Coping with increasing tides: technological change, agglomeration dynamics and climate hazards in an agent-based evolutionary model

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Abstract

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. To explore trade-offs between agglomeration economies and increasing climate-induced hazards, 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 waterfront region leading to self-reinforcing and path-dependent agglomeration processes. We then introduce five scenarios considering flood hazards characterized by different frequency and severity and we study their complex interplay with agglomeration patterns and the performance of the overall economy. We find that when shocks are mild or infrequent, they negatively affect the economic performance of the two regions. If strong 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 absorbing the adverse impacts of climate shocks on the whole economy. Conversely, in presence of climate tipping points which suddenly increase the frequency and magnitude of flood hazards, we find that the consolidated coastal gentrification of economic activities locks-in firms on the waterfront, leading to a harsh downturn for the whole economy.

Keywords: agglomeration, path-dependency, climate, flood, shock, relocation, migration, agent-based model, tipping point, resilience, lock in.
JEL classification: C63, Q54, Q55, R11, R12.

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1 Introduction

Rapid urbanization and climate change exacerbate natural hazard risks worldwide. With the climate conditions which humanity has enjoyed for centuries, coastal and delta regions historically grew faster than landward areas, with all current megacities flourishing along the coast. The richness of natural amenities and resources coupled with transportation advantages created agglomeration forces that have enabled this boom (Fujita and Mori, 1996). Yet, the escalation of climate-induced hazards fundamentally reshapes the trade-offs which firms and households must 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 that do not leave enough time to complete the recovery, and which could lead to economic gentrification and poverty traps (Hallegatte et al., 2007; Hallegatte and Dumas, 2009).

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. Two merits of such discipline have been to link international trade and economic geography giving rise to models that produce emergent spatial structures without assumed agglomeration economies (Krugman, 1992). These 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; Lamperti et al., 2019; Mercure et al., 2016; Ciarli and Savona, 2019) and economic geography (Fowler, 2007; Spencer, 2012). ABMs are versatile in modeling disaster scenarios (Waldrop, 2018; Lamperti et al., 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) - demonstrates how - in line with the evolutionary economic geography tradition (Boschma and Frenken, 2006; Martin and Sunley, 2006; Frenken and Boschma, 2007) - 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; Monasterolo et al., 2019; Lamperti et al., 2020), multi-region economies (Mandel et al., 2009; Wolf et al., 2013) and household-level adaptation (Filatova, 2015; de Koning and Filatova, 2019) - including farmers (Gawith et al., 2020; Coronese et al., 2021) -, 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.

Our goal is to explore how the complex trade-offs between agglomeration economies and a changing severity of location-specific flood hazards affect the economic performance and attractiveness of coastal and inland regions and steer their development. In particular, we aim to address three research questions: (1) How do agglomeration forces shape economic centers in coastal areas? (2) What are the effects of climate shocks of various severity and probability on this agglomeration dynamics? (3) How do the complex interplay between agglomeration economies, technological change and flood hazards affect the economic performance of the regions?

Following previous work on evolutionary macroeconomic ABMs (Dosi et al., 2010, 2013, 2017, 2018b; Lamperti et al., 2018), we use R&D investment and a "Schumpeterian" creative (innovative) destruction process as the engine of endogenous economic growth.[1] We develop a model where firms and households are located in two spatial regions: a safe Inland region and a hazard-prone Coastal region. Agents can migrate between the two zones, whose economic attractivity change over time due to technological change and agglomeration economies which affect profits and wages. Furthermore, different climate shocks can hit firms in the Coastal region impacting on their productivity, capital stock and inventories.

The novel contribution of this article is three-fold. First, we advance economics geography literature by introducing a theoretical out-of-equilibrium framework that employs innovation as the cause of agglomeration and, ultimately, the uneven spatial distribution of economic activities. Second, we go beyond the evolutionary macroeconomic ABMs tradition by introducing two regions and endogenous 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. In this regard, our work studies the importance of an anticipated retreat to avoid increasing exposure of economic activities to climate shocks and of investments that could eventually increase sunk costs (Haasnoot et al., 2021).

Simulation results show that our 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 technical change. The likelihood and the speed of the agglomeration process are contingent to the extent of such location advantage, which depends on transport costs as well as the volume of trade that the two regions have with 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 whole economy. More specifically, infrequent or mild shocks harm the economic performance of the two regions with different effects on the agglomeration process. When flood hazards turn frequent and severe from the beginning of the simulation, firms and household are able to timely adapt retreating to the Inland region. This avoid climate gentrification and lock-ins with possible catastrophic impacts on economic activities (Haasnoot et al., 2021). On the contrary, in the more likely occurrence of late climate tipping points which abruptly increase both the magnitude and frequency of climate shocks, the economic performance is considerable harmed as unfolded agglomeration economies concentrates firms in the Coastal region without the necessary resources to relocate. In all scenarios, we find that climate shocks can affect the economy in an heterogeneous manner, pointing to the importance of different economic channels impacted by the adversity.

The rest of the article proceeds as follows. Section 2 describing the methodology. In Section 3, simulation results are presented and discussed. Finally, Section 4 concludes.

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

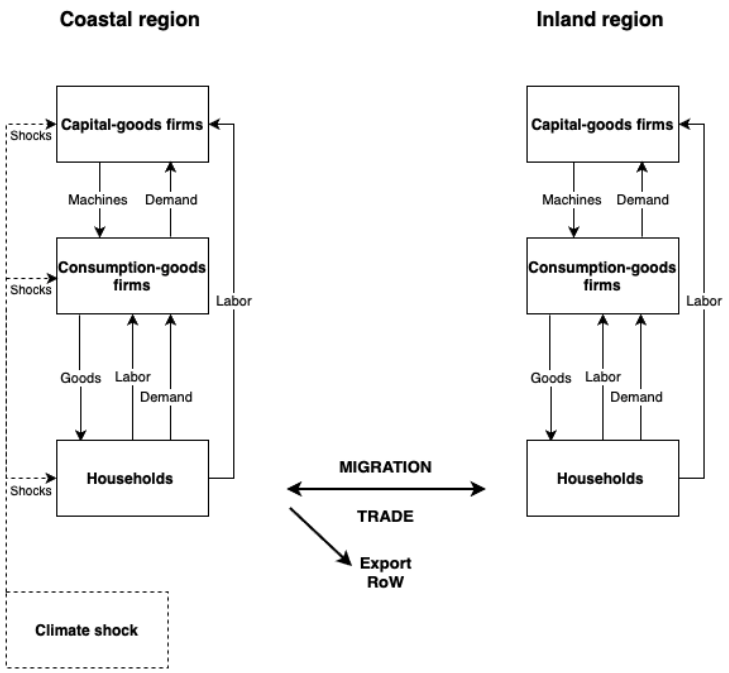

Figure 1: A conceptual representation of the CRAB model.

2 The model

To analyze the effect of coastal flooding on agglomeration dynamics, we build the *Climate-economy Regional Agent-Based* (CRAB) model upon the evolutionary economic engine of the well-known 'Keynes + Schumpeter' ("K+S"; Dosi et al., 2017) extending it by adding two different regions, migration dynamics and climate hazards inspired by the DSK model Lamperti et al. (2018, 2019). A schematic representation of the model is provided in Figure 1.

Our model comprises two regions (r), namely "Coastal" and "Inland", characterized by two-sector economies with three classes of heterogeneous interacting boundedly-rational agents. Specifically, 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. When a decision process is identical for both capital- and consumption-good firms (e.g. migration, cf. Subsection 2.4), we employ the subscript f for both types of firms. 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.

The regional dimension of the model affects market interactions and migration dynamics. The two labour markets are decentralized[2] and local: firms can only hire workers residing in their own region.

[2]For other ABMs that feature decentralized labour markets and matching processes see Fagiolo et al. (2004);

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 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, all firms and households are free to migrate across the two regions when they find it economically-efficient. Migration is costly and increases with size for firms, while it is costless for workers.[3] Climate shocks hit only the Coastal region with an average magnitude Dc. Damages are heterogeneous at the microeconomic level and they affect households' labor productivity, firms' capital stock and inventories.

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

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.[4] 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 are 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 $\epsilon > 0$ which captures geographical barriers to 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 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. 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 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 versa[5].

Dawid et al. (2008, 2012, 2014); Riccetti et al. (2015); Russo et al. (2016); Caiani et al. (2016); Dosi et al. (2018a). Furthermore, for critical surveys on macro ABMs see Gatti et al. (2010); Fagiolo and Roventini (2017); Dawid and Delli Gatti (2018); Dosi and Roventini (2019).

[3] In a future version of the model, we will provide a more detailed characterizazion of worker migration.

[4] For a detailed description of the capital-good and consumption-good sectors, see Appendix A.1 and Dosi et al. (2015)

[5] For more information about demand expectation, capital investments and price formation in the consumption-good sector see Appendix A.2.

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):

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

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, 1996; 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.

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:

$$\overline{E}^m(t) = \sum_{j=1}^{F2} E_j^m(t) f_j^m(t-1) \quad with \quad m = [Co, In, Exp]. \tag{2}$$

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

$$f_j^m(t) = f_j^m(t-1)\left(1 + \chi \frac{E_j^m(t) - \overline{E}^m(t)}{\overline{E}^m(t)}\right) \quad with \quad m = [Co, In, Exp], \tag{3}$$

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 that the demand grows at a constant rate (α):

$$Exp(t) = Exp(t-1)(1+\alpha), \quad \alpha > 0. \tag{4}$$

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

$$D_j(t) = C^{Co}(t) f_j^{Co} + C^{In}(t) f_j^{In} + Exp(t) f_j^{Exp}, \tag{5}$$

with C^{Co} and C^{In} computed by summing up all the wages and unemployed benefits of the households in each region.[6].

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:

$$w_j(t) = w_j(t-1)\left(1 + \psi_1 \frac{\Delta AB_j(t)}{AB_j(t-1)} + \psi_2 \frac{\Delta \overline{AB^r}(t)}{\overline{AB^r}(t-1)} + \psi_3 \frac{\Delta U^r(t)}{U^r(t-1)} + \psi_4 \frac{\Delta cpi^r(t)}{cpi^r(t-1)}\right), \tag{6}$$

[6]For more detail about aggregate consumption see Appendix A.2

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:

$$L^{D,r}(t) = \sum_{i=1}^{F1^r} \sum_{j=1}^{F2^r} L_f^d \quad with \quad f = [i, j], \tag{7}$$

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:

$$L_i^d = \frac{Qo_i^r(t)}{B_i(t)}, \tag{8}$$

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:

$$L_j^d = \frac{Qd_j(t)}{A_j(t)}, \tag{9}$$

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: 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.

2.4 Inter-regional migration

Households and firms can endogenously decide to move to another region. 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, that, if successful, makes the agent willing to migrate.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 Delli Gatti et al., 2010; Caiani et al., 2016; Rizzati et al., 2018) grounded in economic variables. Namely, both employed and unemployed households h compare wages and levels of unemployment in two regions, and their probability to migrate (Pr^m) is:

$$Pr_h^m(t) = \begin{cases} 1 - e^{(\varphi_1 W_d(t) + \varphi_2 U_d(t))}, & \text{if } W_d(t) \text{ and } U_d(t) < 0 \\ 0, & \text{otherwise} \end{cases}. \tag{10}$$

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

$$W_d(t) = \frac{(\overline{W^r}(t) - \overline{W^*}(t))}{\overline{W^r}(t))}, \tag{11}$$

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

$$U_d(t) = \frac{(U^*(t) - U^r(t))}{U^r(t)}. \tag{12}$$

Bigger and more profitable markets work as basins of attraction for firms (Krugman, 1998; Bottazzi et al., 2008). Hence, 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:

$$Pr_f^m(t) = \begin{cases} 1 - e^{(\varphi_3 Dd_f(t) + \varphi_4 DAd(t))}, & \text{if } Dd_f(t) \text{ and } DAd(t) < 0 \\ 0, & \text{otherwise} \end{cases}, \tag{13}$$

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

$$Dd_f(t) = \frac{(D_f^r(t) - D_f^*(t))}{D_f^r(t))}. \tag{14}$$

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

$$DAd_f(t) = \frac{(DAd_f^r(t) - DAd_f^*(t))}{DAd_f^r(t)}, \tag{15}$$

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. 10), and higher demand for firms (cf. Eq. 13).

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

$$\theta^{migr}(t) = Pr_a^m(t) \quad with \quad a = [h, f]. \tag{16}$$

They follow a similar method to determine whether technological innovation or imitation is successful (see Eq. 22, and Eq. 23 in Appendix A.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:

$$Mfc_f(t) = n_f w_f, \tag{17}$$

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.

2.5 Climate shocks

In each time step, there is a probability (Pr_s), that a climate shock, which we interpret as a flood, hits the Coastal region. More specifically, in the same fashion of both migration and technological learning (see Subsection 2.4, and Appendix A.1), a positive draw from a Bernoulli distribution determines whether the shock occurs:

$$\theta^s(t) = Pr_s(t), \quad with \quad Pr_s \in (0, 1]. \tag{18}$$

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. More precisely, each Coastal firm (fc) draws an individual damage coefficient ($Dc_{fc}(t)$) from a $Beta(\alpha_3, \beta_3)$ distribution.[7] 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. $INV_{fc}(t) = INV_{fc}(t-1)(1 - Dc_{fc}(t))$.

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.

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

5. Entry and exit occur.
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 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 have to consider when calculating their export competitiveness (Eq. 1). This implies that the inter-regional transport cost (τ_1) and the amount of export demand (Exp) are key parameters in our model 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 works (Hummels, 2007; Irarrazabal et al., 2015; Desmet et al., 2021) 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).[8]

Before addressing our main research questions, we mute climate shocks and test the ability of the *Baseline* (no flood) 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.[9] 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, as well as 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.[10]

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 1). Given the spatial dimension of the model, we focus on its ability to reproduce empirical regularities concerning the flows of people, businesses and trade that emerge between the two regions. Despite the even distribution of economic activities, resources and technologies in both

[8] See Appendix B for additional information on model calibration.

[9] A more extensive sensitivity analysis is carried out in Appendix C.

[10] 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.

Table 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	(Thomas, 2005; Feldman and Kogler, 2010)
SF3 Industry agglomeration due to natural advantages	(Fujita and Mori, 1996; Ellison and Glaeser, 1999; 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	(Stock and Watson, 1999; Zarnowitz, 1984; Kuznets and Murphy, 1966)
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	(Blanchard and Summers, 1986; Blanchard and Wolfers, 2000; Ball, 2009)
Two-region economy firm-level stylized facts	
SF11 Firm (log) size distribution is right-skewed	(Dosi, 2007)
SF12 Productivity heterogeneity across firm	(Bartelsman and Doms, 2000; Dosi, 2007; Bartelsman et al., 2005)
SF13 Persistent productivity differential across firm	(Bartelsman and Doms, 2000; Dosi, 2007; Bartelsman et al., 2005)
SF14 Lumpy investment rates at firm level	(Doms and Dunne, 1998)

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 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. 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 4). This is triggered by the dynamics of technological progress in the initial steps (SF1 in Table 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 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 1). In our model the majority (86%) of Coastal and the minority (7%) of the Inland firms constitute such a subset of exporters (Table 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 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 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 B.

Table 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.

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 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.

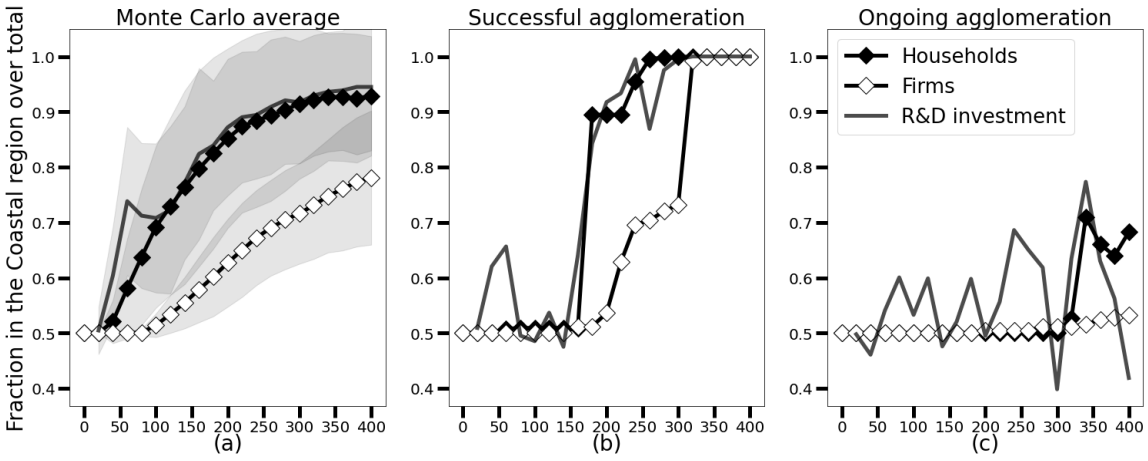

Figure 2: Share of population of firms (white squared curve), households (black squared curve) and the relative volume of R&D investment (solid curve) in the Coastal region over total in the *Baseline scenario*. Panel (a) displays the average values and standard deviations (shaded areas) of firms and 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 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

Table 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.

firms accelerating the technological diffusion. Furthermore, since wages are indexed to both firm and regional productivity (Eq. 6), they grow faster in the more innovative region, thus attracting workers which migrate from the other region (Figure 2, black squared curves). Households' migration ultimately reduces local consumption pushing an increasing number of firms to move to the growing region (Figure 2, white squared curves), typically with a time lag after workers' migration (compare white and black squared curves in Figure 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. However, in a typical Monte Carlo experiment, only 13% of the simulation runs exhibit a successful agglomeration process (Figure 2 and Table 3). This depends on the inter-regional transport costs (τ_1, Eq. 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. 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. 1). 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 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

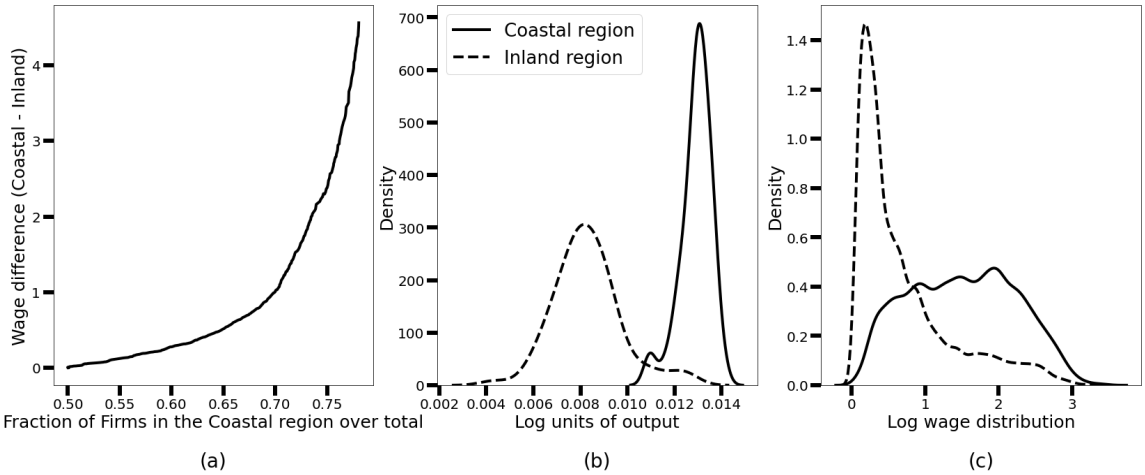

Figure 3: Panel (a) shows the dynamic trend of the difference in the average wage between the Coastal and Inland regions (vertical axis) as economic activities agglomerate (horizontal axis). Panels (b) and (c) compare the distribution of regional output growth and regional wages respectively in the Coastal and Inland regions. *Note*: the values refer to a Monte Carlo of size 100.

in the Coastal region, the wage difference with the Inland region increases exponentially (Figure 3.a), followed by the continuing households' influx (Figure 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.b), productivity (*Baseline*, Table 3) and wage distributions (Figure 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 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 and Figure 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 4, and Table 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 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). Indeed, the higher

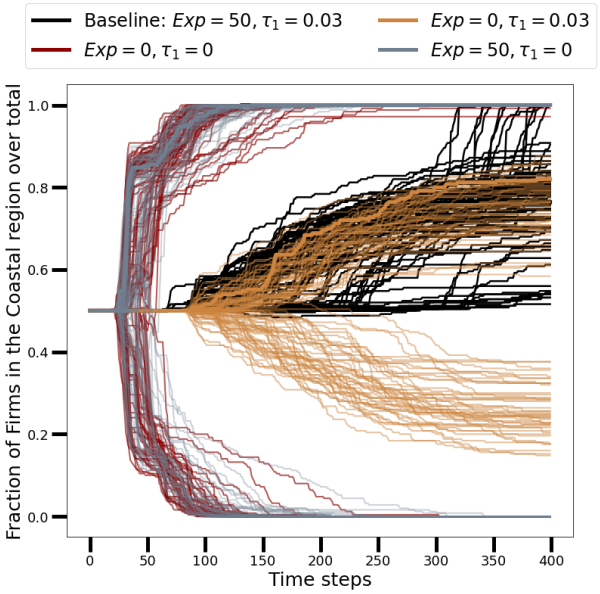

Figure 4: Sensitivity of the model dynamics to the inter-regional transport costs (τ_1) and the initial volume of the export demand (*Exp*). Each curve shows the dynamics of firms' population in the Coastal region across 100 individual Monte Carlo runs. Our *Baseline* scenario is $Exp = 50$ and $\tau_1 = 0.03$, colored in black here.

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[11] (Figure 4, Table 3, more details and extensive sensitivity analyses are in Appendix C).

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 climate-induced shocks, we run the *Baseline* model (Table 3) with floods 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, the low and high severity shocks resemble the damage intensity of such events (Longenecker, 2011), which we parameterize by varying the damage coefficient from 0.01 to 0.25. Notably, the *Climate tipping point* scenario displays an abrupt increase of both probability and severity at $t = 200$. Hence, the shock magnitude and probability vary among our experiments mimicking the uncertain nature of hazard variability

[11] 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 C.5 in Appendix C).

with climate change.[12] 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.

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.

3.3.1 The impacts of climate 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 A.3). 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 regional productivity, and potentially the economic output.[13]

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 4).[14] 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 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 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 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*

[12] 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.

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

[14] Appendix C 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.

Table 4: Comparison of different flood scenarios to the *Baseline* scenario with no shocks.

Scenario		Parameters $Pr_s.$	Parameters 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	$t \leq 200$	0.01	0.01	101.8 (7.6)	0.68***	0.79**	3.42***	0.00
	$t > 200$	0.50	0.25					

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.

scenario hinder firms from fully recovering their equipment due to scarcity of financial resources. Hence, they cannot fully satisfy their demand, undermining 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 scenario with no floods (*LPHS* vs. *Baseline* in Figure 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 5.c and in Table 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 5.b), but significantly higher output

compared to the *LPHS* scenario (compare *HPLS* vs. *LPHS* in Figure 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 5.a and 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 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 5.c and 5.f and in Table 4). Our results are in line with the climate adaptation literature (Moss et al., 2021; Desai et al., 2021) 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 the more likely *Climate tipping point* scenario where the frequency and severity of shocks abruptly increase in the middle of the simulation. Such a scenario show the worst economic performance due to negative spatial lock-in effects (Figure 5.b and Table 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 5.a and Table 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 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 5.c, 5.f and Table 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.[15] 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 A.3). Note that a variable number of firms could even worsen the economic performance as firm population in the Coastal region may collapse.

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

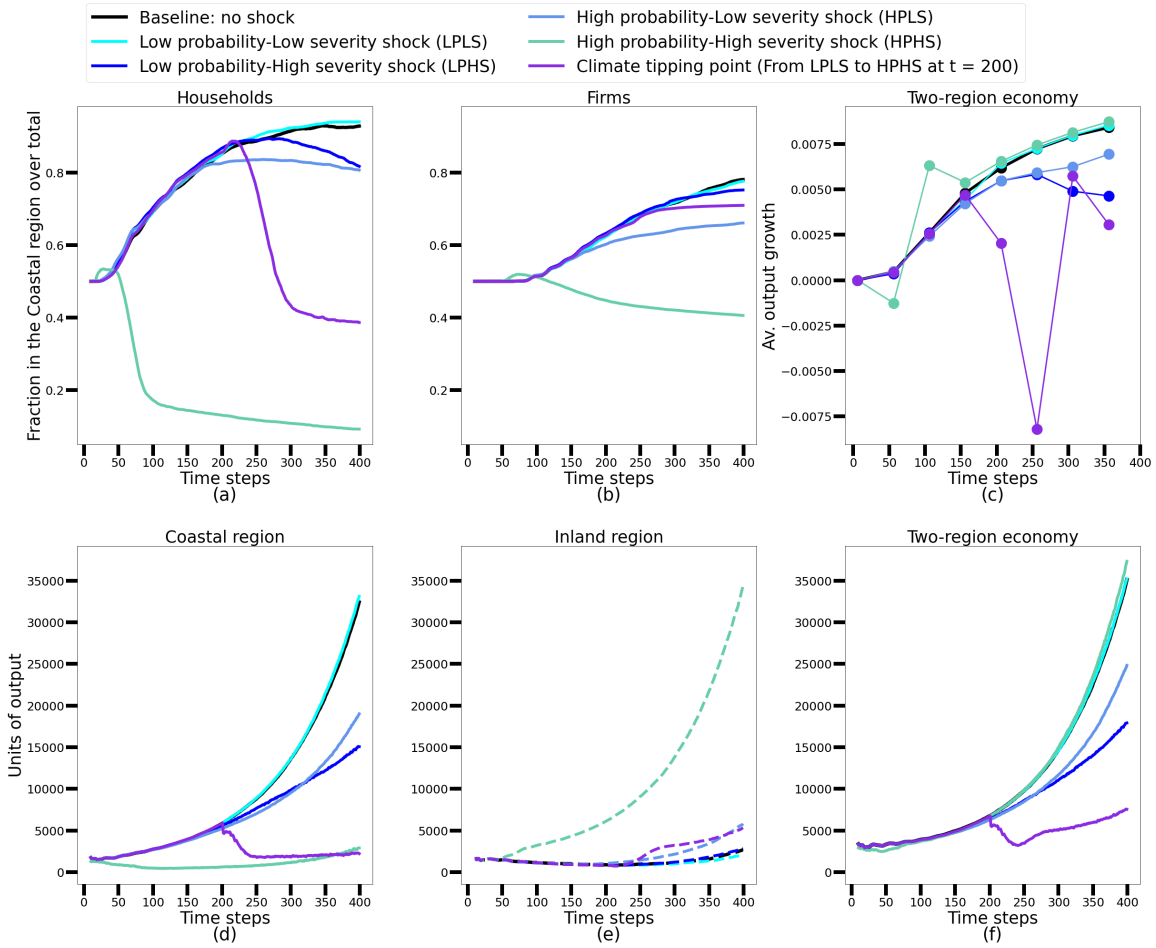

Figure 5: Evolution of the households (a) and firms (b) population in the Coastal region, average output growth of the two-region economy by time slices (c), units of output produced in the Coastal (d) and Inland regions (e), and in the entire two-region economy (f) over time in the *Baseline* and the five flood scenarios (*LPLS, HPLS, LPHS, HPHS* and *Climate tipping*). 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.

3.3.2 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 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 6 illustrates the individual effects of each shock on the evolution of the economy.[16]

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 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 6.c and 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 6.f) since these effects are counterbalanced with productivity gains that the firms obtain through the process of technical change.[17] An exception is the *HPHS* scenario: such shocks lead to intensified economic growth (see black and circled lines in Figure 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., 2010, 2013, 2017; 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 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 6.c, 6.f, 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 6.b) or, at least slows down its abandonment (see black and squared lines in Figure 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, see also). 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

[16] 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.

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

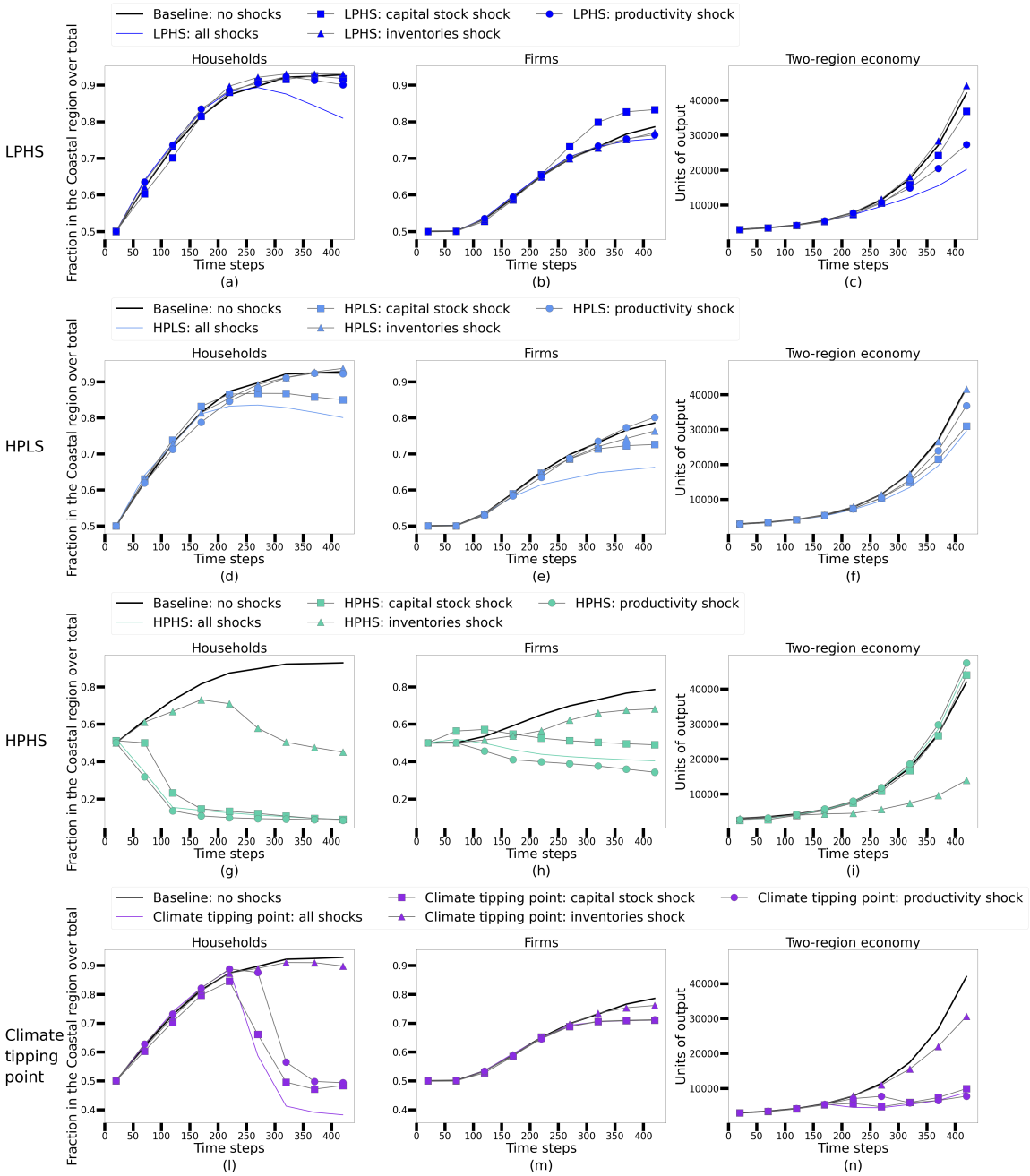

Figure 6: The impact of each individual shock channel on the distribution of population, economic activities and output of the two-region economy over time in the *Baseline*, *HPLS, LPHS, HPHS* and *Climate tipping* scenarios. All values are averages from 100 Monte Carlo runs of each scenario.

(see black and triangle lines in Figure 6.g, 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 6.n).

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 attracted development towards waterfront regions for centuries. Yet, 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., 2021).

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., 2010, 2013, 2015, 2017; 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 (Fowler, 2007; Commendatore, 2015) 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. Relatedly, 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 with no floods. 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., 2021; Wible, 2021). 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 simulated time period, 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 by the coast, locking in the entire economy into a trajectory of climate non-resilient stagnation.

The model can be expanded along different lines. First, the model would benefit from adding behaviorally-rich households choices, firms belonging to economic sectors impacted differently by hazards, floods maps and hazard patterns corresponding to different Representative Concentration Pathway scenarios. Furthermore, governments, households and firms could take actions to reduce adverse impacts of hazards, hence private and public climate change adaptation could be jointly considered. All these could be important future research directions. Nevertheless, the model makes an important contribution to the economic geography literature by exploring spatial distribution of economic activities in a out-of equilibrium fashion. Moreover, in terms of policy implications it assesses the trade-off between natural hazards and agglomeration economies and the possible policy implications in a framework characterized by non-linear dynamics, lock-in effects, and climate tipping points.

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6 Appendices

A Model Complements

A.1 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:

$$p_i(t) = (1 + \mu_1)c_i(t). \tag{19}$$

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

$$c_i(t) = \frac{w_i(t)}{B_i^T}. \tag{20}$$

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:

$$R\&D_i(t) = \nu_1 S_i(t-1) \quad with \quad 0 < \nu_1 < 1. \tag{21}$$

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:

$$\theta_i^{in}(t) = 1 - e^{-\zeta_1 IN_i}(t), \tag{22}$$

$$\theta_i^{im}(t) = 1 - e^{-\zeta_2 IM_i}(t), \tag{23}$$

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. 22) is successful, the firm discovers a new technology, (A_i^{im}, B_i^{im}), according to:

$$A_i^{in}(t) = A_i(t)(1 + x_i^A(t)), \tag{24}$$

$$B_i^{in}(t) = B_i(t)(1 + x_i^B(t)), \tag{25}$$

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 "succesfull" over "failed" innovations, and hence shape the landscape of *technological opportunities*.

Furthermore, firms passing the imitation draw (Eq. 23) 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 A.2):

$$min[p_i^h(t) + bc_i^h(A_i^h, t)] \quad h = T, in, im, \tag{26}$$

where b is a positive payback period parameter (see Eq. 29). 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).

A.2 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., 2010, 2013, 2017), adaptive demand expectations ($D_j^e = f[D_j(t-1), D_j(t-2), ..., D_j(t-h)]$),[18] desired inventories (N_j^d), and the actual stock of inventories (N_j) form the desired level of production:

$$Q_j^d(t) = D_j^e(t) + N_j^d - N_j(t). \tag{27}$$

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:

$$EI_j^d(t) = K_j^d(t) - K_j(t). \tag{28}$$

Furthermore, firms undertake replacement investment RI, scrapping machines with age above $\eta > 0$ and those that satisfy the following *payback rule*:

$$RI_j(t) = \left\{ A_{fc}^{\tau} \in \Xi_j(t) : \frac{p^*(t)}{c(A_{fc,\tau}, t) - c^*(t)} \leq b \right\}, \tag{29}$$

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. 29. Furthermore, firms compare the "brochures" received by capital-good firms and order the machines with the best ratio between price and quality.

Notably, consumption-good firms have to pay in advance both their investments and the worker wages. This implies that, in line with empirical literature (Stiglitz and Weiss, 1981; Greenwald and Stiglitz, 1993; Hubbard, 1997) 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):

$$c_j(t) = \frac{w_j(t)}{A_j}, \tag{30}$$

[18] Heuristic expectations may be the best and more "rational" response in a complex and changing macroeconomic environment. For more information about the impacts and robustness of heterogeneous expectations within an evolutionary economics agent-based model see Dosi et al. (2020)

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:

$$p_j(t) = (1 + \mu_{2,j})c_j(t). \tag{31}$$

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

$$\mu_{2,j}(t) = \mu_{2,j}(t-1)(1 + \nu \frac{f_j(t-1) - f_j(t-2)}{f_j(t-2)}) \quad with \quad 0 \leq \nu \leq 1. \tag{32}$$

The profits of consumption firms are given by:

$$\Pi_j(t) = (S_j(t) - c_j(j)Q_j(t) - rDeb_j(t), \tag{33}$$

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:

$$NW_j(t) = NW_j(t-1) + \Pi_j(t) + cI_j(t), \tag{34}$$

where cI_j is the investment cost of the firm.

A.3 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. The entrants are located in the same region of the bankrupting incumbents, hence keeping constant the regional population. 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 (Caves, 1998; Bartelsman et al., 2005), 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.

A.4 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:

$$W^{u,r}(t) = \delta \overline{W}^r(t), \quad with \quad \delta \in [0, 1], \tag{35}$$

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:

$$C^r(t) = \sum_{h=1}^{L^r} w_h^r(t) + W^{u,r}(L^r(t) - L^{e,r}(t)), \tag{36}$$

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

The model respects the national account identity:

$$\sum_{i=1}^{F1} Q_i(t) + \sum_{j=1}^{F2} Q_j(t) = Y(t) = C(t) + I(t) + \Delta N(t) + EXP(t) - IMP(t). \tag{37}$$

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).

B 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 (Windrum et al., 2007; Fagiolo 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 1).

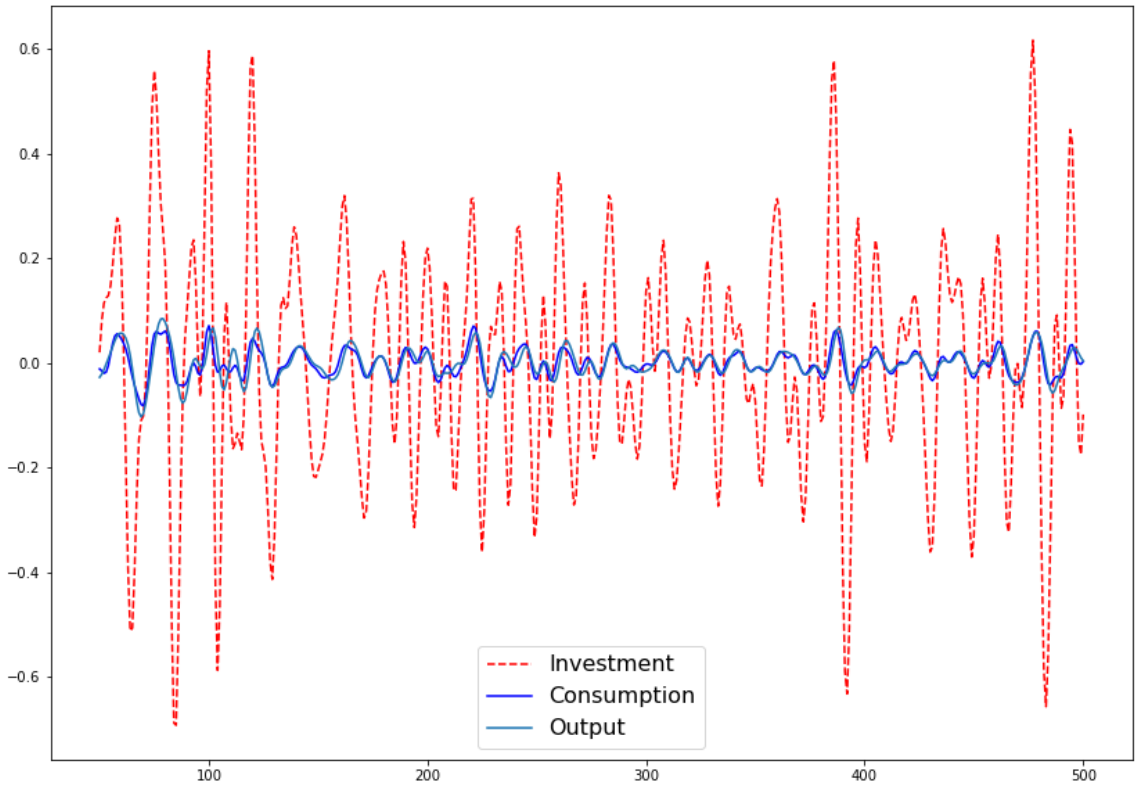

Figure B.1: Bandpass-filtered output, investment, and consumption. *Note*: results present the behavior of selected bandpass-filtered (6, 32, 12) series for a randomly chosen Monte Carlo run.

A more extensive discussion about the empirical regularities reproduced by the "K+S" model can be found in Dosi et al. (2017). Regarding this specific model, Figure B.1 shows the continuous

fluctuations and volatility of output, consumption and investment which is well tuned with real world data. In addition, Figure B.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.

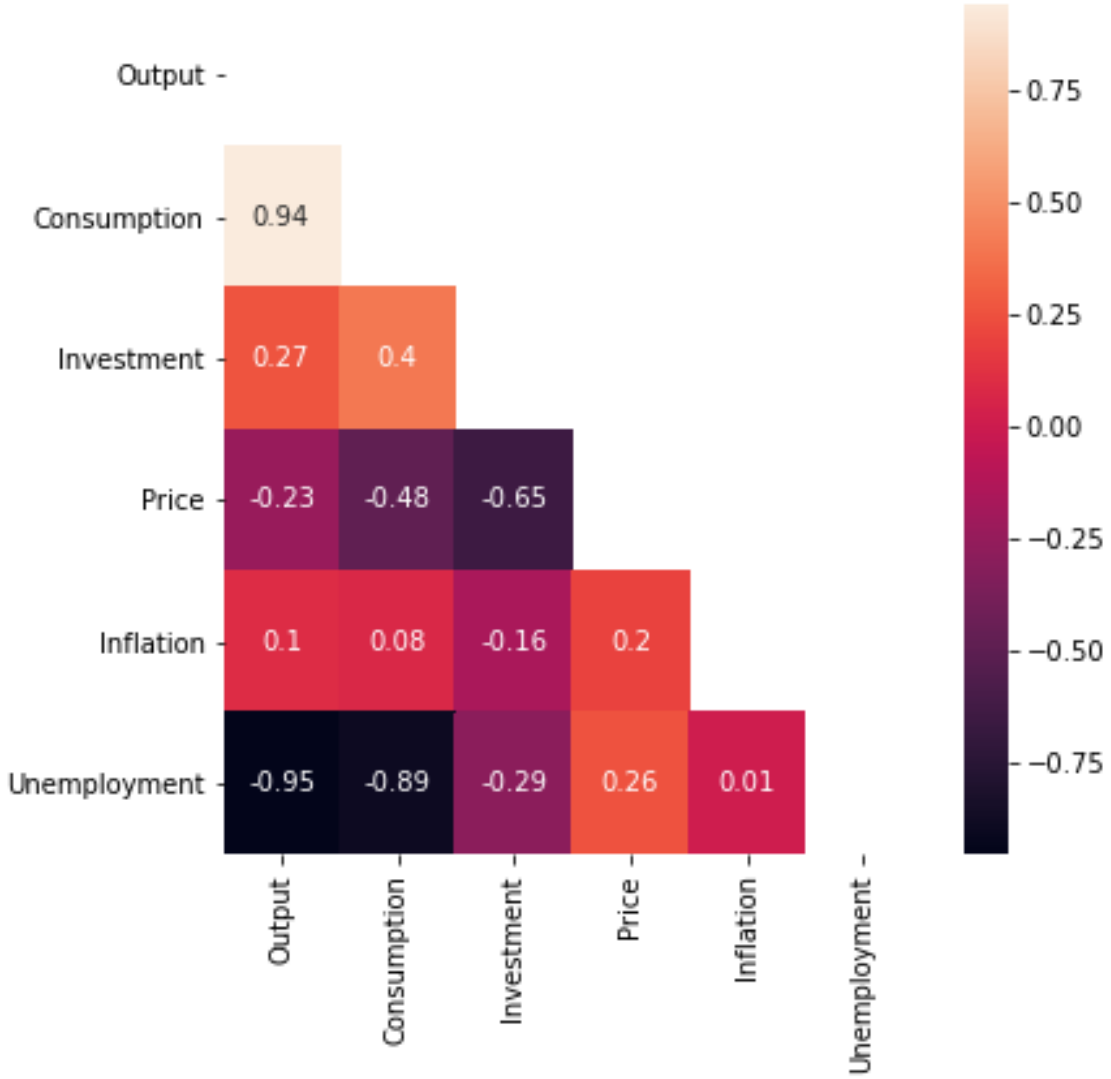

Figure B.2: Correlation structure emerging from filtered series. *Note*: the values refer to a Monte Carlo of size 100. Average values are reported.

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.

C 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., 2008). 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.

C.1 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 C.1). 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 C.3), while the output in the inland region is reduced (Figure C.3). 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 C.2, Figure C.3 and Figure C.4)

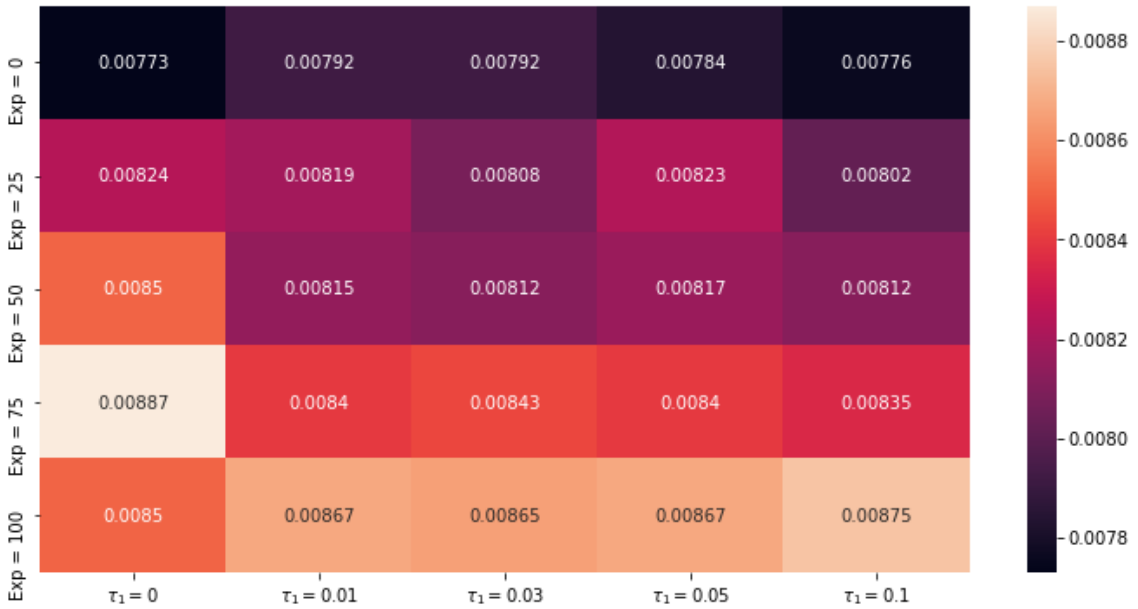

Figure C.1: Sensitivity analysis of the average output growth of the two-region economy to different values of export (*Exp*) and transport cost (τ_1). *Note*: the values refer to a Monte Carlo of size 100. Average values are reported.

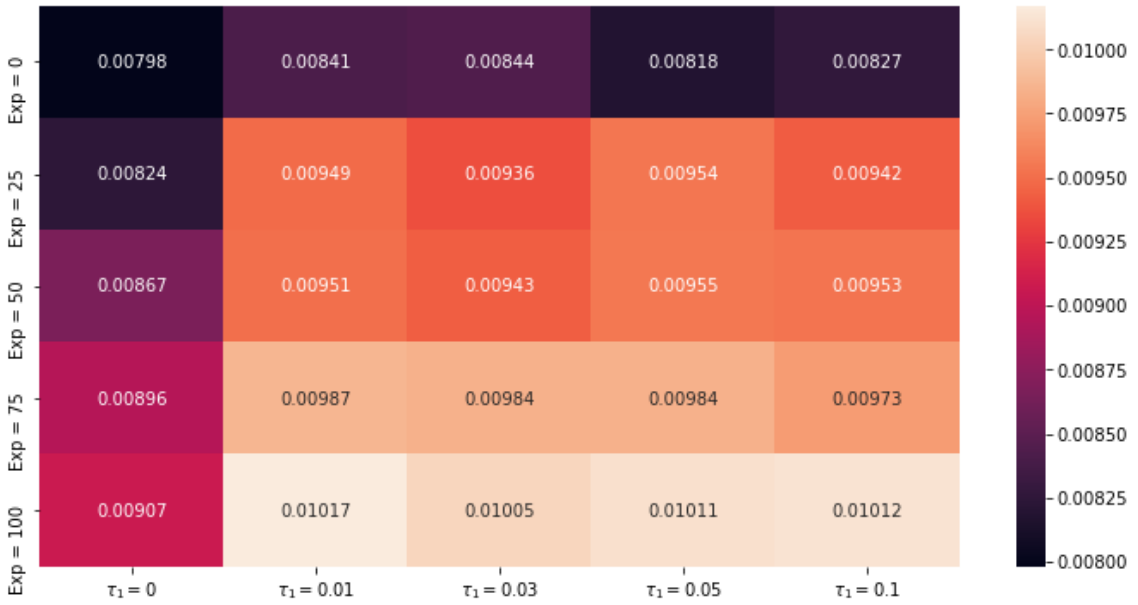

Figure C.2: Sensitivity analysis of the average output growth in the Coastal region to different values of export (*Exp*) and transport cost (τ_1). *Note*: the values refer to a Monte Carlo of size 100. Average values are reported.

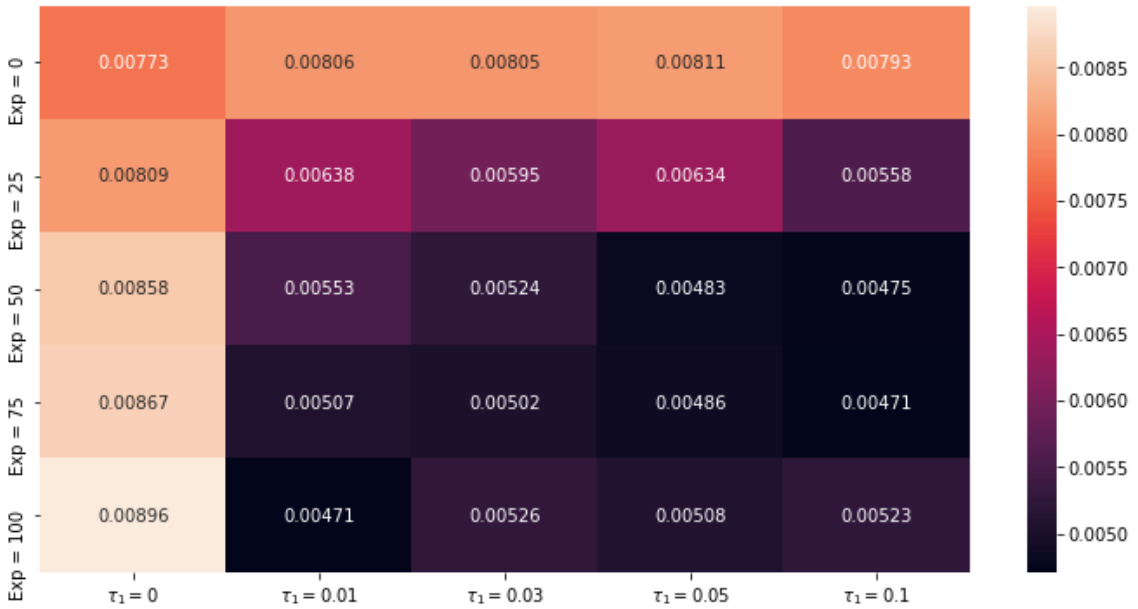

Figure C.3: Sensitivity analysis of the average output growth in the Inland region to different values of export (*Exp*) and transport cost (τ_1). *Note*: the values refer to a Monte Carlo of size 100. Average values are reported.

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 C.4) or its rate of growth (Figure C.5)

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 C.4 and Figure C.5).

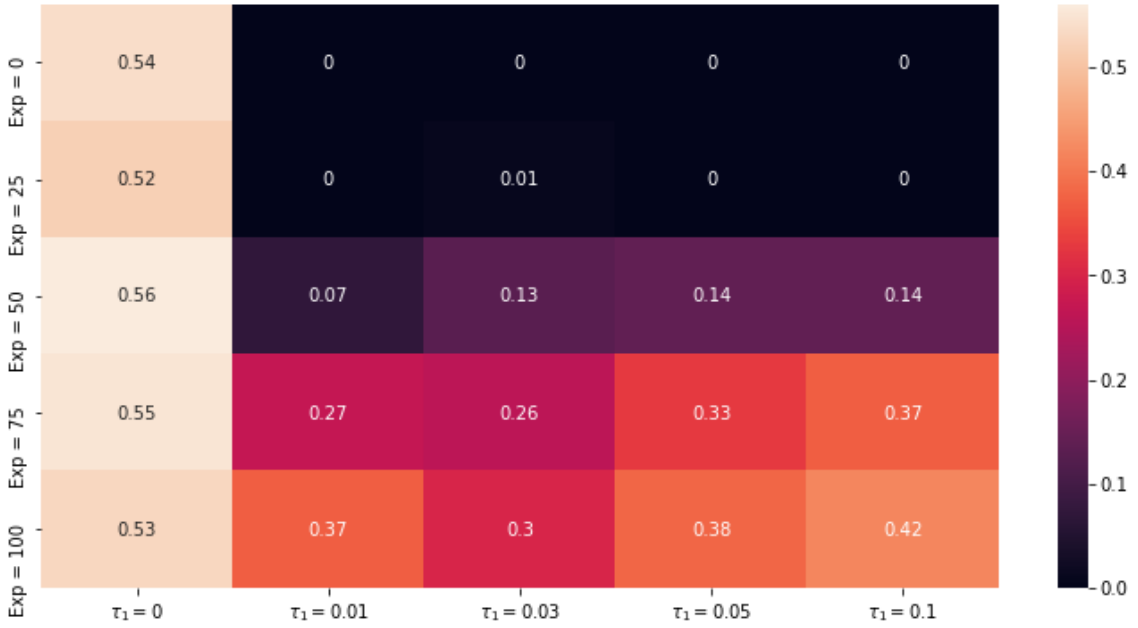

Figure C.4: Sensitivity analysis of the distribution of economic activities under different values for export (*Exp*) and transport cost (τ_1). The values indicates the probability of statistical equilibrium I in the 400th step of each simulation. *Note*: the values refer to a Monte Carlo of size 100. Average values are reported.

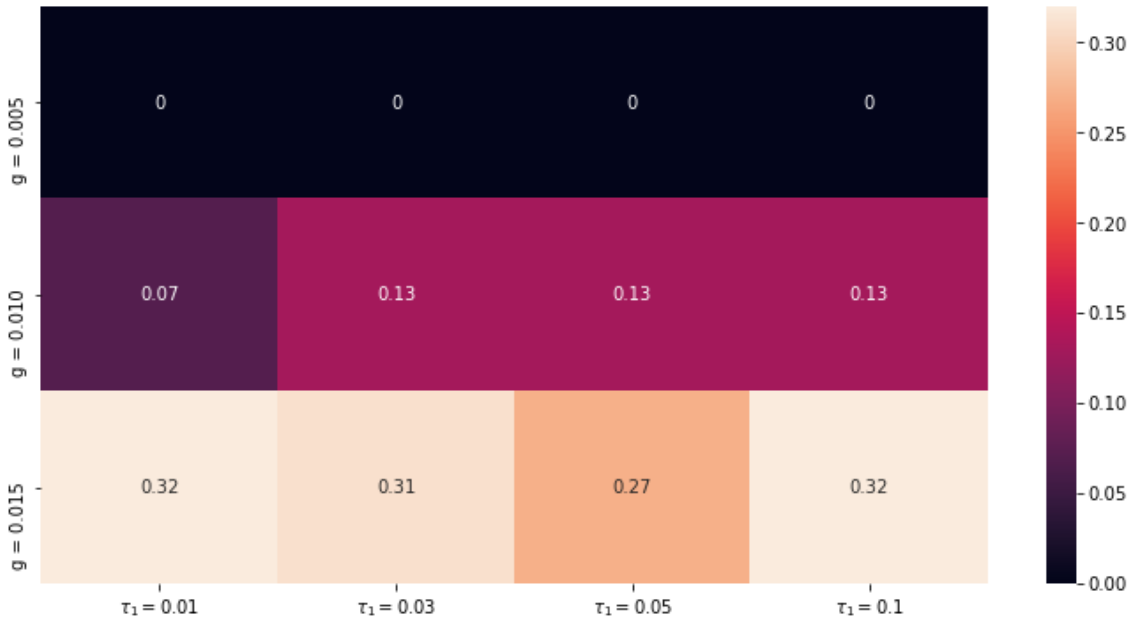

Figure C.5: Sensitivity analysis of the distribution of economic activities under different values for export growth (g) and transport cost (τ_1). The values indicates the probability of statistical equilibrium I in the 400th step of each simulation. *Note*: the values refer to a Monte Carlo of size 100. Average values are reported.

C.2 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 C.2, 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 C.2. 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 C.4), 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 C.4). 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 C.4 (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.

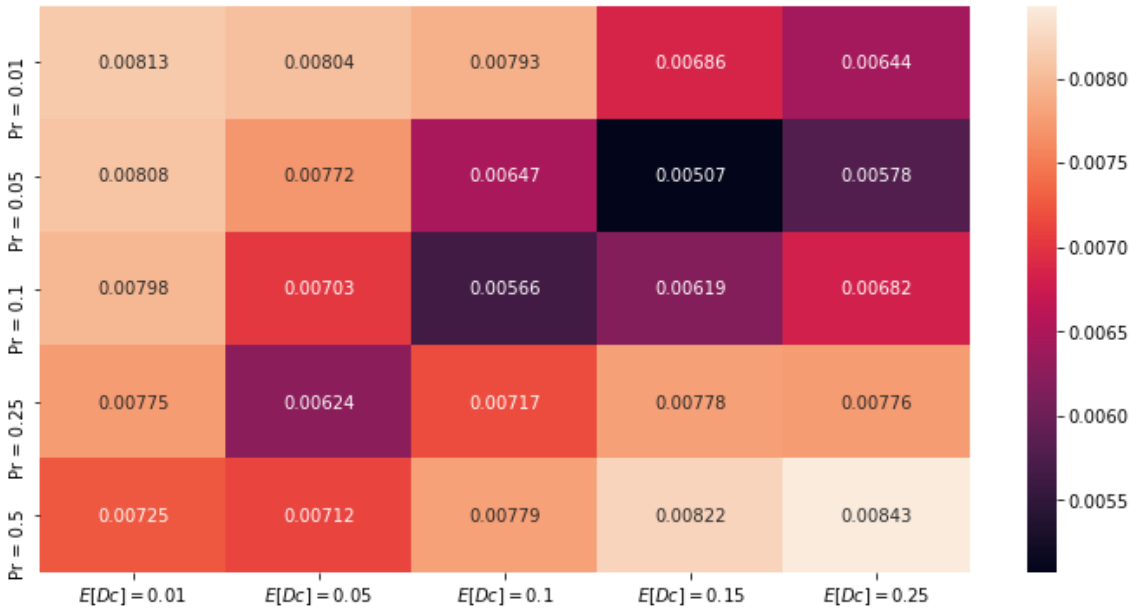

Figure C.6: Sensitivity analysis of the average output growth of the two-region economy to different values of shock probability (Pr) and expected damages ($E[Dc]$). *Note*: the values refer to a Monte Carlo of size 100. Average values are reported.

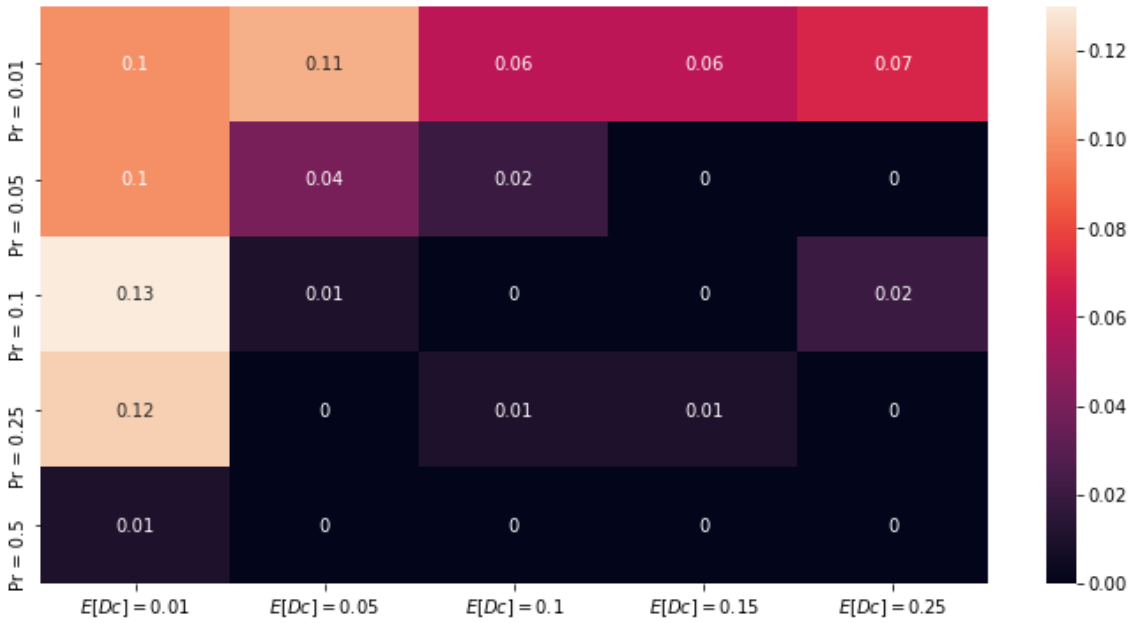

Figure C.7: Sensitivity analysis of the distribution of economic activities to different values of shock probability (Pr) and expected damages ($E[Dc]$). The values indicates the probability of statistical equilibrium I in the 400th time step of each simulation. *Note*: the values refer to a Monte Carlo of size 100. Average values are reported.