are modeled and the objectives they pursue. Households in the MR group compete when choosing locations that offer different spatial tradeoffs between environmental amenities and disamenities. The choice of a spatial location is mediated through social institutions such as housing or land markets (11:12 of articles). Therefore, Households are divided into sub-groups that highlight their role on the market, in the most basic form, buyers and sellers (Filatova et al., 2011, 2009; McNamara and Keeler, 2013; Walls et al., 2018). Chandra-Putra et al. (2015) differentiate between homebuyers, home sellers, and homeowners, where homeowners can become home-sellers only if certain conditions are realized. Households in the SH flood-ABMs act with a single purpose: to minimize future expected flood damages Haer et al. (2019). Hence, they are not split into sub-groups and do not compete with each other, but represent a unique category as long as property markets are not modeled (13:18 of the cases).

A **Real-estate-agent** is a key actor in empirical flood-ABMs that model a decentralized housing market, belonging to the MR group (Chandra-Putra and Andrews, 2019; De Koning and Filatova, 2020; de Koning et al., 2017, 2019; Filatova, 2015). The Realtor agent observes market conditions and successful trades, updating sellers' price expectations. Therefore, it reinforces the Household's agents' learning process through prices that go up or down based on their dynamic preferences.

A **developer** is a profit-maximizing agent whose role is to buy land from land-owners, based on housing demand and supply (Chandra-Putra and Andrews, 2019; Dubbelboer et al., 2017; Walls et al., 2018). The Developer builds new houses and sells them to Households, enriching the urbanization process's representation either through the endogenous housing market or based on past exogenous data (SH group). In the former case, when a housing market institution is modeled, the Developer adds complexity and realism to the bilateral interactions between individual Households on the market (Jenkins et al., 2017; Magliocca and Walls, 2018). In the latter case, different urbanization scenarios shaped by the Developer agent combined with planning authorities allow damages to evolve (Löwe et al., 2017; Mustafa et al., 2018). Scenarios based on past data are a useful shortcut to represent changes in exposure but may appear misleading if urbanization is affected by the increasing flood severity and likelihood.

About 50% of papers (13:28) explore the possibility of undertaking insurance either as a Household agent action (McNamara and Keeler, 2013) or as a policy scenario (Chandra-Putra et al., 2015). However, usually, insurance-related decisions remain simplistic, omit representing heterogeneity or learning, hence missing some of the principal advantages of ABMs. Only six cases (Table 2) model an **Insurer** that makes decisions endogenously: calculate premiums, offer discounts, collect, and pay-out. The Insurer agent increases the complexity of flood risk and resilience dynamics through two channels. First, premiums can be parametrized in a sophisticated way, resembling the real-world schemes such as US NFIP (Chandra-Putra and Andrews, 2019; Han and Peng, 2019) or Flood Re (Crick et al., 2018). Second, an Insurer can interact with other agents in flood-ABMs; for instance, it can offer premium discounts to Households if they implement risk mitigation measure (Haer et al., 2017; Han and Peng, 2019) or may engage in multi-level insurances schemes where Government re-insures risks above a certain threshold (Dubbelboer et al., 2017). The latter, in particular, offers the possibility to test several policy scenarios where premiums' affordability and an interplay between insurance and other long-term risk reduction policies are essential (Crick et al., 2018).

Starting from 2017, flood-ABMs include **Government** (Abebe et al., 2019a; Dubbelboer et al., 2017; Tonn et al., 2019), often alongside the Developer and Insurer agents. As before, we consider the Government as an agent only when it is coded as a separate entity with an endogenous decision-making process. As for the Insurer agent, there are cases where it is included as an external action (Erdlenbruch and Bonté, 2018; Haer et al., 2016) or as a policy scenario (Chandra-Putra et al., 2015). The Government agent is a stylized representation of different policymakers from the state government to municipal planning authorities. Hence, it is a collective agent that acts at the macro level to maximize community welfare by reducing the overall risk. Its actions vary from evaluating and approving development proposals to deciding whether to invest or not and wherein flood protection measures such as dikes and levee (Haer et al., 2019; Michaelis et al., 2020a; Tonn and Guikema, 2018). Given the tradition of estimating floods risks with/without particular engineering protection measures inherent to the SH community, the Government is a common agent within the SH group (Table 2), compared to only one article in the MR group (Chandra-Putra and Andrews, 2019). The inclusion of Government permits testing cross-scale CCA strategies involving public and private adaptation (Haer et al., 2020; Han and Peng, 2019) in faces of increasing risks.

Interactions between agents are the core feature of any computational model of behavioral change and societal dynamics. Agents can interact with each other, with collective agents and social institutions, and with the spatial environment (Figure 4). An ABM's complexity is contingent on the variety of agents being modeled and the type and intensity of interactions among them. In our analysis of the two literature streams we note several differences. While the MR group tends to include fewer agents (Figure 2.3), interactions between them are modeled in a more sophisticated manner, with strong theoretical and empirical foundations as well as granular and shorter time dimension (Table 2.1). The SH group tends to focus more on the diversity of agents, with only a few papers introducing any exchange of information – for example, about risks or effectiveness of CCA options – through social interactions between individual agents. Haer et al. (2017) introduce a probabilistic function that represents a process when Households get new information by talking with others or from the media. Erdlenbruch and Bonté (2018) model information exchange among Households connected via small-world social networks, where the level of influence emerges through the endogenous formation of sub-networks. Alternatively, all Household agents within a specified spatial radius influence each other based on a distance-decay parameter (Chandra-Putra et al., 2015). Yet, due to the reduced spatial scale under consideration, some SH ABMs consider all agents as neighbors (Tonn and Guikema, 2018; Tonn et al., 2019), with only one article that implements a social network structure at the regional level (Haer et al., 2016). The MR group tends to focus on economic interactions, with spatial externalities directly affecting Households agents' decisions to locate (Filatova, 2015; Magliocca and Walls, 2018) or what bid price to offer (De Koning and Filatova, 2020). In particular, such interactions are included in all flood-ABMs with a housing market where Households compete for the same resource: housing/land. In this case, individual agents deal with the collective market institution (Figure 4), channeling individual interactions, and distributing resources by aligning demand and supply. The latter leads to endogenous variations in price signals and, ultimately, changing the attractiveness of locations. Notably, there is a tradeoff between the spatial extent and the complexity of collective institutions that reflects some modeling divergences between the two groups. On the one hand, articles belonging to the SH group that have a detailed spatial scale at the regional level do not forecast future urbanization through market interactions. They either entirely omit relocation or simply extrapolate future demand from past urbanization data (Löwe et al., 2017; Mustafa et al., 2018). On the other hand, within the MR group, the papers that model endogenous housing market and land value dynamics at the regional scale remain stylized (Magliocca and Walls, 2018; Walls et al., 2018).

In both groups, Households interact with collective agents (i.e., Insurer or Government) following pre-defined regulatory rules that are always fixed during the simulation. For instance, these include the amount of damage covered by the Insurer or the Government approval ratio for development proposal (Dubbelboer et al., 2017). In flood-ABMs, Households take these rules as given, except a case when they choose whether to comply with such collective regulatory institutions (Abebe et al., 2019a,b).

The exchange of information among agents is fundamental to study beyond the incremental effect of individual CCA actions and how such actions can trigger path dependency processes that might result in long term societal resilience.

Agents' actions and learning

In computational ABMs, the above stakeholders are endowed with various actions to perform during the simulation. Some actors perform more complex decisions than others. Notably, the Real estate, Developer, and Insurer agents in flood-ABMs often have only one action (e.g., estimation of property values, building or selling houses), and a single

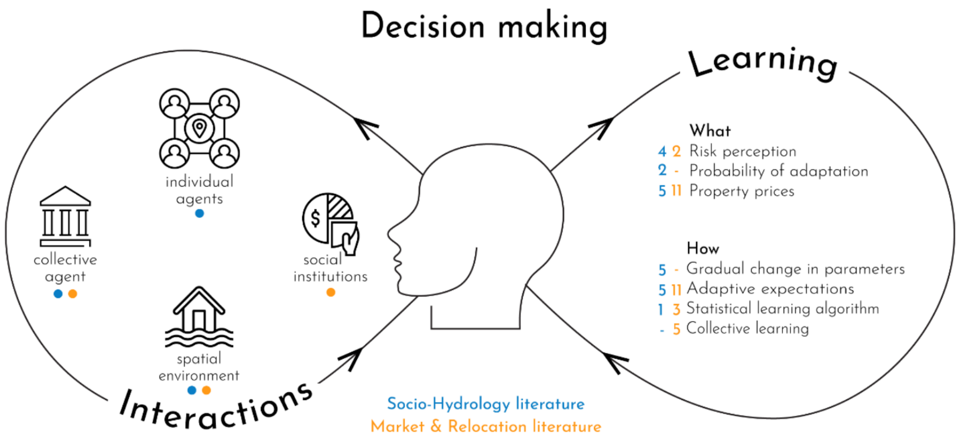

Figure 2.4: Interactions and learning in flood-ABMs. The numbers in orange represent the count of *Markets & Relocation (MR)* papers, while the numbers in light-blue indicate the count of *Socio-Hydrology (SH)*, articles.

behavioral strategy aimed at increasing profits or clearing the market. Therefore, we focus on Household and Government CCA actions because, in flood-ABMs, they often make multiple decisions. Although, responses from community and social initiatives are still lacking.

Actions of Households: in reality, households pursue a wide range of actions to cope with flood risks they face (Koerth et al., 2017). Assuming they remain in the same hazard-prone location, people can take on-site actions: either structural CCA measures (e.g., flood-proofing a house, physical installations, and modifications (Chandra-Putra et al., 2015)) or non-structural measures (e.g., insurance). While on-site CCA can partially offset individual climate risks, in some cases, a relocation within or outside the hazardous area might be a more valuable option (Tonn et al., 2019). Flood-ABMs model all three types.

With its primary focus on dynamic vulnerability, the majority of flood-ABMs from the SH community integrate some sort of structural CCA measures (17:18 of articles compared to 3:12 in the MR group). Many flood-ABMs include permanent building elevation as a measure to prevent damages with a given water level (Abebe et al., 2019a; Chandra-Putra et al., 2015; Han and Peng, 2019; Tonn et al., 2019). Alternatively, Households agents can employ house-level flood barriers that reduce the damage partially (usually 70-80%) (Haer et al., 2017; Michaelis et al., 2020a) and can be combined with other measures (Haer et al., 2016, 2019, 2020). Structural measures are usually assumed to permanently alter a house, except one example of structural temporal measures that expire after seven years (Erdlenbruch and Bonté, 2018). Household agents may also collaborate to implement community-level engineering measures (McNamara and Keeler, 2013).

The most common non-structural CCA is insurance, included in 10:18 and 5:12 of the SH and MR groups' articles correspondingly. Moreover, there is a substantial difference in how insurance is modeled between the two groups, as defined by the type of stakeholders included in flood-ABMs. Indeed, when an Insurer agent is modeled, more complex insurance schemes are implemented. Flood-ABMs start to replicate the complexity of the actual insurance schemes, where the insurance premium is contingent on structural damage mitigation measures, incentives, or governmental subsidies. For instance, Households can get a discount if they adopt any of the aforementioned structural CCA measures (Haer et al., 2016; Han and Peng, 2019). These incentives, coupled with structural CCA, are fundamental to exploit the role of insurance as a disaster risk reduction measure and not merely as a mechanism of risk transfer (Crick et al., 2018). The premium incentives are implemented in 8:18 papers that include insurance in the SH group against only two (Chandra-Putra and Andrews, 2019; Chandra-Putra et al., 2015) in the MR one. Furthermore, regarding non-structural adaptation measures, there are three cases (Michaelis et al., 2020a; Tonn and Guikema, 2018; Tonn et al., 2019) where households can fill a complaint and request a structural CCA by the Government.

When talking about relocation, there are significant differences between the two groups as for the other CCA actions. With location choice and land-use change being the focus of the MR group, relocation is included in all articles and in 11:12 of the cases through housing markets. Hence, household interactions are mediated across the market process, which can be centralized (Chandra-Putra and Andrews, 2019) or decentralized (De Koning and Filatova, 2020; Filatova, 2015). Household agents form expectations, which incorporate advanced methods for the evolution of risk perceptions and market trends, also in response to floods (de Koning et al., 2017; Magliocca and Walls, 2018). Thus, each round of Household agents' interactions will affect further price trends and future individual decisions, bringing transformational changes at the macro-level (i.e., price discount in the flood-prone area). Conversely, in the SH group, Households agents primarily remain in the same location (11:18), hindering the opportunity to model outmigration as a CCA option. Relocation is triggered when a "risk threshold" is reached, causing Households to move out of the flood-prone area (Tonn and Guikema, 2018; Tonn et al., 2019), or is modeled via a simplified housing market (Chandra-Putra et al., 2015; Crick et al., 2018; Dubbelboer et al., 2017; Jenkins et al., 2017; McNamara and Keeler, 2013).

Thus, the Households of the two groups mainly focus on risk components differently (Table 2.2). The MR group concentrates on the evolution of exposure linked to change in Household location decisions and land value. Conversely, the SH group focuses on Household structural CCA actions, transforming the static view on vulnerability, common in flood risk assessment (Aerts et al., 2018). Haer et al. (2017) find that risks are overestimated by 60% if Household adaptive behavior is ignored. Both aspects are important to understand the presence of tipping points that undermine CAS resilience. On the one hand, increasing hazard probabilities due to climate change may trigger a collapse of prices and outmigration from areas that have been previously attractive (De Koning and Filatova, 2020). On the other hand, the cumulative effect of individual adaptation actions might impact urban resilience.

Actions of Government: at the macro level, governments can pursue structural (investments in large-scale physical flood-defenses) or non-structural measures (incentives for individual CCA behavior). As climate change intensifies, increasingly planned relocation and zoning come to the political agenda as CCA actions alter the hazard exposure.

Historically, governments protect their community by implementing structural measures that decrease the risk by reducing the hazard's probability. These measures are the most commonly implemented (Table 2.2) and include raising engineering infrastructure,

Table 2.2: Stakeholders and types of actions modeled in computation agent-based models concerning the hazard, exposure, and vulnerability components of flood risk. The numbers within the orange boxes represent the count of *Market & Relocation (MR)* papers, while the numbers in the light-blue boxes indicate the count of *Socio-Hydrology (SH)* articles.

RISK / ACTORS	**Expousure** *Land Use - Assets value - People affected*	**Vulnerability** *Damage function - Sensitivity*	**Hazard** *Probability*
Government 1 13	Zoning 1 6	Non-structural adaptation 1 8	Structural adaptation 0 11
Developer 3 5	Build new houses 3 5		
Real estate 5 0	Form price expectations 5 0		
Insurer 1 5		Offer insurance 1 5	
Household 12 18	Relocate 12 7	Structural adaptation 3 17	
	Relocate via housing market 11 5	Non-structural adaptation (buy insurance) 5 10	

such as dikes or levees, that protect entire regions (Haer et al., 2017; Michaelis et al., 2020a; Tonn et al., 2019) or improving the drainage system of specific neighborhoods (Abebe et al., 2019a; Dubbelboer et al., 2017; Löwe et al., 2017).

Furthermore, Government agents can encourage private behavior and bottom-up adaptation with information campaigns (Erdlenbruch and Bonté, 2018; Haer et al., 2016; Tonn et al., 2019) and can offer either a discount on insurance premiums (Han and Peng, 2019) or a subsidy for individual structural measures (Abebe et al., 2019a; Jenkins et al., 2017; Löwe et al., 2017). Alternatively, Government can introduce regulations that force CCA actions such as setting a minimum height for new developments in certain areas (Abebe et al., 2019a; Chandra-Putra and Andrews, 2019; Crick et al., 2018). These measures affect the risk through the vulnerability component.

The government plays a crucial role in regulating developments in hazard-prone areas. Flood-ABMs capture this through zoning enforcement by government agents (Löwe et al., 2017; Mustafa et al., 2018). Alternatively, the Government issues building code requirements that guide new urban developments in flood-ABMs Abebe et al. (2019b); Jenkins et al. (2017). This group of actions aims to manage the number of people and assets centrally at risk, thus addressing risk by reducing exposure.

The coordinated anticipatory CCA actions undertaken by both Households and Government are necessary to tackle rising flood risks and deliver CAS resilience. In this aspect, the two groups employ a different approach, with a Government that is excluded in the MR group.

Learning: either at the individual or collective level, the actions and interactions undertaken by agents might change and evolve during the simulation through learning, affecting further the learn-adapt cycle and, consequently, resilience. Indeed, agents learn when they “change their adaptive traits over time as a consequence of their experience” (Grimm et al., 2010). Agents gain information through their past actions or both direct and indirect interactions with other agents. They might use these experiences to update their decision strategies and pursue a behavior change (Figure 2.4). Furthermore, there are several ways to model how agents learn and adapt, with some overlaps as well as distinct characteristics between the two groups.

Within the SH group, 11:18 papers implement a learning process. For half of them, it is a gradual change in agent attributes when exchanging information with other agents or following their experience of certain events. When exchanging information, verbal persuasion or observational learning of actions taken within the household’s social network can alter the probability to adapt by a fixed percent (Erdlenbruch and Bonté, 2018; Haer et al., 2016). When Household agents experience a hazard event, their risk perception increases together with the willingness to adapt. In flood-ABMs, this learning process is modeled either via a linear change of Households’ parameters by a static, fixed amount (Tonn and Guikema, 2018; Tonn et al., 2019) or using a discontinuous function that depends on relative damages and a memory-decay rate (Michaelis et al., 2020a).

Both SH and MR flood-ABMs share examples of Bayesian Learning employed to model the evolution of individual Households’ risk perceptions. Haer et al. (2017) used Bayesian learning to update risk perception dynamically according to a bundle of different attributes such as flood experience, social and media influence, each with a different weight. Alternatively, Household agents observe the occurrence of a hazard event and update their expectations about future floods (Magliocca and Walls, 2018) or their risk perception that affects an individual preference to avoid flood zones (De Koning and Filatova, 2020).

All the papers with an endogenous housing market (Figure 2.4) model the formation of adaptive expectations when observing other agent actions and the overall market conditions. Depending on the excess of supply or demand in specific (flood-prone) neighborhoods, market interactions create spatial price differentials that affect Household agents’ location decisions (De Koning and Filatova, 2020). A practical example is when coastal residents begin to understand the impacts of climate change, and market outcomes reflect that understanding, leading to price change and further adjustments (Magliocca and Walls, 2018). Since ABMs embrace bounded rationality (no optimization, no full information), agent predictions are not perfect. Yet, agents can learn from their mistakes through reinforcement learning algorithms and select a prediction method that reduces the cumulative errors over time (Walls et al., 2018). In the empirical housing market model, price expectations capture not only the temporal trend but also the attributes of a location. In the case when adaptive expectations are formed for different houses, the Real estate agent acts as a mediator who performs collective learning. To learn, the Real estate agent traces price changes based on specific spatial attributes, including the likelihood of flood and anticipated severity of the damage, by performing a hedonic price analysis of successful simulated transactions (de Koning et al., 2017; Filatova, 2015). The Real estate also learns by applying different learning strategies such as mean, projection, mirror, and regional models to capture the market dynamics and suggest a final price to sellers (Filatova, 2015). Otherwise, the task of collective learning is with the Developer agent that runs a hedonic price analysis on specific spatial attributes and directly provides sellers with an estimated value of their property (Chandra-Putra and Andrews, 2019).

2

Theories and data behind agents' decisions Theoretical

Theoretical micro-foundations: within the learn-adapt cycle, the complexity of agents' decision-making process varies. The Developer, Insurer, Real estate, and Government agents typically use simplistic behavioral strategies, lacking solid theoretical or empirical micro-foundations. At most, agents other than Households often rely on a version of a rational decision-maker and weigh costs and benefits of an action, though not always optimizing. The Developer maximizes expected profits (Dubbelboer et al., 2017), and the Insurer sets premiums dividing overall EAD by the number of Households (Haer et al., 2017) or attached to property characteristics (Chandra-Putra and Andrews, 2019; Han and Peng, 2019). The Government agent reacts to specific events, e.g., a flood of acertain magnitude and damage (Tonn and Guikema, 2018; Tonn et al., 2019), or performs a cost-benefit analysis of possible CCA actions (Haer et al., 2017, 2020; Löwe et al., 2017; Michaelis et al., 2020a). An exception is the CLAIM flood-ABM (Abebe et al., 2019a,b), which models regulatory institutions following the Institutional Analysis and Development framework (Ostrom, 2010). With respect to modeling Household behavior, flood-ABMs employ ad-hoc heuristics, Expected Utility theory, or behavioral theories.

Heuristic (ad hoc): despite the recent discussion on the need to ground individual households' decisions in social science theories (Schlüter et al., 2017), almost half of the flood-ABMs still employ ad hoc rules (Figure 2.5). This is particularly true within the SH group (11:18) compared to the MR group (4:12). Without explicit theoretical underpinnings, Household behavior is either guided by equations (Chandra-Putra et al., 2015; Dubbelboer et al., 2017; Hassani-Mahmooei and Parris, 2012; McNamara and Keeler, 2013; Mustafa et al., 2018) or depend on some "threshold" parameters (Abebe et al., 2019a,b; Löwe et al., 2017; Tonn and Guikema, 2018; Tonn et al., 2019).

Expected Utility (EU) is a popular socio-economic theory, especially within the MR group (Figure 2.5). Stemming from urban economics, the MR group borrows a formalization where households choose a location as a tradeoff between economic benefits and environmental amenities. Further, EU weights probabilistic losses in case a flood occurs, but importantly all flood-ABMs depart from the assumption of a fully-informed rational agent. Scholars model bounded rational agents by applying different subjective probabilities (Filatova, 2015; Magliocca and Walls, 2018; Walls et al., 2018), by discounting expected utility (Haer et al., 2019, 2020) via overestimating/underestimating individual EU, or by modeling myopic Households that do not anticipate floods to intensify (De Koning and Filatova, 2020).

Behavioral theories that study individual behavior under risk, including *Prospect Theory (PT)* (Kahneman and Tversky, 1979) or *Protection Motivation Theory (PMT)* (Rogers, 1975), have been taken up by flood-ABMs only recently. PMT studies risky choices as a two-stage procedure – risk appraisal and coping appraisal – to understand that multiple factors affect risk perception, which influences individuals' decision-making process (adaptation or maladaptation). It is implemented in three SH articles, for example, to test the effects of flood risk communication strategies on individual CCA (Erdlenbruch and Bonté, 2018; Haer et al., 2016). Michaelis et al. (2020a) go further by pairing the two-stage procedure with different Households' CCA actions. PT considers that individuals subjectively value probabilities and damages and that framing and loss aversion play a role when choosing between risky options. It is adopted by both MR and SH groups when modeling households' location decision (De Koning and Filatova, 2020; de Koning et al., 2017) or when testing

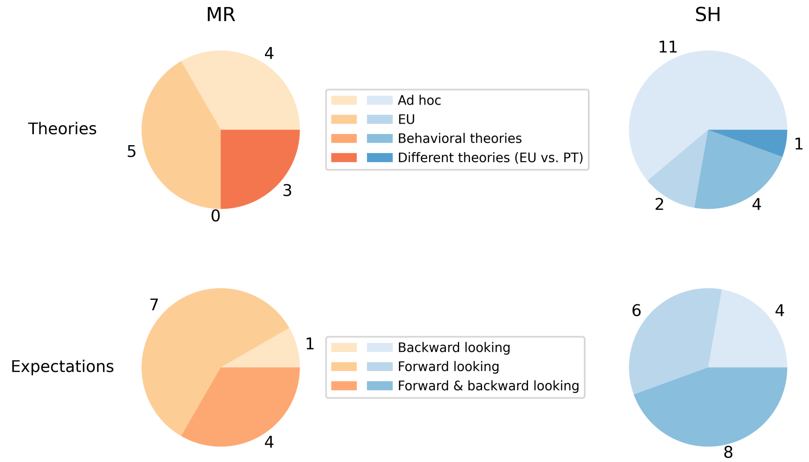

Figure 2.5: Theoretical micro foundations of agents' decisions and expectations in flood-ABMs. The orange shades represent the *Market & Relocation (MR)* papers, while light-blue shades indicate the *Socio-Hydrology (SH)* articles.

on-site CCA actions (Haer et al., 2017; Han and Peng, 2019). Magliocca and Walls (2018) employ PT extension, Salience Theory (Bordalo et al., 2012), to examine risk perception's role in shaping coastal development dynamics. In the MR group PT is always compared to Expected Utility.

Testing alternative theories: since each theory assumes how people make choices under risk differently, it is essential to examine how the adoption of different theoretical assumptions might influence final results, other things being equal. Moreover, when different theories and behavioral hypotheses are tested, we acquire a more comprehensive understanding of the role that behavioral biases play in the dynamics of the coupled human-environment system. Overall, three articles within the MR group (De Koning and Filatova, 2020; de Koning et al., 2017; Magliocca and Walls, 2018) and one in the SH (Haer et al., 2017) test different theoretical frameworks (Figure 2.5).

Nevertheless, the two groups' different theoretical approach mirrors how agents and floods interact (Figure 2.5). When households behave according to socio-economic theories such as EU or PT, future flood probability is always included within decision-making. Thus, they are *forward-looking* (11:12 in MR group) agents that – though subjective and biased – anticipate future risks and account for the expected costs in their actions. Conversely, SH ABMs, largely employ an ad hoc decision-making process that makes agents *backward-looking* when considering CCA actions, reacting to floods they directly experience. In these cases, the natural hazard module runs at the beginning of the simulation and influences agents' subsequent behavior (Dubbelboer et al., 2017; Tonn et al., 2019).

Micro-level data behind agents' behavior: all articles reviewed have agents endowed with different socio- economic and behavioral characteristics. The former are usually retrieved from aggregate socio-demographic data, such as Census, and disaggregated at the individual level. While this data is readily available, it rarely links to the fundamental processes driving agents' decisions in the flooding context. Agents' choices under risk are mainly driven by behavioral factors such as individual preferences (i.e., environmental amenities), subjective risk perception, or self-efficacy, which are challenging to quantify. Hence, flood-ABMs commonly use secondary literature to parameterize these behavioral factors (Dubbelboer et al., 2017; Filatova, 2015; Haer et al., 2017). Alternatively, scholars can calibrate behavioral parameters based on expert judgments (Abebe et al., 2019a; Michaelis et al., 2020a; Tonn and Guikema, 2018; Tonn et al., 2019).

Yet, secondary data may not represent the population under study, and preferences may have also changed over time. Hence, to capture behavioral dynamics, scientists use surveys, lab experiments, or participatory workshops designed for the specific population (Smajgl et al., 2011). Using a mail survey to estimate households' subjective risk perceptions (Filatova et al., 2011) show that the average subjective risk perception is misleading and that the distribution of perceptions within a population matter for the exposure dynamics in flood-ABMs. Relying on the behavioral traits elicited from a household survey, De Koning and Filatova (2020) demonstrate that buyers and sellers treat information about flood risks differently and switch behavioral strategies from EU-driven to risk avoidance when experiencing a flood. Erdlenbruch and Bonté (2018) show that optimal flood communication strategies differ when their empirical flood-ABMs relies on the secondary instead of primary data. Besides survey data on hypothetical choices, flood-ABMs can employ primary data on actual options. For example, all RHEA models use real housing transaction data before and after hurricanes to specify the price expectations of Real estate agents as well as location preferences of Household agents (de Koning et al., 2017; Filatova, 2015). Empirical data is crucial in determining the behavioral strategies for agents' decisions, interactions, or learning. However, only one paper uses such data to model learning through social networks (Erdlenbruch and Bonté, 2018). To specify agents' interactions, flood-ABMs also use semi-structured interviews (Filatova, 2015).

2.3.3 Recovery and reorganization

Within flood-ABMs, we identify three types of feedbacks: social, economic, and financial. The most well-defined *social feedback* is the safe-development paradox (Di Baldassarre et al., 2015). Improvements in flood defenses increase the sense of security among the population living in the floodplain and trigger a further increase of people and assets at risk. Only one article in the SH group explores this paradox in an ABM that connects population growth and the occurrence of flood events (Haer et al., 2020). Rapid urbanization combined with the climate-driven increase in hazard severity and probability may lead to a major disaster, especially for cases with currently low probabilities and high impacts.

Economic feedbacks enter flood-ABMs through housing markets. Hence, they are at the core of the MR group. Agents' endogenous changes in preferences and perceptions influence prices and value at risk, leading to path- dependency and market sorting. When coastal residents begin to understand the impacts of climate change, and markets begin to reflect this in prices, low-income households become locked in hazard-prone areas (De Koning and Filatova, 2020; Magliocca and Walls, 2018).

Another critical feedback concerns the role of insurance and *financial resilience*. Insurance is commonly used as a pure risk transfer mechanism. However, empirical literature reports unintended consequences such as subsidizing developments in flood-prone areas that lead to an excessive tax burden for the rest of the society or to unaffordable premiums (Bagstad et al., 2007; Crick et al., 2018). Therefore, government-subsidized insurance schemes have positive effects in the short term (affordability and uptake), but create unintended consequences in the long run. Flood-ABMs are increasingly used to trace these distributional impacts when the Insurer is modeled as a decision-making agent (Chandra-Putra and Andrews, 2019; Crick et al., 2018; Han and Peng, 2019). When insurance premiums are contingent on the implementation of structural adaptation measures, it not only enhances financial resilience in the short-term but leads to reduced vulnerability and stable premiums.

Recovery: empirical literature on resilience assessment operates with indicators of socio-economic resilience capturing inequality (Cutter et al., 2003; Linkov et al., 2013). Since flood-ABMs employ heterogeneous agents, they may potentially trace the dynamics in financial or social capitals across scales in the 5C-4R terms (Campbell et al., 2019) or economic and institutional resilience in BRIC/DROP terms (Cutter and Derakhshan, 2019). Yet, flood-ABMs hardly highlight the impact of socio-economic heterogeneity on recovery from a natural disaster. Moreover, CCA's affordability is often overlooked in flood-ABMs that omit budget constraints at the agent level, 8:18, and 3:12 in the SH and MR group correspondingly. With budget constraints, flood-ABMs show differences in the implementation of CCA measures among income groups (Han and Peng, 2019) and reveal climate gentrification that undermines urban resilience (De Koning and Filatova, 2020). Walsh and Hallegatte (2019), a pioneer in quantifying socio-economic resilience in an ABM by translating flood damages into wellbeing losses while differentiating among income groups. Eid and El-Adaway (2018); Eid et al. (2017) employ resilience indices to study a recovery after a tornado. Hence, it should also be feasible to integrate them into flood-ABMs. Employment opportunities are another critical factor of a successful recovery, included in most socio-economic indicators of resilience (Cutter and Derakhshan, 2019). However, the backbone of regional resilience and recovery – the role of firms that provide households with jobs and income – is entirely overlooked in flood-ABMs. Flood-ABMs could learn from the first attempts to incorporate firms' behavior in ABMs in response to other hazards (Eid and El-Adaway, 2017, 2018) and immediate disaster response (Coates et al., 2019, 2016).

2.4 Conclusions

There is a growing recognition that socio-environmental systems models need to include behaviorally-rich and dynamic representations of human actors (Schill et al., 2019). This is especially important for climate change models where societies and economies are inadequately represented (Elsawah et al., 2020; Stern, 2016). The critical role of social interactions in influencing adaptation behavior in the real world is increasingly recognized (Wilson et al., 2020). The acknowledgment of the crucial role that human actors play in altering flood-prone cities' risks and resilience drives a paradigm shift in climate risk assessments. This influence can be seen in the proliferation of recently built computational models that explicitly include diverse socio-economic actors. Our systematic literature review analyzes 28 flood-ABMs, distinguishing between ABMs stemming from economics & behavioral sci-

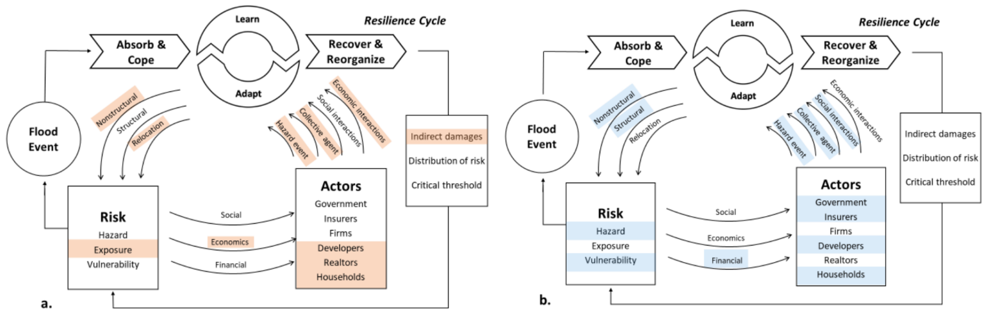

Figure 2.6: CAS resilience in flood-ABMs. Panels (a) and (b) reflect the key focus areas of the *Market & Relocation (MR)* and *Socio-Hydrology (SH)* groups correspondingly, as discussed in Section 3 above.

ences and hydrology. We find that the two groups look at risk components and at the ability of a socio-economic system to cope with flooding from distinct perspectives (Figure 2.6). Likewise, they address the key CAS resilience elements, such as *adaptation*,*interactions*, and *learning*, differently (Figure 2.6). Most flood-ABMs focus on households while representing decisions of government, insurers, and urban developers simplistically. A few flood-ABM in both groups focus on the long-term *recovery* and *reorganizational* element of resilience, which often implies combining modeling of individual actions and changes in social institutions (formal like markets or regulations, and informal like social norms), groups of actors and networks of organizations. Thus, the crucial transition from incremental to transformative adaption is still lacking.

Learning from the current advances in flood-ABMs, the review identifies the following directions for future research.

Learning across disciplinary views: we call for adopting a multidisciplinary and complementary approach, that reconciles the merits of the MR and SH groups, improving their possibilities to trace CAS resilience. The SH community's advances represent a vast pool of stakeholders and dynamic vulnerability (Figure 2.6.b) due to on- site structural CCA in computational ABMs and integration with natural hazard modeling (hydrology, depth-damage curves). While the MR ABMs are firmly grounded in socio-economic theories and data to support agents' decisions and interactions, and model collective social institutions to capture dynamics in exposure and capital at risk endogenously (Figure 6a). The successful examples of the integration of the two views - (Chandra-Putra et al., 2015) and (Dubbelboer et al., 2017) – illustrate the feasibility and need to make some tradeoffs and simplifications. To measure the evolution of both prices and EAD, both articles introduced a simplified form of the housing market. The interdisciplinary dialog can be further supported by promoting reuse of code via open- access libraries and the modular approach to designing ABMs (Bell et al., 2015). Yet, significant progress is still due in the reproducibility of flood-ABMs. Only 35% use the ODD protocol (Grimm et al., 2020), and code is open access in less than 20% of the cases (Abebe et al., 2019a; De Koning and Filatova, 2020; Dubbelboer et al., 2017; Walls et al., 2018).

Behavioral theories and empirical data for agents' decisions: a transition from a representative rational agent to diverse behaviorally-rich actors in computational models may take various pathways. Social sciences offer a rich set of theories and empirical evidence on behavioral change, decisions under uncertainty, and factors influencing CCA decisions (Koerth et al., 2017; Noll et al., 2020) that can make this process scientifically sound. Still, 13:28 articles report flood-ABMs that use ad hoc rules to model behavioral change and social dynamics, undermining the call of the ABM community to have solid theoretical micro foundations (Schlüter et al., 2017). Regarding Household agents, most flood-ABMs go beyond perfect rationality either by employing behavioral theories or relaxing the perfect information condition for decisions driven by Expected Utility (e.g., via information asymmetry, myopia, subjective perceptions, or social influence). Therefore, bounded rationality prevails among theory-driven Household agents. Flood-ABMs rarely compare competing theories' performance and tend to 'grandfather' theories used for that class of decision making earlier, overlooking advances in psychological research. Hence, we recommend to compare different theories and test ABMs with different theoretical micro-foundations against empirical macro patterns (de Koning et al., 2017). Other agents in flood- ABMs – Government, Developer, Insurer – usually follow ad hoc rules or rely on rational decision making, leaving room for improvements. While social sciences offer a rich theoretical basis for modeling, these collective agents and social institutions they represent, are sparsely employed in computational models of CCA. Using more robust theories to manifest agents would allow a more in-depth analysis of the interactions: an underlying component in resilience. Notably, only three flood-ABMs use case-specific micro-level data to support modeling of agents' actions and interactions; the majority still relies on secondary literature data or expert judgments, if any. Using aggregate data to estimate critical behavioral parameters such as preferences or risk perceptions in flood-ABMs may mislead policy (Erdlenbruch and Bonté, 2018). Flood-ABMs need to go beyond employing the data on the physical side and leverage the rich data from CCA studies in the future. Importantly, one needs to think about designing the data collection since adaptation to the 'new normal' foresees choices in response to events of intensity and frequency that humanity has not experienced for thousands of years.

Indirect damages and role of firms: flood-ABMs largely focus on estimating direct damages, with some models capturing relocation and changes in housing prices, but mainly overlooking other indirect effects. Yet, indirect damages, including business interruption, losses of employment opportunities, and tax revenues, may be higher than direct losses (Hallegatte, 2008b). They could significantly exacerbate total risks beyond acceptable levels, bringing societies over the tipping points along climate adaptation pathways (Haasnoot et al., 2013) crucial for resilience. Quantitative metrics of socio-economic resilience (Cutter and Derakhshan, 2019) or well- being losses (Walsh and Hallegatte, 2019) commonly include employment opportunities, stressing the critical role of firms. Yet, none of the reviewed flood-ABMs include firms as agents (Figure 2.1). The inclusion of firms would extend the existing risk framework beyond a change in hazard, exposure, and vulnerability towards dynamic resilience assessment.

Heterogeneity within agent groups and evolution of resilience: we find that core-characteristics of resilience – the ability to learn, adapt and recover and reorganize from a shock – are gradually adopted in flood-ABMs, yet the full power of complex adaptive systems remains underexplored. Additionally, components of coupled systems are rarely equally vulnerable (Turner et al., 2003). While ABMs are designed to capture heterogeneity, most flood-ABMs only report aggregated damages, prices, or adoption rates of CCA actions for entire populations and regions. Attempts to explore the distribution of risks and CCA actions across different socio- economic groups are scarce. The models that do so, do not yet capture risk levels among different sections of the community. Does risk reduction for high-income groups leave low-income groups more vulnerable? Failing to report the distributional impacts in flood-ABMs misrepresents the scope and limits of adaptation and hinders the monitoring of socio-economic resilience over time. Finally, these generalizations have similar drawbacks to using the single 'representative-actor' and fail to utilize one of ABM's greatest strength: analysis of heterogeneity.

From incremental to transformational adaptation: the ramifications of climate change expose the limits of traditional CCA, making transformational adaptation only a question of households' actions (insurance uptake, flood-proofing houses, small scale relocation), hardly looking into transformational actions that include new radical changes in societal responses to hazards. That being said, ABMs can incorporate dynamic social institutions, trace cross-scale feedbacks, and capture non-linear dynamics that instigate transformational CCA (Wilson et al., 2020). Modeling transformational CCA with ABMs could be a natural extension and inherent part of "reorganization" in Figure 2.1.

A complex adaptive systems approach that is grounded in social science theories and behavioral data, covers various stakeholders, including firms, traces heterogeneity of risk distribution, and includes modeling of dynamic behavior and institutions essential to trace the emergence of transformational CCA should be the way forward. One of the main challenges in addressing climate change lies in integrating information, knowledge, experiences, and collaborative projects involving scientists, practitioners, and policymakers from different disciplines. Resilience is an emerging theme in the climate policy domain that provides a systems perspective to structure a multi-community discussion. Therefore, we argue for a resilience-based dialogue to strengthen collaboration significantly and facilitate learning and information exchange across disciplines.

3

3 Coping with increasing tides: Evolving agglomeration dynamics and technological change under exacerbating hazards

By 2050 about 70% of the world's population is expected to live in cities. Cities offer spatial economic advantages that boost agglomeration forces and innovation, fostering further concentration of economic activities. For historic reasons urban clustering occurs along coasts and rivers, which are prone to climate-induced flooding and sea level rise. To explore trade-offs between agglomeration economies and hazards increasing with climate change, we develop an evolutionary agent-based model with heterogeneous boundedly-rational agents who learn and adapt to a changing environment. The model combines migration decision of both households and firms between safe Inland and hazard-prone Coastal regions with endogenous technological learning and economic growth. Flood damages affect Coastal firms hitting their labour productivity, capital stock and inventories. We find that the model is able to replicate a rich set of micro- and macro-empirical regularities concerning economic and spatial dynamics. Without climate-induced shocks, the model shows how lower transport costs favour the Coastal region fueling the self-reinforcing and path-dependent agglomeration processes. We then introduce five scenarios of floods characterized by different frequency and severity to study the complex interplay of hazards with agglomeration patterns affecting the performance of the overall economy. We find that when shocks are mild or infrequent, they negatively affect the economic performance of the economy. If strong flood hazards hit frequently the Coastal region before agglomeration forces trigger high levels of the waterfront urbanization, firms and households can timely adapt and migrate landwards, thus averting the adverse impacts of climate shocks on the whole economy. Conversely, in the presence of climate tipping points where the frequency and magnitude of flood hazards abruptly intensifies, we find that eco-

nomic activities remain trapped in the hazard-prone region, generating lock-ins and leading to a harsh downturn of the overall economy.

This chapter is based on *Taberna, A., Filatova, T., Roventini, A., & Lamperti, F. (2022). Coping with increasing tides: Evolving agglomeration dynamics and technological change under exacerbating hazards. Ecological Economics.* (Taberna et al., 2022).

3.1 Introduction

Rapid urbanization and climate change exacerbate risks worldwide (IPCC, 2022b), particularly impacting coastal areas (Vousdoukas et al., 2020). With the climate conditions that humanity has enjoyed for centuries, coastal and delta regions historically grew faster than inland areas, with all current megacities flourishing along the coast. The richness of natural amenities and resources coupled with transportation advantages facilitated agglomeration forces that have enabled this boom (Fujita and Mori, 1996b). Yet, the escalation of climate-induced hazards fundamentally reshapes the trade-offs which firms and households consider while choosing a location (Coronese et al., 2019). Increasingly, managed retreat becomes plausible for all types of coasts even under low and medium sea level rise scenarios (Carey, 2020), raising a hot debate on how to make this a positive transformation (Haasnoot et al., 2021). This is particularly relevant for areas hit by recurrent hazards, which leave little time for recovery and could lead to economic gentrification and poverty traps (de Koning and Filatova, 2019; Hallegatte and Dumas, 2009; Hallegatte et al., 2007). Notably, displacement after a major flood is a common phenomena (Levine et al., 2007). Hurricane Katrina provided a clear example of interdependencies between households and firms location choices in response to a disaster. In New Orleans, as people out-migrated looking for better employment opportunities (Deryugina et al., 2018), economic sectors relying on local consumption struggled the most, especially in the long-run (Dolfman et al., 2007). In addition, empirical evidence suggests that firms' reopening decisions depend on the return of both their competitors and customers (LeSage et al., 2011).

Understanding the location and agglomeration of productive activities has been at the core of spatial economics for almost two centuries (von Thünen, 1826). The "New Economic Geography" (Krugman, 1998) literature has proposed a coherent analytical framework grounded in general equilibrium analysis of the spatial distribution of economic activities. It links international trade and geographic location of firms and consumers, and relies on increasing returns to explain emergent spatial structures (Krugman, 1992). This literature defines agglomeration economies as a self-reinforcing process that attracts and clusters economic activities and population in specific locations. The agglomeration economies unfold as an interplay between centripetal and centrifugal forces that pull towards a geographical concentration or push towards a dispersion of economic activities respectively. The new economic geography models traditionally assume a unique equilibrium and rational representative agents with perfect information. Yet, heterogeneity of technologies, resources and preferences, as well as the fundamental uncertainty necessitating dynamic expectations and adaptive behavior (Arthur, 2021), challenge these assumptions. Furthermore, analytical tractability confined new economic geography to a largely theoretical equilibrium analysis, with little empirical contributions and receiving critics from both within and outside the field (Gaspar, 2018).

Agent-Based Models (ABMs) have risen as a method to accommodate heterogeneity, learning, interactions and out-of-equilibrium dynamics (Bonabeau, 2002; Tesfatsion and Judd, 2006). In both environmental and climate change economics (Balint et al., 2017; Ciarli and Savona, 2019; Lamperti et al., 2019b; Mercure et al., 2016) and economic geography (Fowler, 2007; Spencer, 2012). ABMs are versatile in modeling disaster scenarios (Coronese et al., 2022; Lamperti et al., 2018; Waldrop, 2018), and flooding in particular (Taberna et al., 2020). Notably, taking into account interactions among heterogeneous agents - traditionally omitted by new economic geography (Ottaviano, 2011) - ABMs demonstrate how - in line with the evolutionary economic geography tradition (Boschma and Frenken, 2006; Frenken and Boschma, 2007; Martin and Sunley, 2006) - stochastic knowledge exchanges in the form of innovation create new market opportunities and trigger the agglomeration process endogenously, even from spatially-even initial conditions. Hence, ABMs are particularly useful to capture evolutionary inter-temporal and path-dependency phenomena such as the mutual relocation of households and firms and feedbacks between climate and the economy.

However, while ABMs are increasingly applied to study climate change mitigation (Lamperti et al., 2018, 2020; Monasterolo et al., 2019), multi-region economies (Mandel et al., 2009; Wolf et al., 2013) and household-level adaptation (de Koning and Filatova, 2019; de Koning et al., 2017; Filatova, 2015) - including farmers (Coronese et al., 2021; Gawith et al., 2020b) - ABMs studying an economy shaped by locations of economic activities and agglomeration forces exposed to climate-induced risks are missing. When studying climate-induced hazards, ABMs rarely focus on firms' adaptive location decisions, despite being the core of a resilient regional economy.

To address this crucial gap, we designed the *Climate-economy Regional Agent-Based* (CRAB) model to study the spatial distribution of economic agents, - firms and households - facing of the costliest climate-induced hazard: flooding. We chose flooding as the costliest, most widespread climate-induced hazard and the first to hit urbanized regions worldwide today. However, the CRAB model primary mechanism could be linked to other climate shocks similarly disrupting the economy, such as droughts and wildfires. Following previous work on evolutionary macroeconomic ABMs (Dosi et al., 2013, 2010, 2017b, 2018b; Lamperti et al., 2018), our model uses R&D investment and a "Schumpeterian" creative (innovative) destruction process as the engine of endogenous economic growth.[1] Our goal is to explore how the complex trade-offs between endogenous agglomeration economies and a changing severity of location-specific climate-induced hazards affect the economic performance and attractiveness of Coastal and Inland regions and steer their development. In particular, we address three research questions: (1) How do agglomeration forces shape economic centers in coastal regions? (2) What are the effects of climate shocks of various severity and probability on this agglomeration dynamics? (3) How does the complex interplay between agglomeration economies, technological change and flood hazards affect the economic performance of the regions?

The novel contribution of this article is three-fold. First, we add to the economic geography literature by introducing a out-of-equilibrium framework that employs innovation diffusing among heterogeneous boundedly-rational agents as the cause of agglomeration, ultimately leading to the uneven spatial distribution of economic activities across regions. Second, we go beyond the evolutionary macroeconomic ABMs tradition by introducing two regions and endogenous inter-region migration decisions for both firms and household. Lastly, the model accounts for climate shocks of varying probabilities and severity, revealing possible tipping points in the coupled climate-economy dynamics that might compromise regional development. Regarding the latter contribution, although our paper provides an illustrative stress test on how a regional economic system reacts to drastically changing hazards, it highlights the importance of anticipating and planing a timely retreat

[1]For a detailed perspective on evolutionary economics see Nelson and Winter (1985).

(Haasnoot et al., 2021). A positive retreat could be facilitated by the power of agglomeration forces essential to avoid increasing exposure of economic activities to intensifying climate-induced shocks and to overcome increasing sunk costs of investments in climate-sensitive areas.

Our simulation results show that this ABM is able to account for a wide ensemble of micro- and macro-empirical regularities concerning economic and spatial dynamics. In absence of floods, the Coastal region holds the natural spatial advantage of being a transportation hub and it experiences an inflow of economic activities from the Inland region driven by the co-evolution of agglomeration economies and endogenous technological change. The likelihood and the speed of the agglomeration process are contingent on the extent of such location advantages, which depend on transport costs and the volume of trade between the two regions have and the rest of the world. Finally, when climate shocks are introduced, their frequency and severity affect the final distribution of economic activities between climate-sensitive and safe regions and the economic growth of the entire economy. Specifically, infrequent or mild shocks harm the economic performance of the two regions with different effects on the agglomeration process. When flood hazards are frequent and severe from the beginning of the simulation, firms and household are able to timely adapt retreating to the Inland region while they still have resource to relocate. This helps avoiding lock-ins with possible catastrophic economic impacts. Conversely, under the occurrence of late climate tipping points when both the magnitude and frequency of climate shocks abruptly increases, the economic performance is substantially harmed as unfolding agglomeration economies concentrate firms in the Coastal region making the relocation unaffordable when it becomes necessary. In all scenarios, we find that climate shocks can affect the economy in an heterogeneous manner, pointing to the importance of studying various economic channels impacted by the adversity.

The rest of the article proceeds as follows. Section 3.2 describing the methodology. In Section 3.3, simulation results are presented and discussed. Finally, Section 3.4 concludes.

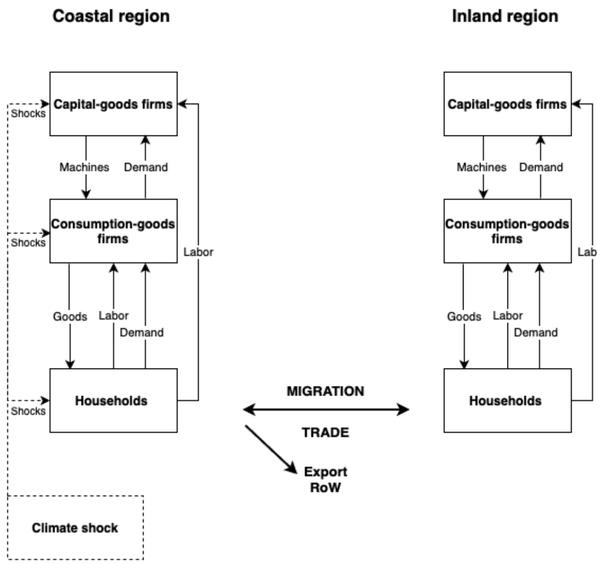

Figure 3.1: A conceptual representation of the CRAB model.

3.2 The model

To analyze the effect of coastal flooding on agglomeration dynamics, we build using Mesa, an open-source Python 3 package (Kazil et al., 2020), the *Climate-economy Regional Agent-Based* (CRAB) model upon the evolutionary economic engine of the "Keynes + Schumpeter" macroeconomic family of models ("K+S"; Dosi et al., 2017a). Specifically, we extend by adding two different regions, endogenous migration dynamics and climate hazards inspired by the DSK model (Lamperti et al., 2019a, 2018). In our CRAB model, firms and households are located in either a safe Inland region or a hazard-prone Coastal region (Figure 3.1). Although stylized at this stage, the spatial scale of each region could be comparable to a European NUTS1 level. Agents can migrate between the two regions, whose economic attractiveness changes over time due to an interplay between centripetal and centrifugal forces. On the one hand, technological change and localized spatial spillovers boost profits and wages and generate a centripetal market-size effect. On the other hand, the increase of competition in one region works as a centrifugal force, making it less attractive for further relocation[2]

More in detail, the economy of region r consists of $F1^r$ heterogeneous capital-good firms (denoted with the subscript i), $F2^r$ consumption-good firms (denoted with the subscript j) and L^r households (denoted with the subscript h) supplying work and consuming the income they receive (Figure 3.1). When a decision process is identical for both capital- and consumption-good firms (e.g. migration, cf. Subsection 3.2.4), we employ the subscript f for both types of firms.[3]

[2]for a comprehensive discussion of such centrifugal and centripetal forces see Krugman (1998).

[3]We assume that the current model focuses on industrialized regions and, hence, omits the agricultural sector

In the CRAB model, all the aforementioned agents are boundedly-rational since they lack full information about e.g., prices, demand, wages or hazards and they make choices under uncertainty, not only due to probabilistic hazards but also due to the unknown production, pricing and consumption strategies of other economic actors. For this reason, they employ *heuristics* to make decisions[4]. Following the seminal contributions of Cyert et al. (1963); March and Simon (1993); Simon (1955), we define a heuristic as "a strategy that ignores part of the information, with the goal of making decisions more quickly, frugally and/or accurately than more complex methods" (Gigerenzer and Gaissmaier, 2011). Specifically, we align with the evolutionary ABM macroeconomic tradition (Dosi et al., 2020) that employs the "less-is-more" principle to balance accuracy between the interpolation of past observations and predictions[5].

Capital-good firms produce heterogeneous machines and invest in R&D to stochastically discover more productive technologies. Hence, technological learning is endogenous in the model. Consumption-good firms combine labour and machines bought from the capital sector to produce a final homogeneous consumer product. A bank lends financial resources to all firms at a fixed interest rate. Finally, a stylized government collects taxes from all firms and pays unemployment subsidies to households in both regions (Figure 3.1).

The regional dimension of the model affects market interactions. The two labour markets are decentralized[6] and local: firms can only hire workers residing in their own region[7]. Conversely, goods market are global: firms from both sectors are able to sell in the other region and export to the rest of the world (RoW) bearing a regional and international iceberg transport cost respectively. We assume that goods are shipped to RoW from a port in the Coastal region, while Inland firms have to first transport their goods to the Coastal region. Hence, Coastal firms have a comparative advantage in trade with RoW as Inland firms pay both the regional and international transport cost when exporting.

Furthermore, different hazards - here floods - can hit firms in the Coastal region, impacting their productivity, capital stock, and inventories. As a first step, we test the impact of floods on agglomeration dynamics by using four stylized climate shock types[8]. Each type is characterized by a specific probability and severity that are stable over time (see Section 3.2.5 for details). In addition, we include a "tipping point scenario" where

because of its minor contribution in terms of employment and output in agglomerated areas. In the future, the model could be extended to account, for example, for rural-urban migration.

[4]This choice comes naturally since both empirical evidence (see, e.g., Carroll, 2003; Coibion and Gorodnichenko, 2012; Gennaioli et al., 2016) and experimental studies (see, e.g., Anufriev and Hommes, 2012; Kahneman, 2003; Kahneman et al., 1982) do not support the fully-informed rational behavior assumption, traditionally included in economics models.

[5]Heuristic expectations may be the best and more logical response in a complex and changing macroeconomic environment. For more information about the impacts and robustness of heterogeneous expectations within an evolutionary economics ABMs see Dosi et al. (2020).

[6]For other ABMs that feature decentralized labour markets and matching processes see Caiani et al. (2016a); Dawid et al. (2008, 2012, 2014); Dosi et al. (2018a); Fagiolo et al. (2004); Riccetti et al. (2015); Russo et al. (2016). Furthermore, for critical surveys on macro ABMs see Dawid and Delli Gatti (2018); Dosi and Roventini (2019); Fagiolo and Roventini (2017); Gatti et al. (2010).

[7]The assumption of a spatially constraint labor market provides a good approximation at the regional level. Our model currently omits teleworking and inter-regional commuting since we primarily focus on the production of goods and machinery that require physical presence; however, both could be added should this becomes a research focus.

[8]In future work, we plan to shift the stylized model of regional economies to more realistic settings and to include the worsening of the conditions following the standard IPCC RCP scenarios.

climate conditions abruptly change from the mildest to the most extreme type in the middle of the simulation. There is significant evidence that human activities have pushed the planetary system close to a climate tipping point (the so-called “Hothouse Earth”) (Lenton et al., 2008; Steffen et al., 2018). Consequently, we might be just few decades ahead to experience cascading effects leading to temperature and sea-level rise significantly higher than at any time in the Holocene (Lenton, 2020).

In the next sub-sections, we discuss the model. Further details are spelled out in Appendix 7.1.1.

3.2.1 The capital- and consumption-good sectors

As in the “K+S’ model, the capital-good sector is characterized by imperfect information and Schumpeterian competition that drives technological learning within each region.[9] To discover newer and more productive technologies, capital-good firms invest a fraction of their past profits in R&D. The latter are divided between the discovery of newer machine-embodied techniques and the imitation of their competitor technologies. Notably, firms have limited information and hence more likely to imitate competitors located in the same region and with similar technologies: the higher the technological distance with a specific firm (computed using an Euclidean metric), the lower the probability to imitate its technology. Moreover, as in Dosi et al. (2019), we augmented the technological distance of firms located in different regions by a factor $\epsilon > 1$ which captures geographical barriers hampering learning. Once the technological change concludes, firms choose the machine to produce and set prices adding a fixed markup over unit costs. The price and productivity of their machines is then communicated sending “brochures” to the current and a sub-sample of new possible customers - the consumption-good firms. Having received orders from their customers, capital-good firms start producing employing solely labour.

Consumption-good firms combine labour and capital to produce a homogeneous good. In line with the “K+S" tradition, adaptive (myopic) demand expectations determine the desired levels of production and capital stock through a fixed capital-output ratio[10]. Notably, if the current capital stock is insufficient to produce the desired output, consumption-good firms order new machines to expand their stock of heterogeneous vintage. Moreover, they replace old and technologically obsolete machines according to a payback period rule. Firms pay for the capital in advance with own liquid resources. Whenever the latter are not sufficient, firms that are not credit-constrained get access to a bank credit. Hence, the labour productivity of consumption-good firms increases over time following the expansion and renovation in the mix of vintages embedded in their capital stock. Consumption-good firms have limited knowledge about the environment and choose their machine-tool supplier comparing the “brochures” they are aware of and select the one with the best quality-price ratio. Finally, they update their price, adding a variable markup on production costs, which depends on the past evolution of their market-share. They balance own market shares and profit margins by increasing their markup whenever the former is expanding and vice

[9]For a detailed description of the capital-good and consumption-good sectors, see Appendix 7.1.1 and Dosi et al. (2015).

[10]Empirical evidences support the assumption of a constant capital-output ratio (Dosi, 1990; Kaldor, 1957).

versa[11].

3.2.2 Consumption-good markets

Consumption-good firms compete in three markets, namely the Coastal (Co), the Inland (In) and the Export (Exp). In a generic market m, firm's competitiveness (E_j) depends on its price, which can account for inter-regional (τ_1), international (τ_2) transport costs, as well as on the level of unfilled demand (l_j):

$$E_j^m(t) = -\omega_1 p_j^m(t)(1+\tau_1+\tau_2) - \omega_2 l_j^m(t) \quad with \quad \omega_{1,2} > 0, m = [Co, In, Exp]. \tag{3.1}$$

Of course, in the Coastal (E_J^{Co}) and Inland (E_j^{In}) market, $\tau_2 = 0$, while they pay no transport cost to compete in the region where they are located. In line with the spatial economics literature that indicates ports as hub for international trade (Fujita and Mori, 1996b; Glaeser, 2010), we model the competitiveness (E_j^{Exp}) in the Export market so that firms located in the Coastal region holds a competitive advantage in trade with the rest of the world, i.e. $\tau_1 = 0$, while Inland firms bear it. Notably, this assumption implies that the magnitude of the comparative advantage depends on the value of the inter-regional transport cost.

In each market (m), the average competitiveness ($\overline{E}^m$) is calculated by averaging the competitiveness of all firms in the corresponding region weighed by their market share in the previous time step:

$$\overline{E}^m(t) = \sum_{j=1}^{F2} E_j^m(t) f_j^m(t-1) \quad with \quad m = [Co, In, Exp]. \tag{3.2}$$

The market shares (f_j) of firms in the three markets evolve according to a quasi-replicator dynamics:

$$f_j^m(t) = f_j^m(t-1)\left(1 + \chi \frac{E_j^m(t) - \overline{E}^m(t)}{\overline{E}^m(t)}\right) \quad with \quad m = [Co, In, Exp], \tag{3.3}$$

with $\chi > 0$ which measures the selective pressure of the market. In a nutshell, the market shares of the less efficient firms shrink, while those of the most competitive ones increases (due to lower prices and less unfilled demand). Firms' individual demand in each market is then calculated by multiplying their market share by the total demand. In the export market, we assume exogenous demand that grows at a constant rate (α):

$$Exp(t) = Exp(t-1)(1+\alpha), \quad \alpha > 0. \tag{3.4}$$

In the two regions, as households spend all their income, total demand for goods equals aggregate regional consumption (C):

$$D_j(t) = C^{Co}(t) f_j^{Co} + C^{In}(t) f_j^{In} + Exp(t) f_j^{Exp}, \tag{3.5}$$

with C^{Co} and C^{In} computed by summing up all the wages and unemployed benefits of the households in each region[12].

[11] For more information about demand expectation, capital investments and price formation in the consumption-good sector see Appendix 7.1.1.

[12] For more detail about aggregate consumption see Appendix 7.1.1

3

3.2.3 Labour market dynamics

Firms in the Coastal and Inland zones offer heterogeneous wages which depends on their productivity, as well as on regional productivity, inflation and unemployment:

$$w_j(t) = w_j(t-1)\left(1+\psi_1\frac{\Delta AB_j(t)}{AB_j(t-1)}+\psi_2\frac{\Delta\overline{AB^r}(t)}{\overline{AB^r}(t-1)}+\psi_3\frac{\Delta U^r(t)}{U^r(t-1)}+\psi_4\frac{\Delta cpi^r(t)}{cpi^r(t-1)}\right), \quad (3.6)$$

With $\psi_1 > 0$, $\psi_2 > 0$ and $\psi_1+\psi_2 \leq 1$ and where r is the region where firm j is located, AB_j is its individual productivity, $\overline{AB^r}$ is the regional productivity, cpi^r is the regional consumer price index and U^r is the local unemployment rate.

Interactions in the local labor markets are decentralized. This process allows to take into account unemployment as a genuine structural disequilibrium phenomenon. As we assume no commuting, households can only work for the firms in the same region where they live. Hence. the labour supply $L^{S,r}$ of region r at time t, is thus equal to the number of households living in that region. The aggregate labour demand $L^{D,r}$ is given by the sum of individual firms labour demand:

$$L^{D,r}(t) = \sum_{i=1}^{F1^r}\sum_{j=1}^{F2^r} L_f^d \quad with \quad f=[i,j], \quad (3.7)$$

where $F1^r$ and $F2^r$ are the populations of capital- and consumption-good firms located in region r. The labour demand of capital-good firm i (L_i^d) is equal to:

$$L_i^d = \frac{Qo_i^r(t)}{B_i(t)}, \quad (3.8)$$

where Qo_i is the quantity ordered to the firm and B_i its productivity. Similarly, the labour demand of consumption-good firm j (L_j^d) is computed as:

$$L_j^d = \frac{Qd_j(t)}{A_j(t)}, \quad (3.9)$$

where Qd_i is its production and A_j its average productivity.

The labour market matching mechanism in the two regions operates as follow:

1. If $L_f^d(t) > n_f(t)$, where $n_f(t)$ is the current labour force of a generic firm f, the firm posts m vacancies on the labour market, with $m = L_f^d(t) - n_f(t)$. Conversely, if $L_f^d(t) < n_f$ the firm fires m employees.
2. Unemployed households have imperfect information and are boundedly-rational: they are aware only of a fraction $\rho \in (0,1]$ of all vacancies posted by the firms in their home region.
3. Unemployed households select the vacancy with highest offered wage in their sub-sample and they are hired by the corresponding firm.

The process is completed when either all households are employed or firms have hired all the workers they need. Note that there is no market clearing and and involuntary unemployment as well as labor rationing are emergent properties generated by the model.

3.2.4 Inter-regional migration

Households and firms can endogenously decide to move to another region. While migration can take a form of seasonal, temporal or permanent, here we assume only permanent migration. As a consequence, our model does not focus on post-hazard evacuation, which is already well-studied elsewhere (Dawson et al., 2011; Micolier et al., 2019). The latter concerns the immediate recovery while we focus on long-term regional dynamics. Hence, the current version of the CRAB model represents the context of industrialized economies, where the long-term economic attractiveness of regions drives households and firms permanent migration. It is still possible that years later, households and firms may relocate again, but only if they find it economically beneficial to move because of the regional advantages, e.g. labour market for workers or better business opportunities for firms.

To capture heterogeneous location preferences and imperfect information about regional variables such as wage levels, we model migration as a probabilistic two-step procedure. In the first step, agents compare selected indicators between the two regions, to obtain an individual migration probability. Clearly, the probability is positive only if their home region performs economically unfavourably. In the second step, the agents with a positive migration probability perform a draw from a Bernoulli distribution. If successful, the household will migrate, while the firm will relocate only if it can afford the relocation costs, which are assumed to be proportional to its size. This captures potential migration costs as well as preference for the home region. Regarding the first step, the probability to migrate depends on a switching test (see Caiani et al., 2016b; Delli Gatti et al., 2010; Rizzati et al., 2018) grounded in economic variables. Namely, both employed and unemployed households h learn about the economic conditions between the regions comparing wages and levels of unemployment, and their probability to migrate (Pr^m) is:

$$Pr_h^m(t) = \begin{cases} 1 - e^{(\varphi_1 W_d(t) + \varphi_2 U_d(t))}, & \text{if } W_d(t) \text{ and } U_d(t) < 0 \\ 0, & \text{otherwise} \end{cases}. \tag{3.10}$$

Where $\varphi_1 + \varphi_2 \leq 1$. W_d is the *wage distance* which captures the average salary difference between the two regions:

$$W_d(t) = \frac{(\overline{W^r}(t) - \overline{W^*}(t))}{\overline{W^r}(t))}, \tag{3.11}$$

where r is the region where the agent is located and $*$ is the other one. Similarly, the *unemployment distance* U_d reads:

$$U_d(t) = \frac{(U^*(t) - U^r(t))}{U^r(t)}. \tag{3.12}$$

Despite being a major attractor for people, we do not include coastal amenities in household migration decisions for two reasons. First, the amenity effect is usually very localized, with an effect that disappears rapidly with distance, sometimes in 1 km (Beltrán et al., 2018; Bin et al., 2008). Second, the COVID-19 pandemic brought mixed evidence on where people move, with less densely populated coastal and landward regions displaying a price increase[13].

[13] Assuming a migration process driven by economic self-interest is supported by empirical evidence that shows how inter-regional migration decisions are influenced to a substantial extent by income prospects (Kennan and Walker, 2011).

3

Bigger and more profitable markets work as basins of attraction for firms (Bottazzi et al., 2008; Krugman, 1998). As firms have limited information about competitors but access to own market data, we assume that firms' mobility choices depend on the local regional demands for their goods. More specifically, firms f calculate the probability to migrate according to:

$$Pr_f^m(t) = \begin{cases} 1 - e^{(\varphi_3 Dd_f(t) + \varphi_4 DAd(t))}, & \text{if } Dd_f(t) \text{ and } DAd(t) < 0 \\ 0, & \text{otherwise} \end{cases}, \tag{3.13}$$

where $\varphi_3 + \varphi_4 \leq 1$. Dd is the *demand distance* of firm f between the two regions:

$$Dd_f(t) = \frac{(D_f^r(t) - D_f^*(t))}{D_f^r(t))}. \tag{3.14}$$

Firms also consider the dynamics of their sales with the *"Demand attractiveness"* (DAd):

$$DAd_f(t) = \frac{(DAd_f^r(t) - DAd_f^*(t))}{DAd_f^r(t)}, \tag{3.15}$$

where $DAd_f^{r,*}(t) = log(s_f^{r,*}(t)) - log(s_f^{r,*}(t-1))$ and s_f are individual firm sales.

As the empirical evidence shows that agents are reluctant to migrate (Linnenluecke et al., 2011, 2013), we assume that they consider to move only if all the economic conditions of the other region are better, i.e higher wage and lower unemployment for households (cf. Eq. 3.10), and higher demand for firms (cf. Eq. 3.13).

In the second step, to finalize migration, economic agents with positive probability ($Pr^m > 0$) perform a draw from a Bernoulli distribution:

$$\theta^{migr}(t) = Pr_a^m(t) \quad with \quad a = [h, f]. \tag{3.16}$$

They follow a similar method to determine whether technological innovation or imitation is successful (see Eq. 7.4, and Eq. 7.5 in Appendix 7.1.1), with a higher probability in the first step leading to a more likely positive outcome from the draw.

If the drawn from the Bernoulli distribution is successful, the agent migrates to the other region. Households leave their job (if employed) and move to the other region as unemployed. Migrant firms fire all their employees, paying a fixed cost that is equal to the sum of their quarterly wages:

$$Mfc_f(t) = n_f w_f, \tag{3.17}$$

where n_f is the number of workers currently employed by the firm and Mfc_f is the total cost to fire them. Note that such firing costs are increasing with firm's size (in line with the empirical evidence, see e.g. Pellenbarg et al., 2002) and they constitute an additional barrier to the mobility of firms, which may not have enough financial resources for transferring their activity in the other region.

3.2.5 Climate-induced shocks

In each time step, there is a probability (Pr_s), that a climate shock, which we interpret here as a flood, hits the Coastal region. Since we focus on the evolutionary dynamics of the economy following a hazard shock, the model is hazard-agnostic and can be adopted to study other climate-induced hazards (e.g. wildfires), whose probability and severity change over time. Future versions of the model can include a richer representation of hazards, possibly adopting a modular approach as in Tesfatsion et al. (2017). As such our model is complementary to socio-hydrology literature (Di Baldassarre et al., 2013; Haer et al., 2020; Michaelis et al., 2020b) interested in the interplay of hydrological hazards and economic development, but focused on the detailed modeling of floods and endogenous changes in hydrological regimes, with a simplified representation of the economic side.

To include hazards in a generic form, the current model draws from a Bernoulli distribution - in the similar fashion as for migration and technological learning (see Subsection 3.2.4, and Appendix 7.1.1) - to determine whether a shock occurs:

$$\theta^s(t) = Pr_s(t), \quad with \quad Pr_s \in (0,1]. \tag{3.18}$$

Notably, the same hazard can cause different damages to the economy depending on the evolution of firms and households population in the Coastal zone. Moreover, since in reality location-specific exposure is unequal, we model the shock at individual level, thus leading to heterogenous impacts hitting firms[14]. More precisely, each Coastal firm (fc) draws an individual damage coefficient ($Dc_{fc}(t)$) from a $Beta(\alpha_3, \beta_3)$ distribution.[15] Once the flood occurs, we model three different damages affecting firms (see also Lamperti et al., 2018):

- A *productivity* shock, which decrease firms' labour productivity for one period: $AB_{fc}(t) = AB_{fc}(t-1)(1-Dc_{fc}(t))$.
- A *capital stock* shock that destroys a fraction $Dc_{fc}(t)$ of the stock of machines of consumption-good firms and a part of the machines produced by capital-good firms.
- An *inventories* shocks that causes a permanent destruction of a fraction of the inventories of consumption-good firms, i.e. $INV_{fc}(t) = INV_{fc}(t-1)(1-Dc_{fc}(t))$.

3.2.6 Timeline of events

In each time step, agents' action take place according to following sequence:

1. Firms in the capital-good sector perform R&D.
2. Consumption-good firms set their desired production, wages, and, if necessary, invest in new machines.
3. Decentralized labor market opens in each region.
4. An imperfect competitive consumption-good market opens.
5. Entry and exit occur.

[14]Given the focus of our paper and in line with climate impact economic literature, we assume only supply-side shocks to firms' productive activities. We plan to include the analysis of damages to household properties as a future development, which will enable us including climate impacts on the economy via consumption patterns.

[15]The choice to employ the *Beta* distribution follows previous work on climate ABMs (Lamperti et al., 2019a, 2021, 2018; Lamperti and Mattei, 2018) and has two advantages. First, because it allows to account for the pattern of damage functions (and to only the mean, see e.g. Coronese et al., 2019; Hallegatte et al., 2007). Second, because its flexibility allows to represent a wide range of scenarios.

6. Machines ordered are delivered.
7. Households and firms decide whether to migrate across regions.
8. A probabilistic climate shock may hit the Coastal region.

3.3 Results and discussions

Typical for complex adaptive systems, our model has no closed-form solutions and requires computer simulations. To account for the inner stochasticity of the model, we implement a set of 100 Monte Carlo runs for each experiment that addresses our research questions. Each simulation run takes 400 steps, each equivalent to a quarter of a year. Hence, the time horizon of our simulations is 100 years.

At initialization, firms and households agents are evenly distributed between the two regions, and firms share the same level of technology and resources. Therefore, the only difference between Coastal and Inland regions is the additional transport cost that Inland firms consider when calculating their export competitiveness (Eq. 3.1). This implies that the inter-regional transport cost (τ_1) and the amount of export demand (Exp) are the key model parameters as they determine the degree of the competitive advantage of the Coastal region in trade with RoW and the volume of such trade. In the *Baseline* scenario, we set international shipping cost (τ_2) equal to 0.06, in line with other work (Desmet et al., 2021; Hummels, 2007; Irarrazabal et al., 2015) and keep the inter-regional transport costs equal to a half of it, that is 0.03. Regarding the export demand, we set the initial value to 50, in line with the net exports/output ratio of a coastal open-economy such as The Netherlands (OECD, 2019).[16]

Before addressing our main research questions, we mute climate shocks and test the ability of the *Baseline* scenario to replicate key economic empirical regularities. Next, in order to explore how agglomeration forces shape economic centers in coastal areas in absence of climate shocks, we analyze the emerging regional economic dynamics, focusing on the sensitivity of the agglomeration results to inter-regional transport costs and initial export demand.[17] Note that we employ the term *successful agglomeration* to indicate a region that hosts 100% of the total country population by the end of a simulation run, and refer to *ongoing agglomeration* otherwise. Finally, we study the impact of climate-induced shocks of different probability and severity on the regional agglomeration dynamics, and on macroeconomic indicators. The latter include: the temporal evolution of the average output and productivity, their growth rates, and the average unemployment rate, all measured at regional and national levels.[18]

3.3.1 Replication of empirical regularities

Following the common validation tradition for ABMs in economics and finance (Fagiolo et al., 2007, 2019), we study whether the *Baseline* model reproduces an ensemble of macro and micro stylized facts (Table 3.1). Given the spatial dimension of the model, we focus

[16] See Appendix 7.1.3 for additional information on model calibration.
[17] A more extensive sensitivity analysis is carried out in Appendix 7.1.4.
[18] The average growth rate ($\overline{GR}$) of a generic variable X is calculated as $\overline{GR_X} = \frac{LogX(T)-LogX(0)}{T+1}$, where $T = 400$ is the last step of the simulation.

on its ability to reproduce empirical regularities concerning flows of people, businesses and trade that emerge between the two regions. Despite the even distribution of economic activities, resources and technologies in both regions at initialization, the fact that they eventually diverge into core and periphery regions is an emergent property of the model. Notably, in our *Baseline* scenario with disabled climate shocks, the Coastal region becomes the technologically advanced core region as it gradually experiences an inflow of firms and households from the Inland region, which turns peripheral over time (Figure 3.2). This stems from the lower transportation costs required to trade with RoW experienced by the Coastal regions, which makes it attractive for businesses and workers. However, the small difference in this transportation advantage is amplified by innovation and technological learning, that self-reinforce agglomeration. This result is in line with the empirical evidence that reveals clustering of economic activities in locations that offer "natural cost advantages" (SF3, Ellison and Glaeser, 1999; Glaeser, 2010). However, when this advantage is removed, instead of an even development we still observe an emergence of the concentration of economic activities in one region, with almost equal probability in either the Inland or Coastal region (see examples with $\tau_1 = 0$ and $Exp = 0$ in Figure 3.4). This is triggered by the dynamics of technological progress in the initial steps (SF1 in Table 3.1) which spread new technologies to firms in the same area (Breschi and Lissoni, 2001), making access to innovations spatially-concentrated (Feldman and Kogler, 2010, SF2, Table 3.1).

Moving to firm-level regularities at the regional level, empirical evidence suggests that – due to the market selection – only a subset of firms trades with RoW (SF4, Table 3.1). In our model the majority (86%) of Coastal and the minority (7%) of the Inland firms constitute such a subset of exporters (Table 3.2). This difference is due to the "natural cost advantage" that eases trade with RoW for Coastal businesses, but creates trade barriers for the Inland ones. As a consequence, the Coastal region becomes an international trade hub, while the Inland area focuses primarily on the domestic market. Moreover, as observed in real data (SF5, Table 3.1), exporting firms are more productive and bigger in terms of employments than their non-exporting counterparts. Importantly, this difference in productivity between exporters and non-exporters is heterogeneous between the two regions (Table 3.2). In the Coastal region, the productivity premium of exporters is less marked, because only a minority is not exporting. Conversely, only the most productive Inland firms are able to counterbalance the additional transport cost and penetrate the export market. The remaining stylized facts are in line with those reproduced by "K+S" family of models and they are discussed in Appendix 7.1.3.

3.3.2 Agglomeration dynamics in a world without shocks

In the *Baseline* scenario, where climate shocks are disabled, simulation results reveal a self-reinforcing and path-dependent agglomeration process (Figure 3.2, squared curves). In line with the empirical evidences (Bottazzi et al., 2008; Feldman and Kogler, 2010), the process is fuelled by endogenous technological change, triggered by the discovery of more productive technologies by capital-good firms which diffuse to the consumption-good sector increasing local wages in the innovating region.

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Table 3.1: Key economic empirical stylized facts replicated by the model.

Stylized facts (SF)	Empirical studies
Regional interactions aggregate-level stylized facts	
SF1 Uneven spatial distribution of economic activity due to technological progress	(Amin, 1994; Feldman and Kogler, 2010)
SF2 Innovation is spatially concentrated	(Feldman and Kogler, 2010; Thomas, 2005)
SF3 Industry agglomeration due to natural advantages	(Ellison and Glaeser, 1999; Fujita and Mori, 1996b; Glaeser, 2010; Krugman, 2010)
Regional interactions firm-level stylized facts	
SF4 Not all firms export	(Bernard and Durlauf, 1995; Bernard et al., 2011)
SF5 Exporters are more productive and larger than non-exporters	(Bernard and Durlauf, 1995; Bernard et al., 2011)
Two-region economy aggregate-level stylized facts	
SF6 Endogenous self-sustained growth with persistent fluctuation	(Kuznets and Murphy, 1966; Stock and Watson, 1999; Zarnowitz, 1984)
SF7 Relative volatility of GDP, consumption, investments	(Napoletano et al., 2004; Stock and Watson, 1999)
SF8 Cross-correlations of macro-variables	(Napoletano et al., 2004; Stock and Watson, 1999)
SF9 Pro-cyclical aggregate R&D investment	(Wälde and Woitek, 2004)
SF10 Persistent unemployment	(Ball, 2009; Blanchard and Wolfers, 2000; Blanchard and Summers, 1986)
Two-region economy firm-level stylized facts	
SF11 Firm (log) size distribution is right-skewed	(Dosi, 2007)
SF12 Productivity heterogeneity across firm	(Bartelsman et al., 2005; Bartelsman and Doms, 2000; Dosi, 2007)
SF13 Persistent productivity differential across firm	(Bartelsman et al., 2005; Bartelsman and Doms, 2000; Dosi, 2007)
SF14 Lumpy investment rates at firm level	(Doms and Dunne, 1998)

Table 3.2: Exporters shares and premia per region.

		Exporters premia	
	Exporting firms, share (%)	Productivity	Size
Coastal	86.68	1.005	1.115
Inland	7.85	1.212	1.682

Note: Firm are considered exporters at t if $f_j^{Exp} > 0.001$. Exporters premia for a specific variable are calculated dividing the exporters average by the regional average. Size is the average number of employees. The numbers are the means of 100 Monte Carlo runs of the *Baseline* scenario.

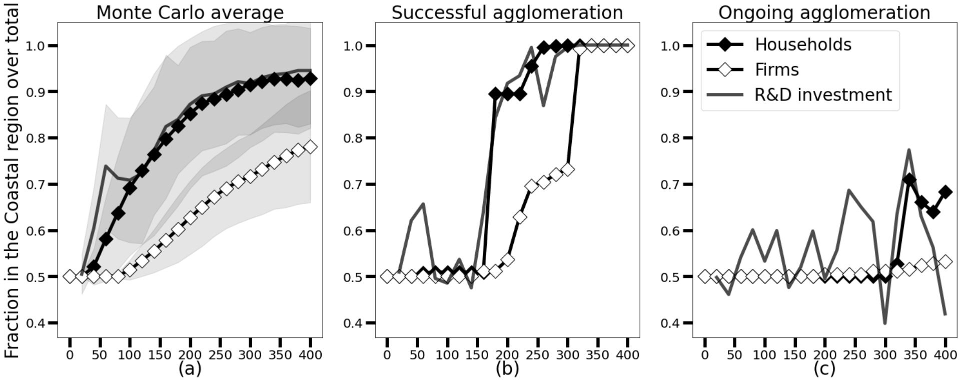

Figure 3.2: Share of population of firms (white squared curve), households (black squared curve) and the relative volume of R&D investment (solid curve) in the Coastal region over total in the *Baseline scenario.* Panel (a) displays the average values and standard deviations (shaded areas) of firms and households population and R&D investments in the Coastal region over the 100 Monte Carlo runs; panels (b) and (c) show single model runs which are representative of cases of successful (i.e. reaching 100%) and ongoing agglomerations respectively.

How do such agglomeration patterns emerge? Due to inter-regional transport costs and physical distance (ϵ), firms are more likely to adopt innovations emerging in their home regions. Hence, local successful innovations diffuse faster in one region, creating a cluster of high-productivity firms which further boosts the adoption of newly-discovered technologies among local businesses. The ensuing increasing R&D investments (Figure 3.2, solid curves) signal the path-dependency in the spatial formation of a cluster, as they lead to higher innovation rates, which in turn attract more firms accelerating the technological diffusion. Furthermore, since wages are indexed to both firm and regional productivity (Eq. 3.6), they grow faster in the more innovative region, thus attracting workers which migrate from the other region (Figure 3.2, black squared curves). Households' migration ultimately reduces local consumption pushing an increasing number of firms to move to the growing region (Figure 3.2, white squared curves), typically with a time lag after workers' migration (compare white and black squared curves in Figure 3.2).

Given the initial settings of the *Baseline* scenario, whenever firms in the Coastal region have a competitive advantage in trade with RoW (i.e., $\tau_1 = 0.03$ and $Exp = 50$), agglomeration mostly emerges there [19]. However, in a typical Monte Carlo experiment, only 13% of the simulation runs exhibit a successful agglomeration process (Figure 3.2 and Table 3.3). This depends on the inter-regional transport costs (τ_1, Eq. 3.1) which reduce the competitiveness of firms in the other region, thus negatively impacting on the dynamics of their market shares. This has two main implications. The first one concerns the speed of the agglomeration process. Firms consider to migrate only if they experience a growing demand outside their home region (Eq. 3.13). Yet, transport costs act like an inter-regional trade barrier, making it harder for firms to sell outside their region. The second implication relates to the RoW market as the inter-regional transport costs increase the competitive advantage of Coastal firms in the export market, penalizing Inland businesses (Eq. 3.1).

[19] The agglomeration process would be reinforced by the inclusion of coastal amenities, which drive workers on the waterfront even without the economic incentive.

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Table 3.3: Comparison of different value of the transport costs (τ_1) and of the initial exports to the rest of the world (*Exp*) to the ones of the *Baseline* scenario.

Parameters		Av. output growth (s.d.)		Av. productivity growth (s.d.)		Av. unemployment rate (s.d.)		Successful agglomeration	
Exp	τ_1	Coastal	Inland	Coastal	Inland	Coastal	Inland	Coastal	Inland
50	**0.03**	**0.009***** **(0.003)**	**0.005** **(0.003)**	**0.007***** **(0.002)**	**0.006** **(0.002)**	**0.061** **(0.052)**	**0.070** **(0.096)**	**0.13**	**0**
0	0	0.008 (0.009)	0.008 (0.008)	0.006 (0.003)	0.006 (0.003)	0.388 (0.345)	0.425 (0.351)	0.54	0.46
0	0.03	0.008 (0.006)	0.008 (0.006)	0.007 (0.002)	0.007 (0.002)	0.113 (0.067)	0.103 (0.071)	0	0
50	0	0.009 (0.009)	0.009 (0.009)	0.007 (0.003)	0.007 (0.003)	0.320 (0.374)	0.448 (0.386)	0.56	0.44

Note: The average growth rate ($\overline{GR}$) of a generic variable X is calculated as $\overline{GR_X} = \frac{LogX(T)-LogX(0)}{T+1}$, where $T = 400$ is the last step of the simulation. Our *Baseline* scenario is $Exp = 50$ and $\tau_1 = 0.03$, highlighted in bold. The last column displays the probability of successful agglomeration, namely the case where one of the two regions hosts 100% the total country population. When a region hosts no workers, the unemployment rate equals to 1, indicating no employment. The latter is the reason behind the higher unemployment rate and standard deviations in the scenarios with $\tau_1 = 0$. All values are averages from the 100 Monte Carlo runs under the same parameter settings. ***p <0.01 refer to P-values for a two-means t-test and indicates whether the difference between Coastal and Inland region is significant for a specific variable.

Moreover, the larger the initial volume of trade with RoW (Exp), the higher the sales captured by Coastal firms. This process leads to a self-reinforcing dynamics wherein the lower competitiveness of Inland firms reduces their share of the export demand, which in turn translates in less profits, less R&D investment and ultimately in a slower technological change.

The increasingly unfavourable conditions in the Inland region worsened by out-migration can trigger a tipping point leading to abrupt step-changes and avalanches of relocating firms (see Figure 3.2.b). The emergence of tipping points is due to positive feedbacks that gradually amplify the economic attractiveness of the Coastal region for Inland firms, further increasing the regional gap in job opportunities, R&D investments and wages levels. As economic activities continue to concentrate in the Coastal region, the wage difference with the Inland region increases exponentially (Figure 3.3.a), followed by the continuing households' influx (Figure 3.2.a, black squared curve). This path-dependent process leads to the divergence of the two regions in terms of output growth trajectories (Figure 3.3.b), productivity (*Baseline*, Table 3.3) and wage distributions (Figure 3.3.c). Notably, the productivity gap is narrower than the output gap because there are two intertwined effects that steer the economic divergence between the two regions: the population migration and the diffusion of new technologies among firms. Specifically, the latter is less likely but still feasible for spatially-distant firms which could still imitate the technology of competitors from another region, hence lowering the inter-regional difference in productivity.

Notably, the accelerating technological learning and spatial spillovers driving the productivity change in the regional economies could still prevail in the Inland region, contingent on the role that inter-regional transport costs and exports to RoW play in this

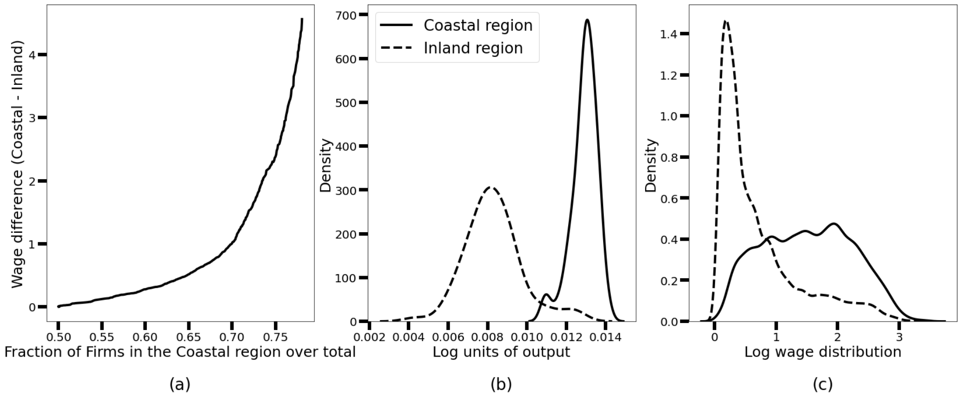

Figure 3.3: Panel (a) shows the dynamic trend of the difference in the average wage between the Coastal and Inland regions (vertical axis) as economic activities agglomerate (horizontal axis). Panels (b) and (c) compare the distribution of regional output growth and regional wages respectively in the Coastal and Inland regions. *Note*: the values refer to a Monte Carlo of size 100.

two-region economy. Our sensitivity analysis on the size of the comparative advantage between the two regions reveals a non-ergodic behavior characterized by two statistical equilibria: a successful agglomeration of economic activities and population in either Coastal (Equilibrium I) or Inland (Equilibrium II), as shown in Table 3.3 and Figure 3.4. As expected, in the absence of inter-regional transport cost (τ_1=0), the Coastal region has no competitive advantage in trade with RoW and there are no idiosyncratic differences between the two regions. In this case, the probability of full agglomeration is roughly the same (dark red and gray in Figure 3.4, and Table 3.3). Moreover, if trade barriers are absent, firms easily penetrate outside their regional market and the agglomeration process speeds up: most runs reach the successful agglomeration in either region before the time step 200. As transport costs increase, trade between the two regions stagnates, hindering the agglomeration process (light brown plots in Figure 3.4). This is in line with the historic evidence, where a decrease in transport costs is associated with a concentration of economic activities (Glaeser, 2010). Furthermore, when inter-regional transport costs are positive, the higher initial value of the export demand volume yields higher economic growth and lower unemployment in the Coastal region vis-á-vis the Inland one (Table 3.3). Indeed, the higher initial volume of export demand to RoW boosts the production of Coastal firms, leading to higher investments and increasing the chance of successful agglomeration at the shore region[20] (Figure 3.4, Table 3.3, more details and extensive sensitivity analyses are in Appendix 7.1.4).

[20]The exogenous rate of export growth (g), which is set to 0.01 in the *Baseline* scenario, interacts with Exp and τ_1 in the dynamics of the agglomeration process. In particular, when inter-regional transport costs are positive, the higher rate of export growth means more resources available for Coastal firms and higher probability of successful agglomeration in the Coastal region (see Figure 7.7 in Appendix 7.1.4).

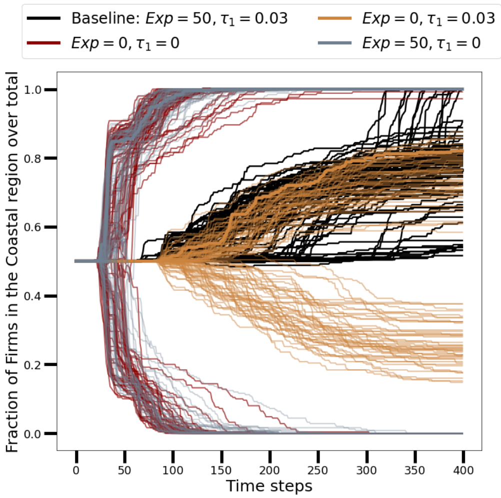

Figure 3.4: Sensitivity of the model dynamics to the inter-regional transport costs (τ_1) and the initial volume of the export demand (*Exp*). Each curve shows the dynamics of firms' population in the Coastal region across 100 individual Monte Carlo runs. Our *Baseline* scenario is $Exp = 50$ and $\tau_1 = 0.03$, colored in black here.

3.3.3 Agglomeration dynamics and climate-induced hazards

The increasing impacts of climate change can affect the economic dynamics of the two regions and the agglomeration economies. To consider stylized climate-induced shocks, we run the *Baseline* model (Table 3.3) with hazards scenarios of different severity and probability. More specifically, we consider five flood scenarios: *Low probability-Low severity flood* (*LPLS*); *High probability-Low severity flood* (*HPLS*); *Low probability-High severity flood* (*LPHS*); *High probability-High severity flood* (*HPHS*) and *Climate tipping point*, that is a shift from *LPLS* to *HPHS*. The high and low probability corresponds to an average of 2:1 year and 1:25 year flood, respectively. Furthermore, we parameterize the damage coefficient of the low and high severity to 0.01 and 0.25, which are the impacts of a five and fifty-centimeter flood accordingly to the US industry depth-damage curve (Huizinga et al., 2017) [21]. Notably, the *Climate tipping point* scenario displays an abrupt increase of both probability and severity at $t = 200$. Namely, it changes the climate of the Coastal region from relatively stable (mild flood every 25 years) to extreme (50-centimeter flood twice a year) conditions. The extreme conditions are somehow comparable to what we can expect in Southeast Asia monsoon season in the coming years (Longenecker, 2011). Hence, the shock magnitude and probability vary among our experiments mimicking the uncertain nature of hazard variability with climate change. Despite being modeled in a stylized manner, such shocks deliver important insights about feedbacks between climate-induced hazards and the economic dynamics through an interplay of push and pull forces: flood damages, which increase over time in the Coastal region, and agglomeration forces, which attract economic activities towards the core region and boost technological innovations.

[21] Given the low sensitivity of the depth-damage curve to small flood depths, five centimeters should be treated as an indicative value of a very mild flood.

In what follows, we first examine the climate-induced disruptions to regional and national economies and the emerging dynamics arising throughout the interactions between the push and pull forces. We then examine for each flood scenario different impact channel — productivity, capital stock and inventories shocks — and analyze their individual and combined impacts on the economy.

The impacts of climate-induced hazards

The first set of experiments concerns the possible impacts of natural hazards on the economy. On the one hand, the negative effects of floods are straightforward and refer to a loss of production factors (machinery, inventories) and a temporal drop in productivity. On the other hand, hazards may accelerate the replacement of capital with new technologically-advanced vintages leading to a positive "productivity effect" (Hallegatte and Dumas, 2009; Leiter et al., 2009). In our model, the latter effect is generated by two processes. The first one concerns the "forced" investments that firms undertake following a climate-induced shock when they need to replace their destroyed old capital with new equipment. The second process relates to the bankruptcy of some firms and the entry of new ones, being endowed with more productive capital technologies (see Appendix 7.1.1). Due to the endogenous technological learning in the model, newer and more productive technologies appear over time, and consequently the production base is possibly upgraded after each flood, boosting the regional productivity, and potentially the economic output.[22]

Interestingly, there are emerging non-linearities in the effects of both probability (Pr_s) and intensity (the damage coefficient Dc) of the shocks on the average unemployment, output and productivity growth of the entire economy across scenarios (Table 3.4).[23] Surprisingly, the two extreme scenarios - *LPLS* and *HPHS* - deliver better economic performance than *Baseline*, mainly because of the "productivity effect" (*LPLS*), which in *HPHS* is amplified by a timely coastal retreat, as we discuss in details below. Conversely, the mixed scenarios - *HPLS* and *LPHS* - perform worse than *Baseline* due to the lock-in effects of ongoing agglomeration, enabled by reducing either flood frequency and intensity. This increases the sunk costs of clustering production and population in the increasingly hazard-prone Coastal region.

As long as shocks are mild and infrequent (*LPLS*), their positive and negative effects are negligible over the simulation time span (compare *LPLS* to *Baseline* in Table 3.4). However, in the second half of the simulation, the growth-stimulus of the capital renewal slightly outweigh the detrimental effects caused by flood shocks (compare the average output growth in *Baseline* and *LPLS* between time steps 200-400 in Figure 3.5.c). This trend explains the additional labor demand required to replace the destroyed capital that decreases the unemployment rate in both regions (compare *Baseline* and *LPLS* in Table 3.4).

When either the probability (*HPLS)* or the severity (*LPHS*) of the climate impacts increases, the economy performs significantly worse than in absence of shocks. Specifically, the high fraction of capital destroyed in the the *LPHS* scenario and the frequent capital disruption in the *HPLS* scenario hinder firms from fully recovering their equipment due to scarcity of financial resources. Hence, they cannot fully satisfy their demand, undermining

[22]For a theoretical explanation of this impact of natural disasters on the economy, see Hallegatte and Przyluski (2010).

[23]Appendix 7.1.4 provides more information about it, including the sensitivity analysis of the economic growth and the agglomeration process on the severity and probability of the shock.

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Table 3.4: Comparison of different flood scenarios to the *Baseline* scenario with no shocks.

Scenario		Parameters Pr_s.	E[Dc]	Number of shocks, Mean (s.d.)	Relative average output growth, Ratio	Relative average productivity growth, Ratio	Relative average unemployment, Ratio	Coastal successful agglomeration, Probability
Baseline		0	0	0 (0.0)	1	1	1	0.13
Low probability Low severity (*LPLS*)		0.01	0.01	4.1 (2.2)	1	1	0.97*	0.1
Low probability High severity (*LPHS*)		0.01	0.25	3.7 (1.8)	0.86***	0.93***	1.98***	0.07
High probability Low severity (*HPLS*)		0.50	0.01	200.0 (10.2)	0.92***	0.94***	1.33***	0.01
High probability High severity (*HPHS*)		0.50	0.25	202.1 (10.6)	1.01**	1.01*	1.43***	0.00
Climate tipping	$t \leq 200$ $t > 200$	0.01 0.50	0.01 0.25	101.8 (7.6)	0.68***	0.79**	3.42***	0.00

Note: The average growth rate ($\overline{GR}$) of a generic variable X is calculated as $\overline{GR_X} = \frac{LogX(T)-LogX(0)}{T+1}$, where $T = 400$ is the last step of the simulation. Here Pr_s. and E[Dc] denote probability and severity (the average damage coefficient Dc) of flooding in each scenario. We compare scenarios in terms of the output and productivity growth, the unemployment rate of the two-region economy, and the probability of successful agglomeration in the Coastal region (statistical equilibrium I, namely the case where such region hosts 100% the total country population). All values are averages from 100 Monte Carlo runs of each scenario. The relative average unemployment, output and productivity growth ratios are calculated by dividing the corresponding value in each scenario by that of *Baseline*. *p <0.1, **p <0.05, ***p <0.01 refer to P-values for a two-means t-test.

firms' long-term competitiveness and profitability. Moreover, the lack of machines forces firms to downscale production and fire workers. The ensuing growth in unemployment in the Coastal region coupled with the drop in wages due to productivity losses, creates a natural push that triggers households' migration landwards. If households' migration is considerable, firms start moving to the Inland region driven by agglomeration forces: i.e. following the shift of workforce and regional market shares these consumers represent. This bottom-up economically-driven relocation to the Inland region can revert, or at least slow down, the agglomeration process in the Coastal region. However, the few infrequent shocks in the *LPHS* scenario are typically insufficient to counter-balance the agglomeration force stemming from the advantages that the Coastal region has in trade with RoW and in the technological leverage that the pre-shock agglomeration offers. Hence, when the coast is firmly protected (*LPHS* but still not 100% safe), the economic activities in the Coastal region are comparable to the *Baseline* scenario (*LPHS* vs. *Baseline* in Figure 3.5.b). Such lock-in of economic activities in the Coastal region implies more assets and population exposed to floods. Consequently, when the shocks do hit, they harm the majority of the country firms and households and the whole economy is more affected and exhibits a negative "hysteresis" characterized by a statistically significant lower output growth (*LPHS* vs. *Baseline* in Figure 3.5.c and in Table 3.4). In contrast, when the economy is exposed to frequent but mild coastal floods (*HPLS* scenario), there are economic forces that gradually drive the population toward the Inland region, which in addition to being safe becomes an economically attractive center of technological innovation. As a result, there are fewer economic activities in the Coastal region as compared to *Baseline* (compare *HPLS* vs. *Baseline* in Figure 3.5.b), but significantly higher output compared to the *LPHS* scenario (compare *HPLS* vs. *LPHS* in Figure 3.5.f).

If both flood probability and severity are high from the start (*HPHS*), the economic agents quickly adapt to frequent and significant losses by migrating to the safe Inland region (compare *HPHS* and *Baseline* in Figure 3.5.a and 3.5.b). This abrupt retreat is driven by purely bottom-up economic adaptation and agglomeration forces that now gravitate to the Inland region. The global economy temporarily contracts but recovers fast (see the negative growth rate in *HPHS* between time steps 0-50 vs. increasing growth rate in steps 100-150, Figure 3.5.c). The firms that escaped to the Inland region avoid any further exposure to the shocks. Moreover, they also need to rebuild their capital stock choosing the most productive technologies of the time. Importantly, many firms in such extreme conditions go bankrupt early in the simulation and are then replaced by more technology advanced newcomers. In the long-term, these major renovations of capital boost the productivity of the Inland region and the aggregate output of the entire two-region economy (compare *Baseline* and *HPHS* curves in Figure 3.5.c and 3.5.f and in Table 3.4). Our results are in line with the climate adaptation literature (Desai et al., 2021; Moss et al., 2021a) discussing the importance of a timely coastal retreat in case of catastrophic impacts. Nonetheless, the benefits from the swift coastal retreats are subjects to a number of caveats: i) relocating abruptly an entire regional economy requires a well prepared and anticipated planning uncommon in the current political agenda; ii) the cost of moving businesses can increase non-linearly with their number, especially for locations where space is a scarce resource; iii) there are high social costs in relocating households and firms. To sum up, the results of the *HPHS* scenario appears to be realistic only for a limited area rather than for a major cluster of economic activities.

Finally, we consider a *Climate tipping point* scenario where the frequency and severity of shocks abruptly increase in the middle of the simulation, and which unfortunately becomes more prominent Kemp et al. (2022). Such a scenario show the worst economic performance due to negative spatial lock-in effects (Figure 3.5.b and Table 3.4). The stable climate that the economy experiences in the first 200 steps, allows economic activities to agglomerate in the Coastal region. However, after the climate tipping point, impacts suddenly become more frequent and severe, thus destroying Coastal firms' capital stocks, reducing their productivity and hence their competitiveness. As a consequence, the region experiences a skyrocketing unemployment rate and a depression of wages that push households Inland (compare *Climate tipping* and *Baseline* scenario in Figure 3.5.a and Table 3.4). However, as climate conditions become extreme, Coastal firms continuously face natural hazards and they rarely manage to migrate or gain market shares in the Inland region (compare *Climate tipping* and *Baseline* scenario in Figure 3.5.b). By the time firms learn the new climate conditions, it is too late to move. Adaptation by relocation needs time and resources, which the Coastal economy lacks by this point. Thus, differently from the *HPHS scenario*, the majority of economic activities remains trapped at the coast and the global economy almost collapses (compare *Climate tipping* and *Baseline* scenario in Figure 3.5.c, 3.5.f and Table 3.4). Although the inability of Coastal firms to compete with the Inland one, and the time lag and resources needed to relocated in the safe region are the main reasons of lock-ins, there are two additional factors to be considered. The first is that, in this version of the model, migration is costless for households but increases with size for firms. Migration costs constitutes an additional barrier for firms whose liquid resources are already invested in rebuilding production capacity at the coast.[24] The second factor depend on the assumption that the population of firms is fixed and bankrupted firms are replaced with new in the same region (see Appendix 7.1.1). Note that a variable number of firms could even worsen the economic performance as firm population in the Coastal region may collapse.

Dissecting the impact channels of climate hazards

The previous analysis shows how climate hazards affect the economy by compounding damages, i.e. without differentiating how shocks propagate in the economy via multiple channels. Yet, each shock hits the Coastal firms in an heterogeneous manner by decreasing their productivity, destroying a fraction of their machinery and inventories (more details in Section 3.2.5). Furthermore, depending on the hazard frequency and severity, each of these individual shocks might have a different impact on the distribution of economic activities across regions and the macroeconomic performance. Figure 3.6 illustrates the individual effects of each shock on the evolution of the economy.[25]

The *productivity* shock increases firms' production costs, by decreasing the production of their workers. Hence, it reduces firm competitiveness and profitability, which propagates throughout the economy leading to lower output growth and real wages. A substantial shock, possible occurring in the *LPHS, HPHS* and *Climate tipping* scenarios, shrinks real

[24]In presence of migration cost for households, the social and economic cost of the *Climate tipping point* scenario would be even higher.

[25]Here we present only the graphs for the *HPLS, LPHS, HPHS* and *Climate tipping point* scenarios. We exclude *LPLS* to keep the figure readable because of the similarity of this scenario with *Baseline*. The *LPLS* results are available from authors upon requests.

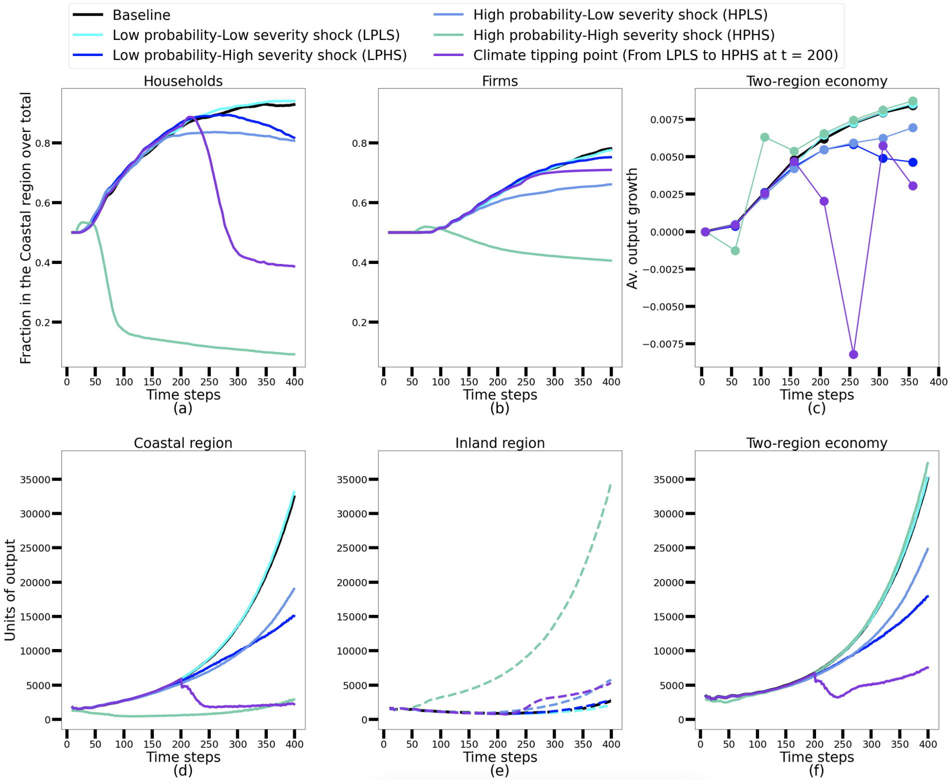

Figure 3.5: Evolution of the households (a) and firms (b) population in the Coastal region, average output growth of the two-region economy by time slices (c), units of output produced in the Coastal (d) and Inland regions (e), and in the entire two-region economy (f) over time in the *Baseline* and the five flood scenarios (*LPLS, HPLS, LPHS, HPHS* and *Climate tipping*). The following abbreviation have been employed in the figure: *LPLS* for *Low probability-Low severity flood*, *HPLS* for *High probability-Low severity flood*, *LPHS* for *Low probability-High severity flood*, and *HPHS* for *High probability-High severity flood*. All values are averages from 100 Monte Carlo runs of each scenario; the standard deviations for each scenario are available from the authors upon request.

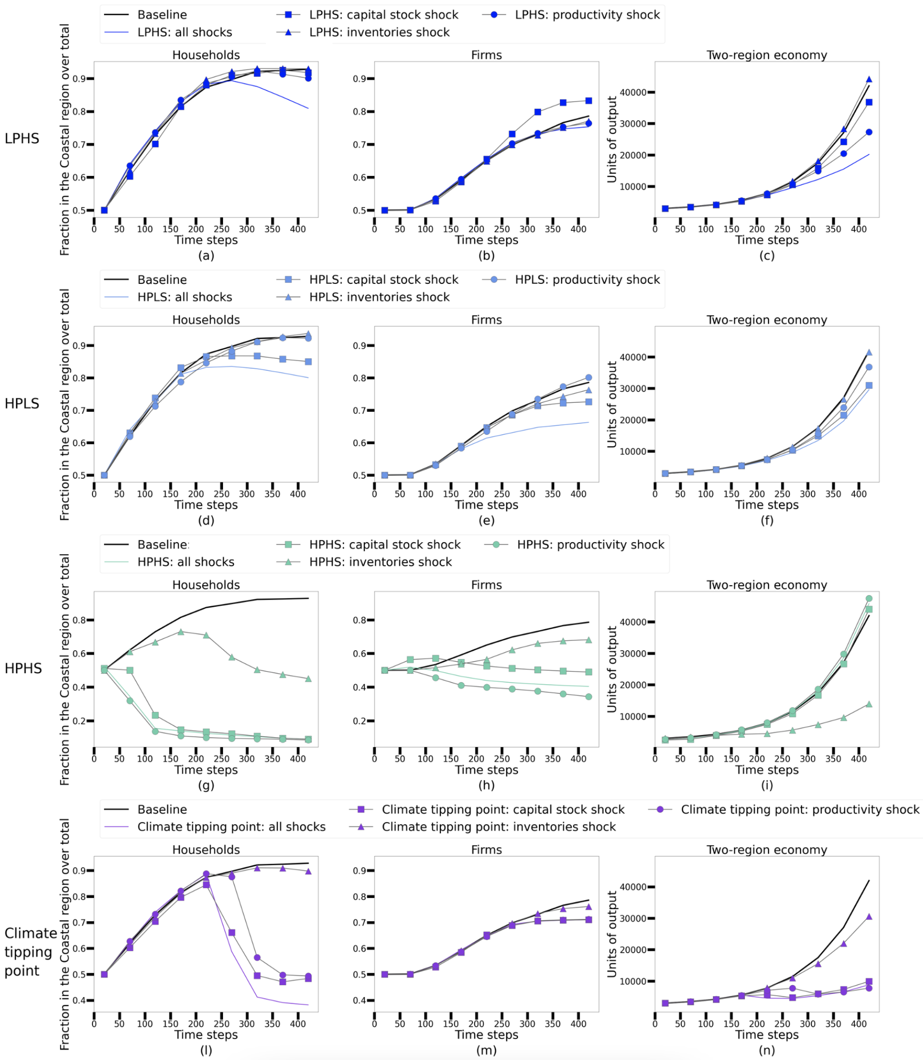

Figure 3.6: The impact of each individual shock channel on the distribution of population, economic activities and output of the two-region economy over time in the *Baseline*, *HPLS*, *LPHS*, *HPHS* and *Climate tipping* scenarios. The following abbreviation have been employed in the figure: *HPLS* for *High probability-Low severity flood*, *LPHS* for *Low probability-High severity flood*, and *HPHS* for *High probability-High severity flood.* All values are averages from 100 Monte Carlo runs of each scenario.

wages, triggers households migration and lowers aggregate demand, generating a negative vicious cycle. As a consequence, in line with other climate ABMs (Lamperti et al., 2018, 2020), the *productivity* shocks delivers the largest harm to the two-region economy when the damage coefficient is high (such as in the *LPHS* and *Climate tipping*, see circled and black lines in Figure 3.6.c and 3.6.n). Conversely, the adverse impact of the productivity shock is negligible for a low value of the damage coefficient (such as in the *HPLS*, compare black and circled line in Figure 3.6.f) since these effects are counterbalanced with productivity gains that the firms obtain through the process of technological change.[26] An exception is the *HPHS* scenario: such shocks lead to intensified economic growth (see black and circled lines in Figure 3.6.i). The reason is linked to the process of entry and exit. As in other models rooted in *K+S* family (Dosi et al., 2013, 2010, 2017b; Lamperti et al., 2018), new entrant consumption-good firms select amongst the most productive machines. Hence, in the *HPHS* scenario the severe and frequent *productivity* shocks initially bankrupt many firms that are then replaced with more technologically advanced entrants.

In a different manner, the *capital-stock* shocks immediately constrain firms' production. Consequently, firms try to reconstruct their capital stock by ordering new machines. As mentioned before, in the *HPHS* scenario the replacement of the destroyed capital with newer and more productive machines, coupled with the migration to the safe inland region, boosts the total units of output produced in the two-region economy (see black and squared lines in Figure 3.6.i). However, in all the other scenarios where the majority of firms is exposed to climate hazards during the whole simulation (*LPHS, HPLS* and *Climate tipping point*), the economy lacks resources to sustain the substitution of capital at such accelerated rate. Hence firms have to undergone production, slowing down economic growth (see black and squared lines in Figure 3.6.c, 3.6.f, 3.6.n). The *capital stock* shocks also generate an increase in the demand of capital by Coastal firms that pushes capital-good firms towards the coast (see black and squared lines in Figure 3.6.b) or, at least slows down its abandonment (see black and squared lines in Figure 3.6.h).

Finally, the *inventories shock* has the smallest impact on both the distribution of population and economic growth in the *LPHS*, *HPLS* and *Climate tipping point* scenarios, suggesting that supply side bottle-necks are mostly relevant in the very short run (Otto et al., 2017; Willner et al., 2018). Yet, damages to inventories are particularly relevant in the *HPHS* case, as they reinforces our previous argument about Coastal retreat. Indeed, by exerting a relatively mild impact, the *inventories shock* triggers less migration of both households and firms towards the Inland region (see black and triangle lines in Figure 3.6.g, 3.6.h). Thus, more firms deal with the hazard for a longer time compared to the other shocks with negative consequence for the economy (compare black and triangle lines in 3.6.n).

3.4 Conclusions

In presence of longstanding urbanization processes, population and economic activities are increasingly exposed to the risks of climate change. Strong economic agglomeration forces have been attracting development towards waterfront regions for centuries. Yet,

[26] Indeed, a negative shock to labour productivity facilitates the adoption of novel and more productive production techniques and machines.

the new climate reality of projected sea level rise and increasing probability and severity of coastal flooding, threatens to revert this trend, making coastal retreat a realistic policy option if proper mitigation strategies are not timely deployed (Haasnoot et al., 2021; Moss et al., 2021a).

To explore the trade-offs between agglomeration economies and the changing face of hazards as well as the macroeconomic and spatial consequences of diverse climate shocks, we have developed the *Climate-economy Regional Agent-Based* (CRAB) model with heterogeneous boundedly-rational interacting agents designed in the evolutionary macroeconomics tradition. The model explicitly captures the endogenous technological learning, that is reinforced by geographical proximity. Specifically, when firms cluster together newly discovered technologies circulate more easily within the cluster creating "localised knowledge spillovers" (Breschi and Lissoni, 2001) that act as Marshallian externalities and trigger agglomeration forces. We study such dynamics in an economy with two regions — Coastal and Inland — in which capital-good firms, consumption-good firms and households agents interact in the local goods and labour markets. Agents choose in which region to reside and whether to relocate driven purely by economic self-interests. Agents are boundedly-rational, but they continuously learn about prices, wages as well as the evolving economic attractiveness of regions and the intensity of climate-induced hazards as the simulation unfolds.

First, we assess the ability of the model to reproduce empirical regularities. Specifically, in line with other macroeconomic evolutionary ABMs (Dosi et al., 2013, 2015, 2010, 2017b; Lamperti et al., 2018), we validate model's output against economic stylized facts at both aggregate and firm-level. We then asses how agglomeration forces shape economic centers in coastal areas in the absence of climate shocks. We find that the model is able to reproduce a self-reinforcing and path-dependent agglomeration process driven by innovation and endogenous technological learning. Such processes are triggered by the additional resources that Coastal firms obtain though the competitive advantage of their strategic location (Glaeser, 2010). These results reinforce previous empirical findings about the correlation between productivity and agglomeration forces (Bottazzi et al., 2008; Feldman and Kogler, 2010; Kogler, 2015). In the absence of the location specific competitive advantage, the model displays a non-ergodic behavior characterized by two possible final statistical equilibria: full agglomeration of economic activities and population in either Coastal or Inland region. This offers an important methodological innovation permitting to integrate the spatial dimension, both in terms of travel costs and location (dis)advantages, into the evolutionary economic models with heterogeneous adaptive agents. It responds to the need for adding the complex adaptive perspective to the economic geography toolkit (Commendatore, 2015; Fowler, 2007) and to the economic analysis of climate change impacts (Safarzyńska et al., 2013; Stern, 2016).

We then explore how the complex interplay between agglomeration forces and climate shocks unfolds the spatial distribution of economic activities as well as the development of regional economies, considering scenarios with climate hazards of various intensity and probability. We find a non-linear responses of the model economic performance to both the intensity and probability of the shocks. Such non-linearity emerges from the complex interplay between the negative consequences of climate damages, and their positive effects in terms of technological renewal of the production capital base and a timely incentive to relocate economic activities from the coast. In general, frequent shocks push economic activities towards the safe Inland region, with the speed of coastal retreat increasing with the size of the shocks, thus reducing the concentration of economic activities in the Coastal area. When the shocks are infrequent or mild the aggregate economic performance worsen due to the prevailing negative impacts of hazards. In particular, when floods are rare but more intense, the low probability shocks generally permit an initial concentration of economic activities in the Coastal region. Yet, the shocks are more likely to hit the economy later in the simulation, affecting a critically high share of firms and households, slowing the economic recovery and its further development. This has direct links to adaptation policies, such as construction of flood defences which while preventing milder floods do fuel the agglomeration forces and endanger the increasing sunk costs due to accelerating urbanization in climate-sensitive hotspots. Our results suggest that while adaptation measures such as dykes and levees are indispensable, one must account for the inter-temporal side-effects in terms of provoked "levee effect"/ "safe development paradox" (Di Baldassarre et al., 2015) driven by agglomeration forces. Furthermore, in the special case when shocks are both severe and frequent, adaptive firms swiftly retreat to the safe Inland region where they replace their destroyed machines with newer and more productive equipment without any government intervention. This capital renovation coupled with the replacement of bankrupting firms with better-technology competitors permits the entire economy to experience a long-run growth trajectory comparable to the baseline scenario. This has important policy implications for designing coastal retreat strategies, that seem increasingly necessary but face unacceptability and are costly to realize (Moss et al., 2021a). However, in the most likely scenario with climate tipping points, which abruptly increase both the frequency and impact of shocks in the middle of the simulation, the most productive firms located in the Coastal area are increasingly exposed to flood hazards severely disrupting their capital and competitiveness. As a consequence, firms lack resources to relocate to safety and remain trapped at the coast, locking in the entire economy into a trajectory of a climate non-resilient stagnation.

This article makes a contribution to the literature in three ways. In terms of the theoretical framework: grounding in the new economic geography literature which focuses on trade and innovation as the cause of agglomeration, we go beyond to study a spatial distribution of economic activities across regions in an out-of equilibrium dynamics emerging from interactions of heterogeneous boundedly-rational agents. Our model employs evolutionary macroeconomic tradition to capture for the first time the dynamic interplay between trade, agglomeration, migration and hazard shocks, generalizable beyond floods which we take as an example here. In terms of methodology: we advance the evolutionary macroeconomic ABMs tradition by introducing two regions and endogenous inter-region migration decisions for both firms and household. Finally, in terms of policy implications: we assess the trade-off between intensifying natural hazards and agglomeration economies accounting for non-linear dynamics, lock-in effects, and climate tipping points. It enables us to reveal economic mechanisms that make coastal retreat economically-efficient for firms and households, opening new strategies to facilitate positive transformational climate change adaptations. A positive retreat could be facilitated by the power of agglomeration forces essential to avoid increasing exposure of economic activities to intensifying climate-induced shocks and to overcome increasing sunk costs of investments in climate-sensitive areas. Although we provide an illustrative stress test on how a regional economy reacts to changing hazards, our results highlight the importance of understanding dynamic responses of socio-economic systems to the "new normal": when the environment and climate to which our civilization was used for centuries is drastically changing.

The CRAB model can be extended in a number of ways. First, the model would benefit from making households behaviorally-richer to enable more detailed migration patterns, e.g. rural-urban migration, risk attitudes and to accommodate the new realities of teleworking. This will require modeling land-use dynamics, allowing the differentiation between urban, peri-urban, and rural areas. In addition, linking land-use maps with households' property will extend the estimation of direct flood damage to the household sector, thereby allowing to incorporate demand side shocks. Second, the model could be extended to multiple regions and calibrated to real-world data, including a finer representation of economic sectors impacted by various hazards. Also, climate shocks could align with hydrological flood maps and hazard patterns corresponding to different impacts under the downscaled IPCC scenarios. Third, governments, households, and firms are known to take climate adaptation action to reduce the adverse impacts of hazards (Leitold et al., 2020; Linnenluecke, 2017; Neise and Revilla Diez, 2019; Noll et al., 2022b; Vousdoukas et al., 2020). Hence, private and public climate change adaptation could be jointly considered to analyze both limits and opportunities that regions have for development despite adversities. Importantly, "on-site" climate change adaptation options might be linked to the process of technological change and infrastructure development (Thacker et al., 2019) that supports climate-resilient growth, although empirical evidence on this is still sparse.

4

Uncertainty in boundedly-rational household adaptation to environmental shocks

Despite the growing calls to integrate realistic human behavior in sustainability science models, the representative rational agent prevails. This is especially problematic for climate change adaptation that relies on actions at various scales: from governments to individuals. Empirical evidence on individual adaptation to climate-induced hazards reveals diverse behavioral and social factors affecting economic considerations. Yet, implications of replacing the rational optimizer by realistic human behavior in nature-society systems models are poorly understood. Using an original evolutionary economic agent-based model we explore different framing regarding household adaptation behavior to floods, leveraging on behavioral data from a household survey in Miami, USA. We find that a representative rational agent significantly overestimates household adaptation diffusion and underestimates damages compared to boundedly-rational behavior revealed from our survey. This "adaptation deficit" exhibited by a population of empirically-informed agents is explained primarily by diverse "soft" adaptation constraints —awareness, social influences —rather than heterogeneity in financial constraints. Besides initial inequality disproportionally impacting low/medium adaptive capacity households post-flood, our findings suggest that even under a nearly complete adaptation diffusion, adaptation benefits are uneven, with late or less-efficient actions locking households to a path of higher damages, further exacerbating inequalities. Our exploratory modeling reveals that behavioral assumptions shape the uncertainty of physical factors, like exposure and objective effectiveness of flood-proofing measures, traditionally considered crucial in risk assessments. This novel combination of methods facilitates the assessment of cumulative and distributional effects of boundedly-rational behavior essential for designing tailored climate adaptation policies, and for equitable sustainability transitions in general.

4.1 Introduction

Contending with the impacts of climate change demands engagement from all levels of society (IPCC, 2022a). Central to dealing with these impacts is the apprehension of how effectively and timely will various actors adapt to climate change. To this end, for scientists to policymakers alike, simulation models are critical tools to quantify effects of adaptation strategies. Large-scale government-led measures to curtail climate change adversities typically rely on aggregated costs and benefits data, and are regularly incorporated into models as rational decisions, either based on cost-benefit analysis (Vousdoukas et al., 2020) or as adaptive policy pathways accounting for uncertainty (Haasnoot et al., 2013). Due to the simplicity of assumptions and the relative data availability, the climate change adaptation (CCA) modeling predominantly focuses on government-led decisions (Kondrup et al., 2022).

Accounting for private actions remains a fundamental challenge in CCA research and policy (Berrang-Ford et al., 2021). Household adaptation is complementary to government-led actions, has the potential to dynamically respond to the accelerating adversities brought on by climate change, and is essential in multi-scale CCA (Adger et al., 2005). Yet, the lack of microdata on individual behavior and the uncertainty which its inclusion begets in simulation models, has engendered that households' actions are widely omitted from CCA models. Modeling human behavior is also a fundamental challenge in climate risks assessments (Aerts, 2020; Aerts et al., 2018; Taberna et al., 2020) and the broader sustainability science, where balancing economic and social priorities alongside interactions with the environment in dynamic nature-society systems is essential (Beckage et al., 2018; Wijermans et al., 2020).

Among the sustainability models that do consider human behavior, many assume rational representative households with perfect information who make optimal choices driven by financial constrains (Walsh and Hallegatte, 2022). However, across various nature-society systems, empirical work consistently demonstrates that the key drivers of human behavior deviate from that of the perfectly-rational optimizer (Steg and Vlek, 2009). For instance, in CCA households rely on heuristics such as affect (worry), social pressure, and perceived coping capacity (Noll et al., 2022b; van Valkengoed and Steg, 2019). Diversity in education, incomes, experiences and institutions endow individuals and societies with diverse adaptive capacities (Adger and Vincent, 2005). In reality CCA uptake is below what would be economically-efficient (Berrang-Ford et al., 2021; Mechler et al., 2020), suggesting that households do not act as homoeconomicus when adapting to environmental shocks and that diverse adaptation constraints shape soft limits to adaptation (Thomas et al., 2021). The gap between the optimal behavior as estimated by a perfectly-rational decision-maker and reality produces an unaccounted 'adaptation deficit'—insufficient (public or private) adaptation compared to what is economically optimal. The fundamental challenge for sustainability science, and for CCA in particular, remains: effective means to represent empirically-rich human behavior in formal models, and to quantify aggregated and distributional impacts of private actions are in paucity.

This chapter is based on *Taberna, A., Filatova, T., Hadjimichael, A., & Noll, B. (2023). Uncertainty in boundedly rational household adaptation to environmental shocks. Proceedings of the National Academy of Sciences, 120(44), e2215675120.* (Taberna et al., 2023a).

Agent-based models (ABMs) are ideal means to simulate boundedly-rational behavior of many heterogeneous actors who interact with each other and their environment, and continuously learn (Arthur, 2021; Farmer and Foley, 2009). As computational models, ABMs rely on social science theories and data to define rules of action, interactions, and learning that drive behavioral change and evolution of institutions (Schlüter et al., 2017; Smajgl et al., 2011). With respect to climate-induced hazards, ABMs increasingly examine cumulative consequences of household adaptations, including ramifications in damages and recovery from climate-induced hazards (de Ruig et al., 2019; Haer et al., 2017; Walsh and Hallegatte, 2022). However, the current models still faces several limitations, including the lack of microdata on human behavior, derivation of distributional impacts, and modeling households interactions with firms that offer jobs and endogenously define incomes crucial for household adaptive capacity and individual and regional socio-economic resilience (Aerts, 2020; Taberna et al., 2020). Here we employ behavioral survey data in the evolutionary economic ABM (Taberna et al., 2022) endowed with firms and households that interact through socio-economic institutions (markets and social networks) to quantitatively explore the spectrum of household adaptation behavior to the most costly climate-induced hazard globally: floods. With urbanization exasperating the growing risk brought on by floods and sea level rise, we focus our model on emulating an urbanized coastal region and populate it using rich behavioral surveys conducted in Miami-Dade county, USA, in 2020 (Noll et al., 2022b). Using empirical data on flood probabilities and on capital-labor ratios of the regional economy, we contrast how various household representations (homogeneous vs. heterogeneous; rational vs. empirically informed boundedly-rational) impact the societal distribution of direct and indirect damages, and equity. In the behaviorally-rich framing, the diverse boundedly-rational agents in our model are embedded into a social network, where they learn from peers and are influenced by evolving social norms. Besides, households are endowed with education, individual awareness about hazards (perceived damages, worry about floods), past experience with floods and undergone adaptations—significantly extending the typical financial constraints to adaptation that a rational optimizer faces. Finally, our introduction of a full macroeconomic framework —where households interact with firms —enables tracing endogenous changes in individual incomes and indirect flood consequences, like firms' bankruptcy leading to unemployment, which undermines households' recovery and widens inequalities. These alternative representations of household adaptation, embedded in a large socio-economic system and exposed to environmental shocks, reflect the inherent epistemic challenges in representing human behavior in sustainability science models in general.

Recognizing these deep uncertainties, we employ exploratory modeling (Bankes, 1993) to study alternative scenarios stemming from various modeling assumptions, including rival framing of behavioral representation and uncertainties in key physical factors shaping risks. Exploratory modeling is uniquely appropriate for contending with diversity of human behavior in complex nature-society systems (Moallemi et al., 2020; Saltelli et al., 2020; Yoon et al., 2022). By combining the evolutionary economic ABM with the survey data on CCA behavior and with exploratory modeling, we examine how uncertainty in the representation of human behavior interacts with physical uncertainties to affect the diffusion of private adaptation, to shape overall regional damages, their distribution, and the corresponding recovery pathways of different households. In systematically analyzing behavioral uncertainty stemming from the various formulations of households' adaptation decisions, we tackle three research questions: (1) How does heterogeneity in financial constraints and socio-behavioral factors affect regional patterns of adaptation diffusion? (2) What are the distributional and indirect economic impacts of hazards and of behavioral change among households with different adaptive capacity? (3) Does physical uncertainty, like exposure and objective effectiveness of measures—factors conventionally crucial for CCA policy design—remain predictable across alternative behavior framing?

To explore the aggregated impacts of private CCA on the regional economy, we incorporate household survey data into an evolutionary ABM and systematically test uncertainties via exploratory modeling along a gradient of assumptions about human behavior subject to diverse adaptation constraints. Integrating various decision-making processes ranging from a representative Rational Agent (*RA*) to a heterogeneous population of Boundedly-rational Agents (*BA*), our model traces the collective consequences of simulated household behavior and maps emerging equity implications across agents with various adaptive capacities. *RA* decides to implement a CCA measure when it becomes economically efficient considering only financial adaptation constraints Fig.4.1.b). Instead, adaptation decisions of *BA* are shaped by diverse adaptation constraints (Thomas et al., 2021): perceptions of worry about floods, of own ability to implement a measure (self-efficacy), past experiences and social influences elicited from a households' survey (Noll et al., 2022b). By going beyond the rational representative agent, we trace how heterogeneity and socio-behavioral factors, embedded in evolving market and social institutions, lead to the emergence of an adaptation deficit, hence quantifying soft adaptation limits which are otherwise challenging to estimate (Berrang-Ford et al., 2021; Mechler et al., 2020). Using state-of-the-art exploratory modeling, we analyze the behavioral and physical uncertainty jointly, estimating how alternative representations of human behavior in computational models interacts with changing physical factors, like hazard exposure. This original combination of methods showcases how simulations and social sciences can be bridged to integrate human behavior in formal models, and to quantify socio-economic and equity implications in the next generation of sustainability science models.

4.2 Computing socio-economic dynamics in adaptation to environmental shocks

4.2.1 Complex evolving economy

We embed computational modeling of human behavior into the evolutionary[1] *Climate-economy Regional Agent-Based* (CRAB) model (Taberna et al., 2022), using Mesa, an open-source Python 3 package (Kazil et al., 2020). The model features a complex evolving economy populated by heterogeneous households and firms of three different economic sectors (Fig.4.1.a) , prone to agglomeration forces following the New Economic Geography

[1]Evolutionary here implies that the model (i) encompasses actions of diverse boundedly-rational agents that form and update their expectations about future as they learn from own experience and interactions with others as they aim to improve their state, (ii) endogenizes the process of technological innovation and possibly structural changes in e.g. market institutions when actors with unfortunate choices do not survive a transformational change. Based on the performance of these learning and adapting agents, there is a type of evolutionary selection occurring in this artificial economy as strategies of successful households and firms get adopted and further improved in the ever-changing environment.

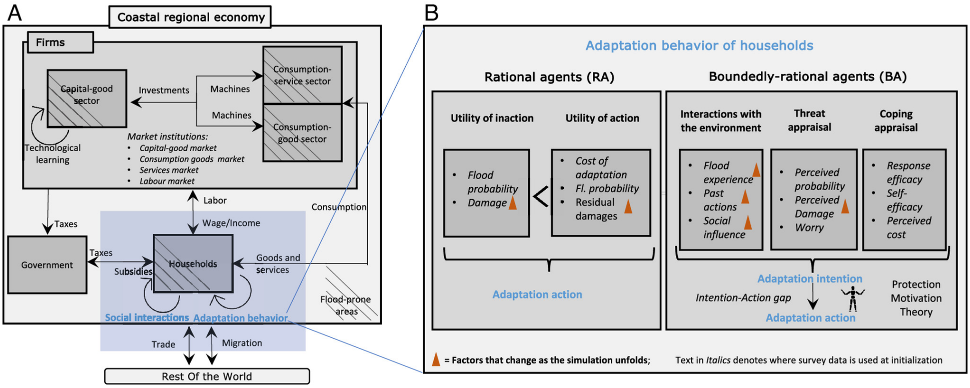

Figure 4.1: Evolutionary agent-based model of a regional economy (Panel a) with heterogeneous adaptive agents prone to social interactions and behavioral factors (Panel b).

theory(Krugman, 1992) adopted for evolutionary non-equilibrium settings. Firms invest in R&D to discover newer and more productive technologies that trigger endogenous economic growth, following the Keynes & Schumpeter ("K +S") evolutionary economics tradition (Dosi et al., 2013, 2010). Firms compete in capital, labor, goods and service markets, which are imperfect and characterized by limited information, hence firms form expectations and update them as they learn. These four market institutions and the technological advancement of firms drive the core economic dynamics—including changes in productivity, Gross Domestic Product (GDP), wages, unemployment, and savings—that endogenously define the economic attractiveness of the region and in/out-migration of population and firms (Materials and Methods, SI Appendix). Households buy goods and services, work in these sectors, and may switch jobs depending on dynamic wages or create new firms themselves. The novel addition of firms interacting with households via market institutions (Fig.4.1.a) is important for quantifying whether unemployment and macroeconomic restructuring in the aftermath of a flood undermines households' recovery, decreases incomes and potentially results in out-migration. In our evolutionary ABM firms pursue technological learning and update market expectations based on experience —a dynamics that leads to either growth or decline of the regional economy; households also learn via social network and own flood experience.

Households and firms can locate in safe or hazard-prone areas. Agents in the hazard-prone area can be impacted by floods, which destroy firms' assets and inventories as well as household assets and productivity. Here we use a single-region version of the CRAB model (Taberna et al., 2022) to evaluate the role of different behavioral assumptions on household adaptation diffusion, damages and regional economic performance. Besides expanding the original model with the service sector and contextualizing it with the aggregated economic and flood data from the greater Miami region (FL, USA), we substantially advance household behavior (Fig.4.1.b). For the latter, we rely on our survey data from Florida (Noll et al., 2022b) eliciting behavioral and social factors of household CCA. To adapt to adversities, households consider three types of structural measures: Wet-proofing, Dry-proofing, and Elevation (Noll et al., 2022a). In CRAB Elevation is costly but provides a complete flood protection.

Conversely, the other two measures entail lower costs but with lower objective effectiveness for damage reduction (Materials and Methods, SI Appendix). Notably, households in our ABM are embedded in a social network where they exchange information about adaptation with their peers, leading to evolving descriptive norms. We initialize our ABM with a synthetic population of $n = 3,000$ households ($\sim 5 : 1000$ of Miami-Dade County) and 250 firms (split among the capital-good, service and consumption-good sectors as 50:100:100), with 40% of these agents randomly allocated to flood-prone areas (Materials and Methods).

4.2.2 Households' climate change adaptation

To model household adaptation, we implement diverse behavioral strategies. As the most widespread representation of human behavior, we first study the dynamics of our regional economy assuming all households are rational agents prone only to financial adaptation constraints. Specifically, *RA* goes through a pure economic assessment of risks by weighting probabilities and damages against the costs of the three adaptation measures (Wet-proofing, Dry-proofing, and Elevation), and adopt them when it is economically efficient (Fig.4.1.b). As the next common step to enrich human behavior in sustainability models, we replace a homogeneous rational agent (RA_{Hom}) by a population of individuals heterogeneous in incomes and damages, yet still rational in their decision-making (RA_{Het}), including their objective perception of probability. We parameterize incomes, probabilities and damages of RA_{Hom} households with the survey means (SI, "Model calibration"), and RA_{Het} with the distributions of the reported survey values.

Yet, ample empirical evidence demonstrates that probabilities and damages used to calculate economic efficiency, alone have little effect on people's intentions to adapt to floods (Bubeck et al., 2012). Instead, we ground *BA* agents in the most prominent social science theory explaining CCA behavior: Protection Motivation Theory (PMT) (Bamberg et al., 2017b; Rogers, 1975). Extended PMT assumes that besides perceived damages and probability, psychological factors—affect heuristics (worry), perceived effectiveness of a measure and of own ability to implement it (response- and self-efficacy), social expectations and past experiences with floods and CCA—drive private adaptation. These socio-behavioral factors either hinder or amplify households' adaptation intentions, and serve as diverse adaptation constraints making individual judgements boundedly-rational. The behavior of *BA* agents explicitly captures mechanisms specified by PMT (Fig.4.1.b), and contextualizes them by relying on the survey data (Noll et al., 2022b) (2020 Florida sub-sample, $N = 965$). To differentiate between three common CCA measures (Kreibich et al., 2015)—Wet-proofing, Dry-proofing, and Elevation—we run three theory-grounded logistic regressions (SI, "Model calibration"). Notably, PMT specifies mechanisms, via which socio-behavioural factors cause behavioral intention and eventually CCA action, and which proved valid worldwide (van Valkengoed and Steg, 2019), hence the behaviorally-rich adaptation in CRAB and the derived insights are generalizable. Similarly to *RA*, we model the population of boundedly-rational households as either homogeneous (BA_{Hom}) or heterogeneous (BA_{Het}).

Additionally, in the *BA* scenarios, households are embedded in a random social network (Erdős et al., 1960), calibrated with our survey data (SI, "Model calibration"). When considering a specific CCA, households interact with other agents in their "Social network" and observe which peers have implemented the measure as the simulation unfolds. As *BA* households observe changes in the descriptive norms in their networks, they also update individual CCA intentions. *BA* households learn over time based on the opinions of others (e.g., perceived social expectations regarding own action on adaptation) and own experiences (e.g., perceived damages after a flood). Importantly, while the simulated mechanisms of behavioral change grounded in PMT persist, the initial data-driven effects of socio-behavioral factors evolve individually for each agent (denoted with triangles, Fig.4.1.b) based on the actions of others and their own.

Exploring behavioral uncertainty

Besides the baseline scenario without private adaptation, we quantify differences in macro-outcomes along a gradient of rival framings of human behavior: RA_{Hom}, RA_{Het}, BA_{Hom}, and BA_{Het}. Hence, we gradually increase the richness of behavior—moving systematically from a representative rational agent to diverse empirically informed agents with boundedly-rational behavior affected by social interactions. We compare these rival assumptions about behavior along macro-metrics (adaptation deficit and damages, SI), each estimated across 100 Monte Carlo runs. By default CRAB also traces regional GDP, unemployment, net savings, and population of households and firms (Taberna et al., 2022). With respect to shocks, we trace the overall performance of the regional economy and the distributional impacts assuming a scenario with no floods vs. two consecutive floods (occurring at time steps 100 and 140 of the simulation).

We broaden the scope of traditional ABM sensitivity analysis by applying exploratory modeling (Moallemi et al., 2020) to diagnose how key conventional drivers of risk interact with alternative behavioral heuristics. Exploratory modeling constructs large ensembles of computational experiments to systematically explore the implications of alternative assumptions. The goal is to elicit interaction mechanisms and to identify uncertainties critical in achieving/avoiding system states of interest (Hadjimichael et al., 2020). Given the complexity of CRAB combined with the effects of structural behavioral uncertainty (agent homogeneity vs. heterogeneity and behavioral heuristics), we focus our parametric diagnostic assessment on the core physical factors affecting households' adaptation behavior: the fraction of population exposed to floods, and the objective effectiveness of the three adaptation measures. Uncertainty in these factors stems from several sources: past data on flood exposure is increasingly uncertain, with climate change exacerbating extreme events, and urbanization affecting hydrological processes. The objective effectiveness of adaptation measures is also highly uncertain due to the scarcity of fragmented empirical data on the actual damage reduction of various adaptations (Kreibich et al., 2015). Our exploratory methodology systematically examines how uncertainties in these four factors shape adaptation outcomes under alternative behavioral framings, by applying global sensitivity analysis (SA) to 460,800 computational runs of the CRAB model, as described below.

SA is a widespread class of model diagnostics methods (Ligmann-Zielinska et al., 2020; Saltelli et al., 2008b). Longitudinal SA, which assesses the importance of uncertain factors over time, is especially pertinent in complex systems (Ligmann-Zielinska and Sun, 2010; Pianosi et al., 2016; Song et al., 2015), as it enables the exploration of the path dependence of critical outcomes, or regime-changing conditions, i.e., tipping points. Our model, as other complex systems models simulating many diverse actors and consequential outcomes, has a large number of varying parameters (fraction of exposed households, measures' effectiveness) and delivers multi-dimensional outputs (fraction of adapted households, household damages, regional or differentiated per level of adaptive capacity). Since they can be variably consequential for different stakeholders, we perform the global SA across all potentially relevant outputs.

4.2.3 Model verification and validation

Following the standard practice in ABM development, we perform both micro- and macro-validation (Fagiolo et al., 2017). Whenever possible, we define agents' micro rules to match the behavioral patterns in the survey data. Where empirical data are unavailable, we indirectly validate CRAB against relevant micro and macro stylized facts (SI, "Model calibration"), as common in the literature (Fagiolo et al., 2017). The CRAB model successfully reproduces 15 empirical stylized facts characterising regional economic development (Taberna et al., 2022), such as that the floods decrease the entry of firms, their output, and employment opportunities (SI, "Model validation").

4.3 Results

Behavioral biases rather than differences in incomes impede adaptation and increase regional residual damages

A representative rational agent pursues adaptation when it becomes economically efficient. This engenders that thousands of identical optimizing households immediately adopt Wet- and Dry-proofing adaptations (RA_{Hom} in Fig.4.2.a-b) as they are affordable from the start given the reported incomes and savings in our survey. Elevation is adopted gradually (Fig.4.2.c) as RA_{Hom} households need to accumulate sufficient savings to afford it. Hence, the top solid curves in Fig.4.2.a-c signal the optimal level of private adaptation in this regional coastal economy. Introducing heterogeneity in factors shaping financial adaptation constraints—incomes, education,

and damages—reduces private adaptation diffusion across all three measures (dotted curves for RA_{Het} adaptation diffusion, Fig.4.2.a-c). This adaptation deficit is just 3-4% for Dry- and Wet-proofing at the end of the simulation (pink area, Fig.4.2.a-Fig.4.2.b), signaling that diversity among household financial adaptation constraints barely matters for these decisions. This insight is essential, since introducing income heterogeneity is the focus of contemporary CCA modeling (Aerts, 2020; Aerts et al., 2018; Jafino et al., 2021) as an advancement over *RA* in representing human decisions. The ability of CRAB to differentiate between types of CCA in a population with diverse incomes permits to disentangle for which CCA measures it is irrelevant, and for which heterogeneity in financial adaptation constraints matters. For example, the diversity in incomes and perceived damages imposes a significant adaptation deficit of 22% lower diffusion of Elevation (dotted curve and pink area in Fig.4.2.c). Elevation is costly, confirming that for more expensive measures financial adaptation constraints matter for households with low incomes or/and low perceived damages.

Furthermore, our novel approach allows to quantitatively compare the inclusion of heterogeneity in financial adaptation constraints (RA_{Het}), with the integration of diverse adaptation constraints that bound rationality by explicitly accounting for socio-behavioral biases ($BA_{Hom/Het}$). Importantly, our results reveal that the diffusion of all three adaptation

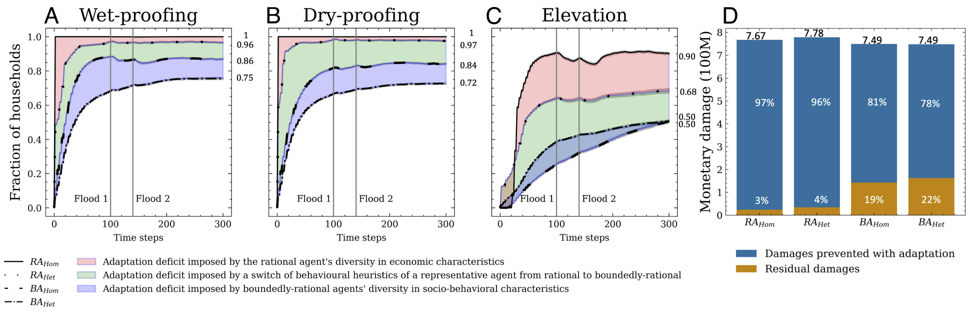

Figure 4.2: Panels a-c: Adaptation deficit across four behavioral strategies: representative rational agent (RA_{Hom}), rational households heterogeneous in incomes, education and damages (RA_{Het}), representative (BA_{Hom}) and diverse (BA_{Het}) boundedly-rational agents. The reported values are averages across the 100 Monte Carlo runs for each of the four behavioral framings, with the shaded areas denoting the standard deviations. Panel d: regional damages households experience in case of a hazard, in hundreds of millions \$. The reported values are averages across the 100 Monte Carlo runs for each of the four behavioral framings.

types is highly sensitive to the switch from RA to BA behavioral heuristics, which appears more influential for adaptation diffusion than income heterogeneity. Specifically, when comparing RA_{Hom} with BA_{Hom} (solid curves vs. dashed curves, Fig.4.2.a-c), the diffusion of adaptations drops by 14%, 16%, and 40% for Wet-, Dry-proofing, and Elevation, respectively (the pink and green areas combined, Fig.4.2). The inclusion of variability in socio-behavioral factors further widens the adaptation deficit by another 11% and 12% in Wet- and Dry-proofing compared to BA_{Hom} (dash-dotted curves for BA_{Het} and the blue areas, Fig.4.2.a-c). The overall adaptation deficit between the optimal level of private adaptation and its uptake by a population of empirically calibrated boundedly-rational households with diverse incomes, perceptions and social norms from the survey constitutes 25%, 28% and 40% for Wet-, Dry-proofing and Elevation correspondingly (solid vs dash-dotted curves for RA_{Hom} and BA_{Het}, Fig.4.2.a-c). Our results imply that even for individual investment decisions, such as the three CCA measures, other soft adaptation constrains like affect heuristics, perceived self-efficacy or social norms are the core source of behavioral uncertainty in the speed and scope of adaptation diffusion, instead of the conventionally-scrutinized heterogeneity of incomes and other financial constraints.

A unique feature of CRAB compared to other ABMs (Aerts, 2020; Taberna et al., 2020) is that household adaptive behavior is embedded in the evolutionary macroeconomy. The endogenous technological change in CRAB induces firm productivity and wage growth. Both increase the attractiveness of this coastal region and trigger an inflow of households and firms, leading to growing property values. Consequently, regional damages to households in the event of a flood increase over time, reaching \$749-778 million at the end of the simulation (Fig.4.2.d). Notably, households which behave as rational optimizers prevent nearly all damages via adaptation (RA_{Hom}&RA_{Het}, Fig.4.2.d). Taking a step further by converting emerging adaptation deficits into damages, our analysis illustrates that replacing a representative rational agent by a population with varied incomes and perceived damages makes a difference of 1% in the total prevented damages to households in the region. Conversely, as with adaptation deficits (Fig.4.2.a-c), switching to a different behavioral heuristic and assuming that households follow empirical patterns of decision-making about adaptation, boosts residual damages (BA_{Hom}&BA_{Het}, Fig.4.2.d). Leveraging the survey data, our ABM uniquely estimates the economic costs of soft adaptation constraints as differences in regional residual damages to households emerging from rationally-optimal vs. empirically-informed adaptation behavior (3-4% vs. 19-22%, Fig.4.2.d). Our results quantify for the first time that the costs of soft adaptation limits imposed by traditional financial adaptation constraints are 5-6 times smaller than of diverse adaptation constraints (i.e., awareness, social norms, education, financial).

4.3.1 Uneven distribution of damages, adaptation diffusion and benefits of adaptation in a population

To explore equity implications of hazards and adaptation, we complement the aggregated damage with the analysis of how damages and benefits of adaptation are distributed among different households. The ability of people and societies to adapt is associated with adaptive capacity, which is contingent on economic wealth, education, experience, social institutions, and governance (Adger and Vincent, 2005). Since the latter three are universal in the CRAB model, we assume that the feasibility of adaptation actions for households depends on their education level and income[2]. Based on this, we distinguish households with Low, Medium and High adaptive capacities (AC), and analyze whether and how—depending on their initial assets and adaptations taken—their damage and recovery trajectories vary after two severe floods shock the regional economy at steps 100 and 140 (Fig.4.3). To compare damages across households, we divide damages (after eventual adaptation) by the household's monthly incomes.

Without private adaptation, damages for an average rational household at the end of the simulation are more than 20 times higher than with adaptation (solid vs. dashed green curves, Fig.4.3.a vs. Fig.4.3.b). After both floods there are spikes of damage that fade back to pre-flood levels as households recover (shaded areas under the solid curves, Fig.4.3.a)—the "resilience triangles" (Abdel-Mooty et al., 2021). Even without adaptation, High AC households recover immediately after both floods (solid red curve, Fig.4.3.a). Low AC households are unable to fully recover following the first flood and maintain higher damages than pre-flood. This is exacerbated after the second flood, making the recovery even longer (blue shaded areas, Fig.4.3.a). Here, CRAB reproduces another stylized fact documented in the empirical literature (Walsh and Hallegatte, 2022): despite Low AC households owning the least costly assets and experiencing the lowest direct damages, their recovery is the longest. Thanks to the methodological novelty of CRAB that combines both macroeconomy (i.e., endogenous GDP and unemployment dynamics) and individual CCA actions, we identify the mechanisms that lead to the long recovery of Low AC. Our analysis reveals that the resilience triangles for Low AC are the largest not only because these households lack resources to recover quickly (i.e., hardly accumulate savings) but also because they are likely to lose income in the aftermath of a flood due to the bankruptcy of firm agents and increased unemployment. Another original insight with respect to the

[2]Notably, incomes change endogenously in our agent-based model as households change jobs and as the economy develops through technological innovations, but other things being equal, higher educated agents get jobs with higher wages. Since household education grants priority in the CRAB labor market and is highly correlated with income, we anchor adaptive capacity to the education level.

distributional impacts, is the emergent vulnerability of the Medium AC households, which develop the highest relative damages in the population (yellow curve, Fig.4.3.a). While Medium AC agents quickly recuperate the immediate losses after floods, following the second flood they perpetually shift to a trajectory of higher damages (8% above initial).

Assuming that households adapt as rational optimizers, the residual damages for all AC levels decrease over time (bottom dashed *RA* curves, Fig.4.3.b). Previous ABMs (Aerts, 2020; Taberna et al., 2020) also report decreasing aggregated damages due to private action, but our analysis goes beyond to provide insights in the distributional effects of adaptation. Notably, rational High and Medium AC households are more likely to afford the costliest adaptation (Elevation), which drops residual damages nearly to zero (dashed red & yellow curves, Fig.4.3.b). Due to financial constraints, rational Low AC households adapt slow or less-effectively. Hence, while adaptation reduces regional damages, its benefits disproportionally benefit High and Medium AC households, with Low AC agents bearing the highest residual damages (dashed blue curves, Fig.4.3.b).

Affected by empirically-revealed behavioral biases and social influences, *BA* households adapt less than rational, and this adaptation deficit raises residual damages 2-10 times depending on AC (dotted vs. dashed curves, Fig.4.3.b). After a flood, *BA* households across all AC levels experience losses but recover almost immediately, confirming the resilience dividend of timely adaptation (Walsh and Hallegatte, 2022). The ability of the model to test rival behavioral framings provides original insights regarding the uneven distribution of adaptation benefits in the population, revealing that shifting assumptions about human behavior from *RA* to *BA* has implications for inequality. Specifically, residual damages after adaptation of rational optimizers reveal the expected: High AC benefit most from adaptation, followed by Medium and Low AC households (dashed *RA* curves, Fig.4.3). This is not the case for boundedly-rational households parameterized with the survey data. When soft adaptation constraints, like subjective perceptions and social expectations, curb private adaptation, Medium AC households suffer the highest residual damages (dotted yellow *BA* curve, Fig.4.3), as they have already substantial assets to lose but have not yet sufficiently invested in CCA. These findings suggest that even under a nearly complete adaptation uptake in the population, CCA is uneven, and could further exacerbate inequalities since late or less-efficient actions lock-in households to a path of higher damages (Low AC for rational population or Medium AC for the boundedly-rational).

Finally, over 30 years scholars scrutinize the concept of a representative agent (Kirman, 1992). Our results show that assuming homogeneity not only fails to identify winners and losers, as commonly discussed in the literature (Jafino et al., 2021), but also misrepresents the behavior of Medium AC households. It is expected to find that the representative agent underestimates the recovery of Low AC households (green vs blue resilience triangles, Fig.4.3.a). Yet, it is surprising to observe that the representative agent in CRAB undervalues the gravity of losses experienced by Medium AC households by almost 1/3, for both *RA* (yellow vs green solid curves, Fig.4.3.a) and *BA* (yellow vs. green dotted curves, Fig.4.3.b) populations. It implies that approximating a population of heterogeneous households with a homogenous agent conceals significant losses and misleads policy design.

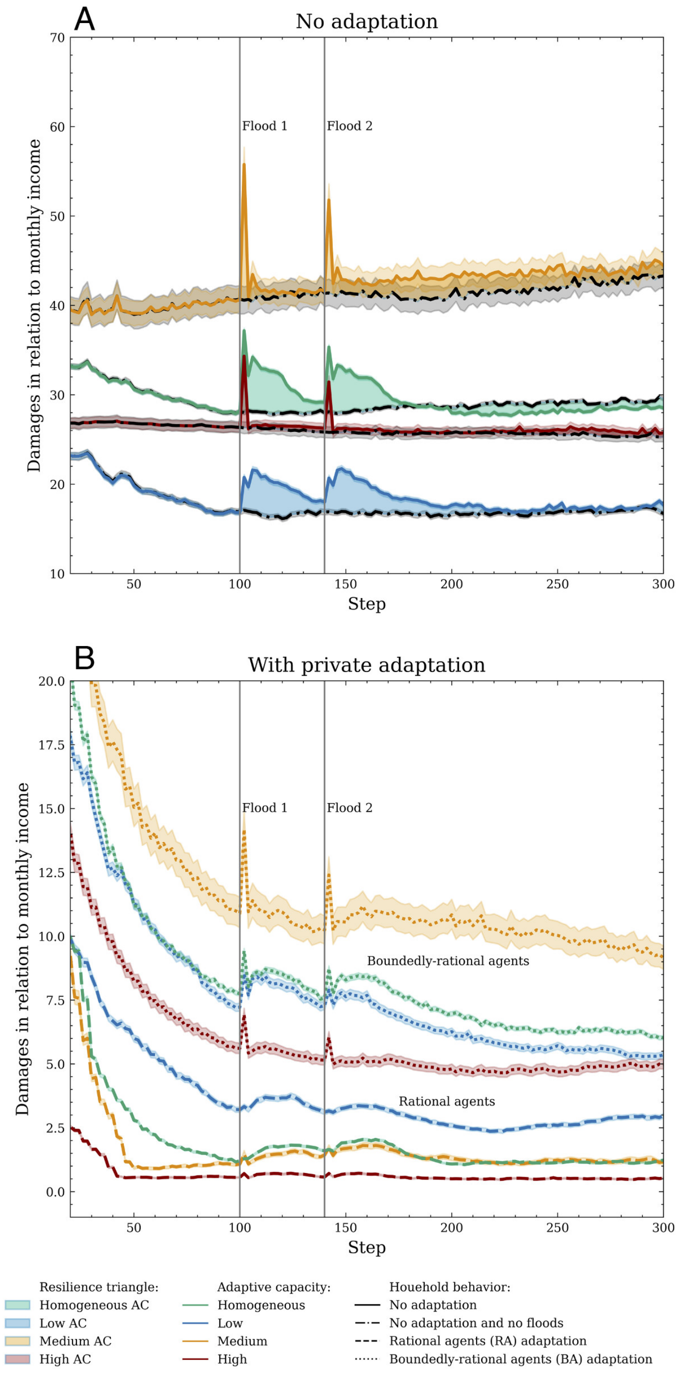

Figure 4.3: Residual damages without (Panel a) and with households' adaptation (Panel b) under rival assumptions about behavior: rational or boundedly-rational; assuming all households are the same (homogeneous) or based on empirical distribution of households' characteristics (heterogeneous). The latter is differentiated by adaptive capacity of households. To make residual damages comparable across households with various income, we divide damages by monthly income. All reported values are averages across the 100 Monte Carlo runs.

4.3.2 Behavioral heuristic choices affect the importance of uncertain physical factors

So far we have discussed the implications of simulating behavior in the formal model holding constant the key physical factors that affect damage estimates and adaptation uptake: the fraction of households exposed to flooding and the objective effectiveness of Wet-, Dry-proofing and Elevation measures. As the baseline values for these factors, we use a conservative fraction of current population in Florida exposed to severe flooding (Foundation, 2020), and average values of adaptation effectiveness found in fragmented literature (Kreibich et al., 2015). Yet, historic exposure changes with climate change, and the reported data on measure effectiveness (Kreibich et al., 2015) vary by 20-80%. Given the uncertainty in these four physical factors, we use SA to quantify their effects on the fraction of households that choose to adopt each adaptation measure (Fig.4.4) and on the regional damages to households (Fig.4.5). To distinguish their interaction with households' heterogeneity and behavioral heuristic choices, we perform this analysis thrice, for three rival framings of household CCA behavior: RA_{Hom}, RA_{Het} and BA_{Het}).

Our results show that the variability of adaptation diffusion trends (measured through standard deviations, Fig.4.4), and the factors driving it, differ substantially across adaptation measures (comparing along a column), and across behavioral heuristics (comparing along a row). To measure the effect of each factor, we use sensitivity indices estimating total-order effects on the variance of each output (details in Materials and Methods, SI). For instance, in panel Fig.4.4.a the sensitivity indices measure how exposure and the objective effectiveness of the three measures contribute to the variability of Wet-proofing adoption as a result of their direct and interactive effects. For rational agents Elevation effectiveness appears to be the major controlling factor in the fraction of households that choose to elevate (orange, Fig.4.4.g-h), but has less of an effect on the fractions of households that choose to apply Wet- or Dry-proofing (orange, Fig.4.4.a-b,d-e). Since Elevation is a costly measure, the importance of its damage reduction effectiveness for its uptake is intuitive. Our novel approach captures individual trade-offs between different CCA measures in the presence of various adaptation constraints, providing unique estimation of the possible interaction effects. Specifically if boundedly-rational households make adaptation decisions as they report in the survey, we see a reversed effect: Elevation effectiveness hardly matters for the uptake of Elevation but is the predominant factor affecting the households that choose to Wet- or Dry-proof (in orange Fig.4.4.c,f). Similar contrasts are seen when comparing the relative importance of Wet- and Dry-proofing effectiveness (Fig.4.4, light and dark pink colors, respectively) across adaptation measures and behavioral heuristics. Hence, a small change in the objective effectiveness of CCA measures is amplified by socio-behavioral factors, like perceived effectiveness or perceived damages, and leads to non-linear effects of physical factors under alternative behavioral framings.

Our results reveal for the first time that socio-behavioral factors mediate the importance of physical factors traditionally thought to be decisive for CCA uptake. Without considering these interactions between physical and behavioral uncertainty, the design of policies could be misguided: resources could be misdirected on factors that are inconsequential, by either investing in collecting data on their effectiveness or in running information policy campaigns. For instance, the uncertainty surrounding the effectiveness of Wet-proofing measures appears to not affect adaptation choices of empirically-grounded agents but

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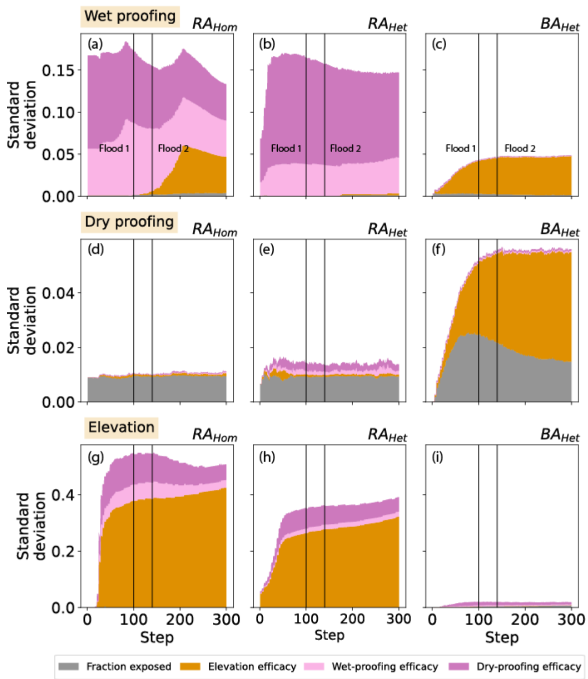

Figure 4.4: Time-varying sensitivity indices of the uncertain factors—exposure and objective effectiveness of measures —affecting households' adaptation diffusion. The three rows show the variance in the proportion of households that adopt Wet-, Dry-proofing and Elevation measures, respectively; the three columns show how sensitivity varies per behavioral heuristics (homogeneous and heterogeneous Rational Agents, RA_{Hom} and RA_{Het}; heterogeneous Boundedly-rational Agents, BA_{Het}). The reported values are from the 460,800 Monte Carlo runs.

matters significantly for rational optimizers (BA_{Het} vs. both RA models, Fig.4.4.a-c). We also note that, again, a shift from a representative to a diverse population of rational households, i.e., accounting for heterogeneity of financial adaptation constraints, hardly changes the relative importance of the four physical factors on adaptation diffusion (left vs. middle column, Fig.4.4). Yet, a switch to a boundedly-rational heuristic transforms the importance of objective factors for CCA uptake (right column). The longitudinal SA also reveals that the relative importance of the four physical factors changes over time. For example, when households mimic empirically-reported behavior, the uncertainty in Dry-proofing uptake depends mostly on exposure in the beginning, with the non-linear interaction with effectiveness of an alternative measure (here Elevation) eventually becoming the dominant factor explaining uncertainty of the Dry-proofing diffusion (Fig.4.4.f), highlighting the importance of accounting for trade-offs between different CCA measures households face.

We also quantify the effects of the four uncertain physical factors on potential damages (Fig.4.5), across three rival behavioral models (RA_{Hom}, RA_{Hom}, and BA_{Het}) and three levels of individual AC (Low, Medium, and High). Results reveal that the introduction of heterogeneity in the RA model changes the relative impact of uncertainty in the fraction of households exposed (comparing panels in Fig.4.5.a-d). This means that in comparison to a representative agent (RA_{Hom}), for rational heterogeneous households (RA_{Het}) the effects of uncertainty in their exposure on the variance of potential damages drops nearly to zero, while the importance of uncertainty in the effectiveness of the three measures becomes more apparent. Accounting for bounded rationality in agents' behavior (Fig.4.5.e-g), the relative importance of physical factors shifts again, with damage variance now dominated by uncertainty in the effectiveness of Dry-proofing. Notably for empirically-based households (BA_{Het}), if policymakers were concerned only with the diffusion of adaptation measures in the region, our analysis would suggest focusing on communicating and improving Elevation effectiveness (right column, Fig.4.4). If they want to minimize regional damages, then policies should focus on Dry-proofing effectiveness (bottom row, Fig.4.5). Therefore, complementing longitudinal SA of damage estimates (Fig.4.5) with monitoring the diffusion of various adaptations (Fig.4.4) is essential to assess what policy instruments improve what type of CCA for what households, and to make informed trade-offs when deciding on CCA policy design.

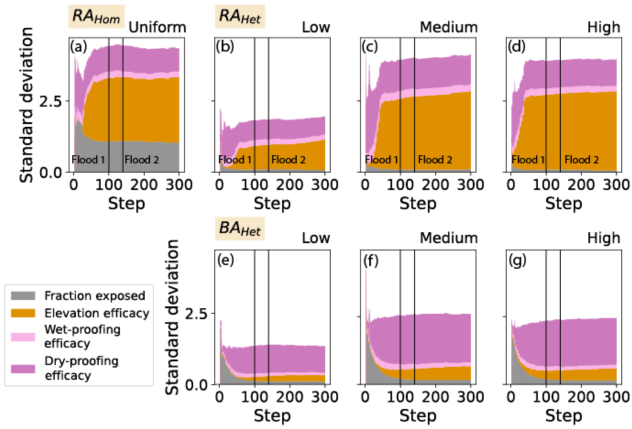

Figure 4.5: Time-varying sensitivity indices of the uncertain physical factors—exposure and objective effectiveness—affecting households' residual damages. The two rows plot the proportion of variance in damages of rational (RA_{Hom} and RA_{Het}) vs. boundedly-rational (BA_{Het}) households explained by exposure and effectiveness; the three right columns show how sensitivity varies across the three adaptation capacity groups (Low, Medium, and High) vs. the top left figure revealing the effects of physical factors for damages experienced by a representative rational agent. The reported values are from the 460,800 Monte Carlo runs.

4.4 Discussion

Methodologically, sustainability sciences have been long concerned with unsatisfactory representations of human behavior in formal models of human-natural systems (Yoon et al., 2022). By combining agent-based simulations, household surveys and exploratory modeling we demonstrate that the traditional use of a representative rational optimizer overestimates adaptation diffusion and overlooks inequalities in the distributional impacts of hazards and of adaptation. For climate adaptation specifically, an understanding of how macro-outcomes change as the richness of microbehavior in models increases addresses a number of key research priorities (Berrang-Ford et al., 2021).

This article advances methods for sustainability science in several ways. Firstly, responding to the calls for methodological advances in ABM (Aerts et al., 2018; Taberna et al., 2020), we provide a solid example of using surveys to populate agents in formal models with data on socio-behavioral factors that environmental psychology considers foundational for representing behavioral change. Complemented with exploratory modeling, this approach offers the first systematic SA of rival behavior framings with nearly 0.5 million simulations exploring interactions between behavioral and physical uncertainties. Secondly, this is the first ABM that embeds fine modeling of households adaptation behavior in a complex evolving macroeconomy prone to hazards, introducing firms as key agents defining regional economic development, endogenous changes in households incomes and in unemployment. This permits combining the standard to ABM modeling of informal social influences with the evolution of formal market institutions, which jointly either boost or hinder the speed of adaptation diffusion and the uneven distribution of its benefits. Thirdly, departing from the common practice of reporting aggregated population-level results of household adaptation (Aerts et al., 2018; de Ruig et al., 2019; Taberna et al., 2020), we explicitly trace trade-offs among various adaptation measures and visualising results per individual adaptive capacity to enable substantiated discussions about equity and tailored policy designs. These methodological novelties offer insights for the science and practice of CCA, and for sustainability modeling efforts that aim to capture human behavior in nature-society systems.

4.4.1 Quantifying soft limits and speed of individual climate adaptation

Assessing the speed of adaptation uptake and its soft limits is among the key challenges for CCA science and policy (Berrang-Ford et al., 2021). Our novel approach goes beyond heterogeneity in financial adaptation constraints, which has been the main step in advancing over the representative rational agent model of human decisions in contemporary CCA literature. The switch from the *RA* to *BA* framing of human decisions fundamentally impacts all model outcomes—adaptation deficits, regional damages and even the effects of uncertain physical factors like hazard exposure and objective adaptation effectiveness. Leveraging theory and survey data, our results reveal that even for investment decisions, soft adaptation constraints like affect heuristics, self-efficacy, and social norms (i.e., bounded rationality) are the core source of behavioral uncertainty in the speed and scope of individual adaptation diffusion. Conversely, the effects of heterogeneity in incomes and other financial constraints are not as essential as commonly assumed in the literature. Following the patters in the survey data, the behavioral (e.g., risk perception, perceived response-efficacy) and social (e.g., descriptive norms) factors either facilitate or curb individual intentions of *BA* agents to adapt. Moreover, in our model some of these adaptation constraints change over time for *BA* agents who learn, for instance from their experience with CCA measures or floods (*RA* agents do not learn). Accounting for both diverse adaptation constraints and learning explains the difference in macro-outcomes of *BA* vs *RA* simulations.

4.4.2 Role of institutions in shaping equity and socio-economic resilience

The individual behavioral changes described above are also affected by institutions on meso (social norms) and macro (economy) levels. Tracing the evolution of these institutions in our framework enables going beyond conventional findings that High AC households adapt quicker and suffer less damage than their Medium and Low AC peers. Instead, we explicitly model the mechanisms that amplify or reduce existing inequalities.

Besides individual learning, *BA* households in CRAB also observe the evolution of descriptive norms. As the number of peers pursuing a specific CCA grows in an agent's social network, the prevailing local social norm shifts from "non-adaptive" to promoting CCA behavior. Hence, *BA* households with larger social networks full of early CCA adopters adapt quicker and better than those with smaller networks dominated by laggers, causing agents to benefit differentially from adaptation. Besides speed, which CCA households adopt also matters. While ABM literature typically models one type of household CCA, our results reveal non-linear trade-offs between the three CCA measures. The social amplification[3] influences the speed and type of CCA adopted, both of which matter for damage reduction in our results, and hence for the (un)even distribution of CCA benefits.

The macroeconomic mechanisms also have differential impact on disparities. In CRAB, households interact with firms that provide jobs. Household incomes change endogenously depending on firms' economic performance, implying that labor market institutions expedite the recovery of some households, but lock others into a path of increasing inequality. Specifically, firms hit by floods decrease their production due to destroyed assets and face higher costs due to productivity losses. Those who bankrupt, leave their workers unemployed. These indirect damages are milder for individuals with High AC who find another job easier due to their higher education; low educated Low AC stay unemployed longer, which slows their recovery and hampers opportunities to adapt on time due to lacking savings. This unique feature of CRAB—integration of households in the macroeconomy—permits tracing another macroeconomic mechanism: indirect benefits of CCA. Besides protecting households from direct damages, private CCA diminishes their post-flood repairs, reducing shocks to goods' markets. It helps firms avoid bankruptcies, reducing labor market shocks and unemployment in the aftermath of a flood. This result reinforces previous statements on the importance of bottom-up CCA actions to build climate-resilient societies (Adger et al., 2005), including the prevention of business interruptions essential for socio-economic resilience (Goldstein et al., 2019). The indirect macroeconomic effects of CCA—faster post-flood recovery, fewer damages after repetitive hazards, and reduced unemployment—also known as resilience dividends, could lift people and regional economies instead of locking population into long-term structural vulnerabilities. As such, our results demonstrate macroeconomic co-benefits of private CCA, with implications for policy design that should embrace a systems' perspective, going beyond direct damages to account for cascading indirect effects for various stakeholders.

4.4.3 Tailored policies for closing the adaptation deficit

While many ABMs model heterogeneous agents, most report only population-level outcomes (de Ruig et al., 2019). Leveraging on this natural strength of ABMs, we present results differentiating per household AC. Our analysis supports previous finding that shocks disproportionally impact Low AC who have the longest recovery despite suffering the lowest damages. Surprising was to find that Medium AC, who have assets to lose and sometimes enough finances, postpone adaptation due to the awareness or self-efficacy constraints. These soft constraints are the main reasons the damages pathways for Medium AC (and the overall adaptation deficit) vary so much for *BA* vs. *RA* agents.

Compared to the optimal, the insufficient level of adaptation pursued by *BA* households with empirically-grounded behavior is so significant that it calls for tailored CCA policies that explicitly motivate private adaptation. Our analysis reveals different channels via which CCA policies could reach various vulnerable households by removing their adaptation constraints. For example, Low AC households will benefit from tailor-made subsidies (e.g., anchored to property values/incomes) for most effective (instead of just any) CCA measures and from uplifted education. Conversely, Medium AC households will benefit from information policies with personalized narratives appealing to perceptions and social identity. Such strategies can complement the communication of climate-driven risks to

[3]Only for *BA* households; *RA* do not learn and are not prone to social influences.

avert households from locating in climate-sensitive regions or investing too late in private CCA. Designing tailored policies to overcome such soft adaptation constraints could result in nearly a fivefold drop of residual damages per household according to our analysis.

4.4.4 Importance of behavioral uncertainty for policy design

Uncertainty is an inherent component of decision-support for CCA policy, which has so far heavily focused on exploring implications of various government-led adaptation choices (Haasnoot et al., 2013) or physical factors (Vousdoukas et al., 2020), omitting behavioral uncertainty of private adaptation. The analysis here considers both uncertainties in physical factors and epistemic behavioral uncertainty—the rival framings from rational to empirically-grounded and from homogeneous to heterogeneous populations.

Our analysis demonstrates that fundamental differences between *RA* vs. *BA* behavior framing are critical for CCA, and for nature-society systems in general, given similar observations for other sustainability applications (Beckage et al., 2018; Wijermans et al., 2020). Additionally, our longitudinal SA shows that behavior framing alters the more predictable variance imposed by physical factors that are conventionally considered crucial in CCA policy (exposure and objective adaptation effectiveness). While introducing heterogeneity in financial constraints (RA_{Het} vs. RA_{Hom}) matters, it is the switch to a realistic representation of behavior shaped by diverse adaptation constraints (RA_{Hom} vs. BA_{Het}) that fundamentally changes how consequential the uncertainties in physical factors become. Notably, the physical uncertainties interacting with behavioral uncertainty manifest differently for households of different adaptive capacity (more damage variability for Medium and High AC) and different CCA measures. For example, for BA_{Het} households, elevation efficacy (and lack thereof) is the most critical factor in how many households choose to apply Wet- and Dry-proofing. This is not the case under the assumption of agent rationality.

When it comes to model-based policy design to address CCA, this implies that assumptions about how we represent human decision making processes influence our expected adaptation outcomes. This is a finding already highlighted in literature widely, but we stress two additional nuances illuminated by the novel combination of methods in this study. Behavioral assumptions also shift what we consider to be our "X factors"—the key variables that might undermine adaptation progress and that we need to monitor and prepare for. An unrealistic representation of human behavior might mislead modelers and policy makers to direct efforts on factors that are in fact inconsequential. For example, if we design CCA policy under a simplified premise of human homogeneity and rationality (in our case, the RA_{Hom} model), we might be misled in either investing in the wrong data collection campaigns or in running information policy campaigns focused on the effectiveness of measures that make no difference. A particular finding we highlight here is that the degree of household exposure might not be as critical in reducing residual damages as other soft socio-economic limitations. Instead, non-linear interactions between alternative CCA measures become apparent, for instance, when households start to substitute CCA measures as uncertainty about their effectiveness changes.

4.4.5 Generalizability of findings

While being applied to CCA, our modeling framework address one of the most sought for challenges in sustainability sciences: representation of human behavior in formal models. Being grounded in social science theories, our model encompasses generic mechanisms shaping both macro and micro dynamics(Dosi et al., 2017a; Krugman, 1998). Generalizability of macro-dynamics has been confirmed by validating the model against stylized facts (SI). For micro behavior specifically, we employ the prominent psychological theory, which assumes human behavior is shaped by perceived awareness (of threat in the risk context), self-efficacy and social norms among other factors –socio-behavioral factors typical in many contexts. The Protection Motivation Theory we have chosen is considered to explain CCA behavior the best and is validated against empirical data worldwide(Noll et al., 2022b; Steg and Vlek, 2009; van Valkengoed and Steg, 2019). Since the mechanisms of behavioral change coded in our model are generic, the derived insights – particularly that socio-behavioral factors rather than income heterogeneity matter more for macro-outcomes, that these factors contribute to shaping inequality, and that they interact with uncertainty of physical factors – are generalizable. Consequently, the presented framework can also be applied to situations where behavioral change of interest has not yet happened, since the mechanisms behind the factors driving potential behavioral changes (at least in the risk context) are encoded and could be activated as the simulation unfolds.

The detailed behavioral data uniquely enabled us to identify which of the socio-behavioral factors/households adaptation constraints matters the most for shaping soft limits to adaptation. While it was crucial for achieving context-specific results, we believe that a lack of possibilities to run own surveys should not hinder the application of such methods for other cases or sustainability challenges. Currently, behavioral data increasingly becomes available via literature publishing case-based surveys on pro-environmental behavior, meta-analyses or cross-cultural surveys (Bamberg et al., 2017b; Noll et al., 2020; van Valkengoed and Steg, 2019), and open-access databases (e.g. World Risk Poll[4]) making such advanced behaviorally-rich models feasible. This said, as with ecological, hydrological or climate models: theory-driven mechanisms and secondary data help elicit system dynamics and draw conclusions in broad lines. Yet, if one wants to perform high-quality work on modeling human behavior in sustainability science models, one needs high-quality data on the behavior in question.

4.4.6 Limitations and future work

Our modeling work can be expanded in several ways. Firstly, the analysis would benefit from a more comprehensive spatial representation of climate shocks aligned with hazard maps corresponding to downscaled Representative Concentration Pathways scenarios (IPCC, 2022a). Future work could also explore hydrological modeling of floods under various climate scenarios (Alfieri et al., 2017) and perform a comparative analysis for other coastal regions, which may require extending to other economic sectors and empirical calibration of sector-specific impacts of hazards. Additionally, the model would benefit from including firms' CCA decisions.

Secondly, while our exploratory modeling accounts for the effects of epistemic uncertainty and stochasticity, it does not consider parametric uncertainties in the socio-economic

[4] https://wrp.lrfoundation.org.uk/

system. Performing global SA on empirically-defined weights for different behavioral factors might interfere with the theoretical grounds of the behavioral model. Sampling and processing large uncertainty ensemble runs using methodological innovations would enable better comprehension of the effects of such uncertainties. Furthermore, while our model captures the evolution in agents' behavior based on their experiences, future work could also account for fundamental changes in preferences (i.e., as opposed to weights estimated using past data), employing longitudinal survey datasets that trace how individual perceptions and preferences change over time (Noll et al., 2022b; Seebauer and Babcicky, 2021). Other "dynamic" methods of data collection, such as laboratory experiments, randomized control trials, and serious gaming, which have been combined with ABMs (Duffy, 2006), could also be employed in CCA applications.

Lastly, such combinations of methods could be used to quantify soft adaptation limits or tipping points at which individual objectives or societal needs cannot be secured from intolerable risks through adaptation (Berrang-Ford et al., 2021; Mechler et al., 2020). Identifying such social tipping points in CCA could also help design policies for transformational adaptations, such as planned and equitable relocation when certain locations reach their adaptation limits (Moss et al., 2021b). ABMs are already accustomed to combining public government-led adaptation with private actions (Aerts, 2020; Taberna et al., 2020) to explore both synergies and unintended effects between public and private adaptations.

4.5 Materials and Methods

To analyze the role of behavioral assumptions on household CCA and regional damages, we combine an evolutionary economic agent-based CRAB model with household survey data and with exploratory modeling. CRAB simulates socio-economic dynamics of regional agglomeration economies exposed to climate-induced risks (for more information about the theoretical foundations of the model see Taberna et al., 2022). It features a regional economy exposed to floods and populated by heterogeneous households and firms that interact, learn and endogenously decide what to do (e.g., how much goods to produce, whether to adapt or relocate). We employ survey data from Florida, US ($n = 965$) to parameterize households' behavior (Noll et al., 2022b). Considering the high uncertainty surrounding hazard, exposure, and vulnerability of the regional economy, we also perform an extensive SA on the fraction of population exposed, and on the effectiveness of private flood-proofing measures.

4.5.1 Socio-economic structure

The CRAB model builds upon the evolutionary economic tradition (Dosi et al., 2010; Lamperti et al., 2018). Here the model features a three-sector regional economy with four classes of heterogeneous agents: households, and capital-good, consumption-good, and consumption-service firms. Firms and households dynamically interact in decentralized labor and good/service markets. The number of agents changes in the course of the simulation depending on the migration of households and entry/exit of firms. The region is divided between hazard-prone and safe areas to mimic the greater Miami case, with 40% of agents exposed to floods. Floods hit agents in the hazard-prone area, destroying households' properties, firm inventories and machines. Households living in the hazard prone-area can take multiple CCA actions to protect themselves.

Firms

The capital-good sector invests in R&D to discover more productive technologies. The latter generates a "Schumpeterian" creative (innovative) destruction process, which is the engine of economic growth. Capital-good firms then advertise their machines via "brochures" to possible customers: consumption-good/service sectors. Once orders are computed, capital-good firms produce machinery using labor. The consumption-good/service sector combines labor and capital to produce a homogeneous good/service. These two sectors follow the same decision-making process using adaptive heuristic demand expectations and fixed capital-output ratios to achieve desired production and capital stock level. Importantly, if capital stock is insufficient to satisfy the desired production, new machines are ordered comparing the "brochures" firms are aware of. In addition, following a pay-back rule, current machinery can also be replaced by more productive ones. The consumption-good sector differs from the service sector in their capital-output ratios. We loosely parameterize this regional economy based on the data for Florida, implying that the consumption-service sector is more capital-intensive than the consumption-good sector (Commission et al., 2019).

Households

Households have multiple socio-economic and behavioral characteristics derived from survey data: property values, education, and initial savings, as well as the influence of social norms. Households spend a fraction of their income if employed, while unemployed households spend their entire unemployment benefits. Savings accumulated over time are spent on protective CCA actions and to repair flood damages. The latter depends on the household property value and the damage coefficient. The value of the household property is indexed to the region's average wage, thus increasing over time. The damage coefficient is calculated overlying flood depth and depth-damage curves for residential buildings, using US data (Huizinga et al., 2017).

4.5.2 Rival framings of human behavior

The model allows for comparing CCA protective actions of rational, fully-informed (*RA*) and of boundedly-rational (*BA*) households. In the *RA* framing, households compute Expected Utility by weighting the costs and benefits of undertaking a CCA action against no-action and choosing the highest-utility option. In the *BA* framing, we assume that households behave as suggested by PMT. Using Florida survey data, we run a Logit regression to estimate effects of relevant socio-behavioral attributes (SI, "Model calibration"). We also differentiate between homogeneous and heterogeneous populations of both *RA* and *BA* households, using either the survey averages or drawing values from empirical distributions of corresponding survey attributes. For example, for BA_{Het} households we use effects from the Logit model to specify the relative weights for each socio-behavioral attribute. Each BA_{Het} household multiplies these weights by their own heterogeneous attributes to estimate a probability to adopt each of the three CCA measures. Since not all households who intend to adapt actually take action, we assume that households in CRAB adapt only if this probability is higher than a threshold randomly drawn between 0 and 1 (SI, "Households").

Households living in flood-prone areas perform this calculation each time step for all the affordable CCA measures that they have not yet implemented. It is important to note that household's probability of adaptation can change over the course of the simulation due to evolving values of the socio-behavioral factors. One factor affecting such probability is the implementation of a measure. Specifically, past undergone measures decrease the probability of future adoption of other measures directly and also indirectly by decreasing expected damages. The diffusion of a particular measure can also affect other households' decision-making by updating the descriptive social norm in own network as new peers undertake the measure. Additionally, the experience of flooding also affects households probability of CCA. While these changes in attributes are limited in scope, they aim to capture the possible behavioral trajectories arising from our models.

4.5.3 Model calibration

We calibrate our regional economy to resemble a coastal agglomerated area in the southeast US, such as Miami-Dade county. In addition to the survey data, we employ publicly available statistics. We include 3,000 households created from the survey data, i.e., about 0.5% of the total owner-occupied properties in the county. We calibrate firms according to the current business-to-population ratio. To calibrate the capital intensity of firms from the three sectors in CRAB, we apply constant US capital-output ratios from a macroeconomic model (Commission et al., 2019). To parameterize heterogeneous household behavior, we generate a synthetic population by conditionally sampling household attributes from the survey data using first moment and cross-correlation among variables as the fitness criteria (see SI, "Model calibration"). When the population is assumed to be homogeneous, the attributes' mean value is used for all households, which will then have the same socio-economic and behavioral initial characteristics. We also employ national statistics to divide household expenditure between goods and services. Lastly, we model the number of agents living in flood-prone areas according to the percentage of properties likely to be affected by a major flood in the next 30 years in Miami-Dade county. We consider two extreme floods of 3m high hitting this regional economy at fixed time steps (100 and 140), equivalent to a storm surge generated by a category five hurricane hitting the low-lying flood-prone areas.

4.5.4 Institutions

Households and firms interact via formal economic institutions (capital, labor, and goods/services markets) and informal (social networks) institutions. In the capital market, capital-good firms send brochures containing the price and productivity of their machines to existing customers and new, randomly selected, potential customers. Consumption-good and -service firms seeking to buy new machines compare the brochure they received and select the supplier with the best price-quality ratio. In the labor market, firms assess their labor demand and post available vacancies or fire the surplus of workers. Unemployed households, sorted by education level, select a sub-sample of available vacancies and choose the one with the highest wage. Hence, households with higher education will get better-paid job opportunities. Wages are then partially spent on goods and services. The aggregate household expenditure in good and service markets defines the local demand in the coastal region. Local demand is summed to export demand and assigned to firms according to their market share. The latter depends on their competitiveness, which, in turn, is calculated according to their prices and unfilled demand. Firms' market share evolves via quasi-replicator dynamics (SI, "Firms"). Furthermore, *BA* households are influenced by social norms, i.e., unwritten rules characterizing how appropriate a certain behavior is within a social group. Our survey elicits the influence of both descriptive and injunctive social norms, which we parameterize in the CRAB model using the estimated logit effects (SI, "Model calibration"). These effects serve as weights impacting individual intention for CCA. For each household in CRAB these weights are multiplied by the number of contacts in the individual's social network that have undertaken the specific CCA actions (SI, "Household."). To instantiate a social network, each household in CRAB links to a number of other agents, and this number we draw from the empirical distribution reported by our survey respondents in Florida. This social network serves as a medium for households to learn about protective actions undertaken by their peers the uptake of which evolves as the simulation unfolds.

4.5.5 Entry and exit of economic agents

The agglomeration process in the regional economy in CRAB is endogenous, with households' and firms' entry (in-migration for households and establishment of firms) and exit (out-migration for households and bankruptcy for firms) processes dependent on how the regional economy performs. Specifically, a migration process linked to regional economic indicators regulates the number of incoming/outgoing households. Aligned with empirical evidence, we use the difference in income per capita, and the unemployment rate (Kennan and Walker, 2011) as indicators of the regional attractiveness for household agents. In a nutshell, an economy with a growing income per capita and a low unemployment rate attracts new households sampled from the synthetic population pool and added to the incumbents. Conversely, a stagnant economy will push households to migrate elsewhere. Households also affect the creation of new firms from the bottom-up. In particular, an employed household decides to create its own firm if the profits of its current employer exceed a certain threshold for a number of consecutive periods. Firms with quasi-zero market share and lack of resources are assumed to go bankrupt and are removed.

4.5.6 Exploratory modeling and sensitivity analysis

We create a large set of alternative model assumptions, representing plausible uncertainty in the estimates of the model's physical factors: flood exposure and the effectiveness of the three adaptation measures (Wet-proofing, Dry-proofing, and Elevation). We use this set perform global SA to identify factors explaining the variability of critical model outputs. To causally apportion output uncertainty to uncertain physical (input) factors we use Sobol' variance decomposition (Sobol, 2001). Assuming parametric independence and uniform distributions, we generate a set of 1,536 parameter combinations across the parameter ranges as detailed in the SI. These ranges are informed by literature estimates (see (Kreibich et al., 2015) and references therein for effectiveness). We note that even though the term "sensitivity analysis" might be common in the literature, it is often a misnomer or it refers to so-called "one-at-a-time" analyses that miss the interactions uncertain factors might have, or they are "local" in that they only test deviations from nominal values. Even though these applications are common due to their computational ease, the analysis performed here examines the full parametric space as well as parameter interactions. The analysis is also exploratory in nature (referring to exploratory modeling as articulated above), as it moves well beyond literature estimates. To do so, we intentionally expand the parametric range we explore to capture consequential interactions that might exist in more extreme regions of the parametric space, such as the entire population being exposed. Each exploratory ensemble is applied to three alternative behavioral heuristics (RA_{Hom}, RA_{Het} and BA_{Het}) to assess how the importance of each factor changes under rival behavioral framings. For each parameter combination we also perform 100 Monte Carlo runs to preserve the effects of stochasticity, creating a total of 460,800 model simulations for the exploratory analysis alone. We calculate total-order Sobol' indices measuring the total contribution of each factor both individually and through its interactions with other factors. To do so, we average the 100 Monte Carlo runs across every time step for every parameter sample and for every uncertain outcome (i.e., the fraction of households that choose each adaptation measure and the potential damages of households with different levels of adaptive capacity). We then calculate the indices using the Sobol' method implementation in the SALib Python package (Herman and Usher, 2017). Each (total-order) index is estimated for every time-step in the simulation, resulting in an estimate of "time-varying" longitudinal significance. This allows us to detect changes in relative importance across all the years, indicative of changes in regimes or other fundamental system shifts. Time-varying sensitivity analyses have been more commonly applied in other modeling domains (Song et al., 2015), but are not prevalent in ABM literature, especially in experiments at the computational expense of the one presented here.

5

Economic implications of autonomous adaptation of firms and households in a resource-rich coastal city

Climate change intensifies the likelihood of extreme flood events worldwide, amplifying the potential for compound flooding. This evolving scenario represents an escalating risk, emphasizing the urgent need for comprehensive climate change adaptation strategies across society. Vital to effective response are models that evaluate damages, costs, and benefits of adaptation strategies, encompassing non-linearities and feedback between anthropogenic and natural systems. While flood risk modeling has progressed, limitations endure, including inadequate stakeholder representation and indirect risks such as business interruption and diminished tax revenues. To address these gaps, we propose an innovative version of the Climate-economy Regional Agent-Based model that integrates a dynamic, rapidly expanding agglomeration economy populated by interacting households and firms with extreme flood events. Through this approach, feedback loops and cascading effects generated by flood shocks are delineated within a socio-economic system of boundedly-rational agents. By leveraging extensive behavioral data, our model incorporates a risk layering strategy encompassing bottom-up and top-down adaptation, spanning individual risk reduction to insurance. Calibrated to resemble a research-rich coastal megacity in China, our model demonstrates how synergistic adaptation actions at all levels effectively combat the mounting climate threat. Crucially, the integration of localized risk management with top-down approaches offers explicit avenues to address both direct and indirect risks, providing significant insights for constructing climate-resilient societies.

This chapter is based on *Taberna, A., Filatova, T., Hochrainer-Stigler, S., Nikolic, I., & Noll, B. (2023). Economic implications of autonomous adaptation of firms and households in a resource-rich coastal city. Scientific Report, s41598-023-46318-2.* (Taberna et al., 2023b).

5.1 Introduction

The effects of climate change are increasing the frequency and severity of floods worldwide, particularly in coastal areas (Vousdoukas et al., 2020). As a result, the likelihood of experiencing two severe flood events in rapid succession increases. This necessitates the exploration of cascades and non-linearities in complex economic systems, which, when interacting with socio-economic dynamics, can amplify such risks. Scholars and policymakers recognize that taking anticipatory action involving actors from all levels of society offers the best chance to address this growing threat (IPCC, 2022b).

Traditionally, climate change adaptation (CCA) studies have primarily focused on government-led actions, such as the construction of dykes or levees (Goldstein et al., 2019). More recently, there has been an increased emphasis on individual actions, though this has been mainly restricted to the household level (Berrang-Ford et al., 2021). Unfortunately, the predominant focus on single protective measures, whether initiated by the government or households, overlooks how various measures deployed by different actors might align or conflict (Adger et al., 2005).

Empirical evidence demonstrates that inadequately coordinated actions or miscommunication can lead to feedback that exacerbates existing flood risks (Di Baldassarre et al., 2015; Filatova, 2014). Nonetheless, the direct and indirect influence of individual adaptation decisions on overall systemic resilience remains largely uncharted territory. This knowledge gap complicates the formulation of adaptation strategies that are both efficient in managing flood risks and effective in mitigating the associated socio-economic fallout.

Present macro models for quantifying flood risks rely on a static approach, failing to incorporate the complexity of path dependency and non-linear interactions between environmental and anthropogenic systems (Stern, 2016). The latter although often adept at managing a singular hazard, might struggle to maintain resilience under the accumulating stress of repetitive or consecutive shocks. Thus, acknowledging and incorporating these intricate dynamics into policy models is a pivotal step toward designing more robust strategies despite escalating climatic risks and for constructing an accurate appraisal of damage and adaptation behavior across varied socio-economic strata (Jafino et al., 2021; Mendelsohn, 2000).

Agent-Based Models (ABMs) have emerged as a useful method for modeling heterogeneity, learning, interactions, and out-of-equilibrium dynamics (Arthur, 2021; Bonabeau, 2002; Tesfatsion and Judd, 2006). ABMs are versatile in simulating climate change (Balint et al., 2017; Ciarli and Savona, 2019; Lamperti et al., 2018; Mercure et al., 2016) and disaster scenarios (Coronese et al., 2022; Waldrop, 2018), flooding in particular (Aerts, 2020; Taberna et al., 2020). Hence, ABMs are particularly useful for capturing evolutionary non-linear and path-dependency phenomena, such as feedback and ripple effects stemming from the interplay of agglomeration economies and a worsening climate (Taberna et al., 2022). However, flood-ABMs still have limitations, such as a focus on households and neglect of the role of firms and indirect losses resulting from business interruption, loss of employment opportunities, and tax revenues. To address these limitations, we developed a novel version of the *Climate-economy Regional Agent-Based* (CRAB) model (Taberna et al., 2022) that includes bottom-up and top-down adaptation strategies.

CRAB models the socio-economic dynamics of regional agglomerated economies, with a growing concentration of people and assets confronting climate-driven risks. The model features a regional economy exposed to flood risk, consisting of varied households and firms that interact, acquire knowledge, and autonomously decide on actions, such as deciding production quantities, adaptation measures, or possible relocation. This novel version features a layered risk framework that includes individual disaster risk reduction measures, insurance, and government subsidies (Hochrainer-Stigler and Reiter, 2021).

The endogenous agglomeration process stemming from the CRAB model facilitates the exploration of the reciprocal relationship between anthropogenic activities, such as the rising population in flood-prone regions, and climate-induced risks. Introducing severe flood events within a brief period to the regional economy makes it highly suitable to study how localized compounding climate shocks create a feedback loop with socio-economic dynamics influenced by human actions. Furthermore, by integrating diverse CCA actions available to agents, the model provides a powerful lens through which we can observe how individual responses can bolster the resilience of socio-economic processes in the face of systemic risks.

The options for risk reduction and management vary based on the severity and frequency of a disaster. Catastrophe modeling methodologies often utilize a loss distribution, associating losses with their respective probabilities, which proves optimal for assessing these options, as well as for estimating future risk changes due to climate and global change (Mitchell-Wallace et al., 2017). These loss distributions are divided into distinct risk-layers. Typically, the low-risk layer encompasses frequent events that can be managed through risk reduction strategies. In the context of flooding, these strategies often involve individual measures aimed at damage reduction, such as home elevation or flood barriers. For the medium risk layer, when risk reduction becomes cost-prohibitive, consideration shifts towards risk-financing options like insurance. Flood insurance typically includes entry and cut-off points determining the deductible and unreimbursed damages beyond a certain limit. The high-risk layer, which includes events resulting in extreme losses, is either treated as a residual risk or covered by external assistance or global funding schemes (Mechler et al., 2014). Since losses must be financed, considerable opportunity costs may be borne by those directly affected by a disaster, such as households, businesses, and the government, as well as by indirectly affected entities (e.g., business interruption) (Botzen et al., 2019). The risk-layer approach usually does not include these indirect risks. Yet, indirect damages from natural hazards can be substantial, occasionally exceeding the direct losses (Hochrainer-Stigler and Reiter, 2021). Thus, for indirect risk management, a variety of strategies may need to be considered. This is especially pertinent for CCA where individual risk reduction measures might efficiently mitigate damages from a single hazard but could falter under repetitive shocks, resulting in damage accumulation across various actors and scales. The exploration of multi-scale adaptation options for reducing risks shaped by both direct and indirect damages is seldom done.

We aim to explore the compound risks stemming from the complex interplay between endogenous economic growth and repetitive climate-induced shocks. Here we focus on floods as an emblematic climate-induced hazard, which accelerating severity and probability threatens the development of coastal urbanized regions. In order to analyze the interactions across different measures undertaken by various stakeholders, we incorporate multiple protective strategies designed for households, as well as insurance options available to both households and firms. These are complemented by government-led subsidies aimed at supporting individual measures. The emphasis of this study is not merely on the isolated effectiveness of each individual action but rather on the cumulative protection that these actions can provide. We are particularly interested in examining how different individual actions may interact with one another and with top-down government financial support, to create a more comprehensive and nuanced understanding of adaptation strategies. Hence, we solely focus on individual actions and we did not include top-down protective measures such as dikes and levees, whose effect has been already extensively studied in the existing socio-hydrology literature (Di Baldassarre et al., 2013; Vousdoukas et al., 2020). In particular, we address the following research questions: 1) How do different private CCA strategies impact regional economic growth and fiscal stability in the face of extreme flooding events? 2) To what extent does a government subsidy affect the distribution of bottom-up CCA uptake? How does it impact households with varying adaptive capacities, and what are the resulting direct and indirect damages? 3) What is the regional consequence of inaction for an agglomeration economy hit by extreme flooding? and how such cost change when top-down subsidies are complemented with bottom-up measures?

To shed some light on these questions, we calibrate households' behavior and socio-economy characteristics using rich survey data from the greater Shanghai area (Noll et al., 2022b). While our model is inspired by the characteristics of a Chinese coastal urban setting, it primarily represents an archetype of a resource-rich city, as defined by the IPCC (IPCC, 2022b). Our aim isn't to emulate a specific urban landscape, but rather to extract overarching insights about the interplay and efficacy of various CCA strategies and their distributional impacts. These insights are targeted at coastal urban areas confronting both population and asset growth, while simultaneously facing the growing threats of sea-level rise and flooding. Specifically, we aspire to contribute to the area of economic modeling of adaptation that lacks the exploration of market-based public adaptation policies (e.g. subsidies). Moreover, while empirical research on adaptation (e.g. surveys, interviews, participatory engagement and ethnographic work) provides important data, which increasingly enters physical damage assessments (Englhardt et al., 2019), understanding private adaptation remains one of the key areas of future research (Berrang-Ford et al., 2021) and modeling wider economic consequences of private adaptation is nearly non-existent (Kondrup et al., 2022).

The results emerging from state-of-the-art simulation modeling and survey data on household CCA, show how single CCA strategies are ineffective and fails to curb compounding risks. Instead, the combination of CCA actions at all levels —top-down government subsidies, bottom-up protective measures from households, and insurance from households and firms —can produce climate-resilient long-term economic growth and development. When accounting for non-linear effects in the economic response to hazards, government subsidies for individual CCA actions appear cost-effective as they do diminish not only direct damages but also create indirect co-benefits like decreasing public spending in unemployment subsidies and sustained tax revenues from firms' profits in the region. In particular, top-down subsidies show particular effectiveness in the case of consecutive events and in providing financial resources to the most vulnerable individuals. However, due to a lack of resources and opportunities, the latter remains the most exposed to direct and indirect risk, highlighting the possible presence of poverty traps.

5.2 Coastal regional economy with consecutive floods and adaptation

The CRAB is an evolutionary economic ABM designed to delve into the intricate interplay between agglomeration forces —those clustering people and assets along coastlines and delta rivers —and climate-induced shocks (Taberna et al., 2022). It features a regional economy exposed to flooding that encompasses four classes of a variable number of agents: households, capital-good firms, consumption-good firms, and consumption-service firms. Each of these agents is underpinned by unique behaviours and decision-making processes. The capital-good firms, for instance, are the innovation vanguards, channelling investments into R&D with the aim of discovering new and more productive technologies, subsequently driving the "Schumpeterian" innovative destruction process and fueling endogenous economic growth. These technological advancements are then sold as machineries to other firms in a decentralized capital market (for detailed information on agents' characteristics and interactions see SI; "Model Complements", "Methods".).

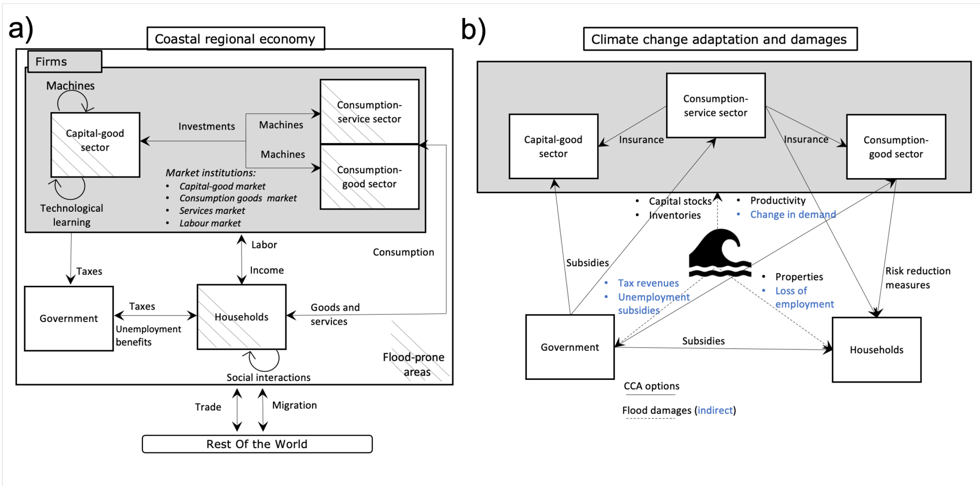

Figure 5.1: A conceptual representation of the CRAB model regional economy (Panel a), and a schematic representation of climate change adaptation actions and damages among agents (Panel b).

The modelled regional economy resembles a coastal archetype of a resource-rich megacity. As a representative example of such archetype, we employ hazard, economic and behavioural data from Shanghai, China. The presented results do not aim to predict the adaptation pathways for this city specifically, and hence could omit case-specific details. Instead, we aim to identify generic dynamics in an economic system driven by agglomeration forces, increasing damages and adaptation needs and capacities of different actors. Specifically, our intent is to simulate a regional economy characterized by an influx in population and investments in assets, driven by job opportunities and economic growth. Economically attractive till recently, the growth in coastal regions is now threatened by accelerating floods and sea-level rise. Notably, in our archetype, the majority of agents are both endowed with the necessary resources and have the intrinsic motivation to employ adaptation strategies that mitigate the adverse effects of floods. Notably, an archetype-driven approach allows us to identify general patterns in climate change adaptation and a comprehensive understanding of their interaction with complex systems. Thus, by focusing on these general patterns, we strive to derive insights applicable to similar regions, enabling an exploration of both public and private adaptation strategies in resource-rich coastal cities.

To achieve our goal, we use survey data from the greater Shanghai area to calibrate household socioeconomic and behavioural characteristics (Noll et al., 2022b). We included 10000 properties created from the survey data, which is about 0.2% of the total owner-occupied units in the region. Additionally, we calibrate the initial number of firms according to the current business-to-population ratio. We employ Shanghai flood maps to calibrate the flood depth for each agent for a 10, 100, and 1000 return period (Yin et al., 2020). The maps include low- and high-end climate scenarios (RCPs 2.6 and 8.5), which affect flood depth, whose level changes in the years 2030, 2050, and 2100. The amount of damage for each agent is calculated by overlaying flood depth with building class-specific depth-damage curves of Shanghai (Ke, 2014). Furthermore, we employ national statistics to divide household expenditure between goods and services. The capital intensity of our macro sectors is calibrated by applying constant capital-output ratios from China (Herd, 2020). Furthermore, for the remaining parameters, we utilize an indirect calibration approach, adjusting them to match specific stylized facts in line with our intent (Fagiolo et al., 2007)(for more information about model calibration see, SI; "Regional economy"). In addition, following this calibration approach, we acknowledge the possibility of equifinality, recognizing that multiple pathways might lead to similar outcomes in a complex model.

Each step of the CRAB model corresponds to one quarter and we run the model for 300 steps, which is 75 years (2005-2080, where the first 15 years are used as a warm-up period). Floods of 10 years return happen randomly in the model. However, given the importance of studying catastrophic climate change scenarios (Coronese et al., 2019; Kemp et al., 2022), we consider two fixed floods, namely a 1000-year return at time 200 and a 100-year return at time step 240, that correspond to the year 2055 and 2065 respectively. While a fully stochastic approach was initially considered to capture the entire range of potential flood events, it was rendered unfeasible due to computational limitations. However, this design choice allowed us to contextualize regular flood events and their interactions with autonomous adaptation mechanisms against the compound effects of extreme flood events that manifest consecutively. The comparison with a baseline scenario where no floods occur provides a clearer understanding of the differences in both impacts and how people adapt.

Our initial experiment investigates the efficacy of various top-down and bottom-up CCA actions available to our agents. The five scenarios considered are: 'None' (indicating no adaptation measures are taken), 'Insurance' (only insurance is implemented), 'DR' (only protective household measures are implemented), 'DR & Insurance' (both protective household measures and insurance are implemented), and 'Subsidy & DR & Insurance' (public subsidy is added to finance private measures alongside protective household measures and insurance). We evaluate the economic performance of each scenario in response to floods by analyzing the GDP growth and the fiscal implications, specifically the Budget deficit to GDP ratio. Additionally, we compare the short- and long-term regional dynamics of the CRAB model under mild and worsening climate conditions (RCP 2.6) and under more extreme climate conditions (RCP 8.5) to simulate possible trajectories of global GHG emissions. Despite some differences in magnitude, the qualitative results of the CRAB model simulations under RCP 2.6 and RCP 8.5 are generally similar. However, the impacts of more extreme climate conditions (RCP 8.5) are more evident and marked in the model outputs. As a result, we have chosen to focus our analysis on the RCP 8.5 scenario in the main text. This approach allows us to more clearly highlight the risk of an extreme climate 'endgame' scenario (Kemp et al., 2022).

5.3 Results

5.3.1 Climate change adaptation uptake, economic growth and fiscal stability

The simulation results indicate that prior to the occurrence of the severe 1000-year flood in 2054, the bottom-up CCA measures available in each scenario are widely adopted even without top-down incentives. Specifically, 'Wet-proofing' and 'Dry-proofing' are adopted by approximately 50-60% of households at risk, while 'Elevation' is adopted by 30-40%, which is expected given the higher cost and implementation difficulties. Additionally, more than 70% of eligible households have insurance coverage. The high adoption rates are attributable to the socio-economic and behavioral characteristics of the population residing in the region. In particular, the majority of households in Shanghai, as in other resource-rich coastal megacities (Noll et al., 2022b), possess both the willingness and necessary resources to implement protective measures (see Figure 7.17 and Table 7.14 - in SI).

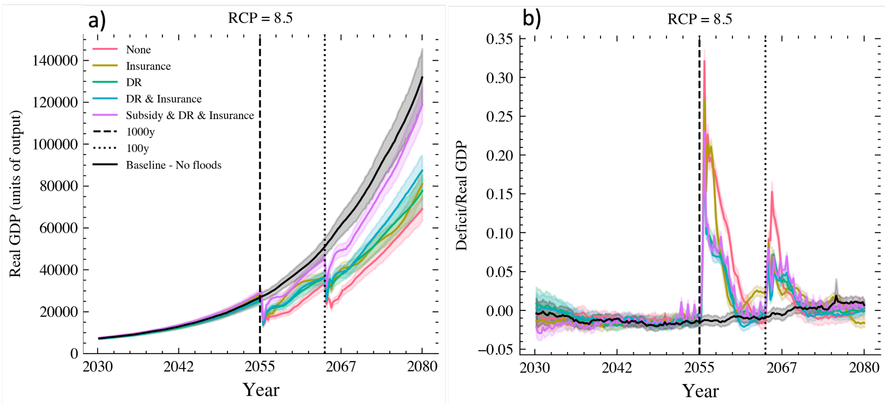

Figure 5.2: Panel (a) shows the average economic growth while panel (b) displays the deficit to GDP ratio of the regional economy under each CCA scenario. The reported values are under RCP 8.5 and average across the 100 Monte Carlo runs with the shaded areas denoting the standard deviations. The vertical lines represent the 1:1000 and 1:100 floods. Deficit (D) at time t is defined as the net of cost and revenues faced by the government, namely $D(t) = C_u(t) + C_s(t) - R_t(t)$, where C_u and C_s are the cost of unemployment and CCA subsidy, respectively. While R_t are revenues from firms' taxes.

However, despite the widespread implementation of bottom-up CCA actions, this extreme flood sequence compounds the direct and indirect effects and harms economic growth and the fiscal balance in both the short and long term across all CCA scenarios. This result is in line with the risk layer approaches, where 'DR' (disaster risk reduction scenario) and 'Insurance' (insurance scenario), either alone or combined ('DR & Insurance scenario'), can protect the economy from high and medium frequency flooding. However, they are insufficient to protect the economy from the devastation of high-return, low-frequency floods such as the one (1000-year return period) that we simulate in 2055. Specifically, the insurance policy has a limit for damages above the 100-year return, and the protective measure is often overwhelmed by a flood of that magnitude. Nevertheless, the magnitude of the negative impact varies considerably across CCA scenarios. Simulation results reveal that the addition of a government subsidy ('Subsidy & DR & Insurance' scenario) maintains economic growth and development on a path that is lower but not statistically significant (the significant level is consistent for a two-means t-test and Wilcoxon test) different from the 'Baseline - No Flood' scenario (compare purple and black lines in Figure 5.2.a). Additionally, the role of the subsidy is not statistically significant in the public budget (compare purple and light blue lines in Figure 5.2).

To understand why the subsidy contributes to the resilient economic development without imposing a heavy burden on public expenses, we must first examine its added value in the regional economy. Specifically, we analyze the difference in adaptation coverage and the related direct and indirect consequences between the scenarios of 'DR & Insurance' and 'Subsidy & DR & Insurance' across households with different adaptive capacities (ACs). AC is commonly associated with the ability of people and societies to adapt, which is contingent on economic wealth, education, experience, social institutions, and governance (Adger et al., 2005). Since the experience, social institutions, and governance are universal for all agents in the CRAB model, we assume that the feasibility of adaptation actions for households depends on their education level and income. Notably, incomes change endogenously in our agent-based model as households change jobs and as the economy develops through technological innovations, but other things being equal, higher educated agents get jobs with higher wages. Since household education grants priority in the CRAB labor market and is highly correlated with income, we anchor adaptive capacity to the education level (for a more detailed description of the labor market, see "Methods"). Based on this, we distinguish households with Low, Medium, and High ACs. The ACs distribution among households is 25% High AC, 35% Medium AC, 40% Low AC.

Regarding the individual DR measures (Dry-proofing, Wet-proofing, and Elevation), the subsidy is particularly effective for Low AC households that see a 20-40% increase in all the measures (blue lines in Figure 5.3.b, 5.3.c, and 5.3.d) displaying a willingness to adapt that is more likely constrained by financial resources than the other segment of the population. Conversely, the impact on other ACs is relatively minor, suggesting the presence of 'soft' adaptation limits related to individual perceptions, implementation capacity, and social norms (Mechler et al., 2020). Consequently, the uptake of disaster risk reduction measures facilitated by subsidies highly benefits households with low adaptive capacity, which experience a reduction of approximately 50% in direct damages following the first flood (see bright to Figure 5.4.a at the year 2055). Furthermore, simulation results indicate that the subsidy is a crucial factor for insurance when sudden climate changes require households to adapt quickly (see Figure 5.3.a after the year 2050) and when they need protection in the aftermath of a flood. This is because insurance schemes have a

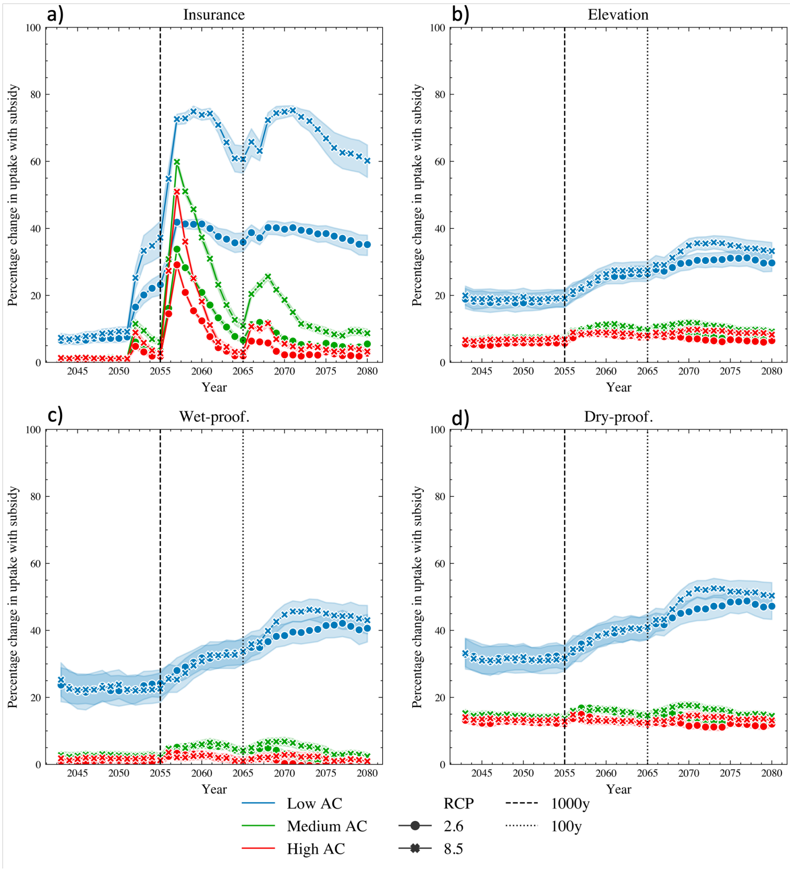

Figure 5.3: Percentage difference in households CCA actions uptake between 'Subsidy & DR & Insurance' and 'DR & Insurance' scenarios under RCP 2.6 and RCP 8.5 across households of various adaptive capacities (ACs). The reported values are averages across the 100 Monte Carlo runs with the shaded areas denoting the standard deviations. The vertical lines indicate the timing of the 1:1000 and 1:100 floods in our simulation.

5

limit beyond which damages are not covered, which in our simulation is set to damages resulting from a 1:100 years flood. As a result, insurance does not cover a substantial portion of the damages caused by the 1000-year flood that occurs in the year 2055. Under such circumstances, households prioritize their resources towards repair costs and do not renew their insurance subscriptions unless the government subsidizes them (see Figure 5.3.a after the year 2055). Notably, with the subsidy, they remain fully covered, and households of all AC levels recovers faster, resulting in an increasing difference in remaining damages over time compared with the scenario with no subsidy (see increasing areas of bright colors in Figure 5.4.a after the year 2065).

Overall, the implementation of top-down and bottom-up CCA actions reduces damages for all households, yet residual damages, particularly from extreme 1000-year floods, remain significant as individual measures cannot guarantee full protection (see Figure 5.4.b at the year 2055). Particularly, households with lower adaptive capacity still bear higher residual damages and require more time to recover. The issue of recovery is compounded when these households are subjected to consecutive shocks, challenging their resilience and amplifying the extent of damages. The ability to recover is also influenced by indirect damages as captured by the CRAB model through labor market interactions. Households with low adaptive capacity are more prone to job losses and experience difficulties finding new employment, thus losing their steady income post-flooding. Consequently, they increasingly depend on unemployment subsidies and lack adequate resources for property repair and flood recovery. In the CRAB model, households aim to repair their property as swiftly as possible by saving each additional income above the unemployment subsidy, which we assume is the minimum level to satisfy basic needs. Nevertheless, it is noteworthy that the incorporation of CCA actions, specifically a mix of top-down and bottom-up measures, creates indirect advantages for the wider economy. These economic benefits in turn positively affect household income levels, reducing the compounding effect of recurrent risks (shaded regions in Figure 5.4.a). The exploration of how these indirect dynamics unfold and their role in mitigating the compounding effects of repetitive hazards forms the focus of the following section.

5.3.2 Top-down and bottom-up CCA strategies offer the best chance to build a climate-resilient regional economy against compounding hazards

This section explores the potential for combining a top-down subsidy with bottom-up CCA actions to enhance economic resilience in the CRAB regional economy in a cost-effective manner. The CRAB model examines the direct consequences of floods, such as the destruction of properties and machinery, as well as the indirect consequences and feedback loops that arise from the interactions among economic agents following the shock.

One key interaction that unfolds in the aftermath of floods is the destruction of firms' machinery, which creates a need for liquid resources to rebuy capital. However, not all firms have sufficient resources to replace their capital stock, resulting in downscaled production and layoffs (see brown areas in Figure 5.5.a). This, in turn, leads to an increase in the unemployment rate and a decline in income per capita, making the region less attractive economically and leading to household out-migration (see purple areas in Figure 5.5.a). Furthermore, in the long-term, the out-migration of households leads to lower

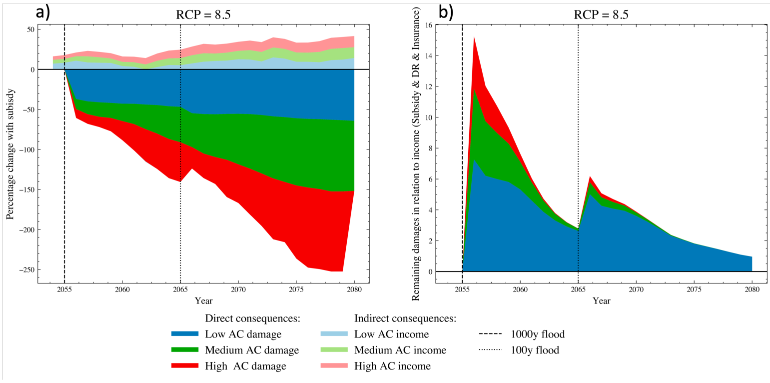

Figure 5.4: Panel (a) displays the percentage difference in direct (repair expenditure) and indirect (changes income) consequences for households with various adaptive capacities (ACs) between the 'Subsidy & DR & Insurance' and 'DR & Insurance'. Panel (b): Ratio of the repair cost in relation to the income of households with various adaptive capacities under the 'Subsidy & DR & Insurance' scenario. The reported values are under RCP 8.5 and average across the 100 Monte Carlo runs. The vertical lines represent the 1:1000 and 1:100 floods.

consumption and reduced internal demand for goods and services (see orange area in Figure 5.6). Additionally, damaged households allocate more resources to repairing their properties, resulting in increased spending on goods and less on services. Firms in the CRAB model are boundedly rational and have imperfect information, making steady demand beneficial for their production plans and hiring process. Abrupt changes in consumption patterns due to floods make planning harder for firms and increase the likelihood of an economic downturn. All of these factors combined make the region less profitable for firms, resulting in a lower entry rate compared to the baseline scenario. Despite the initial surge of investment to replace destroyed capital (see read area peak at the year 2055 in Figure 5.6.a), the lack of profitability and resources hampers long-term investment by firms, thereby limiting technological development and productivity growth in this regional economy, hence triggering the compounding of the longer-term losses. Simulation results suggest that the cost of inaction in response to these extreme events could weaken or even break the agglomeration that drives the high economic growth and development of regions with coastal megacities.

Importantly, the combination of top-down and bottom-up CCA action can help mitigate these negative effects. In particular, protective measures such as disaster risk reduction can decrease repair costs and keep expenditures stable, thereby aiding firms' production plans. Timely paid insurance also plays a critical role in providing firms with enough liquidity to replace their damaged machinery, minimizing business interruption, and output losses. This has a positive impact on the unemployment rate, which, in turn, softens the negative effect on income per capita and discourages household out-migration from the region (see brown and purple areas in Figure 5.5.b). Furthermore, households and firms with more resources to speed up in the post-flood period results in higher investment, minimizing long-term losses of profitability, productivity and technological innovation. The 'forced' investment and capital replacement that firms undertake following climate-induced shocks can even trigger a creative destruction process during the post-flood period (the so-called

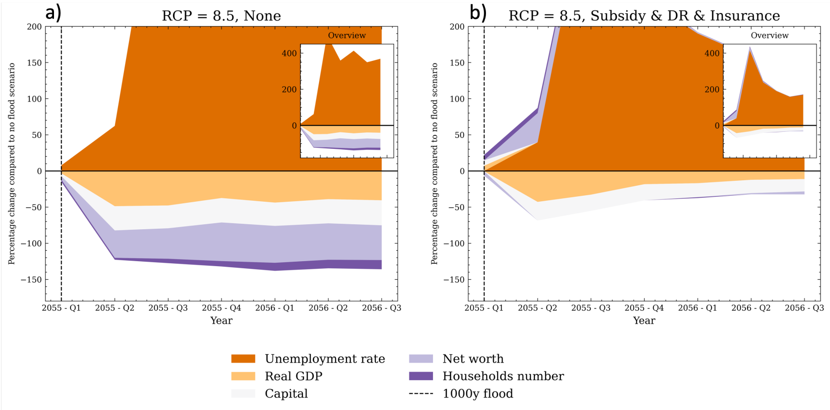

Figure 5.5: Panel (a) shows the percentage difference of the short-term direct and indirect consequences in the CRAB regional economy when no adaptation action is taken ('None') compared to the 'Baseline - No flood' scenario. Panel (b) makes the same comparison with the 'Subsidy & DR & Insurance' scenario. The reported values are under RCP 8.5 and average across the 100 Monte Carlo runs. The vertical lines represent the 1:1000 and 1:100 floods.

'productivity effect' or 'build back better' (Hallegatte et al., 2007) see zoomed area in Figure 5.6.b). However, it is important to note that this effect fades over time as residuals investments are still lower than the baseline no flood scenario.

A top-down subsidy plays a crucial role in maintaining the protection of economic agents against the compounding effect of the second flood while recovering from the first and increasing coverage for more vulnerable individuals and businesses. This approach is cost-effective for the government, as it allows firms to maintain business activity and not get bankrupt, indirectly increasing government revenues via taxes. Another co-benefit of this multi-scale CCA is that fewer workers are laid off, reducing government expenditure on unemployment subsidies. The initial government expenditure works to reduce the compounding indirect consequences of consecutive floods, eventually benefiting the government budget.

The role played by the top-down government subsidy highlights the need for coordinated CCA actions across scales to build climate-resilient societies and limit compounding risks and spillovers between anthropogenic and natural processes. The integration of bottom-up and top-down approaches enables a more comprehensive and effective strategy to enhance economic resilience to climate-induced shocks, protecting vulnerable individuals and businesses and reducing the negative impact on the government budget.

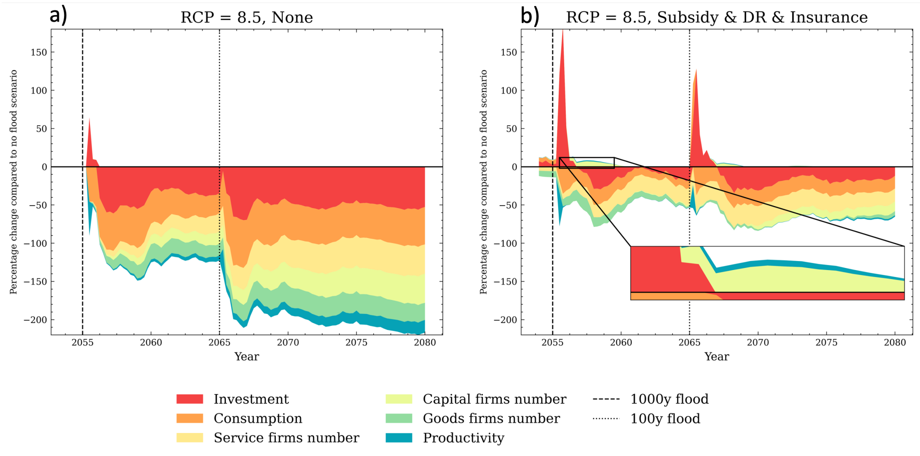

Figure 5.6: Panel (a) shows the percentage difference of the long-term direct and indirect consequences in the CRAB regional economy when no adaptation action is taken ('None') compared to the 'Baseline - No flood' scenario. Panel (b) makes the same comparison with the 'Subsidy & DR & Insurance' scenario. The reported values are under RCP 8.5 and average across the 100 Monte Carlo runs. The vertical lines represent the 1:1000 and 1:100 floods.

5.4 Discussion

The primary objective of this study was to address the impact of various private and government-driven CCA strategies on regional economic growth and fiscal stability amidst extreme flooding, the differential effects on households with varied adaptive capacities, and the regional implications of inaction for an agglomeration economy under extreme flooding. This exploration aims to bridge the gap in understanding the compounded effects of recurring hazards in the context of anthropogenic and natural processes. We do that by employing an innovative combination of evolutionary economic ABM, risk management strategies, and rich survey data to analyze the role of different CCA strategies in a complex evolving regional economy. We demonstrated how it is possible to jointly include direct flood damages, which dynamically vary depending on agents' protective CCA actions, indirect damages, and recovery, which evolve following the interactions among different stakeholders in the aftermath of the disaster. The latter are aspects that are largely omitted in the flood-ABMs literature. To inform households' socioeconomic and behavioral attributes, we utilized rich behavioral data from the Shanghai area and loosely calibrated the regional economy to resemble an archetype of an agglomerating coastal resource-rich megacity with characteristics akin to that of Shanghai.

Our analysis focuses on ripple effects generated by the interactions of firms and households in a regional economy that experience extreme climate-induced flooding. Specifically, our work intends to shed light on possible indirect costs and benefits of different CCA strategies and explore possible synergies that generate positive externalities on socio-economic resilience cost-effectively. Using 600 runs of the agent-based model, with each individual experiment being conducted 100 Monte Carlo runs, we quantify the implications of private CCA measures and its combination with such public measure as subsidy on the economic and fiscal resilience of a fast-growing coastal regional economy. This work contributes to a new generation of computational models encompassing risk and applying a resilience perspective to complex adaptive systems (Folke, 2006; Taberna et al., 2020).

In addressing our first research question, we explored the impacts of two severe floods on the regional economic growth and fiscal budget under different CCA adaption strategies. We found that only with actions undertaken at all levels of society, both top-down and bottom-up, it is possible to build a climate-resilient society with long-term economic growth and development comparable to a stable climate. These findings highlight the indirect fiscal benefits of a government subsidy by maintaining tax revenues from firms' profits and reducing costs related to unemployment subsidies. These results align with previous research on preventive public expenditure, which can improve economic resilience, hasten recovery, and mitigate the impact of shocks, with indirect benefits that can outweigh initial costs (Bachner and Bednar-Friedl, 2019). Additionally, the simulation results reinforce the significance of incorporating CCA strategies across scales that take into account multiple stakeholders beyond direct damages, which has been extensively discussed in previous literature (Hochrainer-Stigler and Reiter, 2021) and highlight how inadequate actions result in feedback loops that do not reduce existing flood risks. Furthermore, the conclusions emphasize the need to revise current adaptation measures that focus primarily on singular flood events. The escalating frequency and intensity of such incidents, driven by climate change, underscore the necessity to address the compounded risks arising from both direct and indirect damage channels. This approach ensures resilience not just to one-off disasters, but also to their repeated and intensifying occurrences that could otherwise trigger cascading socio-economic repercussions (Jongman et al., 2012; Mechler et al., 2014).

To answer the second research question, we focused on assessing the effectiveness of the subsidy in promoting adaptation measures and reducing both direct and indirect damages for individuals with heterogenous adaptive capacity. Our results indicate that the subsidy is particularly effective in increasing the uptake of protective measures among the most vulnerable individuals who are mainly constrained by financial reasons and lack of resources. Additionally, the model results demonstrate that the subsidy is helpful in sustaining insurance uptake when climate change is fast, and individuals prioritize spare resources for repair costs after a flood, resulting in vulnerability to further compounding shocks. Our analysis also highlights that while the subsidy is essential in situations of rapid climate change and in the aftermath of floods, it may not be adequate in overcoming other non-financial soft limits that can generate an 'adaptation deficit', leading to adaptation levels remaining below optimal levels (Berrang-Ford et al., 2021). These findings support existing research on the role of subsidies in overcoming financial constraints and emphasize the need for targeted interventions that can address other soft limits of adaptation (Mechler et al., 2020). Furthermore, the CRAB modeling framework reveals that by decreasing the repair cost needed after a flood and speeding up the recovery of residual damages, particularly for the 100-year flood, the subsidy generates indirect benefits to the regional economy. This generates positive feedback to households, resulting in fewer income losses in the long run. It is crucial to note that despite these benefits, more vulnerable households are still the category that is most affected by floods, primarily due to difficulties experienced in the reshuffling of the labor market. Our simulation results reinforce previous literature findings that poor people are marginally more impacted by disasters and struggle to recover due to job and income losses (Cutter and Derakhshan, 2019; Walsh and Hallegatte, 2019). Moreover, they highlight the critical but not sufficient role played by bottom-up protective actions in reducing flood risk (Adger et al., 2005). Overall, our study underscores the importance of implementing targeted and multifaceted approaches for building resilience to climate change, particularly among vulnerable populations. This perspective resonates with a growing body of academic work that highlights the need of convergence between state-driven economic growth and strategies for climate resilience and adaptation (Liao et al., 2023).

To address our third research question, we compared the evolution of several variables, both short- and long-term, between the 'None' and 'Subsidy & DR & Insurance' scenarios. Specifically, we examined regional dynamics and explored the cost of inaction, as well as how such costs change in the case of top-down and bottom-up CCA strategies. Our findings demonstrate that the additional resources provided by insurance enable firms to minimize business interruption, leading to a positive impact on output and the unemployment rate. This contributes to maintaining the economic attractiveness of the region and minimizes outmigration in the aftermath of a flood. Moreover, these additional resources increase the amount of post-flood investment, opening up the possibility of a window of opportunity, in which destroyed machinery is replaced with new and more productive equipment. Our results are consistent with previous literature highlighting the critical role of business interruption in reducing indirect damages and enhancing socio-economic resilience (Neise and Revilla Diez, 2019). These results have significant policy implications, demonstrating how the cost of inaction can reach a tipping point that breaks agglomeration forces, resulting in high opportunity costs for potential future development. Conversely, providing resources that expedite recovery after a flood has invaluable indirect benefits for the overall region. Additionally, our results emphasize that a 'build back better' pathway is possible but requires sustained investment to transform risk into opportunities. Our framework advances previous flood-ABMs literature by being the first model that includes both firms' and households' CCA actions in a complex socio-economic environment calibrated with rich behavioral data (Taberna et al., 2020).

The CRAB model can be extended in several ways. First, the model would benefit from more extensive Monte Carlo simulations. Specifically, a full stochastic approach to extreme flooding would measure the full spectrum of risks associated with rare but impactful events. While this would pose significant computational challenges, given the rarity of these events, it would greatly enhance our insights into the multitude of ways in which consecutive extreme events could impact the socio-economic system. Second, a richer calibration on the economic side, such as including empirically calibrated NAICS sectors, would lead to more precise estimation of economic impacts. Furthermore, governments and firms are known to take protective CCA actions, such as dykes and levees, to reduce the adverse impacts of hazards. Hence, protective actions across multiple scales and stakeholders could be jointly considered to analyze both limits and opportunities that regions have for development despite adversities. In addition, in our exploration of adaptation strategies, it's pertinent to consider the evolution of the insurance market. A more sophisticated insurance paradigm, where premiums are discounted for agents actively engaging in protective measures, can serve as a significant incentive. This not only fosters proactive risk management but also mirrors the dynamic interplay between market-driven mechanisms and adaptation behaviors. Another important avenue for future research would be the introduction of more detailed migration patterns coupled with land-use dynamics, allowing the differentiation between urban, peri-urban, and rural areas. Regardless of these limitations, the CRAB model provides a general understanding of the importance of a comprehensive framework that includes both firms and households and how their interactions and cumulative individual actions shape regional climate-induced damage and resilience. Importantly, the model offers new ways forward to tackle not only the direct but also indirect risk in an explicit way and therefore offers new ways forward how to transform emerging risk challenges into long-term opportunities.

5.5 Methods

5.5.1 The Model

We introduce a novel version of the Climate-economy Regional Agent-Based (CRAB) model (Taberna et al., 2022), coded with Mesa, an open-source library of Python 3 (Kazil et al., 2020), to account for indirect damages caused by floods. This model combines households and firms in a regional economy, where they interact through market institutions, migration, climate, and technological learning. Such interactions enable the mapping of feedback loops and cascading effects generated by flood shocks. Additionally, we incorporate a risk layering strategy consisting of bottom-up and top-down adaptation strategies that range from individual risk reduction to insurance. By leveraging rich behavioral data, we parameterize the model to represent an archetype of a coastal resource-rich megacity. The CRAB model builds on the evolutionary economic engine of the 'Keynes + Schumpeter' (Dosi et al., 2013, 2010, 2017a) and 'Dystopian Schumpeter meeting Keynes' (Lamperti et al., 2018, 2019b) models. This novel version features a three-sector regional economy with four classes of heterogeneous, boundedly-rational agents that dynamically interact in decentralized capital, labor, and good/service markets with households. The number of agents varies depending on the migration flow for households, while firms follow independent entry and exit processes (for a detailed description, see SI; "Model Complements"). The region is exposed to flooding with varying return periods, whose severity increases with climate change over time. Floods impact agents at the microeconomic level, resulting in the destruction of household properties, firm inventories, and machines. Households and firms residing in flood-prone areas can take multiple adaptation actions to protect themselves. Technological learning and economic growth are driven by a creative destruction 'Schumpeterian' process.

5.5.2 Firms

In this novel version, all the macro sectors in the regional economy require both capital and labor as production inputs. In line with the 'K+S' tradition, the capital-good sector invests in R&D and tries to discover more productive technologies. The latter generates a 'Schumpeterian' creative (innovative) destruction process, which is the engine of endogenous economic growth. Machines are then advertised through "brochures" to possible customers, which in this version are all the other firms. Once orders are received, capital-good firms estimate their expected demand and required machines to produce it . If the current stock of machines is insufficient to satisfy the desired production, additional ones are ordered from other capital-good firms. We assume that capital-good firms cannot self-produce the capital they need for themselves, but they need to order it from other capital-good firms. Once the capital market closes, capital-good firms enter the labor market, trying to hire the optimal number of workers for their feasible production. Finally, they combine capital and labor to produce machineries that will be delivered in the next step. In a similar manner, consumption-good/-service firms combine labor and machines to produce a homogenous good/service for consumption. The latter two sectors follow the same decision-making process by using adaptive heuristic demand expectations and fixed capital-output ratios. Importantly, if capital stock is insufficient to satisfy the desired production, new machines are ordered comparing the 'brochures' they are aware of. In addition, all the firms can replace current machines by using a pay-back rule. Importantly, the three macro sectors' capital requirements are different as they have different capital-output ratios. Following empirical evidence (Herd, 2020), we parametrize the capital sector to be the less capital intensive, followed by goods, and finally, services, which is the most capital intensive. In addition, firms living in flood-prone areas can buy insurance that refunds destroyed machineries and inventories in case of a flood.

Households

In the CRAB model, households are characterized by multiple socio-economic and behavioral factors, calibrated with survey data. Socio-economic characteristics include property values, education, and initial savings. Households' income evolves through interactions with firms in the labor market, where more educated households have better access to job opportunities. Unemployed households receive a subsidy from the government.

In each time step, households spend all their income unless they plan to save for a protective action or insurance premium. Household intention to undertake a protective action depends on behavioral characteristics, including social interactions in a random social network. The Protection Motivation Theory (PMT) is used to estimate households' protective actions against flooding.

Weights of each PMT attribute are estimated with a logit regression. Each household calculates its intention to undertake a climate change adaptation action using the PMT attributes and their weights. The intention-action gap is accounted for by multiplying the intention probability by a factor lower than one. Household action probability is determined by comparing it to a random number.

Households with a positive action probability save all income above the minimum wage until they have enough resources to implement the protective measure. Protective measures affect monetary damages in case of a flood, with the amount of damages depending on the household property value and the damage coefficient. Damaged households follow the same saving mechanism for protective actions.

The value of household property is indexed to the region's average wage, increasing over time with technological learning and economic growth. The cost of the action and repair cost is added to the aggregate demand of the consumption-good sector.

5.5.3 Markets

In an economy, households and firms interact through socio-economic institutions, such as markets for capital, labor, and goods/services. In the capital market, capital-good firms send brochures to their existing and new potential customers, which contain the price and productivity of their machines. Firms seeking to buy new machines compare the brochures and select the supplier offering the best price-quality ratio. In the labor market, firms assess their labor demand, post available vacancies, or fire surplus workers. Unemployed households, sorted by education level, choose available vacancies and select the one offering the highest wage, resulting in a correlation between income and education.

Salaries earned by households are spent on goods and services, including insurance, which is a subcategory of the service market. The insurer calculates the expected annual damages for an agent by integrating the damages caused by a flood with the flood probability at the entry point. For households, damages are calculated by multiplying the house value by the damages coefficient, while for firms, damages are calculated by multiplying the fraction of capital stock and inventories that would be destroyed by the flood with their current market prices.

The insurer determines the market price of insurance cost for an agent at time t by adding a fixed markup to the expected annual damages. All agents are assumed to be risk-averse, so they will subscribe to the insurance if they have the resources. The model's underlying assumption of agents being risk-averse stems from empirical evidence indicating heightened risk aversion following natural disasters, particularly at a localized level (Bourdeau-Brien and Kryzanowski, 2020). Importantly, insurance expenditures contribute to the aggregate demand of the service sectors. In the event of a flood, the insurer claims are shared among the service firms proportionally to their market share. Protective measures and repair costs incurred are added to the aggregate demand of the goods sector.

The local demand is defined by the aggregate household expenditure in the goods and service markets, which is summed with export demand and assigned to firms based on their market share. Firms' market share evolves through quasi-replicator dynamics, which depend on their competitiveness, calculated according to their prices and unfilled demand.

5.5.4 Entry and exit process

In order to integrate the agglomeration process into the regional economy, households' and firms' entry and exit processes are independent in this novel version of the CRAB model. Specifically, a migration process linked to regional economic indicators regulates the number of households. In tune with empirical evidence, we use the difference in income per capita and the unemployment rate as reference variables (Kennan and Walker, 2011). In a nutshell, an economy with growing income per capita and a low unemployment rate attracts new entrants sampled from the synthetic population pool and added to the incumbents. Conversely, a stagnant economy will push households to leave. Households also affect the creation of new firms from the bottom up. In particular, an employed household decides to create its own firm if the profits of its current employer exceed a certain threshold for a number of consecutive periods. Firms with quasi-zero market share and lack of resources are removed.

6

Conclusion

6.1 Conclusions

Climate change presents an unprecedented challenge in our times, and its effects are intensified by a simultaneous and unparalleled wave of urbanization. Together, these converging trends lock us into developmental pathways that magnify risks, especially for global coastal regions. The overlapping of these phenomena urges the development of robust tools capable of assessing risks, damages, and effectiveness of climate change adaptation strategies to effectively guide policy making. While traditional methods have provided insights, they often fall short in capturing the inherent non-linearities, path-dependencies, and distributional impacts that characterize this multifaceted threat.

Agent-based models (ABMs) have emerged as promising instruments, demonstrating the potential to surmount such limitations. Their dynamic nature and ability to model complex socio-environmental systems make them uniquely suitable for such tasks. However, current ABMs still grapple with certain limitations. These include a confined representation of stakeholders, a deficit of behavioral data for more nuanced modeling of human actors, and a static vision of risk, which hinders the ability to accurately capture the evolving feedbacks between climate and socio-economic systems. Recognizing these gaps, it becomes clear that enhancing the sophistication and robustness of ABMs is a crucial pathway toward designing methods to explore design of strategies for building climate-resilient societies.

This dissertation takes a deep dive into the interplay of ABMs for flood risk, macroeconomic elements, and spatial dynamics to formulate a comprehensive model embodying regional socio-economic dynamics in the face of flood risk. Employing an advanced simulation approach coupled with primary survey data, this work addresses a wide array of research questions, all converging toward a central research goal:

Deepen the scientific understanding of the complex interactions between intensifying climate shocks, regional economic development, and societal responses, encompassing adaptation at various levels.

6.1.1 General Conclusions

The main findings of this thesis in response to this overarching goal are as follows:

1. ABMs are promising tools to drive a paradigm shift in climate risk assessments. In Chapter 2, with a systematic review of flood-ABMs, I show how the need to include distributional impacts, behavioral theories, and non-linear dynamics led to the proliferation of recently built computational models that explicitly include diverse socio-economic actors. However, existing ABMs have yet to effectively integrate the role of firms, often prioritize direct damages over indirect ones, and neglect critical recovery and distributional components, ultimately limiting their ability to explore transformational adaptation strategies. Importantly, in Chapter 3 I made a further step in this direction building the first theoretical version of the *Climate-economic Regional Agent-Based* (CRAB) model to show how you could simulate the development of regional economies in the face of climate hazards with different severity and probabilities. The CRAB features heterogeneous boundedly-rational agents who learn and adapt to a changing environment. In addition, it combines, for the first time, location decision of both households and firms between safe Inland and hazard-prone Coastal regions with endogenous technological learning and economic growth.

2. Probability and severity of climate shocks in interaction with agglomeration forces can undermine the resilience of regional economies. In Chapter 3, using the CRAB model, I show that if flood hazards hit frequently the Coastal region before agglomeration forces trigger high levels of waterfront urbanization, firms and households can timely adapt and migrate landwards, thus averting the adverse impacts of climate shocks on the whole economy. Conversely, in the presence of climate tipping points where the frequency and magnitude of flood hazards abruptly intensifies, I find that economic activities remain trapped in the hazard-prone region, generating lock-ins and leading to a harsh downturn of the overall economy. In Chapter 5, utilizing a novel version of the CRAB model calibrated to an archetype of a Chinese coastal megacity, I demonstrate that severe compound shocks can induce hysteresis, potentially transitioning a rapidly growing agglomeration economy into a phase of stagnant growth, unless CCA measures are implemented at various level of society .

3. Behavioral theories and primary microdata are key components in evaluating private adaptation and subsequent impacts of climate hazards. In Chapter 4, I integrate the CRAB model with primary survey data and employ exploratory modeling to assess the "adaptation deficit" —a comparison between the observed level of public or private adaptation and the economically optimal level —displayed by a population of empirically-informed agents. Model simulations reveal that this deficit primarily arises from various "soft" adaptation constraints —such as awareness and social influences —rather than differences in financial constraints. Additionally, in both Chapter 4 & 5, I find that initial inequalities disproportionately affect low/medium adaptive capacity households after a flooding event. Even with widespread adoption of adaptation measures, the benefits are unequally distributed, exacerbating existing inequalities. Furthermore, model results demonstrate that behavioral uncertainty

mediate the importance of physical factors traditionally thought to be decisive for the uptake of adaptation measures, and draw suggestions for a tailored policy design.

4. Synergies between CCA actions across scales offer the best chance to build climate resilience societies. In Chapter 5, I present an advanced version of the CRAB model that incorporates a risk-layering strategy, bridging bottom-up and top-down adaptation measures, spanning from individual risk reduction to insurance. This approach underscores the shortcomings of singular CCA actions, revealing their inability to mitigate compounding risks effectively. Instead, these findings highlights the benefits of combining CCA initiatives at multiple levels to foster long-term economic growth and development that is resilient to climate change.

6.1.2 Answering to the Research Questions

Research Question 1: What are the advancements and gaps in employing ABMs to explore the dynamics of (flood) risk and adaptation assessments? What are the future literature directions?

We address these questions exclusively in Chapter 2. In the socio-environmental modeling literature, there is a growing recognition that flood risk assessment must incorporate behaviorally-rich and dynamic representations of human actors, as they significantly shape the risks and resilience of flood-prone cities. The latter is particularly crucial in the context of climate change models, where traditionally, the representation of societies and economies has been relatively inadequate. This is clearly supported by our finding that recent computational models are increasingly featuring diverse socio-economic actors, indicating an evolving and multidisciplinary state of the art in ABMs for flood risk.

Through a systematic literature review of 28 flood-ABMs focused on urban areas from the Scopus database, I found a significant dichotomy in the origin and orientation of the models. I noticed they stem from either economics & behavioral sciences or hydrology. These two groups view risk components and a socio-economic system's resilience to flooding from distinct perspectives and approach the critical elements of Complex Adaptive Systems (CAS) resilience, such as adaptation, interactions, and learning, differently.

There has been a discernible trend in the increasing incorporation of diverse socio-economic actors in computational models. Most flood-ABMs focus on households while often simplifying the representation of decisions made by government entities, insurers, and urban developers. In terms of damages, flood-ABMs primarily focus on estimating direct damages, largely neglecting indirect effects and the role of firms in flood risk.

Despite strides made in incorporating behaviorally-rich diverse actors, a significant proportion of these models, specifically 13 out of the 28 papers I analyzed, still rely on ad hoc rules to model behavioral changes and social dynamics. This approach often neglects valuable insights from social sciences about behavioral change and decision-making under uncertainty.

In addition, flood-ABMs highly rely on secondary literature or expert judgments, for the calibration of relevant parameters, rather than leveraging case-specific micro-level data to support the modeling of agents' actions and interactions. The true power of ABMs lies in their ability to analyze heterogeneity, and I believe that future models should utilize this strength more effectively. Presently, many flood-ABMs only report aggregated damages, prices, or adoption rates of CCA actions for entire populations and regions, disregarding the distribution of risk and CCA actions across different socio-economic groups.

In the direction of future research, I see a promising path in the integration of social sciences' behavioral theories and empirical data into agents' decisions. This could instigate a shift from a representative rational agent to behaviorally-rich diverse actors in computational models. I emphasize the importance of learning across disciplinary views, advocating for a multidisciplinary approach that combines the strengths of economics, behavioral sciences, and hydrology.

Furthermore, I encourage a shift from incremental to transformational adaptation in flood-ABMs. This involves incorporating dynamics of social institutions, tracing cross-scale feedbacks, and identifying non-linear dynamics that can trigger transformative CCA. To this end, the consideration of long-term recovery and reorganizational aspects of resilience, often overlooked in current models, becomes crucial.

In conclusion, the future of ABMs for flood risk lies in a complex adaptive systems approach grounded in social science theories and behavioral data. Such an approach should involve various stakeholders, trace the heterogeneity of risk distribution, include dynamic behaviors and institutions, and enable the analysis of the emergence of transformational CCA. To facilitate this, I advocate for a CAS resilience-based dialogue to strengthen collaborations and promote learning and information exchange across disciplines.

Research Question 2: How do agglomeration forces and technological change shape the evolution of economic centers in coastal regions? How do climate shocks of varying severity and probability interplay with such dynamics?

We delve into this question in Chapter 3, presenting the first theoretical version of the *Climate-economy Regional Agent-Based* (CRAB) model. This model addresses a significant gap in flood-ABMs literature outlined in Chapter 2: the need to cohesively incorporate households and firms within a dynamic socio-economic system susceptible to flood risks. The CRAB model, conceived within the principles of evolutionary macroeconomics, portrays an economy dichotomized into two regions - the hazard-prone Coastal region and the safer Inland region. The model encapsulates interactions among different agents —households, capital-good firms, and consumption-good firms —within their respective local goods and labor markets. Guided by economic self-interest and bounded rationality, economic agents continually determine their actions and adapt to shifting economic landscapes and climate-induced shocks. In a first exercise, I validate the model according to its ability to replicate micro and macro empirical regularities concerning the flows of people, businesses, and trade that emerge between the two regions.

A defining feature of the CRAB model is its capacity to simulate an endogenous agglomeration process that stems from stochastic knowledge exchanges in the form of innovation. Due to their strategic positioning along major transport routes, firms located in the Coastal region enjoy an advantage in terms of access to resources and trade channels which increase their capacity to invest in R&D activities. The amplified investments in turn spur the pace of innovation, culminating in higher productivity levels. Importantly, these productivity increases are not confined to individual firms. The geographic proximity of firms within the Coastal region leads to inter-firm diffusion of innovation, sparking off localized knowledge spillovers. The resultant Marshallian externalities stimulate a regional productivity surge, paving the way for increased wages and greater employment opportunities. This economic stimulus attracts households from other regions, leading to the growth of the local economy. The growing local market, in turn, push firms from other regions to relocate to these economically attractive areas, fostering a continuous cycle of agglomeration. Under these dynamics, the model depicts a self-perpetuating, path-dependent process of economic concentration, with the potential to agglomerate economic activities and population predominantly in the Coastal region. In this Chapter, I also found that the larger the location advantage, the more rapid and substantial the agglomeration process, indicating the critical role of this factor in the overall dynamism of regional economic concentration.

Expanding on our initial findings, I explore the nuanced dynamics between agglomeration forces and climate shocks, and their role in shaping the geographic distribution of economic activities and the growth trajectories of regional economies. In this context, our model considers a spectrum of scenarios, accounting for climate hazards of differing intensities and probabilities.

A crucial insight from our exploration is the manifestation of non-linear responses in the model's economic performance with respect to the severity and likelihood of climate shocks. This non-linearity encapsulates the dualistic nature of climate damages; they hold the potential to induce harm but concurrently stimulate technological innovation in the capital base and inspire strategically timed relocation of economic activities away from high-risk coastal regions.

Our model demonstrates a clear trend in response to frequent climate shocks. Economic activities tend to migrate toward the relatively safe Inland region, with the rate of this coastal retreat directly correlating with the severity of the shocks. This dynamic results in a notable reduction in the concentration of economic activities within Coastal areas, underscoring the malleability of economic geography in the face of environmental pressures.

Conversely, the model shows a decline in aggregate economic performance when climate shocks are of low frequency or mild intensity. This decline is largely due to the detrimental effects these hazards bring. In scenarios where high-severity events are rare, economic activities initially tend to cluster in the Coastal region. However, when such intense events occur, they heavily impact a substantial portion of firms and households clustered along the coast. This situation results in a pronounced deceleration in economic recovery and hampers future growth and development prospects.

We link these findings to the crucial role of adaptation policies in shaping the economic landscape. For instance, measures such as the construction of flood defenses, while invaluable in mitigating milder floods, can unintentionally reinforce agglomeration forces and compound the risks associated with accelerating urbanization in climate-sensitive hotspots.

When shocks are both severe and frequent, the landscape changes dramatically. Our model indicates that adaptable firms retreat swiftly to the safer Inland region. Here, they substitute their damaged machines with state-of-the-art, more productive equipment without requiring any governmental intervention. This adaptive capital renovation, coupled with the displacement of bankrupt firms by more technologically advanced competitors, facilitates a resilience mechanism that allows the economy to maintain a long-term growth trajectory analogous to the baseline scenario without shocks.

Nevertheless, this transformative process is notably absent in the most likely scenario involving climate tipping points, which sharply increase both the frequency and impact of shocks midway through the simulated period. In such scenarios, even the most productive firms located in Coastal areas find themselves increasingly vulnerable to flood hazards, leading to severe disruptions in their capital and competitiveness. The consequences are far-reaching, as firms find themselves unable to relocate to safer regions, leaving the economy locked in a trajectory of climate non-resilient stagnation.

Research Question 3: How does the interaction of financial constraints, socio-behavioral factors, and households' adaptive capacity shape regional patterns of adaptation diffusion and distributional economic impacts of hazards?

In Chapter 4, I utilized a novel version of the CRAB model from Chapter 3, combined with survey data and exploratory modeling, to investigate household CCA strategies and associated damages in a regional economy mimicking a flood-prone southeastern US coastal megacity.

Overall, our analysis revealed that traditional sustainability models that depict households as rational agents with perfect information fall short of reflecting reality. Instead, I found that bottom-up CCA uptake is significantly below economically-efficient levels due to a variety of socio-behavioral and financial factors.

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The methodology proposed in this chapter significantly improves flood-ABMs state-of-the-art by integrating adaptation behavior towards flooding into a multifaceted, continually evolving economy populated by heterogeneous households and firms. This framework enables us to quantify the influence of different behavioral assumptions on CCA adoption and its distributive consequences among households with different adaptive capacities (ACs). In the context of household adaptation to flooding, I integrate a variety of behavioral options, spanning from homogeneous rational agents to heterogeneous boundedly-rational actors.

Adaptation to flooding encompasses three principal structural measures: Wet-proofing, Dry-proofing, and Elevation. These measures, differentiated by their cost and objective effectiveness for damage reduction, provide varied responses to flood challenges. To strengthen our results, I calibrate households' behavioral and socio-economic attributes using surveys conducted in Miami-Dade County, USA.

Our results highlight the significant influence of behavioral factors, such as affect heuristics, perceived self-efficacy, and social norms on the speed and scope of adaptation diffusion. Interestingly, I find these factors can outweigh financial constraints, thereby challenging traditional assumptions that focus heavily on financial constraints.

When households act as rational optimizers, damages from hazards are significantly reduced due to efficient adaptation practices. However, when households mimic empirical decision-making patterns grounded in behavioral psychology, I observe an eightfold increase in residual damages. I quantify these "soft adaptation limits" by comparing the adaptation uptake of rationally-optimal and empirically-informed adaptation behaviors.

Our model also allowed us to examine the distributional impacts of climate change adaptation measures across households with different ACs. I found that while high AC households recover quickly from flood events, low AC households suffer the most and take the longest to recover because they are more likely to lose income in the aftermath of a flood due to the bankruptcy of firm agents. Importantly, model results show that without adaptation, damages for an average household at the end of the simulation are significantly higher, more than 20 times in the case of rational decision-making. However, I found that the benefits of adaptation are not distributed equally. Under the assumption of rational adaptation, high and medium AC households benefit the most, while low AC households bear the highest residual damages. We delve into the role of physical factors on adaptation behavior. For rational agents, the effectiveness of the elevation measure significantly influences their decision to adopt it. However, the effectiveness of Wet- and Dry-proofing measures appears to be more critical for those who opt for these methods. The importance of these physical factors evolves over time and is heavily influenced by socio-behavioral factors.

Our innovative approach offers a nuanced understanding of adaptation diffusion, highlighting the role of behavioral uncertainty and the importance of socio-behavioral factors in shaping adaptation decisions. I emphasize the need to look beyond purely financial adaptation constraints and advocate for a more inclusive exploration of the "soft limits" affecting adaptation uptake.

Research Question 4: How do private CCA strategies and governmental subsidies affect regional development, fiscal stability, and CCA uptake under extreme flooding events?

In Chapter 5 I employ an enriched version of the CRAB model previously discussed in Chapters 3 and 4, which embeds a diverse array of CCA strategies available to agents. CCA strategies align with a risk-layering framework where frequent and low-risk events are managed through risk reduction strategies, while less frequent but more severe events are addressed through risk-financing options like insurance. I also include top-down government subsidies to finance private CCA actions. By simulating the dynamics between households, firms, and extreme flood events within a fast-growing agglomerated economy, the CRAB model furnishes a unique framework through which to evaluate climate-related risks and assess the efficacy of adaptation strategies deployed at different societal levels.

The results indicate that single CCA strategies prove ineffective in mitigating the compounding risks associated with extreme flooding. Instead, a combination of adaptation actions at multiple scales proved most successful in fostering climate-resilient, long-term economic growth and development.

Our model simulations highlighted that bottom-up CCA actions, despite being widely adopted due to the socio-economic structure of the region, which I calibrate using rich survey data from the Greater Shanghai area, are not enough to safeguard the economy against high-return, low-frequency floods. However, the tide turns when I add a government subsidy in support of private actions.

Our deeper analysis of the effect of the subsidy reveals its added value for households with low adaptive capacities (Low AC) which are able to increase the uptake of disaster risk reduction measures by 20-40%, leading to a 50% reduction in direct damages after the first flood. In addition, the subsidy also plays a crucial role in insurance coverage when sudden climate changes require households to adapt quickly and when they need protection in the aftermath of a flood. Without the subsidy, households prioritize their resources toward repair costs and do not renew their insurance subscriptions.

Our simulations also demonstrate how floods could have substantial indirect and long-standing consequences on the economy. Post-flood, firms often cannot rebuy entirely destroyed machineries and are forced to downscale production leading to layoffs, lower income per capita, and out-migration, all of which reduce long-term consumption, investment, and internal demand for goods and services. By providing subsidies, the government can help firms maintain their business activity, thereby increasing tax revenues and reducing unemployment subsidies. Thus, while causing an initial burden on the budget, the subsidy indirectly increases government revenues through taxes and decreases expenditure on unemployment benefits, fostering fiscal stability. Additionally, our findings suggest that by facilitating supplementary investments, government subsidies can play a critical role in converting climate-related risks into opportunities. This transformation is particularly evident through the implementation of "build back better" strategies, which not only help communities recover from disasters but also improve their resilience to future climate-related events. Notably, the effectiveness of the combined strategies never ensures complete protection against extreme flooding, particularly among Low-AC households, which face the lowest amount of direct damages due to fewer assets possession, but are more significantly impacted indirectly due to job and income losses, which slow their recovery.

Without proactive measures, our research underlines the substantial direct and indirect effects of flooding on the regional economy. Such impacts could potentially destabilize the agglomeration forces, leading to stagnant growth. Our findings stress that a concerted effort, comprising both private CCA measures and public governmental subsidies, is necessary to sustain long-term economic growth, ensure fiscal stability, and increase CCA uptake in the face of increased flood risk due to climate change.

In conclusion, I argue that our research contributes valuable insights to the ongoing discussion on climate adaptation, and the CRAB model provides a policy laboratory for further investigations into this societal problem.

6.1.3 Contributions to science

In general, the CRAB model presents a pioneering framework that intertwines individual CCA actions and their effectiveness within a dynamic, evolving economy. This feature enables an in-depth exploration of the interplay between agglomeration forces, extreme flooding due to climate change, and the aggregate impact of autonomous CCA actions. As such, this dissertation makes a number of contributions to the interdisciplinary literature on CCA and complexity approaches, such as ABMs, applied to adaptation to climate-induced floods.

Firstly, a critical contribution is a conceptual framework that advances the resilience concept beyond mere coping, emphasizing adaptive behavior, learning, and long-term recovery and reorganization. By challenging the conventional 'risk' paradigm, it provides an innovative perspective on computational models through the lens of Complex Adaptive Systems (CAS) resilience. This sets the stage for a transformative shift from the representative rational agent approach to a more dynamic representation of behaviorally-rich actors.

Secondly, in response to the insights gained from this review, this dissertation introduces the *Climate-economy Agent-Based* (CRAB) model, built using Mesa, an open-source Python 3 package, which presents several advancements in the current literature. The CRAB model grounds its theoretical foundation in the New Economic Geography literature, focusing on trade and innovation as causes of agglomeration. However, the model exceeds this foundational principle, employing innovation diffusing among heterogeneous boundedly-rational agents as the cause of agglomeration, ultimately leading to the uneven spatial distribution of economic activities across regions. The model endogenously captures the complex interplay between agglomeration forces and hazard shocks, thereby offering a unique methodological approach applicable beyond the flood-specific context. Methodologically, the CRAB model advances the evolutionary macroeconomic ABMs tradition by introducing two regions with endogenous economic growth, characterized by migration decisions of both firms and households. This innovation enables a deeper investigation into spatial economic dynamics in an out-of-equilibrium fashion.

Thirdly, the CRAB model also enhances the modeling of climate change adaptation. It stands as the first model to integrate a detailed representation of household adaptation behavior within a complex, evolving macroeconomy under hazards. This methodological novelty enables to design CCA policy by explicitly accounting for behavioral and social factors shaping private adaptation grounded in empirical survey microdata. Concurrently, it keeps track of macroeconomic fluctuations within the broader regional economy characterized by decentralized markets. For the first time, this approach allows us to quantify the soft limits of adaptation, emphasizing the significance of diverse adaptation constraints. In this context, behavioral biases often exceeds the effects of financial constraints, providing a unique insight into the complexities of adaptation dynamics.

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Fourthly, a significant contribution lies in the detailed quantitative exploration of distributional impacts of disasters. Leveraging on its novel framework that uniquely considers households with varying adaptive capacities, the CRAB model quantitatively displays how economically disadvantaged households bear a disproportionate brunt of disaster impacts. Beyond immediate damages, they often grapple with extended recovery challenges stemming from job and income losses. These findings emphasize the need for policymakers to craft development strategies that specifically address these disparities, ensuring interventions that actively work to reduce, rather than exacerbate, existing inequalities.

6.1.4 Limitations and future work

Despite the innovative contributions made by the CRAB model, certain areas present opportunities for future development and refinement. To begin with, a more behaviorally nuanced depiction of migration patterns, like the surge in rural-urban migration, shifts in risk attitudes, and the integration of the emerging teleworking phenomenon. This additional behavioral layer would, in turn, necessitate a more detailed model of land-use dynamics that differentiate between urban, peri-urban, and rural locales and would allow us to assess the risk of climate-induced gentrification in coastal megacities.

Additional enhancements of the model can be achieved by integrating protective CCA decisions at the firm and governmental levels. This integration could create a more detailed portrayal of interactions originating from diverse CCA actions implemented across various scales. There's potential to link these protective CCA strategies with advancements in technology and infrastructure development. Despite the current scarcity of empirical data supporting this connection, its exploration could shed light on the physical constraints and feasibility of specific CCA options.

Further research on the development of the model could focus on a richer representation of economic sectors. Specifically, the integration of empirically calibrated sectors, such as from the North American Industry Classification System (NAICS) and their corresponding sensitivities to climate shocks could prove instrumental. The employment of existing input-output tables for this purpose may facilitate a more accurate estimation of cross-sectoral economic impacts.

In terms of the model's sensitivity to uncertainty, while it currently accounts for the influences of epistemic uncertainty and randomness, it does not fully grapple with the inherent parametric uncertainties within the socio-economic system. To address this, future iterations could make use of longitudinal survey datasets to trace temporal shifts in individual perceptions and preferences, contributing to the dynamism and realism of the model. The incorporation of innovative data collection techniques, like laboratory experiments, randomized control trials, or serious gaming, could add further depth to the CCA applications of the model.

Despite these limitations, the contributions of the CRAB model are significant. It provides a novel understanding of the importance of a comprehensive framework that includes both firms and households, illuminating how their interactions and cumulative individual actions shape regional climate-induced damage and resilience. The model offers new approaches to tackle not only the direct but also the indirect risk in an explicit way, thereby providing a novel perspective on transforming emerging risk challenges into long-term opportunities.

6.1.5 Policy Implications

The methodological developments and analysis pursued in this thesis offers a number of implications for the design of climate change adaptation policy.

Feedbacks, synergies, and the need for integrated CCA strategies

This thesis underscores the double-edged nature of top-down protective adaptation strategies and the potential pitfalls of an over-reliance on autonomous adaptation. While protective measures serve as crucial buffers against milder climate adversities, they might inadvertently turbocharge agglomeration forces. This domino effect catalyzes increased urbanization in areas sensitive to climate shifts, subjecting communities to heightened risks and potential economic entrenchment. Conversely, an exclusive reliance on autonomous adaptation can exert undue pressure on these very agglomeration forces, edging the economy closer to a perilous tipping point.

To navigate this intricate landscape, it becomes paramount to weave together bottom-up individual undertakings with broader top-down governmental measures. These shouldn't be confined just to protective actions but should also encapsulate strategies like subsidies, aimed at mitigating indirect repercussions and feedback loops. Such a holistic approach can fortify resilience without inadvertently escalating vulnerabilities. The framework delineated in this thesis provides policymakers with an artificial society to simulate the interplay amongst varied CCA strategies. Embracing this comprehensive lens, we can channel potential climatic threats into opportunities for resilient and sustainable growth.

Behavioral insights and economic implications in CCA planning
Traditional CCA policies have been rooted in the idea that individuals act as perfectly rational optimizers, potentially leading to overestimations in their anticipated efficacy. While we now can utilize the rich behavioral data from surveys that are increasingly available to model behavioral complexity, these datasets alone cannot display the economy-wide implication of such behavior. With the framework from this thesis, we can bridge this gap. This allows for a more comprehensive understanding, enabling policymakers to explore the realistic patterns of CCA over time and their broader economic implications.

Tailored policy design
Given our findings on household adaptation to climate shocks, we strongly recommend the formulation and implementation of tailored CCA policies. It's essential to acknowledge the diversity in adaptive capacities and the specific challenges various households face. A tailored policy design that addresses heterogeneity in adaptation responses and constraints—whether financial, physical, or perception-based—can significantly amplify the effectiveness of CCA measures.

Integration of CCA and broader development policies
There is a pronounced linkage between climate vulnerabilities and existing socio-economic disparities, a relationship further intensified by the unfolding challenges of climate change. It is crucial for policymakers to explore the possible synergies stemming from the combination of CCA and development strategies. Merging these two domains offers a unique avenue to not only tackle the immediate threats of climate change but also to systematically address longstanding socio-economic inequalities, setting the stage for comprehensive and just developmental outcomes.

In summary, this thesis offers valuable insights into the nuanced policy implications of climate change adaptation. It strongly advocates for a comprehensive and dynamic policy framework that can effectively address the intricate interactions of socio-economic factors, behavioral uncertainties, and escalating climate risks.

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7

Appendix

7.1 Appendix for Chapter 3

7.1.1 Model Complements

The capital-good sector and technological learning

The technology of each firm i is captured by two labor productivity coefficients, A_i^T and B_i^T. The former coefficient indicates the productivity of the machines in the consumption-good sector, while the latter stands for the productivity of the manufacturing technique required to produce the machines.

Capital-good firms determine their price p_i applying a fixed markup ($\mu_1 > 0$) to their unit cost c_i[1]:

$$p_i(t) = (1 + \mu_1)c_i(t). \tag{7.1}$$

The unit cost c_i is the ratio between individual nominal wage w_i and its productivity coefficient:

$$c_i(t) = \frac{w_i(t)}{B_i^T}. \tag{7.2}$$

Capital firms aim to improve their productivity coefficients (A^T, B^T) via technological learning. To do so, they actively invest in R&D a fraction ν_1 of their past sales:

$$R\&D_i(t) = \nu_1 S_i(t-1) \quad with \quad 0 < \nu_1 < 1. \tag{7.3}$$

Furthermore, firms split their R&D between innovation (IN) and imitation (IM) according to the parameter $\xi \in [0,1]$. Both innovation and imitation are modeled employing a two-step procedure. In both cases, the first step determines whether innovation or imitation is successful through a draw from a Bernoulli distribution:

$$\theta_i^{in}(t) = 1 - e^{-\zeta_1 IN_i}(t), \tag{7.4}$$

$$\theta_i^{im}(t) = 1 - e^{-\zeta_2 IM_i}(t), \tag{7.5}$$

[1] Survey data evidence summarized in Fabiani et al. (2006) show that European firms mostly set prices according to mark-up rules.

where $0 \leq \zeta_{1,2} \leq 1$ capture the *search capabilities* of firms. The probability of a positive outcome depends on the amount of resources invested.

Successful firms get access to the second step. If the innovation draw (Eq. 7.4) is successful, the firm discovers a new technology, (A_i^{im}, B_i^{im}), according to:

$$A_i^{in}(t) = A_i(t)(1 + x_i^A(t)), \tag{7.6}$$

$$B_i^{in}(t) = B_i(t)(1 + x_i^B(t)), \tag{7.7}$$

where $x^{A,B}(t)$ are independent draws form a $Beta(\alpha_1, \beta_1)$, over the support $[\underline{x_1}, \overline{x_2}]$, with $\underline{x_1} \in [-1, 0]$ and $\overline{x_2} \in [0, 1]$. The supports of the Beta distribution determine the probability of "successful" over "failed" innovations, and hence shape the landscape of *technological opportunities.*

Furthermore, firms passing the imitation draw (Eq. 7.5) get access to the technology of one competitor (A_i^{im}, B_i^{im}). Notably, firms are more likely to imitate competitors with similar technology and we calculate the technological distance between every pair of firms using a Euclidean metric. Moreover, in tune with empirical evidence (Dosi, 1990; Fagerberg and Godinho, 2006), firms in the other region are more difficult to imitate than domestic ones, hence technological distance between foreign Fims is augmented by a factor $\epsilon > 1$. The physical distance plays an important role within the agglomeration process because it makes innovation spatially concentrated (Feldman and Kogler, 2010).

Once both processes are completed, all the firms succeeding in either imitation or innovation select the most efficient production technique they can master according to the following payback period rule (see Subsection 7.1.1):

$$min[p_i^h(t) + bc_i^h(A_i^h, t)] \quad h = T, in, im, \tag{7.8}$$

where b is a positive payback period parameter (see Eq. 7.11). Finally, capital-good firms send a "brochure" containing price and productivity of their machines to a random samples of potential new clients (NC_i) as well as its historical customers (HC_i). The capital-good market is indeed characterized by imperfect information and (Phelps and Winter, 1982).

The consumption-good sector

Consumption-good firms combine labour and capital with constant returns to scale to produce a homogeneous good. In line with K+S tradition (Dosi et al., 2013, 2010, 2017b), adaptive demand expectations $(D_j^e = f[D_j(t-1), D_j(t-2), ..., D_j(t-h)])$, desired inventories (N_j^d), and the actual stock of inventories (N_j) form the desired level of production:

$$Q_j^d(t) = D_j^e(t) + N_j^d - N_j(t). \tag{7.9}$$

The latter is constrained by firms' capital stock K_j, with a desired capital stock K_j^d required to produce Q_j^d. In case $K_j^d(t) > K_j(t)$, the firm calls for a desired expansionary investment such that:

$$EI_j^d(t) = K_j^d(t) - K_j(t). \tag{7.10}$$

In addition, in any given time step, we assume that firm capital expansionary investments are constraint by the maximum growth rates found in the empirical literature on firm investment patterns and capital growth rate (Doms and Dunne, 1998). Furthermore, firms undertake replacement investment RI, scrapping machines with age above $\eta > 0$ and those that satisfy the following *payback rule*[2]:

$$RI_j(t) = \left\{ A^{\tau}_{fc} \in \Xi_j(t) \, : \, \frac{p^*(t)}{c(A_{fc,\tau},t) - c^*(t)} \leq b \right\}, \tag{7.11}$$

where p^* and c^* are the price and unit cost of production upon the new machines and $b > 0$ is the payback period parameter. The total replacement investment is then calculated summing up all the old vintages that satisfy Eq. 7.11. Furthermore, firms compare the "brochures" received by capital-good firms and order the machines with the best ratio between price and quality. Notably, firms are financially constrained, and we assume that firms prioritize capital stock expansion to the substitution of old machines if investment plans cannot be fully realized.

Notably, consumption-good firms have to pay in advance both their investments and the worker wages. This implies that, in line with empirical literature (Greenwald and Stiglitz, 1993; Hubbard, 1997; Stiglitz and Weiss, 1981) capital markets are imperfect. As a consequence, external funds are more expensive than internal ones and firms may be credit rationed. More specifically, consumption-good firms finance their investment first by using their stock of liquid assets (NW_j). When the latter does not fully cover investment costs, firms that are not credit-constrained can borrow the remaining part paying an interest rate r up to a maximum debt/sales ratio of $\Lambda > 1$.

Each firm is characterized by heterogenous vintages of capital-goods with different average productivity (A_j) which reflects in it unit cost of production (c_j):

$$c_j(t) = \frac{w_j(t)}{A_j}, \tag{7.12}$$

where w_j is the average wage paid by firm j. The prices in the consumption-good sector are computed applying a *mark-up* ($\mu_{2,j}$) on unit cost:

$$p_j(t) = (1 + \mu_{2,j})c_j(t). \tag{7.13}$$

The evolution of firm's market share (f_j), determines the variation of its markup ($\mu_{2,j}$):

$$\mu_{2,j}(t) = \mu_{2,j}(t-1)(1 + \nu \frac{f_j(t-1) - f_j(t-2)}{f_j(t-2)}) \quad with \quad 0 \leq \nu \leq 1. \tag{7.14}$$

The profits of consumption firms are given by:

$$\Pi_j(t) = (S_j(t) - c_j(j)Q_j(t) - rDeb_j(t), \tag{7.15}$$

where $S_j(t)$ are the sales of the firm, Q_j is the quantity produced, Deb is the stock of debt and r is the interest rate. Finally, firm liquid assets $NW_j(t)$ are updated according to:

$$NW_j(t) = NW_j(t-1) + \Pi_j(t) + cI_j(t), \tag{7.16}$$

where cI_j is the investment cost of the firm.

[2]This aligns with multiple empirical studies that demonstrate how replacement investment is typically not proportional to the capital stock (Eisner, 1972; Feldstein and Foot, 1971; Goolsbee, 1998).

Firms entry and exit

At the end of each period consumption firms with (quasi) zero market shares and capital good firms with negative net assets are replaced by a new breed of firms. Hence, we assume a constant total population, with the entrants located in the same region of the bankrupting incumbents. We are aware that entry and exit rates might be independent processes and that spillovers play an important role in agglomeration dynamics (Bischi et al., 2003; Frenken and Boschma, 2007). However, we tried to keep the model as simple as possible, given the numerous dynamics already in play and leave that for further research. In line with the empirical findings on firm entry (Bartelsman et al., 2005; Caves, 1998), we assume that entrants are on average smaller than incumbents. In particular, the stock of capital of new consumption-good firms is equal to a draw from a Uniform distribution with support $[\phi_1, \phi_2]$, with $0 < \phi_1, < \phi_2 \leq 1$, multiplied by the average stocks of the incumbents. Similarly, the stock of liquid assets of entrants in both sectors is obtained by multiplying the average stock in the market by a draw from a Uniform distribution with support $[\phi_3, \phi_4]$, with $0 < \phi_3, < \phi_4 \leq 1$. Concerning the technology of entrants, new consumption-good firms select amongst the most productive machines. Conversely, the technological frontier of new capital-good firms is drawn from a Beta distribution $Beta(\alpha_2, \beta_2)$. The parameters of the latter determine whether entrants enjoy an advantage or a disadvantage with respect to the incumbents.

7.1.2 Consumption, taxes, and public expenditures

Each region has a government that taxes profits of firms at fixed rate and pays subsidies ($W^{u,r}$) to unemployed households. The latter is a fraction of the regional average wage:

$$W^{u,r}(t) = \delta \overline{W}^r(t), \quad with \quad \delta \in [0,1], \tag{7.17}$$

with $\delta \in [0,1]$. Workers spend all their income, hence aggregate regional consumption (C^r) is equal to the sum of individual wages and unemployment subsidies:

$$C^r(t) = \sum_{h=1}^{L^r} w_h^r(t) + W^{u,r}(L^r(t) - L^{e,r}(t)), \tag{7.18}$$

where $L^{e,r}(t)$ is the population of employed households at time t in region r.

The model respects the national account identity:

$$\sum_{i=1}^{F1} Q_i(t) + \sum_{j=1}^{F2} Q_j(t) = Y(t) = C(t) + I(t) + \Delta N(t) + EXP(t) - IMP(t). \tag{7.19}$$

Since there are no intermediate goods and no imports, the sum of values added of both production sectors (Y), equals their aggregate production which respectively matches the sum of aggregate consumption (C), investment (I), exports (EXP), imports (IMP) and variations of inventories (ΔN).

7.1.3 Model calibration and validation against stylized facts

In line with the computational economics agent-based modelling literature, we tuned the parameters of the model following the indirect calibration approach (Fagiolo et al., 2007; Windrum et al., 2007).

Table A1: Main parameters and initial conditions in the economic system.

Description	Symbol	Value
Number of firms in capital-good industry	F_1	50
Number of firms in consumption-good industry	F_2	250
Number of households	H	3500
R&D investment propensity	ν	0.04
R&D allocation to innovative search	ξ	0.5
Firm search capabilities parameters	$\zeta_{1,2}$	0.3
Beta distribution parameters (innovation process)	(α_1, β_1)	$(3, 3)$
Beta distribution support (innovation process)	$[\underline{x_1}, \overline{x_2}]$	$[-0.1, 0.1]$
Physical distance	ϵ	5
New-customer sample parameter	γ	0.5
New-customer from the same region	ι	0.75
Capital-good firm mark-up rule	μ_1	0.04
Desired inventories	l	0.1
Payback period	b	3
“Physical” scrapping age	η	20
Mark-up coefficient	υ	0.04
Competitiveness weights	$\omega_{1,2}$	1
Inter-regional iceberg transport cost	τ_1	0.03
International iceberg transport cost	τ_2	$2\tau_1$
Replicator dynamics coefficient	χ	1
Maximum debt/sales ratio	Λ	2
Interest rate	r	0.01
Uniform distribution supports (consumption-good entrant capital)	$[\phi_1, \phi_2]$	$[0.10, 0.90]$
Uniform distribution supports (entrant stock of liquid assets)	$[\phi_3, \phi_4]$	$[0.10, 0.90]$
Beta distribution parameters (capital-good entrants technology)	(α_1, β_2)	$(2, 4)$
Wage setting $\Delta\overline{AB}$ weight	ψ_1	0.2
Wage setting ΔAB_i weight	ψ_2	0.8
Wage setting Δcpi_r weight	ψ_3	0
Wage setting ΔU_r weight	ψ_4	0
Household labour search sample parameter	ρ	0.3
Migration setting W_d weight	φ_1	1
Migration setting U_d weight	φ_2	0
Migration setting D_d weight	φ_3	0.5
Migration setting DA_d weight	φ_4	0.5
Tax rate	tr	0.3
Unemployment subsidy rate	u	0.4
Export demand initial value	Exp	50
Export growth rate	g	0.01

In particular, we selected a set of relevant empirical features - economic stylized facts - that the model is ought to reproduce, and subsequently search the parameter space to find the values that match such results. Furthermore, we tested the robustness of the chosen values in two ways. First, by exploring consistency in the neighbourhood of the selected point. Second, to control for randomness, we changed the seed of the pseudo-random number generator via Monte Carlo simulation exercise. For the present work, we select the following empirical stylized facts to reproduce in our model:

- Pattern of self-sustained growth with persistent fluctuations.
- Average growth rate for output around 1%.
- Average unemployment rate between 5% and 15%.
- Output is less volatile than investment and more than consumption.
- Innovation is spatially concentrated.
- Spatial distribution of economic activities does not converge over time.

Once the model is calibrated (Table A1), we validate simulation results against their ability to replicate both micro- and macro- economic stylized facts observed in the empirical literature (Table 7.10).

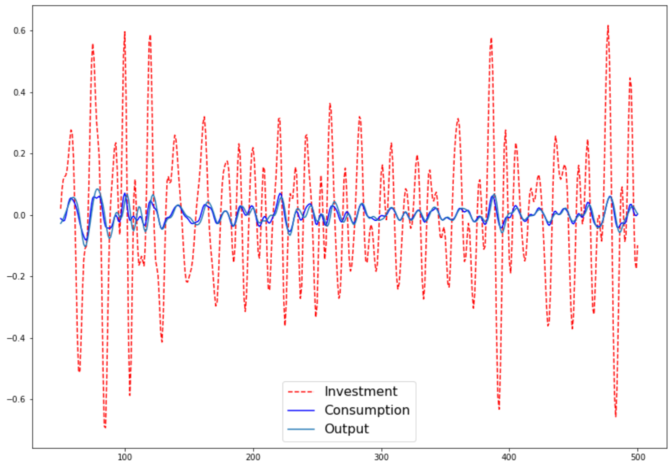

Figure 7.1: Bandpass-filtered output, investment, and consumption. *Note*: results present the behavior of selected bandpass-filtered (6, 32, 12) series for a randomly chosen Monte Carlo run.

A more extensive discussion about the empirical regularities reproduced by the "K+S" model can be found in Dosi et al. (2017b). Regarding this specific model, Figure 7.1 shows the continuous fluctuations and volatility of output, consumption and investment which is well tuned with real world data. In addition, Figure 7.2 displays the cross-correlation among the main macro-economic variables. The results fairly represent empirical data with pro-cyclical consumption and investment and counter-cyclical unemployment rate.

Inflation is slightly pro-cyclical and prices which are counter-cyclical, in particular with investments.

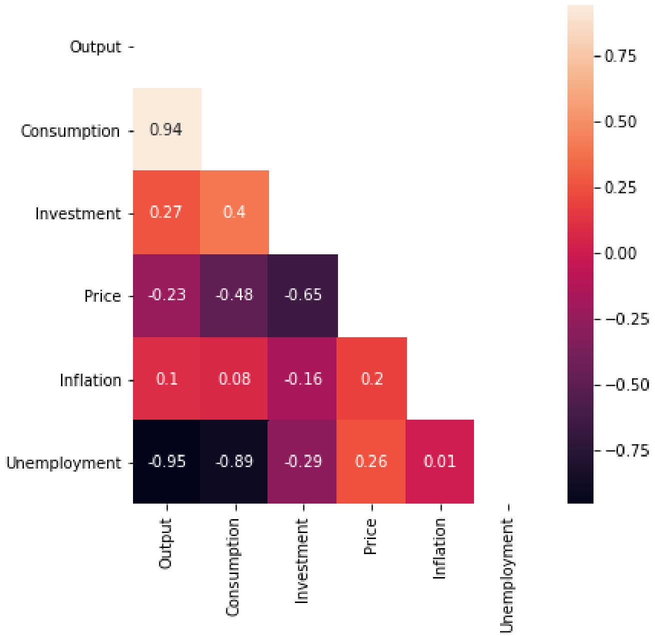

Figure 7.2: Correlation structure emerging from filtered series. *Note*: the values refer to a Monte Carlo of size 100. Average values are reported.

Regarding micro-economic regularities, due to regional transport cost that act as a trade barrier, not all firms are able to gain market share in the other region. in particular, those that do, are on average more productive and bigger than firms selling only in the domestic market.

7.1.4 Sensitivity analysis

In this section we use *one-factor-at-a-time* (OFAT) sensitivity analysis (SA), namely varying one parameter at a time while keeping all the other parameters constant to analyze output uncertainty (Schervish et al., 1983). We opted for OFAT SA because it is less computationally intense than global SA methods such as variance decomposition (Saltelli et al., 2008a). Moreover, as argued in ten Broeke et al. (2016), global SA methods often fail to capture nonlinear dynamics, feedbacks and emergent properties, which are typical in ABMs. For clarity, we measure the effect of such changes in parameters on the main output we use throughout the results: economic growth and spatial distribution of economic activities, which we measure as the probability of statistical equilibrium I. Importantly, we also kept the same experiment settings by first analyzing change in export (Exp) and regional transport cost (τ_1) without climate shocks and subsequently we use the *Baseline* scenario ($Exp = 50 \quad and \quad \tau_1 = 0.03$) to analyze different probabilities and severity of flooding. Nonetheless, as in the results section, to wash away randomness we performed a Monte

Carlo exercise of size 100 on the seed of the pseudo number generator, for each change in parameter value.

7.1.5 Sensitivity analysis on export and regional transport cost

The SA output on export and regional transport cost is consistent with our previous analysis on output growth and probability of statistical equilibrium I.
Specifically, if we look at the two-region economy, as export increases also economic growth does. Conversely, there is not a clear trend between the increase of transport cost and the average output of the two-region economy (Figure 7.3). Furthermore, if we look at the two regions individually we see that as the comparative advantage in trade with the rest of the world increases (i.e. more export and transport cost) also the output growth in the Coastal region is reinforced (Figure 7.5), while the output in the inland region is reduced (Figure 7.5). Notably, the two regions share similar output growth as well as probability of agglomeration whenever the competitive advantage is removed (either $Exp = 0$ or $\tau_1 = 0$ in Figure 7.4, Figure 7.5 and Figure 7.6)

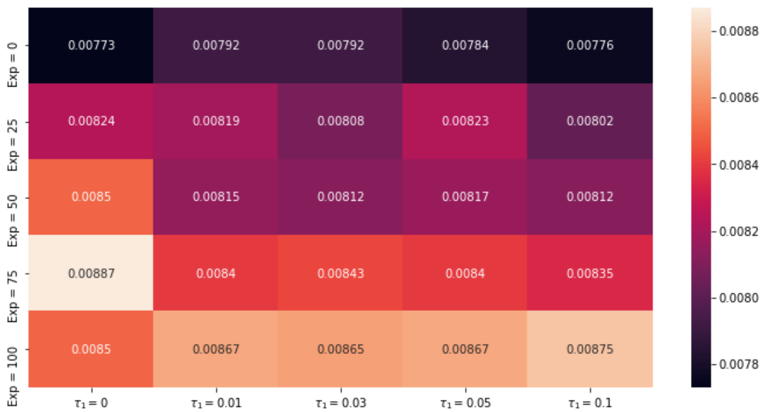

Figure 7.3: Sensitivity analysis of the average output growth of the two-region economy to different values of export (*Exp*) and transport cost (τ_1). *Note*: the values refer to a Monte Carlo of size 100. Average values are reported.

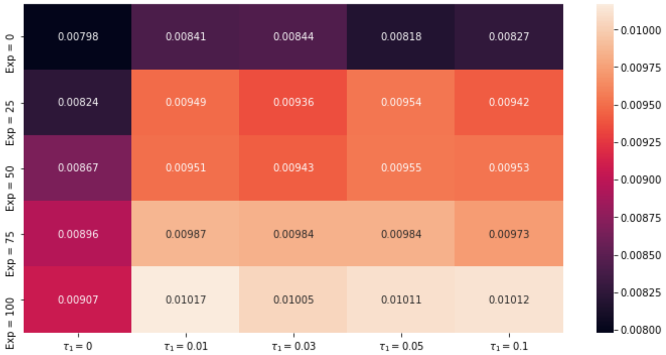

Figure 7.4: Sensitivity analysis of the average output growth in the Coastal region to different values of export (*Exp*) and transport cost (τ_1). *Note*: the values refer to a Monte Carlo of size 100. Average values are reported.

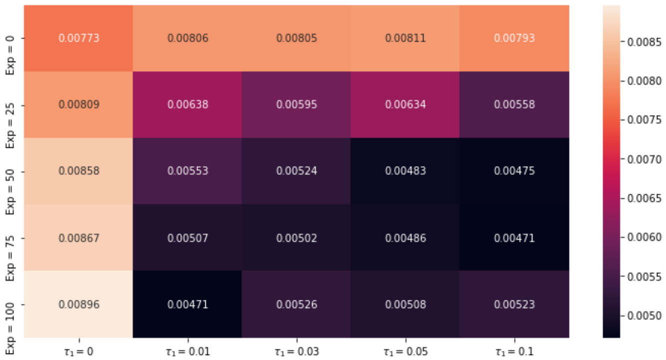

Figure 7.5: Sensitivity analysis of the average output growth in the Inland region to different values of export (*Exp*) and transport cost (τ_1). *Note*: the values refer to a Monte Carlo of size 100. Average values are reported.

Nonetheless, SA results confirm that as long as $\tau_1 > 0$, an increase of export means more demand for Coastal firms and hence more investment resulting in an higher probability of statistical equilibrium I. Importantly, other things being equal, an higher concentration of economic activities in the Coastal region can be obtained by either increasing the initial amount of export demand (Figure 7.6) or its rate of growth (Figure 7.7)

Similarly, an increase of regional transport cost increases the degree of the competitive advantage that the Coastal region has in trade with the rest of the world. On the one hand, the increase of transport cost allows Coastal firms to get an higher share of export demand, increasing the probability of statistical equilibrium I. On the other hand, an increase of τ_1 also raises trade barriers between the two regions, making the agglomeration process slower. In general, the first effect seems to prevail, but the interplay between these two forces generates some non-linearity in the final likelihood of statistical equilibrium I (Figure 7.6 and Figure 7.7).

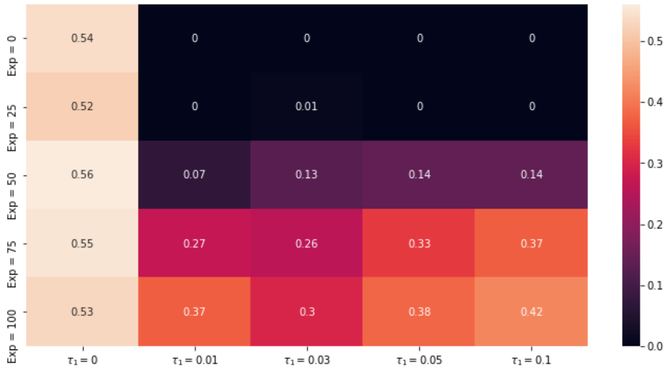

Figure 7.6: Sensitivity analysis of the distribution of economic activities under different values for export (*Exp*) and transport cost (τ_1). The values indicates the probability of statistical equilibrium I in the 400th step of each simulation. *Note*: the values refer to a Monte Carlo of size 100. Average values are reported.

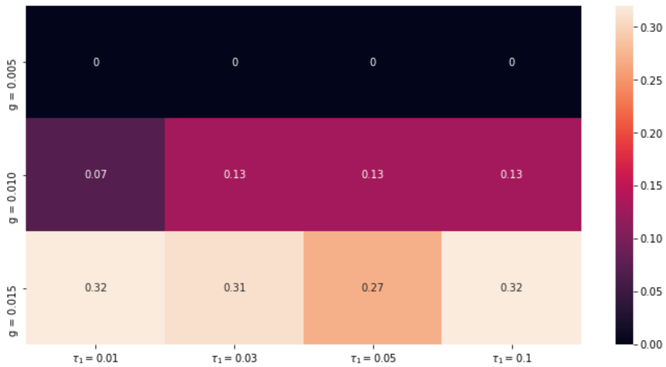

Figure 7.7: Sensitivity analysis of the distribution of economic activities under different values for export growth (g) and transport cost (τ_1). The values indicates the probability of statistical equilibrium I in the 400th step of each simulation. *Note*: the values refer to a Monte Carlo of size 100. Average values are reported.

Sensitivity analysis on shock probability and severity

The results appear to be robust also when analyzing a wider range of shocks probabilities and severity.

In particular, the output growth of the two-region economy is the lowest around to the top right corner of Figure 7.8, where floods are intense but not frequent. The reason is that rare events generate the lock-in of economic activities in Coastal region and that once they do happen, the majority of the firms is heavily damaged. Furthermore, the higher output growth of the two-region economy is on the top-left and bottom-right of Figure 7.8. On the one hand, in the top-left, the higher economic growth is stemming from the “productivity effect” (Hallegatte and Dumas, 2009). On the other hand, in the bottom-right corner is the combination of “productivity effect” and coastal retreat that offset the damages from the climate shocks.

Interestingly, departing from the lowest probability and severity (*LPLS*, top-right corner in Figure 7.6), and keeping one parameter constant while increasing the other, the model displays some non-linearities in the probability of statistical equilibrium I (see $Pr_s = 0.01$ and $E[Dc] = 0.01$ columns in Figure 7.6). The reason is linked to the additional labor demand generated by the shocks, which for some combinations of both low probability and severity increases job opportunities and hence households migration in the Coastal region. Notably, the lower but higher than zero probabilities of statistical equilibrium I in the right-bottom of Figure 7.6 (such as the 0.01 with $E[Dc] = 0.15$ and $Pr_s = 0.25$) are rare -and unrealistic- cases of full gentrification. In the latter, initial rebuilding opportunities lock in all households and firms in the Coastal region, with devastating consequences for the economy.

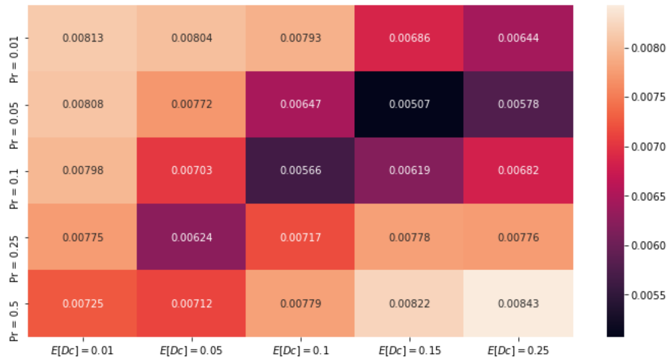

Figure 7.8: Sensitivity analysis of the average output growth of the two-region economy to different values of shock probability (Pr) and expected damages ($E[Dc]$). *Note*: the values refer to a Monte Carlo of size 100. Average values are reported.

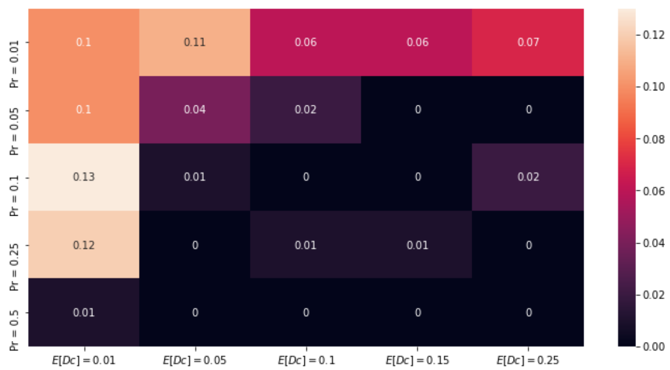

Figure 7.9: Sensitivity analysis of the distribution of economic activities to different values of shock probability (Pr) and expected damages ($E[Dc]$). The values indicates the probability of statistical equilibrium I in the 400th time step of each simulation. *Note*: the values refer to a Monte Carlo of size 100. Average values are reported.

7.2 Appendix for Chapter 4

7.2.1 Methods

To analyze the role of behavioral assumptions on household climate change adaptation and regional damages, we connect an evolutionary [3] economic agent-based model (ABM), household survey data, and exploratory modeling. ABMs are computer simulations where a number of decision-makers (agents) and institutions act, interact and learn following predefined rules Farmer and Foley (2009). Agent actions affect their individual performance and the world around them, shaping the environment and other agent behaviors. Agent-based economy is rarely in an equilibrium, as it keeps unfolding following agent actions over time. Our model represent a regional economy prone to agglomeration forces following the New Economic Geography theory Krugman (1998) adopted for evolutionary non-equilibrium settings and builds upon the evolutionary economic engine of the well-validated "Keynes + Schumpeter" ("K+S" see, e.g. Dosi et al., 2013, 2010) and the "Dystopian Schumpeter meeting Keynes" ("DSK" see, e.g. Lamperti et al., 2019a, 2018) models. In the *Climate-economy Regional Agent-Based* (CRAB) model, the economy consists of $F1$ heterogeneous capital-good firms (denoted with the subscript i), $F2$ consumption-good firms (denoted with the subscript j), $F3$ consumption-service firms (denoted with the subscript l) and L households (denoted with the subscript h) supplying work and consuming the income they earn. When a decision process is identical for all firms (e.g., labor market), we employ the subscript f. In addition, to generally refer to consumption firms (both service and good), we use the subscript s.

Households

This version of the CRAB model expands a representation of human behavior by including a variety of behavioral framing: from rational homogeneous decision-making to behaviorally-rich heterogeneous boundedly-rational representation of household agents. Specifically, heterogeneous households vary in the education level between *Low*, *Medium* or *High* ($Edu_h = [Low, medium, high]$)[4]. Unemployed households sort in ascending order by their education level, visit the labor market and select a sub-sample of available vacancies (if any), choosing the one with the highest wage. Having priority in the queue, more educated households are more likely to get better-paid job opportunities than their less-educated peers. As a result of the job search, households income (i_h) at time t is:

$$i_h(t) = \begin{cases} w_f(t), & \text{if } employed \\ w^u(t), & \text{otherwise} \end{cases}, \tag{7.20}$$

[3] Evolutionary here implies that the model (i) encompasses actions of diverse boundedly-rational agents that form and update their expectations about future as they learn from own experience and interactions with others as they aim to improve their state, (ii) endogenizes the process of technological innovation and possibly structural changes in e.g. market institutions when actors with unfortunate choices do not survive a transformational change. Based on the performance of these learning and adapting agents, there is a type of evolutionary selection occurring in this artificial economy as strategies of successful households and firms get adopted and further improved in the ever-changing environment.

[4] *Low* education level can be considered as having concluded secondary school, while *Medium* can be considered as having terminated high school and *High* is graduated level. Note that households with lower levels of education have not been included as their share of the working population is too small.

Where w_f is the job paid by the firm employer and w^u is the unemployed subsidy paid by the government at time t. Households consume a fraction of their income if employed, while the whole unemployed subsidy otherwise:

$$c_h(t) = \begin{cases} \delta i_h(t) - e_h^r(t), & \text{if } w_f(t) > w^u(t) \\ i(t), & \text{otherwise} \end{cases}, \tag{7.21}$$

with $\delta < 1$, which is the fraction of consumed wage and e^r is repair expenditure at time t. Should a flood hazard hit the region, the impacted households perform repair expenditures proportional to the damage, which depends on property values and the damage curve ($D_h(t) > 0$, see Subsection "Hazard shock" for more detail about direct damages calculation). Such repair expenditures decrease households' consumption. As we assume that households try to repair their property as soon as possible, they divert into repair expenditure all their income but the amount of the unemployment subsidy (that in our model is the minimum to satisfy basic needs) until all damages are repaired:

$$e_h^r(t) = i_h(t) - w^u(t). \tag{7.22}$$

Note that only employed households can spare resources to repair their properties. As a consequence, households savings (s_h) evolve over time according to:

$$s_h(t) = s_h(t-1) + i_h(t) - c_h(t) - cost_{cca_m}(t), \tag{7.23}$$

where $cost_{cca_m}$ being the cost of undergone protective actions m (if any, described below) at time t.

Importantly, households also use their savings to cover the damages, which decrease over time accordingly to:

$$D_h(t) = D_h(t-1) - e_h^r(t) - s_h(t). \tag{7.24}$$

To reduce flood damages to their properties, households can undertake adaptation measures to reduce damage from floods. Our survey elicits households intentions to invest in 18 CCA measures, which we group into three classes here: *Dry-proofing*, *Wet-proofing*, *Elevation* Kreibich et al. (2015); Noll et al. (2022a). The data on effectiveness of these various CCA is scattered, so here we take averages reported in the literature Kreibich et al. (2015) and later test the model sensitivity to them via the global sensitivity analysis. The *Dry-proofing* and *Wet-proofing* measures decrease households damage coefficient Dc with a fixed amount $\alpha_{Dry,Wet}$:

$$Dc_h(t) = (1 - \alpha_{Dry} - \alpha_{Wet}) Dc_h(t), \quad with \quad \begin{cases} 0 < \alpha_{Dry,Wet} < 1, & \text{if Dry, Wet is implemented} \\ \alpha_{Dry,Wet} = 0, & \text{otherwise.} \end{cases} \tag{7.25}$$

We assume that *Elevation* raises household property above the flood height and, consequently delivering a complete protection $Dc_h(t) = 0$ if such measure is undergone.

Depending on the behavioral scenario, households can undertake a CCA action following either a "rational" (RA) or "boundedly-rational" (BA) decision-making process. *RA* households have full information about the cost-efficiency of each measure and they use Expected Utility (EU) to evaluate the trade-offs between investing into a CCA action (EU_{ccm}) and inaction (EU_{NOcca_m}):

$$EU_{cca_m,h} = (p)ln(Hv_h - D_{cca_m,h} - C_{cca_m}) + (1-p)ln(Hv_h - C_{cca_m}) \quad with \quad cca = [Dry, Wet, Elev], \tag{7.26}$$

$$EU_{NOcca_m,h} = (p)ln(Hv_h - D_{NOcca_m,h}) + (1-p) * ln(Hv_i) \quad with \quad cca_{=}[Dry, Wet, Elev], \tag{7.27}$$

with p being the cumulative probability of a flood in 30 years, D_{NOcca_m} and D_{cca_m} are the damage coefficients with the adaptation actions and no action, respectively, C_{cca_m} is the cost of action, and Hv_h is the households property value. The latter evolves with average regional salaries:

$$Hv_h(t) = Hv_h(t-1)\frac{\overline{W}(t) - \overline{W}(t-1)}{\overline{W}(t-1)}, \tag{7.28}$$

with $\overline{W}$ being the average salary of the regional economy[5] In addition, the expected values depends on the average of past increase values:

If $EU_{cca_m,h} > EU_{NOcca_m,h}$ and $s_h(t) > cost_{cca_m}$ the household will undertake the adaptive action.

Boundedly-rational agents (BA) employ an extended version of Protection Motivation Theory (PMT) Rogers (1975). PMT stands out as the predominant psychological theory to study individual CCA decisions. In the context of most social science theories, including PMT, the decision-making process is conceptualized as a system of elements driving a certain process causally towards a specific outcome Hedström and Ylikoski (2010). More specifically, this process involves a set of elements that collaboratively push an individual to perceive a threat and strategize a response to cope with it. In our application of PMT's extended version, an individual's intention to undertake CCA actions is fueled by their threat appraisal (comprising perceived probability, perceived damage, and worry) and coping appraisal (encompassing response-efficacy, self-efficacy, and perceived costs). Additionally, this intention is influenced by factors like social norms, past encounters with floods, and familiarity with CCA Noll et al. (2022b). Each time step in CRAB, households living in the flood-prone area calculate the adaptation *intention* probability $p^{int}_{cca_m} \in [0,1]$ for each cca_m measure by multiplying individual behavioral attributes at time t by their effect size, obtained from a Logit regression (for a detailed description of behavioral attributes see Table 7.3, while for effect sizes see Table 7.7 in the main text).

$$p^{int}_{cca_m,h}(t) = \frac{1}{1 + e^{\beta_0 + \sum_{a=1}^{15} \beta_a X_a(t)}} \tag{7.29}$$

Here, β_a and $X_a(t)$ are the effect sizes and attributes, respectively. Notably, some attributes change over time. When contemplating any specific action cca_m from $cca = \{Dry, Wet, Elev\}$, the historical adaptation measures for all other actions are represented by:

$$UG_n = \begin{cases} 1 & \text{if } cca_n \text{ adaptation measure undertaken previously, } n \neq m \\ 0 & \text{otherwise} \end{cases} \tag{7.30}$$

[5]The assumption is reasonable as wage levels are strongly correlated with house price Davidoff (2006).

for all n in CCA where $n \neq m$. This denotes whether household h has implemented other measures in the past while considering a particular action cca_m.

Also *Fl. damage* takes into account previously undergone measures as empirical evidence shows that past actions affect perceived damages Noll et al. (2022a):

$$Fl.\ damage_h(t) = \alpha_{cca_m} Fl.\ damage(t) \quad with \quad cca = [Dry, Wet, Elev]. \tag{7.31}$$

The overall regional adaptation level affects households through social interaction, with *Soc. network* that evolves endogenously as:

$$Soc.\ network_{cca_m,h}(t) = \sum_{h=0}^{H_{cca_m}^{net,h}} 1, \tag{7.32}$$

with $H_{cca_m}^{net,h}$ being the set of households connected to household h and that have already implemented the *cca* under consideration.

Empirical evidence shows that there is a consistent gap between intentions and the actual behavior Noll et al. (2022a), hence, in CRAB we assume that the probability to act p^{act} at time t as:

$$p_{cca_m,h}^{act}(t) = \Phi p_{cca_m,h}^{int}(t), \tag{7.33}$$

with $\Phi < 1$ that reflects the degree of the intention-behavior gap.

Finally, households with $p_{cca_m}^{act} > 0$ draws from a Bernoulli distribution - in the similar fashion as for migration and technological learning (described below) - to determine whether adaptation occurs:

$$\theta_h^{cca_m}(t) = p_{cca_m,h}^{act}(t), \quad with \quad p_{cca_m,h}^{act}(t) \in (0,1). \tag{7.34}$$

If the draw is successful and $s_h(t) > cost_{cca_m}$, the household undertakes the chosen action. Adaptation actions are permanent, except dry-profing that expires after $\eta_{dry} > 0$ years Du et al. (2020).

By modeling structural differences between *RA* vs. *BA* adaptive behavior we aim to capture the fundamental uncertainty arising from human behavior in the context of climate change adaptation, a crucial point to advance the broader sustainability science Beckage et al. (2018); Fulton et al. (2011); Wijermans et al. (2020)

Firms in the consumption-good and consumption-service sectors

Firms in the consumption-good and service sectors follow the same rules of consumption-good firms outlined in the Subsection 7.1.1. Notably, their behavior could differ since the two sectors have different capital-output ratios, Ko_{gd} and Ko_{serv} mimicking the different degrees of capital intensity required to produce goods vs. services.

Consumption markets

Consumption-good and -service firms compete in two markets: Domestic (*Dom*) and Export (*Exp*). In a generic market m, firm's competitiveness (E_s) depends on its price, which can account for international (τ) transport cost, as well as on the level of unfilled demand (l_s):

$$E_s^m(t) = -\omega_1 p_s^m(t)(1+\tau) - \omega_2 l_s^m(t) \quad with \quad \omega_{1,2} > 0, m = [Dom, Exp]. \tag{7.35}$$

In each market (m), the average competitiveness ($\overline{E}^m$) is calculated by averaging the competitiveness of all firms in the corresponding region weighed by their market share in the previous time step:

$$\overline{E}^m(t) = \sum_{j=1}^{F2} E_s^m(t) f_s^m(t-1) \quad with \quad m = [Dom, Exp]. \tag{7.36}$$

The market shares (f_s) of firms in the three markets evolve according to the quasi-replicator dynamics:

$$f_s^m(t) = f_s^m(t-1)\left(1 + \chi \frac{E_s^m(t) - \overline{E}^m(t)}{\overline{E}^m(t)}\right) \quad with \quad m = [Dom, Exp], \tag{7.37}$$

with $\chi > 0$, which measures the selective pressure of the market. In a nutshell, the market shares of the less efficient firms shrink, while those of the most competitive ones increase (due to lower prices and less unfilled demand). Firms' individual demand in each market is then calculated by multiplying their market share by the total demand. In the export market, we assume exogenous demand that grows at a constant rate (α): Finally, firm s calculates individual domestic demand(D^{Dom}) by multiplying market shares and aggregate regional consumption in goods (C^{gd}) or services (C^{serv}), depending on its sector (sec) (for more information about aggregate consumption and export calculation see Subsection "Consumption, taxes, and public expenditures"):

$$D_s^{Dom}(t) = C^{sec}(t) f_s^{Dom} \quad with \quad sec = [gd, serv]. \tag{7.38}$$

In a similar fashion, the firm calculates the demand from export (D^{Exp}) as:

$$D_s^{Exp}(t) = Exp^{sec}(t) f_s^{Exp} \quad with \quad sec = [gd, serv], \tag{7.39}$$

hence, firm s obtains its total demand (D_s) at time t by summing domestic and export demands:

$$D_s(t) = D_s^{Dom}(t) + D_s^{Exp}(t). \tag{7.40}$$

Labour market dynamics

Firms offer heterogeneous wages which depend on their productivity, as well as on regional productivity, inflation, and unemployment. The wage and labor demand mechanisms do not differ from the original version of the model. However, in this version, households are endowed with different education levels. In this novel version, the labor market matching mechanism in the region operates as follows:

1. If $L_f^d(t) > n_f(t)$, where $n_f(t)$ is the current labour force of a generic firm f, the firm posts m vacancies on the labour market, with $m = L_f^d(t) - n_f(t)$. Conversely, if $L_f^d(t) < n_f$ the firm fires m employees.
2. Unemployed households have imperfect information and are boundedly-rational: they are aware only of a fraction $\rho \in (0,1]$ of all vacancies posted by the firms in their home region.

3. Unemployed households sorted by education level, select the vacancy with the highest offered wage in their sub-sample, and they are hired by the corresponding firm.

All things equal, higher education households are prioritized in the labor, and therefore they are likely to get higher salaries than the lower educated. The hiring process is completed when either all households are employed, or when firms have hired all the workers they need. In this out-of-equilibrium market, there is no market clearing. Hence, involuntary unemployment and labor rationing are emergent phenomena generated by the CRAB model.

Households' migration

The migration flow of households depends on the regional economic performance. Empirical evidence shows that income per capita and employment opportunities are the main factors driving inter-regional household migration Kennan and Walker (2011). Hence, we use these two factors in regulating the inflow and outflow of households in the region in this novel version of the CRAB model.

$$\Delta H(t) = \begin{cases} \varphi_1 \overline{\Delta Ipc}(t) H(t), & \text{if } \overline{\Delta Ipc}(t) > 0 \text{ and } U(t) < U_{max}(t) \\ \varphi_1 \overline{\Delta Ipc}(t) H(t), & \text{if } \overline{\Delta Ipc}(t) < 0 \text{ and } U(t) > U_{min}(t) \end{cases}. \tag{7.41}$$

With $\varphi_1 < 1$ that reflects the impact of income per capita change on overall migration flow. $U_{[min,max]}$ are the minimum and maximum unemployment rates that make people come and leave, respectively. Where H is the total households population and $\overline{\Delta Ipc}$ is the average change in income per capita at time t, defined as the average income per capita of the past n periods:

$$\overline{\Delta Ipc} = \frac{(\Delta Ipc(t) + \Delta Ipc(t-1) + ... + \Delta Ipc(t-n))}{n}. \tag{7.42}$$

With $n > 1$ and ΔIpc defined as:

$$\Delta Ipc(t) = \frac{Ipc(t) - Ipc(t-1)}{Ipc(t-1)} \tag{7.43}$$

Finally, Ipc In conclusion, Ipc at tie (t) is given by the sum of all wages divided by households population as:

$$Ipc(t) = \frac{\sum_{h=1}^{H} w_h^p(t)}{H(t)} \tag{7.44}$$

Where w^p is the real wage.

If positive new households are added, sampled randomly from the synthetic population pool. If negative random households are selected and removed from the simulation.

Hazard shock

CRAB models how agglomeration and economic development evolves in the presence of climate-driven hazards. Here we contextualize the CRAB model to a coastal regional economy hit by floods (coastal, pluvial, fluvial). The information about flood exposure and severity is exogenous, and loosely mimics the situation in greater Miami. In principle, the CRAB model can be parameterized for any other hazard, like wildfires, droughts or heatwaves, depending on the research question.

In the current version, floods with a pre-determined depth can hit the agents living in flood-prone areas at a given time step. When a flood does happen, exposed agents calculate their damage coefficient (Dc) overlying flood depth and class-specific depth-damage curve. Hence, despite the severity of the flood being homogenous among agents, individual differences (i.e., agent type, socio-economic characteristic, and undergone adaptation actions) lead to heterogeneity in damage estimates. In this novel version of the CRAB model, the flood hits both supply and demand sides of the economy. On the demand side, households calculate direct damages ($D(t)$) multiplying the damage coefficient by their house value ($Hv(t)$):

$$D_h(t) = Hv_h(t) * Dc_h(t) \tag{7.45}$$

In addition, households with $D(t) > 0$ set their attribute related to flood experience (fl_{exp}) equal to 1.

On the supply side, floods affect firms via multiple channels:

- A *productivity* shock, which decreases firms' labour productivity for one period: $AB_f(t) = AB_f(t-1)(1-Dc_f(t))$.
- A *capital stock* shock that destroys a fraction $Dc_f(t)$ of the stock of machines of consumption- and service-good firms and a part of the machines produced by capital-good firms.
- An *inventories* shocks that causes a permanent destruction of a fraction of the inventories of consumption- and service-good firms, i.e. $INV_f(t) = INV_f(t-1)(1-Dc_f(t))$.

Firms entry and exit

In this version of the CRAB model, firms' entry and exit processes are independent. At the end of each period, consumption firms with (quasi) zero market shares and capital-good firms with negative net assets go bankrupt and are removed from the simulation. Conversely, we model the entry process at the microeconomic level, following empirical evidence that shows spillovers as an essential component of agglomeration dynamics (Bischi et al., 2003; Frenken and Boschma, 2007). More concretely, we assume that if firms make profits above a certain threshold ($\pi_f > q$, where $q = \epsilon w_f$ with $\epsilon > 1$), for $\iota > 1$ periods, an employee will open its firm to join the profitable market. Note that the count is restarted if in a period $\pi_f < q$. In line with the empirical findings on firm entry (Bartelsman et al., 2005; Caves, 1998), we assume that entrants are on average smaller than incumbents. In particular, the stock of capital of new consumption-good firms is equal to a draw from a Uniform distribution with support $[\phi_1, \phi_2]$, with $0 < \phi_1, < \phi_2 \leq 1$, multiplied by the average stocks of the incumbents. Similarly, the stock of liquid assets of entrants in both sectors is obtained by multiplying the average stock in the market by a draw from a Uniform distribution with support $[\phi_3, \phi_4]$, with $0 < \phi_3, < \phi_4 \leq 1$. Concerning the technology of entrants, new consumption-good firms select among the most productive machines. Conversely, the technological frontier of new capital-good firms is drawn from a Beta distribution $Beta(\alpha_2, \beta_2)$. The parameters of the latter determine whether entrants enjoy an advantage or a disadvantage over the incumbents.

In a nutshell, a thriving economy brings the number of firms to increase, triggering agglomeration. Conversely, a stagnant economy generates a higher rate of bankruptcy and, consequently, a progressive abandonment of the region.

Consumption, taxes, and public expenditures

A region is regulated by a government agent that taxes the profits of firms and income of households at fixed rates and pays subsidies (w^u) to unemployed households. The latter is a fraction of the regional average wage:

$$w^u(t) = \sigma \overline{W}(t), \quad with \quad \sigma \in [0, 1], \tag{7.46}$$

with $\sigma \in [0, 1]$. Workers spend a fraction of their income if employed, hence aggregate regional consumption (C) is equal to the sum of individual consumption:

$$C(t) = \sum_{h=1}^{H} c_h(t), \tag{7.47}$$

Consumption if further divided between goods (C^{gd}) and services (C^{serv}):

$$C^{gd}(t) = \kappa_1 C(t), \tag{7.48}$$

and $C^{serv}(t) = C(t) - C^{gd}(t)$

The model respects the national account identity:

$$\sum_{i=1}^{F1} Q_i(t) + \sum_{j=1}^{F2} Q_j(t) + \sum_{l=1}^{F3} Q_l(t) = Y(t) = C(t) + I(t) + \Delta N(t) + EXP(t) - IMP(t). \tag{7.49}$$

Since there are no intermediate goods and no imports, the sum of values added to both production sectors (Y), equals their aggregate production, which respectively matches the sum of aggregate consumption (C), investment (I), exports (EXP), imports (IMP) and variations of inventories (ΔN).

Export demand exogenously evolves at a fixed rate g

$$Exp(t) = Exp(t-1)(1+g), \quad g > 0. \tag{7.50}$$

As internal demand, also export is divided between goods (Exp^{gd}) and services (Exp^{serv}):

$$Exp^{gd}(t) = \kappa_2 Exp(t), \tag{7.51}$$

and $Exp^{serv} = Exp(t) - Exp^{gd}(t)$

Timeline of events

Each time step, agents' actions take place in the following sequence:

1. Firms in the capital-good sector perform R&D.
2. Consumption firms set their desired production, wages, and, if necessary, invest in new machines.
3. Decentralized labor market opens in each region.
4. An imperfect competitive consumption-good market opens.
5. Entry and exit occur.
6. Machines ordered are delivered.
7. Households migration flow is computed.
8. Households consider protective CCA actions.
9. A flood may hit flood-prone areas, causing damage to firms and households.
10. Economic performance and attractiveness of the region is updated.

7.2.2 Key model outputs

The CRAB model by default produces various socio-economic metrics, including regional economic output (or regional GDP); unemployment; wages; prices for produced machines, goods and services; and tracks investments in R&D and the population of firms and households in the region. Given the research questions here, we omit reporting many of these and focus on the essential metrics that are most relevant to monitor progress in CCA and its impacts in terms of damage reduction. Firstly, we report households' bottom-up protective adaption diffusion rate across different behavioral scenarios (see "Adaptation diffusion rate" and "Adaptation deficit" in Table 7.2 for more information). Secondly, we calculate what the difference in adaptation rate entails in terms of direct damages (see "Residual damages" in Table 7.2) and in terms of damages relative to income, for households with various adaptive capacity levels (see "Damages in relation to monthly income" in Table 7.2).

Table 7.2: The CRAB model outputs analyzed in the Main text: definitions and estimation

Adaptation diffusion rate	Cumulative number of households over time who take an adaptation measure (Wet-proofing, Dry-proofing and Elevation) in relation to the entire population living in hazard-prone areas.
Adaptation deficit	Insufficient adaptation compared to what is optimal. To quantify it here, we estimate the difference between the diffusion rate of the cost-effective adaptation uptake (i.e RA_{Hom}) and the rate of private adaptation adoption under more realistic behavioral assumptions (i.e. RA_{Het}, RA_{Hom} or BA_{Het}). $Gap_{RA_{Hom},bt}(t) = RA_{Hom}(t) - bt(t)$ with $bt(t) = [RA_{Het}, BA_{Hom}, BA_{Het}]$.
Residual damage	Damage that remains uneliminated after households have taken private climate change adaptation actions. Damage without adaption at time t: $D_h(t) = Hv_h(t)Dc_h(t)$, where Hv_h is the house value and Dc_h is household h individual damage coefficient. Damage prevented by adaptation at time t: $DP_h(t) = \alpha_{cca_m} Hv_h(t)Dc_h(t)$, where $cca = [Dry, Wet, Elev]$ are the adaptation options and $\alpha_{cca_m} < 1$ is the damage reduced by such actions. Residual damage at time t: $DR(t) = \sum_h^H D_h(t) - DP_h(t)$.
Damages in relation to monthly income	Average residual damage in relation to households monthly income. Potential damage for each household h at time t are calculated as $\frac{DR_h(t}{wage_h/3}(t)$, where $wage_h$ is the quarterly wage of household h.

Furthermore, to account for the inner stochasticity of the model, we compute the mean and standard deviation of a set of 100 Monte Carlo runs for each experiment that addresses our research questions. To assess the size of the Monte Carlo set we employ the Variance stability approach Lee et al. (2015). The latter consist of increasing the number of simulations until the coefficient of variation between two sets of runs falls below a certain threshold. In our case, 100 appears to be a robust choice as the difference in coefficient of variation is quite low already after 30 simulations and converges to zero after 80 (see Fig. 7.10). In addition, the choice to employ the mean as a reference value for comparison appears reasonable given that the values are approximately normally distributed around the mean over time (see Fig. 7.11). Each simulation run takes 300 steps, each equivalent to a quarter of a year. Hence, the time horizon of our simulations is 75 years.

7.2.3 Model calibration

We utilize multiple data sources, from national statistics to a survey questionnaire on flood adaptation behavior, combined with different calibration techniques to obtain robust results from the CRAB model.

Creating households synthetic population and social network

To create a synthetic population of households, we employ the rich behavioral and socio-economic survey data Noll et al. (2022b) in the state of Florida ($n = 965$). In the scenarios where households are initialized with heterogeneous socio-economic and behavioral attributes, we employ the same algorithm to sample individual attributes from the empirical data (Table 7.4 contains summary statistics of the socioeconomic variables, while for the full list of behavioral attributes see Table 7.3):

Algorithm 1 Pseudo-code representing the generation of synthetic population of households from empirical data.

for *attributes* $= 1, \ldots, N$ **do**
  Get the *empirical distribution* of the attribute from the survey data
  if I have sampled other attributes before **then**:
    for *sampled attributes* $= 1, \ldots, N - n$ where n are attributes still to be sampled **do**
      is the distribution of the previously *sampled attribute* correlated with *empirical distribution*?
      if Yes **then**
        empirical distribution→ *empirical distribution* | *sampled attribute*
      end if
    end for
  end if
  random sample a value from the *empirical distribution*
end for

The cross-correlation among variables and mean difference have been used to evaluate criteria between the populations, which are summarized in Fig. 7.12-7.13 and Table 7.5.

Table 7.3: Socio-behavioral factors of private adaptation intentions. Source: 2020 households' survey in FL, USA (N= 965) (Noll et al., 2022b)

		Mean (std. dev)	Question	Scale
Flood damage		3.25 (1.00)	In the event of a future major food in your area on a similar scale to [flood name] how severe (or not) do you think the physical damage to your house would be?	From 1 (not at all severe) to 5 (very severe)
Flood probability		0.28 (0.28)	Imagine you stay in your house for the next 30 years what is the likelihood you believe your household will experience a flood?	0-100%
Worry		2.34 (1.18)	How worried or not are you about the potential impact of flooding on your home?	From 1 (not at all severe) to 5 (very severe)
Response efficacy			How effective do you believe that implementing this measure would be in reducing the risk of flood damage to your home and possessions?	From 1 (extremely ineffective) to 5 (extremely effective)
	Dry-proof.	3.42 (1.16)		
	Wet-proof.	3.42 (1.16)		
	Elevation	3.39 (1.39)		
Self efficacy			Do you have the ability to undertake this measure either yourself or paying a professional to do so?	From 1 (I am unable) to 5 (I am very able)
	Dry-proof.	2.79 (1.40)		
	Wet-proof.	2.60 (1.38)		
	Elevation	2.29 (1.51)		
Perceived costs			When you think in terms of your income and your other expenses, do you believe that implementing (or paying someone to implement) this measure, would be cheap or expensive?	From 1 (very cheap) to 5 (very expensive)
	Elevation	4.24 (1.09)		
	Wet proof.	3.93 (0.88)		
	Dry proof.	3.68 (1.01)		
Flood experience		0.30 (0.46)	Have you ever personally experienced a flood of any kind?	0 - No 1 - Yes
Social expectations (Injunctive social norm)		3.174(1.36)	Do your family, friends and/or social network expect you to prepare your household for flooding?	From 1 (do not expect) to 5 (strongly except)
Social network (Descriptive social norm)		2.05 (1.99)	Thinking about your friends, families, and neighbours, how many households have taken some adaptive action towards flooding?	0-8
Undegone (UG) measure			Please indicate if you have already implemented any of these structural measures or if you intend to do so in the future:	0-8
	Dry-proof.	0.18 (0.60)	Installing anti-back flow valves on pipes; Installing a pump and/or one or more system(s) to drainflood water; Fixing water barriers(e.g., water-proof basement windows).	
	Wet-proof.	0.20 (0.62)	Strengthen the housing foundations to withstand waterpressures; Reconstructing or reinforcing the wallsand or the ground floor with water-resistant materials; Raising the electricity meter above the most likely flood level or on an upper floor.	
	Elevation	0.08 (0.28)	Raising the level of the ground floor above the most likely flood level.	0-8

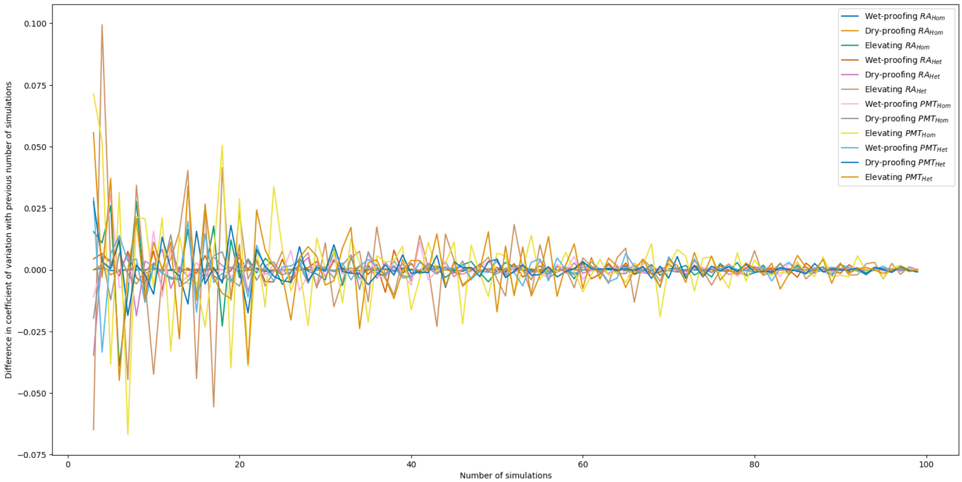

Figure 7.10: In the y-axis, the difference between the coefficient of variation in n and $n-1$, where n is the number of simulations on the x-axis.

Table 7.4: Households socio-economic attributes and survey-related questions.

	Mean (std. dev)	Question	Scale
Education	2.766 (0.807)	What is the highest level of education you have completed?	From 0 (Less than secondary education) to 4 (Post graduate degree)
House value	394,700 (769,234)	If you were to put your accommodation on the market today, how much do you believe it would sell for? Please provide your best estimation in the full amount	Open choice
Savings	2.1483 (1.691)	With regards to your household's savings, what statement most closely reflects your current household situation?	From 0 (We use practically all of the money we earn each month)to 4 (My household has 4 or more month's wages in savings)

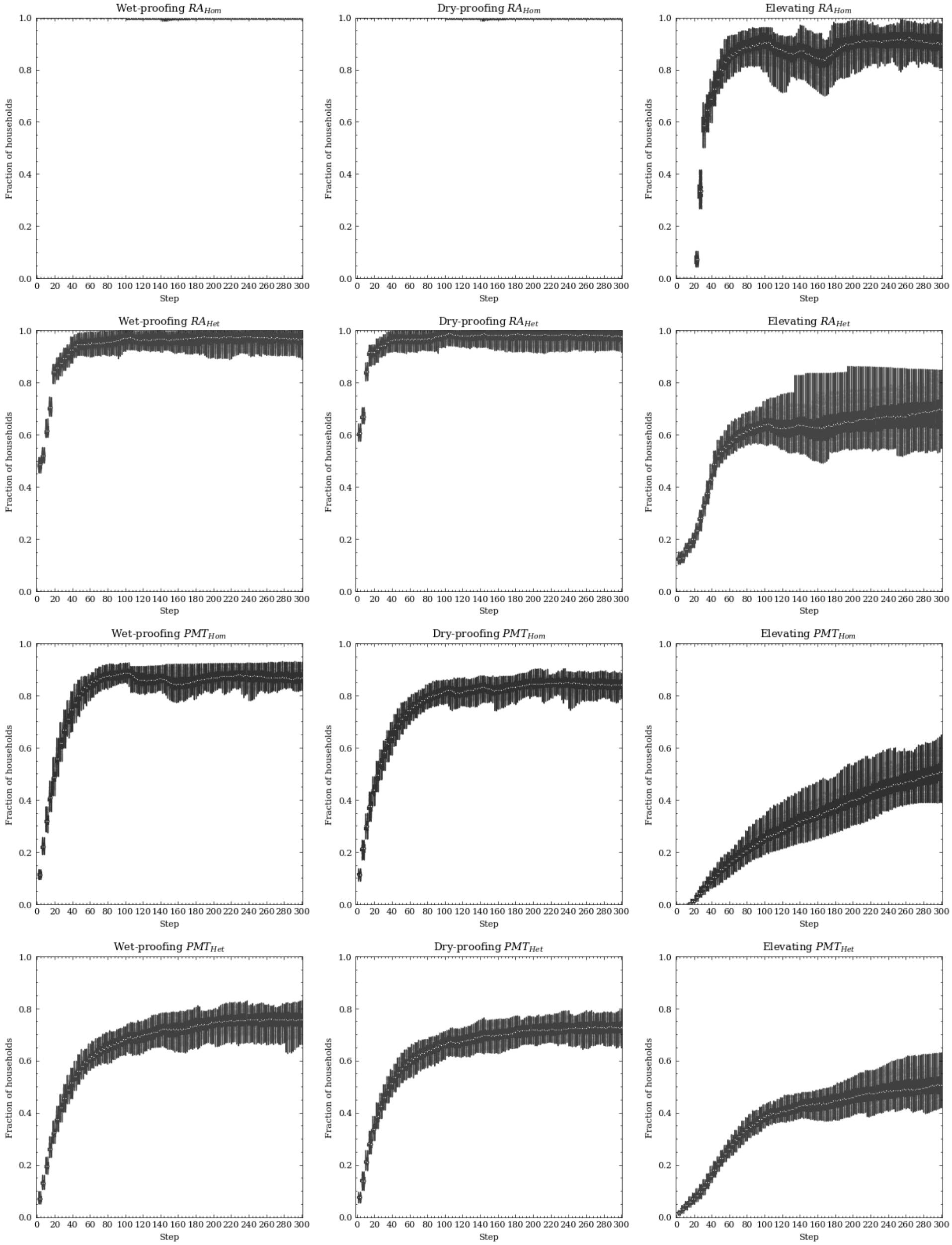

Figure 7.11: Distribution of the Monte Carlo simulation in each time step, for all the protective CCA, for each behavioral scenario.

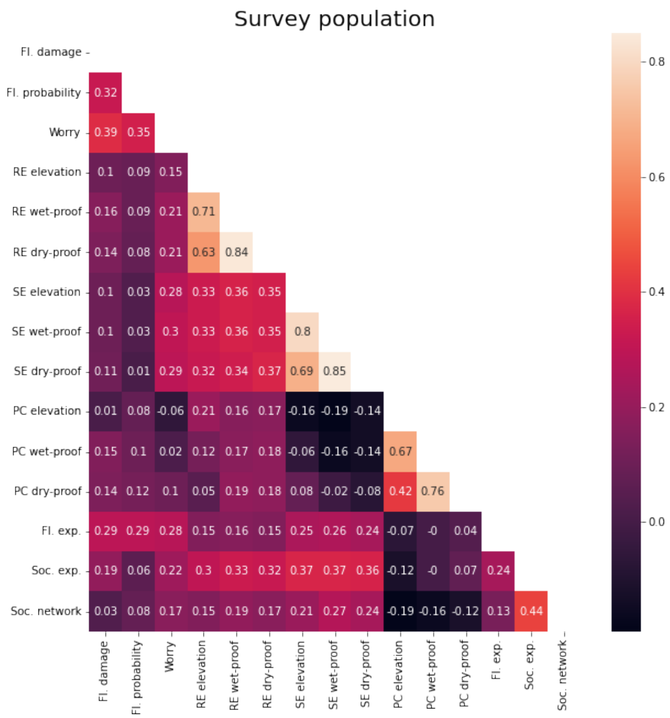

Figure 7.12: Pearson correlation among variables from the survey population.

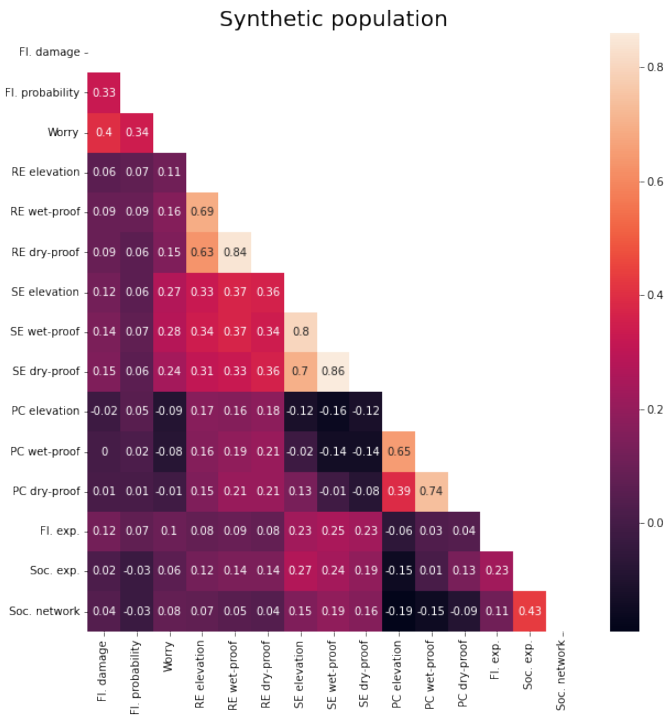

Figure 7.13: Pearson correlation among variables from the synthetic population.

Table 7.5: Mean difference between households survey and synthetic populations.

Variable		Mean difference (Survey - Synthetic)
1. Flood damage		0.00
2. Flood probability		-0.01
3. Worry		0.01
4. Response efficacy		-0.03
	Dry-proof.	-0.01
	Wet-proof.	0.02
	Elevation	-0.03
5. Self efficacy		
	Dry-proof.	0.03
	Wet-proof.	0.03
	Elevation	0.03
6. Perceived cost		
	Dry-proof.	0.01
	Wet-proof	-0.01
	Elevation	-0.02
7. Flood experience		0.01
8. Social expectations		0.04
9. Social network		0.06

Notably, households are embedded into a random network, which takes the form of a dynamic Erdos-Reny random graph Erdős et al. (1960). Each node of the graph contains a household and it has a number of edges that connects it to the initial number (n) of nearest neighbors. At initialization, we set $n = 7$ to align the initial number of household connections in the survey data. However, the number of connections evolves over time in the simulation, for example due to migration. Specifically, when a new household enters the regional economy, the existing network adds a new node and connects it to n existing nodes, which are randomly sampled. Furthermore, when a household leaves the region, its node is removed with all its edges. Hence, together with the network, the number of household connections evolves endogenously and it is contingent on the migration flow.

Climate Change Adaptation actions

We selected seven structural CCA measures from our survey data and grouped them in three categories: *Dry-* and *Wet-proofing*, *Elevation*. Using Florida survey data, we run a Logit regression to estimate the effects of relevant socio-behavioral attributes (Table 7.7). For each category, we estimated cost and protection by averaging past literature from the Global North Kreibich et al. (2015). The related inputs for the current work are summarized in Table 7.6.

Table 7.6: Grouping, costs, and efficacy of structural CCA measures in the CRAB model. Cost and effectiveness are averaged from past literature Kreibich et al. (2015).

Structural CCA measure	Cateogry	Cost	Flood protection
1. Installing anti-backflow valves on pipes 2. Installing a pump and/or one or more system(s) to drain flood water 3. Fixing water barriers (e.g. water-proof basement windows)	Dry-proofing	6,000$	50%
4. Strengthen the housing foundations to withstand water pressures 5. Reconstructing or reinforcing the walls and/or the ground floor with water-resistant materials 6. Raising the electricity meter above the most likely flood level or on an upper floor	Wet-proofing	7,000$	40%
7. Raising the level of the ground floor above the most likely flood level	Elevation	37,000$	100%

Regional economy

We calibrate the CRAB model economy to a stylized agglomerated coastal region, to loosely resemble the greater Miami area, in two ways. First, we employ publicly available flood data to determine 30 years' cumulative flood probability and exposure. In a similar fashion, we use national statistics to determine household expenditure on goods and income as well the relative capital intensity of each economic sector. These parameters are summarized in Table 7.8.

Table 7.8: Empirically funded parameters in the CRAB model regional economy.

Parameter	Value	Source
Fraction of population living in flood-prone areas	40%	Foundation (2020)
Cumulative probability of floods in 30 years (p)	26%	
Intention-behavior gap Φ	0.25	Noll et al. (2022b)
Dry-proofing measure lifetime (η_{Dry})	20	Noll et al. (2022a)
Households expenditure for goods (% of total consumption, k_1)	35%	Garner et al. (2022)
Households expenditure for services (% of total consumption)	65%	
Capital-output ratio consumption-goods firms (Ko_{gd})	0.7	Commission et al. (2019)
Capital-output ratio consumption-services firms (Ko_{serv})	1.3	

Table 7.7: Effect sizes of socio-behavioral factors of households' adaptation to climate-driven floods, estimated using logistic regression from the survey data (N=965).

	Elevation		Wet proof.		Dry proof.	
	Coeff	Std err.		Std err.	Coeff	Std err.
Intercept	-6.95***	1.40	-4.50***	1.13	-5.45***	0.95
Flood damage	0.94***	1.41	0.51**	1.21	0.52**	1.07
Flood probability	-0.17	0.51	-0.51	-0.50	-0.69	0.46
Worry	2.41***	0.43	1.67***	0.38	1.55***	0.35
Flood damage * Worry	-2.32***	0.53	-1.34***	-0.50	-1.16***	0.44
Response efficacy	0.19	0.13	0.27**	0.14	0.02	0.12
Self efficacy	0.69***	0.10	0.68***	0.11	0.69***	0.10
Perceived costs	-0.79***	-0.13	-0.74***	0.16	-0.50***	0.12
Flood experience	0.22	0.29	0.86***	0.29	0.20	0.27
Social expectations	0.57***	0.19	0.45***	0.14	0.53***	0.13
Social network	0.71***	0.21	0.51***	0.19	0.67***	0.17
Social expectations * Social network	-0.18***	0.06	-0.14***	-0.05	-0.14***	0.04
UG Dry-proof.	-0.84**	0.39	0.76*	0.40	\	\
UG Wet-proof.	-1.19***	0.39	\	\	-0.91***	0.35
UG Elevation	\	\	1.75***	0.54	-0.14	-0.38

For the rest, the study follows the established methodologies in computational economics and agent-based modeling. The parameters of the model were adjusted through an indirect calibration approach Fagiolo et al. (2019). A set of relevant empirical features, referred to as economic stylized facts, were selected to be replicated by the model, and the search for parameter values that match these results was carried out. The stability of the selected values was tested in two ways, including the examination of consistency in the surrounding area of the selected point, and the alteration of the seed of the pseudo-random number generator through Monte Carlo simulation. The following economic stylized facts were selected to be represented in the model:

- A pattern of self-sustained growth with persistent fluctuations and an average growth rate of 1% for output.
- An average unemployment rate between 5% and 15%.
- Output that is less volatile than investment and more volatile than consumption.
- An increase in income per capita and a low unemployment rate leading to an inflow of migration.
- An increase in population resulting in an increase in profitability and the number of firms.

It is noteworthy that the increase in people and firms due to favorable economic conditions should imitate the agglomeration process that characterized the original two-region versions of the CRAB model.

The parameters from the indirect calibration approach are summarized in Table A1.

Table 7.9: Past literature and indirect calibration parameters in the CRAB regional economy.

Description	Symbol	Value
Number of firms in capital-good industry	F_1	50
Number of firms in consumption-good industry	F_2	100
Number of firms in consumption-service industry	F_3	150
Number of households	H	3500
R&D investment propensity	ν	0.04
R&D allocation to innovative search	ξ	0.5
Firm search capabilities parameters	$\zeta_{1,2}$	0.3
Beta distribution parameters (innovation process)	(α_1, β_1)	$(2, 4)$
Beta distribution support (innovation process)	$[\underline{x_1}, \overline{x_2}]$	$[-0.05, 0.05]$
Profits to wage ratio	ϵ	2
Consecutive number of periods for new firms creation	ι	6
New-customer sample parameter	γ	0.2
Capital-good firm mark-up rule	μ_1	0.15
Desired inventories	l	0.1
Payback period	b	3
"Physical" scrapping age	η	20
Mark-up coefficient	υ	0.04
Competitiveness weights	$\omega_{1,2}$	1
international transport cost	τ	0.06
Replicator dynamics coefficient	χ	1
Maximum debt/sales ratio	Λ	2
Interest rate	r	0.01
Uniform distribution supports (consumption-good entrant capital)	$[\phi_1, \phi_2]$	$[0.10, 0.90]$
Uniform distribution supports (entrant stock of liquid assets)	$[\phi_3, \phi_4]$	$[0.10, 0.90]$
Beta distribution parameters (capital-good entrants technology)	(α_1, β_2)	$(2, 4)$
Wage setting $\Delta\overline{AB}$ weight	ψ_1	0.2
Wage setting ΔAB_i weight	ψ_2	0.8
Wage setting Δcpi_r weight	ψ_3	0
Wage setting ΔU_r weight	ψ_4	0
Fraction of consumed wage	δ	0.9
Labour search sample parameter	ρ	0.3
Migration income per capita weight	φ	0.5
Tax rate	tr	0.25
Unemployment subsidy rate	σ	0.5
Export demand initial value	Exp	300
Export growth rate	g	0.005

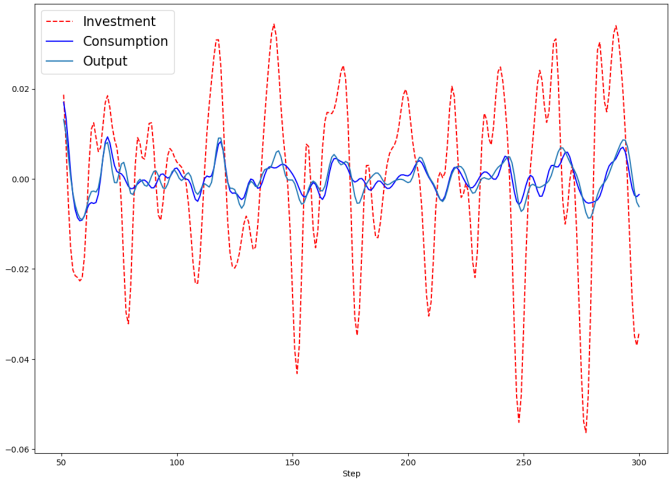

Figure 7.14: bandpass-filtered output, investment, and consumption. Note: results present the behavior of selected bandpass-filtered (6, 32, 12) series for a randomly chosen Monte Carlo run.

7.2.4 Replication of empirical regularities

Once the model was calibrated, the simulation results were evaluated against their ability to replicate both micro- and macro-economic stylized facts from the empirical literature (as presented in Table 7.10). A more comprehensive discussion of the empirical regularities replicated by the CRAB model is described in Taberna et al. (2022), while a more detailed dive in the "K + S" model validation can be found in Dosi et al. (2017a). In particular, Fig. 7.14 illustrates the continuous fluctuations and volatility of output, consumption, and investment, which are well-tuned to real-world data. Fig. 7.15 displays the cross-correlation among the main macro-economic variables, with the results closely resembling empirical data, including pro-cyclical consumption and investment, counter-cyclical unemployment rate, and slightly pro-cyclical inflation and counter-cyclical prices, especially with investments. Regarding micro-economic regularities, not all firms are able to gain market share in the export market, with those that do being, on average, more productive and larger than firms that only sell in the domestic market.

7.2.5 Calculation of sensitivity indices

We causally apportion output uncertainty to uncertain physical (input) factors through the use of Sobol' sensitivity analysis Sobol (2001). This SA method is widely applied to decompose the outcome variance into shares contributed by each uncertain factor, without making assumptions about the model's linearity or interactions. To create our exploratory set of uncertain conditions we use Sobol' sequence sampling, a quasi-random low-discrepancy sequence used to generate uniform samples across the space of uncertain parameters Saltelli (2002). Our parameter ranges are informed by literature estimates and are assumed to be uniformly distributed and independent. The ranges of all parameters are reported in Table 7.11. Sobol' decomposes the variance of a given response variable (in this case, the fraction of households that choose each adaptation measure and the

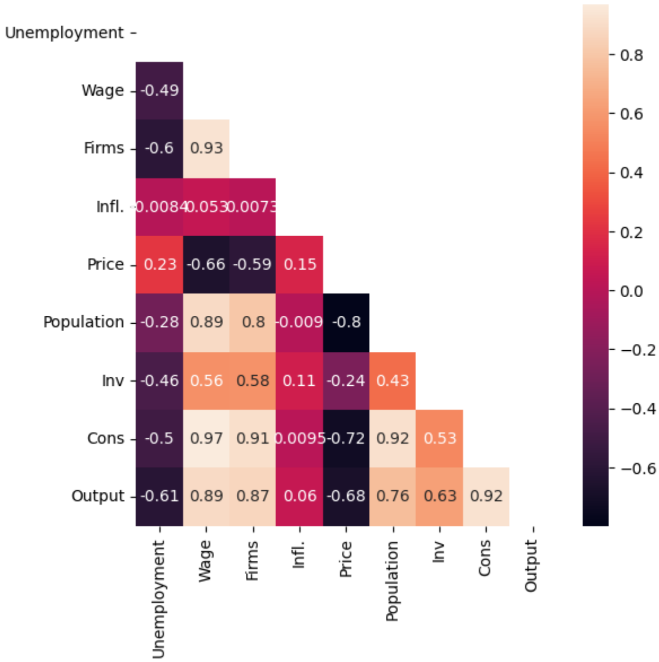

Figure 7.15: Correlation structure emerging from filtered series. Note: Unemployment: unemployment rate; Wage: average wage, Firms: number of firms, Infl: inflation; Prices: consumer price level; Population: number of households, Inv: investments; Cons: consumption; Output: gross domestic product.

Table 7.10: Key economic empirical stylized facts replicated by the model.

Stylized facts (SF)	Empirical studies
Flood related aggregate-level stylized facts	
SF1 Flood decreases economic output	(Amin, 1994; Feldman and Kogler, 2010)
SF2 Flood decreases employment	(Feldman and Kogler, 2010; Thomas, 2005)
SF3 Flood decreases entry of firms	Jia et al. (2022)
SF4 Flood widens economic inequality	Qiang (2019)
Region economy aggregate-level stylized facts	
SF5 Endogenous self-sustained growth with persistent fluctuation	(Kuznets and Murphy, 1966; Stock and Watson, 1999; Zarnowitz, 1984)
SF6 Relative volatility of GDP, consumption, investments	(Napoletano et al., 2004; Stock and Watson, 1999)
SF7 Cross-correlations of macro-variables	(Napoletano et al., 2004; Stock and Watson, 1999)
SF8 Pro-cyclical aggregate R&D investment	(Wälde and Woitek, 2004)
SF9 Persistent unemployment	(Ball, 2009; Blanchard and Wolfers, 2000; Blanchard and Summers, 1986)
Region economy firm-level stylized facts	
SF10 Not all firms export	(Bernard and Durlauf, 1995; Bernard et al., 2011)
SF11 Exporters are more productive and larger than non-exporters	(Bernard and Durlauf, 1995; Bernard et al., 2011)
SF12 Firm (log) size distribution is right-skewed	(Dosi, 2007)
SF13 Productivity heterogeneity across firm	(Bartelsman et al., 2005; Bartelsman and Doms, 2000; Dosi, 2007)
SF14 Persistent productivity differential across firm	(Bartelsman et al., 2005; Bartelsman and Doms, 2000; Dosi, 2007)
SF15 Lumpy investment rates at firm level	(Doms and Dunne, 1998)

Table 7.11: Uncertain factors and sampling ranges

Uncertain factor	Default value	Lower bound	Upper bound
Fraction of exposed households	0.4	0.1	1
Wet proofing effectiveness (%)	40	15	55
Dry proofing effectiveness (%)	50	10	85
Elevation effectiveness (m)	3	1	5

residual damages to households with different levels of adaptive capacity) into the amounts contributed by each of the independent variables (the fraction of population exposed and the effectiveness of each measure), both individually and through their interactions. The method estimates several indices. The first-order Sobol index reflects how much variance in the response variable is attributed to each uncertain factor individually (i.e., ignoring its interactions with the other factors). Higher-order Sobol indices measure the additional variance caused through factor interaction, and the total-order sensitivity index of each factor measures its total effects (individually and through all its interactions). For the results reported we use this total-order index (S_T), defined for each uncertain factor i as:

$$S_{T_i} = 1 - \frac{\mathbb{V}(\mathbb{E}(Y|X_{\sim i}))}{\mathbb{V}(Y)} \tag{7.52}$$

where X is the vector of all sampled values of all uncertain factors, $X_{\sim i}$ denotes all the components of X except for the sampled values of the i-th factor, and Y is a dependent response variable being analyzed Saltelli et al. (2008b). We perform the calculation of total-order sensitivity indices for every timestep of the simulation across all combinations of response variables and behavioral heuristics. This calculation is performed using the Sobol' method implementation in the SALib Python package Herman and Usher (2017).

7.3 Appendix for Chapter 5

The *Climate-economy Regional Agent-Based* (CRAB) model builds upon the evolutionary economic engine of the well-validated "Keynes + Schumpeter" Dosi et al. (2013, 2010) and the "Dystopian Schumpeter meeting Keynes" Lamperti et al. (2019a, 2018) models. The regional economy of the model consists of $F1$ heterogeneous capital-good firms (denoted with the subscript i), $F2$ consumption-good firms (denoted with the subscript j), $F3$ consumption-service firms (denoted with the subscript l) and H households (denoted with the subscript h) supplying work and consuming the income they earn. When a decision process is identical for all firms (e.g. migration), we employ the subscript f. In addition, to generally refer to consumption firms (both service and good), we use the subscript s.

7.3.1 Households

The CRAB model includes behaviorally rich and heterogenous household agents, whose attributes are summarized in Table 7.3. Notably, households are embedded into a random network, which takes the form of a dynamic Erdos-Reny random graph Erdős et al. (1960). Each node of the graph contains a household and it has a number of edges that connects it to the initial number (n) of nearest neighbors. At initialization, we set $n = 7$ to align the initial number of household connections in the survey data (see Table 7.3). However, the number of connections evolves over time in the simulation, for example due to migration. Specifically, when a new household enters the regional economy, the existing network adds a new node and connects it to n existing nodes, which are randomly sampled. Furthermore, when a household leaves the region, its node is removed with all its edges. Hence, together with the network, the number of household connections evolves endogenously and it is contingent on the migration flow.

Migration

The migration flow of households depends on the regional economic performance. Empirical evidence shows that expected income and employment opportunities are the main factors driving inter-regional household migration Kennan and Walker (2011). Hence, we use these two factors in regulating the inflow and outflow of households (b^h) at time t in the region:

$$b^h(t) = H(t)[(1-o)IA(t) + o\pi(t)], \quad with \begin{cases} b \leq 0 & \text{if } U(t) < U_{max}(t) \\ b \geq 0 & \text{if } U(t) > U_{min}(t) \end{cases} \tag{7.53}$$

where $H(t)$ is the existing number of incumbents households, $IA(t)$ is the "income attractiveness" of the region, $0 \leq o \leq 1$ is a mix balance parameter, and $\pi(t)$ is a random draw from a uniform distribution on the fixed support $[\underline{x_2}, \overline{x_2}]$. $U_{[min,max]}$ are the minimum and maximum unemployment rates that make people come and leave, respectively. The number of entrants stochastically depends on the number of incumbents (recalling a spin-off process of the former from the latter), with the income conditions influencing the decision of potential entrants Dosi et al. (2019). The "income attractiveness" $IA(t)$ is defined as:

$$IA(t) = Ipc(t) - Ipc(t-1), \text{ bounded to } [\underline{x_2}, \overline{x_2}], \tag{7.54}$$

with Ipc at time t is given by the sum of all individual income In_h (defined below see Eq.7.65) and wealth, divided by households population as:

$$Ipc(t) = log(\sum_{h=1}^{H} In_h(t) + \sum_{h=1}^{H} W_h(t)) - logH(t) \tag{7.55}$$

Where $W_h(t)$ is the value of household h property (for its evolution, see Eq.7.57) at the net of monetary damages (D_h, for more information about damages calculation see Eq.7.58) to be repaired at time t:

$$W_h(t) = Hv_h(t) - D_h(t) \tag{7.56}$$

If positive ($b > 0$), new households are added, sampled randomly from the synthetic population pool (for more information about the creation of the synthetic population, see Subsection "Model calibration"). If negative ($b < 0$), random households are selected and removed from the simulation.

Damages and adaptation

We assume that every household resident in the region owns a property, whose value (Hv_h) is indexed to average regional salaries[6]:

$$Hv_h(t) = Hv_h(t-1)\frac{\overline{W}(t) - \overline{W}(t-1)}{\overline{W}(t-1)}, \tag{7.57}$$

with $\overline{W}$ being the average salary of the regional economy.

Importantly, household properties can be damaged by flooding. Flood property damages ($D(t)$) at time t are calculated by multiplying household h damage coefficient (Dc_h) by its house value:

$$D_h(t) = Hv_h(t) * Dc_h(t). \tag{7.58}$$

The damage coefficient ($Dc \in [0,1]$) is obtained from overlying flood depth hitting the property (for more information about the distribution of flood depths, see Subsection "Floods") as a function of the specific residential depth-damage curve Lechner (2022). Notably, households can decrease their damage coefficient by undertaking adaptation measures to their property. Our survey elicits households' intentions to invest in 7 structural CCA measures, which we group into three classes here: *Dry-proofing*, *Wet-proofing*, *Elevation* Kreibich et al. (2015); Noll et al. (2022a). The data on the effectiveness of these various CCA is scattered, so here we take average values previously employed in the literature. The *Dry-proofing* and *Wet-proofing* measures decrease households damage coefficient Dc with a fixed amount $\alpha_{Dry,Wet}$, while *Elevation* diminishes flood depth (d) of α_{Elev}:

$$Dc_h(t) = (1 - \alpha_{Dry} - \alpha_{Wet})f(d - \alpha_{Elev})(t), \quad with \quad \begin{cases} 0 < \alpha_{Dry,Wet} < 1 & \text{if Dry, Wet is implemented} \\ \alpha_{Dry} = 0 & \text{if d > fe} \\ \alpha_{Elev} > 0 & \text{if Elev is implement} \\ \alpha_{Dry,Wet,Elev} = 0, & \text{if measure is not implemented} \end{cases}, \tag{7.59}$$

With fe being the maximum flood height that *Dry-proofing* measures can stand (i.e. not over-topping flood barriers, for an overview of the relevant parameters for the protective measures see Table 7.15).

Households are boundedly-rational and employ an extended version of Protection Motivation Theory (PMT) Rogers (1975) to decide upon protective actions. PMT is currently the most widely used psychological theory to study individual CCA decisions. Here we employ its extended version where an individual intention to take CCA actions is driven by own threat appraisal (perceived probability; perceived damage; worry) and coping appraisal (response-efficacy; self-efficacy; perceived costs) as well as the influence of social norms, previous experience with floods and with CCA Noll et al. (2022b). Each time step in CRAB, households at risk of flooding calculate the adaptation *intention* probability $p^{int}_{cca_m} \in [0,1]$ for each *cca* measure (m) by multiplying individual behavioral attributes at time t by their effect size, obtained from a Logit regression (for a detailed description of behavioral attributes see Table 7.13, while for effect sizes see Table 7.14).

$$p^{int}_{cca_m,h}(t) = \frac{1}{1 + e^{\beta_0 + \sum_{a=1}^{15} \beta_a X_a(t)}} \tag{7.60}$$

[6]The assumption is reasonable as wage levels are strongly correlated with house price Davidoff (2006).

Here, β_a and $X_a(t)$ are the effect sizes and attributes, respectively. Notably, some attributes change over time. When contemplating any specific action cca_m from $cca = \{Dry, Wet, Elev\}$, the historical adaptation measures for all other actions are represented by:

$$UG_n = \begin{cases} 1 & \text{if } cca_n \text{ adaptation measure undertaken previously, } n \neq m \\ 0 & \text{otherwise} \end{cases} \tag{7.61}$$

for all n in CCA where $n \neq m$. This denotes whether household h has implemented other measures in the past while considering a particular measure cca_m. The overall regional adaptation level affects households through social interaction, with *Soc. network* that evolves endogenously as:

$$Soc.\ network_{cca_m,h}(t) = \sum_{h=0}^{H^{net,h}_{cca_m}} 1, \tag{7.62}$$

with $H^{net,h}_{cca_m}$ being the set of households connected to household h and that have already implemented the cca under consideration.

Empirical evidence shows that there is a consistent gap between intentions and the actual behavior Noll et al. (2022a). Hence, relying on this empirical data, in CRAB we assume that the probability to act p^{act} at time t as:

$$p^{act}_{cca_m,h}(t) = \Phi p^{int}_{cca_m,h}(t), \tag{7.63}$$

with $\Phi < 1$ that reflects the degree of the intention-behavior gap.

Finally, households with $p^{act}_{cca_m} > 0$ draws from a Bernoulli distribution - in the similar fashion as for migration and technological learning (see Subsection "Migration" and Subsection "Capital-good sector and technological learning") - to determine whether adaptation occurs:

$$\theta^{cca_m}_h(t) = p^{act}_{cca_m,h}(t), \quad with \quad p^{act}_{cca_m,h}(t) \in (0,1). \tag{7.64}$$

If the draw is successful, the household starts to save a fraction of its personal income until she can cover the implementation cost ($cost_{cca_m}$).

Households get their income (In_h) from labor when employed, while unemployed households get a subsidy from the government (w^u):

$$In_h(t) = \begin{cases} w_h(t), & \text{if employed} \\ w^u(t), & \text{if unemployed} \end{cases}. \tag{7.65}$$

Each time step, unemployed households sort in ascending order by their education level, visit the labor market, and select a sub-sample of available vacancies (if any), choosing the one with the highest wage (for more information about the labor market, see Subsection "Labor"). Having priority in the queue, more educated households are more likely to get better-paid job opportunities than their less-educated peers. Households consume all their income unless two conditions happen, namely, they want to implement protective CCA actions to their house, or they have to undertake repair damages due to floods. When these conditions happen, we assume households want to minimize the time to acquire the necessary resource and save all their extra income above the unemployment subsidy (which we assume is the minimum to satisfy basic needs). Thus, household consumption (c_h) at time (t) is:

$$c_h(t) = In_h(t) - Sav_h(t), \tag{7.66}$$

where $Sav(t)$ are the savings of household h at time t and are defined as:

$$Sav_h(t) = \begin{cases} In_h(t) - w^u(t), & \text{if } D_h(t) > 0 \quad or \quad cost_{cca_m}(t) > 0 \\ 0, \text{otherwise} \end{cases}, \tag{7.67}$$

Each time step, savings go first into residual damages to be repaired, which hence decrease over time accordingly to:

$$D_h(t) = D_h(t-1) - Sav_h(t). \tag{7.68}$$

Alternatively, households without without damages to be repaired ($D(t) = 0$) and with a planned *cca* measure, will gradually cover its cost:

$$cost_{h,cca_m}(t) = cost_{h,cca_m}(t-1) - Sav_h(t). \tag{7.69}$$

Once the cost are fully covered ($cost_{h,cca_m} = 0$) the household undertakes the chosen action. Adaptation actions are active since the following step and are permanent, except *dry-profing* that expires after $\eta_{dry} > 0$ years Du et al. (2020).

In addition to protective CCA actions to their properties, households can also buy insurance, which upon the payment of an annual premium, refunds to the households the damages experience (or part of it, for more detail about the insurance market, see Subsection “Insurance”).

7.3.2 Firms

An important novelty in this version of the CRAB model is that all the sectors combine labor and capital with constant returns to scale to produce a homogeneous product. On the one hand, capital-good firms employ capital and labor to produce capital goods (machines) sold to other firms and invest in R&D to discover more productive technologies. On the other hand, service- and good- produce a consumption product sold to households. Hence, all the firms operate on the capital, labor, and goods/service markets which are characterized by imperfect information. The number of firms is variable and depends on two independent entry and exit processes. Firm might be expiosed to flood and can buy insurance to protect themselves.

Capital-good sector and technological learning

The technology of each capital-firm i is captured by two labor productivity coefficients, A_i^T, and B_i^T. The former coefficient indicates the productivity of the machines that are produced by the firm i and sold to other firms, while the latter stands for the productivity of the firms itself, and it depends on a heterogenous vintage of machines bought from other capital-good firms[7] (for more information about the capital market, see Subsection “Capital”).

[7]We assume that capital-good firms cannot self-produce the capital they need for themselves, but they need to order it from other capital-good firms.

Capital-good firms determine their price p_i applying a fixed markup ($\mu_1 > 0$) to their unit cost c_i[8]:

$$p_i(t) = (1+\mu_1)c_i(t). \tag{7.70}$$

The unit cost c_i is the ratio between individual nominal wage w_i and its productivity coefficient:

$$c_i(t) = \frac{w_i(t)}{B_i^T}. \tag{7.71}$$

Capital firms aim to improve the productivity of the machines they sell (A^T) via technological learning. To do so, they actively invest in R&D a fraction ν_1 of their past sales:

$$R\&D_i(t) = \nu_1 S_i(t-1) \quad with \quad 0 < \nu_1 < 1. \tag{7.72}$$

Furthermore, firms split their R&D between innovation (IN) and imitation (IM) according to the parameter $\xi \in [0,1]$. Both innovation and imitation are modeled by employing a two-step procedure. In both cases, the first step determines whether innovation or imitation is successful through a draw from a Bernoulli distribution:

$$\theta_i^{in}(t) = 1 - e^{-\zeta_1 IN_i}(t), \tag{7.73}$$

$$\theta_i^{im}(t) = 1 - e^{-\zeta_2 IM_i}(t), \tag{7.74}$$

where $0 \leq \zeta_{1,2} \leq 1$ capture the *search capabilities* of firms. The probability of a positive outcome depends on the amount of resources invested.

Successful firms proceed to the second step. If the innovation draw (Eq.7.4) is successful, the firm discovers a new technology, (A_i^{in}), according to:

$$A_i^{in}(t) = A_i(t)(1 + x_i^A(t)), \tag{7.75}$$

where $x^A(t)$ is an independent draw form a $Beta(\alpha_1, \beta_1)$, over the support $[\underline{x_1}, \overline{x_2}]$, with $\underline{x_1} \in [-1,0]$ and $\overline{x_2} \in [0,1]$. The supports of the Beta distribution determine the probability of 'successful' over 'failed' innovations, and hence shape the landscape of *technological opportunities*.

Furthermore, firms passing the imitation draw (Eq.7.5) get access to the technology of one competitor (A_i^{im}). Notably, firms are more likely to imitate competitors with similar technology, and we calculate the technological distance between every pair of firms using a Euclidean metric.

Once both processes are completed, all the firms succeeding in either imitation or innovation select the most efficient production technique they can master according to the following payback period rule (see Subsection "Firms in the consumption-good and consumption-service sectors"):

$$min[p_i^h(t) + bc_{A_i(t)}^h] \quad h = T, in, im \tag{7.76}$$

where b is a positive payback period parameter (see Eq.7.11).

[8]Survey data evidence show that European firms mostly set prices according to mark-up rules Fabiani et al. (2006).

Firms in the consumption-good and consumption-service sectors

"Firms in the consumption-good and consumption-service sectors"

Each consumption firm is characterized by heterogenous vintages of capital-goods with different average productivity (A_s), for more information about the capital market see Subsection "Capital", which reflects in its unit cost of production (c_s):

$$c_s(t) = \frac{w_s(t)}{A_s}, \tag{7.77}$$

where w_s is the average wage paid by firm j. The prices in the consumption-good sector are computed applying a *mark-up* ($\mu_{2,s}$) on unit cost:

$$p_s(t) = (1 + \mu_{2,s})c_s(t). \tag{7.78}$$

The evolution of firm's market share (f_s), determines the variation of its markup ($\mu_{2,s}$):

$$\mu_{2,s}(t) = \mu_{2,s}(t-1)(1 + \nu \frac{f_s(t-1) - f_s(t-2)}{f_s(t-2)}) \quad with \quad 0 \leq \nu \leq 1. \tag{7.79}$$

The profits of consumption firms are given by:

$$\Pi_s(t) = (S_s(t) - c_s(j)Q_s(t) - rDeb_s(t), \tag{7.80}$$

where $S_s(t)$ are the sales of the firm, Q_s is the quantity produced, Deb is the stock of debt and r is the interest rate. Finally, firm liquid assets $NW_s(t)$ are updated according to:

$$NW_s(t) = NW_s(t-1) + \Pi_s(t) - cI_s(t) - cP_s(t), \tag{7.81}$$

where cI_s and cP_s are the investment and insurance premium costs, respectively.

Flood shock

Firms operating in the regional economy are exposed to flood shocks with different severity and probability (for more information about flood modelling in the CRAB model, see Subsection "Floods"). When a flood does happen, as households, firms calculate their damage coefficient (Dc) overlying flood depth and class-specific depth-damage curve. In this case, we employ the damage coefficients relative to commercial building contents as the main goal of this paper is to analyze the impact of floods on production factors (i.e. destruction of machineries) and inventories. Thus, for firms, we omit the direct damages to buildings. Specifically, floods affect firms via multiple channels:

- A *productivity* shock, which decreases firms' labour productivity for one period: $AB_f(t) = AB_f(t-1)(1 - Dc_f(t))$.
- A *capital stock* shock that destroys a fraction $Dc_f(t)$ of the stock of machines employ by firms.
- An *inventories* shocks that causes a permanent destruction of a fraction of the inventories i.e. $INV_f(t) = INV_f(t-1)(1 - Dc_f(t))$.

7.3.3 Markets

In the CRAB model, there are four markets namely Capital, Labor, Consumption, and Insurance. The Consumption and Labor markets are the same as the previous version of the model (see 7.2.1 7.2.1 for more information). The markets evolve endogenously, shaped by interactions among economic agents and act as formal socio-economic institutional framework.

Capital

The capital-good market is characterized by imperfect information Phelps and Winter (1982). After updating the productivity coefficient of the machines they are selling (A^T, see Eq.7.76) capital-good firms send a "brochure" containing the price and productivity of their machines to a random sample of potential new clients (NC_i) as well as its historical customers (HC_i).

All the firms employ adaptive demand expectations ($D_f^e = f[D_f(t-1), D_f(t-2), ..., D_f(t-h)]$), desired inventories ($N_f^d$), and the actual stock of inventories (N_f) form the desired level of production (either if it is machined for capital-firms of consumption product for good- and service- sectors):

$$Q_f^d(t) = D_f^e(t) + N_f^d - N_f(t). \tag{7.82}$$

The latter is constrained by firms' capital stock K_f, with the desired capital stock K_s^d required to produce Q_s^d. Notably, all the three sectors have different capital-output ratios, Ko_{f1}, Ko_{f2}, and Ko_{f3} mimicking the different degrees of capital intensity required to produce goods vs. services. In case $K_f^d(t) > K_f(t)$, the firm calls for a desired expansionary investment such that:

$$EI_f^d(t) = K_f^d(t) - K_f(t). \tag{7.83}$$

Furthermore, firms undertake replacement investment RI, scrapping machines with an age above $\eta > 0$ and those that satisfy the *payback rule* outlined in Subsection 7.1.1 (Eq. 7.11).

Insurance

In this version of the model, the insurance market is a sub-category of the service market (being one of the industry included in the macro sector of services, to see how this is managed at macro level see subsection "Consumption, taxes, and public expenditures"). During each time step, the market unfolds as follows:

- A central insurer calculated the expected annual damages (EAD) for all the agents exposed to floods:

$$EAD_a(t) = \int_{p_i}^{p_I} p_i D_{i,a}(t) dp \text{ with } D_i = \begin{cases} Hv_a(t) Dc_a(t) \text{ if } a = h \\ (\Xi_a(t)\overline{p_{f1}} + INV_a(t) p_a(t)) Dc_a(t) \text{ if } a = f \end{cases}, \tag{7.84}$$

  where p_i is the probability of flood event i and p_I is the set of events whose probability is refunded by insurance. Note that the insurance has an entry point p_{max} and an exit point p_{min}, meaning that the damages from floods with $p_i \geq p_{max}$ and $p_i \leq p_{min}$ are not covered by insurance. $D_{i,a}$ is the damages that the flood i causes, which, for households, depends on house value, see Eq.7.58. Whereas the damages to firms are calculated by multiplying the fraction of whole capital stock (Ξ) and inventories (Inv) that would be destroyed by the flood (according to damage coefficient Dc) by their current market prices. Note that for inventories we use the price of the affected firm, p_a, while for machineries we use the average market price in the capital sector, $\overline{p_{f1}}$, at time t.

- The insurer determines the market price of insurance cost (cP) for agent a at time t by adding a fixed markup to EAD:

$$cP_a(t) = EAD_a(t)(1+\delta), \tag{7.85}$$

with $\delta > 0$.

- All agents are assumed to be risk-averse. Hence, they will subscribe to the insurance if they have the resources. This assumption is justified by empirical evidence indicating heightened risk aversion following natural disasters, particularly at a localized level Bourdeau-Brien and Kryzanowski (2020).

7.3.4 Consumption, taxes, and public expenditures

A region is regulated by a government agent that taxes the profits of firms and income of households at fixed rates and pays subsidies (w^u) to unemployed households. The latter is a fraction of the regional average wage:

$$w^u(t) = \sigma \overline{W}(t), \quad with \quad \sigma \in [0,1], \tag{7.86}$$

with $\sigma \in [0,1]$. Workers spend a fraction of their income if employed, hence aggregate regional consumption (C) is equal to the sum of individual consumption:

$$C(t) = \sum_{h=1}^{H} c_h(t), \tag{7.87}$$

Consumption if further divided between goods (C^{gd}) and services (C^{serv}):

$$C^{gd}(t) = \kappa_1 C(t) + \sum_{h}^{H} cost_{h,cca}(t) + \sum_{h}^{H} cost_{h,repair}(t), \tag{7.88}$$

With $\kappa \in [0,1]$ being the fraction of good-consumption. In addtion, $\sum_h^H cost_{h,cca}$ and $\sum_h^H cost_{h,repair}$ are the sum of all the money spend in structural adaptation and repair at time t, respectively (being the construction sector a sub-category of the macro goods sector). Furthermore, the aggregate demand for services is:

$$C^{serv}(t) = C(t) - C^{gd}(t) + \sum_{a}^{A} cP_a(t) - \sum_{a}^{H} cC_a(t), \tag{7.89}$$

with $\sum_a^A cP_a(t)$ being the revenues from insurance premiums (for more detail see Subsection "Insurance") and $\sum_a^H cC_a(t)$ all the claims to refund if a flood happened at time step t.

The model respects the national account identity:

$$\sum_{i=1}^{F1} Q_i(t) + \sum_{j=1}^{F2} Q_j(t) + \sum_{l=1}^{F3} Q_l(t) = Y(t) = C(t) + I(t) + \Delta N(t) + EXP(t) - IMP(t). \tag{7.90}$$

Since there are no intermediate goods and no imports, the sum of values added to both production sectors (Y), equals their aggregate production, which respectively matches the sum of aggregate consumption (C), investment (I), exports (EXP), imports (IMP) and variations of inventories (ΔN).

Export demand exogenously evolves at a fixed rate α_{exp}

$$Exp(t) = Exp(t-1)(1+g), \quad g > 0. \tag{7.91}$$

As internal demand, also export is divided between goods (Exp^{gd}) and services (Exp^{serv}):

$$Exp^{gd}(t) = \kappa_2 Exp(t), \tag{7.92}$$

and $Exp^{serv} = Exp(t) - Exp^{gd}(t)$

7.3.5 Model calibration

Floods

CRAB models how agglomeration and economic development evolves in the presence of climate-driven hazards. Here we employ the CRAB model to contextualize the impact of SLR on flood hazards for Shanghai, one of the most exposed delta megacities. To map the flood exposure of our agents, we combine flood maps of the Shanghai metropolitan area and OpenStreetMap (OSM) residential building data in a two-step procedure Lechner (2022).

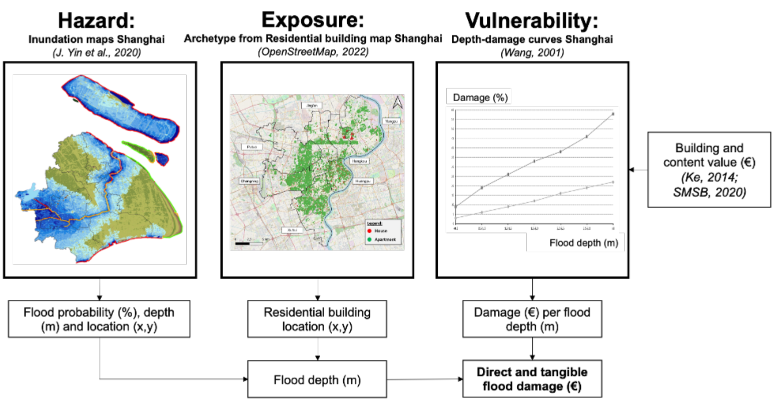

Figure 7.16: Data for flood risk assessment, re-elaboration from Lechner (2022).

First, we create a set of possible locations and related flood depths. The latter includes the 33,374 buildings of the Huangpu, Changning, Yangpu, Xuhui, Jing'an, and Hongkou

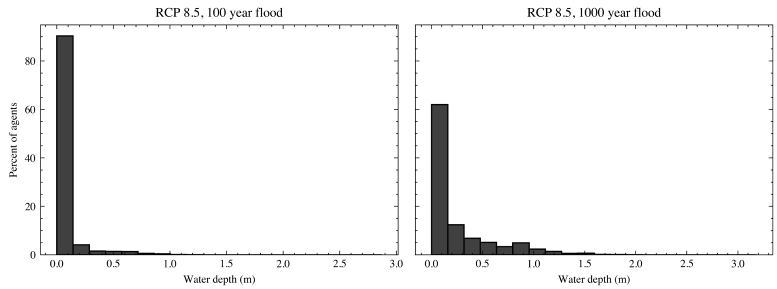

Figure 7.17: Snapshot of the 100y flood-depth distribution in 2050 in the simulated region. Synthetic flood distribution is generated from Yin et al. (2020).

districts which are around 50% of total residential buildings in OSMs Shanghai. For an example of the resulting synthetic flood distribution see Figure 7.17. We use the following districts because they provide an accurate representative of survey respondents[9]. Secondly, when an agent is created is randomly assigned to one of these buildings[10]. Notably, following Yin et al. (2020), each building has 18 possible flood depths attached to it, which are the ones of three return periods (10y, 100y and 1,000y) for three time periods (> 2030, $2030 - 2050$, $2050 - 2100$) mapping the worsening of climate conditions and SLRs under two possible scenarios (RCP 2.6 and 8.5) ($3 * 3 * 2 = 18$). As a result, when a flood happens, each agent can determine the water level hitting his location depending on the severity of the floods, the time step of the model and the climate change mitigation scenario assumed for that specific model run. Notably, for comparative purposes, we set two fixed floods with a pre-determined return period of $1,000y$ return at $t = 2050$ and $100y$ return at $t = 2060$, conversely $10y$ floods happen stochastically (with an average probability of 1 in 40 steps, i.e. 10 years of model simulation).

Survey methodology

Table 7.12 compares the two "background" socio-economic variables included in the analysis and age. In general, the survey sample is representative of the population. In China many elderly people live with their children or younger family members. As our objective is to study adaptation at the household level, and only one member per household was allowed access to our survey, the lack of older respondents from this country was anticipated, and we do not regard it as problematic for our analysis. In addition, respondents in our sample are more educated than the general population. Importantly, Education is not correlated with any of the other households attributes (see Figure 7.19). Hence, we calibrate our initial population with the education census data.

[9]These districts are mainly located in the city center of Shanghai which is more exposed to flooding than the rest of the city. However, the data do not include rural and peri-urban areas of the region, which are the most exposed to sea level rise and exacerbating hazards Yin et al. (2020). Hence, we can expect our model to provide an average flood depth that is higher than the city of Shanghai but lower than the surrounding region. Overall, we believe it does not represent a problem with our work as we aim to infer general results for an archetype of a fast-growing economy highly exposed to flood and sea level rise, rather than deriving conclusions from an empirical case study.

[10]Due to limit in data availability, residential building are also assigned to firms.

Table 7.12: Comparison of socio-economic variables between Census and survey data.

Survey (n = 731)			Census	
Variable	*Cat.*	Values	*Cat.*	Values
Gender	Male	52%	Male	50%
	Female	48%	Female	50%
Age	16-24	19%	$\leq$ 17	12%
	25-34	50%	18-34	16.%
	35-44	23%	35-59	37%
	45-54	2%	60+	35%
	55-64	2%		
	65+	1%		
Education	$\leq$ High School	0.4%	$\leq$ High School	47%
	High School	2%	High School	19%
	College degree	69%	College	34%
	Post Graduate	29%		

Given the diminished significance of risk-reducing measures for participants residing in high-rise apartment buildings, we took an additional step to specifically assess the adaptation tendencies of households located on the ground floor ($n = 141$). It's worth highlighting that since our model simulates the first flood occurrence after a span of 50 years (equivalent to 200 time steps), there is no discernible variation in the adoption of wet- and dry-proofing measures (Figure 7.17.b and 7.17.c). Nevertheless, based on our projections, there's an anticipated 10% surge in the number of agents affected who might contemplate elevating their dwellings (Figure 7.17.a). However, high-rise structures aren't necessarily exempt from flood threats. Often, essential infrastructures like boilers, elevators, generators, and water pumps are situated underground in such buildings, making them vulnerable during flood events. Safeguarding these systems is paramount to avert significant damages and disruptions. Moreover, when considering the elevation of a multi-story edifice, the decision typically rests with the building proprietor or the property management team, not exclusively with the residents of the ground floor. In light of these considerations, and given that our complete survey data offers a six-fold increase in data points, we opted to utilize the full dataset. We believe this offers a more nuanced and authentic portrayal of household adaptation responses.

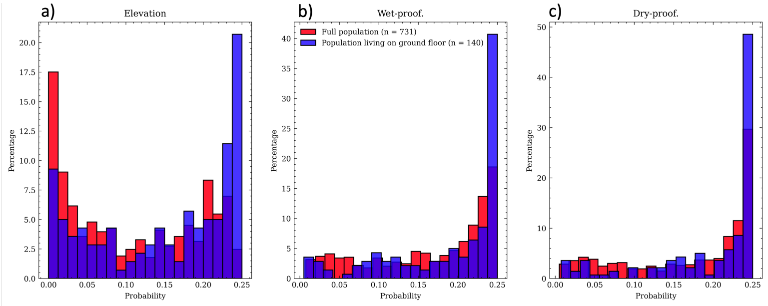

Figure 7.18: Probability distribution of agents living on the ground floor against the whole population.

Table 7.14: Effect sizes of socio-behavioral factors of households' adaptation to climate-driven floods, estimated using logistic regression from the survey data (N=731)

	Elevation (Pseudo R-squared = 0.39)		Wet-proof. (Pseudo R-squared = 0.43)		Dry-proof. (Pseudo R-squared = 0.41)	
	Coeff	Std err.	Coeff	Std err.	Coeff	Std err.
Intercept	-3.96***	0.94	-3.71***	0.97	-7.03***	1.05
Flood damage	0.564***	1.21	0.208*	0.55	0.50**	1.07
Flood probability	0.29	0.70	0.33	0.77	-0.18	0.70
Worry	1.41***	0.37	0.50***	0.12	1.46***	0.42
Flood damage * Worry	-1.54***	0.56	\	\	-1.42***	0.57
Response efficacy	0.15	0.10	0.14**	0.13	0.16	0.13
Self efficacy	0.64***	0.09	0.83***	0.11	0.93***	0.11
Perceived costs	-0.83***	0.11	-0.44***	0.14	0.09	0.60
Flood experience	0.47**	0.26	0.27	0.27	0.41	0.37
Social expectations	0.57***	0.12	0.45***	0.11	0.54***	0.12
Social network	0.26***	0.06	0.37***	0.07	0.55***	0.08
UG Dry-proof.	-0.74**	0.39	-0.74	0.50	\	\
UG Wet-proof.	-0.91**	0.39	\	\	-0.28	0.41
UG Elevation	\	\	-1.67***	0.46	-1.42***	0.54

Households

We utilized the comprehensive behavioral and socio-economic survey data from the municipality of Shanghai ($n = 731$) Noll et al. (2022b)[11] to formulate a synthetic population of households. To construct a set of agents that reflects the diversity in socio-economic and behavioral characteristics found in the survey, we adopted the same algorithm employed in the previous chapter to sample individual attributes from the empirical data. Table 7.13 provides summary statistics for both socio-economic and behavioral attributes.

The cross-correlation among variables and mean difference have been used to evaluate criteria between the populations, which are summarized in Fig. 7.19-7.20.

Climate Change Adaptation actions

We selected seven structural CCA measures from our survey data and grouped them in three categories: *Dry-* and *Wet-proofing*, *Elevation*. For each category, we estimated cost

[11]The reference pertains to the utilization of the same dataset, rather than the specific statistical method used.

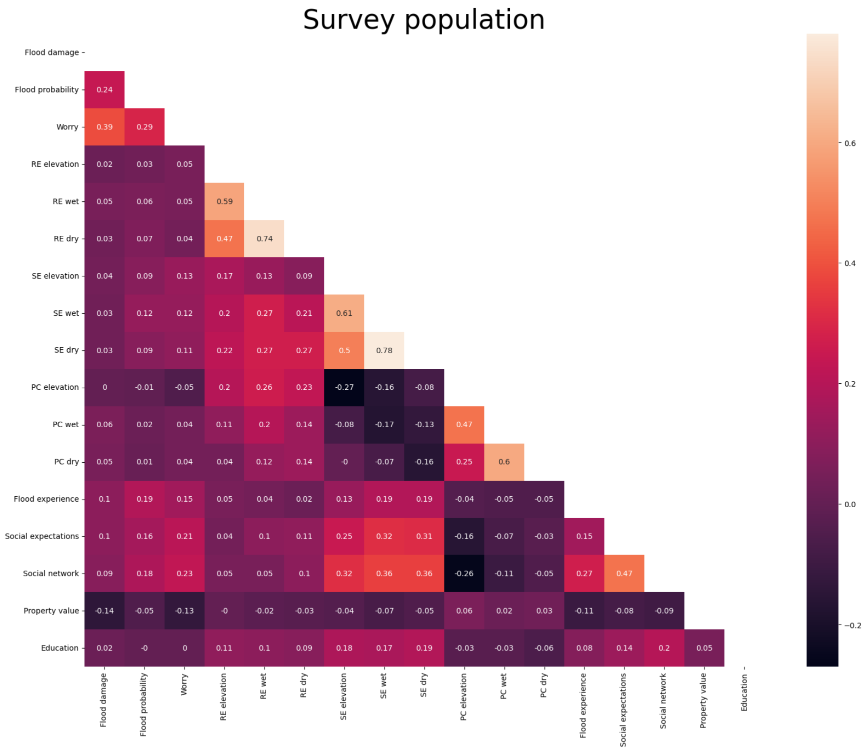

Figure 7.19: Pearson correlation among variables from the survey population.

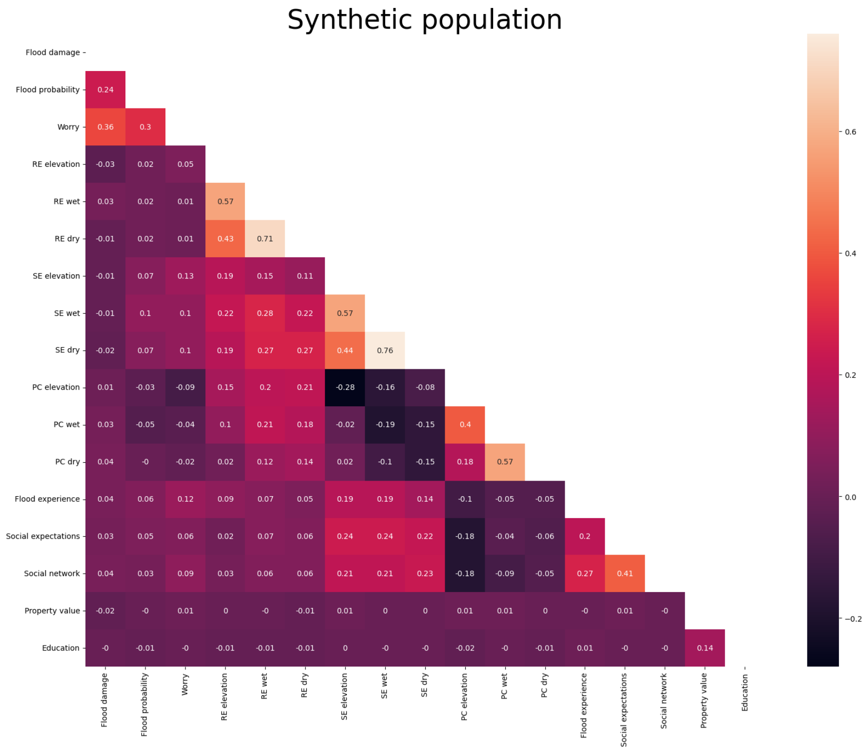

Figure 7.20: Pearson correlation among variables from the synthetic population.

Table 7.13: Socio-behavioral factors of private adaptation intentions. Source: 2020 households' survey in Shanghai, China (N= 731).Noll et al. (2022b)

Attribute		Mean (std. dev)	Question	Scale
Flood probability		0.12 (0.15)	Imagine you stay in your house for the next 30 years what is the likelihood you believe your household will experience a flood?	0-100%
Worry		2.04 (0.98)	How worried or not are you about the potential	
impact of flooding on your home?	From 1 (not at all severe) to 5 (very severe)			
Response efficacy			How effective do you believe that implementing this measure would be in reducing the risk of flood damage to your home and possessions?	From 1 (extremely ineffective) to 5 (extremely effective)
	Dry-proof.	3.48 (0.89)		
	Wet-proof.	3.44 (0.88)		
	Elevation	3.15 (1.11)		
Self efficacy			Do you have the ability to undertake this measure either yourself or paying a professional to do so?	From 1 (I am unable) to 5 (I am very able)
	Dry-proof.	2.50 (1.16)		
	Wet-proof.	2.49 (1.12)		
	Elevation	2.00 (1.17)		
Perceived costs			When you think in terms of your income and your other expenses, do you believe that implementing (or paying someone to implement) this measure, would be cheap or expensive?	From 1 (very cheap) to 5 (very expensive)
	Dry-proo	3.23 (0.81)		
	Wet proof.	3.35 (0.75)		
	Elevation	3.80 (1.08)		
Flood experience		0.16 (0.3)	Have you ever personally experienced a flood of any kind?	0 - No 1 - Yes
Social expectations (Injunctive social norm)		1.67(1.89)	Do your family, friends and/or social network expect you to prepare your household for flooding?	From 1 (do not expect) to 5 (strongly except)
Social network (Descriptive social norm)		1.69 (1.89)	Thinking about your friends, families, and neighbours, how many households have taken some adaptation action towards flooding?	0-8
Undegone (UG) measure			Please indicate if you have already implemented any of these structural measures or if you intend to do so in the future:	0-8
	Dry-proof.	0.13 (0.48)	Installing anti-back flow valves on pipes; Installing a pump and/or one or more system(s) to drainflood water; Fixing water barriers"(e.g., water-proof basement windows).	
	Wet-proof.	0.16 (0.56)	Strengthen the housing foundations to withstand waterpressures; Reconstructing or reinforcing the wallsand/or the ground floor with water-resistant materials; Raising the electricity meter above the mostlikely flood level or on an upper floor.	
	Elevation	0.05 (0.20)	Raising the level of the ground floor above the most likelyflood level.	
Education		3.179 (0.51)	What is the highest level of education you have completed?	From 0 (Less than secondary education) to 4 (Post graduate degree)
House value		3,380,646 (2,603,162)	If you were to put your accommodation on the market today, how much do you believe it would sell for? Please provide your best estimation in the full amount	Open choice (in RMB)
Savings		2.859 (1.452)	With regards to your household's savings, what statement most closely reflects your current household situation?	From 0 (We use practically all of the money we earn each month) to 4 (My household has 4 or more month's wages in savings)

and protection by averaging past literature from the Global North Kreibich et al. (2015). The related inputs for the current work are summarized in Table 7.15.

Following FEMA's recommendation, we assume a fixed *Elevation* of 1 meter above the ground Federal Emergency Management Agency (2017). Therefore, households that elevate their property subtract 1 meter from the water depth at their location and are affected by the corresponding damages as per the depth-damage curve. In the context of *Wet-proofing*, we apply a 40% effectiveness rate in reducing both building and content damage Defra (2008); Egli (2002); Kreibich et al. (2015). In determining the effectiveness level, we adhere to the body of work assuming that households typically place valuable goods on the second floor, approximately 3 meters high de Moel et al. (2014); Lasage et al. (2014).

Dry-Proofing involves a different approach, with an effectiveness value of 85%, if the water level remains below 1 meter, a threshold widely employed in the literature Bubeck and de Moel (2010); de Moel et al. (2014); Lasage et al. (2014). However, if the water level is above one meter, the measure is overtopped, and it has no effectiveness. This aligns with empirical evidence highlighting that *dry-proofing* walls above a specific level may be counterproductive since the pressure difference between the external water and the lack of water inside the building could render it structurally unstable, potentially leading to the failure of the outer walls de Moel et al. (2014); Kreibich et al. (2015).

The application of these data has inherent limitations. The effectiveness of the measures is strongly influenced by local flood conditions Kreibich et al. (2015). Furthermore, the values we selected are primarily derived from studies conducted in Europe and North America, and may not translate directly to our context in Shanghai city. Local building conditions, content value, and the specific damages caused by floods might vary significantly, and these factors should be taken into consideration in the interpretation of our findings.

Table 7.15: Grouping, costs, and efficacy of structural CCA measures in the CRAB model, estimate from Survey data Noll et al. (2022a), n =

Structural CCA measure	Cateogry	Cost measure ($)	Cost category ($)	Protection
1. Installinganti-backflow valves on pipes		240		85 % d < 1m 0% d > 1
2. Installing a pump and/or one or more system(s) to drain flood water	Dry-proofing	443	1,313	
3. Fixingwater barriers (e.g.water-proof basement windows)		630		
4. Strengthen the housing foundations towithstand water pressures		1572		
5. Reconstructingor reinforcing the walls and/or the ground floor with water-resistant materials	Wet-proofing	1203	3,226	40%
6. Raisingthe electricity meter above the most likely flood level or on an upper floor		485		
7. Raising the level of the ground floorabove the most likely flood level	Elevation	4,040	4,040	d = d - 1m

Regional economy

We calibrate the CRAB model economy to a stylized agglomerated coastal region, to loosely resemble the greater Shanghai area, in two ways. First, we employ publicly available flood data to determine 30 years' cumulative flood probability and exposure. In a similar fashion, we use national statistics to determine household expenditure on goods and income as well the relative capital intensity of each economic sector. These parameters are summarized in Table 7.16.

Table 7.16: Empirically funded parameters in the CRAB model regional economy.

Parameter	Value	Source
Properties Dry-proofed at initialization	0.08	Noll et al. (2022b)
Properties Wet-proofed at initialization	0.09	Noll et al. (2022b)
Properties Elevated at initialization	0.05	Noll et al. (2022b)
Properties Insured at initialization	0.13	Noll et al. (2022b)
Intention-behavior gap Φ	0.25	Noll et al. (2022b)
Dry-proofing measure lifetime (η_{Dry})	20	Noll et al. (2022a)
Households expenditure for goods (% of total consumption, k_1)	35%	United States Census Bureau (2021)
Households expenditure for services (% of total consumption)	65%	
Capital-output ratio consumption-goods firms (Ko_{gd})	0.7	Commission et al. (2019)
Capital-output ratio consumption-services firms (Ko_{serv})	1.3	

When we refer to the model as being "loosely calibrated", we emphasize the nature of our study, which aims to construct an archetype of a resource-rich coastal megacity rather than an empirical representation of a specific location. Hence, in line with methodologies commonly adopted in agent-based macro-modelling, we tailored the remaining parameters of the CRAB model's regional economy to emulate six empirical attributes of real-world systems Fagiolo et al. (2017); Windrum et al. (2007). At its core, the indirect calibration process identifies particular empirical features for the model to replicate. This involves utilizing a search strategy, frequently employing Monte Carlo sampling, to pinpoint suitable parameter values. This is followed by a rigorous assessment of the robustness of these chosen conditions in the simulated outputs by considering nearby parameter values and altering the pseudo-random number generator's seed. In particular, the six conditions to be satisfied by the simulated data are:

- Pattern of self-sustained growth with persistent fluctuations.
- Average annual growth rate for output around 3%.
- Average unemployment rate between 5% and 15%.
- Output is less volatile than investment and more than consumption.
- Technological innovation generates agglomeration.
- Floods decrease entry and exit of firms.

The parameters from the indirect calibration approach are summarized in Table 7.17.

Table 7.17: Past literature and indirect calibration parameters in the CRAB regional economy

Description	Symbol	Value
Number of firms in capital-good industry	F_1	250
Number of firms in consumption-good industry	F_2	400
Number of firms in consumption-service industry	F_3	600
Number of households	H	$10,000$
R&D investment propensity	ν	0.04
R&D allocation to innovative search	ξ	0.5
Firm search capabilities parameters	$\zeta_{1,2}$	0.3
Beta distribution parameters (innovation process)	(α_1, β_1)	$(2, 4)$
Beta distribution support (innovation process)	$[\underline{x_1}, \overline{x_2}]$	$[-0.05, 0.05]$
Profits to wage ratio	ϵ	2
Consecutive number of periods for new firms creation	ι	6
New-customer sample parameter	γ	0.2
Capital-good firm mark-up rule	μ_1	0.15
Desired inventories	l	0.1
Payback period	b	3
“Physical” scrapping age	η	20
Mark-up coefficient	υ	0.04
Competitiveness weights	$\omega_{1,2}$	1
international transport cost	τ	0.06
Replicator dynamics coefficient	χ	1
Maximum debt/sales ratio	Λ	2
Interest rate	r	0.01
Uniform distribution supports (consumption-good entrant capital)	$[\phi_1, \phi_2]$	$[0.10, 0.90]$
Uniform distribution supports (entrant stock of liquid assets)	$[\phi_3, \phi_4]$	$[0.10, 0.90]$
Beta distribution parameters (capital-good entrants technology)	(α_1, β_2)	$(2, 4)$
Wage setting $\Delta\overline{AB}$ weight	ψ_1	0.2
Wage setting ΔAB_i weight	ψ_2	0.8
Wage setting Δcpi_r weight	ψ_3	0
Wage setting ΔU_r weight	ψ_4	0
Labour search sample parameter	ρ	0.3
Tax rate	tr	0.2
Insurer mark-up	δ	0.05
Mix balance parameter	o	0.3
Minimum unemployment for exit	U_{min}	0.05
Maximum unemployment for entry	U_{max}	0.2
Unemployment subsidy rate	σ	0.5
Export growth rate	g	0.01

7.3.6 Model validation

We validate the model according to its ability to reproduce a wide ensemble of micro and macro stylized facts, which are summarized in Table 7.18. For additional detail about the CRAB model validation see Taberna et al. (2022).

Table 7.18: Key economic empirical stylized facts replicated by the model.

Stylized facts (SF)	Empirical studies
Flood related aggregate-level stylized facts	
SF1 Flood decreases economic output	Amin (1994); Feldman and Kogler (2010)
SF2 Flood decreases employment	Feldman and Kogler (2010); Thomas (2005)
SF3 Flood decreases entry of firms	Jia et al. (2022)
Region economy aggregate-level stylized facts	
SF4 Endogenous self-sustained growth with persistent fluctuation	Kuznets and Murphy (1966); Stock and Watson (1999); Zarnowitz (1984)
SF5 Relative volatility of GDP, consumption, investments	Napoletano et al. (2004); Stock and Watson (1999)
SF6 Cross-correlations of macro-variables	Napoletano et al. (2004); Stock and Watson (1999)
SF7 Pro-cyclical aggregate R&D investment	Wälde and Woitek (2004)
SF8 Persistent unemployment	Ball (2009); Blanchard and Wolfers (2000); Blanchard and Summers (1986)
Region economy firm-level stylized facts	
SF9 Not all firms export	Bernard and Durlauf (1995); Bernard et al. (2011)
SF10 Exporters are more productive and larger than non-exporters	Bernard and Durlauf (1995); Bernard et al. (2011)
SF11 Firm (log) size distribution is right-skewed	Dosi (2007)
SF12 Productivity heterogeneity across firm	Bartelsman et al. (2005); Bartelsman and Doms (2000); Dosi (2007)
SF13 Persistent productivity differential across firm	Bartelsman et al. (2005); Bartelsman and Doms (2000); Dosi (2007)
SF14 Lumpy investment rates at firm level	Doms and Dunne (1998)

7.3.7 Sensitivity analysis

We apply the one-factor-at-a-time (OFAT) sensitivity analysis, where a single parameter is adjusted while the rest are held constant to examine the potential variability in results Schervish et al. (1983). The OFAT method was chosen for its lower computational demands in comparison to more intensive techniques such as variance decomposition Saltelli et al. (2008b). Moreover, while comprehensive sensitivity analysis methods can sometimes overlook the complexities of intricate dynamics and emergent behaviors typical of agent-based models, the OFAT approach provides better insight into such dynamics ten Broeke et al. (2016). We then measure the influence of these parameter changes on our primary outcome: difference in economic growth and development across specific scenarios.

Considering the architectural landscape of many cities, where a significant portion of the population resides in high-rise buildings, our methodology might present a skewed estimation of households vulnerable to flooding. For instance, our findings suggest that around 20% could be exposed to a 100-year flood by 2050 (refer to Figure 7.17). As a result, we employed the OFAT SA on the percentage of households exposed, utilizing our baseline (20% for a 100-year flood in 2050) as the upper limit, and then progressively reducing this exposure down to zero. While the proportion of households affected by flooding influences our results, with more exposure correlating to reduced long-term economic growth, the overarching insights remain consistent. This consistency arises primarily from the economic upheaval triggered by the disruption to firms, which subsequently generates indirect economic implications on households (for an in-depth exploration of the different channels affecting the economy in the CRAM model individually, see Taberna et al. (2022)). Our investigations bolstered our initial conclusions: integrating bottom-up CCA with

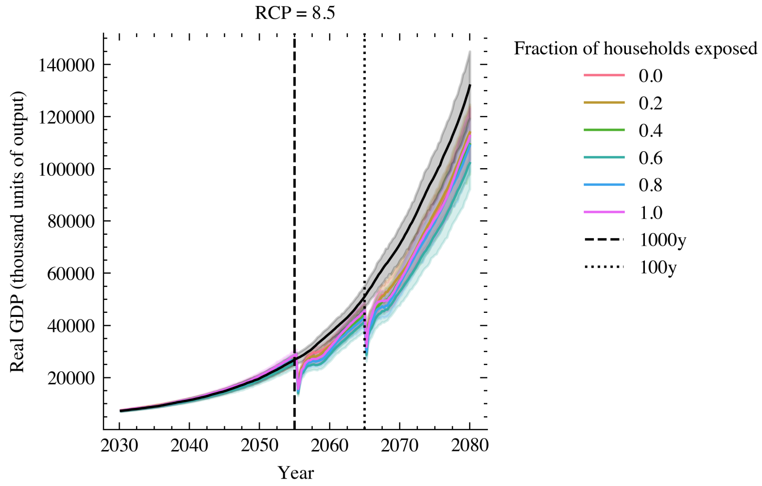

Figure 7.21: Sensitivity analysis that shows the average economic growth under each different fraction of households exposed to floods. Note that 1 indicated the fraction of households exposed in the Baseline scenario. The reported values are under RCP 8.5 and average across the 100 Monte Carlo runs with the shaded areas denoting the standard deviation.

overarching subsidies generates the most robust societal frameworks to withstand climate adversities. Sole reliance on autonomous measures falls short in countering severe climatic incidents. Furthermore, the average adverse outcomes experienced by households persist, with those in the lower-income bracket disproportionately facing the indirect aftermath.

Additionally, recognizing the pivotal role of migration parameters and the unpredictability they introduce, we undertook a sensitivity analysis on the balance parameters (o) and the unemployment thresholds required for either the entry or the exit of households (U_{min} and U_{max}, Eq.7.53, see Table 7.17 for original values). The oscillations in the scale of results, however, did not alter the central conclusion: the repercussions of inaction in the face of a potential flood are distinct and significant ('None' scenario in Figure 7.22). Yet, when juxtaposing the outcomes of implementing bottom-up CCA measures and the top-down subsidy against the baseline scenario, the difference is often subtle, underscoring that the combination of such measures bears similar outcomes to the baseline conditions in terms of economic growth and development ('Subsidy & DR & Insurance' in Figure 7.22).

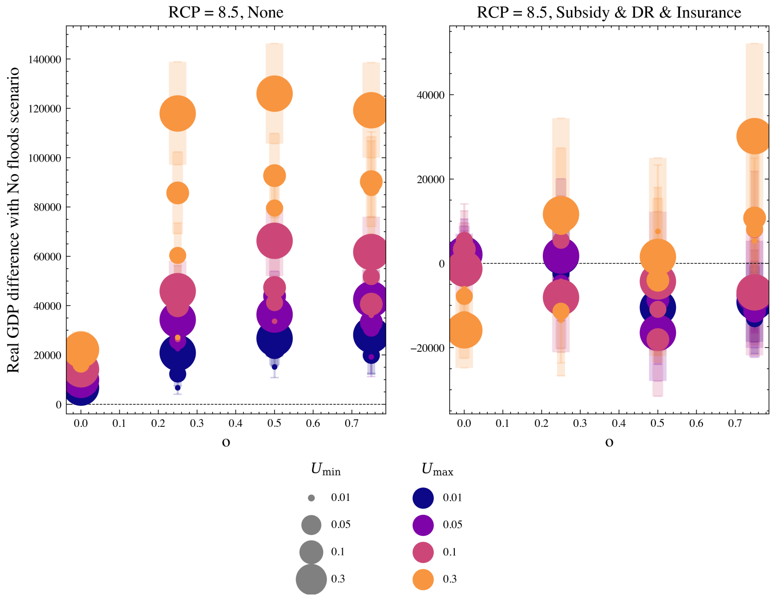

Figure 7.22: Panel (a) shows the Real GDP (unit of output produced) difference when no adaptation action is taken ('None') compared to the 'Baseline - No flood' scenario. Panel (b) makes the same comparison with the 'Subsidy & DR & Insurance' scenario. The reported values are under RCP 8.5 and average across the 100 Monte Carlo runs. The horizontal dashed line indicated when there is no difference.

Publications and Conferences

Peer-Reviewed Publications

1. Taberna, A., Filatova, T., Roy, D., & Noll, B. (2020). Tracing resilience, social dynamics and behavioral change: a review of agent-based flood risk models. *Socio-Environmental Systems Modelling*.
2. Noll, B., Filatova, T., Need, A., & Taberna, A. (2022). Contextualizing cross-national patterns in household climate change adaptation. Nature climate change, 12(1), 30-35.
3. Taberna, A., Filatova, T., Roventini, A., & Lamperti, F. (2022). Coping with increasing tides: Evolving agglomeration dynamics and technological change under exacerbating hazards. *Ecological Economics*, 202, 107588.
4. Taberna, A., Filatova, T., Hadjimichael, A., & Noll, B. (2023). Uncertainty in boundedly rational household adaptation to environmental shocks. *Proceedings of the National Academy of Sciences*, 120(44).
5. Taberna, A., Filatova, T., Hochrainer-Stigler, S., Nikolic Igor & Noll, B. (2023). Economic implications of autonomous adaptation of firms and households in a resource-rich coastal city. *Scientific Report*.

Included in this thesis.

Conference and Other Publications

1. Taberna, A. (Dec 2021). Agent-Based Models for Climate Change Adaptation. *Delta Links*.

2. Taberna, A., Filatova, T., Roventini, A., & Lamperti, F. (2022, March). Exploring Regional Agglomeration Dynamics in Face of Climate-Driven Hazards: Insights from an Agent-Based Computational Economic Model. In Advances in Social Simulation: Proceedings of the 16th Social Simulation Conference, 20–24 September 2021 (pp. 145-160). Cham: Springer International Publishing.

3. Taberna, A., Filatova, T., & Hochrainer-Stigler, S. (2023). Integrating top-down and bottom-up risk management strategies against indirect effects of natural disasters: Insights from an agent-based modelling approach. *IIASA - YSSP Report*, 2022 cohort.

1. Taberna, A., Filatova, T., Hochrainer-Stigler, S., Nikolic, I., and Noll, B. (2023). “Integrating top-down and bottom-up risk management strategies against indirect effects of natural disasters”. Conference of the European Association of Environmental and Resource Economists (EAERE).

2. 🏆 Taberna, A., Filatova, T., Hochrainer-Stigler, S., Nikolic, I., and Noll, B. (2023). “Integrating top-down and bottom-up risk management strategies against indirect effects of natural disasters: Insights from an agent-based modelling approach”. Herrenhausen Conference.

3. Taberna, A., Filatova, T., Noll, B., and Hadjimichael, A. (2022). “Integrating households climate change adaptation in a complex evolving economy: the role of different behavioral assumptions”. Social Simulation Conference (SSC).

4. Taberna, A., Filatova, T., Roventini, A., and Lamperti, F. (2022). “Shifting faith of coastal economies: regional evolutionary agglomeration dynamics in face of climate-induced hazards”. INQUIMUS Workshop.

5. Taberna, A., Filatova, T., Roventini, A., and Lamperti, F. (2022). “Shifting faith of coastal economies: regional evolutionary agglomeration dynamics in face of climate-induced hazards”. Knowledge Action Network on Emergent Risks and Extreme Events (Risk KAN).

6. Taberna, A., Filatova, T., Roventini, A., and Lamperti, F. (2021). “Exploring regional agglomeration dynamics in face of climate-driven hazards: insights from an agent-based computational economic model”. Social Simulation Conference (SSC).

7. Taberna, A., Filatova, T., Roventini, A., and Lamperti, F. (2021). “Exploring regional agglomeration dynamics in face of climate-driven hazards: insights from an agent-based computational economic model”. Workshop on Economic science with Heterogeneous Interacting Agents (WEHIA).

8. Taberna, A., Filatova, T., Roventini, A., and Lamperti, F. (2021). “Exploring regional agglomeration dynamics in face of climate-driven hazards: insights from an agent-based computational economic model”. European Regional Science Association (ERSA).

9. Taberna, A., Filatova, T., Roventini, A., and Lamperti, F. (2021). “Exploring regional agglomeration dynamics in face of climate-driven hazards: insights from an agent-based computational economic model”. Grupo de Investigación en Dinámica Económica (GIDE).

10. Taberna, A., Filatova, T., Roy, D., and Noll, B. (2020). “Computational agent-based models of social dynamics and behavioral change in response to flood risks: a review”. Joint International Resilience Conference (JIRC).

🏆 Won a travel grant.