



SCHOOL OF  
ECONOMICS AND  
MANAGEMENT

MSc Economic Development and Growth [MEDEG]

*Understanding the Macroeconomic Effects of Climatic Disasters:  
Implications for Economic Development and Resilience*

by

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**Abstract:** This thesis estimates the dynamic macroeconomic effects of climatic disasters on GDP per capita and human capital, using local projections on a panel of 173 countries from 1970 to 2022. The analysis focuses on droughts, floods, and storms, three unambiguously climate-driven disaster types. The main finding is a divergence between output and human capital responses. GDP per capita rises cumulatively after climatic shocks in both income groups, consistent with reconstruction-driven demand effects, while human capital declines in lower-income countries in the years immediately following shocks. Foreign aid is associated with a weaker GDP per capita response but a smaller human capital decline in lower-income countries, suggesting aid prioritises humanitarian objectives over productive investment. Evidence on domestic credit and remittances is mixed. The results underscore that short-run GDP recovery can mask slower-moving human capital losses, and that adaptation policies must distinguish reconstruction spending from genuine welfare gains.

**Key words:** Climate Shocks, Economic Growth, Human Capital, Local Projections, Income Heterogeneity

Course code: EKHS42  
Master's Thesis (15 credits ECTS)  
May 2026  
Supervisor: Jaco Zijderduijn  
Examiner: Josef Taalbi  
Word Count: 16,311

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## *1. Introduction*

Climate change represents one of the defining challenges of the twenty-first century. Global surface temperatures have already risen by more than 1.1 degrees Celsius relative to pre-industrial levels, and projections indicate further warming of up to 4 degrees Celsius by the end of this century if current emission trends persist (Cevik & Jalles, 2024). This warming is not simply a gradual shift in average conditions. It fundamentally alters the distribution of weather outcomes, increasing both the frequency and intensity of extreme climate-related events, such as heatwaves or storms (IPCC, 2023). These climatic disasters impose immediate humanitarian costs through loss of life, displacement, and destruction of infrastructure, but they also generate longer-term economic consequences that may persist for years or even decades. The international community has long recognised the urgency of addressing climate change through multilateral frameworks, from the 1992 UNFCCC to the 2015 Paris Agreement's commitment to limit warming to well below 2°C. Yet despite these commitments, the gap between stated goals and actual progress remains substantial. Greenhouse gas emissions continue to rise, adaptation efforts lag behind the scale of the challenge, and the most vulnerable populations, typically in lower-income countries, face disproportionate exposure to climate risks without adequate resources to cope (OECD, 2024). These countries often lack the institutional capacity, financial buffers, and infrastructural resilience that enable wealthier nations to absorb shocks and recover more quickly. Understanding how climate-related disasters affect economic performance in these vulnerable settings, and identifying which factors might mitigate or amplify their impact, is therefore of growing importance.

Recent climate-related disasters, from the prolonged droughts in the Horn of Africa and the repeated cyclones striking Mozambique, to the severe heatwaves across South Asia, demonstrate that climate risks have become frequent, systemic, and economically consequential. These events underscore that climate-related physical risks are no longer rare events but material threats to macroeconomic stability, investment, and public finances, particularly for lower-income economies. By examining how countries respond to climate shocks, the study highlights both the broad macroeconomic consequences and the disproportionate vulnerabilities that lower income economies face due to structural constraints shaping their recovery trajectories. In doing so, it aims to clarify whether climate shocks reinforce existing development gaps or weaken long term growth prospects.

The economic consequences of climatic shocks extend well beyond immediate output losses. Disasters damage physical capital, disrupt supply chains, reduce labour productivity,

and impose fiscal burdens on governments that must fund relief and reconstruction efforts. Recent evidence suggests that the costs of climate change may be substantially larger than previously understood, particularly when accounting for the occurring disasters rather than focusing solely on rising global temperatures (Bilal & Känzig, 2026). Beyond Gross Domestic Product (GDP), these shocks also threaten human capital accumulation by disrupting education, worsening health outcomes, and reducing household investment in children's development, effects that may compound over time and undermine long-term growth prospects (Cuaresma, 2010; Acevedo et al., 2020). Existing research on the macroeconomic effects of natural disasters yields mixed findings. Early cross-country evidence from Skidmore and Toya (2002) suggested that climatic disasters might support long-run growth by inducing human capital accumulation and technological upgrading through a substitution mechanism. However, more recent studies tend to find that disasters reduce output, particularly when shocks are severe or occur in vulnerable economies with limited adaptive capacity (Raddatz, 2009; Felbermayr & Gröschl, 2014). Analyses by Cevik and Jalles (2024) and Ehlers et al. (2025) document persistent negative effects on GDP growth and inflation, with stronger impacts in developing countries. Yet despite this growing body of evidence, key gaps remain. Most studies focus on aggregate GDP effects without examining whether human capital, a critical driver of long-run development, responds differently. Moreover, while vulnerability clearly varies across countries, there is limited systematic evidence on whether access to external financial resources, such as foreign aid and remittances, effectively buffers disaster impacts or whether domestic financial development plays a more decisive role. These questions are especially relevant for lower-income countries, where resource constraints are binding and policy options are limited. Accordingly, this study seeks to answer the following research question: *How do climatic disasters affect GDP per capita and human capital accumulation and what role do financial buffers and structural characteristics play in moderating these effects?*

This thesis addresses these gaps by examining the macroeconomic effects of climatic disasters on both GDP per capita and human capital accumulation, with attention to heterogeneity across income groups and the role of financial buffers. I use a panel dataset covering 173 countries from 1970 to 2022 and employ a local projections framework to estimate the dynamic responses to climatic disaster shocks. The analysis focuses on droughts, floods, and storms, three disaster types that are unambiguously climate-driven, geographically dispersed, and sufficiently frequent to allow robust econometric identification. For GDP per capita, I find a positive cumulative response to climatic shocks in both higher- and lower-

income countries, with the full-sample effect peaking at approximately 1.75 percentage points eight years after the shock, and broadly comparable magnitudes across income groups. This finding appears inconsistent with the notion that disasters uniformly reduce output. This can be interpreted as evidence of reconstruction-driven demand effects, where post-disaster spending on infrastructure rebuilding and emergency relief can boost GDP per capita growth. By contrast, the human capital results paint a different picture. In lower-income countries, climatic shocks generate immediate and persistent declines in human capital, with statistically significant negative effects of approximately 0.06 percentage points one year after the shock and 0.07 percentage points after two years. This finding is consistent with disrupted schooling, increased mortality, deteriorating health outcomes, and reduced household investment in children's education. The divergence between GDP and human capital effects underscores a critical tension, where short-run reconstruction spending may inflate measured output while simultaneously eroding the foundations of long-term development.

The heterogeneity analysis yields additional insights. Among financial buffers, domestic credit provision shows a positive moderating effect on GDP per capita in lower-income countries but the opposite pattern in higher-income ones, suggesting that well-functioning domestic financial systems matter more for post-disaster adjustment where access to credit is otherwise constrained. Foreign aid, by contrast, shows a clear divergence across outcomes. High-aid countries experience a GDP per capita response that is roughly 3 percentage points weaker than low-aid countries eight years after a shock in the full sample, with the gap widening to nearly 5 percentage points among lower-income countries. The pattern reverses for human capital, where high-aid lower-income countries see a human capital decline about 1 percentage point smaller than their low-aid counterparts a decade after the shock. Together, these findings indicate that aid flows may prioritise humanitarian and social objectives over productive investment. Remittances, meanwhile, show a divergent pattern across income groups for GDP per capita, with higher inflows associated with weaker post-shock responses in lower-income countries but stronger responses in higher-income ones. This likely reflects the fact that remittances tend to support consumption smoothing rather than productive investment, particularly in contexts of limited financial development as is typical of lower-income economies.

The thesis is structured as follows. Section 2 reviews the relevant literature on climate-change impacts and natural disasters, positioning the study within the existing empirical landscape. Section 3 develops the theoretical framework guiding the analysis. Section 4 details the data sources and variable construction. Section 5 outlines the

local-projections methodology, including the baseline specification and the heterogeneity analysis. Section 6 presents the core empirical results for GDP per capita and human capital, and documents the presence of buffer effects. Section 7 reports the robustness checks, while section 8 discusses the interpretation and broader implications of the findings. Section 9 reflects on the study's limitations, and section 10 concludes.

## *2. Literature review*

### *2.1 Climate change impact literature*

Geography and environmental conditions have long been recognised as fundamental determinants of economic outcomes, shaping agricultural productivity, disease burden, transport costs and access to markets (Gallup et al., 1999; Sachs, 2003). Climate change represents a fundamental shift in these baseline conditions, with rising temperatures, changing rainfall patterns, and more frequent extreme weather threatening agriculture, infrastructure, and macroeconomic stability. This has motivated a growing literature on the effects of climate-related shocks. Early panel evidence from Dell et al. (2012) shows that a 1°C temperature increase reduces annual growth in poor countries by around 1.3 percentage points, with no robust effect for rich countries. Burke and Tanutama (2019) use district-level GDP data and find a nonlinear relationship between temperature and local economic growth. Their results suggest that output growth declines sharply at higher temperatures and that poorer regions are more exposed to damaging temperatures. Building on this pattern, Acevedo Mejia et al. (2019) focus on low-income countries and identify the channels at work, temperature increases reduce output through lower productivity, weaker investment, and reduced labour supply. While Kahn et al. (2021) find that persistent temperature deviations reduce long-run GDP per capita growth across both rich and poor countries, suggesting some universality in climate impacts, the magnitude and persistence of these effects remain systematically larger in developing economies. The distributional effects of climate change are further examined by Cevik and Jalles (2023). They find that climate vulnerability is associated with higher income inequality. The effect is concentrated in developing countries, where the coefficient is much larger and statistically significant, while the effect is not significant for advanced economies. This suggests that climate shocks not only widen the gap between rich and poor countries but also exacerbate inequality within already vulnerable nations. Beyond output, climate variability also affects prices. Moessner (2022) finds that precipitation has nonlinear effects on food CPI

inflation, with both unusually low and unusually high precipitation raising food prices. Acevedo et al. (2020) further examine the channels through which weather shocks affect growth. They find that higher temperatures reduce output in hot countries through lower investment, weaker labour productivity, poorer health, and lower agricultural and industrial output. In a median low-income country, a 1°C temperature increase leaves output around 2 percent lower and investment around 10 percent lower after seven years. Using subnational data, they find that hot regions in high-income countries experience smaller losses than similarly hot regions in low-income countries, suggesting that economic development partly moderates the damage.

Taken together, the literature suggests that changes in temperature and precipitation have economically meaningful effects across a range of outcomes, including output, prices, and inequality. The strongest and most consistent evidence concerns the adverse effects of higher temperatures on economic performance, particularly in poorer and more vulnerable economies, with estimates likely understating the true costs (Tol, 2024).

## *2.2 Natural disasters literature*

More closely aligned with the focus of this thesis is the literature on the economic effects of climate shocks and climate-related disasters. This literature has expanded considerably as climate change increasingly alters the distribution of weather outcomes through changes in temperature, precipitation, and other meteorological conditions, making extreme events such as droughts, floods and heat waves part of broader climate-related shifts (Chambwera et al., 2014). As global warming intensifies, such shocks are expected to become more frequent, severe, and overlapping, increasing their relevance for long-run economic outcomes such as income growth and human capital accumulation (IPCC, 2023). Recent high-impact disasters further illustrate the scale of potential economic disruption, with climate-related physical risks affecting investment and wider macroeconomic stability (OECD, 2024).

A substantial body of research shows that climate change can hinder economic development by increasing the frequency and intensity of natural disasters (Loyaza et al., 2012; Noy, 2009; Raddatz, 2009). Another strand of the literature examines disaster impacts at a more disaggregated level, focusing on specific countries, regions, or events. Naguib et al. (2022) find that cyclones reduce local economic activity in India, but the effect is short-lived, fading after roughly eight months. Weerasekara et al. (2021) show that climate-induced disasters in Sri Lanka generate differing outcomes. Agriculture is found to be the most vulnerable, while some

service and reconstruction-related activities appear to benefit after disasters. Lee (2021) similarly finds that Hurricanes Harvey and Irma had local labour-market effects, but that these effects on unemployment and employment dissipated within one year. This heterogeneity is also supported by Loayza et al. (2012), who examine the sectoral effects of droughts, floods, storms and earthquakes. They find that impacts vary by both disaster type and sector, droughts reduce agricultural growth, while floods can have positive effects, and some storms are associated with short-run gains.

Considerable cross-country literature has also emerged. Earlier contributions mainly examine the macroeconomic effects of natural disasters at the aggregate output level. Skidmore and Toya (2002) provide one of the earliest cross-country analyses of the relationship between natural disasters and long-run economic growth. They measure disaster exposure mainly through event frequency and distinguish between climatic and geologic disasters. Their results point to an important asymmetry where climatic disasters are positively associated with long-run GDP growth, human capital accumulation and productivity, whereas geologic disasters are negatively associated with growth. They explain this through a substitution mechanism. Since climatic disasters tend to destroy physical capital more than human life, they may reduce the expected return to physical capital relative to human capital, shifting investment incentives toward human capital accumulation. This, in turn, can raise productivity through positive externalities and technological upgrading, supporting higher long-run growth. Geologic disasters, by contrast, are less predictable and more destructive to both life and property, so they are less likely to generate the same growth-enhancing adjustment. Raddatz (2009) on the other hand, finds that climatic disasters significantly reduce real GDP per capita by approximately 0.6 percent, with most of the impact occurring contemporaneously and persisting over the medium term, with the most damaging impact caused by droughts. He also finds that low-income countries respond much more strongly to climate shocks experiencing larger output drops. Similarly, Noy (2009), finds adverse short-run effects on output with largest losses occurring in developing countries and smaller economies. Cavallo et al. (2013), on the other hand, find that most natural disasters, even those fairly large ones, have no significant effect on GDP growth in either the short or long run. Cavallo et al. (2021) revisit this and conclude that while disasters may not systematically reduce growth across all countries, the most catastrophic events can still generate lasting output losses in more vulnerable economies. They find that catastrophic natural disasters reduce real GDP per capita growth by 2.1 to 3.7 percentage points in the year of the event. Felbermayr and Gröschl (2014) also show that natural disasters reduce real GDP per capita in the year they occur. The effects

are strongest for severe events: the worst 1% of disaster years lower GDP per capita by at least 6.83%, while the worst 5% reduce it by around 0.33-0.46 percentage points, depending on the specification. The paper also finds little evidence for the “creative destruction” argument that disasters may stimulate growth by forcing replacement of old capital. Instead, the results are more consistent with a neoclassical interpretation where disasters destroy capital or reduce productivity, causing output to fall. Cevik and Jalles (2024) and Ehlers et al. (2025) provide complementary evidence on the macroeconomic effects of climate-related natural disasters. Using a local projections framework, Cevik and Jalles (2024) examine droughts, extreme temperatures, and storms, showing that climate-induced disasters generally reduce real GDP growth, with larger and more persistent effects in developing countries than in advanced economies. They also find heterogeneous inflation effects, droughts and storms tend to raise inflation, particularly food inflation, while extreme temperature shocks generate more mixed responses, with outcomes shaped by country characteristics such as income level, fiscal capacity, institutional strength, and the state of the business cycle. Ehlers et al. (2025) extend this analysis by using estimates of direct economic damages from a broader set of weather disasters, including cold waves, droughts, floods, heat waves, landslides, storms, and wildfires. Also employing local projections, but at a more granular level looking at quarterly data, they find that output losses can be sizeable and persistent, average-size droughts, landslides, and wildfires reduce GDP by around 2%, 1%, and 0.4%, respectively, over a four-year horizon. Headline inflation effects are usually smaller and short-lived, while food prices rise more persistently, indicating stronger household-level effects.

Beyond GDP and inflation, the literature also examines how natural disasters affect trade, fiscal responses, and broader real-economy indicators. Studies on international trade find mixed but generally unequal effects. Gassebner et al. (2010) show that disasters tend to reduce both imports and exports, especially in smaller and less democratic countries, while Liu et al. (2023) find that climate disasters can increase overall trade mainly through higher imports in developing countries, often reflecting reconstruction needs and weaker domestic recovery capacity. Other work focuses on sovereign risk, showing that greater climate vulnerability is linked to lower credit ratings and higher sovereign borrowing costs, while stronger resilience reduces yields and spreads, especially in developing countries (Cevik & Jalles, 2020; Cevik & Jalles, 2021). More recent macro-financial evidence also shows that disasters affect broader financial conditions and public finances, suggesting that their effects extend well beyond headline output losses (Eickmeier et al., 2024).

Overall, the literature shows that the economic effects of natural disasters are heterogeneous and depend on the type, severity and context of the shock. While early evidence suggested that some climatic disasters may support long-run growth (Skidmore and Toya, 2002), most subsequent studies find that disasters tend to reduce output, particularly when shocks are severe or occur in vulnerable economies (Raddatz, 2009; Noy, 2009; Felbermayr & Gröschl, 2014). Taken together, the literature suggests that disasters are not uniformly growth-reducing, but their adverse effects fall disproportionately on lower-income and more vulnerable economies. This creates an unequal distribution of impacts, with the heaviest burden borne by those least able to adapt. Through the destruction of physical capital, production interruptions, lower investment, and weaker trade flows, such shocks are expected to disrupt economic activity, leading to the following hypothesis:

**H1:** *Natural disasters have an immediate negative effect on GDP per capita.*

### *2.3 Human Capital and climate shocks*

While the macroeconomic literature on climate shocks and human capital remains limited, the theoretical link is well-established, and a growing body of micro-level evidence supports it. Caruso et al. (2023) provide a framework showing that climate change affects human capital through both direct channels, such as health, nutrition, and wellbeing, and indirect channels, such as income losses, infrastructure damage, and disrupted education. This theoretical grounding is supported by micro-level evidence. Baez et al. (2010) review the empirical literature on natural disasters and human capital in developing countries, focusing on consumption, education, and health. They show that disasters can affect human capital not only through direct damage to schools and other essential infrastructure, but also through a decline in household budgets. In these settings, households may reduce spending on food, health, and education. These early-life nutritional losses can have persistent effects on schooling, productivity, and later-life outcomes. Country-specific studies provide further support for these channels. Kim (2008) uses survey-based data to show that climate shocks reduce educational attainment through drought exposure in Cameroon and Burkina Faso, and through wildfire exposure in Mongolia. High temperatures and severe climate shocks have also been shown to lower school performance, which ultimately slows human capital accumulation (Olurotimi, 2025). de la Mata and Valencia-Amaya (2014) find that severe rainfall variability in Colombia increased dengue incidence, illustrating how climate shocks can erode human capital through disease burden as well as schooling. Diallo (2026) shows that early-life temperature shocks in

sub-Saharan Africa are linked to higher disability and lower education, while above-average rainfall improves health and educational outcomes. Disasters are also found to disrupt schooling through household coping responses, as income losses can lead families to rely more heavily on child labour (Baez & Santos, 2007; De Janvry et al., 2006).

However, macro-level evidence on the effects of climate change and climate-related disasters on human capital remains relatively limited. Cuaresma (2010) is one of the early and few that examine whether natural disaster risk affects human capital accumulation, measured mainly through secondary school enrollment. The author argues that the theoretical effect is ambiguous, disasters could reduce education by damaging schools, increasing child labour, or lowering expected returns to schooling, but they could also raise the relative return to human capital by shortening the expected lifespan of physical capital, consistent with Skidmore and Toya (2002). The main finding is that geologic disaster risk is robustly and negatively associated with secondary school enrollment across countries, while climate disaster risk is not found to be a robust determinant. McDermott (2012) provides macro-level evidence that natural disasters can have both immediate and delayed effects on human capital accumulation. The paper measures disasters by the share of the population affected and examines outcomes including secondary school enrollment, life expectancy, and mortality. The results show that disasters reduce school enrollment and life expectancy while increasing mortality, with stronger effects in poorer countries. These effects are found to persist for 10 to 15 years, suggesting that disasters harm human capital both directly and through later reductions in household investment in education and health.

Despite the growing body of evidence on the macroeconomic consequences of climatic disasters, the literature on their effects on human capital accumulation remains thin. This study aims to contribute to filling that gap by explicitly estimating how human capital evolves following a climatic shock in a cross-country panel setting. Based on the literature, natural disasters are expected to reduce human capital through education disruption, health deterioration and household coping responses. Since these channels operate gradually, the effect is expected to appear with a lag rather than immediately after the shock. This leads to the following hypothesis:

**H2:** *Climatic disasters reduce human capital accumulation, with delayed but persistent effects.*

## *2.4 Buffering effects*

The literature generally finds limited evidence of historical adaptation to temperature shocks in aggregate economic outcomes. Dell et al. (2012) show that higher temperatures reduce growth in poorer countries, with persistent effects, while Burke et al. (2015) find that the relationship between temperature and aggregate productivity has remained broadly stable since 1960. However, other studies suggest that future adjustment may partly reduce these losses. Costinot et al. (2016), for example, show that allowing farmers to reallocate production across crops and locations can substantially lower the welfare costs of climate change. Other studies highlight the role of resilience factors, including policy buffers, foreign aid, remittances, institutions, infrastructure, financial development, and insurance coverage (Acevedo Mejia et al., 2019; Cevik and Jalles, 2024; Ehlers et al., 2025). Overall, the evidence suggests that while climate shocks can have adverse effects, their magnitude depends on countries' ability to reallocate resources, finance recovery and build resilience. This motivates the inclusion of three buffering mechanisms in the analysis, foreign aid, remittances, and domestic credit, each of which is discussed in turn below.

### *2.4.1 Aid*

Foreign aid's role in disaster recovery has been extensively studied, though findings reveal tensions between short-term relief and longer-term development. Arezki et al. (2025) use natural disasters as natural experiments to examine bilateral aid responses, finding that aid commitments rise significantly after disasters but are dominated by humanitarian relief rather than long-term reconstruction financing, implying that aid flows are largely reactive rather than directed toward rebuilding productive capacity. This helps explain why the broader aid-growth literature finds mixed effects, as aid often pursues objectives other than economic development. While some studies find conditional effectiveness, aid works when countries maintain good policies (Burnside & Dollar, 2000) or face structural vulnerabilities (Guillaumont & Chauvet, 2001; Collier & Dehn, 2001), others document adverse long-term effects, with aid potentially undermining governance and export competitiveness through Dutch Disease (Rajan & Subramanian, 2011). Some studies, on the other hand, document positive unconditional effects (Clemens et al., 2004; Hoeffler, 2012), which highlights the continued lack of consensus regarding the effectiveness of aid. For human capital, the evidence is more encouraging. Kinda (2017) shows that aid cushions the impact of climatic shocks on food security by stabilising public spending, particularly in health, education and infrastructure. This highlights education

spending as a key channel through which aid helps protect human capital after disasters. More broadly, it suggests that aid to social sectors can safeguard human capital even when aid has limited effects on short-term output recovery. This channel remains relatively underexamined in the disaster-resilience literature.

#### *2.4.2 Remittances*

Remittances are often viewed as a relatively stable, counter-cyclical source of income that enables household consumption smoothing during crises (Combes & Ebeke, 2011; Ratha, 2006). In disaster contexts, remittances can function as private insurance. Household-level studies consistently find that remittances rise following disasters and are associated with improved outcomes including higher consumption and better housing conditions (Suleri & Savage, 2006). Mohapatra et al. (2009) provide micro-level evidence, showing that remittance-receiving households are better able to sustain spending after floods and avoid selling their assets to cope with the effects of these shocks. This household-level resilience supports research by Acevedo Mejia et al. (2019) where they find that remittances function as a short-run buffer following climate shocks. Combes and Ebeke (2011) show that while natural disasters raise output volatility, remittances dampen this effect by acting as a private insurance mechanism that smooths consumption and mitigates the macroeconomic impact of shocks. For human capital, the evidence is similarly positive. De and Ratha (2012), looking at Sri Lanka, find that remittances increase school enrolment, reduce child labour, and raise investment in private schooling, suggesting improvements in both access to and quality of education. Calero et al. (2009) obtain comparable results for Ecuador and further show that remittances protect schooling investments when households face economic shocks. Thus, remittances seem to buffer both growth, through consumption smoothing, and human capital, through maintained educational investment, with effects operating primarily at the household level. However, long-run growth effects remain contested, as large inflows may be directed toward consumption rather than productive investment (Chami et al., 2005), suggesting remittances cushion households immediately but may not support sustained growth.

#### *2.4.3 Financial depth*

Economic recovery after disasters also depends heavily on the strength of the financial system and the availability of domestic credit to support reconstruction. Noy (2009) finds that countries with higher domestic credit experience smaller output losses after disasters, while McDermott et al. (2014) show directly that disasters have persistent negative growth effects

where financial development is weak, as credit constraints delay investment and capital replacement. Felbermayr and Gröschl (2014) similarly treat domestic credit as a key determinant of post-disaster recovery speed. The mechanism operates by reducing the extent to which households and firms are constrained by limited access to credit. When credit markets are deep, households, firms and governments can finance reconstruction without facing liquidity constraints that could otherwise amplify the economic impact of a disaster. For human capital, the role of financial depth is less clear. Cuaresma (2010) shows that private-sector credit is positively associated with schooling, indicating that credit constraints influence medium-run human capital accumulation. However, this relationship does not translate directly into a post-disaster buffer. McDermott (2012) shows that domestic credit helps limit the longer-term effects of disasters on school enrolment, whereas aid is more effective in mitigating health impacts such as mortality and life expectancy. Credit access supports income smoothing and continued schooling, but it cannot address health shocks like malnutrition or disease, which require humanitarian assistance.

These three buffers operate through distinct channels with asymmetric effects on growth and human capital. Domestic credit acts as an investment-recovery mechanism, when capital is destroyed, deeper credit markets can speed up replacement and restore production (Noy, 2009), but credit does little to address the household constraints and school closures through which disasters damage human capital (McDermott, 2012). In contrast, aid and remittances act as transfer mechanisms that smooth household consumption and protect social spending. Remittances serve as decentralised private insurance, rising counter-cyclically after shocks (Mohapatra et al., 2009; Combes & Ebeke, 2011), and help protect school enrolment and educational quality in affected households (De and Ratha, 2011; Calero et al., 2009). Aid can support health outcomes and public investment in education and infrastructure when directed to social sectors (Kinda, 2017; McDermott, 2012), though its growth effects may be limited (Arezki et al., 2025). Based on the discussed literature, the following hypotheses are derived:

**H3:** *Aid is expected to be more effective in protecting human capital rather than in accelerating GDP recovery.*

**H4:** *Remittances are expected to moderate the effects of climatic disasters on both GDP per capita and human capital.*

**H5:** *Domestic credit is expected to shape the effects of climatic disasters more strongly for GDP per capita than for human capital.*

## *2.5 Research gap*

This thesis fills a gap by integrating three areas often studied separately: the macroeconomic effects of climatic disasters, their implications for human capital, and the role of financial buffers in shaping recovery. While most existing work focuses on GDP, inflation or sectoral outcomes, macro-level evidence on human capital remains limited. Moreover, although aid, remittances and domestic credit have each been linked to resilience, less is known about whether these buffers operate differently across economic and human-capital outcomes after climatic shocks. This study addresses these gaps using a global panel and a local-projections framework to estimate the dynamic effects of droughts, floods and storms on GDP per capita and human capital, and to test whether financial buffers moderate these responses. By tracing effects over a ten-year horizon, it also captures longer-run dynamics typically overlooked in the literature.

## *3. Theoretical framework*

This study draws on economic resilience theory. The empirical literature reviewed has shown that the realised response varies substantially across disaster types, countries, and time horizons. Resilience theory provides an "umbrella" framework that accommodates this heterogeneity rather than imposing a single prediction. It locates the determinants of the disaster response not in the shock itself but in the economic, social and institutional context in which the shock occurs (Briguglio et al., 2009; Hallegatte, 2014). Following Martin (2012), economic resilience can be understood as a multi-dimensional concept comprising four interrelated capacities. Resistance refers to the sensitivity of the economy to the initial shock; absorption to its ability to maintain function during the shock; recovery to the speed and completeness of returning to the pre-shock trajectory; and reorientation to the structural adjustments that emerge in the aftermath, including the possibility of building back stronger (Hallegatte et al., 2007). These capacities are not properties of the disaster but of the affected economy, and they vary systematically with the resources, institutions and household conditions that determine how a shock propagates through the system.

This framework matters analytically because the dynamics underlying these capacities can produce empirical patterns that are easily misread. The recovery and reorientation phases involve reconstruction spending and capital replacement, which can mechanically increase measured output even as long-run welfare deteriorates (Hallegatte & Dumas, 2009; Hallegatte et al., 2007). The Caballero and Hammour (1994) creative-destruction logic adds the possibility that renewed capital incorporates newer technology, raising measured productivity in ways that are not equivalent to welfare gains. Hallegatte and Dumas (2009) are explicit that these mechanisms can reduce disaster losses but cannot make disasters positive overall, and that any apparent gains depend critically on the speed, quality and financing of reconstruction. Aggregate output therefore captures only one face of the disaster response. It reflects the macroeconomic adjustments through reconstruction and capital replacement reasonably well, but it can mask the household-level adjustments through which disasters can erode long-run welfare, since these operate through consumption and human capital. The framework clarifies why GDP per capita and human capital may respond differently to the same shock. Physical capital is largely substitutable and can be rebuilt through reconstruction spending, allowing measured output to recover or even exceed pre-shock levels in the short run (Hallegatte & Dumas, 2009; Caballero & Hammour, 1994). Human capital, by contrast, is embodied in people and accumulates slowly through education and health. Once eroded through disrupted schooling, deteriorating child health, mortality or migration, it is difficult to restore (Baez et al., 2010; Cuaresma, 2010; Loayza et al., 2012). Resilience is multidimensional, varying across physical and human capital and across population groups (Hallegatte, 2014). Aggregate GDP measures may therefore obscure the human capital costs concentrated among vulnerable populations. Studying GDP per capita and human capital as distinct outcomes is the natural way to give these different dimensions of resilience separate empirical content.

A further proposition from the resilience literature is that these capacities are in large part policy-induced. Briguglio et al. (2008) draw a sharp distinction between inherent vulnerability, which countries cannot easily change, and nurtured resilience, which can be built through the policies, institutions and financial arrangements that determine how shocks propagate through the economy. Hallegatte (2014) builds on this idea, pointing to financial depth, insurance, social transfers, and fiscal capacity as mechanisms that shape how economies absorb shocks and recover from them. This is the theoretical space in which financial resources such as aid, remittances and credit become analytically relevant. They are not themselves resilience, but they are concrete channels through which economies and households can

strengthen absorption and recovery capacity. Examining whether these resources moderate the disaster response is therefore a direct test of whether the resilience mechanisms postulated by the theory are doing observable work.

#### *4. Data*

##### *4.1 Data and variable construction*

This study uses a global country sample, excluding microstates, dependent territories, historical entities, and countries missing the required Penn World Table GDP data.<sup>1</sup> These adjustments improve comparability and maintain consistent country definitions. After these exclusions, the baseline sample comprises 173 countries.<sup>2</sup> The period from 1970 to 2022<sup>3</sup> provides a sufficiently long panel dimension, allowing the analysis to exploit the longitudinal structure of the data and estimate the dynamic effects of climatic shocks over time.

The data is compiled from multiple databases to ensure the analysis is both reliable and informative. To measure economic performance per capita, the analysis uses real GDP and population data from the Penn World Tables PWT version 11.0 (Feenstra et al., 2015). The first dependent variable is constructed as the log difference of real GDP per capita, calculated by dividing real GDP ('rgdpna') by population. The second outcome variable, human capital, is measured using the human capital index from the Penn World Tables 11.0 (Feenstra et al., 2015), constructed based on average years of schooling from Barro and Lee (2013) and returns to education estimated by Psacharopoulos (1994). The outcome variable is defined as the cumulative log change in the index at each horizon  $h$ , so that coefficients are interpretable as approximate percentage changes in the human capital level.

The study uses data on ODA, personal remittances received, and domestic credit<sup>4</sup>, to analyse potential shock buffers. These variables are all sourced from the World Development Indicators (2026). ODA<sup>5</sup> is measured as a percentage of gross national income (GNI). Remittances are expressed as a percentage of GDP. Financial depth is proxied by domestic credit to the private sector provided by banks, expressed as a percentage of GDP. All control

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<sup>1</sup> Due to the unavailability of raw GDP data required to estimate the response functions, the following countries are excluded from the analysis: Afghanistan, Cuba, Eritrea, Kiribati, Korea (Democratic People's Republic), Kosovo, Libya, Micronesia (Federated States), Papua New Guinea, Samoa, Solomon Islands, Timor-Leste, Tonga, Vanuatu.

<sup>2</sup> The full list of countries is shown in the appendix (Table A.1).

<sup>3</sup> The final shock under the main definition occurs in 2022 for horizon  $h=1$ .

<sup>4</sup> For brevity, domestic credit to the private sector by banks is referred to as domestic credit throughout the analysis.

<sup>5</sup> Throughout the study, the terms ODA, aid, and development aid are used interchangeably.

variables, discussed in section 4.2, are also sourced from World Bank data to ensure consistency and reliability across the sample.<sup>6</sup> While the main variables generally cover the full sample period at the aggregate level, coverage is uneven across countries and years and as a result, the panel is unbalanced. Data availability tends to be lower for lower-income countries, which is often the case for cross-country macro panels. All variables have been winsorised at the 1st and 99th percentiles to avoid the effects of extreme outliers.

The climate-shock variables are constructed using the Emergency Events Database (EM-DAT), maintained by the Centre for Research on the Epidemiology of Disasters (CRED, 2025). EM-DAT records the type, location, timing, and impacts of over 27,000 disasters worldwide from 1900 onward, drawing on a range of institutional and media sources. EM-DAT defines a disaster as an event that overwhelms local capacity and requires national or international assistance. Disasters are classified as either natural or technological, with natural disasters covering climatic, geophysical, and biological hazards, and technological disasters covering transport, industrial, and other accidents. Technological disasters are excluded because the focus is on climatic rather than man-made events. Geophysical disasters, including earthquakes, volcanic activity, and tsunamis, and biological disasters, including epidemics and insect infestations, are also removed because they are not direct climatic shocks although some may be climate sensitive. Glacial lake outburst floods and asteroid or meteorite impacts are additionally excluded because they are rare, geographically localised, and not meaningfully climatic in nature. Wildfires and wet mass movements are excluded from the main specification because they are relatively rare, geographically concentrated, and less likely to generate the economy-wide effects this study aims to identify. Regarding extreme temperature, EM-DAT records it as a discrete disaster outcome, a heatwave or cold snap, rather than as the underlying climatic driver it more properly represents. Since temperature variability is in many cases the mechanism through which droughts arise, including extreme temperature events alongside droughts risks double counting the same underlying climatic signal.

The final sample focuses on droughts, floods, and storms<sup>7</sup>. The selection of these three types rests on two criteria. First, all three are unambiguously climatic in origin, driven by variability in precipitation and atmospheric conditions rather than by geophysical or biological processes. Second, these disaster types are sufficiently frequent and geographically widespread

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<sup>6</sup> Extended summary statistics of all variables can be found in the Appendix (Table A.2)

<sup>7</sup> Definitions of these as defined by EM-DAT can be found in the Table A.3 in the Appendix.

to plausibly affect aggregate national outcomes, which is necessary for identification in a cross-country panel setting.

While EM-DAT also records information on economic damages, deaths, and the number of people affected by each disaster, these variables are not used in constructing the shock indicator in this study. A first concern is data completeness. A substantial share of entries for these variables is missing, which would introduce systematic bias by underweighting countries where disasters are less thoroughly documented. Ehlers et al. (2025) highlight that economic cost estimates in EM-DAT are systematically underestimated, partly because the database draws heavily on sources such as news reports, introducing measurement error that would further bias any damage-based shock measure. A second and more fundamental concern is endogeneity. Economic damages from disasters are not independent of a country's income level but are shaped by it in ways that are difficult to disentangle. Wealthier countries tend to have more high-value physical capital, which mechanically inflates recorded damage figures. Yet their infrastructure is also typically more resilient, which may dampen total losses. In lower-income countries the reverse tension applies, less valuable capital stock may suppress reported damage figures even when the physical destruction is widespread, precisely because resilience is lower. A similar logic applies to the number of people affected, which itself tends to fall with income. As Skidmore and Toya (2002) note, damage and impact figures in disaster databases are therefore not fully reliable as objective measures of shock severity. Constructing the shock variable from binary disaster occurrence rather than from recorded damages or casualties avoids these endogeneity and measurement problems, and produces the plausibly exogenous variation needed for a more credible interpretation of the Local Projection estimates that follow. While intensity-based measures would in principle allow for estimating differential effects across disaster severity, as per the estimation concerns outlined above, binary occurrence indicators are preferred on methodological grounds. This construction is further consistent with the broader empirical literature on natural disasters, where binary shock variables are a commonly used approach (see Cevik & Jalles, 2024; Ehlers et al., 2025).

The main shock variable, referred to hereafter as climatic shock or disaster shock, is a binary indicator equal to one if at least one drought, flood, or storm occurred in a given country and year, and zero otherwise. Separate binary indicators are also constructed for each individual disaster category, following the same definition, each variable equals one if at least one event of the respective type occurred in a given country and year, and zero otherwise. These are denoted *shock\_drought*, *shock\_flood*, and *shock\_storm*, and are used to examine whether the aggregate effect captured by *climate\_shock* is driven by a particular disaster type. The selected

disasters are considered country-wide shocks, either because of their direct scale and severity or because their effects are propagated across the economy through market and trade linkages (Cevik & Jalles, 2024).

## *4.2 Control variables*

The empirical specification includes a set of control variables to account for observable factors that may influence exposure to climatic shocks and macroeconomic outcomes. This is intended to reduce omitted-variable bias while avoiding multicollinearity and over-specification.

### *4.2.1 Controls for GDP per capita regression*

For GDP per capita growth regressions, I include five baseline controls, following common choices in similar literature. Following the approach of Abbas et al. (2021), population growth is included to account for shifts in the consumption base. Inflation is also controlled for, following Khan and Senhadji (2000), who find that higher inflation is associated with lower economic growth. Inflation is also commonly used to capture domestic policy conditions in disaster-growth regressions (Noy, 2009). Government consumption, as a percentage share of GDP, controls for the size of the public sector and potential crowding-out effects, following McDermott et al. (2014). A larger public sector may facilitate faster post-disaster response by enabling greater resource mobilisation (Noy, 2009). At the same time, government consumption is found to be negatively associated with long-run growth (McDermott et al., 2014). Gross capital formation is included as a percentage of GDP to capture the investment rate, a key determinant of growth. Felbermayr and Gröschl (2014) incorporate it in their baseline specification to account for capital accumulation and expectations about future economic conditions. Trade openness, measured as exports plus imports as a share of GDP, captures external-sector dynamics. Openness may support growth through larger markets and technology adoption (Balasubramanyam et al., 1996), but can also increase output volatility by exposing economies to external shocks (Easterly et al., 2000). In the disaster context, Noy (2009) finds that more open economies experience smaller output losses, possibly due to easier access to imported capital goods and sustained export demand.

#### *4.2.2 Controls for Human Capital regressions*

Human capital accumulation operates through mechanisms distinct from GDP growth and therefore requires controls tailored to the determinants of education and health investment. Following Cevik and Jalles (2024), urbanisation, measured as the urban share of total population, is included to capture structural differences in access to human-capital-enhancing services. This is supported by Bertinelli and Zou (2008), who find that urbanisation can foster human capital accumulation by facilitating knowledge spillovers and strengthening incentives to invest in education. I also control for the fertility rate as demographic pressures are closely linked to human capital formation. Becker et al. (1990) argue that high-fertility societies tend to invest less in each child, while lower fertility allows greater investment in education and skills. Inflation is also controlled for, to account for macroeconomic instability. Government consumption is included to capture the public sector's role in providing goods and services relevant to education and health. Andrews et al. (2019) emphasise that such spending can support human capital, although its effectiveness depends on composition. Life expectancy, included following Cuaresma et al. (2010), captures the complementarity between health and education investments. Healthier children attend school more consistently and learn more effectively, while longer life expectancy increases the value of education by giving people more years to benefit from it (Jayachandran & Lleras-Muney, 2009). GDP per capita is included in logarithmic form to control for differences in countries' level of economic development. Wealthier countries generally have greater capacity to finance education, healthcare, and other services that support human capital accumulation. This mirrors the initial income variable used by Cuaresma et al. (2010) and Cavallo et al. (2013) in their cross-country analysis.

Following Felbermayr and Gröschl (2014), all controls are lagged by one period to reduce endogeneity concerns, as disasters may contemporaneously affect inflation, government consumption, and trade. Lagging these variables makes them predetermined relative to the shock and provides a more conservative specification. The exception is population growth, which is included contemporaneously because it reflects past demographic dynamics and is unlikely to respond within the same year to a disaster.

#### *4.3 Effects of financial buffers on Post-Shock Recovery*

The analysis is extended by evaluating whether financial support, specifically, official development assistance (ODA), remittances, and financial depth, help facilitate post-shock recovery. To assess these effects, I construct four binary variables, ‘*high\_aid*’, ‘*high\_remittances*’, and ‘*high\_domestic\_credit*’, indicating whether annual values of these buffers fall below or above a specified threshold in a given year. Each indicator equals one when a country’s annual value exceeds the relevant threshold, and zero otherwise. The thresholds are defined as the median of each variable, computed separately for the lower- and higher-income country subsamples. This income-group-specific threshold ensures that the benchmarks reflect meaningful variation within each group, rather than being distorted by the large differences in financial indicator levels that typically exist between low- and high-income countries. For remittances and domestic credit, I apply time-varying thresholds by dividing the sample into two periods and calculating separate benchmarks for each subsample. This approach is motivated by the skewed distribution of these inflows, as static thresholds may understate their relative importance in more recent periods. This approach departs from the more common use of a fixed threshold, such as in the case of remittances with an often fixed 1% threshold to define remittance dependence (World Bank, 2015). Aid inflows are however assigned a single benchmark. While the inflow levels are indeed volatile across years, they do not exhibit a clear upward trend over time. Given the lack of a directional shift in aid flows, a single benchmark is used. Figure 1 provides a graphical presentation of these buffer flows over time, while Table 1 reports the corresponding thresholds used to construct the binary indicators. The dummy variables are assigned on a year-by-year basis, reflecting the state of these inflows at the time each climatic shock occurs. A similar methodological approach is used in other studies, such as Acevedo Mejia et al. (2019) and Hosny (2020). One of the main limitations of this strategy is its dependence on data availability. While annual data on domestic credit is relatively accessible and comprehensive, aid and remittances data is more limited, resulting in missing values for a significant share of climatic shock observations. Nevertheless, this method remains valuable as it captures the inherent volatility of financial inflows.

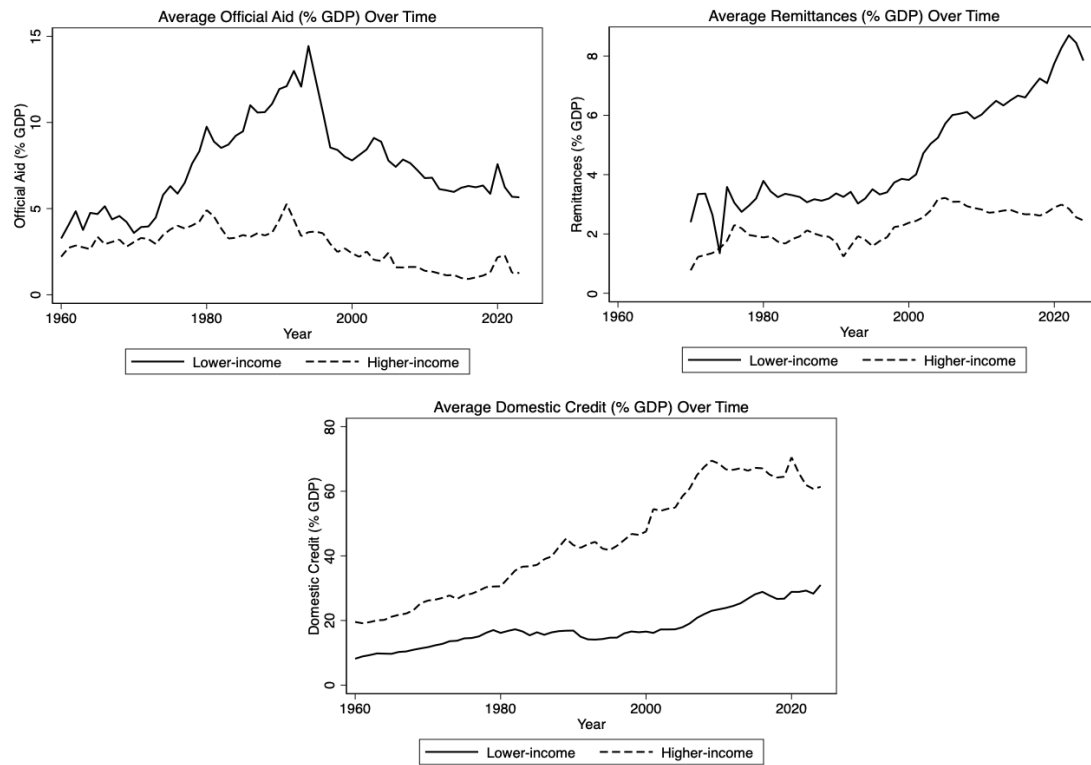


**Figure 1:** Average values for the levels of financial buffers.

Note: The figure presents the development of the levels of the official development assistance expressed as % of GNI, the levels of remittances as % of GDP, and domestic credit to the private sector provided by banks expressed as % of GDP.

**Table 1:** Financial buffer thresholds.

| Variable                          | Income group   | Pre-2000 | Post-2000 | Full period |
|-----------------------------------|----------------|----------|-----------|-------------|
| <b>Aid (% of GDP)</b>             | Lower (1 & 2)  | —        | —         | 5.21        |
|                                   | Higher (3 & 4) | —        | —         | 0.83        |
| <b>Remittances (% of GDP)</b>     | Lower (1 & 2)  | 1.20     | 3.56      | —           |
|                                   | Higher (3 & 4) | 0.56     | 0.80      | —           |
| <b>Domestic credit (% of GDP)</b> | Lower (1 & 2)  | 11.35    | 16.70     | —           |
|                                   | Higher (3 & 4) | 27.39    | 53.13     | —           |

Note: The table reports the thresholds used to construct the binary indicators for each financial buffer. Lower (1 & 2) refers to the lower-income country group, while Higher (3 & 4) refers to the higher-income country group. For remittances, and domestic credit, thresholds are calculated separately for the pre-2000 and post-2000 periods; for aid, thresholds are calculated over the full period.

#### 4.4 Summary statistics

The descriptive statistics are provided below in Table 2, reporting the full initial dataset at the first forecast horizon in the Local Projections framework. The GDP per capita specification includes 6,072 observations, compared to 5,773 for human capital due to data availability differences. Control variables show substantial cross-country heterogeneity, with high dispersion in investment, trade openness, inflation, and key demographic indicators such as life expectancy and urbanization. Overall, the sample exhibits strong variation in both macroeconomic and demographic characteristics.

**Table 2:** Summary statistics

|                        | GDP per capita specification |          |       |        |       | Human capital specification |          |        |        |       |
|------------------------|------------------------------|----------|-------|--------|-------|-----------------------------|----------|--------|--------|-------|
|                        | Mean                         | St. Dev. | Min.  | Max.   | Obs.  | Mean                        | St. Dev. | Min.   | Max.   | Obs.  |
| Climate shock          | 0.50                         | 0.50     | 0.00  | 1.00   | 6,072 | 0.50                        | 0.50     | 0.00   | 1.00   | 5,773 |
| Population Growth      | 1.60                         | 1.38     | -1.99 | 7.46   | 6,070 |                             |          |        |        |       |
| Capital Formation      | 23.95                        | 7.66     | 4.03  | 48.43  | 6,063 |                             |          |        |        |       |
| Inflation              | 10.49                        | 23.66    | -2.84 | 207.69 | 6,063 | 10.64                       | 23.33    | -2.84  | 207.69 | 5,763 |
| Government consumption | 15.60                        | 5.65     | 4.90  | 46.17  | 6,063 | 15.42                       | 5.50     | 4.90   | 46.17  | 5,765 |
| Trade                  | 77.26                        | 50.42    | 12.59 | 320.15 | 6,066 |                             |          |        |        |       |
| GDP per capita growth  | 0.02                         | 0.05     | -0.53 | 0.47   | 6,072 |                             |          |        |        |       |
| Human Capital          |                              |          |       |        |       | 0.009                       | 0.007    | -0.058 | 0.075  | 5,773 |
| Fertility rate         |                              |          |       |        |       | 3.41                        | 1.92     | 1.16   | 7.82   | 5,773 |
| Life Expectancy        |                              |          |       |        |       | 67.93                       | 10.10    | 36.28  | 83.09  | 5,773 |
| Urbanisation           |                              |          |       |        |       | 56.55                       | 23.49    | 5.08   | 100.00 | 5,773 |

The correlation matrix of the variables can be found in the appendix (Table A.4). It suggests significant but relatively weak correlations among most variables, indicating limited multicollinearity. Firstly, looking at the two dependent variables, GDP per capita and human capital and the main explanatory variable, that is the climatic shock, we can observe statistically significant relationships. For GDP per capita the relationship is positive and for human capital negative, consistent with the initial hypotheses. In addition, most control variables exhibit significant associations with GDP per capita and human capital, supporting their inclusion in the model as they appear to capture relevant aspects of their variations.

## 5. Methodological framework

### 5.1 Baseline Local Projection Model

The output per capita growth and human capital dynamics following a climatic disaster shock are estimated following Jordà's (2005) Local Projection (LP) method. The LP framework is chosen for its flexibility in tracing the dynamic effects of various external shocks over time, while requiring fewer structural assumptions than traditional dynamic models such as the Vector Autoregression (VAR) model. This method directly estimates the impulse response function by using the forecast equation to predict output  $h$  periods into the future. Montiel Olea and Plagborg-Møller (2021) demonstrate that local projection estimates remain valid even in the presence of highly persistent data and when estimating impulse responses over extended horizons. By estimating each horizon's response directly, rather than relying on the full structure of a dynamic system, as in VAR models, LPs are well-suited for analysing outcomes across any horizon length. Moreover, LP estimation allows for the flexible inclusion of control variables or additional shock terms, which is particularly important when analysing global growth dynamics. In contrast, VAR models, due to their aggregate structure, tend to be highly sensitive to specification errors, especially when incorporating multiple lags. Local projections, however, are more robust to such misspecifications, because the model's flexibility limits the impact of misspecification to a smaller set of parameters. As the LP model is especially suited for studying nonlinear macroeconomic dynamic, it has been widely adopted when analysing the effects of monetary policy shocks (Jeenas, 2018), fiscal policy shocks (Ramey & Zubairy, 2018), temperature shocks (Ehlers et al., 2025), and the effects of climate disasters (Cevik & Jalles, 2024), supporting its application in this context as well.

The basic LP regression model I estimate is thus of the following form:

$$\begin{aligned} \log y_{i,t+h} - \log y_{i,t} = & \beta_{1jh} \sum_{j=0}^2 CS_{i,t-j} + \beta_{2lh} \sum_{l=0}^2 (\log y_{i,t-l} - \log y_{i,t-1-l}) + \beta_{3h} \sum_{h=1}^{dmax} CS_{i,t+h} + \\ & \beta_{4h} X_{i,t} + \alpha_i + \sigma_t + \varepsilon_{i,t+h} \end{aligned} \quad (1)$$

Where the dependent variable,  $\log y_{i,t+h} - \log y_{i,t}$ , denotes the cumulative growth rate over the forecast horizon. It is estimated separately for two outcomes, real GDP per capita and human capital.  $CS_{i,t}$  is the climatic disaster shock indicator, constructed as a dummy variable equal to 1 if a shock in country ' $i$ ' starts in year  $t$  and 0 otherwise.  $h = 1, \dots, 10$  is the forecast

horizon, as the effect of climatic disasters shocks will take time to materialise in the country's overall economic performance. The selected horizon of 10 years is to capture both immediate and long-term effects of climate shocks on economic output and human capital. This choice aligns with existing empirical studies employing local projection methods to assess the dynamic impacts of various shocks on economic growth (e.g., Montiel Olea & Plagborg-Møller, 2021; Cevik & Jalles, 2024; Acevedo et al., 2019). Country and time fixed effects,  $\alpha_i$  and  $\sigma_t$ , respectively, are included following Acevedo Mejia et al. (2019).<sup>8</sup> Country fixed effects are particularly important, as much of the variation in national growth patterns stems from unobservable characteristics such as geography or ethnolinguistic fractionalisation. Time fixed effects, meanwhile, help absorb common economic shocks or disruptions affecting all countries in a given year.

I include two lags of both the climatic shock and the outcome variable ( $\beta_{2lh} \sum_{l=0}^2 (\log y_{i,t-l} - \log y_{i,t-1-l})$ ), following the specification used by Cevik and Jalles (2024) in their closely related study on climate shocks and growth.<sup>9</sup> As previous disaster shocks may impact the outcome variables ahead of time, the number of leads of the disaster shock indicator, equal to the number of forecast horizons, is also included. Furthermore, failing to incorporate the shock variable for any events occurring between the current period and the forecast horizon introduces attenuation bias in the estimates (Teulings & Zubanov, 2014). This bias grows more pronounced as the forecast horizon widens, because the likelihood of an additional shock arising during that interval increases. Consequently, I include the Teulings and Zubanov (2014) correction term, presented as:  $\beta_{3h} \sum_{h=1}^{dmax} CS_{i,t+h}$ , which is the sum of future disaster shocks occurring between the treatment period and the forecast horizon. This correction accounts for overlapping forecast horizons and mitigates this potential underestimation.  $X_{i,t}$  is the vector of control variables, a discussion of these can be found in section 4.2. Cumulative output per capital growth and human capital responses are estimated using a series of regressions based on a binary indicator capturing the onset of climatic disaster shocks. The error term,  $\varepsilon_{i,t+h}$ , may exhibit both heteroskedasticity and cross-country

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<sup>8</sup> While the local projections model does not directly accommodate a Hausman test, fixed effects are standard in macro-level studies to control for time-invariant country-specific heterogeneity. To validate this choice, I apply the Hausman test to a baseline panel regression at the first horizon. The results, which support using fixed effects, are presented in Appendix Table A.5.

<sup>9</sup> The decision is supported by a comparison of different specifications, both the 2-lag and 3-lag models yield statistically significant effects, but the 2-lag model produces slightly tighter standard errors with nearly identical model fit. As the third lag adds complexity without contributing additional insight, the 2-lag specification is preferred on grounds of parsimony and efficiency.

correlation, as common shocks or omitted variables can affect multiple units simultaneously. Within the local projections framework this can be addressed by clustering standard errors, which is applied consistently across all regressions following Acevedo Mejia et al. (2019).

Based on the literature review and the hypotheses outlined above, I expect the main coefficient,  $\beta_{1jh}$ , to be negative in the short-run for the baseline GDP per capita growth regression, indicating an immediate negative effect of disaster shocks. For human capital, I also expect a negative effect, thus a negative coefficient, though not immediate. The PWT human capital index combines schooling and returns to education, reflecting long-run accumulation and responding slowly to short-run shocks. While shocks affect schooling, health, and infrastructure through income and disruption channels, these effects materialise only gradually as affected cohorts progress through the system. I therefore expect negative effects to appear mainly at medium horizons rather than on impact.

## *5.2 Local Projections Model for the role of buffers*

The analysis further investigates whether four distinct financial channels, aid, remittances, and domestic credit, alter the effects of climatic shocks on output and human capital. To study these effects, I modify the baseline regression model by including an interaction term between the climatic shock and the buffer variable. This allows for the response of GDP per capita or human capital to vary with the various financial inflows, thereby partially capturing potential nonlinear effects. The buffers variables are binary indicators estimating whether a country has high or low inflows of these in a given year as explained in section 4.3. This follows Acevedo Mejia et al. (2019), who use interaction terms to assess whether policies and institutions mitigate the effects of temperature and precipitation volatility. The specification mirrors the baseline in retaining the same lag structure, forward corrections, estimation horizons, controls, and country and time fixed effects. A separate LP regression is estimated for each buffer indicator.

The extended LP regression model I estimate is of the following form:

$$\begin{aligned} \log y_{i,t+h} - \log y_{i,t} = & \beta_{1jh} \sum_{j=0}^2 CS_{i,t-j} + \gamma_1^h (CS_{i,t} \times B_{i,t-1}) + \delta_1^h B_{i,t-1} + \beta_{2lh} \sum_{l=0}^2 (\log y_{i,t-l} - \\ & \log y_{i,t-1-l}) + \beta_{3h} \sum_{h=1}^{dmax} CS_{i,t+h} + \beta_{4h} X_{i,t} + \alpha_i + \sigma_t + \varepsilon_{i,t+h} \end{aligned} \quad (2)$$

Following Acevedo Mejia et al. (2019), the shock indicator is interacted with a lagged binary buffer indicator,  $\gamma_1^h (CS_{i,t} \times B_{i,t-1})$ , which takes the value of one if country ‘i’ exceeds the income-group specific threshold of the relevant inflow variable in year ‘t-1’. The buffer indicator is lagged one period to ensure it reflects the financial conditions in place prior to the shock, thereby reducing reverse causality concerns<sup>10</sup>. The lagged continuous inflow variable,  $\delta_1^h B_{i,t-1}$ , is also included separately as a control to isolate the differential effect of the shock from any direct level effect of the inflow on the outcome. The coefficient  $\gamma_1^h$  captures the differential impulse response at horizon h, that is, how the cumulative effect of the shock differs between high- and low-buffer countries. A positive  $\gamma_1^h$  indicates that high-buffer countries experience a more favourable cumulative response relative to low-buffer countries following a shock, while a negative  $\gamma_1^h$  indicates the opposite.

Drawing on the theoretical framework and existing literature, I expect the financial buffers to moderate the effects of climatic shocks in different ways across GDP per capita and human capital estimations. A positive  $\gamma_1^h$  coefficient would indicate that countries with higher levels of a given buffer experience a more favourable cumulative response following a shock relative to low-buffer countries. Remittances are expected to buffer both GDP per capita and human capital by smoothing household income and supporting continued investment in capita, education and health. Domestic credit is expected to matter more for GDP per capita, as deeper credit markets can finance reconstruction, capital replacement and recovery investment, its role in protecting human capital is likely more limited. For aid, I expect limited or insignificant effects on GDP per capita, as post-disaster aid is often relief-oriented and may also reflect underlying vulnerability. However, aid is expected to play a more protective role for human capital as it is often directed toward health, education and social spending.

## 6. Results

### 6.1 GDP per capita estimation results

The baseline local projection (LP) estimates, based on Equation 1, are presented in the appendix. For these initial results see Table A.6. The corresponding impulse response functions are shown below in Figure 2. As previously noted, results are shown across ten horizons, each

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<sup>10</sup> Acevedo Mejia et al. (2019) additionally interacts each lagged shock term with the correspondingly lagged buffer variable allowing the response to lagged shocks to also vary by buffer status. The present analysis includes lagged shocks as controls without re-interacting them with the buffer, a simplification motivated by a smaller sample size, where adding further interaction terms could substantially reduce degrees of freedom and risk overfitting.

incorporating a corresponding number of leads of the treatment, climatic shock, along with two lags of both the dependent variable and the main explanatory variable. Across all horizons, the sum of the coefficients on the lagged dependent variables remains below one, suggesting a stationary growth process. The within R-squared values are relatively low, indicating limited explanatory power for within-country variation over time. However, this is not unexpected in a macroeconomic panel setting, particularly when using local projections. GDP per capita growth and human capital changes are influenced by many unobserved and country-specific factors, so relatively modest within R-squared values are common. The regression statistics are reported for the  $h = 1$  estimation sample, corresponding to the immediate effect of the shock.

The baseline results, which include the full sample of countries and the aggregate climatic shock measure, show a positive cumulative GDP per capita response across all horizons. The coefficient is statistically significant at every horizon except horizon 2. In the first year after the shock, GDP per capita growth is estimated to be approximately 0.25 percentage points higher relative to the no-shock counterfactual. The effect then increases over time, peaking at horizon 8, where the coefficient indicates a 1.75 percentage points increase in cumulative GDP per capita growth, and is statistically significant at the 1 percent level. Although the magnitude declines slightly thereafter, the response remains positive and statistically significant 9 and 10 years after the shock, at approximately 1.65 and 1.44 percentage points higher, respectively. Overall, this pattern suggests a persistent positive GDP per capita response following climatic shocks.

I then examine GDP per capita responses separately by disaster type. The results are reported in Table A.6 in the Appendix, with the corresponding IRFs shown in Figure 3. The findings reveal substantial heterogeneity. Floods display the clearest and most persistent positive response, becoming statistically significant from horizon 2 and reaching about 4.2 percentage points higher cumulative GDP per capita growth by horizon 10, suggesting that they partly drive the aggregate result. Droughts show a positive and significant effect only one year after the shock, while later estimates are unstable and insignificant. Storm coefficients are mostly positive but remain statistically insignificant throughout, providing limited evidence of a robust GDP per capita response.

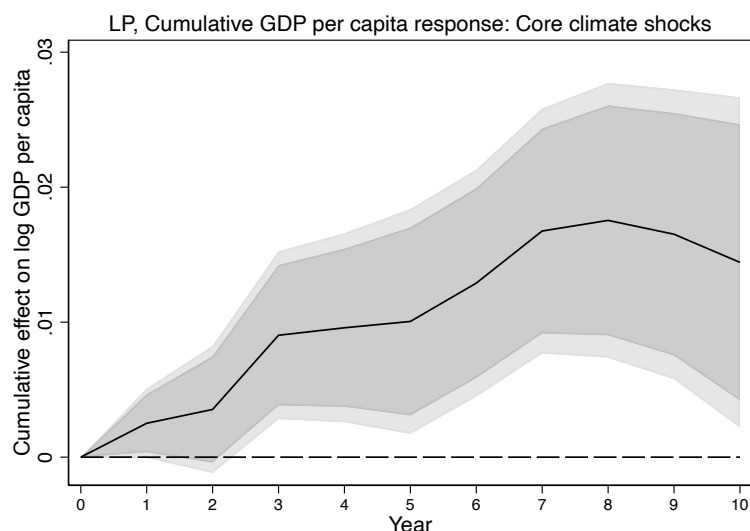


**Figure 2:** Impulse responses of LP estimate of the effect of a climatic shock on cumulative GDP per capita growth.

Note: Year 1 denotes the first year following the climatic shock, which occurs at Year 0. By Year 5, the line reflects the cumulative impact of the shock on GDP per capita growth five years after the shock, expressed in percentage terms. The solid black line plots the impulse response estimates based on the regression results presented in table A.6 in the appendix. The dark and light shaded areas represent the 90% and 95% confidence intervals, respectively, both calculated using standard errors clustered at the country level.

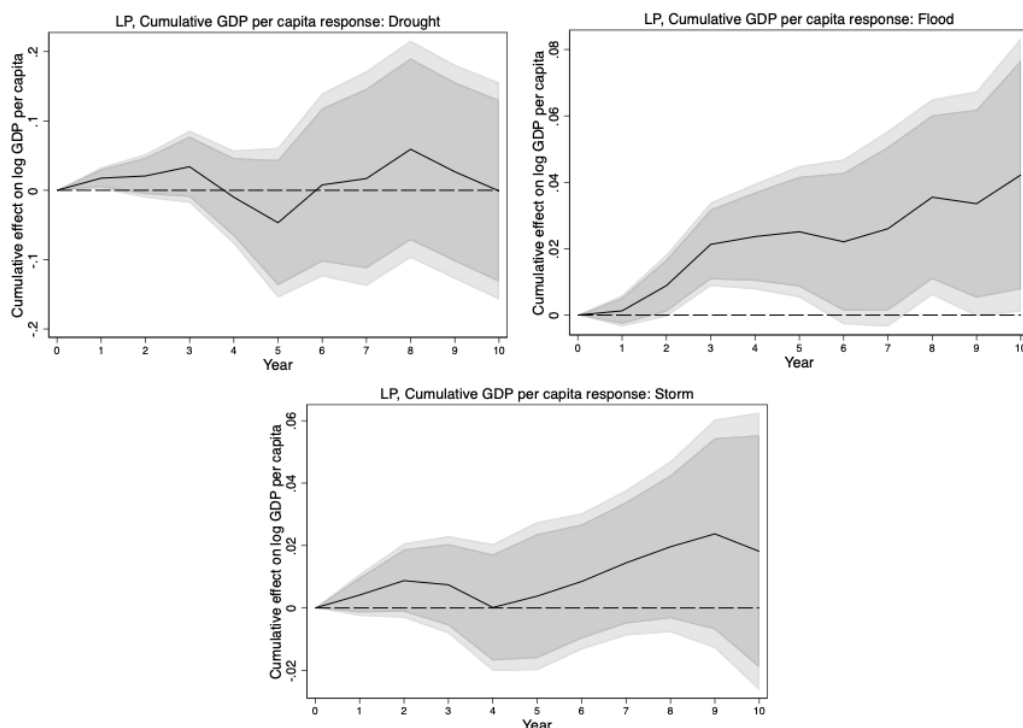


**Figure 3:** Impulse responses of LP estimate of the effect of a climatic shock on cumulative GDP per capita growth, distinguished by shock type.

Note: Year 1 denotes the first year following the climatic shock, which occurs at Year 0. By Year 5, the line reflects the cumulative impact of the shock on GDP per capita growth five years after the shock, expressed in percentage terms. The solid black line plots the impulse response estimates based on the regression results presented in Table A.6 in the appendix. The dark and light shaded areas represent the 90% and 95% confidence intervals, respectively, both calculated using standard errors clustered at the country level.

I further divide the sample into lower- and higher-income countries, based on the World Bank income classification. The results are reported in Table A.7 in the Appendix, with the corresponding IRFs presented in Figure 4 below. For the aggregate climatic shock indicator, the estimated GDP per capita response is positive in both income groups, although the timing and magnitude differ. In lower-income countries, the effect becomes statistically significant from horizon 3 and remains significant across most medium-run horizons, reaching the coefficient of 0.0187 at horizon 8. This suggests that cumulative GDP per capita growth is around 1.9 percentage points higher relative to the no-shock counterfactual 8 years after the shock. In higher-income countries, the response is initially smaller and becomes statistically significant from horizon 6 onward, peaking at roughly 1.3 percent point increase between horizons 7 and 9.

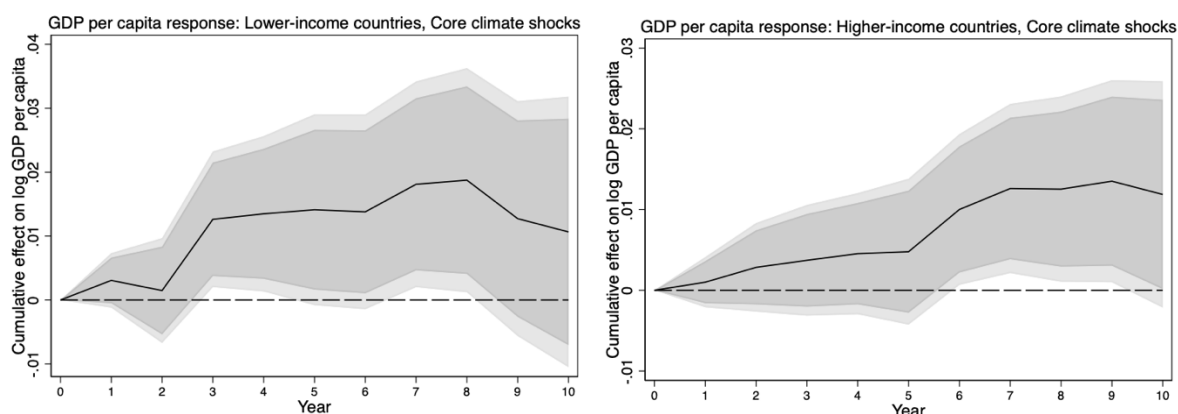


**Figure 4:** Impulse responses of LP estimate of the effect of a climatic shock on cumulative GDP per capita growth, by income group.

Note: *Year 1* denotes the first year following the climatic shock, which occurs at *Year 0*. By *Year 5*, the line reflects the cumulative impact of the shock on GDP per capita growth five years after the shock, expressed in percentage terms. The solid black line plots the impulse response estimates based on the regression results presented in table A.7 in the appendix. The dark and light shaded areas represent the 90% and 95% confidence intervals, respectively, both calculated using standard errors clustered at the country level.

## 6.2 Human Capital results

Next, I consider the effect of a climatic shock on the second dependent variable considered in this study, the log of the human capital index. Table A.8 in the appendix and Figures 5 and 6 report the cumulative human capital response to the aggregate climatic shock indicator and to the three individual disaster types. For the aggregate climatic shock measure, the estimated response is negative across all horizons. The effect is statistically significant first year after the shock (0.0003), indicating an immediate reduction of approximately 0.03

percentage points in cumulative human capital growth following a climate shock. To put this in perspective, average annual human capital growth in the sample is around 0.9 percent (Table 2), so a 0.03 percentage point reduction corresponds to roughly 3 percent of the typical annual change. While coefficients at later horizons lose statistical significance, they remain persistently negative, with the cumulative response reaching approximately 0.12 percentage points lower human capital growth ten years after the shock. Given the slow-moving nature of the human capital index, which reflects both average years of schooling and returns to education, even small percentage changes may represent economically meaningful shifts in a country's human capital base. The consistently negative coefficients across all ten horizons suggest that aggregate climatic shocks are associated with persistent declines in human capital, with the clearest effect concentrated in the immediate aftermath of the shock.

Disaggregating by disaster type reveals substantial heterogeneity. Storms generate a consistently negative human capital response. The effect is statistically significant from horizon 1 through horizon 5, beginning with an estimated 0.05 percentage point decline in cumulative human capital one year after the shock and reaching its largest statistically significant magnitude four years after the shock, corresponding to a 0.37 percentage point reduction. This effect is sizeable in the context of human capital dynamics as it represents roughly half a standard deviation of annual human capital growth in the sample. The coefficients remain negative through horizon 10, although they become less precisely estimated at longer horizons. This pattern suggests that storms may have persistent adverse effects on human capital accumulation. Droughts and floods show unexpected positive effects at medium-to-long horizons: droughts peak at a 2.22-percentage-point increase at horizon 7, while floods rise by 0.8 percentage points at horizon 10. However, due to their smaller sample size these should be interpreted with caution, especially the effects at later horizons.

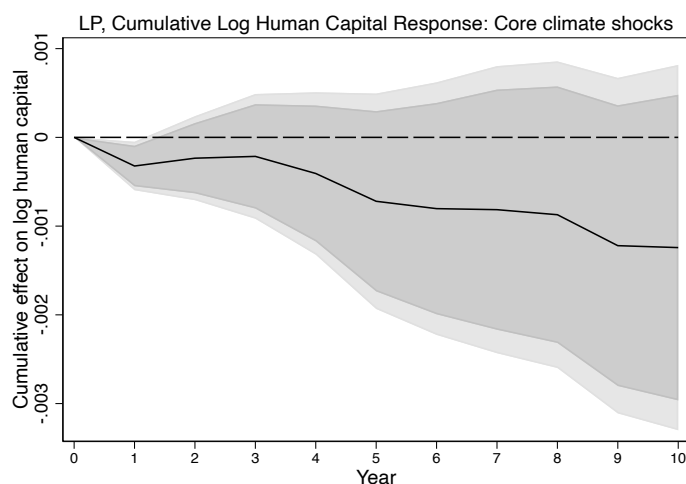


**Figure 5:** Impulse responses of LP estimate of the effect of a climatic shock on the cumulative log changes in the Human Capital Index.

Note: *Year 1* denotes the first year following the climatic shock, which occurs at *Year 0*. By *Year 5*, the line reflects the cumulative impact of the shock on the cumulative log changes in the Human capital index five years after the shock, expressed in percentage terms. The solid black line plots the impulse response estimates based on the regression results presented in Table A.8 in the appendix. The dark and light shaded areas represent the 90% and 95% confidence intervals, respectively, both calculated using standard errors clustered at the country level.

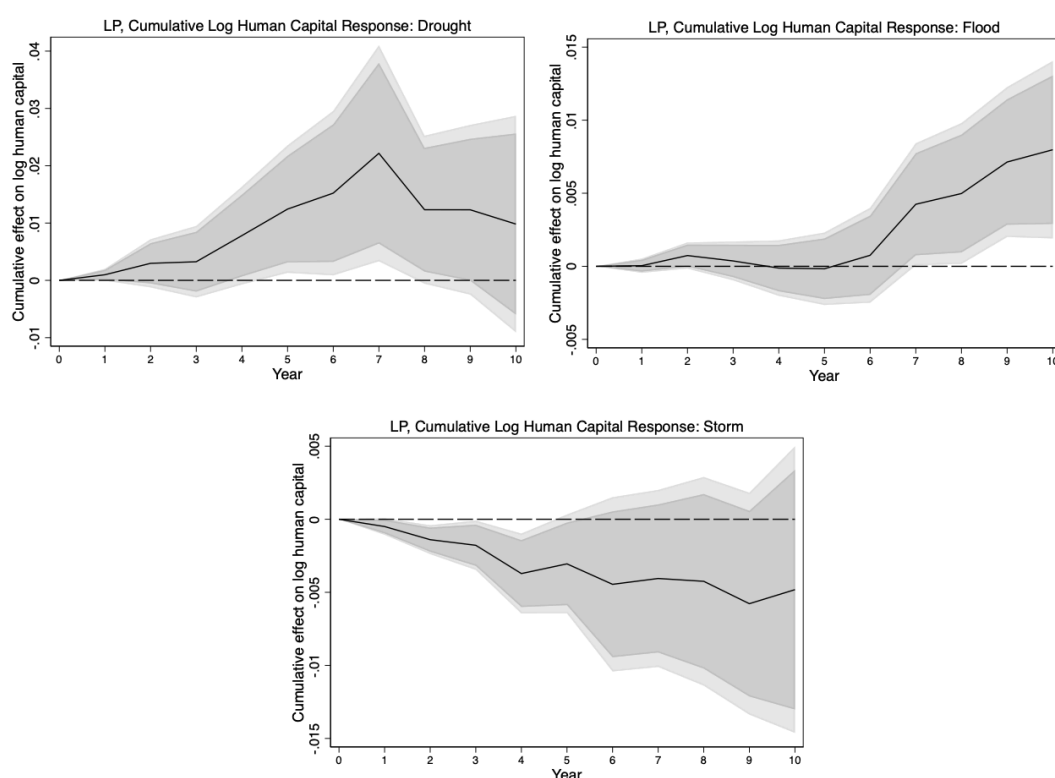


**Figure 6:** Impulse responses of LP estimate of the effect of a climatic shock on the cumulative log changes in the Human Capital Index, by shock type.

Note: *Year 1* denotes the first year following the climatic shock, which occurs at *Year 0*. By *Year 5*, the line reflects the cumulative impact of the shock on the cumulative log changes in the Human Capital Index, expressed in percentage terms. The solid black line plots the impulse response estimates based on the regression results presented in Table A.8 in the appendix. The dark and light shaded areas represent the 90% and 95% confidence intervals, respectively, both calculated using standard errors clustered at the country level.

I also disaggregate the human capital results by income group. The estimates are reported in Table A.9 in the Appendix, with the corresponding impulse responses shown in Figure 7. The results reveal clear differences across income groups. In lower-income countries, climatic shocks are associated with an immediate and statistically significant decline in human capital. The estimated effect corresponds to 0.06 percentage points lower human capital growth at horizon 1, increasing slightly to around 0.07 percentage points drop two years after the shock. From horizon 3 onward, however, the coefficients lose statistical significance and gradually move back toward zero, indicating no clearly identifiable longer-run effect. For higher-income countries, the estimated response is statistically insignificant throughout. The coefficients are close to zero at the earlier horizons and become more negative over time, corresponding to approximately 0.10 percentage points lower cumulative human capital growth by horizon 5 and around 0.20 percentage points lower cumulative growth by horizon 10, although these estimates remain imprecisely estimated. Taken together, the findings suggest that climatic shocks pose a more immediate risk to human capital accumulation in lower-income countries.

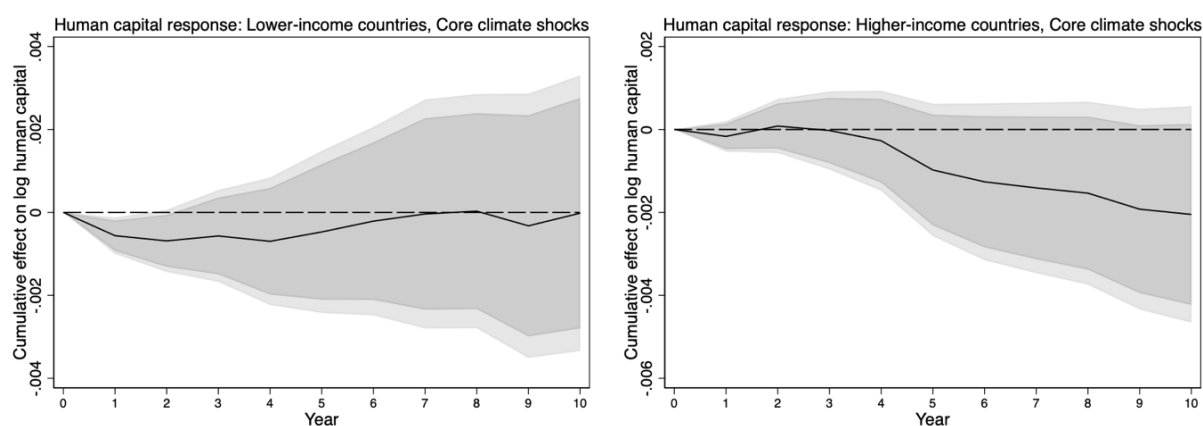


**Figure 7:** Impulse responses of LP estimate of the effect of a climatic shock on the cumulative log changes in the Human Capital Index, by income group.

Note: *Year 1* denotes the first year following the climatic shock, which occurs at *Year 0*. By *Year 5*, the line reflects the cumulative impact of the shock on the cumulative log changes in the Human Capital Index five years after the shock, expressed in percentage terms. The solid black line plots the impulse response estimates based on the regression results presented in Table A.9 in the appendix. The dark and light shaded areas represent the 90% and 95% confidence intervals, respectively, both calculated using standard errors clustered at the country level.

### 6.3 Financial buffer results

The analysis is further extended by examining the role of financial buffers, that is aid, remittances, and financial depth, proxied by domestic credit. The construction of the high- and low-buffer indicators is described in section 4.3. The coefficients reported below are the

interaction terms, which measure the difference in the cumulative GDP per capita and human capital responses between high-buffer and low-buffer countries following a climatic disaster shock. I first consider the interaction results for GDP per capita, results are presented in table A.10 in the appendix and Figure 8. Since the baseline estimates indicate a positive cumulative GDP per capita growth response after a climatic shock, a negative interaction coefficient means that high-buffer countries experience a smaller positive response than low-buffer countries.

The high-aid interaction term is negative across all horizons, suggesting that countries with higher aid levels experience a weaker positive GDP per capita growth response following a climate shock. The coefficients are statistically significant between horizons 4 and 8, with the largest effect at horizon 8, where the estimate is -0.0291. This implies that eight years after the shock, the cumulative GDP per capita growth response is approximately 2.9 percentage points lower in high-aid countries than in low-aid countries.

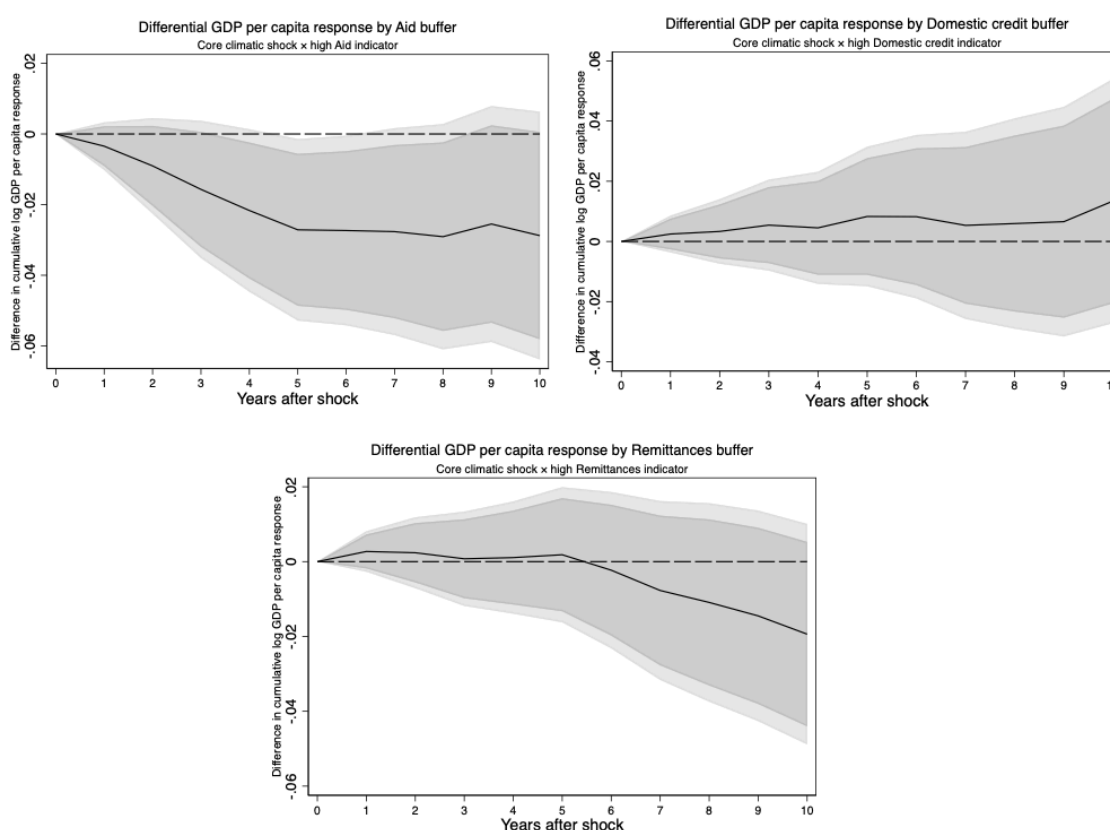


**Figure 8:** Impulse responses of LP estimate of the effect of a climatic shock on the cumulative GDP per capita growth, buffering effects.

Note: Year 1 denotes the first year following the climatic shock, which occurs at Year 0. Each panel plots the interaction coefficient between core climate shocks and high buffer indicators from local projection regressions. The solid black line shows the differential cumulative GDP per capita response between high-buffer and low-buffer countries at each horizon based on the regression results presented in table A.10 in the appendix. The dark and light shaded areas represent the 90% and 95% confidence intervals, respectively, both calculated using standard errors clustered at the country level.

I further disaggregate the interaction results by income group to examine whether the role of financial buffers differs between lower- and higher-income countries. This comparison assesses the effect of higher buffer levels within each respective income group. Results are presented in Table A.11 in the appendix and the corresponding IRFs are presented in Figure 9 below.

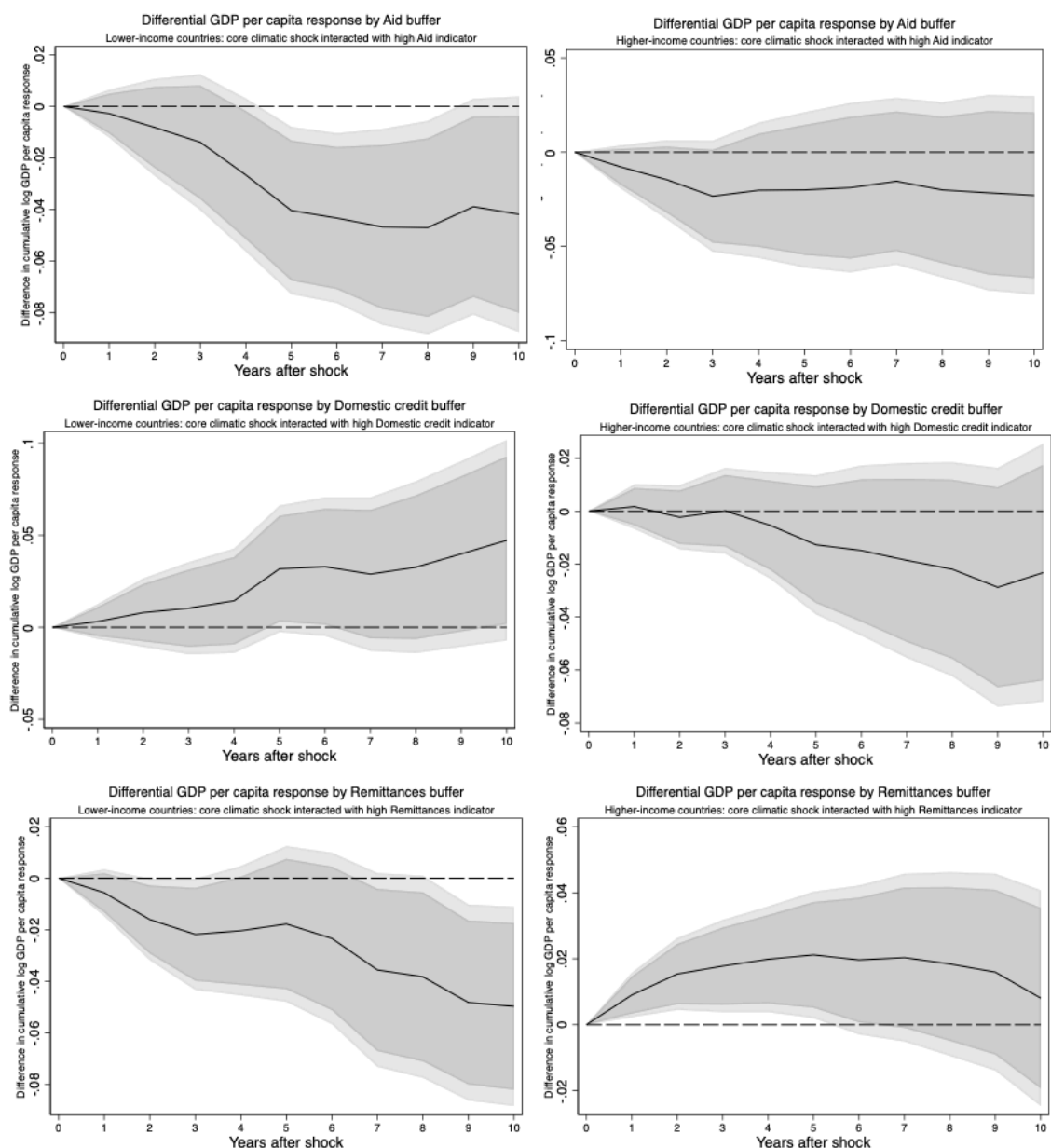


**Figure 9:** Impulse responses of LP estimate of the effect of a climatic shock on the cumulative GDP per capita growth, buffering effects by income.

Note: Year 1 denotes the first year following the climatic shock, which occurs at Year 0. Each panel plots the interaction coefficient between core climate shocks and high buffer indicators from local projection regressions. The solid black line shows the differential cumulative GDP per capita response between high-buffer and low-buffer countries at each horizon based on the regression results presented in table A.11 in the appendix. The dark and light shaded areas represent the 90% and 95% confidence intervals, respectively, both calculated using standard errors clustered at the country level.

For aid, the results suggest that lower-income countries with high aid levels experience smaller GDP per capita gains following a climatic shock. These effects become statistically significant from horizon 4 onward and remain significant through the end of the period considered. The largest difference appears at horizon 8, where the coefficient indicates that lower-income countries with high aid levels experience a cumulative GDP per capita response approximately 4.7 percentage points smaller than lower-income countries with low aid levels. The domestic credit results are not statistically significant, but the signs are relatively persistent and therefore provide some suggestive evidence. In lower-income countries, higher levels of domestic credit are associated with larger GDP per capita gains after a climatic shock. By contrast, in higher-income countries, higher domestic credit is associated with smaller positive cumulative GDP per capita growth responses. Finally, remittances reveal an especially interesting contrast across income groups. Among lower-income countries, higher remittance inflows are associated with smaller GDP per capita growth following a climatic shock relative to lower-remittance countries. In higher-income countries, the pattern is reversed, countries with higher remittance inflows experience higher GDP per capita growth after the shock.

Next, I examine the buffering effects for the log human capital index. The results are reported in Table A.12 in the Appendix, with the corresponding impulse responses presented in Figure 10 below. For the full sample remittances and domestic credit do not yield clearly interpretable results, as the interaction coefficients are generally close to zero and statistically insignificant. Aid, however, shows a more consistent positive pattern. In the first two years after the shock, the coefficients are small in magnitude but positive and statistically significant, indicating that countries with higher aid levels experience a smaller decline in human capital growth following a climatic shock than countries with lower aid levels.

The income-group disaggregation is reported in Table A.13 and Figure 11. Once again, the results for remittances and domestic credit remain inconclusive, with coefficients that are generally close to zero and statistically insignificant. Aid continues to provide the most interpretable evidence. Among lower-income countries, the interaction term is persistently positive, suggesting that higher aid levels are associated with smaller post-shock human capital growth drops. The coefficients are statistically significant during the first three years after the shock, although their magnitude is modest. A larger significant effect also appears ten years after the shock. The estimate suggests that lower-income countries with higher aid levels

experience a human capital decline approximately 0.98 percentage points smaller than lower-income countries with lower aid levels.

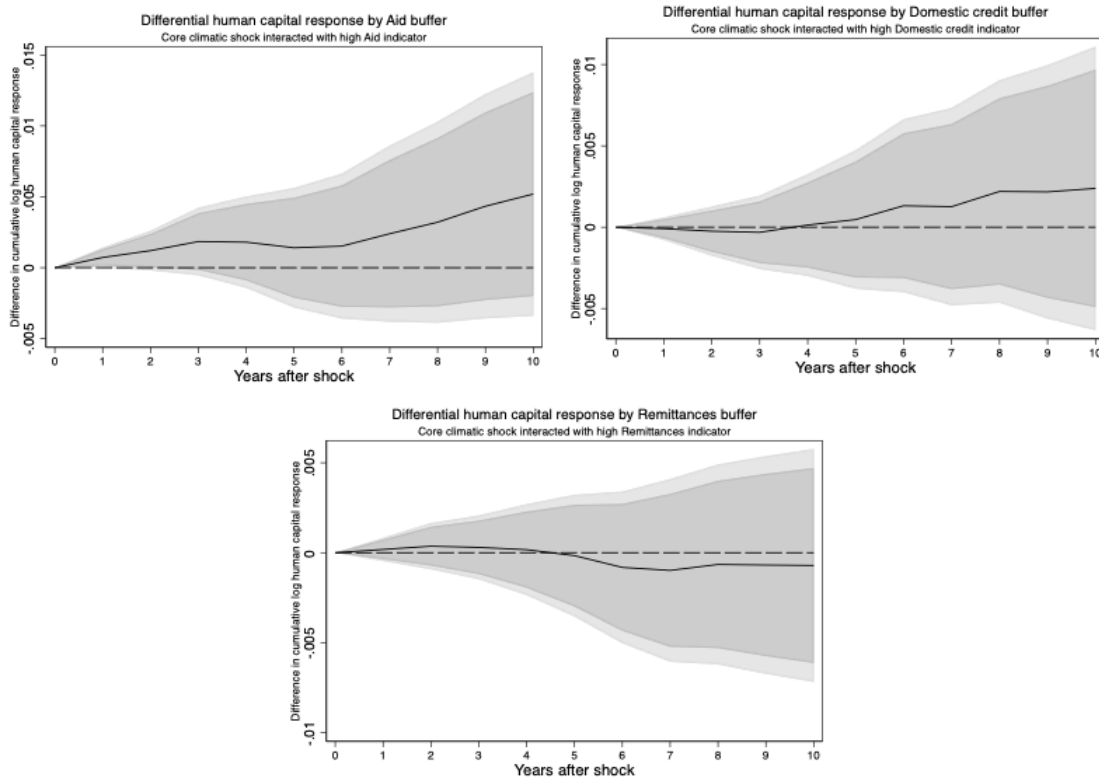


**Figure 10:** Impulse responses of LP estimate of the effect of a climatic shock on cumulative Human Capital Index, buffering effects.

Note: Year 1 denotes the first year following the climatic shock, which occurs at Year 0. Each panel plots the interaction coefficient between core climate shocks and high buffer indicators from local projection regressions. The solid black line shows the differential cumulative Human Capital response between high-buffer and low-buffer countries at each horizon based on the regression results presented in table A.12 in the appendix. The dark and light shaded areas represent the 90% and 95% confidence intervals, respectively, both calculated using standard errors clustered at the country level.

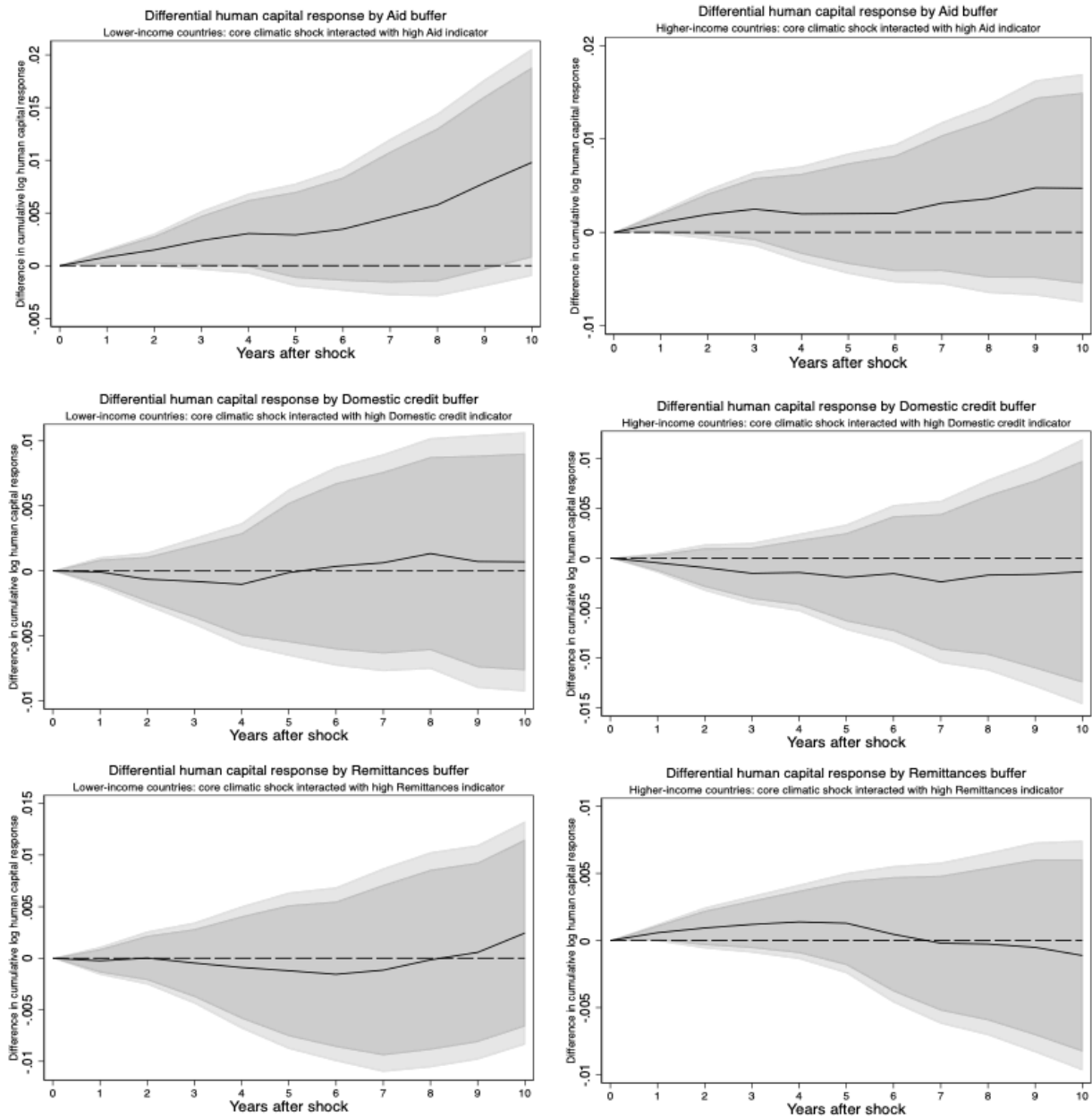


**Figure 11:** Impulse responses of LP estimate of the effect of a climatic shock on cumulative Human Capital Index, buffering effects by income.

Note: Year 1 denotes the first year following the climatic shock, which occurs at Year 0. Each panel plots the interaction coefficient between core climate shocks and high buffer indicators from local projection regressions. The solid black line shows the differential cumulative Human Capital response between high-buffer and low-buffer countries at each horizon based on the regression results presented in table A.13 in the appendix. The dark and light shaded areas represent the 90% and 95% confidence intervals, respectively, both calculated using standard errors clustered at the country level.

## *7. Sensitivity analysis*

To assess whether results depend on the specific definition of climatic shocks, I re-estimate the baseline model using three alternative shock indicators that incorporate progressively broader sets of disaster types:

1. `shock_core4`: Adds extreme temperature events to the baseline definition.
2. `shock_nowildfire`: Further adds wet mass movements (landslides), encompassing all climate-related disasters except wildfires.
3. `shock_any`: Includes all climatically-driven disasters in EM-DAT: droughts, floods, storms, extreme temperatures, wet mass movements, and wildfires.

Results are presented in tables A.14 and A.15 in the appendix and the corresponding IRFs are in Figures 12 and 13 below. The results for both the gdp per capita and human capital estimations follow a similar pattern as the baseline definition. While the magnitudes and significance change slightly, the signs remain unchanged. Across all specifications and regressions, the findings consistently indicate that climatic disaster shocks generate an immediate positive response in GDP per capita growth, while simultaneously producing an immediate short-run decline in human capital growth in the affected country.

Additionally, I assess the robustness of the baseline results to three alternative regression specifications. First, I restrict the estimation sample. Because longer horizons require observing outcomes further into the future, fewer observations are available for estimation at higher horizons. Consequently, the effective estimation sample decreases with the horizon (Jordà, 2005). To ensure that the results are not driven by differences in sample composition across horizons, I re-estimate the impulse responses using the same truncated sample for all horizons, that is, I set the sample for all  $h$  equal to the sample size when  $h=10$ . Second, I re-estimate using random effects instead of country fixed effects, testing whether results depend on within-country variation or also hold when exploiting cross-country differences. Third, following Cevik and Jalles (2024), I estimate pooled OLS with year fixed effects only, excluding country fixed effects to address potential bias from their interaction with country-specific developments (Teulings & Zubanov, 2014). The estimation results are presented in Tables A.16 to A.17 in the Appendix for GDP per capita and human capital respectively. The corresponding IRFs are presented below in Figures 14 and 15. The IRFs for GDP per capita follow a pattern similar to that of the baseline results. While the magnitudes and significance change slightly, the signs

remain unchanged. Across all specifications and regressions, the results consistently show that climatic disaster shocks are associated with an increase in GDP per capita growth. The robustness checks show that the negative human capital effect is robust to sample composition concerns but sensitive to the inclusion of country fixed effects. The fixed  $h=10$  sample produces results similar to the baseline, though with wider confidence intervals due to the smaller sample. By contrast, the random effects and pooled OLS specifications show much weaker effects, suggesting that the negative human capital response is primarily identified from within-country variation over time. This indicates that controlling for country-specific factors correlated with both disaster exposure and human capital trends is important for isolating the estimated effect.

Overall, the robustness checks confirm that the main results are broadly stable across alternative shock definitions and samples, with climatic disasters consistently associated with higher GDP per capita growth and lower human capital growth.

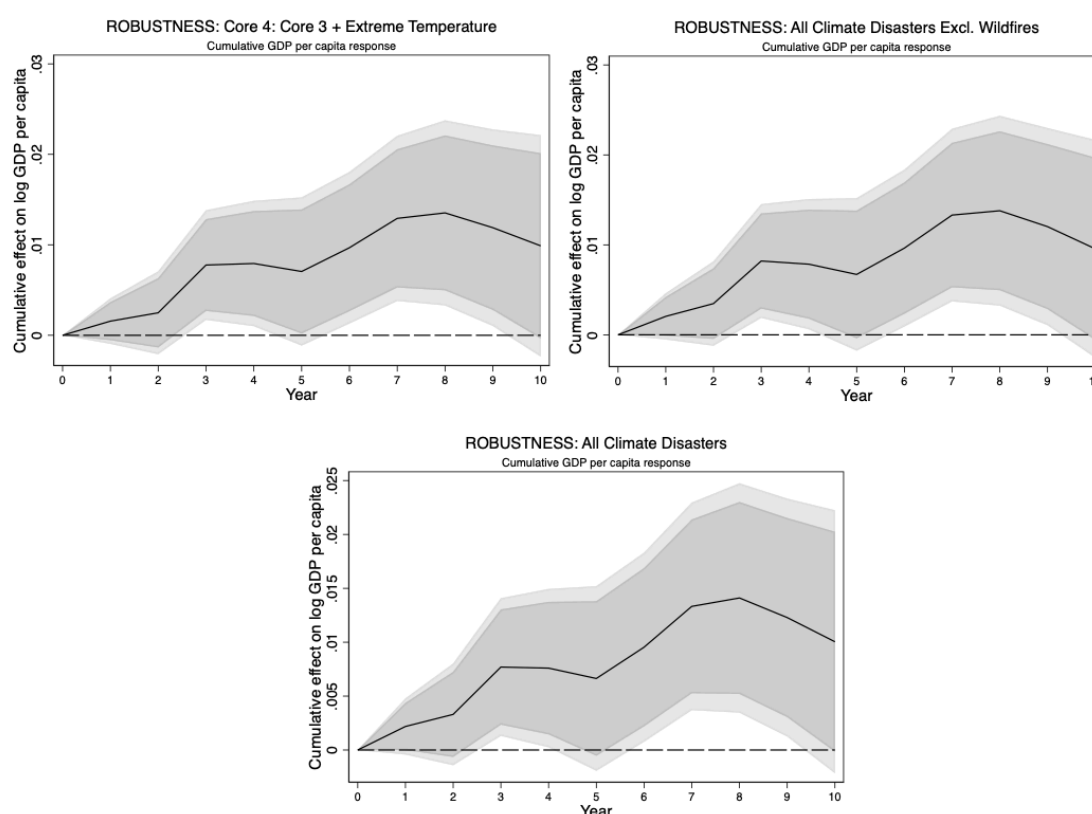


**Figure 12:** Impulse responses of LP estimate of the effect of a climatic shock on cumulative GDP per capita growth, alternative shock specifications.

Note: *Year 1* denotes the first year following the climatic shock, which occurs at *Year 0*. By *Year 5*, the line reflects the cumulative impact of the shock on GDP per capita growth five years after the shock, expressed in percentage terms. The solid black line plots the impulse response estimates based on the regression results presented in table A.14 in the appendix. The dark and light shaded areas represent the 90% and 95% confidence intervals, respectively, both calculated using standard errors clustered at the country level.

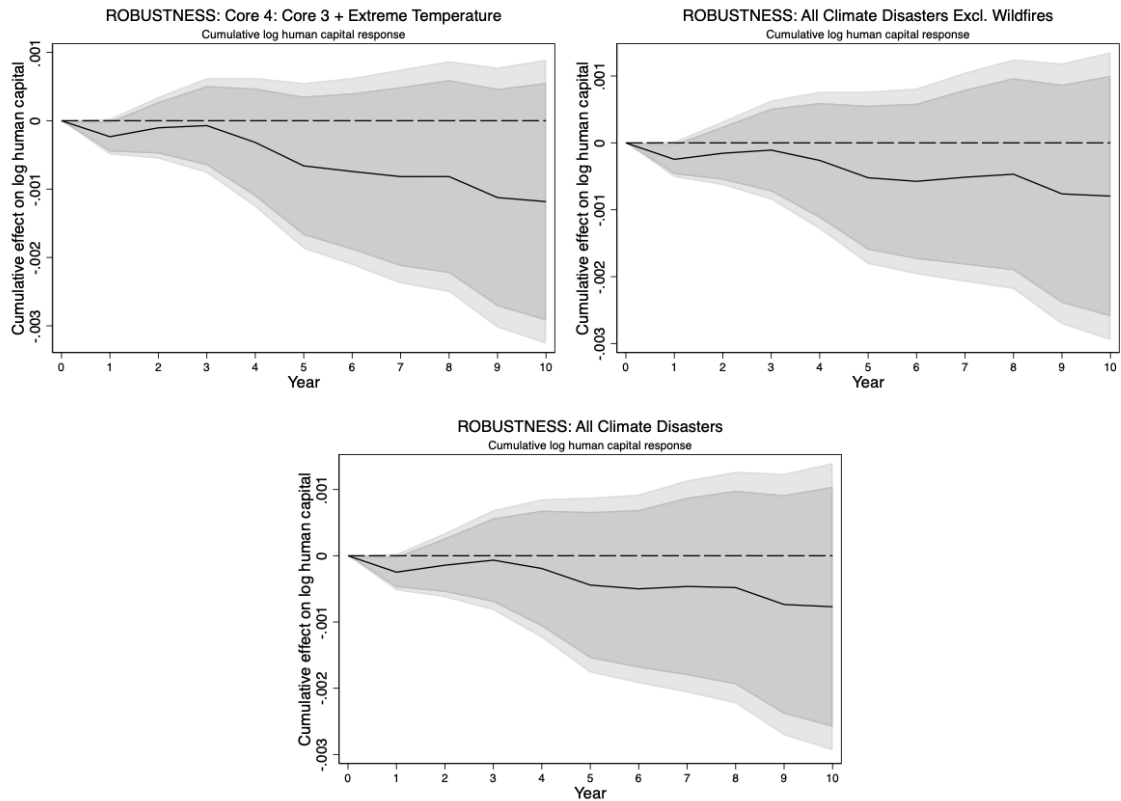


**Figure 13:** Impulse responses of LP estimate of the effect of a climatic shock on the cumulative log changes in the Human Capital Index, alternative shock specifications.

Note: *Year 1* denotes the first year following the climatic shock, which occurs at *Year 0*. By *Year 5*, the line reflects the cumulative impact of the shock on the cumulative log changes in the Human Capital Index, expressed in percentage terms. The solid black line plots the impulse response estimates based on the regression results presented in table A.15 in the appendix. The dark and light shaded areas represent the 90% and 95% confidence intervals, respectively, both calculated using standard errors clustered at the country level.

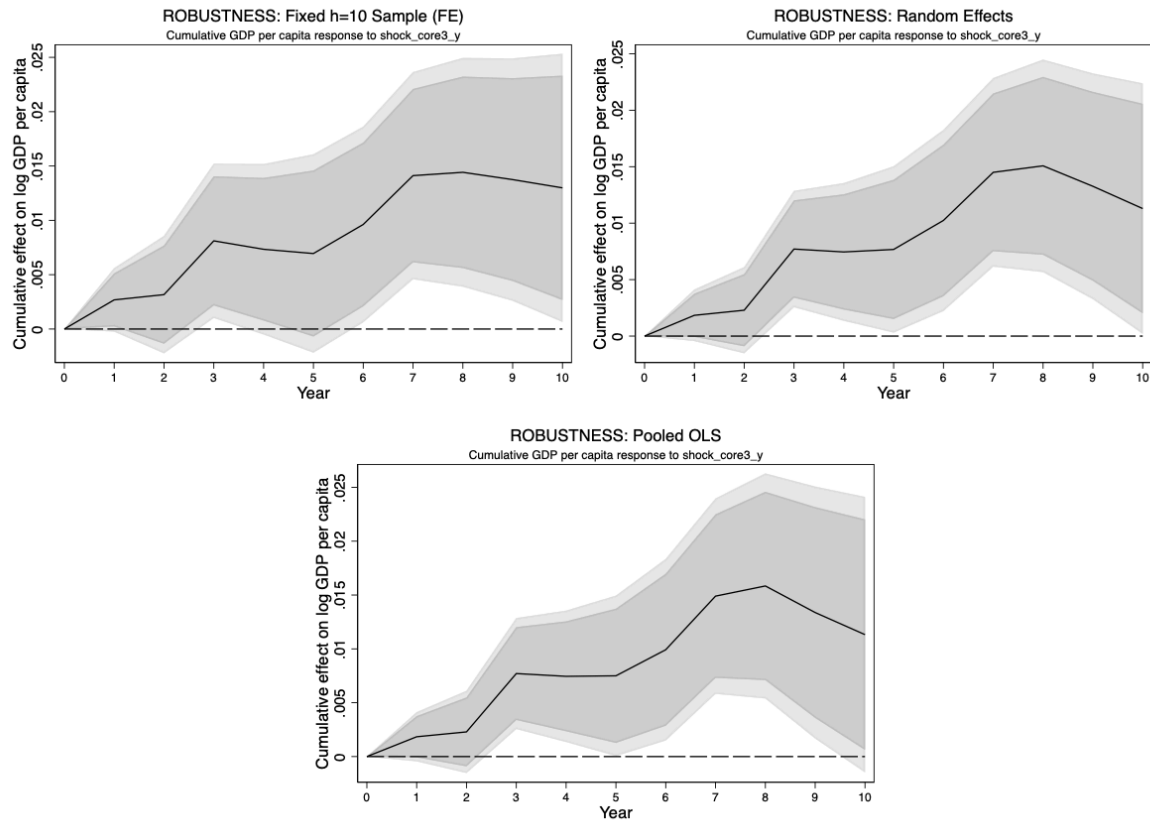


**Figure 14:** Impulse responses of LP estimate of the effect of a climatic shock on cumulative GDP per capita growth, alternative robustness checks.

Note: *Year 1* denotes the first year following the climatic shock, which occurs at *Year 0*. By *Year 5*, the line reflects the cumulative impact of the shock on GDP per capita growth five years after the shock, expressed in percentage terms. The solid black line plots the impulse response estimates based on the regression results presented in table A.16 in the appendix. The dark and light shaded areas represent the 90% and 95% confidence intervals, respectively, both calculated using standard errors clustered at the country level.

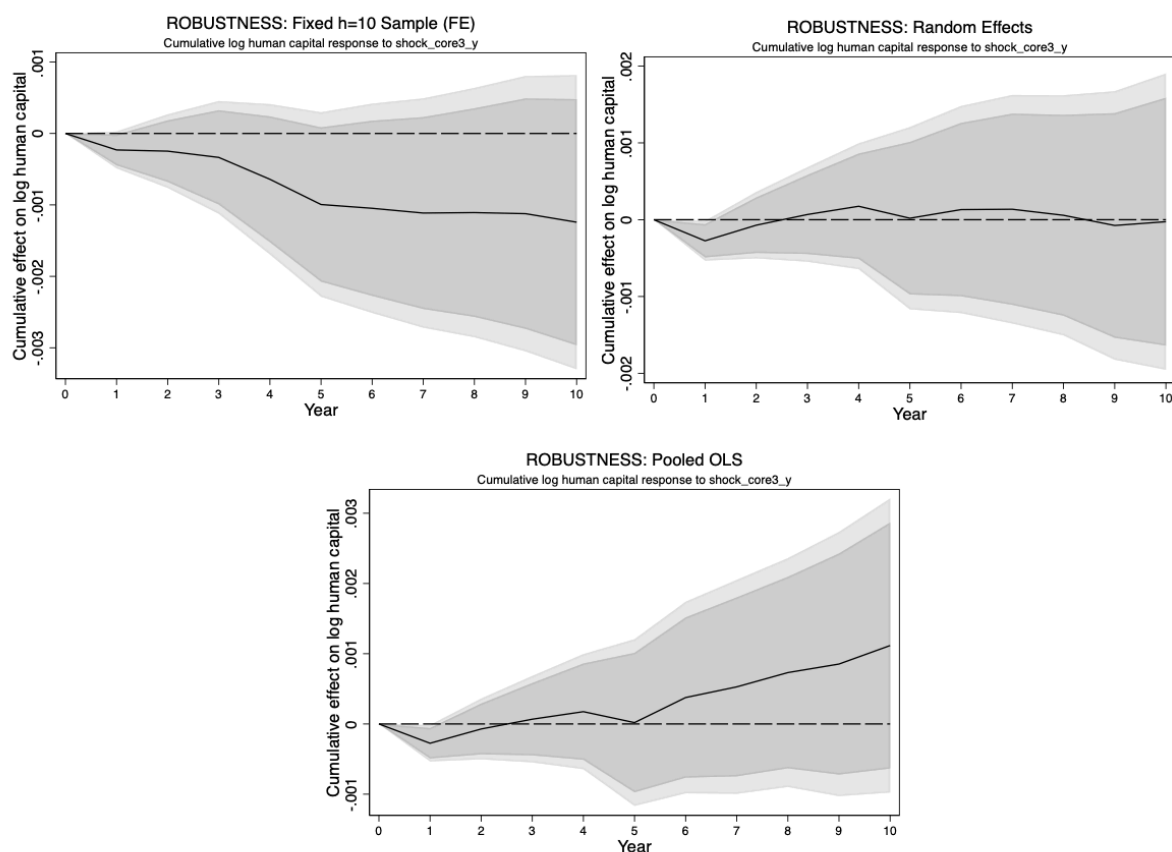


**Figure 15:** Impulse responses of LP estimate of the effect of a climatic shock on the cumulative log changes in the Human Capital Index, alternative robustness checks.

Note: *Year 1* denotes the first year following the climatic shock, which occurs at *Year 0*. By *Year 5*, the line reflects the cumulative impact of the shock on the cumulative log changes in the Human Capital Index, expressed in percentage terms. The solid black line plots the impulse response estimates based on the regression results presented in table A.17 in the appendix. The dark and light shaded areas represent the 90% and 95% confidence intervals, respectively, both calculated using standard errors clustered at the country level.

## 8. Discussion

A key finding is the positive cumulative GDP per capita response following climatic shocks. This goes against H1 but aligns with Skidmore and Toya (2002), who find positive long-run growth effects of climatic disasters, and Loayza et al. (2012), who document positive short-run effects for some disaster types, especially floods. The result is most consistent with a reconstruction-driven demand channel, as emphasised in the creative destruction literature (Caballero & Hammour, 1994; Hallegatte & Dumas, 2009). Disaster-related destruction can trigger rebuilding and replacement investment, temporarily raising measured output above the no-shock path. However, this should not be interpreted as a welfare gain. GDP per capita captures current production rather than accumulated wealth, and reconstruction can offset losses without making disasters beneficial overall. The positive response may also partly reflect

composition effects if disasters reduce or displace populations, mechanically increasing GDP per capita even when aggregate output falls. Interestingly, lower-income countries exhibit larger positive GDP per capita responses to climatic shocks than higher-income countries. This is consistent with 'creative destruction' mechanisms whereby capital destruction enables technological upgrading (Hallegatte & Dumas, 2009; Skidmore & Toya, 2002). Lower-income countries have older capital stocks further from the frontier, so replacement embodies substantial quality improvements rather than like-for-like restoration (Cuñado & Ferreira, 2014; Loayza et al., 2012), while higher-income countries' modern capital stocks could limit upgrading opportunities.

The baseline human capital results show an immediate and statistically significant decline following climatic shocks, concentrated in lower-income countries. This partly supports H2, which predicted delayed but persistent losses. Although the immediate effect was not explicitly expected, it is consistent with evidence that disasters can directly reduce human capital through mortality, skilled migration, disrupted schooling, and damaged health infrastructure (Loayza et al., 2012; Cuaresma, 2010; Baez et al., 2010; McDermott, 2012). The negative coefficients persist across all horizons, even where longer-run estimates are not statistically significant, suggesting that these losses might be persistent. Importantly, the negative human capital response contrasts with Skidmore and Toya's (2002) substitution mechanism, according to which disasters that destroy physical capital may encourage investment in human capital. The findings suggest that this mechanism does not operate in lower-income countries exposed to droughts, floods, and storms. Instead, disasters reduce human capital accumulation, implying that the positive GDP per capita effects are more likely driven by reconstruction demand than by human capital gains. Further, the concentration of human capital losses in lower-income countries is consistent with the broader climate-growth literature, which consistently finds that poorer countries suffer larger output and welfare losses from climatic shocks (Dell et al., 2012; Noy, 2009; Acevedo Mejia et al., 2019). This underscores the role of adaptive capacity and resilience in shaping disaster impacts. Higher-income countries have better-quality infrastructure, more resilient health and education systems and deeper financial markets that enable households to smooth consumption and maintain schooling investments after shocks (Acevedo Mejia et al., 2019).

Together, the GDP and human capital results point to an imbalance in the recovery dynamics following climatic shocks. Physical rebuilding accelerates and lifts measured output, while the human capital foundations of long-run growth quietly weaken. The resulting trajectory appears strong in the short run but may prove fragile over time, as the schooling,

child health and embodied skills that sustain future productivity erode even while headline output rises. The divergence is precisely the pattern the resilience framework anticipates when macroeconomic and microeconomic resilience operate on different margins: reconstruction strengthens the visible, capital-intensive side of the recovery, while the slower, household-level adjustments that determine human capital accumulation are left exposed.

The clearest buffer result concerns aid. For GDP per capita, the high-aid interaction is negative, suggesting that higher-aid countries experience smaller post-shock growth increases. This should, however, not be interpreted as aid worsening recovery. High-aid countries are often more vulnerable, institutionally weaker, and less able to absorb shocks, so the coefficient may reflect underlying fragility rather than a causal effect of aid. Moreover, Arezki et al. (2025) show that post-disaster aid is driven mainly by humanitarian relief rather than long-term reconstruction finance. Such aid addresses immediate needs, but does not directly support productive investment or capital replacement, the channels most relevant for GDP recovery. This is supported by the positive high-aid interaction in the human capital estimates, consistent with H3, which predicted that aid would be more effective in protecting human capital than in improving GDP per capita outcomes. The finding is consistent with Kinda (2017), who shows that aid mitigates the effects of climatic shocks by stabilising spending on food security, health, education, and infrastructure, and with McDermott (2012), who finds that aid is more effective in cushioning adverse health outcomes than in promoting output recovery.

Domestic credit shows a positive, though statistically insignificant, differential effect on GDP per capita in lower-income countries. The relatively persistent signs suggest that higher credit levels are associated with stronger post-shock GDP responses, broadly consistent with H5. This interpretation aligns with Noy (2009) and McDermott et al. (2014), who show that deeper financial systems can support recovery by easing liquidity constraints and financing reconstruction. These mechanisms may be especially important in lower-income countries, where access to formal credit is more limited. By contrast, domestic credit shows no clear effect on human capital outcomes. Credit may help smooth income losses and sustain schooling expenditures, but it does not directly address damaged schools or health shocks.

Remittances show limited and inconsistent effects, providing little overall support for H4. In the full sample, there is no clear moderating pattern for either GDP per capita or human capital. By income group, higher remittances are associated with smaller GDP per capita gains after shocks in lower-income countries, but larger gains in higher-income countries. This may reflect differences in both remittance use and country structure. In lower-income settings, remittances are often used for consumption smoothing and basic household needs rather than

productive investment (Chami et al., 2005). Although they can help households cope with crises and maintain spending (Mohapatra et al., 2009; Combes & Ebeke, 2011), they may not translate into faster aggregate recovery. Moreover, high remittance inflows often occur in countries facing deeper economic or political fragility and may rise further after shocks. Weaker GDP outcomes may therefore reflect greater underlying vulnerability and more difficult recovery conditions, rather than the ineffectiveness of remittances themselves. For human capital, remittances show no clear moderating effect in either income group. This contrasts with micro-level evidence that remittances support school enrolment and protect educational investment after shocks (De & Ratha, 2012; Calero et al., 2009). The absence of a macro-level effect may reflect aggregation, as benefits experienced by individual households may be too dispersed to appear in national estimates. It may also reflect the slow-moving nature of the human capital index, which may not capture short-run changes in schooling or health.

The mechanisms underlying this heterogeneity are well-established. Lower-income countries have weaker infrastructure, less resilient health and education systems, shallower financial markets, weaker fiscal capacity, and limited adaptive capacity (Acevedo et al., 2020; Ehlers et al., 2025). Households are more likely to be liquidity-constrained, lack access to insurance, and face higher opportunity costs of maintaining schooling when income falls. The buffer results reflect these structural differences. Aid protects human capital most clearly in lower-income countries, where humanitarian support addresses immediate needs that would otherwise go unmet. Domestic credit shows suggestive evidence of supporting GDP recovery where credit access is constrained and financial deepening yields higher marginal benefits. By contrast, higher-income countries already possess well-developed financial systems and stronger social protection, so the distinctions between high and low buffer levels capture less meaningful variation.

## *9. Limitations*

The results are sensitive to shock definition, as the disaster literature shows heterogeneous effects across types (Loayza et al., 2012; Felbermayr & Gröschl, 2014). The focus on droughts, floods, and storms, while excluding extreme temperature, wildfires, and geophysical disasters, reflects both conceptual and empirical considerations. As Cevik and Jalles (2024) note, these three types are unambiguously climatic in origin and sufficiently geographically dispersed to generate economy-wide effects. Robustness checks using broader shock definitions produce qualitatively unchanged results, supporting the main findings.

Nevertheless, this focus could still be seen as a limitation. While prioritising disasters most likely to affect national macroeconomic outcomes improves analytical precision, findings may not generalise to more localised or non-climatic events. Results should therefore be interpreted as effects of these specific climatic shocks rather than natural disasters broadly.

Further, the aggregate climatic shock variable is constructed as a binary indicator. While this approach follows established practice in the disaster-economics literature (Cevik & Jalles, 2024; Ehlers et al., 2025), it also imposes important limitations. The binary construction treats all disaster occurrences equally, regardless of their intensity. A relatively minor localised flood is therefore coded in the same way as a catastrophic nationwide event, which may weaken estimated effects and hide important differences in how various in magnitude disasters affect economies differently. Although intensity-based measures would in principle allow for more nuanced analysis, the endogeneity and measurement problems associated with damage figures in EM-DAT, as discussed by Skidmore and Toya (2002) and Ehlers et al. (2025), led me to prioritise binary occurrence indicators. Moreover, while the analysis disaggregates by disaster type, income group, and financial buffers, these distinctions cannot capture within-type severity variation, gradual differences in adaptive capacity, or effects of compound disasters within the same year. As Loayza et al. (2012) and Cavallo et al. (2013) emphasise, large catastrophic events may generate different economic dynamics from more moderate shocks, a dimension that the binary occurrence indicator used here cannot fully capture.

One limitation of the local projection method, as applied in this study, is that it assumes a linear relationship between climatic shocks and outcome variables within each estimation. In other words, the impact of a shock is treated as constant across all observations within each group or time horizon. Although the analysis divides the sample by income group and interacts shocks with high- and low-buffer indicators, these binary classifications cannot fully capture more gradual nonlinear relationships. For example, the effect of aid, remittances, or domestic credit may vary depending on the magnitude of the inflow, institutional capacity, absorptive constraints, or the severity of the shock. The interaction estimates should therefore be interpreted as broad comparisons between high- and low-buffer observations, rather than as evidence of precise threshold effects or fully nonlinear recovery dynamics.

The buffer interaction analysis introduces additional identification concerns. The binary buffer indicators are constructed based on whether a country exceeds income-group-specific median thresholds in the year prior to the shock. While lagging the buffer variables reduces reverse causality concerns, it does not eliminate the possibility that buffer levels themselves are endogenous to underlying structural characteristics that also determine shock responses.

For instance, as discussed above, countries with higher aid inflows may be systematically more vulnerable, not because aid itself worsens outcomes, but because aid is often targeted toward countries already facing greater risks. This complicates causal interpretation of the negative aid interaction coefficients observed for outcome variables. Similarly, remittance may respond to disaster expectations or may be concentrated in countries with specific structural characteristics (e.g., diaspora networks, natural resource endowments) that independently affect shock resilience. As discussed by Acevedo Mejia et al. (2019), aid allocation is endogenous to recipient country characteristics, and even after controlling for the lagged buffer level, the interaction term may still capture unobserved heterogeneity in shock exposure or adaptive capacity rather than a pure moderating effect of the financial flow. The estimates therefore represent differential shock responses conditional on pre-existing buffer levels, which is policy-relevant for understanding heterogeneity in climate vulnerability. However, they do not constitute a causal evaluation of aid, remittances, or domestic credit as resilience-building interventions.

## *10. Conclusion*

This thesis examines the macroeconomic effects of climatic disasters on GDP per capita and human capital accumulation, using a local projections framework applied to panel data covering 173 countries. Focusing on droughts, floods, and storms, the analysis estimates dynamic impulse responses over ten-year horizons and investigates heterogeneity across income groups and buffer mechanisms.

The main findings reveal a divergence between GDP per capita and human capital responses. For GDP per capita, baseline estimates show a positive cumulative response in lower-income countries, robust across alternative shock definitions and sample restrictions. This positive response reflects reconstruction-driven demand effects, where post-disaster spending on infrastructure repair and rebuilding temporarily boosts measured GDP. By contrast, human capital shows immediate declines following climatic shocks in lower-income countries. The patterns point to an imbalance in recovery dynamics where physical rebuilding accelerates, while the human capital foundations weaker, creating a trajectory that looks expansionary in the short-run but might be fragile over time. The analysis is further extended to account for heterogeneous outcomes across financial buffer levels. I focus on three financial buffers, aid, remittances, and domestic credit. Each captures a distinct channel of post-disaster resilience, that is, external public support, household-level income transfers, and the domestic

financial system's capacity to finance recovery. Domestic credit provision shows suggestive evidence of moderating GDP impacts in lower-income countries. Foreign aid shows a contrasting pattern across outcomes, with a negative differential effect on GDP per capita but a positive effect on human capital, particularly in lower-income countries. This indicates prioritisation of aid towards humanitarian and social objectives over productive investment. Remittances show a divergent pattern across income groups for GDP per capita, with higher remittance inflows associated with weaker post-shock GDP responses in lower-income countries but stronger responses in higher-income ones. This may reflect the fact that remittances are often not channelled into productive investment, particularly in contexts of limited financial development as is typical of lower-income countries.

Taken together, these findings show that the macroeconomic costs of climatic disasters are not uniform in outcomes, and that aggregate output figures tell only part of the story. The positive GDP per capita response in lower-income countries should not be read as a sign of successful recover. It instead reflects reconstruction-driven activity that runs alongside, and partly masks, a slower deterioration in the human capital base of these economies. The buffer results reinforce this asymmetry. Domestic credit and aid each operate on a different margin of resilience, supporting GDP recovery and human capital protection respectively, but neither addresses both, and remittances show little systematic moderating role at the macroeconomic level. The countries most exposed to these shocks are therefore also the ones whose recovery is shaped most directly by the financial constraints limiting their adaptive capacity in the first place.

This matters because climate change is set to intensify the frequency and severity of weather-related disasters, and the countries that have contributed least to the problem are bearing its sharpest human costs. Mitigating climate change at source remains essential, but the evidence here underscores that adaptation and resilience need to be equally central to the policy response. These findings carry several policy implications. First, strengthening domestic financial systems should be prioritised. While foreign aid effectively protects human capital through humanitarian assistance, it does not accelerate productive recovery, suggesting that long-term resilience requires deeper domestic credit markets to finance reconstruction and smooth household consumption. Second, policies must distinguish between GDP recovery and genuine development progress. The positive GDP responses observed in lower-income countries reflect reconstruction spending, not restored welfare, and mask persistent human capital losses that could undermine long-term growth prospects. Finally, climate adaptation strategies must explicitly address distributional impacts through targeted social protection and

investments in resilient health and education infrastructure, ensuring that the poorest populations do not bear disproportionate costs of climate shocks.

## *11. AI Statement*

Throughout the research and writing process, I used AI tools to work more efficiently while maintaining full control over all intellectual decisions. For coding, I consulted Claude when I needed help with Stata commands and when checking whether my econometric approach made logical sense. For managing literature, I used NotebookLM to quickly find and extract relevant information from papers I had already selected for my research. For language editing, I used Claude and Microsoft Copilot to improve grammar and sentence structure. All core intellectual work, including developing the research question, designing the empirical approach, defining variables, choosing model specifications, interpreting results, and building theoretical arguments, is entirely my own. These AI tools helped me work faster and present my ideas more clearly. My use of these tools follows LUSEM's academic integrity guidelines, and I take full responsibility for all content, methods, and conclusions in this thesis.

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### 13. Appendix

Table A.1: List of sampled countries by income group

| Lower-income countries                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                           |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Algeria, Angola, Bangladesh, Benin, Bhutan, Bolivia, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Central African Republic, Chad, Comoros, Democratic Republic of Congo, Republic of Congo, Cote d'Ivoire, Djibouti, Egypt, El Salvador, Eswatini, Ethiopia, Gambia, Ghana, Guinea, Guinea-Bissau, Haiti, Honduras, India, Indonesia, Islamic Republic of Iran, Kenya, Kyrgyz Republic, Laos, Lebanon, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mongolia, Morocco, Mozambique, Myanmar, Nepal, Nicaragua, Niger, Nigeria, Pakistan, Philippines, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Federal Republic of Somalia, South Sudan, Sri Lanka, Sudan, Syrian Arab Republic, Tajikistan, Tanzania, Togo, Tunisia, Uganda, Ukraine, Uzbekistan, Vietnam, West Bank and Gaza, Republic of Yemen, Zambia, Zimbabwe                                                                                                                                                                                                                                                                                             |
| Higher-income countries                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          |
| Albania, Antigua and Barbuda, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Barbados, Belarus, Belgium, Belize, Bosnia and Herzegovina, Botswana, Brazil, Brunei, Darussalam, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Croatia, Cyprus, Czechia, Denmark, Dominica, Dominican Republic, Ecuador, Equatorial Guinea, Estonia, Fiji, Finland, France, Gabon, Georgia, Germany, Greece, Grenada, Guatemala, Guyana, Hong Kong, Hungary, Iceland, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Republic of Korea, Kuwait, Latvia, Lithuania, Luxembourg, Malaysia, Maldives, Malta, Mauritius, Mexico, Moldova, Montenegro, Namibia, Netherlands, New Zealand, North Macedonia, Norway, Oman, Panama, Paraguay, Peru, Poland, Portugal, Qatar, Romania, Russian Federation, Saudi Arabia, Serbia, Seychelles, Singapore, Slovak Republic, Slovenia, South Africa, Spain, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Suriname, Sweden, Switzerland, Thailand, Trinidad and Tobago, Turkiye, Turkmenistan, United Arab Emirates, United Kingdom, United States, Uruguay |

Table A.2: Variables description and summary statistics

| Variables              | Description                                                                                                                                                                                                                                                       | Source          | Mean   | SD     | Min     | Max     | N      |
|------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------|--------|--------|---------|---------|--------|
| GDP per capita         | Annual log change in real GDP per capita.                                                                                                                                                                                                                         | PWT             | 1.985  | 5.118  | -16.507 | 18.911  | 9,606  |
| Human Capital Index    | Annual log change in the Human Capital Index, based on average years of schooling (Barro and Lee, 2013) and an assumed rate of return to education (Psacharopoulos, 1994).                                                                                        | PWT             | 0.009  | 0.007  | -0.058  | 0.075   | 8,250  |
| Aggregate shock        | Binary indicator equal to one if at least one drought, flood, or storm occurred in a given country-year, and zero otherwise.                                                                                                                                      | EM-DAT          | 0.374  | 0.484  | 0.000   | 1.000   | 11,418 |
| Drought shock          | Binary indicator equal to one if at least one drought occurred in a given country-year, and zero otherwise.                                                                                                                                                       | EM-DAT          | 0.095  | 0.293  | 0.000   | 1.000   | 7,491  |
| Flood shock            | Binary indicator equal to one if at least one flood occurred in a given country-year, and zero otherwise.                                                                                                                                                         | EM-DAT          | 0.310  | 0.462  | 0.000   | 1.000   | 9,823  |
| Storm shock            | Binary indicator equal to one if at least one storm occurred in a given country-year, and zero otherwise.                                                                                                                                                         | EM-DAT          | 0.222  | 0.416  | 0.000   | 1.000   | 8,721  |
| Aid                    | Official Development Assistance (ODA) refers to the net disbursement of concessional loans and grants provided by official agencies with the primary aim of promoting economic development and welfare in eligible recipient countries.                           | World Bank, WDI | 5.500  | 7.576  | -0.017  | 48.117  | 6,971  |
| Remittances            | Personal Remittances include personal transfers and compensation of employees. They capture cash or in-kind transfers between resident and nonresident households, as well as income earned by nonresident workers or residents employed by nonresident entities. | World Bank, WDI | 3.547  | 5.587  | 0.005   | 31.182  | 6,488  |
| Domestic Credit        | Domestic credit to the private sector by banks captures the flow of financial resources that deposit-taking institutions (other than central banks) extend to private firms and households.                                                                       | World Bank, WDI | 35.503 | 33.595 | 1.468   | 161.960 | 8,262  |
| Population Growth      | Population Growth Rate is the yearly percentage change in the number of people living in a country, based on the total number of residents, regardless of citizenship or legal status.                                                                            | World Bank, WDI | 1.736  | 1.456  | -1.991  | 7.461   | 11,040 |
| Inflation              | Inflation (CPI) measures the yearly percentage change in the average cost of a set basket of goods and services typically bought by consumers.                                                                                                                    | World Bank, WDI | 11.560 | 26.291 | -2.844  | 207.692 | 8,369  |
| Government Consumption | Government Consumption (% of GDP) includes all current spending by the government on goods and services, including wages and most defense and security costs.                                                                                                     | World Bank, WDI | 15.436 | 5.922  | 4.903   | 46.167  | 7,742  |

|                   |                                                                                                                                                                                 |                 |        |        |        |         |        |
|-------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------|--------|--------|--------|---------|--------|
| Capital Formation | Expressed as a share of Gross Domestic Product (GDP), it reflects the portion of total economic output devoted to expanding or maintaining the economy's productive asset base. | World Bank, WDI | 23.298 | 8.202  | 4.033  | 48.429  | 7,696  |
| Trade             | Trade (% of GDP) is the total value of a country's exports and imports of goods and services.                                                                                   | World Bank, WDI | 74.824 | 49.064 | 12.591 | 320.146 | 7,843  |
| Fertility Rate    | Total Fertility Rate is the average number of children a woman would have over her lifetime based on current age-specific fertility rates.                                      | World Bank, WDI | 3.892  | 2.027  | 1.162  | 7.822   | 11,040 |
| Life Expectancy   | Life expectancy at birth represents the average number of years a newborn is expected to live.                                                                                  | World Bank, WDI | 64.427 | 11.286 | 36.277 | 83.093  | 11,038 |
| Urbanisation      | Urban population refers to people living in urban areas, expressed as % of total population.                                                                                    | World Bank, WDI | 49.971 | 23.674 | 5.083  | 100.000 | 11,245 |

Table A.3: Disaster type definitions

| Term                      | Level                          | Definition                                                                                                                                                                                                                                  |
|---------------------------|--------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <u>Flood</u>              | <u>Type, Subtype (General)</u> | A general category for events in which water spreads beyond its usual boundaries onto normally dry land.                                                                                                                                    |
| Coastal flood             | Subtype                        | Elevated water levels along the coast caused by tidal changes or thunderstorms, producing flooding that can persist for days or weeks.                                                                                                      |
| Flash flood               | Subtype                        | Flooding caused by heavy rainfall over a short period, producing immediate runoff and onset within minutes to a few hours.                                                                                                                  |
| Riverine flood            | Subtype                        | Flooding caused by water overflowing from a stream or river channel onto adjacent floodplain land that is normally dry.                                                                                                                     |
| Ice jam flood             | Subtype                        | Flooding caused by accumulations of floating ice that restrict or block a river's flow and drainage, often forming near bends and obstructions such as bridges.                                                                             |
| <u>Drought</u>            | <u>Type, Subtype</u>           | A prolonged period of unusually low precipitation that creates a water shortage for human, animal, and plant needs. Unlike most other hazards, droughts develop slowly, sometimes over years, and their onset is often difficult to detect. |
| <u>Storm</u>              | <u>Type Subtype (General)</u>  |                                                                                                                                                                                                                                             |
| Derecho                   | Subtype                        | Widespread, fast-moving windstorms associated with convective storms, including downbursts and straight-line winds. Their damage is often mistaken for that of tornadoes.                                                                   |
| Hail                      | Subtype                        | Solid precipitation falling as irregular ice pellets or balls larger than 5 mm in diameter.                                                                                                                                                 |
| Lightning / Thunderstorms | Subtype                        | A high-voltage electrical discharge from a thunderstorm, accompanied by thunder.                                                                                                                                                            |

|                       |         |                                                                                                                                                                                                                                                                                                                                               |
|-----------------------|---------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Sand/Dust storm       | Subtype | Strong winds carrying sand particles aloft, generally to the heights below 15 m and most common in arid and semi-arid regions. Dust storms involve the same mechanism but lift smaller dust particles over wider areas.                                                                                                                       |
| Storm surge           | Subtype | An abnormal rise in sea level produced by a tropical cyclone or other intense storm.                                                                                                                                                                                                                                                          |
| Tornado               | Subtype | A violently rotating column of air extending to the ground or, over water, forming a waterspout.                                                                                                                                                                                                                                              |
| Winter storm/Blizzard | Subtype | A winter low-pressure system producing significant accumulations of snow, freezing rain, sleet, or ice. A blizzard is a severe variant with winds above 56 km/h for at least three hours and visibility reduced to under 400 m.                                                                                                               |
| Extra-tropical storm  | Subtype | A mid-latitude low-pressure cyclonic system that draws energy from atmospheric temperature contrasts, with cold-front variants (e.g. European windstorms, Nor'easters) being especially damaging.                                                                                                                                             |
| Tropical cyclone      | Subtype | A warm-core, non-frontal cyclonic system originating over tropical or subtropical waters, characterised by a low-pressure centre, spiral rain bands, and strong winds. Depending on location, these storms are known as hurricanes (Atlantic, Northeast Pacific), typhoons (Northwest Pacific), or cyclones (South Pacific and Indian Ocean). |

Notes: Disaster types and subtypes follow the classification used by the Emergency Events Database (EM-DAT). Definitions are based on Delforge et al. (2025) and have been paraphrased for use in this thesis. "Type" refers to the main hazard category; "subtype" refers to a more specific event class within that category. Subtypes shown here cover the disaster types used in the empirical analysis (droughts, floods, and storms).

Table A.4: Correlation matrix

| Variables                   | (1)        | (2)        | (3)        | (4)       | (5)        | (6)        | (7)       | (8)       | (9)       | (10)     | (11) |
|-----------------------------|------------|------------|------------|-----------|------------|------------|-----------|-----------|-----------|----------|------|
| (1) GDP per capita          | 1          |            |            |           |            |            |           |           |           |          |      |
| (2) Log Human Capital       | -0.00907   | 1          |            |           |            |            |           |           |           |          |      |
| (3) Climatic shock          | 0.0469***  | -0.0250**  | 1          |           |            |            |           |           |           |          |      |
| (4) Population Growth       | -0.112***  | 0.184***   | -0.0633*** | 1         |            |            |           |           |           |          |      |
| (5) Gross Capital Formation | 0.0827***  | 0.133***   | -0.00184   | -0.104*** | 1          |            |           |           |           |          |      |
| (6) Inflation               | -0.117***  | 0.105***   | 0.00607    | -0.00195  | -0.0822*** | 1          |           |           |           |          |      |
| (7) Government Consumption  | -0.0562*** | -0.0964*** | -0.142***  | -0.173*** | 0.104***   | -0.0998*** | 1         |           |           |          |      |
| (8) Trade                   | 0.0618***  | 0.00813    | -0.162***  | -0.129*** | 0.222***   | -0.133***  | 0.178***  | 1         |           |          |      |
| (9) Fertility rate          | -0.0894*** | 0.0541***  | -0.132***  | 0.667***  | -0.297***  | 0.0659***  | -0.229*** | -0.350*** | 1         |          |      |
| (10) Life expectancy        | 0.0653***  | 0.0195*    | 0.129***   | -0.434*** | 0.318***   | -0.131***  | 0.267***  | 0.365***  | -0.865*** | 1        |      |
| (11) Urbanisation           | -0.0166    | 0.0162     | 0.0429***  | -0.246*** | 0.210***   | -0.0305*** | 0.278***  | 0.343***  | -0.650*** | 0.752*** | 1    |

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table A.5: Hausman (1978) specification test.

|                              | Chi-square test value | P-value |
|------------------------------|-----------------------|---------|
| GDP per capita specification | 504 - 1,407           | 0.000   |
| Human Capital specification  | 622 - 1,069           | 0.000   |

Table A.6: Local Projections: GDP per capita response to climate shocks

|                        | (1)                     | (2)                  | (3)                   | (4)                |
|------------------------|-------------------------|----------------------|-----------------------|--------------------|
| Horizon                | Aggregate climate shock | Drought              | Flood                 | Storm              |
| Horizon 1              | 0.0025*<br>(0.0013)     | 0.0175**<br>(0.0079) | 0.0013<br>(0.0024)    | 0.0041<br>(0.0034) |
| Horizon 2              | 0.0035<br>(0.0024)      | 0.0206<br>(0.0159)   | 0.0089*<br>(0.0048)   | 0.0088<br>(0.0061) |
| Horizon 3              | 0.0090***<br>(0.0032)   | 0.0340<br>(0.0265)   | 0.0213***<br>(0.0064) | 0.0074<br>(0.0079) |
| Horizon 4              | 0.0096***<br>(0.0036)   | -0.0100<br>(0.0343)  | 0.0236***<br>(0.0081) | 0.0001<br>(0.0103) |
| Horizon 5              | 0.0101**<br>(0.0042)    | -0.0468<br>(0.0551)  | 0.0251**<br>(0.0101)  | 0.0038<br>(0.0121) |
| Horizon 6              | 0.0129***<br>(0.0043)   | 0.0078<br>(0.0673)   | 0.0221*<br>(0.0127)   | 0.0085<br>(0.0111) |
| Horizon 7              | 0.0168***<br>(0.0046)   | 0.0169<br>(0.0789)   | 0.0260*<br>(0.0150)   | 0.0144<br>(0.0119) |
| Horizon 8              | 0.0175***<br>(0.0052)   | 0.0591<br>(0.0799)   | 0.0355**<br>(0.0150)  | 0.0196<br>(0.0140) |
| Horizon 9              | 0.0165***<br>(0.0055)   | 0.0266<br>(0.0787)   | 0.0336*<br>(0.0173)   | 0.0237<br>(0.0187) |
| Horizon 10             | 0.0144**<br>(0.0062)    | -0.0010<br>(0.0799)  | 0.0422**<br>(0.0210)  | 0.0181<br>(0.0227) |
| Within R-squared       | 0.154                   | 0.148                | 0.145                 | 0.170              |
| Number of Countries    | 155                     | 118                  | 154                   | 135                |
| Number of Observations | 6,071                   | 1,385                | 3,274                 | 2,222              |

Notes: The table presents local projection estimates of the effect of a climatic disasters shock on cumulative GDP per capita growth. All control variables are included with a one-year lag, except population growth, which enters contemporaneously. The regressions are based on Equation 1 and include treatment leads corresponding to each forecast horizon, as well as two lags of both the treatment and the outcome variables. Country and year fixed effects are included. Summary statistics are based on the h=1 estimation sample. Standard errors are clustered at the country level, report in the parentheses. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01

Table A.7: Local Projections: GDP per capita response to climate shocks by income group

|                        | Aggregate climate shock |                         |
|------------------------|-------------------------|-------------------------|
| Horizon                | Lower-income countries  | Higher-income countries |
| Horizon 1              | 0.0031<br>(0.0022)      | 0.0010<br>(0.0016)      |
| Horizon 2              | 0.0015<br>(0.0042)      | 0.0028<br>(0.0028)      |
| Horizon 3              | 0.0126**<br>(0.0054)    | 0.0037<br>(0.0035)      |
| Horizon 4              | 0.0135**<br>(0.0062)    | 0.0045<br>(0.0038)      |
| Horizon 5              | 0.0141*<br>(0.0076)     | 0.0048<br>(0.0046)      |
| Horizon 6              | 0.0138*<br>(0.0078)     | 0.0100**<br>(0.0048)    |
| Horizon 7              | 0.0181**<br>(0.0082)    | 0.0126**<br>(0.0053)    |
| Horizon 8              | 0.0187**<br>(0.0089)    | 0.0125**<br>(0.0059)    |
| Horizon 9              | 0.0127<br>(0.0094)      | 0.0135**<br>(0.0064)    |
| Horizon 10             | 0.0106<br>(0.0108)      | 0.0119<br>(0.0072)      |
| Within R-squared       | 0.1414                  | 0.2310                  |
| Number of Countries    | 65                      | 90                      |
| Number of Observations | 2,255                   | 3,816                   |

Notes: The table presents local projection estimates of the effect of a climatic disasters shock on cumulative GDP per capita growth by income group. All control variables are included with a one-year lag, except population growth, which enters contemporaneously. The regressions are based on Equation 1 and include treatment leads corresponding to each forecast horizon, as well as two lags of both the treatment and the outcome variables. Country and year fixed effects are included. Summary statistics are based on the h=1 estimation sample. Standard errors are clustered at the country level, report in the parentheses. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01

| Table A.8: Local Projections: Human capital response to climate shocks |                         |                      |                       |                        |
|------------------------------------------------------------------------|-------------------------|----------------------|-----------------------|------------------------|
|                                                                        | (1)                     | (2)                  | (3)                   | (4)                    |
| Horizon                                                                | Aggregate climate shock | Drought              | Flood                 | Storm                  |
| Horizon 1                                                              | -0.0003**<br>(0.0001)   | 0.0010*<br>(0.0005)  | 0.0000<br>(0.0002)    | -0.0005*<br>(0.0003)   |
| Horizon 2                                                              | -0.0002<br>(0.0002)     | 0.0030<br>(0.0021)   | 0.0007<br>(0.0005)    | -0.0014***<br>(0.0005) |
| Horizon 3                                                              | -0.0002<br>(0.0004)     | 0.0032<br>(0.0032)   | 0.0004<br>(0.0007)    | -0.0018**<br>(0.0009)  |
| Horizon 4                                                              | -0.0004<br>(0.0005)     | 0.0078*<br>(0.0043)  | -0.0001<br>(0.0010)   | -0.0037***<br>(0.0014) |
| Horizon 5                                                              | -0.0007<br>(0.0006)     | 0.0124**<br>(0.0057) | -0.0002<br>(0.0013)   | -0.0031*<br>(0.0017)   |
| Horizon 6                                                              | -0.0008<br>(0.0007)     | 0.0152**<br>(0.0073) | 0.0008<br>(0.0017)    | -0.0045<br>(0.0030)    |
| Horizon 7                                                              | -0.0008<br>(0.0008)     | 0.0222**<br>(0.0096) | 0.0042**<br>(0.0021)  | -0.0041<br>(0.0031)    |
| Horizon 8                                                              | -0.0009<br>(0.0009)     | 0.0123*<br>(0.0066)  | 0.0050**<br>(0.0025)  | -0.0042<br>(0.0036)    |
| Horizon 9                                                              | -0.0012<br>(0.0010)     | 0.0123<br>(0.0075)   | 0.0071***<br>(0.0026) | -0.0058<br>(0.0039)    |
| Horizon 10                                                             | -0.0012<br>(0.0011)     | 0.0098<br>(0.0096)   | 0.0080**<br>(0.0031)  | -0.0048<br>(0.0050)    |
| Within R-squared                                                       | 0.313                   | 0.348                | 0.302                 | 0.292                  |
| Number of Countries                                                    | 135                     | 102                  | 135                   | 118                    |
| Number of Observations                                                 | 5,773                   | 1,335                | 3,140                 | 2,100                  |

Notes: The table presents local projection estimates of the effect of a climatic disasters shock on cumulative human capital growth. All control variables are included with a one-year lag. The regressions are based on Equation 1 and include treatment leads corresponding to each forecast horizon, as well as two lags of both the treatment and the outcome variables. Country and year fixed effects are included. Summary statistics are based on the h=1 estimation sample. Standard errors are clustered at the country level, report in the parentheses. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01

Table A.9: Local Projections: Human capital response to climate shocks by income group

|                        | Aggregate climate shock |                         |
|------------------------|-------------------------|-------------------------|
| Horizon                | Lower-income countries  | Higher-income countries |
| Horizon 1              | -0.0006**<br>(0.0002)   | -0.0002<br>(0.0002)     |
| Horizon 2              | -0.0007*<br>(0.0004)    | 0.0001<br>(0.0003)      |
| Horizon 3              | -0.0006<br>(0.0006)     | -0.0000<br>(0.0005)     |
| Horizon 4              | -0.0007<br>(0.0008)     | -0.0003<br>(0.0006)     |
| Horizon 5              | -0.0005<br>(0.0010)     | -0.0010<br>(0.0008)     |
| Horizon 6              | -0.0002<br>(0.0012)     | -0.0013<br>(0.0010)     |
| Horizon 7              | -0.0000<br>(0.0014)     | -0.0014<br>(0.0010)     |
| Horizon 8              | 0.0000<br>(0.0014)      | -0.0015<br>(0.0011)     |
| Horizon 9              | -0.0003<br>(0.0016)     | -0.0019<br>(0.0012)     |
| Horizon 10             | -0.0000<br>(0.0017)     | -0.0020<br>(0.0013)     |
| Within R-squared       | 0.3730                  | 0.2962                  |
| Number of Countries    | 56                      | 79                      |
| Number of Observations | 2,192                   | 3,581                   |

Note: The table presents local projection estimates of the effect of a climatic disasters shock on cumulative human capital growth by income group. All control variables are included with a one-year lag. The regressions are based on Equation 1 and include treatment leads corresponding to each forecast horizon, as well as two lags of both the treatment and the outcome variables. Country and year fixed effects are included. Summary statistics are based on the h=1 estimation sample. Standard errors are clustered at the country level, report in the parentheses. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01

Table A.10: Local Projection Estimates: GDP per capita response to core climatic shocks interacted with high buffer values

| Horizon                | High Aid              | High Remittances    | High Domestic credit |
|------------------------|-----------------------|---------------------|----------------------|
| Horizon 1              | -0.0035<br>(0.0034)   | 0.0027<br>(0.0028)  | 0.0025<br>(0.0031)   |
| Horizon 2              | -0.0090<br>(0.0069)   | 0.0024<br>(0.0048)  | 0.0033<br>(0.0055)   |
| Horizon 3              | -0.0157<br>(0.0099)   | 0.0008<br>(0.0064)  | 0.0054<br>(0.0077)   |
| Horizon 4              | -0.0217*<br>(0.0117)  | 0.0011<br>(0.0076)  | 0.0045<br>(0.0095)   |
| Horizon 5              | -0.0271**<br>(0.0131) | 0.0018<br>(0.0092)  | 0.0083<br>(0.0118)   |
| Horizon 6              | -0.0273**<br>(0.0137) | -0.0023<br>(0.0107) | 0.0082<br>(0.0138)   |
| Horizon 7              | -0.0276*<br>(0.0149)  | -0.0077<br>(0.0122) | 0.0053<br>(0.0159)   |
| Horizon 8              | -0.0291*<br>(0.0163)  | -0.0109<br>(0.0135) | 0.0059<br>(0.0178)   |
| Horizon 9              | -0.0255<br>(0.0170)   | -0.0145<br>(0.0143) | 0.0066<br>(0.0195)   |
| Horizon 10             | -0.0288<br>(0.0179)   | -0.0194<br>(0.0150) | 0.0134<br>(0.0207)   |
| Within R-squared       | 0.1401                | 0.2263              | 0.1715               |
| Number of Countries    | 121                   | 149                 | 154                  |
| Number of Observations | 4,107                 | 4,690               | 4,540                |

Notes: The table presents local projection estimates of the interaction between a climatic disaster shock and the lagged high-buffer indicator on cumulative GDP per capita growth. The reported coefficient measures the difference in the cumulative human capital response between high-buffer and low-buffer observations. The regressions are based on Equation 2 and include treatment leads corresponding to each forecast horizon, as well as two lags of both the treatment and outcome variables. All control variables are included with a one-year lag, except population growth, which enters contemporaneously. The continuous buffer variable is included with a one-year lag. Country and year fixed effects are included. Summary statistics are based on the  $h = 1$  estimation sample. Standard errors are clustered at the country level, report in the parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table A.11: Local Projection Estimates: GDP per capita response to core climatic shocks interacted with high buffer values by income group

|                        | Lower-income countries |                       |                      | Higher-income countries |                       |                      |
|------------------------|------------------------|-----------------------|----------------------|-------------------------|-----------------------|----------------------|
| Horizon                | High Aid               | High Remittances      | High Domestic credit | High Aid                | High Remittances      | High Domestic credit |
| Horizon 1              | -0.0028<br>(0.0047)    | -0.0056<br>(0.0046)   | 0.0032<br>(0.0048)   | -0.0078<br>(0.0058)     | 0.0090***<br>(0.0034) | 0.0017<br>(0.0043)   |
| Horizon 2              | -0.0081<br>(0.0096)    | -0.0161*<br>(0.0080)  | 0.0080<br>(0.0095)   | -0.0146<br>(0.0107)     | 0.0154***<br>(0.0055) | -0.0023<br>(0.0062)  |
| Horizon 3              | -0.0139<br>(0.0134)    | -0.0218*<br>(0.0110)  | 0.0104<br>(0.0127)   | -0.0233<br>(0.0150)     | 0.0178**<br>(0.0071)  | 0.0001<br>(0.0082)   |
| Horizon 4              | -0.0266*<br>(0.0151)   | -0.0204<br>(0.0128)   | 0.0144<br>(0.0144)   | -0.0202<br>(0.0183)     | 0.0198**<br>(0.0082)  | -0.0054<br>(0.0103)  |
| Horizon 5              | -0.0403**<br>(0.0165)  | -0.0178<br>(0.0154)   | 0.0318*<br>(0.0175)  | -0.0200<br>(0.0210)     | 0.0212**<br>(0.0098)  | -0.0127<br>(0.0134)  |
| Horizon 6              | -0.0433**<br>(0.0168)  | -0.0234<br>(0.0170)   | 0.0330*<br>(0.0192)  | -0.0188<br>(0.0229)     | 0.0196*<br>(0.0115)   | -0.0149<br>(0.0164)  |
| Horizon 7              | -0.0467**<br>(0.0194)  | -0.0356*<br>(0.0192)  | 0.0289<br>(0.0213)   | -0.0154<br>(0.0225)     | 0.0203<br>(0.0130)    | -0.0186<br>(0.0188)  |
| Horizon 8              | -0.0469**<br>(0.0211)  | -0.0383*<br>(0.0200)  | 0.0327<br>(0.0238)   | -0.0200<br>(0.0237)     | 0.0184<br>(0.0142)    | -0.0219<br>(0.0206)  |
| Horizon 9              | -0.0389*<br>(0.0213)   | -0.0483**<br>(0.0194) | 0.0399<br>(0.0257)   | -0.0215<br>(0.0264)     | 0.0159<br>(0.0152)    | -0.0287<br>(0.0230)  |
| Horizon 10             | -0.0418*<br>(0.0233)   | -0.0498**<br>(0.0197) | 0.0473*<br>(0.0278)  | -0.0229<br>(0.0268)     | 0.0081<br>(0.0167)    | -0.0232<br>(0.0248)  |
| Within R-squared       | 0.1506                 | 0.1937                | 0.1517               | 0.2166                  | 0.3566                | 0.2785               |
| Number of Countries    | 65                     | 64                    | 64                   | 56                      | 85                    | 90                   |
| Number of Observations | 2,229                  | 1,798                 | 1,971                | 1,878                   | 2,892                 | 2,569                |

Notes: The table presents local projection estimates of the interaction between a climatic disaster shock and the lagged high-buffer indicator on cumulative GDP per capita growth by income group. The reported coefficient measures the difference in the cumulative human capital response between high-buffer and low-buffer observations. The regressions are based on Equation 2 and include treatment leads corresponding to each forecast horizon, as well as two lags of both the treatment and outcome variables. All control variables are included with a one-year lag, except population growth, which enters contemporaneously. The continuous buffer variable is included with a one-year lag. Country and year fixed effects are included. Summary statistics are based on the  $h = 1$  estimation sample. Standard errors are clustered at the country level, report in the parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table A.12: Local Projection Estimates: Human capital response to core climatic shocks interacted with high buffer values

| Horizon                | High Aid             | High Remittances    | High Domestic credit |
|------------------------|----------------------|---------------------|----------------------|
| Horizon 1              | 0.0007**<br>(0.0004) | 0.0002<br>(0.0003)  | -0.0001<br>(0.0004)  |
| Horizon 2              | 0.0012*<br>(0.0007)  | 0.0004<br>(0.0007)  | -0.0002<br>(0.0008)  |
| Horizon 3              | 0.0018<br>(0.0012)   | 0.0003<br>(0.0009)  | -0.0003<br>(0.0011)  |
| Horizon 4              | 0.0018<br>(0.0016)   | 0.0002<br>(0.0013)  | 0.0001<br>(0.0016)   |
| Horizon 5              | 0.0014<br>(0.0021)   | -0.0002<br>(0.0017) | 0.0005<br>(0.0022)   |
| Horizon 6              | 0.0015<br>(0.0026)   | -0.0008<br>(0.0021) | 0.0013<br>(0.0027)   |
| Horizon 7              | 0.0024<br>(0.0032)   | -0.0010<br>(0.0026) | 0.0013<br>(0.0031)   |
| Horizon 8              | 0.0032<br>(0.0036)   | -0.0007<br>(0.0028) | 0.0022<br>(0.0035)   |
| Horizon 9              | 0.0043<br>(0.0040)   | -0.0007<br>(0.0031) | 0.0022<br>(0.0040)   |
| Horizon 10             | 0.0052<br>(0.0044)   | -0.0007<br>(0.0033) | 0.0024<br>(0.0044)   |
| Within R-squared       | 0.3577               | 0.2485              | 0.2549               |
| Number of Countries    | 101                  | 131                 | 134                  |
| Number of Observations | 3,803                | 4,403               | 4,281                |

Notes: The table presents local projection estimates of the interaction between a climatic disaster shock and the lagged high-buffer indicator on cumulative log human capital growth. The reported coefficient measures the difference in the cumulative human capital response between high-buffer and low-buffer observations. The regressions are based on Equation 2 and include treatment leads corresponding to each forecast horizon, as well as two lags of both the treatment and outcome variables. All control variables are included with a one-year lag. The continuous buffer variable is included with a one-year lag. Country and year fixed effects are included. Summary statistics are based on the  $h = 1$  estimation sample. Standard errors are clustered at the country level, report in the parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table A.13: Local Projection Estimates: Human capital response to core climatic shocks interacted with high buffer values by income group

| Horizon                | Lower-income countries |                     |                      | Higher-income countries |                     |                      |
|------------------------|------------------------|---------------------|----------------------|-------------------------|---------------------|----------------------|
|                        | High Aid               | High Remittances    | High Domestic credit | High Aid                | High Remittances    | High Domestic credit |
| Horizon 1              | 0.0008**<br>(0.0004)   | -0.0003<br>(0.0007) | -0.0001<br>(0.0006)  | 0.0010*<br>(0.0006)     | 0.0006*<br>(0.0003) | -0.0005<br>(0.0005)  |
| Horizon 2              | 0.0015*<br>(0.0008)    | 0.0000<br>(0.0013)  | -0.0006<br>(0.0010)  | 0.0019<br>(0.0014)      | 0.0009<br>(0.0008)  | -0.0009<br>(0.0012)  |
| Horizon 3              | 0.0024*<br>(0.0014)    | -0.0005<br>(0.0020) | -0.0008<br>(0.0017)  | 0.0025<br>(0.0020)      | 0.0012<br>(0.0011)  | -0.0015<br>(0.0016)  |
| Horizon 4              | 0.0030<br>(0.0019)     | -0.0009<br>(0.0030) | -0.0010<br>(0.0024)  | 0.0020<br>(0.0026)      | 0.0014<br>(0.0014)  | -0.0014<br>(0.0020)  |
| Horizon 5              | 0.0029<br>(0.0025)     | -0.0012<br>(0.0039) | -0.0001<br>(0.0033)  | 0.0020<br>(0.0033)      | 0.0013<br>(0.0019)  | -0.0019<br>(0.0027)  |
| Horizon 6              | 0.0035<br>(0.0030)     | -0.0016<br>(0.0043) | 0.0003<br>(0.0039)   | 0.0020<br>(0.0038)      | 0.0005<br>(0.0026)  | -0.0015<br>(0.0035)  |
| Horizon 7              | 0.0046<br>(0.0038)     | -0.0012<br>(0.0050) | 0.0006<br>(0.0043)   | 0.0031<br>(0.0044)      | -0.0002<br>(0.0031) | -0.0024<br>(0.0041)  |
| Horizon 8              | 0.0058<br>(0.0044)     | -0.0002<br>(0.0053) | 0.0013<br>(0.0045)   | 0.0036<br>(0.0052)      | -0.0003<br>(0.0035) | -0.0017<br>(0.0049)  |
| Horizon 9              | 0.0078<br>(0.0050)     | 0.0006<br>(0.0053)  | 0.0007<br>(0.0050)   | 0.0048<br>(0.0059)      | -0.0005<br>(0.0040) | -0.0016<br>(0.0057)  |
| Horizon 10             | 0.0098*<br>(0.0055)    | 0.0024<br>(0.0055)  | 0.0007<br>(0.0051)   | 0.0047<br>(0.0062)      | -0.0011<br>(0.0044) | -0.0014<br>(0.0068)  |
| Within R-squared       | 0.3399                 | 0.2747              | 0.3051               | 0.4193                  | 0.2663              | 0.2505               |
| Number of Countries    | 56                     | 56                  | 55                   | 45                      | 75                  | 79                   |
| Number of Observations | 2,144                  | 1,708               | 1,897                | 1,659                   | 2,695               | 2,384                |

Notes: The table presents local projection estimates of the interaction between a climatic disaster shock and the lagged high-buffer indicator on cumulative log human capital growth by income group. The reported coefficient measures the difference in the cumulative human capital response between high-buffer and low-buffer observations. The regressions are based on Equation 2 and include treatment leads corresponding to each forecast horizon, as well as two lags of both the treatment and outcome variables. All control variables are included with a one-year lag. The continuous buffer variable is included with a one-year lag. Country and year fixed effects are included. Summary statistics are based on the  $h = 1$  estimation sample. Standard errors are clustered at the country level, report in the parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table A.14: Local Projections: GDP per capita response to climate shocks; Robustness check: Alternative Climate Shock Definitions

| Horizon                | Core 4: Core 3 +<br>Extreme Temperature | All Climate Disasters<br>Excl. Wildfires | All Climate<br>Disasters |
|------------------------|-----------------------------------------|------------------------------------------|--------------------------|
| Horizon 1              | 0.0016<br>(0.0013)                      | 0.0021<br>(0.0013)                       | 0.0022<br>(0.0013)       |
| Horizon 2              | 0.0025<br>(0.0023)                      | 0.0035<br>(0.0024)                       | 0.0033<br>(0.0024)       |
| Horizon 3              | 0.0078**<br>(0.0031)                    | 0.0082**<br>(0.0032)                     | 0.0077**<br>(0.0033)     |
| Horizon 4              | 0.0079**<br>(0.0035)                    | 0.0079**<br>(0.0037)                     | 0.0076**<br>(0.0037)     |
| Horizon 5              | 0.0071*<br>(0.0042)                     | 0.0067<br>(0.0043)                       | 0.0066<br>(0.0044)       |
| Horizon 6              | 0.0097**<br>(0.0043)                    | 0.0096**<br>(0.0044)                     | 0.0095**<br>(0.0045)     |
| Horizon 7              | 0.0129***<br>(0.0047)                   | 0.0133***<br>(0.0049)                    | 0.0133***<br>(0.0049)    |
| Horizon 8              | 0.0135**<br>(0.0052)                    | 0.0138**<br>(0.0054)                     | 0.0141**<br>(0.0054)     |
| Horizon 9              | 0.0119**<br>(0.0055)                    | 0.0120**<br>(0.0056)                     | 0.0123**<br>(0.0056)     |
| Horizon 10             | 0.0099<br>(0.0062)                      | 0.0096<br>(0.0062)                       | 0.0100<br>(0.0062)       |
| Within R-squared       | 0.1487                                  | 0.1487                                   | 0.1486                   |
| Number of Countries    | 155                                     | 155                                      | 155                      |
| Number of Observations | 6,072                                   | 6,072                                    | 6,072                    |

Notes: The table presents local projection estimates of the effect of alternative climatic disasters shock definitions on cumulative GDP per capita growth. All control variables are included with a one-year lag, except population growth, which enters contemporaneously. The regressions are based on Equation 1 and include treatment leads corresponding to each forecast horizon, as well as two lags of both the treatment and the outcome variables. Country and year fixed effects are included. Summary statistics are based on the h=1 estimation sample. Standard errors are clustered at the country level, report in the parentheses. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01

Table A.15: Local Projections: Human capital response to climate shocks, Robustness check: Alternative Climate Shock Definitions

| Horizon                | Core 4: Core 3 + Extreme Temperature | All Climate Disasters Excl. Wildfires | All Climate Disasters |
|------------------------|--------------------------------------|---------------------------------------|-----------------------|
| Horizon 1              | -0.0002*<br>(0.0001)                 | -0.0002*<br>(0.0001)                  | -0.0002*<br>(0.0001)  |
| Horizon 2              | -0.0001<br>(0.0002)                  | -0.0002<br>(0.0002)                   | -0.0001<br>(0.0002)   |
| Horizon 3              | -0.0001<br>(0.0004)                  | -0.0001<br>(0.0004)                   | -0.0001<br>(0.0004)   |
| Horizon 4              | -0.0003<br>(0.0005)                  | -0.0003<br>(0.0005)                   | -0.0002<br>(0.0005)   |
| Horizon 5              | -0.0007<br>(0.0006)                  | -0.0005<br>(0.0007)                   | -0.0004<br>(0.0007)   |
| Horizon 6              | -0.0007<br>(0.0007)                  | -0.0006<br>(0.0007)                   | -0.0005<br>(0.0007)   |
| Horizon 7              | -0.0008<br>(0.0008)                  | -0.0005<br>(0.0008)                   | -0.0005<br>(0.0008)   |
| Horizon 8              | -0.0008<br>(0.0009)                  | -0.0005<br>(0.0009)                   | -0.0005<br>(0.0009)   |
| Horizon 9              | -0.0011<br>(0.0010)                  | -0.0008<br>(0.0010)                   | -0.0007<br>(0.0010)   |
| Horizon 10             | -0.0012<br>(0.0011)                  | -0.0008<br>(0.0011)                   | -0.0008<br>(0.0011)   |
| Within R-squared       | 0.3126                               | 0.3125                                | 0.3125                |
| Number of Countries    | 135                                  | 135                                   | 135                   |
| Number of Observations | 5,773                                | 5,773                                 | 5,773                 |

Notes: The table presents local projection estimates of the effect of alternative climatic disasters shock definitions on cumulative human capital growth. All control variables are included with a one-year lag. The regressions are based on Equation 1 and include treatment leads corresponding to each forecast horizon, as well as two lags of both the treatment and the outcome variables. Country and year fixed effects are included. Summary statistics are based on the  $h=1$  estimation sample. Standard errors are clustered at the country level, report in the parentheses. \*  $p<0.10$ , \*\*  $p<0.05$ , \*\*\*  $p<0.01$

Table A.16: Local Projections: GDP per capita response to climate shocks; Robustness check: Different regression specifications.

| Horizon                | Fixed h=10 sample     | Random Effects        | Pooled OLS            |
|------------------------|-----------------------|-----------------------|-----------------------|
| Horizon 1              | 0.0027*<br>(0.0015)   | 0.0018<br>(0.0012)    | 0.0018<br>(0.0012)    |
| Horizon 2              | 0.0032<br>(0.0028)    | 0.0023<br>(0.0019)    | 0.0023<br>(0.0019)    |
| Horizon 3              | 0.0081**<br>(0.0036)  | 0.0077***<br>(0.0026) | 0.0077***<br>(0.0026) |
| Horizon 4              | 0.0073*<br>(0.0040)   | 0.0075**<br>(0.0031)  | 0.0075**<br>(0.0031)  |
| Horizon 5              | 0.0069<br>(0.0047)    | 0.0077**<br>(0.0038)  | 0.0075*<br>(0.0038)   |
| Horizon 6              | 0.0096**<br>(0.0046)  | 0.0102**<br>(0.0041)  | 0.0099**<br>(0.0043)  |
| Horizon 7              | 0.0141***<br>(0.0049) | 0.0145***<br>(0.0043) | 0.0149***<br>(0.0046) |
| Horizon 8              | 0.0144***<br>(0.0054) | 0.0151***<br>(0.0048) | 0.0158***<br>(0.0053) |
| Horizon 9              | 0.0137**<br>(0.0057)  | 0.0133***<br>(0.0051) | 0.0134**<br>(0.0060)  |
| Horizon 10             | 0.0130**<br>(0.0063)  | 0.0113**<br>(0.0057)  | 0.0113*<br>(0.0065)   |
| Within R-squared       | 0.0920                | 0.1379                | N/A                   |
| Number of Countries    | 150                   | 155                   | 155                   |
| Number of Observations | 4,742                 | 6,072                 | 6,072                 |

Notes: The table presents local projection estimates of the effect of a climatic disasters shock on cumulative GDP per capita growth introducing different robustness regression specifications. All control variables are included with a one-year lag, except population growth, which enters contemporaneously. The regressions are based on Equation 1 and include treatment leads corresponding to each forecast horizon, as well as two lags of both the treatment and the outcome variables. Country and year fixed effects are included. Summary statistics are based on the h=1 estimation sample. Standard errors are clustered at the country level, report in the parentheses. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01

Table A.17: Local Projections: Human capital response to climate shocks, Robustness check: Different regression specifications

| Horizon                | Fixed h=10 sample    | Random Effects        | Pooled OLS            |
|------------------------|----------------------|-----------------------|-----------------------|
| Horizon 1              | -0.0002*<br>(0.0001) | -0.0003**<br>(0.0001) | -0.0003**<br>(0.0001) |
| Horizon 2              | -0.0002<br>(0.0003)  | -0.0001<br>(0.0002)   | -0.0001<br>(0.0002)   |
| Horizon 3              | -0.0003<br>(0.0004)  | 0.0001<br>(0.0003)    | 0.0001<br>(0.0003)    |
| Horizon 4              | -0.0006<br>(0.0005)  | 0.0002<br>(0.0004)    | 0.0002<br>(0.0004)    |
| Horizon 5              | -0.0010<br>(0.0007)  | 0.0000<br>(0.0006)    | 0.0000<br>(0.0006)    |
| Horizon 6              | -0.0010<br>(0.0007)  | 0.0001<br>(0.0007)    | 0.0004<br>(0.0007)    |
| Horizon 7              | -0.0011<br>(0.0008)  | 0.0001<br>(0.0008)    | 0.0005<br>(0.0008)    |
| Horizon 8              | -0.0011<br>(0.0009)  | 0.0001<br>(0.0008)    | 0.0007<br>(0.0008)    |
| Horizon 9              | -0.0011<br>(0.0010)  | -0.0001<br>(0.0009)   | 0.0009<br>(0.0010)    |
| Horizon 10             | -0.0012<br>(0.0011)  | -0.0000<br>(0.0010)   | 0.0011<br>(0.0011)    |
| Within R-squared       | 0,4763               | 0,2935                | N/A                   |
| Number of Countries    | 131                  | 135                   | 135                   |
| Number of Observations | 4,607                | 5,773                 | 5,773                 |

Notes: The table presents local projection estimates of the effect of a climatic disasters shock on cumulative human capital growth introducing different robustness regression specifications. All control variables are included with a one-year lag. The regressions are based on Equation 1 and include treatment leads corresponding to each forecast horizon, as well as two lags of both the treatment and the outcome variables. Country and year fixed effects are included. Summary statistics are based on the h=1 estimation sample. Standard errors are clustered at the country level, report in the parentheses. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01