Floods, Collaborative Matching, and the Geography of Innovation *

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Abstract

We investigate a novel channel of collaborative innovation: innovators respond to climate risk by forming cross-regional patent collaborations as an adaptation strategy. We develop a search-and-matching theoretical framework that highlights a risk-sharing mechanism, in which innovators in flood-prone regions seek partners in less-exposed areas as a form of insurance. To test this mechanism, we focus on China, where innovation activity is heavily concentrated in flood-prone regions. Using detailed patent records and satellite-based flood data from 2008 to 2018, we construct a comprehensive dataset of cross-county patent collaborations. Our empirical results strongly support the model. At the county level, greater flood exposure increases the likelihood of forming cross-county collaborations. At the county-pair level, we find evidence of an intensive margin channel: pairs with prior collaboration experience or greater similarity are more likely to strengthen their partnership after floods occur. Together, these results reveal a previously understudied channel through which knowledge production adapts to climate risk by strategically readjusting collaboration networks.

JEL classification: D83, O31, Q54, Q55

Keywords: Flood, Collaborative Innovation, Risk-sharing, Knowledge Spillover

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1 Introduction

Does knowledge production adjust in response to climate risk? We explore this question in the context of floods—an increasingly frequent and destructive natural disaster that has affected over 1.8 billion people globally (Tellman et al. 2021) and is estimated to double in frequency across 40% of the world's land area by 2050 (Arnell and Gosling 2016). Emerging evidence indicates that adaptation to floods takes place through shifts in innovation, investment, and firm entry decisions (Moscona 2021; Jia et al. 2022; Balboni et al. 2023; Hsiao 2024). In this paper, we extend the analysis of adaptation by examining whether floods affect knowledge production and hence reshape the geography of innovation. Specifically, we investigate whether firms in flood-prone areas adapt to floods by forming patent collaborations with firms in less flood-exposed regions.

Innovation activities exhibit strong spatial concentration (Audretsch and Feldman 1996; Kalyani et al. 2025). Firms and inventors tend to cluster in specific regions to benefit from agglomeration economies such as knowledge spillovers, labor market pooling, and the sharing of specialized inputs and infrastructure (e.g., Ellison et al. 2010; Duranton and Overman 2005). These agglomeration forces foster an environment where ideas diffuse more rapidly and innovation is more productive. However, when these innovation hubs are located in flood-prone areas, the increasing exposure to climate risk introduces a countervailing force. In particular, the threat of floods may incentivize firms to diversify their innovation collaborative partnerships geographically, thereby reducing their vulnerability to local disruptions. This trade-off between the benefits of agglomeration and the risks associated with climate exposure may lead firms to reorganize their innovation networks across different regions.

We develop a search-and-matching model that captures how floods affect firms' collaboration choices in innovation. The model builds on the idea that floods temporarily reduce productivity, therefore disrupting production and innovation processes. In response, firms reoptimize by seeking cross-county partnerships that are less affected by the disruption. We interpret it as a risk-sharing mechanism, as in the seminal work by Rosenzweig and Stark (1989). This shift toward cross-regional collaboration mitigates the productivity loss from localized shocks. The model delivers two key predictions. First, experiencing a flood or

facing elevated flood risk encourages firms to reallocation innovation away from local collaboration to cross-county collaboration. Second, in the search and collaborative matching process, firms are more likely to collaborate with regions that have a lower probability of being simultaneously affected by floods.

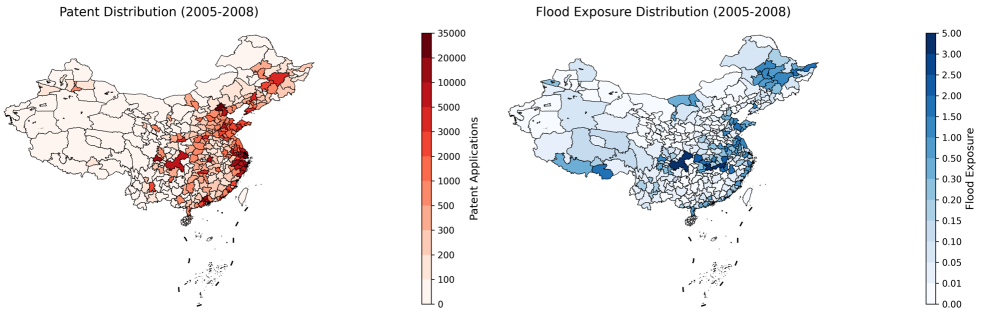


Figure 1: China's patent activities are more concentrated in flood zones.

Furthermore, we validate the theoretical model with empirical results. China provides an ideal empirical setting for this study. First, China is one of the most flood-exposed countries in the world, with 395 million people exposed to floods annually and over $150 billion in flood-related economic losses between 2000 and 2017, according to the EM-DAT International Disaster Database. Second, similar to the United States, in which innovation is highly concentrated in a few regions (Kalyani et al. 2025), patenting activity in China, a major global innovation hub, is also heavily concentrated in the flood-prone areas (see Figure 1). Floods themselves are also spatially concentrated, typically affecting the same regions repeatedly over time. The co-location of innovation hubs and flood-prone areas provides a unique setting to study how climate risks interact with agglomeration forces in shaping the geography of innovation. Third, despite ongoing population shifts toward coastal regions in China (Hoffmann et al. 2024), we find a striking inland movement of the patenting activity. The geographical center of innovation activity has gradually moved away from the coastal hubs toward more central and southern inland regions.[1] Meanwhile, the number of cross-county patent collaborations in China has increased by more than 600% between 2008 and 2018. These patterns suggest that innovation networks may be adapting in response to

[1]According to our calculation, more than 50% of the patenting activity is located in cities with flood exposure in the top 25% percentile. The geographical center of patenting activity in China shifted by approximately one degree westward and one degree southward between 2008 and 2018.

rising climate risk. Taken together, it allows us to observe whether and how firms in China restructure their innovation networks in response to climate risk.

Our baseline results provide evidence of firms adapting to flood events by expanding their innovation networks through cross-county collaborations. We construct a novel dataset that combines flood exposure measures from Tellman et al. (2021), detailed patent records from the China National Intellectual Property Administration (CNIPA), and firm location data from Tianyancha. We follow the existing literature (e.g., Wu et al. 2022, and König et al. 2022) and focus on an episode of rapid expansions of China's patenting activities between 2008 and 2018. Finally, we identify 452,734 collaborative patents that involve 29,429 unique county pairs during the 2008–2018 period. Using county-level fixed effects regressions, we find a positive and statistically significant relationship between flood exposure, as measured by the number of flooded days in a county, and the number of patent collaborations with other counties. Specifically, each additional day of flood exposure is associated with a 4.7% increase in cross-county collaborative patents. In terms of economic magnitude, a one standard deviation increase in flood exposure corresponds to approximately 302 additional cross-county collaborative patents nationwide. The results are also robust when using patent level regressions and suggest that firms respond to local flood shocks by searching collaborative partners in other counties.

To test the risk-sharing mechanism proposed by our theoretical framework, we hypothesize that firms are more likely to collaborate with partners located in regions that are less affected by floods. In seeking collaborative partners, firms located in flooded counties would prefer partners in less flooded areas. That way, when one region is hit by a flood, its partner in a less-affected area can maintain continuity in research and development activities. This form of spatial risk-sharing allows firms to reduce the likelihood that climate shocks will completely disrupt their innovation activities. To examine this channel, we conduct a county-pair level analysis using differences in flood exposure between counties as our main independent variable. Results show that patent collaborations are more frequent among county pairs with larger differences in flood exposure. This finding supports the model's prediction that innovators strategically form cross-county partnerships with regions facing less climate risk, thereby hedging against the adverse effects of local flood shocks. In a het-

erogeneity analysis, we alternatively define flood exposure difference as the gap between the counties with the highest and lowest nightlight intensity within each county pair. We find that when more productive counties face greater flood risks, they are more inclined to seek innovation partners in less-exposed areas.

We then decompose the risk-sharing mechanism from three aspects: search costs, matching probability, and success rate. Following our theoretical framework, We hypothesize that innovators prefer to seek partners in regions where search is easier, probability of being simultaneously affected by flood is lower, and innovation quality is higher, thereby increasing the probability of successful patent outcomes. To test these hypotheses, we estimate county-pair fixed effects regressions with interaction terms. Our results reveal three key patterns: (i) reductions in transportation costs significantly increase the likelihood of collaboration, consistent with findings in the existing literature (e.g., Berger and Prawitz 2024, and Koh et al. 2024); (ii) counties with experience of being simultaneously flooded are less likely to collaborate with each other; and (iii) counties with a history of high patent quality are more likely to form collaborations. Together, these findings provide empirical support for the predictions of our theoretical framework.

While floods are generally considered exogenous natural shocks, potential endogeneity remains a concern in our OLS estimations. First, firms in flood-prone areas may adjust their behavior in response to floods. Second, unobserved factors—such as local government capacity—could influence both flood exposure and innovation activities. Third, sample selection bias may arise from focusing only on county pairs with existing collaborations. Although we have partially addressed this concern by constructing a balanced panel including all county pairs with at least one patent collaboration during the study period, we still employ instrumental variables to mitigate the endogeneity issue. Results are robust.

Our findings are important for several reasons. First, we contribute to the growing literature on climate adaptation. While Kocornik-Mina et al. (2020) find little evidence that the spatial pattern of nighttime lights shifts in response to floods, more micro-level studies suggest that adaptation occurs. Jia et al. (2022), Balboni et al. (2023), and Hu and Wang (2024) show that firms adjust their location decisions based on flood risks in the United States, Pakistan, and China, respectively. Castro-Vincenzi et al. (2024) find that firms

diversify sourcing strategies to mitigate floods. In the context of innovation, most existing research has focused on agricultural technologies (e.g., Moscona 2021; Cui and Xie 2022; Moscona and Sastry 2023). Beyond agriculture, studies such as Miao and Popp (2014) and Long and Wang (2025) find that climate change leads to an increase in climate mitigation patents. We contribute to the adaptation literature in two key ways. First, to our knowledge, we are the first to incorporate floods, an increasingly frequent and inevitable disaster in many parts of the world, into the analysis of technological adaptation. Second, we provide evidence that innovation adapts to climate risks not only through climate-related patents, but also through the broader process of knowledge production across all patent types.

Second, we contribute to the strand of literature on collaborative matches in innovation by proposing a novel mechanism that patent collaborations can be established as a way of hedging climate risk. Previous literature mainly focuses on the role of geographical proximity in facilitating innovation (e.g., Almeida and Kogut 1999; Breschi and Lissoni 2009; Bernard et al. 2019; Koh et al. 2024; Berger and Prawitz 2024; Cotterlaz and Guillouzouic 2025) as well as the importance of innovation productivity and capability (e.g., Wuchty et al. 2007; Akcigit et al. 2018). We find results similar to the existing literature. However, beyond those two key factors, we propose that climate risks also play a significant role in shaping patent collaborations. Hence, our paper identifies a previously under-recognized determinant, the intention to hedge against climate risks, as a force shaping the geography of innovation networks.

Third, our paper extends the discussion of knowledge spillovers to the context of climate risk. A fundamental assumption for growth theory is that knowledge will have positive externalities (Aghion and Jaravel 2015). And that constitutes an important force of agglomeration (e.g., Ellison et al. 2010; Duranton and Overman 2005; Glaeser and Gottlieb 2009). China faces substantial inequalities between coastal and inland regions.[2] Under conventional theories, firms in innovation-intensive coastal hubs have limited incentives to

[2]In 2023, the distribution of firms in China's manufacturing and service sectors remained uneven, with the eastern coastal regions accounting for 53.1% of businesses, while the western inland regions represented only 20%. The Chinese government has actively promoted regional economic convergence since the early 2000s. A key milestone was the Third Plenary Session of the Sixteenth Central Committee of the Communist Party of China in 2003, which officially launched policies such as the Western Development Strategy to stimulate growth in inland provinces.

collaborate with less-developed inland areas. In contrast, our paper identifies a new, market-based mechanism: the incentive to spatially diversify climate risk. Specifically, we find that firms in flood-prone coastal regions are more likely to form partnerships with inland counties that face lower climate risk. Since a well-established body of research (e.g., Howitt 2000; Greenstone et al. 2010; Bloom et al. 2013; Acemoglu et al. 2016) has highlighted the importance of knowledge spillovers in promoting regional growth, our findings imply that climate-induced inland–coastal collaborations could contribute to cross-regional economic convergence in China.

The remainder of the paper is organized as follows. Section 2 describes the measurement of flood exposure and the construction of the cross-county patent collaboration dataset. Section 3 presents the theoretical framework, and Section 4 provides empirical evidence in support of the model's predictions. Section 6 concludes.

2 Data

This section provides an overview of how we measure floods and collaborative patents.

2.1 Measuring Floods

We gather data on flood events from the Global Flood Database (GFD), which provides comprehensive tracking of floods in China from 2000 to 2018. This database documents a total of 189 flood events across the country. Since the GFD offers satellite-derived flood maps at the county level, we are able to collect data on the duration of flooding for each 30m $\times$ 30m pixel. Additionally, the database identifies whether a pixel contains permanent water bodies, which are defined by the GFD as pixels that "are consistently identified with the presence of surface water for the majority of observations in 2000-2018 at 30-meter resolution, which was resampled to 250m resolution in Google Earth Engine using nearest neighbor resampling." Using this dataset, we construct a county-level proxy to quantify flood exposure ($FloodExposure$) following the two steps:

First, we calculate **Cumulative Flood Duration (CFD)**, which captures the extent of flood exposure in a given county. It quantifies the total number of flood-experienced days across all pixels within a county in a given year. Specifically, CFD is measured in pixel-days, meaning that it accounts for both the spatial distribution and temporal persistence of floods. A higher CFD value indicates a more severe and prolonged presence of floods. It is constructed using the following equation:

$$CFD_{it} = \sum_{j \in A_i} FloodDuration_{jt} \tag{1}$$

where CFD_{it} denotes the cumulative flood duration for county i in year t. A_i represents the set of non-permanent water pixels, excluding permanent water bodies such as lakes and reservoirs. Hence, $FloodDuration_{jt}$ refers to the number of days that non-permanent water pixel j experiences flooding in year t.

Then, we construct the key variable $FloodExposure$ used in our regressions, which captures the average flood exposure per pixel within a given county. It is calculated as CFD

divided by the total number of non-permanent water pixels in the county. Unlike CFD, which reflects the total flood exposure in pixel-days, $FloodExposure$ normalizes this measure by county size and provides a standardized metric of flood exposure that is comparable across regions. A higher $FloodExposure$ value indicates that, on average, each pixel in a county experiences flooding for a greater number of days. It is constructed using the following equation:

$$FloodExposure_{it} = \frac{CFD_{it}}{|A_i|} = \frac{\sum_{j \in A_i} FloodDuration_{jt}}{|A_i|} \tag{2}$$

where $FloodExposure_{it}$ indicates the pixel-adjusted flood exposure of county i at year t, $|A_i|$ represents the total number of non-permanent water pixels in county i. By adjusting the total sum of flood duration by the size of non-permanent water pixels, we are able to measure the average number of flooded days experienced by non-permanent water pixels in county i at year t.

To capture the risk-sharing mechanism, Section 4.2 and 4.3 introduce $FloodDiff$ and $FloodMean$ at the county-pair level:

$$FloodDiff_{ijt} = |FloodExposure_{it} - FloodExposure_{jt}| \tag{3}$$

$$FloodMean_{ijt} = \frac{FloodExposure_{it} + FloodExposure_{jt}}{2} \tag{4}$$

where $FloodDiff$ denotes the absolute difference in flood exposure between county i and county j in year t, while $FloodMean$ denotes the average flood exposure of county i and county j in year t.

2.2 Measuring Collaborative Patents

Our primary data source is the China National Intellectual Property Administration (CNIPA)[3]. Patents are typically categorized into three types: invention, design patents, and utility models [4]. Invention patents are called "invention applications" initially, and some of

[3]More detailed information about patent samples can be found in Appendix B.

[4]More detailed information about patents can be found at https://english.cnipa.gov.cn/col/col2995/index.html. According to the definition of CNIPA, an invention patent is a new technical solution related to a product, a process, or an improvement; An utility model is a new technical solution related to a product's shape, structure, or a combination thereof fit for practical use; A design patent is a

them are approved eventually, which are called "invention grants". In our study, we focus on invention patent applications. In the subsequent empirical results of this paper, we will refer "patent applications" as "invention patents application" for short. For each patent, we record a unique patent identifier number, along with the dates of application and publication, International Patent Classification (IPC) codes, the names of applicant(s) and inventor(s), and an associated address. We use the application date because it more accurately reflects when new knowledge was created and formalized (Moretti 2021). Moreover, since inventors are mainly individuals while applicants can be firms, research institutes, individuals, or other types of entities, and patents assigned to firms usually take up a dominant share in recent decades (Akcigit et al. 2022), we finally adopt "applicants" as the proxy for innovators in our empirical analysis (Koh et al. 2024).[5]

To identify cross-county patent collaborations, a central challenge with our analysis is to identify the county in which all applicants are located. The CNIPA database only reports the first-listed applicant's exact address, and the address of other applicants is not reported. Hence, we are not able to identify the address of all applicants using only CNIPA database. To solve this issue, we constructed a search database following the work of Koh et al. (2024) and used Tianyancha, a firm-level database with detailed firm location data, to manually cross-check our identification. Specifically, we address this issue using two approaches following Koh et al. (2024).

Firstly, we construct a search database that includes accurate county-level addresses for applicants of solo patent applications and for first-listed applicants of collaborative patents. Although our sample period covers 2008-2018, we can retrieve patent addresses from the CNIPA database for the years 2000 to 2022 to extend our search database. To prevent the misidentification of distinct entities that may share identical applicant names, we limit the extension of the time range. Then, we standardize all applicant names in a consistent format. And we search patents in both earlier and later years[6].

new design of the shape, pattern, or a combination thereof.

[5]We would like to note that for each patent, we exclude individual applicants from the applicant list using both automated and manual methods. That is because it is difficult to obtain the address of an individual applicant. For example, if a patent application lists two applicants - one is a company and another is an individual - we treat it as a single application. And if a patent only has an individual applicant, then we remove this observation from our database.

[6]For example, we have a patent in 2008, we search sequentially in 2008, 2007,...,2000, then 2011, 2012,...,

Secondly, we obtain firms' addresses from the Tianyancha database, which we use both to match firms that are not identified in the first step and to double-check the addresses provided by the patent database. Finally, we have addresses for 452,734 collaborative patents and 29,429 county pairs.

The primary outcome of interest is patent collaborations over time and across regions. We classify a patent with multiple applicants as a "collaborative patent." Our key outcome variable is $CollaborativePatents_{ij,t}$, the count of patents in which applicants are located in both paired counties in a given year t for the county-level and county-pair-level data. For example, suppose a patent has 3 applicants located in counties A, B, and C, respectively, in the year 2008. Then this patent would be counted in the variable $CollaborativePatents$ for the county pairs (A, B), (B, C), (A, C) in the year 2008.

up to 2022.

3 Theoretical Framework

3.1 Environment

3.1.1 Floods

Consider an economy with two counties, indexed by $c = 1, 2$, which differ exogenously in local demand A_c and flood probabilities pr_c, and endogenously in intrinsic productivity $z_{c,t}$. Let $\tau_t = \{\tau_{1,t}, \tau_{2,t}\}$ represent the global flood event at time t, where $\tau_{c,t} = 1$ if county c experiences a flood, and $\tau_{c,t} = 0$ otherwise. A flood temporarily reduces county productivity:

$$\hat{z}_{c,t}(\tau_t) = z_{c,t} e^{-\eta \tau_{c,t}}, \tag{5}$$

where $\eta > 0$ quantifies the proportional flood damage. The realized productivity $\hat{z}_{c,t}(\tau_t)$ subsequently impacts both production and innovation activities.

3.1.2 Firms and Productivity Evolution

In each county, a representative firm maximizes lifetime discounted profits through local market sales and productivity-enhancing investments. At the start of period t, the firm in county c inherits intrinsic productivity $z_{c,t}$ and decides on patent acquisitions $s_{c,t}$ to improve productivity in period $t + 1$. After the realization of the flood event τ_t, the firm maximizes static profits by supplying final goods in the local market. Here, we abstract from the concrete profit maximization problem and assume that the profit function $\pi(z_{c,t}, \tau_t, A_c)$ satisfies $\frac{\partial^2 \pi_{c,t}}{\partial z_{c,t} \partial A_c} > 0$. This simplified setup highlights the endogenous effect of local market access on innovation while abstracting from general equilibrium demand-side feedback. We will extend the framework to incorporate households' decisions in the full model.

Given static profits, the firm's dynamic profit maximization problem is:

$$\begin{aligned} V_c(z_{1,t}, z_{2,t}) = \max_{s_{c,t}, z_{c,t+1}} \; & \mathbb{E}_{\tau_t}[\pi(z_{c,t}, \tau_t, A_c) - p_{c,t}(\tau_t) s_{c,t}] + \beta V(z_{1,t+1}, z_{2,t+1}) \\ \text{s.t.} \quad & z_{c,t+1} = (1 - \delta) z_{c,t} + \theta s_{c,t}^{\gamma}, \end{aligned} \tag{6}$$

where $s_{c,t}$ represents patents acquisition that the local firm decides before the flood realiza-

tion, and $p_{c,t}(\tau_t)$ denotes the realized unit patent price contingent on flood events. Regarding the productivity evolution process, we assume that the intrinsic productivity depreciates at a constant rate δ. More importantly, the acquisition of patents improves the productivity by a fixed step size θ. We assume diminishing marginal benefit of patent accumulation governed by $\gamma < 1$.

3.1.3 Innovators and Patent Production

Patent production occurs after flood realization in two stages. First, innovators incur a fixed search cost κ_{ij}^s to search for cross- or within-county research collaboration. Denote $v_{ij,t}(\tau_t)$ as the measure of innovators in county i searching for collaboration with county j innovators, resulting in successful matches described by the following matching function:

$$m_{ij,t}(\tau_t) = \xi v_{ij,t}(\tau_t)^{\alpha} v_{ji,t}(\tau_t)^{\alpha}, \tag{7}$$

where ξ denotes the matching efficiency parameter. $\alpha < \frac{1}{2}$ captures the decreasing return to scale of the matching process, and we make this assumption to guarantee the uniqueness of equilibrium. Here, we assume the matching process is symmetric for both side of collaboration seekers, which implies elasticities of successful matching with respect to potential innovators are independent of their origins. Successful teams then pay an R&D cost κ^i producing patents, the measure of which can be described by:

$$q_{ij,t}(\tau_t) = f_{ij,t}(\tau_t) m_{ij,t}(\tau_t), \tag{8}$$

where $f_{ij,t}(\tau_t) = \mu_{ij} \hat{z}_{i,t}(\tau_t)^{0.5} \hat{z}_{j,t}(\tau_t)^{0.5}$ is the innovation success rate, dependent on the realized productivity of team members. Here, μ_{ij} denotes the innovation efficiency parameter and captures heterogeneity across collaboration patterns. Flood-induced productivity shocks directly affect innovation success. Intuitively, higher productivity represents higher research capability, while flood temporarily reduces productivity and thus interrupts the innovation process. That provides a mechanism through which floods shift collaboration from local to cross-county. Provided the matching and innovation function, the value of a successful

research team is described by:

$$J_{ij,t}(\tau_t) = -\kappa^i + p_{i,t}(\tau_t) f_{ij,t}(\tau_t). \tag{9}$$

The underlying intuition is that the value of a successful team equals the expected patent sales revenue net of R&D cost. The free-entry condition implies:

$$\kappa^s_{ij} = \frac{m_{ij,t}(\tau_t)}{v_{ij,t}(\tau_t)} J_{ij,t}(\tau_t), \tag{10}$$

where κ^s_{ij} denotes the search cost between county i and j. We assume that the search costs across counties exceed local search costs $\kappa^s_{ij} > \kappa^s_{ii}$. $\frac{m_{ij,t}(\tau_t)}{v_{ij,t}(\tau_t)}$ represents the matching probability for a potential innovator in county i searching for collaboration with innovators in county j.

3.1.4 Market Clearing Condition

Patent prices $p_{i,t}(\tau_t)$ clear the market for each county and flood realization:

$$s_{c,t} = \sum_{j=1}^{2} q_{cj,t}(\tau_t) \quad \forall c, \tau \tag{11}$$

Intuitively, since the local firms decide their patent acquisitions before the realization of flood events, the patent prices adapt to incentive innovators to produce adequate patent outputs in specific flood events.

3.1.5 Timeline

The timeline of the framework unfolds as follows: County-specific intrinsic productivity $z_{c,t}$ act as the state variables of the system upon entering period t. At the start of period t, local firms choose patent acquisitions $s_{c,t}$ based on their expectations of possible flood events. After the flood realization τ_t, intrinsic productivity adjusts to realized productivity $\hat{z}_{c,t}$. Innovators then incur search costs κ^s_{ij} to form teams $m_{ij,t}(\tau_t)$, which pay R&D cost κ^i and produce patents $q_{ij,t}(\tau_t)$. Firms subsequently supply final goods and pay for patent

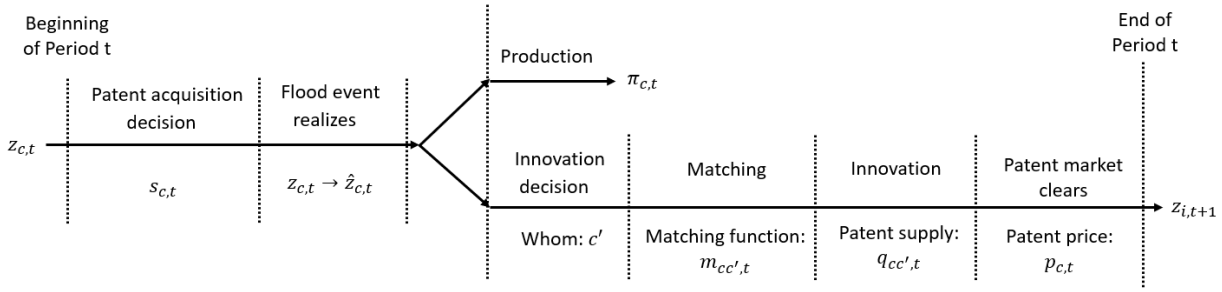


Figure 2: Model Timeline

purchases, which realizes static profits $\pi_{i,t}(\tau_t)$, and update productivity for the next period $z_{i,t+1}$.

3.1.6 Equilibrium

The steady state spatial general equilibrium consists of county-specific intrinsic productivity $\{z_i\}$ and patent demand $\{s_i\}$, and county-pair- and flood-specific collaboration value $J_{ij}(\tau)$, vacancy posting $v_{ij}(\tau)$, collaboration formation $m_{ij}(\tau)$ and patent production $q_{ij}(\tau)$, and county- and flood-specific patent price $p_i(\tau)$, such that

1. Before the realization of flood event τ

   (i) $\{z_i\}$ and $\{s_i\}$ satisfy local firms' optimal patent acquisition in Equation 6;

2. After the realization of flood event τ

   (i) $\{J_{ij}(\tau)\}$ satisfy the value function Equation 9 and $\{v_{ij}(\tau)\}$ satisfy the free entry condition Equation 10;

   (ii) $\{m_{ij}(\tau)\}$ satisfy the matching function Equation 7 and $\{q_{ij}(\tau)\}$ satisfy the innovation function 8;

   (iii) $\{p_i(\tau)\}$ satisfy the patent market clearing condition 11.

3.2 How Flood Affects Collaboration Patents

Based on the model setup, we propose a key mechanism driving firms' collaborative behavior in response to flood events: the risk-sharing channel. First we will make three

intuitive assumptions to simplify our analysis.

Assumption 1 *The following conditions hold:*

(i) $\gamma > 1 - 2\alpha$

(ii) $\kappa^i \to 0$

(iii) $\eta \to 0$

The intuition behind the assumptions is as follows: In Assumption (i), γ captures the elasticity of productivity with respect to patent acquisition, while $\frac{1}{1-2\alpha}$ reflects the elasticity of patent production with respect to productivity. This implies that a marginal increase in productivity raises patent supply more than patent demand ($\frac{\gamma}{1-2\alpha} > 1$). Assumption (ii) requires the innovation cost κ^i to be sufficiently low, ensuring that innovation is always profitable upon successful matching. Assumption (iii) restricts the flood damage parameter η to be small enough such that flood events are not so severe as to eliminate incentives for production and innovation altogether.

Let a flood event be represented by $\tau = \{\tau_1, \tau_2\}$, and consider the following scenarios:

$$\begin{cases} \tau^{\text{no flood}} = \{0, 0\} \\ \tau^{\text{single-flooded}} = \{1, 0\} \\ \tau^{\text{both-flooded}} = \{1, 1\} \end{cases}$$

Then, we can use the following lemma to characterize the relationship of patent prices in the steady state of the economy:

Lemma 1 *Provided Assumption 1 holds, assume that the cross-county search cost* κ_{ij}^s *is sufficiently large, then* $p_1(\tau^{no\ flood}) < p_2(\tau^{no\ flood})$ *if* $z_1 > z_2$.

In addition to Assumption 1, we assume that κ_{ij}^s is sufficient large to decouple the innovation decisions of two counties so as to simplify the analysis. Intuitively, Lemma 1 implies that if a marginal productivity improvement boosts patent supply more than patent demand ($\frac{\gamma}{1-2\alpha} > 1$), then counties with higher intrinsic productivity z_c will have lower equilibrium patent

prices in the no-flood scenario, $p_c(\tau^{\text{no flood}})$. Based on Lemma 1, the following proposition characterizes the direct effect of flood events on cross-county collaboration:

Proposition 1 *Provided Assumption 1 holds, then, in the steady-state equilibrium of the economy, if the productivity ratio* $\frac{z_1}{z_2}$ *is sufficiently large, the following conditions hold:*

$$\begin{cases} q_{c,c'}(\tau^{\textit{single-flooded}}) > q_{c,c'}(\tau^{\textit{no flood}}) \\ q_{c,c'}(\tau^{\textit{single-flooded}}) > q_{c,c'}(\tau^{\textit{both-flooded}}) \end{cases}$$

Proposition 1 implies that, if the high-productivity county is flooded, the quantity of cross-county collaborative patents, $q_{c,c'}$, increases relative to the no-flood and both-flooded scenarios. The intuition is as follows: when county c is hit by a flood, its realized productivity $\hat{z}_c(\tau)$ declines proportionally, which reduces the innovation success rates - both the local one $f_{c,c}(\tau)$ and the cross-county one $f_{c,c'}(\tau)$. However, since cross-county collaboration partially depends on the unaffected county c', its success rate declines less than that of local collaboration.

Simultaneously, the drop in success rates reduces the local patent supply $q_c(\tau)$. Given that patent demand s_c is set prior to the realization of flood events, the resulting supply contraction drives up the local patent price p_c, creating stronger incentives for innovators to sustain their innovation output. Taken together, these two forces incentivize firms to diversify away from local collaboration in favor of cross-county partnerships, as a way to hedge against flood-induced localized innovation disruption. What is worth noting is that, under the assumption that productivity ratio $\frac{z_1}{z_2}$ is sufficiently large, county c' also has the incentive to promote its collaboration with county c, as the realized productivity of county c is still larger than that of county c'.

Figure 3 provides a numerical illustration of Proposition 1. The scenario $\tau^{\text{single-flooded}}$ refers to a case in which county 1 experiences a flood while county 2 does not. The figure shows that the collaborative patenting activity increases relative to the no-flood baseline only when county 1 is sufficiently more productive than county 2. The figure also demonstrates that the critical threshold for $\frac{z_1}{z_2}$ depends on the magnitude of flood damage η. Specifically, as

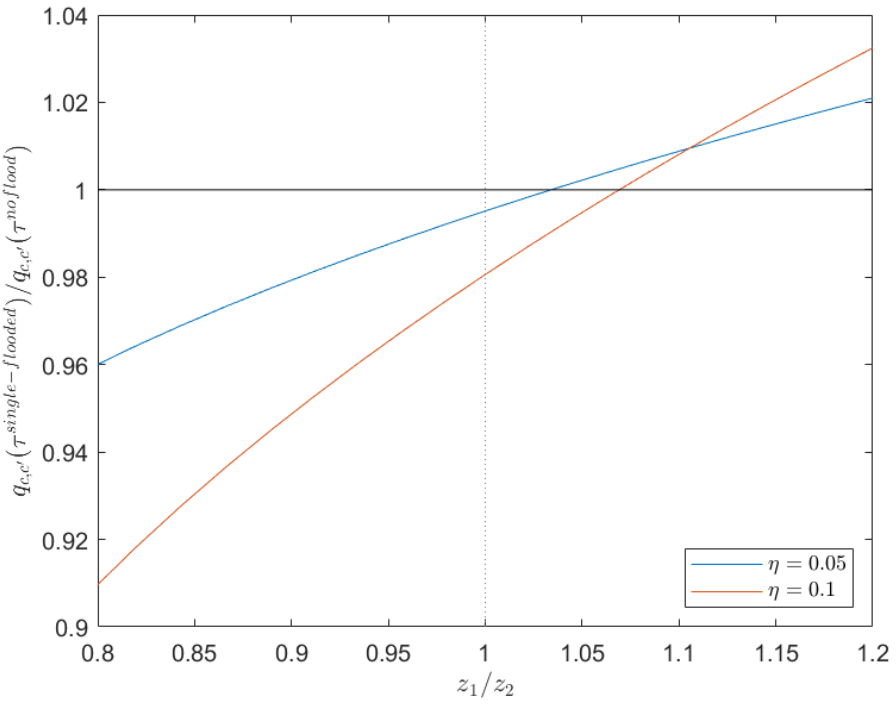
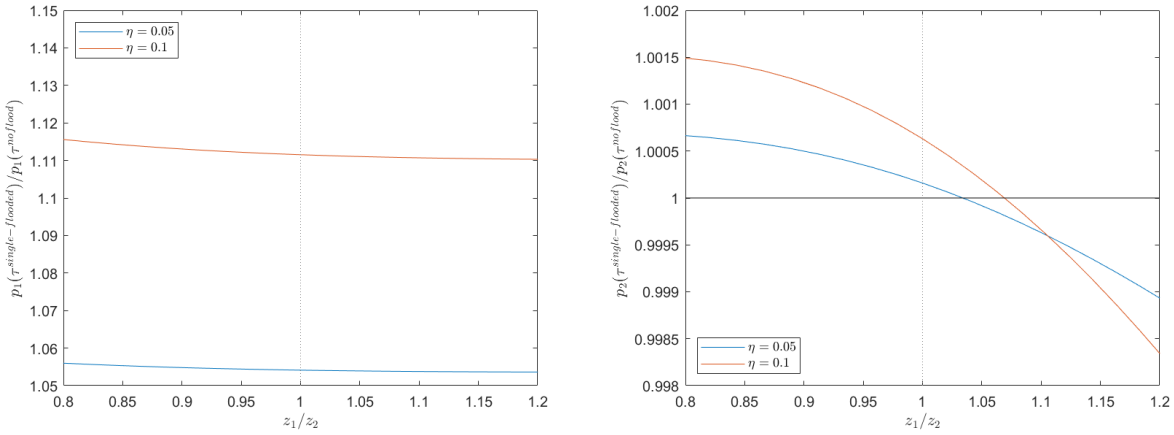


Figure 3: Flood Enhances Collaboration When Flooded County is Sufficiently Productive

η increases from 0.05 to 0.1, a larger productivity advantage in county 1 is required for cross-county collaboration to increase. One can further show that if flood damage becomes too severe, collaboration will no longer increase - even as $\frac{z_1}{z_2} \to \infty$. This aligns with our earlier assumption that for collaboration to remain attractive for both counties, flood damage must not be excessively high.

Figure 4 illustrates the mechanisms underlying the rise in cross-county collaboration shown in Figure 3, from both the demand and supply sides. Panel A shows that when county 1 is hit by a flood, its ex-post patent price unambiguously increases (i.e., $\frac{p_1(\tau^{\text{single-flooded}})}{p_1(\tau^{\text{no flood}})} > 1$). This increase provides an incentive for innovators in county 1 to seek collaboration outside the local area as a means of hedging against local shocks.

Panel B shows how the same flood event affects the patent price in county 2 through general equilibrium effect. When county 1 is relatively unproductive (i.e., $\frac{z_1}{z_2} < 1$), it becomes suboptimal for innovators in county 2 to collaborate with those in county 1, since doing so reduces the overall success rate of innovation and pushes up the local patent price (i.e., $\frac{p_2(\tau^{\text{single-flooded}})}{p_2(\tau^{\text{no flood}})} > 1$). Conversely, when county 1 is sufficiently more productive (i.e., $\frac{z_1}{z_2}$



(a) Price Change in Flooded County 1 (b) Price Change in Non-flooded County 2

Figure 4: How Flood Affects Local Patent Prices

is large), the productivity advantage largely offset the negative impacts of the flood event. Combined with an increased number of potential innovators seeking for cross-county collaboration from county 1, it enhances the innovation environment in county 2, leading to a decline in the local patent price (i.e., $\frac{p_2(\tau^{\text{single-flooded}})}{p_2(\tau^{\text{no flood}})} < 1$). This reduction makes it profitable for innovators in county 2 to accept collaboration requests from county 1.

In summary, the rise in collaboration following a flood event is jointly driven by both demand and supply forces, with the relative productivity between the two counties serving as the key underlying determinant.

4 Empirical Results

In this section, we provide empirical evidence supporting our theoretical framework. We begin by presenting baseline results at the county level, showing that cross-county patent collaborations increase with greater flood exposure. Next, we test the proposed risk-sharing mechanism by examining the role of flood exposure differences using county-pair regressions. Finally, we further decompose the mechanism into three channels: search costs, matching probability, and success rates. Taken together, our findings validate the theoretical prediction that firms in flood-prone counties form collaborative partnerships as a strategy to hedge against climate risk.

4.1 Baseline Results: Floods and Cross-County Patent Collaborations

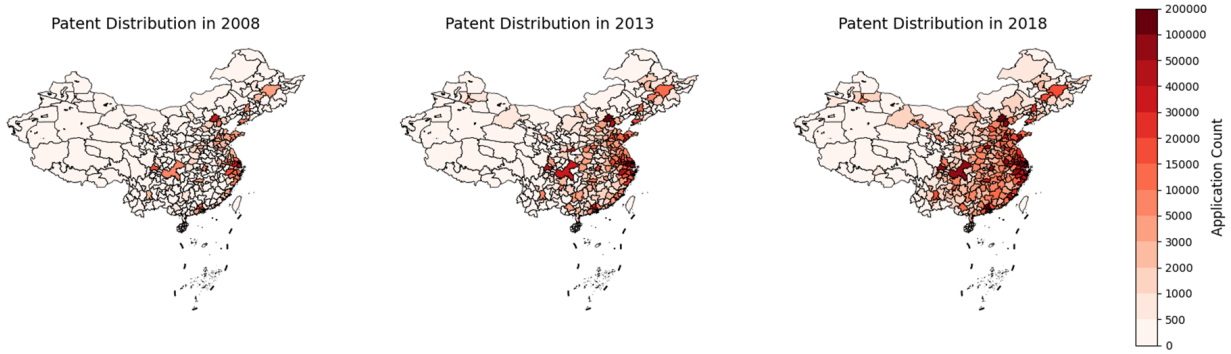
We begin by presenting our baseline finding that innovators tend to seek cross-county collaborators as they are exposed to more floods. Panel A of Figure 5 shows a marked inland shift in the spatial distribution of patent applications between 2008 and 2018. Initially, patent activities were concentrated in flood-prone provinces. However, patent activity gradually expanded to inland regions. Panel B reveals a concurrent increase in cross-county collaborations during the same period, with collaborative networks growing outward from a few coastal hubs to include a broader set of inland regions. These trends suggest that while floods may harm local innovation, they may also prompt firms to collaborate across regions and thus change the spatial distribution of innovation in the long run.

We then conduct a county-level analysis to understand the impact of floods on county-level patent applications. The regression is as follows:

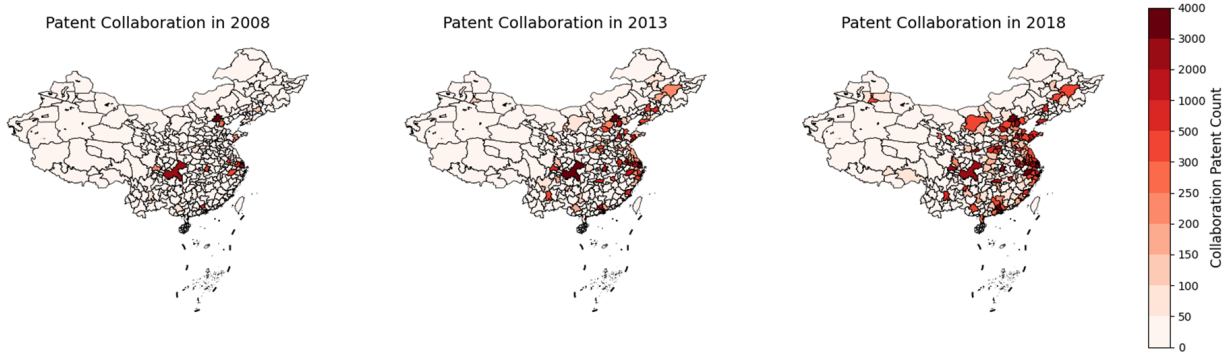
$$Patents_{it} = \beta_1 + \beta_2 FloodExposure_{i,t-1} + \lambda_t + \eta_i + \epsilon_{it} \tag{12}$$

Here, $Patents_{it}$ represents the number of patent applications in county i and year t, and is transformed through the Inverse Hyperbolic Sine (IHS). $FloodExposure_{i,t-1}$ denotes the lagged pixel-adjusted flood duration of county i, and the detailed calculation is introduced

in Section 2.1. λ_t represents time fixed effects, η_i denotes county fixed effects, and ϵ_{it} is the standard error, clustered at the county level. Accordingly, β_2 captures the impact of floods on county-level patent applications.



(a) Patents are gradually shifting inlands.



(b) Patent collaborations are increasingly prevalent over time.

Figure 5: Spatial Distribution of Patents and Patent Collaborations in 2008, 2013, and 2018

Note: (1) Data Source: China National Intellectual Property Administration (CNIPA); (2) We introduce how we identify collaborative patents in Section 2.2.

Table 1: Impacts of Flood on Patents
- County Level

(IHS)	N(Patent Applications)				N(Collaborative Patents)			
	Total		Single-Applicant		Within-County		Cross-County	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FloodExposure	-0.082**	-0.077**	-0.102***	-0.096**	-0.018	-0.018	0.042**	0.047**
	(0.036)	(0.037)	(0.038)	(0.038)	(0.014)	(0.013)	(0.021)	(0.022)
Control	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.879	0.881	0.871	0.873	0.698	0.699	0.798	0.799
Obs	29,344	29,344	29,344	29,344	29,344	29,344	29,344	29,344

Notes: (1) Time: 2008-2018; Number of counties: 2,679 ; (2) 'Flood Exposure' represents the number of flooded days in a county, and the detailed calculation is introduced in Section 2.1; (3)'Total' refers to the total number of patent applications; 'Single-Applicant' refers to the number of applications filed by a single applicant; 'Within-County' refers to the number of patent collaborations occurring within the same county; and 'Cross-County' refers to the number of collaborations involving applicants from at least two different counties; (4) All dependent variables are transformed using Inverse Hyperbolic Sine (IHS); (5) Controls include population size, GDP, total loan value, number of firms above the designated size, and service sector output; (6)* 0.1, ** 0.05, *** 0.01.

Table 1 reports the estimated effects of flood exposure on different types of patenting activity at the county level. Columns (1) to (4) show that flood exposure is associated with a significant decline in the number of patent applications, regardless of whether they are filed by single or multiple applicants. Columns (5) to (8) examine the relationship between flood exposure and patent collaborations. While columns (5) and (6) show no significant effect on within-county collaborations, columns (7) and (8) reveal a positive and statistically significant association between flood exposure and cross-county collaborations. The results show that applicants adapt to climate risks by broadening their innovation networks beyond county borders.

In terms of economic magnitude, a one-day increase in flood exposure is associated with a 4.7% rise in cross-county collaborative patents. A one standard deviation increase in flood exposure (0.167, see Figure C2) then corresponds to a 0.78% increase in cross-county collaborations. Given that the average number of cross-county patent applications is 14.52 per county, this implies an increase of approximately 302 cross-county collaborative patents nationwide if flood exposure increases by one standard deviation. Our results are also robust when conducting a patent-level analysis (see Table C3).

4.2 Testing the Risk-Sharing Mechanism

In our theoretical framework (Section 3), we present the risk-sharing mechanism as the key mechanism to explain why innovators tend to seek cross-county collaborators. According to Proposition 1, innovators tend to collaborate with those located in less flooded areas. Hence, the difference in flood exposure across counties plays a key role here in fostering cross-county patenting collaboration ties. Given county level analysis could not analyze the role of flood difference across counties, we extend our analysis to a county-pair level analysis. The regression is as follows:

$$CollaborativePatents_{ijt} = \alpha + \beta_1 FloodDiff_{ij,t-1} + \lambda_t + \gamma_{ij} + \epsilon_{ijt} \tag{13}$$

where $CollaborativePatents_{ij,t}$ denotes the the number of collaborative patent applications between county i and county j at time t and is transformed using Inverse Hyperbolic Sine

(IHS). $FloodDiff_{ij,t-1}$ represents the difference in lagged pixel-adjusted flood duration of county i and county j. Additionally, we incorporate time fixed effects λ_t, and county-pair fixed effects γ_{ij}. Standard errors are clustered at the county-pair level.

Table 2: Impacts of Flood on Collaborative Patents
- County Pair Level

(IHS)	N(Collaborative Patents)			
	(1)	(2)	(3)	(4)
FloodMean	0.035***	0.042***		
	(0.011)	(0.011)		
FloodDiff			0.019***	0.021***
			(0.006)	(0.006)
Control	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
County Pair FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.425	0.425	0.425	0.425
Obs	323,719	323,719	323,719	323,719

Notes: (1) Time: 2008-2018; Number of county-pairs: 29,429; (2)'FloodMean' denotes the average number of flooded days for a given county pair, while 'FloodDiff' denotes the absolute difference in flood exposure between two counties within a county pair. Details on the construction of the flood exposure measure are provided in Section 2.1; (3) The dependent variable, 'N(Collaborative Patents)', measures the number of collaborative patents within each county pair and is transformed using the inverse hyperbolic sine (IHS) function; (4) Controls include population size, GDP, total loan value, number of firms above the designated size, and service sector output; (5)* 0.1, ** 0.05, *** 0.01.

In Table 2, we provide empirical support for the risk-sharing hypothesis. Using a county-pair level analysis, columns (1) and (2) replicate our earlier county-level findings in Table 1. We find that a higher average flood exposure between county pairs (*FloodMean*) is associated with a significant increase in the number of collaborative patents. The magnitude of this effect is also comparable to that in Table 1, confirming the robustness of our results. Columns (3) and (4) then test the risk-sharing mechanism proposed in Proposition 1 of Section 3. We find that differences in flood exposure across counties (*FloodDiff*) are positively and significantly associated with collaboration. A one-day difference in flood exposure between

two counties is associated with an approximate 2% increase in patent collaborations between them. This result supports the theoretical prediction that innovators are more likely to form cross-county partnerships with regions that face different levels of climate risk, as a strategy to hedge against local flood shocks. Our results are also robust when using alternative methods (see Table C4) and using a patent level analysis (see Table C5).

Table 3: Nightlight-Based Flood Difference and Patent Collaborations

(IHS)	N(Collaborative Patents)				
	(1)	(2)	(3)	(4)	(5)
Light-Sorted FloodDiff *03-07 Mean*	0.014** (0.006)				
Light-Sorted FloodDiff *04-07 Mean*		0.014** (0.006)			
Light-Sorted FloodDiff *05-07 Mean*			0.016*** (0.006)		
Light-Sorted FloodDiff *06-07 Mean*				0.016*** (0.006)	
Light-Sorted FloodDiff *07*					0.016*** (0.006)
Control	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
County Pair FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.425	0.425	0.425	0.425	0.425
Obs	323,719	323,719	323,719	323,719	323,719

Notes: (1) Time: 2008-2018; Number of county-pairs: 29,429; (2) 'FloodDiff' refers to the difference in flood exposure between the county with the highest nightlight intensity and the one with the lowest within each county pair. Details on the construction of the flood exposure measure are provided in Section 2.1. (3) '03–07 Mean' indicates that nightlight intensity is averaged over the years 2003 to 2007 when computing the county ranking used to define 'FloodDiff'; (4) The dependent variable, 'N(Collaborative Patents)', measures the number of collaborative patents within each county pair and is transformed using the inverse hyperbolic sine (IHS) function; (5) Controls include population size, GDP, total loan value, number of firms above the designated size, and service sector output; (6)* 0.1, ** 0.05, *** 0.01.

4.2.1 Heterogeneity Analysis

Table 3 presents a heterogeneity analysis based on the distance between counties within a county pair. In this analysis, flood exposure difference is calculated as the difference between the county with the highest nightlight intensity and the one with the lowest within each county pair. Unlike an absolute measure, this directional definition allows us to identify

whether more economically active counties (as proxied by nightlight intensity) are more or less exposed to floods relative to their paired counterparts. Across all specifications, the estimated coefficients remain positive and statistically significant. This suggests that greater difference in flood exposure is associated with stronger cross-county patent collaboration. More importantly, the results indicate that when more productive counties face greater flood risk, they are more likely to seek innovation partners in less-exposed regions. This pattern supports the interpretation that firms strategically form spatially diversified collaborations to hedge against localized climate shocks. The consistency of these results across different time windows and model specifications underscores the robustness of the risk-sharing mechanism we propose.

In Table 4, we examine the impact of flood exposure differences across county pairs grouped by geographical distance. As expected, counties in the closest distance group (Quantile 1) exhibit the highest average number of collaborative patents, consistent with the literature on lower search and coordination costs in geographically proximate collaborations (e.g., Koh et al. 2024). However, the pattern is not strictly monotonic: collaboration intensity decreases in the mid-distance groups (Quantiles 2 and 3) but rises again in the more distant groups (Quantiles 4 and 5), which is counterintuitive given the typical assumption that distant counties are less likely to collaborate. To better understand this, we examine the coefficients on flood exposure difference. We find a positive and statistically significant relationship in Quantile 1, suggesting that counties tend to form innovation partnerships with others that are both geographically closer and exhibit larger differences in flood exposure. Notably, we also find significant effects in Quantiles 4 and 5, indicating that the intention to hedge against climate risk can probably offset the costs induced by distance. This implies that climate risk provides a strong incentive for spatially diversified collaborations, even between geographically distant counties.

Figure 6 illustratively presents the findings in Table 4. The left panel plots the average number of collaborative patents across distance quantiles. As expected, county pairs in the shortest distance group (Quantile 1) exhibit the highest collaboration intensity, reflecting lower search and coordination costs. However, the pattern is not monotonic—collaboration does not consistently decline as distance increases. Instead, we observe an unexpected rise

in collaboration in Quantiles 4 and 5, which is counterintuitive given the general assumption that geographical distance discourages long-distance partnerships. The right panel presents the estimated coefficients of flood exposure difference for each distance group, along with 90% confidence intervals. Interestingly, the shape of the two figures is visually similar: both display a dip in the middle quantiles and a rebound in the later ones. This resemblance reinforces our interpretation that spatial risk-sharing may drive collaboration patterns across distant county pairs, particularly when large differences in flood exposure create incentives for innovation partnerships beyond what geographic proximity alone would suggest.

Table 4: Impact of Flood Difference by Different Distance Groups

(IHS)	N(Collaborative Patents)				
	(1)	(2)	(3)	(4)	(5)
FloodDiff	0.032**	-0.011	0.015	0.037***	0.019*
	(0.016)	(0.014)	(0.010)	(0.014)	(0.010)
Distance Quantile	1	2	3	4	5
Mean(*Colloborative Patents*)	2.755	0.879	0.962	1.714	1.022
Control	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
County Pair FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.543	0.314	0.329	0.433	0.349
Obs	64,746	64,746	64,746	64,746	64,735

Notes: (1) Time: 2008-2018; Number of county-pairs: 29,429; (2) 'FloodDiff' refers to the difference in flood exposure between the county with the highest nightlight intensity and the one with the lowest within each county pair. Details on the construction of the flood exposure measure are provided in Section 2.1. (3) '03–07 Mean' indicates that nightlight intensity is averaged over the years 2003 to 2007 when computing the county ranking used to define 'FloodDiff'; (4) The dependent variable, 'N(Collaborative Patents)', measures the number of collaborative patents within each county pair and is transformed using the inverse hyperbolic sine (IHS) function; (5) Controls include population size, GDP, total loan value, number of firms above the designated size, and service sector output; (6)* 0.1, ** 0.05, *** 0.01.

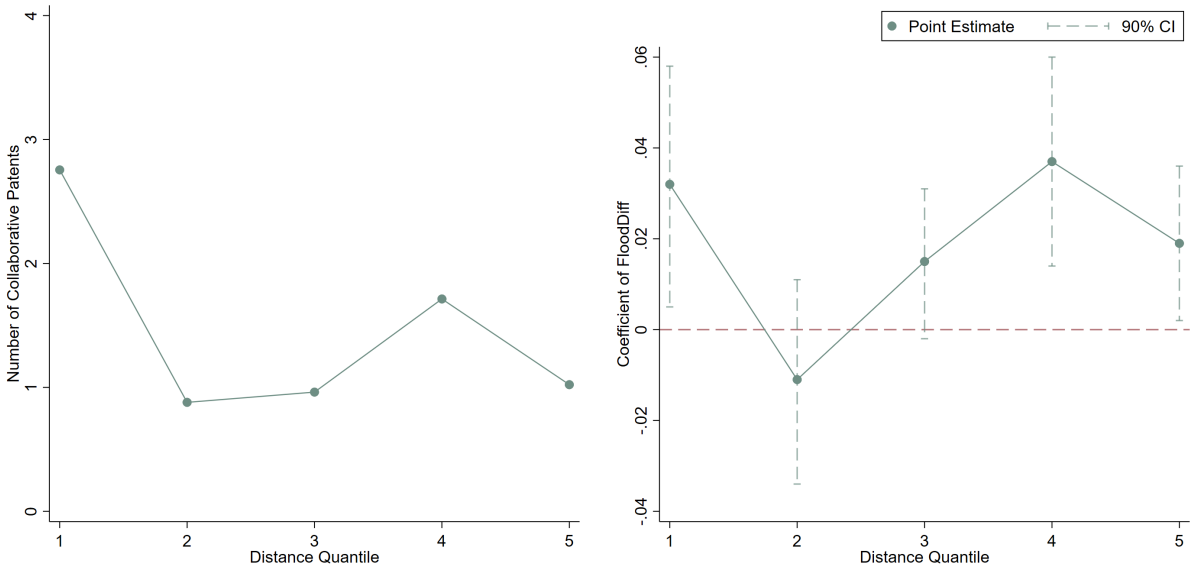


Figure 6: Number of Collaborative Patents and Impact of Flood Difference by Distance.

4.2.2 Robustness Check: IV Estimation

Although floods, as a type of natural disaster, can normally be interpreted as exogenous events, endogeneity concerns may still arise in the ordinary least squares (OLS) estimations. First, firms located in areas with higher flood risk may anticipate the occurrence of floods and adjust their strategies accordingly, even before the actual events. Second, omitted variable bias may be a concern. For instance, local governments with stronger administrative capacities may not only be more effective in mitigating flood impacts—thus reducing $FloodExposure$—but also actively promote patent collaborations through policy support or fiscal incentives. Third, potential endogeneity may also stem from sample selection bias, as the analysis includes only county pairs with existing patent collaborations. To some extent, we have addressed this concern by constructing a balanced panel that includes all county pairs with at least one collaboration during the sample period, which also partially accounts for the influence of the external margin.

For the above reasons, we construct two instrumental variables (IVs) based on geo-climatic features across counties. Both IVs use two sources of variation. The first IV is constructed as the interaction between slope and evaporation rate ($Evapo \times Slope$), while

the second IV is the product of slope and vegetation coverage ($Vege \times Slope$). Slope is time-invariant, whereas vegetation coverage and evaporation rate are time-varying. The two IVs satisfy the relevance condition. The slope of a terrain significantly influences flood risk: steeper gradients can amplify the intensity and destructiveness of flash floods, whereas flatter landscapes are more prone to prolonged water retention and waterlogging, both conditions are strongly correlated with floods. Slope, vegetation coverage, and evaporation rate are relatively stable physical and climatic conditions, shaped primarily by geographic location, topography, and long-term climate patterns, rather than by short-term economic decisions. The coefficients are estimated using the two-stage least squares (2SLS) method according to the following equation:

$$FloodDiff_{ij,t-1} = \alpha IV_{ij,t-1} + \lambda_t + \gamma_{ij} + \epsilon_{ijt} \tag{14}$$

$$CollaborativePatents_{ijt} = \gamma FloodDiff_{ij,t-1} + \lambda_t + \gamma_{ij} + \epsilon_{ijt} \tag{15}$$

The results of IV estimations are presented in Table 5. Panel A presents the first-stage estimation results, confirming the relevance of the instrumental variable to flood exposure. Panel B reports the second-stage estimates, where the coefficient on the main explanatory variable remains significantly positive. These findings indicate that endogeneity is unlikely to threaten the validity of our main results.

Table 5: Robustness Check: IV Estimation

IV	Evapo×Slope		Vege×Slope	
Panel A: First Stage	FloodMean	FloodDiff	FloodMean	FloodDiff
	(1)	(2)	(3)	(4)
EvapoMean×SlopeMean	-0.060***			
	(0.006)			
EvapoDiff×SlopeDiff		-0.110***		
		(0.028)		
VegeMean×SlopeMean			-0.032***	
			(0.001)	
VegeDiff×SlopeDiff				-0.013***
				(0.002)
Kleibergen-Paap F-statistic	112.488	15.893	795.579	38.622
Panel B: Second Stage	*(IHS)* N(Collaborative Patents)			
	(1)	(2)	(3)	(4)
FloodMean (estimated)	3.392***		1.499***	
	(0.754)		(0.292)	
FloodDiff (estimated)		3.357**		1.391**
		(1.316)		(0.627)
Control	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County Pair FE	Yes	Yes	Yes	Yes
Obs	323,719	323,719	323,719	323,719

Notes:(1) Time: 2008-2018; Number of county-pairs: 29,429; (2) The dependent variables in ***Panel A***, 'FloodMean' denotes the average number of flooded days for a given county pair, while 'FloodDiff' denotes the absolute difference in flood exposure between two counties within a county pair. Details on the construction of the flood exposure measure are provided in Section 2.1; (3) 'Vege' is the vegetation coverage, 'Evapo' is the evaporation rate, 'Slope' is the slope of the county without time variation; (4) The dependent variable in ***Panel B***, 'N(Collaborative Patents)', measures the number of collaborative patents within each county pair and is transformed using the inverse hyperbolic sine (IHS) function; (5) Controls include population size, GDP, total loan value, number of firms above the designated size, and service sector output; (6)* 0.1, ** 0.05, *** 0.01.

4.3 Decomposing the Risk-Sharing Mechanism

Consistent with our theoretical framework (see Section 3), we further decompose the risk-sharing mechanism along two dimensions. First, we examine how collaborative partnerships are formed through the search and matching process. Second, we investigate a key determinant of whether these collaborations can be established—the likelihood of success, or the matching success rate.

4.3.1 Search Costs and Matching Probability

In Table 6, we explore the conditions under which cross-county collaborations are established, focusing on two key dimensions: search costs and matching probability.

To examine search costs, we draw on prior literature that emphasizes the role of geographic distance in shaping patent collaborations (e.g., Koh et al. 2024; Berger and Prawitz 2024), and investigate the effect of high-speed railways (HSR) on facilitating cross-county partnerships. Consistent with prior findings, Columns (1) and (2) of Panel A in Table 6 show that the number of collaborative patents between county pairs increases with the number of high-speed railway (HSR) connections linking them. This result supports our model assumption that the likelihood of forming a successful patent collaboration rises as the searching cost is reduced.

In Panel B of Table 6, we test Proposition **??** from our theoretical framework (see Section 3). According to this proposition, counties that are both highly exposed to flood risk are less likely to form collaborations. To empirically test this prediction, we interact our main explanatory variable, *FloodDiff*, with two dummy variables: *HHFlood* and *BothFDB*, which identify county pairs where both counties face high flood risks. Specifically, *HHFlood* is equal to one if both counties experience a major flood within the last five years - defined as exceeding the 70th percentile of annual flood exposure levels, while *BothFDB* equals one if both counties are designated as Flood Detention Basin (FDB) counties. These FDB counties are intentionally exposed to higher flood risk, as the national government would redirect floodwaters to them during severe flood events.[7] Columns (3) to (6) show that

[7]The Flood Detention Basin (FDB) policy is a national flood control strategy aimed at enhancing economic resilience to flooding. In 2000, the central government designated 98 low-lying wetlands across

the number of county-pair patent collaborations decreases when both counties face high flood risk, consistent with the prediction of Proposition **??**. The effect is more pronounced when both counties are designated as FDBs, likely because the national flood control policy increases public awareness of their heightened flood risk.

96 counties as FDBs. Hu and Wang (2024) show that flood exposure in FDB counties is 55% higher than in comparable counties without such designation.

Table 6: Examining the Role of Searching Costs and Matching Probability in Establishing Collaborations - County Pair Level

(IHS)	N(Collaborative Patents)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Search Costs						
FloodDiff×HSRNum	0.063**	0.064**				
	(0.029)	(0.029)				
HSRNum	0.003	0.003				
	(0.006)	(0.006)				
Panel B: Matching Probability						
FloodDiff×HHFlood			-0.029***	-0.027**		
			(0.011)	(0.011)		
FloodDiff×BothFDB					-0.119*	-0.118**
					(0.062)	(0.060)
FloodDiff	0.022***	0.025***	0.028***	0.030***	0.019***	0.022***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)
Control	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.425	0.425	0.425	0.426	0.425	0.425
Obs	323,719	323,719	323,719	323,719	323,719	323,719

Notes: (1) Time: 2008-2018; Number of county-pairs: 29,429; (2)'FloodDiff' denotes the absolute difference in flood exposure between two counties within a county pair. Details on the construction of the flood exposure measure are provided in Section 2.1; (3) 'HSRNum' indicates the total number of high-speed railway (HSR) connections between the two counties in a county pair, measured in hundreds. 'HHFlood' is a dummy variable equal to one if both counties have experienced a major flood within the past five years. 'BothFDB' equals one if both counties are designated by the national government as Flood Detention Basin (FDB) counties, intended to absorb floodwaters during severe flood events; (4) The dependent variable, 'N(Collaborative Patents)', measures the number of collaborative patents within each county pair and is transformed using the inverse hyperbolic sine (IHS) function; (5) Controls include population size, GDP, total loan value, number of firms above the designated size, and service sector output; (6) * 0.1, ** 0.05, *** 0.01.

4.3.2 Success Rate

In another dimension, we examine how the likelihood of success—measured by the quality of patents—affects the formation of cross-county collaborations.

To empirically test this aspect of our model, we interact our main explanatory variable, *FloodDiff*, with three dummy variables: *HHKnowledge*, *HHNewTech*, and *HHNewIPc*. These variables identify county pairs in which both counties demonstrate strong patenting capacity in terms of patent quality and number of new innovations.

HHKnowledge is a dummy variable equal to one if the patent quality measures in both counties of a county pair ranked above the median during the two years before the sample period. Following Aghion et al. (2015) and Akcigit et al. (2016), we measure patent quality using an index similar to the Herfindahl index, which captures the distribution of patents across different types of patents to reflect the breadth of innovation scope. A higher index value reflects a broader scope of innovation.[8] *HHNewTech* is a dummy variable that equals one if both counties have the above-median count of filed patents classified under new patent types during the two years before the sample period, and *HHNewIPC* equals one if both counties have the above-median count of new IPC codes during the two years before the sample period.

Columns (1) to (6) show that county-pair patent collaborations are more likely when both counties are identified as high patent-quality counties. This finding supports our model's assumption that the probability of establishing a successful collaboration increases with the expected success rate of joint innovation.

[8]The formula is as follows:

$$Knowledge = 1 - \Sigma\phi^2$$

where ϕ denotes the share of patents falling into a particular three-digit IPC code.

Table 7: Examining the Role of Success Rate in Establishing Collaborations
- County Pair Level

(IHS)	N(Collaborative Patents)					
	(1)	(2)	(3)	(4)	(5)	(6)
FloodDiff×HHKnowledge	0.018	0.023*				
	(0.012)	(0.012)				
FloodDiff×HHNewTech			0.021*	0.021*		
			(0.012)	(0.012)		
FloodDiff×HHNewIPC					0.022*	0.023*
					(0.012)	(0.013)
FloodDiff	0.004	0.003	0.011	0.014**	0.012*	0.015**
	(0.011)	(0.010)	(0.007)	(0.007)	(0.007)	(0.007)
Control	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.425	0.425	0.425	0.425	0.425	0.425
Obs	323,719	323,719	323,719	323,719	323,719	323,719

Notes: (1) Time: 2008-2018; Number of county-pairs: 29,429; (2)'FloodDiff' denotes the absolute difference in flood exposure between two counties within a county pair. Details on the construction of the flood exposure measure are provided in Section 2.1; (3) 'HHKnowledge' is a dummy variable that equals one if the patent quality measure in both counties ranked above the median in the two years before the sample period, 'HHNewTech' is a dummy variable that equals one if both counties have the above-median count of filed patents classified under new patent types, and 'HHNewIPC' is a dummy variable that equals one if both counties have the above-median count of new IPC codes; (4) The dependent variable, 'N(Collaborative Patents)', measures the number of collaborative patents within each county pair and is transformed using the inverse hyperbolic sine (IHS) function; (5) Controls include population size, GDP, total loan value, number of firms above the designated size, and service sector output; (6) * 0.1, ** 0.05, *** 0.01.

5 Full Model to Quantify Flood-Induced Knowledge Spillover

5.1 Environment

5.1.1 Floods

The full model features multiple counties indexed by $n = 1, 2, ..., N$, where in each county there is a mass of firms $i \in \Omega_{n,t}$. Denote a flood event at time t as $\tau_t = \{\tau_{1,t}, \tau_{2,t}, ..., \tau_{N,t}\}$, where $\tau_{n,t} = 1$ if county n experiences a flood, and $\tau_{n,t} = 0$ otherwise. Being hit by the flood is assumed to impose two direct impacts on the local economy. First, it will temporarily reduce firms' productivity,

$$\hat{z}_{in,t} = z_{in,t} e^{-\eta_Z \tau_{n,t}}, \tag{16}$$

where $\eta_Z > 0$ quantifies the flood-induced disruption of production. $z_{in,t}$ and $\hat{z}_{in,t}$ describes respectively the intrinsic and realized productivity of firm i locating in county n.

On the other hand, being hit by a flood will also temporarily reduce Poisson arrival rate of innovation,

$$\hat{\lambda}_{in,jm,t} = \lambda_{in,jm,t} e^{-\eta_I \tau_{n,t} \tau_{m,t}}, \tag{17}$$

where $\eta_I > 0$ quantify the flood-induced disruption of innovation. $\lambda_{in,jm,t}$ and $\hat{\lambda}_{in,jm,t}$ describes respectively the intrinsic and realized Poisson arrival rate of successful innovation. Here, we further assume the flood disruption only applies to scenario where either both locations of the collaboration are flooded or the single location of the stand-alone innovation is flooded.

5.1.2 Households

We assume that there is a representative household in each county n, who maximizes her utility by consuming a single final good:

$$\begin{aligned} U_{n,t} \;=\; & \max_{c_{n,t}} \; u(c_{n,t}) \\ & \text{s.t.} \;\; p_{n,t} c_{n,t} = w_{n,t} L_n, \end{aligned} \tag{18}$$

where $w_{n,t}$ denotes the wage rate of county n and L_n denotes the labour supply. Here we abstract from the migration decisions of local workers by assuming that labour supplies are time-invariant. $p_{n,t}$ denotes the price of the final good in county n. More specifically, local final good $c_{n,t}$ is produced by combining intermediate goods supplied by manufacturers $i \in \Omega_{n,t}$ in county n with a CES technology:

$$c_{n,t} = \left[\int_{\Omega_{n,t}} y_{in,t}^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}}. \tag{19}$$

5.1.3 Manufacturing Firms

There is an exogenous measure of Ω_n firms operating in county n, characterized by endogenous heterogeneous productivity distribution.

At the beginning of each period t, flood event τ_t realizes and firms not in ongoing collaboration are randomly matched with each other. Then firm $i \in \Omega_{n,t}$ makes the static production decision and dynamic innovation and collaboration decision described as follows.

Production Firm i in county n produces its variety and supplies the intermediate output $y_{in,t}$ to local consumers. To produce $y_{in,t}$ units of a variety, a firm requires an amount of effective labour:

$$l_{in,t} = f + \frac{y_{in,t}}{\hat{z}_{in,t}},$$

where f denotes the fixed cost of operation and $\hat{z}_{in,t}$ measures the realized productivity of the firm. Hence, the profit maximization problem of firm i in county n can be summarized by the following equation:

$$\begin{aligned} \pi_n(z_{in,t}, \tau_t) \; = \; & \max_{p_{in,t}, y_{in,t}, l_{in,t}} \; p_{in,t} y_{in,t} - w_{n,t} l_{in,t} \\ & \text{s.t.} \quad y_{in,t} = c_{n,t} \frac{p_{in,t}}{p_{n,t}}^{-\sigma} \\ & \qquad\; l_{in,t} = f + \frac{y_{in,t}}{\hat{z}_{in,t}}. \end{aligned} \tag{20}$$

Innovation Firm i can enhance its productivity by doing innovation. The evolution of productivity is given by:

$$\log(z_{in,t+1}) = \log(z_{in,t}) + \gamma Q_{in,t}, \tag{21}$$

where $Q_{in,t}$ denotes the number of successful innovation for firm i in year t. Each successful innovation improves productivity by a fixed step size γ. Further, we assume $Q_{in,t}$ follows a Poisson process with arrival rate $\hat{\lambda}_{in,jm,t}$, which can be described by the following equation:

$$\lambda_{in,jm,t} = \alpha \xi^{\mathbb{I}_{i \neq j}} z_{in,t}^{\frac{\rho}{2}} z_{jm,t}^{\frac{\rho}{2}}. \tag{22}$$

Equation 22 captures the idea that firms use existing knowledge measured by intrinsic productivity $z_{in,t}$ and $z_{jm,t}$ to facilitate new innovation. Further, we assume collaboration across firms $i \neq j$ accelerate the innovation process by amplifying the Poisson arrival rate of innovation by $\xi > 1$. In order to initiate a R&D activity, the firm needs to pay a fixed cost κ^I units of effective labour. Hence, firm i's value function of not doing innovation and doing single innovation can be described as follows:

$$V_{n,t}^{\text{No Inn}}(z_{in,t}, \tau_t) = \pi_n(z_{in,t}, \tau_t) + \beta(1-\delta)\mathbb{E}_{\tau_{t+1},z',n'} V_{nn',t+1}(z_{in,t+1}, z', \tau_{t+1}), \tag{23}$$

$$V_{n,t}^{\text{Single}}(z_{in,t}, \tau_t) = \pi_n(z_{in,t}, \tau_t) - w_{n,t}\kappa^I + \beta(1-\delta)\mathbb{E}_{\tau_{t+1},z',n'}\mathbb{E}_Q V_{nn',t+1}(z_{in,t+1}, z', \tau_{t+1}), \tag{24}$$

where $Q \sim \text{Poisson}(\hat{\lambda}_{in,in,t})$. Here, $V_{nn',t+1}$ denotes the value function of firm i at the beginning of time $t+1$, after the realization of flood event τ_{t+1} and random matching between firms. The matching can be characterized by the productivity of the matched firm z' and its location n'. Further, we define an outside option value:

$$V_{n,t}^{\text{Out}}(z_{in,t}, \tau_t) = \max\{V_{n,t}^{\text{No Inn}}(z_{in,t}, \tau_t), V_{n,t}^{\text{Single}}(z_{in,t}, \tau_t)\}, \tag{25}$$

and two corresponding optimal choice indicator:

$$\mathbb{I}_{n,t}^{\text{No Inn}}(z_{in,t}, \tau_t) = 1\left\{V_{n,t}^{\text{No Inn}}(z_{in,t}, \tau_t) > V_{n,t}^{\text{Single}}(z_{in,t}, \tau_t)\right\}, \tag{26}$$

$$\mathbb{I}_{n,t}^{\text{Single}}(z_{in,t}, \tau_t) = 1\left\{V_{n,t}^{\text{No Inn}}(z_{in,t}, \tau_t) \leq V_{n,t}^{\text{Single}}(z_{in,t}, \tau_t)\right\}. \tag{27}$$

Next we will formally introduce the matching process and the formation of collaboration.

Random Matching Denote the density of firms in county n with productivity z that

are not in ongoing collaborative innovation at the beginning of period t by $\mu^S_{n,t}(z)$, and let $\Omega^S_{n,t} \equiv \int \mu^S_{n,t}(z)\, dz$ denote the corresponding mass of single firms. Let $\mu^C_{nm,t}(z,x)$ denote the joint density of collaborative pairs consisting of a firm in county n with productivity z and a firm in county m with productivity x.[9] [10]

The random matching process generates a pre-decision meeting density $\mu^M_{nm,t}(z,x)$ in two steps. First, each single firm in county n draws a potential partner county m with probability

$$\Pr_{nm,t} = \frac{\omega(d_{nm})\, \Omega^S_{m,t}}{\sum_{n'=1}^{N} \omega(d_{nn'})\, \Omega^S_{n',t}}, \tag{28}$$

where $\omega(d)$ captures how matching efficiency declines in distance. The measure of matches formed between counties n and m is given by the symmetric matching function

$$M_{nm,t} = \alpha \left[\Pr_{nm,t} \Omega^S_{n,t} \right]^{\frac{1}{2}} \left[\Pr_{mn} \Omega^S_{m,t} \right]^{\frac{1}{2}}, \tag{29}$$

which implies that only a fraction of potential targets is realized as one-to-one matches.

Second, conditional on a county pair (n,m), matched firms are drawn randomly from the singles distributions in the two counties. Hence the joint density of pre-decision matches is

$$\mu^M_{nm,t}(z,x) = M_{nm,t} \frac{\mu^S_{n,t}(z)}{\Omega^S_{n,t}} \frac{\mu^S_{m,t}(x)}{\Omega^S_{m,t}}. \tag{30}$$

Collaboration Formation Upon successful match, firm i in county n and firm j in county m will decide whether to establish collaboration. If they reach bilateral consensus to form collaboration, then each firm will pay a R&D fixed cost κ^I units of effective labour in each period, and the Poisson arrival rate of successful innovation follows Equation 17 and 22. Further, we assume mechanical separation of established collaboration governed by separation rate ϵ. Hence, firm i's value function of establishing collaboration can be

[9] Since collaborations are one-to-one and undirected, the collaboration densities satisfy the symmetry condition $\mu^C_{nm,t}(z,x) = \mu^C_{mn,t}(x,z)$.

[10] Since we assume the mass of firms Ω_n remain unchanged in each county n, we have the following mass equality: $\Omega^S_{n,t} + \sum_{m=1}^{N} \iint \mu^C_{nm,t}(z,x) dx dz = \Omega_n$.

described as follows:

$$V^{\text{Collab}}_{nm,t}(z_{in,t}, z_{jm,t}, \tau_t) = \pi_n(z_{in,t}, \tau_t) - w_{n,t}\kappa^I + \beta(1-\delta)^2(1-\epsilon)\mathbb{E}_{\tau_{t+1}}\mathbb{E}_Q V^{\text{Collab}}_{nm,t+1}(z_{in,t+1}, z_{jm,t+1}, \tau_{t+1}) + \beta(1-\delta)[\delta + (1-\delta)\epsilon]\mathbb{E}_{\tau_{t+1},z',n'}\mathbb{E}_Q V_{nn',t+1}(z_{in,t+1}, z', \tau_{t+1}), \tag{31}$$

where $Q \sim \text{Poisson}(\hat{\lambda}_{in,jm,t})$. Let $\mathbb{I}^{\text{Accept}}_{nm,t}(z_{in,t}, z_{jm,t}, \tau_t)$ denote the indicator that firm i's unilateral acceptance of collaboration:

$$\mathbb{I}^{\text{Accept}}_{nm,t}(z_{in,t}, z_{jm,t}, \tau_t) = 1\left\{V^{\text{Collab}}_{nm,t}(z_{in,t}, z_{jm,t}, \tau_t) > V^{\text{Out}}_{n,t}(z_{in,t}, \tau_t)\right\}. \tag{32}$$

Since the establishment of collaboration requires bilateral acceptance, hence define the indicator of collaboration establishment as:

$$\mathbb{I}^{\text{Collab}}_{nm,t}(z_{in,t}, z_{jm,t}, \tau_t) = \mathbb{I}^{\text{Accept}}_{nm,t}(z_{in,t}, z_{jm,t}, \tau_t)\mathbb{I}^{\text{Accept}}_{mn,t}(z_{jm,t}, z_{in,t}, \tau_t). \tag{33}$$

Hence, the value function of an unpaired firm upon flood realization and successful match can be described by:

$$V_{nm,t}(z_{in,t}, z_{jm,t}, \tau_t) = V^{\text{Out}}_{n,t}(z_{in,t}, \tau_t) + \mathbb{I}^{\text{Collab}}_{nm,t}(z_{in,t}, z_{jm,t}, \tau_t)\left[V^{\text{Collab}}_{nm,t}(z_{in,t}, z_{jm,t}, \tau_t) - V^{\text{Out}}_{n,t}(z_{in,t}, \tau_t)\right]. \tag{34}$$

Firm Exit and Entry After the realization of innovation outcomes, firms exit at a constant rate δ. New firms of the same mass enter the economy mechanically, with initial productivity draw from $\phi(z)$.

Evolution of Productivity Distribution Denote the mass density of single and collaborative firms after firms' making optimal choices Equation 26, 27 and 33 as $\tilde{\mu}^S_{n,t}(z)$ and $\tilde{\mu}^C_{nm,t}(z,x)$:

$$\tilde{\mu}^S_{n,t}(z, \tau_t) = \mu^S_{n,t}(z) - \sum_{m=1}^{N}\int \mu^M_{nm,t}(z,x)\mathbb{I}^{\text{Collab}}_{nm,t}(z,x,\tau_t)dx, \tag{35}$$

$$\tilde{\mu}^C_{nm,t}(z,x,\tau_t) = \mu^C_{nm,t}(z,x) + \mu^M_{nm,t}(z,x)\mathbb{I}^{\text{Collab}}_{nm,t}(z,x,\tau_t). \tag{36}$$

Define the single and collaborative transition kernels as follows:

$$K^S(z'|z;\lambda) = \sum_{q=0}^{\infty} e^{-\lambda}\frac{\lambda^q}{q!}\delta(z' - ze^{\gamma q}), \tag{37}$$

$$K^C(z',x'|z,x;\lambda) = \sum_{q=0}^{\infty} e^{-\lambda}\frac{\lambda^q}{q!}\delta(z' - ze^{\gamma q})\delta(x' - xe^{\gamma q}), \tag{38}$$

where $\delta(\cdot)$ is the Dirac equation. Then the evolution of the density functions is governed by the following equations:

$$\begin{aligned}\mu^S_{n,t+1}(z') = \underbrace{\delta\Omega_n\phi(z')}_{\text{Entry}} + (1-\delta)\int \tilde{\mu}^S_{n,t}(z,\tau_t)\Bigg[\underbrace{\mathbb{I}^{\text{No Inn}}_{n,t}(z,\tau_t)\delta(z'-z) + \mathbb{I}^{\text{Single}}_{n,t}(z,\tau_t)K^S(z'|z;\lambda_{in,in,t})}_{\text{Single firms that remain single}}\Bigg]dz \\ + (1-\delta)[\epsilon + (1-\epsilon)\delta]\sum_{m=1}^{N}\iint \tilde{\mu}^C_{nm,t}(z,x,\tau_t)\Bigg[\int K^C(z',x'|z,x;\lambda_{in,jm,t})dx'\Bigg]dxdz, \\ \underbrace{\qquad\qquad\qquad\qquad\qquad\qquad}_{\text{Collab firms break and return to single}}\end{aligned} \tag{39}$$

$$\mu^C_{nm,t+1}(z',x') = (1-\delta)^2[1-\epsilon]\underbrace{\iint \tilde{\mu}^C_{nm,t}(z,x,\tau_t)K^C(z',x'|z,x;\lambda_{in,jm,t})dxdz}_{\text{Collab firms that stay collab}}. \tag{40}$$

5.1.4 Market Clearing Conditions

Local wage rates $w_{n,t}$ clear local labour markets for each county n and flood event τ_t:

$$L_n = \int_{\Omega_{n,t}} l_{in,t}di + \kappa^I\sum_{m=1}^{N}\iint \tilde{\mu}^C_{nm,t}(z,x,\tau_t)dxdz + \kappa^I\int \mathbb{I}^{\text{Single}}_{n,t}(z,\tau_t)\tilde{\mu}^S_{n,t}(z,\tau_t)dz. \tag{41}$$

Local final good prices satisfy the one-price principle:

$$p_{n,t} = \left[\int_{\Omega_{n,t}} p^{1-\sigma}_{in,t}di\right]^{\frac{1}{1-\sigma}}. \tag{42}$$

5.1.5 Equilibrium

The spatial general equilibrium consists of mass of firms by innovation modes $\mu^S_{n,t}(z)$, $\mu^C_{nm,t}(z,x)$, $\tilde{\mu}^S_{n,t}(z)$ and $\tilde{\mu}^C_{nm,t}(z,x)$, households' consumption $\{c_{n,t}(\tau_t)\}$, firms' static choices including outputs $\{y_{n,t}(z,\tau_t)\}$, prices $\{p_{n,t}(z,\tau_t)\}$ and labour demands $\{l_{n,t}(z,\tau_t)\}$, firms' start-of-period value function $\{V_{nm,t}(z,x,\tau_t)\}$, value functions of different innovation modes

$\{V_{n,t}^{\text{No Inn}}(z,\tau_t)\}$, $\{V_{n,t}^{\text{Single}}(z,\tau_t)\}$, $\{V_{n,t}^{\text{Out}}(z,\tau_t)\}$ and $\{V_{nm,t}^{\text{Collab}}(z,x,\tau_t)\}$, firms' dynamic choices of innovation modes $\{\mathbb{I}_{n,t}^{\text{No Inn}}(z,\tau_t)\}$, $\{\mathbb{I}_{n,t}^{\text{Single}}(z,\tau_t)\}$, $\{\mathbb{I}_{nm,t}^{\text{Accept}}(z,x,\tau_t)\}$ and $\{\mathbb{I}_{nm,t}^{\text{Collab}}(z,x,\tau_t)\}$, local final good prices $\{p_{n,t}(\tau_t)\}$ and wage rates $\{w_{n,t}(\tau_t)\}$, such that under each flood event τ_t,

(i) $\{c_{n,t}(\tau_t)\}$ solve households' utility maximization problems 18;

(ii) $\{y_{n,t}(z,\tau_t)\}$, $\{p_{n,t}(z,\tau_t)\}$ and $\{l_{n,t}(z,\tau_t)\}$ solve firms' static profit maximization problems 20 given Equation 16;

(iii) $\{V_{n,t}^{\text{No Inn}}(z,\tau_t)\}$, $\{V_{n,t}^{\text{Single}}(z,\tau_t)\}$, $\{V_{n,t}^{\text{Out}}(z,\tau_t)\}$, $\{V_{nm,t}^{\text{Collab}}(z,x,\tau_t)\}$ and $\{V_{nm,t}(z,x,\tau_t)\}$ satisfy Equation 23, 24, 25, 31 and 34 given Equation 17 and 22;

(iv) $\{\mathbb{I}_{n,t}^{\text{No Inn}}(z,\tau_t)\}$, $\{\mathbb{I}_{n,t}^{\text{Single}}(z,\tau_t)\}$, $\{\mathbb{I}_{nm,t}^{\text{Accept}}(z,x,\tau_t)\}$ and $\{\mathbb{I}_{nm,t}^{\text{Collab}}(z,x,\tau_t)\}$ solve Equation 26, 27, 32 and 33;

(v) $\{w_{n,t}\}$ clear local labour markets 41 and $\{p_{n,t}\}$ satisfy the one-price principle 42.

(vi) Dynamics of $\mu_{n,t}^{S}(z)$, $\mu_{nn',t}^{C}(z,x)$, $\tilde{\mu}_{n,t}^{S}(z)$ and $\tilde{\mu}_{nm,t}^{C}(z,x)$ satisfy the law of motion 35, 36, 39 and 40.

6 Conclusion

This paper examines whether and how innovation networks adapt to rising climate risks in the context of floods in China. We provide new evidence that firms adapt to climate risk through strategic reconfiguration of their innovation networks.

We develop a theoretical search-and-matching model in which firms facing flood-related disruptions seek cross-county partnerships as a form of risk-sharing. Using a novel dataset that combines satellite-based flood exposure data, detailed patent records, and firm-level location information, we test the model's predictions. We find that greater flood exposure is associated with a significant increase in cross-county patent collaborations. Moreover, firms are more likely to collaborate with partners in regions less exposed to flooding, and the likelihood of collaboration increases with lower search costs, reduced joint flood exposure, and higher patent quality. Our empirical results support our theoretical framework.

Our findings contribute to three strands of literature. First, we extend the climate adaptation literature by showing that firms adapt not only through climate-related patents but also via broader shifts in knowledge production across patent types. Second, we contribute to the innovation literature by proposing a novel mechanism, hedging against climate risk, as a driver of collaborative matches, in addition to geographic proximity and innovation capacity. Third, we add to the literature on knowledge spillovers by including climate risk into the discussion.

In particular, our results suggest that cross-regional collaboration can serve as a channel for both climate adaptation and regional convergence. In China, where coastal-inland inequality remains significant, knowledge spillovers from coastal to inland regions not only reduce climate exposure for coastal firms but also expand innovation opportunities inland. These findings highlight the potential for regional innovation policy to achieve both environmental resilience and equitable growth.

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A Institutional Background

A.1 Floods in China

China ranks among the top countries globally for flood risk, due to its large population exposed to both coastal and river flooding. According to the Aqueduct Global Flood Risk Country Rankings, China ranks third in the world for the absolute number of people exposed to flood risks, with approximately 395 million people at risk annually. This places China among the most flood-exposed countries, alongside India and Bangladesh. About 27.5% of China's population is vulnerable to flooding, driven by river floods in the Yangtze, Huai, and Yellow River basins, as well as coastal areas prone to typhoons and rising sea levels. From 2000 to 2017, floods caused economic damage exceeding $150 billion, according to the EM-DAT International Disaster Database. Furthermore, Arnell and Gosling (2016) predicts that the likelihood of a 100-year flood occurring in China could increase by 33-67% by 2050.

A key feature of China's floods is their disproportionate impact on economically important regions. Jiangsu Province, for instance, ranks second in GDP among China's provinces, yet faces severe flood risks due to its location along the Yangtze River and Huai River. Fegions with higher flood risks are also more economically significant. For instance, the Yangtze River Basin, home to one-third of China's population, is a crucial economic hub. Frequent flooding, exacerbated by seasonal rainfall and extreme weather events, poses significant risks to infrastructure and livelihoods in these areas. Similarly, the Huai River Basin, another key region, faces recurring flood threats. Flooding in these economically vital regions could hinder China's overall economic growth, making flood management a critical concern for the government.

Due to rapid urbanization, urban populations in major cities (e.g., Beijing, Wuhan, and Nanjing) are increasingly exposed to severe flood risks. The urbanization rate surged to 64.72% in 2021, up from 36.00% in 2000, which has significantly heightened the vulnerability of urban areas to flooding. For instance, the 2012 Beijing flood, triggered by extreme rainfall, resulted in over 79 fatalities and caused approximately $2 billion in economic damage. The 2021 Zhengzhou flood led to over 350 deaths and caused around $6 billion in economic losses. This underscores the severe impact of urban flooding on densely populated areas.

A.2 Patents in China

China has sustained a fairly long period of rapid economic growth over the past decade, to which the contributions from innovation have become increasingly important. Among numerous measurements, patents are often considered an indicator of technological change, which play a central role in research on innovation (Basberg 1987; He et al. 2018) and attract considerable attention from researchers. The Early phase of innovation development was marked by Chinese representatives attending all international IPR conventions in the 1980s and 1990s[11]. And in April 1985, *Patent Law of China* was officially implemented, marking the beginning of patent modernization.

Since then, it took about 15 years for China to reach the first one million patent applications, but merely 1 year and 4 months to reach the fifth million patent applications in 2008 from the fourth million. After that period, China's patent applications began to experience an extraordinary surge. Specifically, China overtook the U.S. and Japan in terms of patent applications in 2009 and 2010, respectively (Hu et al. 2017). Furthermore, China in 2019 surpassed the U.S. to become the leading source of international patent applications filed with the WIPO[12].In 2023, the number of patent applications in China exceeded 5.5 million[13].

Figure A1 illustrates a more detailed picture of patent application. Among China's provinces and municipalities directly under the central government, the number of patent applications in Guangdong province has always ranked the top 1, and the number of patent applications has reached 0.96 million in 2023. Jiangsu, Zhejiang, Shandong, and Shenzhen follow closely. In addition, Beijing and Shanghai are another two municipalities directly under the central government ranking in the Top 10.

Both the quantity and quality of patent applications in China have significantly increased recently, while a single entity often faces problems such as high R&D investment, high risks, and a low achievement transformation rate under the fierce technological competition. In order to sustain the robust growth in patents, we need to further understand the importance of collaboration (anderson2022collaborative), which can stimulate knowledge creation and

[11]For example, in June 1980, the Chinese government rode the wave of reform and became a member of the World Intellectual Property Organization (WIPO)

[12]See https://www.wipo.int/pressroom/en/articles/2020/article_0005.html for more details.

[13]See https://www.cnipa.gov.cn/tjxx/jianbao/year2023/a.html for more details.

innovation. Patent collaboration not only helps to integrates advantageous resources, but also promotes the efficient transformation and utilization of intellectual property rights. Therefore, conducting deep research on patent collaboration mechanism is an important aspect to achieve high-quality patent development.

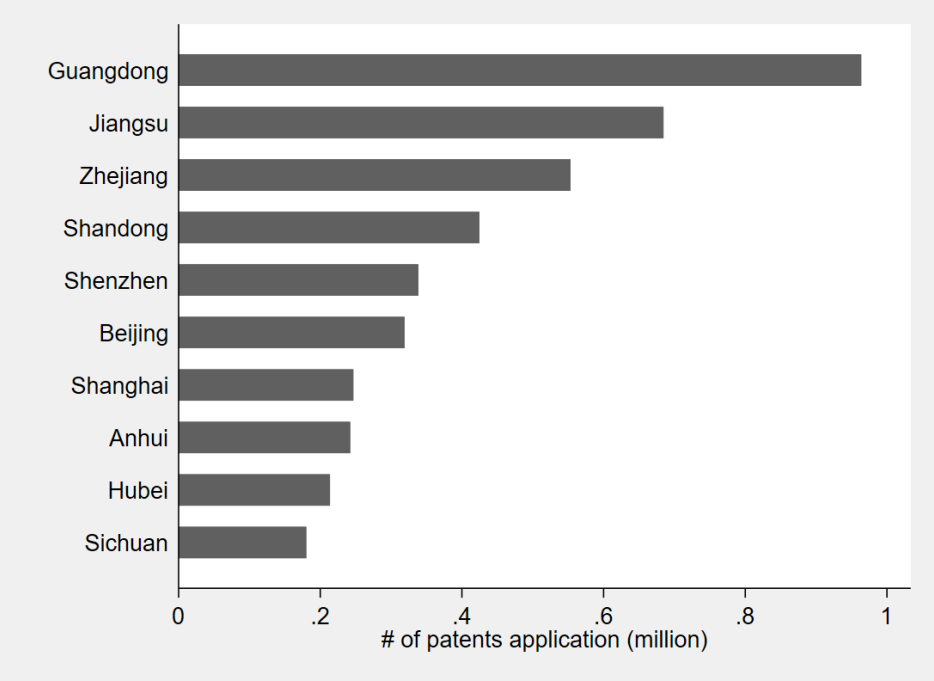


Figure A1: Patent Applications of Top 10 Provinces or Municipalities in 2023.

B Details for Patent Data

B.1 Patents Sample

The patent data used in this study comes from the China National Intellectual Property Administration (CNIPA), formerly known as the State Intellectual Property Office (SIPO). There are three types of patents: invention patents, utility models, and design patents. Invention patents are granted for new technical solutions related to a product, a process, or improvements thereof. Utility models refer to new technical solutions related to the shape, structure, or combination thereof of a product that is suitable for practical use. Design patents cover new designs relating to the shape, pattern, or combination of the two, as well as combinations involving color, applied to a product (either in whole or in part), which are aesthetically appealing and suitable for industrial application.

Patents must first be submitted by the applicants. After a formal examination process, qualified applications will be granted patent rights. This study primarily examines invention patents and, following Koh et al. (2024), focuses on patent applications rather than approved patents. Although not all applications are ultimately approved, the act of applying itself is a critical initial step in securing legal protection for innovations. It also marks the establishment of a collaborative relationship in the process of innovative production.

To validate the completeness and reliability of our dataset, we compare the aggregated annual application counts with those published in the *China Intellectual Property Statistical Yearbook*[14]. Figure B1 presents the comparison, where the blue line denotes the official statistics and the blue bars represent our collected data. The two datasets exhibit a high degree of consistency.

The sample period begins in 2008, marking a phase of rapid expansion in China's patent system. Following the implementation of the Patent Law in 1985, it took 15 years to reach the first one million patent applications. However, subsequent milestones were reached progressively faster: the second million in 4 years, the third in just over 2 years, and the fifth in only 1 year and 4 months. This accelerated growth motivates our choice of 2008 as the starting point. Between 2008 and 2018, a total of 8.72 million invention patents were filed.

[14]See https://english.cnipa.gov.cn/jianbao/ for more details.

To focus on collaborative patenting within the Chinese Mainland, we exclude applications from Hong Kong, Macao, Taiwan, and foreign applicants, yielding approximately 7.32 million invention applications. We further exclude patents filed all by individual applicants due to difficulties in accurately identifying their geographic locations, which are crucial for analyzing collaboration patterns. Prior to address matching, the dataset comprises approximately 6.16 million invention patent applications.

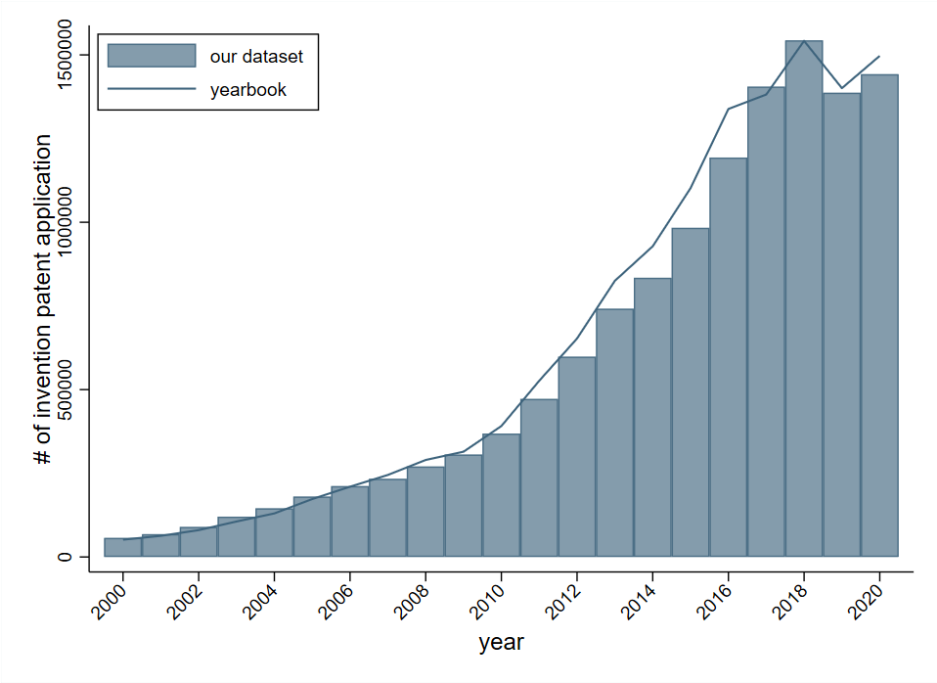


Figure B1: Number of Invention Patents Applications from 2000 to 2020.

B.2 Assignment of Applicants to Counties

To obtain accurate geographic information, we primarily matched applicant addresses following two steps.

First, we construct a search database that includes accurate county-level addresses for applicants of solo patent applications and first-listed applicants of collaborative patents. Although our sample period covers 2008 to 2018, we can retrieve patent addresses from the CNIPA database for the years 2000 to 2022 to extend our search database. To prevent the misidentification of distinct entities that may share identical applicant names, we limit the extension of the time range. Then, we standardize all applicant names in a consistent format.

We search patents in both earlier and later years. For example, we have a patent in 2008, we search sequentially in 2008, 2007,...,2000, then 2011, 2012,..., up to 2022.

Second, we obtain firms' addresses from the Tianyancha database, which we use both to match firms that are not identified in the first step and to double-check the addresses provided by the patent database.

Finally, we obtain address information for 6.12 million patents, of which 452,734 (approximately 8%) are collaborative patents, spanning 29,429 county pairs.

B.3 Definitions and Regression Sample

In this paper, a collaborative patent is defined as one that has at least two non-individual applicants. This means that individual applicants are not considered when identifying collaborative patents. For instance, a patent with two applicants — A (an individual) and B (a firm) — would be classified as a single-applicant patent rather than as a collaborative one.

In the calculation, each collaborative patent contributes one unit to the total number of patents for every relevant county pair. For example, suppose a patent has three applicants located in counties A, B, and C in 2008. In this case, the patent would be counted in the variable *Collaborative Patents* for the county pairs (A, B), (B, C), and (A, C) in 2008.

For the regression sample, we construct a balanced panel at the county-pair level from 2008 to 2018, including county pairs that have engaged in at least one patent collaboration during the sample period. This approach allows us to examine both the intensive margin (the strength of existing collaborations) and the extensive margin (the formation of new collaborations over time).

C Empirical Appendix

C.1 Summary Statistics

Table C1: Variable Definitions

Variable	Definition
County - Pair Level:	
CollaborativePatents	The number of collaborative patents within each county pair and transformed using the inverse hyperbolic sine (IHS) function. The detailed calculation is introduced in Section 2.2.
FloodMean	The average number of flooded days for a given county pair.
FloodDiff	The absolute difference in flood exposure between two counties within a county pair.
ln(Population)	The average of the logarithm of population for a given county pair, in 10 thousand people.
ln(GDP)	The average of the logarithm of gross domestic product for a given county pair, in 10 thousand yuan RMB.
ln(Loan)	The average of the logarithm of loan balance of financial institutions at the end of the year for a given county pair, in 10 thousand yuan RMB.
ln(# of Firm)	The average of the logarithm of the number of firms above the designated size for a given county pair.
ln(Third)	The average of the logarithm of added value of the tertiary industry for a given county pair, in 10 thousand yuan RMB.
County Level:	
Total	The total number of patent applications and transformed using the IHS function.
Single-Applicant	The number of applications filed by a single applicant and transformed using the IHS function.
Within-County	The number of patent collaborations occurring within the same county and transformed using the IHS function.
Cross-County	The number of collaborations involving applicants from at least two different counties and transformed using the IHS function.
Flood Exposure	The number of flooded days in a county, and the detailed calculation is introduced in Section 2.1.
ln(Population)	The logarithm of the population, in 10 thousand people.
ln(GDP)	The logarithm of gross domestic product, in 10 thousand yuan RMB.
ln(Loan)	The logarithm of loan balance of financial institutions at the end of the year, in 10 thousand yuan RMB.
ln(# of Firm)	The logarithm of the number of firms above the designated size.
ln(Third)	The logarithm of added value of the tertiary industry, in 10 thousand yuan RMB.

Notes: This table reports the detailed definitions of main variables.

Table C2: Summary Statistics

	Obs	Mean	St.D	P1	P50	P99
County - Pair Level:						
Collaborative Patents	323,719	1.466	17.346	0.000	0.000	22.000
FloodMean	323,719	0.020	0.109	0.000	0.000	0.383
FloodDiff	323,719	0.034	0.197	0.000	0.000	0.673
ln(Population)	323,719	3.489	2.318	-6.215	4.040	5.007
ln(GDP)	323,719	14.646	1.512	9.192	14.986	16.682
ln(Loan)	323,719	13.879	2.040	6.588	14.199	16.805
ln(# of Firm)	323,719	4.869	1.538	0.000	5.112	7.444
ln(Third)	323,719	13.705	1.596	8.220	14.002	16.016
County Level:						
Total	29,344	160.361	656.607	0.000	9.000	3068.000
Single-Applicant	29,344	143.870	591.688	0.000	8.000	2757.000
Within-County	29,344	1.969	27.023	0.000	0.000	37.000
Cross-County	29,344	14.522	87.652	0.000	0.000	271.000
Flood Exposure	29,344	0.013	0.167	0.000	0.000	0.236
ln(Population)	29,344	3.600	0.881	0.920	3.726	5.096
ln(GDP)	29,344	13.829	1.177	10.592	13.907	16.220
ln(Loan)	29,344	13.087	1.387	8.904	13.137	16.335
ln(# of Firm)	29,344	4.010	1.427	0.000	4.127	7.014
ln(Third)	29,344	12.773	1.237	9.626	12.790	15.610

Notes: This table shows summary statistics of county-pair level and county level data, respectively. The control variables include population size, GDP, total loan value, number of firms above the designated size, and service sector output.

C.2 Robustness Checks

Table C3: Robustness Check of Table 1
- Changing to a Patent-Level Analysis

	Cross-County Collab Dummy			
	(1)	(2)	(3)	(4)
Flood	0.032***	0.017**	0.022***	0.018*
	(0.007)	(0.008)	(0.008)	(0.010)
Patent Type FE	No	No	Yes	No
County1 FE	Yes	Yes	Yes	Yes
County2 FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No
Patent Type×Year	No	No	No	Yes
Adjusted R^2	0.332	0.334	0.393	0.454
Obs	452,734	452,734	452,734	452,734

Notes: (1) Time: 2008-2018; (2) 'Flood' represents the number of flooded days of the county in which the first applicant is located, and the detailed calculation is introduced in Section 2.1; (3) The dependent variable is a dummy variable that equals one if the patent includes applicants from at least two different counties; (4)* 0.1, ** 0.05, *** 0.01.

D Theory Appendix

D.1 Steady-State Equilibrium

The steady state of the spatial general equilibrium consists of county-specific intrinsic productivity $\{z_i\}$, patent acquisition value function $\{\lambda_i^z\}$ and patent demand $\{s_i\}$, and county-pair- and flood-specific collaboration value $\{J_{ij}(\tau)\}$, vacancy posting $\{v_{ij}(\tau)\}$, collaboration formation $\{m_{ij}(\tau)\}$, innovation success rate $\{f_{ij}(\tau)\}$ and patent production $\{q_{ij}(\tau)\}$, and county- and flood-specific patent price $\{p_i(\tau)\}$, such that they satisfy the following set

Table C4: Robustness Check of Table 2
- Changing Method to Long-Difference

	ΔN(Collaborative Patents)			
	(1)	(2)	(3)	(4)
ΔFloodMean	0.109***	0.156***		
	(0.032)	(0.033)		
ΔFloodDiff			0.061***	0.079***
			(0.018)	(0.018)
Control	No	Yes	No	Yes
Adjusted R^2	0.0003	0.006	0.0002	0.006
Obs	29,429	29,429	29,429	29,429

Notes: (1) Method: Long Difference; (2) Number of county-pair: 29,429; (3) 'ΔFloodMean' denotes the change of average number of flooded days for a given county pair between the two periods: $\Delta FloodMean = FloodMean_{2012-2018} - FloodMean_{2008-2012}$, where $FloodMean_{2012-2018}$ and $FloodMean_{2008-2012}$ are the average $FloodMean$ during these periods. 'ΔFloodDiff' denotes the change of the absolute difference in flood exposure between two counties within a county pair between two periods: $\Delta FloodDiff = FloodDiff_{2012-2018} - FloodDiff_{2008-2012}$, where $FloodDiff_{2012-2018}$ and $FloodDiff_{2008-2012}$ are the average $FloodDiff$ during these periods. Details on the construction of the flood exposure measure are provided in Section 2.1; (4) The dependent variable, 'ΔN(Collaborative Patents)', measures the change of the number of collaborative patents within each county pair between the two periods, and is transformed using the inverse hyperbolic sine (IHS) function; (5) Controls include population size, GDP, total loan value, number of firms above the designated size, and service sector output; (6)* 0.1, ** 0.05, *** 0.01.

of time-invariant first-order conditions:

$$
\begin{cases}
\lambda_i^z = \dfrac{\beta}{1-\beta(1-\delta)} \mathbb{E}_\tau \dfrac{\partial \pi(z_i, \tau; A_i)}{\partial z_i} & \forall i = 1, 2 \\
\mathbb{E}_\tau p_i(\tau) = \lambda_i^z \theta \gamma s_i^{\gamma - 1} & \forall i = 1, 2 \\
\delta z_i = \theta s_i^\gamma & \forall i = 1, 2 \\
\kappa_{ij}^s = \dfrac{m_{ij}(\tau)}{v_{ij}(\tau)} J_{ij}(\tau) & \forall i, j = 1, 2 \text{ and } \forall \tau \\
J_{ij}(\tau) = -\kappa^i + p_i(\tau) f_{ij}(\tau) & \forall i, j = 1, 2 \text{ and } \forall \tau \\
f_{ij}(\tau) = \mu_{ij} \hat{z}_i(\tau)^{0.5} \hat{z}_j(\tau)^{0.5} & \forall i, j = 1, 2 \text{ and } \forall \tau \\
m_{ij}(\tau) = \xi v_{ij}(\tau)^\alpha v_{ji}(\tau)^\alpha & \forall i, j = 1, 2 \text{ and } \forall \tau \\
q_{ij}(\tau) = f_{ij}(\tau) m_{ij}(\tau) & \forall i, j = 1, 2 \text{ and } \forall \tau \\
s_i = \sum_{j=1}^{2} q_{ij}(\tau) & \forall i = 1, 2 \text{ and } \forall \tau
\end{cases}
\tag{43}
$$

Table C5: Robustness Check of Table 2
- Changing to a Patent-Level Analysis

	Cross-County Collab Dummy			
	(1)	(2)	(3)	(4)
FloodDiff	0.151***	0.150***	0.164***	0.150***
	(0.007)	(0.008)	(0.009)	(0.010)
Patent Type FE	No	No	Yes	No
County1 FE	Yes	Yes	Yes	Yes
County2 FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No
Patent Type×Year FE	No	No	No	Yes
Adjusted R^2	0.334	0.336	0.395	0.455
Obs	452,734	452,734	452,734	452,734

Notes: (1) Time: 2008-2018; (3) 'FloodDiff' denotes the maximum difference in flood exposure among all applicants associated with a given patent. Details on the construction of the flood exposure measure are provided in Section 2.1; (4) The dependent variable is a dummy variable that equals one if the patent includes applicants from at least two different counties; (5)* 0.1, ** 0.05, *** 0.01.

Equation 43 can be summarized by the intrinsic productivity $\{z_i\}$ and patent prices $\{p_i(\tau)\}$ characterized by the following equations:

$$\mathbb{E}_\tau p_1(\tau) = \theta^{\frac{1}{\gamma}} \delta^{\frac{\gamma-1}{\gamma}} \gamma \lambda_1^z z_1^{-\frac{1-\gamma}{\gamma}} \tag{44}$$

$$\mathbb{E}_\tau p_2(\tau) = \theta^{\frac{1}{\gamma}} \delta^{\frac{\gamma-1}{\gamma}} \gamma \lambda_2^z z_2^{-\frac{1-\gamma}{\gamma}} \tag{45}$$

$$B_{ij}\left[\mu p_1(\tau)\sqrt{\hat{z}_1\hat{z}_2}-\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\left[\mu p_2(\tau)\sqrt{\hat{z}_1\hat{z}_2}-\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\sqrt{\hat{z}_1\hat{z}_2}+B_{ii}\left[\mu p_1(\tau)\hat{z}_1-\kappa^i\right]^{\frac{2\alpha}{1-2\alpha}}\hat{z}_1 = z_1^{\frac{1}{\gamma}} \tag{46}$$

$$B_{ij}\left[\mu p_1(\tau)\sqrt{\hat{z}_1\hat{z}_2}-\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\left[\mu p_2(\tau)\sqrt{\hat{z}_1\hat{z}_2}-\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\sqrt{\hat{z}_1\hat{z}_2}+B_{ii}\left[\mu p_2(\tau)\hat{z}_2-\kappa^i\right]^{\frac{2\alpha}{1-2\alpha}}\hat{z}_2 = z_2^{\frac{1}{\gamma}} \tag{47}$$

where $B_{ij} = \xi^{\frac{1}{1-2\alpha}} \mu \delta^{-\frac{1}{\gamma}} \theta^{\frac{1}{\gamma}} \kappa_{ij}^{s\,-\frac{2\alpha}{1-2\alpha}}$.

D.2 Proofs

Lemma 1: Proof. Consider the no-flood scenario $\tau^{\text{no flood}} = \{0, 0\}$. Denote the patent prices as $p_i(\tau^{\text{no flood}}) = p_i$. Then denote the first part Equation 46 and 47 as $C(z_1, z_2)$:

$$C(z_1, z_2) = \left[\mu p_1 \sqrt{z_1 z_2} - \kappa^i\right]^{\frac{\alpha}{1-2\alpha}} \left[\mu p_2 \sqrt{z_1 z_2} - \kappa^i\right]^{\frac{\alpha}{1-2\alpha}} \sqrt{z_1 z_2}$$

Then, Equation 46 and 47 can be re-written as:

$$B_{ij} C(z_1, z_2) + B_{ii} \left[\mu p_1 z_1 - \kappa^i\right]^{\frac{2\alpha}{1-2\alpha}} z_1 = z_1^{\frac{1}{\gamma}} \tag{48}$$

$$B_{ij} C(z_2, z_1) + B_{ii} \left[\mu p_2 z_2 - \kappa^i\right]^{\frac{2\alpha}{1-2\alpha}} z_2 = z_2^{\frac{1}{\gamma}} \tag{49}$$

Equation 48 can be re-arranged as follows:

$$p_1 = \mu^{-1} B_{ii}^{-\frac{1-2\alpha}{2\alpha}} \left[z_1^{\frac{1}{\gamma} - \frac{1}{1-2\alpha}} - B_{ij} C(z_1, z_2) z_1^{-\frac{1}{1-2\alpha}}\right]^{\frac{1-2\alpha}{2\alpha}} + \frac{\kappa^i}{\mu} z_1^{-1}$$

Denote the first part as:

$$D(z_1, z_2) = z_1^{\frac{1}{\gamma} - \frac{1}{1-2\alpha}} - B_{ij} C(z_1, z_2) z_1^{-\frac{1}{1-2\alpha}}$$

Then the first-order derivative of $D(z_1, z_2)$ is as follows:

$$\frac{\partial D(z_1, z_2)}{\partial z_1} = \left[\left(\frac{1}{\gamma} - \frac{1}{1-2\alpha}\right) z_1^{\frac{1}{\gamma}} + \frac{B_{ij}}{1-2\alpha} C(z_1, z_2) - B_{ij} z_1 \frac{\partial C(z_1, z_2)}{\partial z_1}\right] z_1^{-\frac{2-2\alpha}{1-2\alpha}}$$

Hence, if $B_{ij} \to 0$ ($\kappa_{ij}^s \to \infty$) and $\gamma > 1 - 2\alpha$ (Assumption 1), then $\frac{\partial D(z_1, z_2)}{\partial z_1} < 0$. Since $\frac{\kappa^i}{\mu} z_1^{-1}$ decreases in z_1. Therefore, $\frac{\partial p_1}{\partial z_1} < 0$.

Since Equation 48 and 49 are symmetric when we interchange $\{z_1, p_1\}$ and $\{z_2, p_2\}$, the result we obtain from Equation 48 also applies to Equation 49. Put together, $p_1 < p_2$ if $z_1 > z_2$.

Proposition 1: Proof. Following Equation 46 and 47, we will compare the quantities of cross-county collaborative patents $q_{c,c'}$ in two different scenarios - $\tau^{\text{single-flooded}}$ and $\tau^{\text{no flood}}$.

Denote the patent prices in $\tau^{\text{no flood}}$ and $\tau^{\text{single-flooded}}$ as $\{p_1, p_2\}$ and $\{p_1', p_2'\}$, respectively. Then the equilibrium prices can be characterized by the following four equations:

$$B_{ij}\left[\mu p_1\sqrt{z_1z_2}-\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\left[\mu p_2\sqrt{z_1z_2}-\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\sqrt{z_1z_2}+B_{ii}\left[\mu p_1 z_1-\kappa^i\right]^{\frac{2\alpha}{1-2\alpha}}z_1=z_1^{\frac{1}{\gamma}} \tag{50}$$

$$B_{ij}\left[\mu p_1\sqrt{z_1z_2}-\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\left[\mu p_2\sqrt{z_1z_2}-\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\sqrt{z_1z_2}+B_{ii}\left[\mu p_2 z_2-\kappa^i\right]^{\frac{2\alpha}{1-2\alpha}}z_2=z_2^{\frac{1}{\gamma}} \tag{51}$$

$$B_{ij}\left[\mu p_1'\sqrt{z_1z_2}e^{-\frac{\eta}{2}}-\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\left[\mu p_2'\sqrt{z_1z_2}e^{-\frac{\eta}{2}}-\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\sqrt{z_1z_2}e^{-\frac{\eta}{2}}+B_{ii}\left[\mu p_1' z_1e^{-\eta}-\kappa^i\right]^{\frac{2\alpha}{1-2\alpha}}z_1e^{-\eta}=z_1^{\frac{1}{\gamma}} \tag{52}$$

$$B_{ij}\left[\mu p_1'\sqrt{z_1z_2}e^{-\frac{\eta}{2}}-\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\left[\mu p_2'\sqrt{z_1z_2}e^{-\frac{\eta}{2}}-\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\sqrt{z_1z_2}e^{-\frac{\eta}{2}}+B_{ii}\left[\mu p_2' z_2-\kappa^i\right]^{\frac{2\alpha}{1-2\alpha}}z_2=z_2^{\frac{1}{\gamma}} \tag{53}$$

The quantities of cross-county collaborative patents can be described by the following equations:

$$q_{c,c'}(\tau^{\text{no flood}})=B_{ij}\left[\mu p_1\sqrt{z_1z_2}-\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\left[\mu p_2\sqrt{z_1z_2}-\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\sqrt{z_1z_2} \tag{54}$$

$$q_{c,c'}(\tau^{\text{single-flooded}})=B_{ij}\left[\mu p_1'\sqrt{z_1z_2}e^{-\frac{\eta}{2}}-\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\left[\mu p_2'\sqrt{z_1z_2}e^{-\frac{\eta}{2}}-\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\sqrt{z_1z_2}e^{-\frac{\eta}{2}} \tag{55}$$

Hence, we would like to show that $q_{c,c'}(\tau^{\text{single-flooded}}) > q_{c,c'}(\tau^{\text{no flood}})$ if $\frac{z1}{z2}$ is sufficiently large. We will prove by contradiction: first, suppose $p_2' = p_2$. Then Equation 51 and 53 show that:

$$q_{c,c'}(\tau^{\text{single-flooded}})=q_{c,c'}(\tau^{\text{no flood}}) \tag{56}$$

Then Equation 50 and 52 show that:

$$\begin{aligned}
& B_{ii}\left[\mu p_1' z_1e^{-\eta}-\kappa^i\right]^{\frac{2\alpha}{1-2\alpha}}z_1e^{-\eta}=B_{ii}\left[\mu p_1 z_1-\kappa^i\right]^{\frac{2\alpha}{1-2\alpha}}z_1 \\
\Rightarrow\ & \mu p_1' z_1e^{-\eta}-\kappa^i=\left[\mu p_1 z_1-\kappa^i\right]e^{\frac{1-2\alpha}{2\alpha}\eta} \\
\Rightarrow\ & \mu p_1' z_1e^{-\eta}=e^{\frac{1-2\alpha}{2\alpha}\eta}\mu p_1 z_1+\left[1-e^{\frac{1-2\alpha}{2\alpha}\eta}\right]\kappa^i \\
\Rightarrow\ & p_1'=e^{\frac{1}{2\alpha}\eta}p_1+\frac{1}{\mu z_1}\left[e^{\eta}-e^{\frac{1}{2\alpha}\eta}\right]\kappa^i
\end{aligned}$$

Plugging the expression of p_1' into Equation 55 yields:

$$
\begin{aligned}
q_{c,c'}(\tau^{\text{single-flooded}}) &= B_{ij}\left[\mu p_1'\sqrt{z_1z_2}e^{-\frac{\eta}{2}} - \kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\left[\mu p_2\sqrt{z_1z_2}e^{-\frac{\eta}{2}} - \kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\sqrt{z_1z_2}e^{-\frac{\eta}{2}} \\
&= B_{ij}\left[\mu\sqrt{z_1z_2}e^{-\frac{\eta}{2}}e^{\frac{1}{2\alpha}\eta}p_1 + \mu\sqrt{z_1z_2}e^{-\frac{\eta}{2}}\frac{1}{\mu z_1}\left(e^{\eta} - e^{\frac{1}{2\alpha}\eta}\right)\kappa^i - \kappa^i\right]^{\frac{\alpha}{1-2\alpha}} \\
&\quad \left[\mu p_2\sqrt{z_1z_2}e^{-\frac{\eta}{2}} - \kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\sqrt{z_1z_2}e^{-\frac{\eta}{2}} \\
&= B_{ij}\left[\left(\mu p_1\sqrt{z_1z_2} - \kappa^i\right)e^{(\frac{1}{2\alpha}-\frac{1}{2})\eta} + e^{(\frac{1}{2\alpha}-\frac{1}{2})\eta}\kappa^i + \sqrt{\frac{z_2}{z_1}}\left(e^{\frac{\eta}{2}} - e^{(\frac{1}{2\alpha}-\frac{1}{2})\eta}\right)\kappa^i - \kappa^i\right]^{\frac{\alpha}{1-2\alpha}} \\
&\quad \left[\left(\mu p_2\sqrt{z_1z_2} - \kappa^i\right)e^{-\frac{\eta}{2}} + e^{-\frac{\eta}{2}}\kappa^i - \kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\sqrt{z_1z_2}e^{-\frac{\eta}{2}} \\
&= B_{ij}\left[\left(\mu p_1\sqrt{z_1z_2} - \kappa^i\right) + \kappa^i + \sqrt{\frac{z_2}{z_1}}\left(e^{\frac{2\alpha-1}{2\alpha}\eta} - 1\right)\kappa^i - e^{(\frac{1}{2}-\frac{1}{2\alpha})\eta}\kappa^i\right]^{\frac{\alpha}{1-2\alpha}} \\
&\quad \left[\left(\mu p_2\sqrt{z_1z_2} - \kappa^i\right) + \kappa^i - e^{\frac{\eta}{2}}\kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\sqrt{z_1z_2}e^{-\frac{\eta}{2}}
\end{aligned}
$$

Denote $C_1 = 1 + \left(e^{\frac{2\alpha-1}{2\alpha}\eta} - 1\right)\sqrt{\frac{z_2}{z_1}} - e^{(\frac{1}{2}-\frac{1}{2\alpha})\eta}$ and $C_2 = e^{\frac{\eta}{2}} - 1$, then

$$
\begin{aligned}
&q_{c,c'}(\tau^{\text{single-flooded}}) > q_{c,c'}(\tau^{\text{no flood}}) \\
&\Leftrightarrow \left[\left(\mu p_1\sqrt{z_1z_2} - \kappa^i\right) + C_1\kappa^i\right]\left[\left(\mu p_2\sqrt{z_1z_2} - \kappa^i\right) - C_2\kappa^i\right] > \left[\mu p_1\sqrt{z_1z_2} - \kappa^i\kappa^i\right]\left[\mu p_2\sqrt{z_1z_2} - \kappa^i\kappa^i\right] \\
&\Leftrightarrow -\left(\mu p_1\sqrt{z_1z_2} - \kappa^i\right)C_2\kappa^i + \left(\mu p_2\sqrt{z_1z_2} - \kappa^i\right)C_1\kappa^i - C_1C_2{\kappa^i}^2 > 0 \\
&\Leftrightarrow -\left(\frac{\mu p_1\sqrt{z_1z_2}}{\kappa^i} - 1\right)\frac{1}{C_1} + \left(\frac{\mu p_2\sqrt{z_1z_2}}{\kappa^i} - 1\right)\frac{1}{C_2} > 1
\end{aligned}
$$

Since Lemma 1 shows $p_1 < p_2$, the above inequality holds if

$$
\left(\frac{\mu p_2\sqrt{z_1z_2}}{\kappa^i} - 1\right)\left(-\frac{1}{C_1} + \frac{1}{C_2}\right) > 1 \tag{57}
$$

Next, we would like to show that if $\frac{z_1}{z_2}$ is sufficiently large, then $C_1 > C_2$:

$$\begin{aligned}
&C_1 > C_2 \\
&\Rightarrow 1 + \left(e^{\frac{2\alpha-1}{2\alpha}\eta} - 1\right)\sqrt{\frac{z_2}{z_1}} - e^{(\frac{1}{2}-\frac{1}{2\alpha})\eta} > e^{\frac{\eta}{2}} - 1 \\
&\Rightarrow \left(e^{\frac{2\alpha-1}{2\alpha}\eta} - 1\right)\sqrt{\frac{z_2}{z_1}} > e^{\frac{\eta}{2}} + e^{(\frac{1}{2}-\frac{1}{2\alpha})\eta} - 2 \\
&\Rightarrow \sqrt{\frac{z_1}{z_2}} > \frac{1 - e^{\frac{2\alpha-1}{2\alpha}\eta}}{2 - e^{\frac{\eta}{2}} - e^{(\frac{1}{2}-\frac{1}{2\alpha})\eta}}
\end{aligned}$$

If $\eta \to 0$, then the RHS of the inequality yields:

$$\begin{aligned}
\lim_{\eta\to 0} \frac{1 - e^{\frac{2\alpha-1}{2\alpha}\eta}}{2 - e^{\frac{\eta}{2}} - e^{(\frac{1}{2}-\frac{1}{2\alpha})\eta}} &= \lim_{\eta\to 0} \frac{\left(1 - e^{\frac{2\alpha-1}{2\alpha}\eta}\right)'}{\left(2 - e^{\frac{\eta}{2}} - e^{(\frac{1}{2}-\frac{1}{2\alpha})\eta}\right)'} \\
&= \lim_{\eta\to 0} \frac{-\frac{2\alpha-1}{2\alpha} e^{\frac{2\alpha-1}{2\alpha}\eta}}{-\frac{1}{2}e^{\frac{\eta}{2}} - (\frac{1}{2} - \frac{1}{2\alpha})e^{(\frac{1}{2}-\frac{1}{2\alpha})\eta}} \\
&= \frac{-\frac{2\alpha-1}{2\alpha}}{-\frac{1}{2} - (\frac{1}{2} - \frac{1}{2\alpha})} \\
&= 1
\end{aligned}$$

Trivially, the RHS of the inequality is continuous and strictly increasing in η for $\eta > 0$ sufficiently close to zero. Hence, in the right-sided neighborhood of $\eta = 0$, the RHS of the equality is larger than one and upper-bounded. Hence, there exists a cutoff value $M > 1$ such that if $\sqrt{\frac{z_1}{z_2}} > M$, then the above inequality holds and $C_1 > C_2$.

Provided $-\frac{1}{C_1} + \frac{1}{C_2}$ is positive, if κ^i is sufficiently large (Assumption 1), then inequality 57 holds, and thus $q_{c,c'}(\tau^{\text{single-flooded}}) > q_{c,c'}(\tau^{\text{no flood}})$. That contradicts equation 56, so $p_2' = p_2$ does not hold.

Now suppose $p_2' > p_2$, then Equation 51 and 53 show that

$$q_{c,c'}(\tau^{\text{single-flooded}}) < q_{c,c'}(\tau^{\text{no flood}}) \tag{58}$$

Then Equation 50 and 52 show that:

$$
\begin{aligned}
& B_{ii}\left[\mu p_1' z_1 e^{-\eta} - \kappa^i\right]^{\frac{2\alpha}{1-2\alpha}} z_1 e^{-\eta} > B_{ii}\left[\mu p_1 z_1 - \kappa^i\right]^{\frac{2\alpha}{1-2\alpha}} z_1 \\
\Rightarrow \quad & p_1' > e^{\frac{1}{2\alpha}\eta} p_1 + \frac{1}{\mu z_1}\left[e^{\eta} - e^{\frac{1}{2\alpha}\eta}\right]\kappa^i
\end{aligned}
$$

Applying the inequality of p_1' and the assumption that $p_2' > p_2$ into Equation 55 yields:

$$
\begin{aligned}
q_{c,c'}(\tau^{\text{single-flooded}}) &= B_{ij}\left[\mu p_1' \sqrt{z_1 z_2} e^{-\frac{\eta}{2}} - \kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\left[\mu p_2' \sqrt{z_1 z_2} e^{-\frac{\eta}{2}} - \kappa^i\right]^{\frac{\alpha}{1-2\alpha}} \sqrt{z_1 z_2} e^{-\frac{\eta}{2}} \\
&> B_{ij}\left[\mu p_1' \sqrt{z_1 z_2} e^{-\frac{\eta}{2}} - \kappa^i\right]^{\frac{\alpha}{1-2\alpha}}\left[\mu p_2 \sqrt{z_1 z_2} e^{-\frac{\eta}{2}} - \kappa^i\right]^{\frac{\alpha}{1-2\alpha}} \sqrt{z_1 z_2} e^{-\frac{\eta}{2}} \\
&> B_{ij}\left[\left(\mu p_1 \sqrt{z_1 z_2} - \kappa^i\right) + \kappa^i + \sqrt{\frac{z_2}{z_1}}\left(e^{\frac{2\alpha-1}{2\alpha}\eta} - 1\right)\kappa^i - e^{(\frac{1}{2}-\frac{1}{2\alpha})\eta}\kappa^i\right]^{\frac{\alpha}{1-2\alpha}} \\
&\quad \left[\left(\mu p_2 \sqrt{z_1 z_2} - \kappa^i\right) + \kappa^i - e^{\frac{\eta}{2}}\kappa^i\right]^{\frac{\alpha}{1-2\alpha}} \sqrt{z_1 z_2} e^{-\frac{\eta}{2}}
\end{aligned}
$$

The last RHS expression of is exactly what we obtain in the proof for $p_2' \neq p_2$. Hence, following the same derivation, we can show that, if Assumption 1 holds, then we have again $q_{c,c'}(\tau^{\text{single-flooded}}) > q_{c,c'}(\tau^{\text{no flood}})$, which contradicts with Inequality 58.

Put together, we have $p_2' < p_2$. Then Equation 51 and 53 show that $q_{c,c'}(\tau^{\text{single-flooded}}) > q_{c,c'}(\tau^{\text{no flood}})$

Table D6: Calibration Targets

Parameter	Value	Source/Targeted Moments
Panel A: Exogenously Calibrated Parameters		**Source:**
β - Discount factor	0.95	Standard calibration
δ - Depreciation of productivity	0.15	Hall (2007)
μ - Elasticity of productivity to new patents	0.30	Bloom, Schankerman and Van Reenen (2013)
η - Separation rate of collaboration	0.25	Lobo and Strumsky (2008)
ξ - Elasticity of matching/generating new ideas	0.60	Bloom et al. (2020)
ϵ_z - Flood-induced productivity loss	-0.06	Hu, Ma and Wang (2025)
ϵ_i - Flood-induced innovation loss	-0.10	Estimation of local patent reduction
Panel B: Internally Calibrated Parameters		**Targeted Moments:**
θ - Scalar of productivity improvement	0.10	Averaged innovation success rate $\approx 15\%$
w_h/w_l - Wage rate ratio	0.93	Flooded and non-flooded counties output per capita ratio ≈ 1.2
κ^i - Innovation fixed cost	0.10	R&D return rate $\approx 10\%$ (Hall, Mairesse and Mohnen, 2010)
κ^s_{ii} - Local searching cost	0.10	Local to cross-county patent ratio ≈ 2.0
κ^s_{ij} - Cross-county searching cost	$1.1^*\kappa^s_{ii}$	10% higher than local search