

Natural Disasters and Financial Stress: Can Macroprudential Regulation Tame Green Swans?

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ABSTRACT

We empirically investigate the impact of natural disasters on the external finance premium (EFP), conditional on the stringency of macroprudential regulation. The intensity of natural disasters is measured through an original set of geophysical indicators for a sample of 88 countries over the period 1996-2016. Using local projections, we show that, following storms, the EFP significantly rises (drops) when macroprudential regulation is lax (stringent). This suggests that regulated financial systems could foster favorable financing conditions to replace destroyed capital with more productive capital. Macroprudential stringency seems less crucial in the case of floods, which are more predictable and thus may prompt self-discipline.

Keywords: Financial Stress, External Finance Premium, Macroprudential Policy, Natural Disasters, Local Projections.

JEL classification: E43, E5, Q54, C23.

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NON-TECHNICAL SUMMARY

Banks and other financial institutions are exposed and vulnerable to natural disasters (NDs), whose frequency and intensity are increasing with climate change. The impact of NDs on financial systems remains largely unexplored. In the same time, financial shocks and crises have motivated the implementation of macroprudential (MP) measures. Whereas, thus far, these policies have been introduced independently of the growing importance of climate-related financial risks, they may help to cope with them.

Against this background, the objective of this paper is to investigate the financial impact of natural disasters (NDs), characterized by their physical intensity, and to empirically assess the extent to which it might be mitigated by a stringent macroprudential framework.

We use the local projections (LP) method to estimate the financial impact of natural disasters, conditionally to the degree of stringency of the national macroprudential framework. Financial stress is proxied by the change in the external finance premium (EFP), i.e., the spread between the bank lending rate and the riskless interest rate. NDs are gauged by meteorological intensity of storms and floods, with the data being collected from different sources stemming from meteorological stations and satellites. Our measure of prudential stringency refers to the number of macroprudential instruments that have actually been implemented in each country.

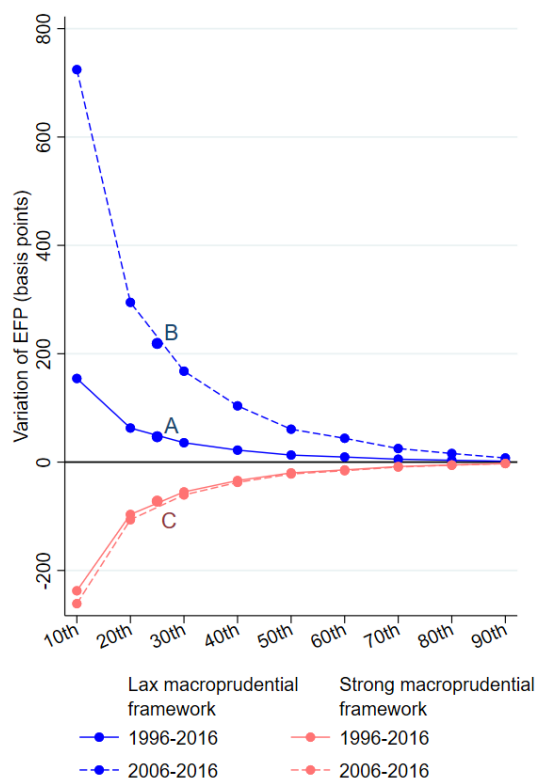


Figure 1 - Reaction of the external financial premium to a Katrina-like hurricane

Note: This figure represents the variation in the external finance premium (EFP) two years after a Katrina-like storm, depending on the size of the country, in terms of surface area. The x-axis represents the percentiles of country area. The blue (red) lines refers to a lax (strong, resp.) macroprudential framework. The solid (dotted) lines deals with the period from 1996 (2006) to 2016.

Our results, based on a panel of 88 countries over the period 1996-2016, show that storms significantly impact the EFP at the national level, with opposite effects depending on the stringency of the macroprudential framework. A relatively small country (corresponding to the first quartile of the country size distribution in terms of surface area) with a lax macroprudential framework would suffer the largest rise in domestic EFP – of 44 basis points (bps) two years after a Katrina-like hurricane, as shown below by the point A in Figure 1. This deterioration in financing conditions persists beyond 3 years, which suggests a large overall impact in the long run. Importantly, we find that this impact is stronger if estimated over the recent period: when focusing on the data for the second decade of our sample, the estimated hike reaches 219 bps (i.e. point B). By contrast, a small country with a stringent macroprudential framework could benefit from a decrease in the EFP of approximately 67 bps (i.e. point C) two years after a category 5 hurricane.

One potential explanation for the decreasing spread in the case of a stringent macroprudential framework is that an initially healthy financial environment fosters favorable financing conditions to replace destroyed capital with more productive capital. Further investigations suggest that this is precisely the case for middle-income countries, which can be presumed to have sufficient absorption capacity to fully exploit new facilities.

Finally, our results on the financial effects of flooding are not conclusive. As floods are usually clearly located along rivers and coasts, they are also more foreseeable. Hence, this may induce spontaneous discipline and greater insurance coverage, which could render macroprudential measures less crucial.

Catastrophes naturelles et instabilité financière : la réglementation macroprudentielle peut-elle dompter les cygnes verts ?

RÉSUMÉ

Nous étudions empiriquement l'impact des catastrophes naturelles sur la prime de financement externe (PFE), conditionnellement à la rigueur de la réglementation macroprudentielle. L'intensité des catastrophes naturelles est mesurée par des indicateurs géophysiques, sur un échantillon de 88 pays et pour la période 1996-2016. En utilisant la méthode des projections locales, nous montrons que, suite à des tempêtes, la PFE augmente (diminue) de manière significative lorsque le cadre macroprudentiel est laxiste (rigoureux). Cela suggère que les systèmes financiers rigoureusement régulés favoriseraient le remplacement du capital détruit par du capital plus productif à des conditions de financement relativement avantageuses. La politique macroprudentielle semble être moins cruciale pour ce qui concerne l'impact financier des inondations, dont la prévisibilité pousserait à l'autodiscipline.

Mots-clés : instabilité financière, prime de financement externe, politique macroprudentielle, catastrophes naturelles, projections locales.

Codes JEL : E43, E5, Q54, C23.

Les Documents de travail reflètent les idées personnelles de leurs auteurs et n'expriment pas nécessairement la position de la Banque de France. Ils sont disponibles sur publications.banque-france.fr

1 Introduction

While the adverse real economic effects of climate change are now widely acknowledged, its impact on financial systems remains largely unexplored. However, banks and other financial institutions are particularly exposed to physical risks related to climate change damages. They are especially vulnerable to “green swan events”: these are climate hazards that occur outside the normal range of expected events, with increasing frequency and severity. The financial sector may be strongly affected by these hazards that may rise above traditional economic shocks or financial crises. Recently, the latter have motivated the implementation of macroprudential (MP) measures. Whereas, thus far, these policies have been introduced independently of the growing importance of climate-related financial risks, they may help to cope with them.¹

Against this background, the objective of this paper is to investigate the financial impact of natural disasters (NDs), and to empirically assess the extent to which it might be mitigated by a stringent macroprudential framework.

In line with the literature on financial frictions, market failures and crises, *financial stress* can be associated with increasing information asymmetries in lending activity, which is conducive to a rise in agency and risk premiums. Identifying how NDs can theoretically induce financial stress is a prerequisite for our empirical analysis. Hence, as a first step of our investigation, we highlight different channels through which NDs may generate financial stress: a high probability of negative wealth effects, the deterioration of banks and borrowers’ balance sheets, and an increase in credit and sovereign risks. The transmission and amplification of NDs effects through these mechanisms might nonetheless be mitigated by a restrictive macroprudential framework. Indeed, if household debt is brought under control, if banks are highly capitalized, if they have sufficient reserves, and if they are not excessively leveraged, any shock to (collateralized) financial or real assets might be smoother than in a situation in which macroprudential regulation is absent or less binding.

To estimate the financial impact of natural disasters, conditional on the degree of stringency of the national macroprudential framework, we use the local projection (LP) method. Financial stress is proxied by the external finance premium (EFP), i.e., the spread between the bank lending rate and the riskless interest rate, in line with the literature that captures financial stress through interest rate spreads (Bernanke et al., 1999; Gilchrist and Zakrajsek, 2012; Christiano et al., 2014). NDs are gauged by meteorological intensity, with the data being collected from different sources stemming from meteorological stations and satellites. The original dataset that we construct focuses on two types of NDs, storms and floods, which are the two most frequent and damaging climate events.² Storm events are gauged with respect to the maximum wind speed registered in the affected areas. The intensity of flooding is measured by rainfall deviation with respect to the long-term average rainfall in affected areas. These two measures are normalized by the country area and correspond to the first category of ND indicators we build. Furthermore, they are augmented by population density, to consider a (exogenous) factor of exposure: these new indexes are our second indicators of NDs. Overall, these measures of severity are well suited for causal empirical analysis, contrary to damage-based data, which are more prone to endogeneity issues. Finally, our measure of prudential stringency refers to the

¹To the best of our knowledge macroprudential frameworks had never previously been officially developed to address climate-related financial risks. Initiatives intended to take account for climate risks in finance are very recent. For example, the Network for Greening the Financial System (NGFS), which promotes “*the development of climate risk management in the financial sector*”, was created at the end of 2017.

²Conversely, chronic global risks such as rising sea levels and increasing temperatures have a real and financial impact that is much more gradual over time.

number of macroprudential instruments that have actually been implemented in each country. This “extensity” measure of stringency is based on the recent integrated Macroprudential Policy (iMaPP) database, which provides comprehensive coverage in terms of macroprudential instruments, countries, and time periods.

Our results, based on a panel of 88 countries over the period 1996-2016, show that storms, while affecting only one or several regions within a country, significantly impact the EFP at the national level and do so in opposite ways depending on the stringency of the macroprudential framework. According to our estimates, a relatively small country (corresponding to the first quartile of the country size distribution) with a lax macroprudential framework would suffer the largest rise in domestic EFP – of 44 basis points (bps) – two years after a Katrina-like hurricane. This deterioration in financing conditions persists beyond 3 years, which suggests a large overall impact in the long run. Importantly, we find that this impact is stronger if estimated over the recent period: when focusing on the data for the second decade of our sample, the estimated hike reaches 219 bps. By contrast, a small country with a stringent macroprudential framework could benefit from a decrease in the EFP of approximately 67 bps two years after a category 5 hurricane. One potential explanation is that an initially healthy financial environment fosters favorable financing conditions to replace destroyed capital with more productive capital. Further investigations suggest that this is precisely the case for middle-income countries, which can be presumed to have sufficient absorption capacity to fully exploit new facilities. On the contrary, credit conditions worsen in low-income countries irrespective of the stringency of their macroprudential framework. Last, high-income countries with stringent macroprudential policy do not significantly benefit from a drop in the EFP following storms, possibly because no substantial technological leap is expected if new replacement capital is used. Nonetheless, they have to bear an increasing EFP in the case of a lax macroprudential framework.

Finally, our results regarding the financial effects of flooding are not conclusive. As floods are usually clearly located along rivers and coasts, they are also more foreseeable. Hence, this may induce spontaneous discipline (risk avoidance) and greater insurance coverage, which could render macroprudential measures less crucial.

Through this study we connect two strands of literature that have henceforth been distant from one another: the impact of natural disasters and the benefits of macroprudential policy. On the one hand, there is a rich literature on the impact of NDs on the real sector of the economy³. While the negative economic effects of catastrophes appear to increase over time (Klomp and Valckx, 2014), some structural features such as the level of development and the quality of institutions could act as mitigating factors (Kahn, 2005; Loayza et al., 2012). However, the impact of NDs on the financial sector is much less documented. Basic intuitions and warnings are increasingly disseminated by international institutions and central banks. Nonetheless, we still lack clear-cut quantitative evaluations of the consequences of climate-induced financial shocks, especially at the macroeconomic level. Some studies report that local bank performance deteriorated (Berg and Schrader, 2012; Klomp, 2014; Schuwer et al., 2019) or that a possible durable contraction of credit was registered (Noy, 2009; Horvath, 2021). However, others emphasize the existence of a Schumpeterian creative destruction effect in affected regions, with recovery lending⁴ driven by investment opportunities in physical capital (Skidmore and Toya, 2002; Crespo Cuaresma et al., 2008; Cavallo et al., 2013; Klomp, 2017).

On the other hand, our research addresses the growing literature on the macroeconomic effects

³See the surveys of Cavallo and Noy (2011) and Botzen et al. (2019), as well as the meta-analysis of Lazzaroni and van Bergeijk (2014).

⁴See, e.g., the microeconomic investigation of Cortés and Strahan (2017).

of macroprudential policy. The benefits of macroprudential measures are already highlighted by the theoretical literature (Farhi and Werning, 2016; Korinek and Simsek, 2016; Bianchi and Mendoza, 2018), especially in a context of low interest rates. Empirical studies tend to confirm that macroprudential measures reduce risks by cleaning balance-sheets (Vandenbussche et al., 2015; Cerutti et al., 2017; De Jonghe et al., 2020).

Our contribution is manifold with respect to these two branches of the literature. First, we theoretically identify key channels through which an ND can cause financial stress. Second, we propose a quantitative macroeconomic evaluation of the effects of NDs on the external finance premium. Third, to this end, we build two new sets of ND indicators based on physical intensity, hazard and exposure. We do this by exploiting granular information from meteorological stations and satellites. Fourth, to the best of our knowledge, we are the first to regard macroprudential tools as possible mitigating features of climate-induced financial shocks. Fifth, by building a bridge between two hitherto independent research avenues, this paper is the first to address the ability of macroprudential policy to ensure the resilience to shocks that are exogenous, which is always a challenge in economics.⁵

The rest of the paper is organized as follows. Section 2 highlights the different transmission mechanisms through which NDs can generate financial stress and theoretically explains how the macroprudential framework can dampen the financial impact of NDs. Our empirical methodology is described in Section 3. Data are presented in Section 4. The results are reported and discussed in Section 5. Several robustness checks on the baseline results are presented in Section 6. Section 7 proposes further extensions of our results. Section 8 concludes.

2 The financial impact of natural disasters and the role of macroprudential regulation

The aim of our empirical approach is to assess the overall financial effect of NDs. We do not seek to identify the contribution of any particular transmission channel: as there are multiple channels that vary in importance over time and across countries, it is extremely difficult to assess which channel might dominate. However, it is important to pinpoint, at a more general level, the main mechanisms that could theoretically explain climate-induced financial stress. Having identified these mechanisms at stake, we then explain how prudential regulation, particularly macroprudential policy, can mitigate the financial impact of NDs.

2.1 How can natural disasters impact credit conditions?

Referring to the literature on the transmission channels of financial shocks, we highlight five theoretical mechanisms through which a natural disaster can generate financial stress. In practice, it is difficult to disentangle these channels within a multi-country framework at the macroeconomic level, as they may interact and reinforce one another. Nevertheless, it seems important to emphasize the theoretical underpinnings of the macro-financial effects of natural disasters and thus to theoretically justify our empirical relations. They are represented in Figure A in Appendix A.

(1) First, NDs affect land, residential and commercial property values (Stern, 2013; Bernstein et al., 2019). This reduces the collateral that households and firms have to pledge when they apply for bank loans. Furthermore, the shock induced by the ND generates more information asymmetry. This implies

⁵In this vein, Fratzscher et al. (2020) investigate the performance of inflation targeting as shock absorber in response to NDs.

higher agency premiums through the financial accelerator mechanism (Bernanke et al., 1999; Mian and Sufi, 2011; Cerqueiro et al., 2016) and possibly triggers a Fisherian debt-deflation mechanism.⁶

(2) Moreover, NDs destroy physical capital (see, e.g. Fankhauser and Tol, 2005). Combined with supply-chain breaks (Carvalho et al., 2020), this induces uncertainty and lower production for firms.⁷ The inherent lower profits are conducive to a reduction in firms' debt service capability. This entails higher credit risk.

(3) By lowering the actual and expected profitability of firms, NDs may cause a decline in equity prices. In addition to the slump in real estate prices, this induces negative wealth effects for households (Campbell and Cocco, 2007; Carroll et al., 2011), which impairs their credit worthiness.

(4) The banking sector may also be highly affected by NDs. First, a drop in stock prices has a negative impact on the value of equity portfolios held by banks. Furthermore, the deterioration of economic activity increases non-performing loans (Klomp, 2014; Dafermos et al., 2018). Moreover, banks may suffer from missing savings and immediate withdrawals of deposits used to replace lost physical assets and finance medical care (Brei et al., 2019). Given a maturity mismatch, this worsens liquidity risk. Last, banks themselves are exposed to an operational risk, as NDs may destroy their offices, equipment and information systems. As a consequence, large-scale NDs may significantly increase the likelihood of bank default (Klomp, 2014). Hence, banks have to bear higher funding costs, which they ultimately pass on to firms' credit conditions, as depicted by the bank capital channel (Levieuge, 2009; Gertler and Karadi, 2011). From this perspective, an ND can be regarded as a loan supply shock, which negatively affects private investment (Hosono et al., 2016) and may impair the recovery of the economy.⁸

(5) Finally, NDs lead to an increase in government spending, dedicated to emergency assistance and financial help, for the reconstruction of public infrastructures, medical services, and the bailout of insolvent banks (Lamperti et al., 2019). Since tax revenue also decreases, public debt increases, as does the risk of sovereign debt default (Melecky and Raddatz, 2014; Klomp, 2017; Lamperti et al., 2019).⁹ Interestingly, the sovereign risk and banks' balance sheet adjustments are strongly linked, through a so-called "diabolic" or "doom loop" (Brunnermeier et al., 2016; Farhi and Tirole, 2018). A deterioration of sovereign creditworthiness reduces the market value of banks' holdings of domestic sovereign debt. This reduces the perceived solvency of domestic banks and increases the perceived risk that banks will have to be bailed out by the government. This further worsens sovereign distress.

These five key transmission channels predict an increase in bank lending rates in the wake of an ND, particularly due to the increases in the agency and risk premiums.¹⁰ Further, we analyze how

⁶This channel may explain the relatively stronger effects of NDs in developing countries, where information asymmetry is initially stronger and credit worthiness lower (McDermott et al., 2013).

⁷Baker et al. (2020) find that higher uncertainty – proxied by NDs – lowers growth. Furthermore, Di Tella (2017) shows that weak balance sheets amplify the effects of the uncertainty shocks, further depressing investment and asset prices in a two-way feedback loop. See Weitzman (2009) for further developments on uncertainty about climate change damages.

⁸More generally, see Chava and Purnanandam (2011) and Amiti and Weinstein (2018) for evidence on the impact of idiosyncratic bank shocks on lending conditions.

⁹As a result, Cevik and Jalles (2020) find that (especially developing) countries with greater vulnerability to climate change pay a higher interest rate on government bonds. At local level, Painter (2020) also finds that an increase in climate risk is associated with an increase in the issuance costs of municipal bonds.

¹⁰The results in the literature regarding credit volume are rather mixed. Several studies report a contraction of credit (Noy, 2009; Berg and Schrader, 2012). On the contrary, Cortés and Strahan (2017), Schuwer et al. (2019) and Koetter et al. (2020) find evidence of recovery lending, especially by local banks. The latter usually have superior local knowledge, notably by engaging in long-term customer relationships; hence, they have an advantage in screening and monitoring local borrowers, as well as in pricing new loans despite depressed collateral values (see, e.g., Berger et al., 2005; Agarwal and Hauswald, 2010). Moreover, as credit supply may have positive externalities on local house prices, local banks may be more prone to continue lending to an area in which they have a high share of outstanding loans (Favara and Gianetti, 2017).

this increase in financial stress can be mitigated by macroprudential regulation. To do so, we will define and characterize the macroprudential policy framework and then explain how it can limit the deepening of financial instability in case of natural disasters.

2.2 Why could macroprudential policy dampen the financial impact of natural disasters?

Macroprudential regulation has developed considerably over recent decades through the implementation of quantitative restrictions on borrowing, such as loan-to-value and debt-to-income caps, and with the development of lender-based tools such as capital, reserve and provisioning requirements and surcharges, limits on credit growth, Pigouvian levies, etc.¹¹ These policy tools are intended to protect economies from market failures and externalities related to the activity of financial intermediaries (De Nicolo et al., 2012). They are therefore expected to mitigate financial stress.¹² This is supported by a growing empirical literature, which shows that macroprudential tools are effective in curbing credit cycles, mitigating asset prices fluctuations, and reducing bank risk.¹³

Overall, stringent macroprudential regulation strengthens the resilience of the financial sector by reinforcing balance sheets, restricting risk-taking, reducing leverage, and limiting foreign currency exposure. In such a context, any shock to (possibly pledged) financial or real assets that is likely to worsen financial frictions may have a higher impact in a country where macroprudential regulation is absent or less stringent. Hence, we can expect that an economy with a sound banking sector is likely to better resist to the financial impacts of natural disasters. Moreover, a stringent macroprudential framework allows central banks to respond counter-cyclically to shocks: otherwise, they might be reluctant to cut policy rates when financial conditions tighten, to preserve the stability of the exchange rate and capital flows. Prudential requirements also make economies less sensitive to capital flows (Bergant et al., 2020), which is salutary in the aftermath of an ND.

Finally, macroprudential regulation may even prompt an easing of credit conditions in the wake of an ND. Indeed, a sound financial system may support the short-run recovery by reducing the procyclicality of lending standards, reducing uncertainty and fostering the funding of reconstruction (Cortés and Strahan, 2017; Schuwer et al., 2019). This may tame financial tensions. Furthermore, by financing the replacement of capital by more modern and more productive technologies, a resilient banking sector supports medium- and long-term growth; the higher inherent expected productivity is conducive to more lending opportunities and easier funding conditions. On the contrary, in the absence of macroprudential measures, an affected economy may suffer from highly deteriorated financial conditions, and enter a disaster-related poverty trap (Hallegatte and Dumas, 2009).

Against this background, the next section presents the methodology that we use to examine the impact of NDs on the external finance premium, conditional on the stringency of macroprudential regulation.

¹¹See Cerutti et al. (2017) and Alam et al. (2019) for a broad assessment of macroprudential tools.

¹²See, for instance, Farhi and Werning (2016), Korinek and Simsek (2016), and Bianchi and Mendoza (2018) who theoretically demonstrate the efficiency of macroprudential regulation.

¹³See, for example, the evidence provided by Vandebussche et al. (2015), Jiménez et al. (2017), Altunbas et al. (2018), Akinci and Olmstead-Rumsey (2018) and Araujo et al. (2020), who consider different policy instruments and targeted variables.

3 Methodology

We denote $D_{i,t}^d$ the variable representing the intensity of a natural disaster d occurring in a country i at time t . The natural disaster d can be associated, alternatively, either with a storm or a flood. We thus are able to capture different disaster types and their potential heterogeneous effects on financial stability. More specifically, $D_{i,t}^d$ is defined as a continuous variable representing the physical intensity, or exposure, associated with a natural disaster d , with $D_{i,t}^d > 0$ if a disaster d occurs and $D_{i,t}^d = 0$ otherwise. Once we control for the geographical position and size of country i , which can influence the occurrence and geophysical intensity of NDs, $D_{i,t}^d$ can be considered as a treatment (or event) variable, with random assignment. In a panel setting, individual fixed effects may control for geographical characteristics that are correlated with the incidence of natural hazards. We denote by $Y_{i,t}$ the dependent variable for country i at time t . In our analysis, Y will represent the external finance premium (EFP), i.e., the spread between the lending interest rate and the risk-free interest rate (details are provided below). By definition, the average treatment effect (ATE) of a natural disaster d on the evolution of $Y_{i,t}$ with respect to its pre-shock value, $Y_{i,t-1}$, is

$$\text{ATE} = \mathbb{E}_t \left[\mathbb{E}_t \left(Y_{i,t} - Y_{i,t-1} \mid D_{i,t}^d > 0; \Omega_t \right) - \mathbb{E}_t \left(Y_{i,t} - Y_{i,t-1} \mid D_{i,t}^d = 0; \Omega_t \right) \right] \quad (1)$$

with \mathbb{E}_t denoting the mathematical expectation operator upon the global information set available at time t (denoted Ω_t). The estimated ATE at time t is equivalent to $\hat{\beta}$, the estimator of β in the following simple linear model:

$$Y_{i,t} - Y_{i,t-1} = \alpha_i + \beta D_{i,t}^d + \varepsilon_{i,t} \quad (2)$$

where α_i are country fixed effects and $\varepsilon_{i,t}$ the residuals. We make the reasonable assumption that residuals are uncorrelated with shocks once geographical features are controlled for through country fixed effects. This corresponds to the conditional independence assumption (CIA): conditional on a set of covariates the potential outcomes are independent of the allocation of the treatment. Moreover, including control variables $Z_{i,t}$ in (2) is recommended to improve efficiency.

As a shock can have lasting effects that can differ in intensity over time, it is interesting to assess the ATE at different successive horizons, corresponding to quarters in our case. The ATE of an ND on the evolution of $Y_{i,t}$ can be obtained with impulse responses by comparing the variable from the period before the shock occurred ($t-1$) to the quarters $t+h$, for $h = 0, 1, 2, \dots, H$, such that:

$$\mathcal{R}(h) = \mathbb{E}_t \left[\mathbb{E}_t \left(Y_{i,t+h} - Y_{i,t-1} \mid D_{i,t}^d > 0, Z_{i,t}; \Omega_t \right) - \mathbb{E}_t \left(Y_{i,t+h} - Y_{i,t-1} \mid D_{i,t}^d = 0, Z_{i,t}; \Omega_t \right) \right] \quad (3)$$

In line with [Jordà \(2005\)](#) and [Jorda et al. \(2013\)](#), among others, we use local projections (LPs) to approximate ATEs at different horizons, such that

$$Y_{i,t+h} - Y_{i,t-1} = \alpha_{i,h} + \beta_h D_{i,t}^d + \theta_h Z_{i,t} + \varepsilon_{i,t+h} \quad (4)$$

In this configuration, we have $\mathbb{E}_t \left(Y_{i,t+h} - Y_{i,t-1} \mid D_{i,t}^d > 0, Z_{i,t} \right) = \alpha_{i,h} + \beta_h D_{i,t}^d + \mathbb{E}_t \left(\varepsilon_{i,t+h} \mid D_{i,t}^d > 0, Z_{i,t} \right)$, and $\mathbb{E}_t \left(Y_{i,t+h} - Y_{i,t-1} \mid D_{i,t}^d = 0, Z_{i,t} \right) = \alpha_{i,h} + \mathbb{E}_t \left(\varepsilon_{i,t+h} \mid D_{i,t}^d = 0, Z_{i,t} \right)$. Under the CIA, we note that $\mathbb{E}_t \left(\varepsilon_{i,t+h} \mid D_{i,t}^d > 0, Z_{i,t} \right) = \mathbb{E}_t \left(\varepsilon_{i,t+h} \mid D_{i,t}^d = 0, Z_{i,t} \right) = 0$. Thus, the ATE of natural disasters on the evolution of Y_i , considering h periods after the beginning of the shock, is given by:

$$\mathcal{R}(h) = \beta_h, \quad \forall h \quad (5)$$

Then, we denote by $P_{i,t-1}$ the macroprudential context prevailing in country i at time $t-1$. $P_{i,t-1}$ is an indicator variable equal to 1 in the case of stringent macroprudential regulation and 0 otherwise. The definition of stringency is explained in the next section. The impact of a natural disaster on $Y_{i,t+h}$, conditional on the macroprudential environment, is gauged by the following interactive model:

$$Y_{i,t+h} - Y_{i,t-1} = \alpha_{i,h} + \beta_h D_{i,t}^d + \gamma_h [D_{i,t}^d \times P_{i,t-1}] + \omega_h P_{i,t-1} + \theta_h Z_{i,t} + \varepsilon_{i,t+h} \quad (6)$$

As before, we note that $\mathbb{E}_t(Y_{i,t+h} - Y_{i,t-1} | D_{i,t}^d = 0, Z_{i,t}) = \alpha_{i,h} + \omega_h \mathbb{E}_t(P_{i,t-1} | D_{i,t}^d = 0, Z_{i,t})$, while $\mathbb{E}_t(Y_{i,t+h} - Y_{i,t-1} | D_{i,t}^d > 0, Z_{i,t}) = \alpha_{i,h} + \beta_h D_{i,t}^d + \gamma_h \mathbb{E}_t(P_{i,t-1} | D_{i,t}^d > 0, Z_{i,t}) D_{i,t}^d + \omega_h \mathbb{E}_t(P_{i,t-1} | D_{i,t}^d > 0, Z_{i,t})$. As macroprudential frameworks are primarily established to deal with macro-financial imbalances, we can reasonably assume that having a stringent macroprudential framework or not is independent of the occurrence of an ND at time t . For instance, the recommendations of the Basel Committee on Banking Supervision have, since the 1980s, been motivated primarily by major financial and banking crisis, never by NDs *per se*. At most, NDs have very recently started to be a concern for macroprudential authorities, which have included climate risks in banking stress tests.¹⁴, albeit without reforming the macroprudential framework. This implies that $\mathbb{E}_t(P_{i,t-1} | D_{i,t}^d > 0, Z_{i,t}) = \mathbb{E}_t(P_{i,t-1} | D_{i,t}^d = 0, Z_{i,t}) = P_{i,t-1}$.¹⁵ Hence, the ATE derived from equation (6), designating the impact of natural disasters on Y at quarter h , conditional on the stringency of macroprudential regulation, is equal to:

$$\mathcal{R}_P(h) = \beta_h + \gamma_h P_{i,t-1} \quad (7)$$

Finally, we add L lags of the dependent variable and a set of one-year (four-quarter) lagged control variables ($X_{i,t-4}$) capturing macroeconomic and financial characteristics (see the next section for details). In addition, time fixed effects ($\tau_{h,t}$) are introduced to control for common trends. In particular, they should capture the global downward trend in the natural rate of interest (Holston et al., 2017) which has led to a decline in lending rates and a reduction in intermediation margins, especially after 2008. They may also capture the impact of the increasing use of macroprudential measures over time. Moreover, we add forward values of NDs inside the projection horizon to avoid downward bias, following the recommendations of Teulings and Zubanov (2014). We also control for the possible occurrence of banking crises over the horizon of evaluation ($C_{i,t+h-j}$), as they may explain large movements in the external finance premium that would be unrelated to any natural disaster. Hence, the model actually estimated is the following:

$$Y_{i,t+h} - Y_{i,t-1} = \alpha_{i,h} + \beta_h D_{i,t}^d + \gamma_h [D_{i,t}^d \times P_{i,t-1}] + \omega_h P_{i,t-1} + \sum_{l=1}^L \rho_h \Delta Y_{i,t-l} + \theta_h Z_{i,t-4} + \sum_{j=1}^{h-1} \delta_h D_{i,t+h-j}^d + \sum_{j=1}^{h-1} \eta_h C_{i,t+h-j} + \tau_{h,t} + \varepsilon_{i,t+h}, \quad (8)$$

with robust standard errors clustered at the country level to overcome the potential problem of heteroscedastic and serially correlated standard errors due to the overlapping structure of the residuals.

¹⁴For example, the Network of central banks and supervisors for Greening the Financial System (NGFS), which in part seeks to integrate climate-related risks into supervision and financial stability monitoring, was created very recently, in December 2017.

¹⁵To ensure this hypothesis, we will consider as a robustness check only NDs for which the macroprudential regime remains the same up to 3 years after the disaster (see Section 6.1).

It is worth highlighting that local projections are relevant for our investigation, particularly in comparison with VAR models that are often used to compute impulse responses. (i) LPs are simple, as they can be estimated by standard regression techniques. (ii) LPs are flexible, in that one singular model is estimated for each projection quarter (contrary to VAR models with a fixed state-space representation). Hence, LPs are especially appropriate to address potential nonlinearities (Jordà, 2005). Such nonlinearities are possible in our case, as there might be a period of adjustment before the shock is translated to the EFP, depending on the velocity of the transmission channels represented in Fig. A. (iii) LPs are a parsimonious method for estimation and inference of the dynamics of a treatment effect, contrary to panel VAR models, the high dimensionality of which can make IRFs' estimation prohibitive (Jorda et al., 2013). Additionally, parsimony gives room for conditioning the estimation on a richer set of control variables, which may improve identification. (iv) Finally, by generating projections that are local to each forecast quarter for which the model has been estimated, LPs may be more robust than VAR models, the specification errors of which can accumulate as the projection horizon increases.

4 Data

This section describes the data we use to compute our ND indicators, characterize the macroprudential policy framework and capture financial stability and economic activity in general.

4.1 Natural disaster data

This subsection presents our two new country-level quarterly indexes of NDs. Note that in this setting, three concomitant elements make a geophysical event an ND: *hazard*, *exposure* and *vulnerability* (Yonson et al., 2018). As defined by the Intergovernmental Panel on Climate Change (Field et al., 2012), *hazard* corresponds to the occurrence of an event with a given magnitude. *Exposure* refers to the structural characteristics of the area in which a hazard occurs (e.g., population, infrastructure). *Vulnerability* concerns the propensity of exposed elements to suffer adverse effects when impacted by hazard events.

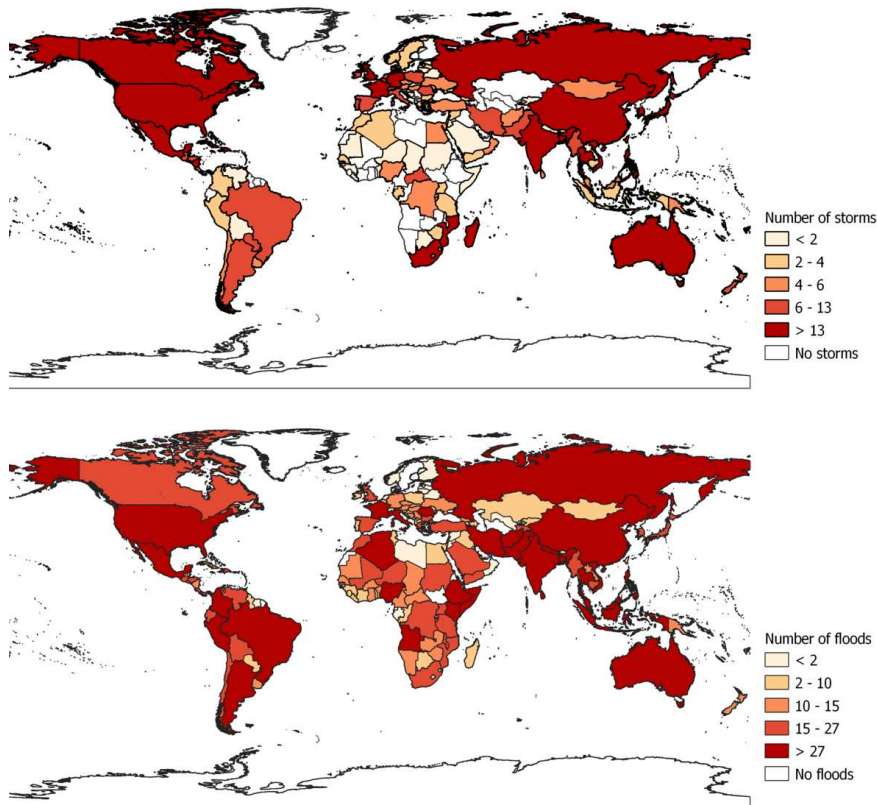
The vulnerability component entails an endogeneity dimension when investigating the economic and financial effects of an ND. Indeed, it is often measured through economic or human damages, which are strongly correlated with the economic, financial and social contexts (Noy, 2009; Felbermayr and Groschl, 2014; McDermott et al., 2013). On the contrary, the geophysical characteristics of natural hazards, such as the wind speed or quantity of precipitation, can be considered as exogenous. Hence, measures of geophysical intensity are preferred to damage-based data for causal empirical analysis (Noy, 2009; Cavallo et al., 2013; Felbermayr and Groschl, 2014). Using this perspective, many studies rely either on the binary occurrence of NDs (Klomp, 2014) or on more granular measures of geophysical intensity (Felbermayr and Groschl, 2014; Acevedo et al., 2019). However, relying solely on amplitude to define events as natural disasters is overly restrictive with regard to the three above mentioned components. In particular, it could lead to considering many insignificant climate events, whereas a relevant identification strategy requires somewhat large shocks.

Against this background, we develop and use a new dataset of NDs (i) the types, locations, and dates of which are first identified with the EM-DAT database, (ii) that are gauged by meteorological intensity measures, (iii) which are weighted by potential exposure (country size, population density). Generally, additional information about the data we use and how we combine them is provided in Appendix C. Selecting events recorded by EM-DAT as a starting point for our analysis involves con-

sidering hazards related to a certain threshold of vulnerability. Moreover, through this approach, we avoid any endogeneity problems, as the geophysical intensity of natural events obviously does not depend on financial conditions, and the identification of events by EM-DAT is not based on the financial consequences of NDs. Hence, we are unlikely to neglect important events that would have few financial effects due to the stringency of the macroprudential framework.¹⁶

Specifically, we focus on the financial impact of storms and floods, which are two of the most frequent and damaging climate events. The measure of their geophysical intensity stems from localized information recorded by satellites and meteorological stations at regional level. A region is defined as the first administrative level area within a country, in line with GADM (version 3.6) maps. While we focus on the geophysical magnitude of the events as in the influential analysis of [Felbermayr and Groschl \(2014\)](#), we extend their setting in several ways: (i) by selecting events first identified in the EM-DAT database, (ii) by adopting a bottom-up approach for assessing the amplitude of floods, with country-level indexes of geophysical intensity built from local measures, (iii) by addressing exogenous exposure (i.e., population density), and thus creating a new index, and (iv) by building quarterly, not annual, indicators. Figure 1 depicts the geographical distribution of storms and floods. We observe that all continents and countries were impacted by at least one disaster over the period 1996-2016.

Figure 1: Total number of storms and floods over the period 1996-2016



Note: The legend is determined by the percentiles of the distribution (20th, 40th, 60th, 80th).

We express the geophysical intensity of each storm in terms of wind speed. This information comes from two complementary datasets: the International Best Track Archive for Climate Stewardship (IBTrACS) provided by the National Climatic Data Center of the National Oceanic and Atmospheric

¹⁶In any case, if one were to neglect some events with consequences that would have been mitigated by macroprudential policy, our estimates would underestimate the true effects of macroprudential policy. Overly conservative estimates are preferable to the opposite.

Administration (NOAA), and the Global Surface Summary of Day (GSOD). We select the maximum wind speed recorded by the two datasets within a 5-day window before and after the day of a storm identified in EM-DAT.

The intensity of floods is gauged in terms of rainfall deviation from the long-term average precipitation of the affected areas. First, for any flood event identified by EM-DAT, we compute the total amount of monthly precipitation in the affected area by using the Global Unified Gauge-Based Analysis of Daily Precipitation dataset provided by NOAA Climate Prediction Center (CPC). This dataset gathers weather station rainfall gauge measures and satellite information. Hence, contrary to [Felbermayr and Groschl \(2014\)](#), we compute intensity at a regional level, not a national level: this is done for accuracy purposes, as floods are highly localized. Specifically, as that data are provided in millimeters for 0.5 latitude and longitude degree grid nodes (i.e., over an area of approximately 55m²), we aggregate precipitation data at the regional (first administrative) level in each country by using QGIS software and following the GADM maps (version 3.6). Last, we compute the monthly deviation of precipitation from the long-term (i.e., over the years 1990-2016) monthly regional average rainfall.

Finally, we compute quarterly and country-level indicators of geophysical intensity for storms and floods by considering the maximum intensity reported each quarter in all the country's regions, normalized by country area (denoted τ_i , expressed in 1000 km²). This normalization is justified because smaller countries might be more vulnerable if they experience extreme events ([Skidmore and Toya, 2002](#)), while larger countries are generally more likely to be affected by natural disasters. Hence, our first measure of hazard, the indicator of geophysical intensity (IGI), is defined as:

$$IGI_{i,t} = \begin{cases} \frac{\text{geophysical intensity}_{i,t}}{\tau_{i,t}} & \text{if an ND occurred in the quarter } t \text{ in country } i. \\ 0 & \text{otherwise.} \end{cases}$$

The worldwide distribution of IGI is represented in Figure [B.1](#) in Appendix [B](#).

As a refinement, we construct an additional indicator that consists of augmenting the IGI by a measure of exposure: population density (i.e., This captures the extent to which people might be affected by an ND). This augmented IGI (labeled AIGI) measures the *potential* impact of a natural hazard exogenous to financial stability. It reads as follows:

$$AIGI_{i,t} = \begin{cases} \frac{\text{geophysical intensity}_{i,t} \times \text{pop. density}_{i,t-1}}{\tau_{i,t}} & \text{if an ND occurred in the quarter } t \text{ in country } i, \\ 0 & \text{otherwise,} \end{cases}$$

where population density is rescaled to have the same range as geophysical intensity. Details on how we match population density to the location information provided by EM-DAT are provided in Appendix [C](#). Figure [B.2](#) in Appendix [B](#) represents the worldwide distribution of AIGI. Comparing it with Figure [B.1](#), we can see that considering the population density may change the measure of NDs' magnitude that countries had to face, on average. For example, India is considered to be affected by shocks of very low intensity, on average, according to IGI. However, given its highly populated areas affected by disasters, India is included in the second percentile of affected countries if the measure of intensity is AIGI.

Table [1](#) combines the descriptive statistics of the geophysical magnitude (IGI and AIGI) with the human and monetary costs reported by EM-DAT. It covers 859 storms and 1,262 floods identified from 1996 to 2016 in our sample of 88 countries, which are listed in Appendix [G](#). According to our calculations, storm intensity is equal to 109 km/h on average. Interestingly, some events registered

as natural disasters in EM-DAT exhibit low magnitudes: the least severe storm in the sample shows a wind speed of 18km/h. Conversely, the strongest hurricane reaches 300 km/h. The average flood’s deviation for “normal” rainfall is equal to 166.8 mm. Once again, we can see that our sample includes some low-amplitude events. [Felbermayr and Groschl \(2014\)](#) emphasized that EM-DAT sometimes reports substantial damage from low-amplitude events. This entails that our “selection” of NDs has not been very drastic. Turning to our indicators, the mean value of IGI is the same for storms and floods (0.8). In both cases, taking exposure into account, as AIGI does, significantly increases the average value of the indicators (6.8 and 27.5, respectively). Last, we can see that the human and monetary costs of storms reported in EM-DAT are significantly higher than those of floods, although they occur one and a half times less often.

Table 1: Our (A)IGI measures and EM-DAT variables: descriptive statistics (1996-2016)

	Our measures						Costs reported in EM-DAT		
		Mean	Sd	Min	Max	Nb ^c	Killed ^d	Affected ^d	Damages ^e
Storm	Geophysical intensity ^a	109.0	43.8	18.0	305.6				
	<i>IGI</i>	0.8	3.3	0.0	49.4	859	0.0004	0.6392	0.1924
	<i>AIGI</i>	6.8	69.4	0.0	1836.9				
Flood	Geophysical intensity ^b	166.8	174.9	0.2	1541.1				
	<i>IGI</i>	0.8	1.9	0.0	31.5	1262	0.0001	0.5920	0.1109
	<i>AIGI</i>	27.5	250.9	0.0	6769.4				

Note: (a) Expressed in km/h. (b) Expressed in terms of mm of deviation from the regional long-term average rainfall. (c) The total number of events in our sample. (d) The average percentage of killed/affected people over the country’s population affected by ND the year prior to the ND. (e) The average percentage of damages over the nominal GDP of the affected country the year prior to the natural disaster.

4.2 Measure of stringency of the macroprudential framework

Our measure of macroprudential stringency is based on the recent integrated Macroprudential Policy (iMaPP) database provided by [Alam et al. \(2019\)](#). By combining information from many sources, this dataset provides comprehensive coverage in terms of macroprudential instruments (17 categories described in Appendix D), countries (134 countries), and time spans (from 1990 to 2016). In particular, it delivers information on the tightening, loosening or the lack of change in each macroprudential instrument from quarter to quarter. Nevertheless, the initial value of each instrument and the amplitude of the respective changes are ignored. Moreover, equal weight is attributed to changes in any instrument. As a result, the information delivered cannot be strictly transposed in terms of the stance or intensity of macroprudential policy.

However, we can infer from the iMaPP database the number of instruments that are actually activated in each country. We consider that an instrument is available in a country once it has been changed over the period 1990-2016. Hence, our measure of the stringency of macroprudential frameworks is the cumulative number of macroprudential instruments actually used in each country since 1990. It represents a measure of the *extensity* of the implementation of macroprudential policy ([Aizenman et al., 2020](#)): the higher the number of available instruments is, the stronger the macroprudential requirements.

Countries are differentiated according to whether their macroprudential policy framework is stringent ($P = 1$ in Eq. 8) or lax ($P = 0$). At each quarter t , a country i is considered to have a strong (lax) macroprudential framework if it has implemented at least (fewer than) two instruments, which is the

median number of instruments implemented over the whole period when considering all the countries in our sample.

Note that we will also study the marginal effects of implementing additional instruments using the number of activated instruments instead of a dummy variable for P . In addition, as robustness checks, the level of macroprudential policy extensity will be replaced by the *prompt corrective action* index provided by [Barth et al. \(2013\)](#). This measures the ability of the regulator to react promptly to shocks. A rigorous prudential framework is supposed to provide more room for maneuvers in the case of shocks.

Figures 2 and 3 report the total number of catastrophes per year, between 1996 and 2016, and the annual mean values of IGI and AIGI for countries with a lax macroprudential framework and those with a strong macroprudential framework. We observe that both groups of countries are equally affected by numerous shocks and are hit by shocks of similar amplitude.¹⁷ Hence, comparison between the two groups is relevant.

4.3 Dependent and control variables

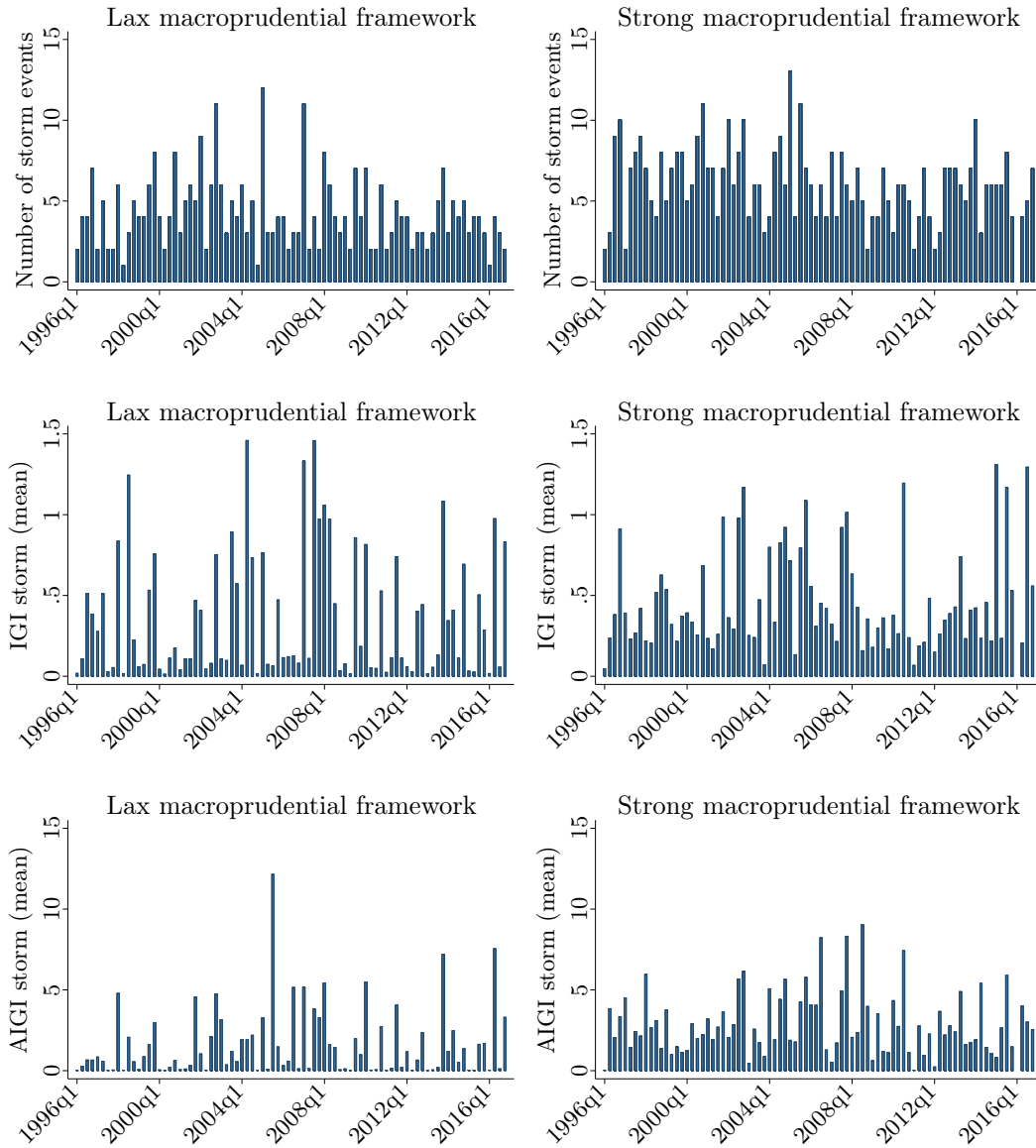
As argued in Section 2.1, and in line with Figure A, our dependent variable is the external finance premium (EFP). It is defined as the difference between the bank lending rate (BLR) and the risk-free interest rate, proxied by the 3-month money market rate. Figure B.3 in Appendix B represents the worldwide average value of the EFP over the period 1996-2016. In light of the geographical breakdown of the NDs shown in Figures B.1 and B.2, countries with a high EFP do not seem to be more prone to disasters than those that exhibit lower EFP on average. Note that the list of countries included in our sample ultimately depends on the availability of the interest rates required to compute this premium. This information is available for 88 countries (see Appendix G).

Next, we consider a set of control variables that are likely to explain the EFP. This concerns some traditional the financial characteristics, such as bank concentration and credit-to-GDP ratio. The occurrence of banking crises is also taken into account through a dummy variable, following the events reported by [Laeven and Valencia \(2020\)](#). Moreover, the Chinn-Ito index (KAOPEN) is used to capture the potential effects of financial openness.

The macroeconomic environment is represented by the annual growth of real GDP and the inflation rate. Furthermore, the level of development is considered, as differences in financial development can induce differences in information asymmetry and, hence, in terms of EFP. It is represented by the logarithm of GDP per capita. Finally, we include institutional quality (POLITY2 score). Details on the definition of data and their sources are available in Appendix E. Summary statistics are presented in Appendix F.

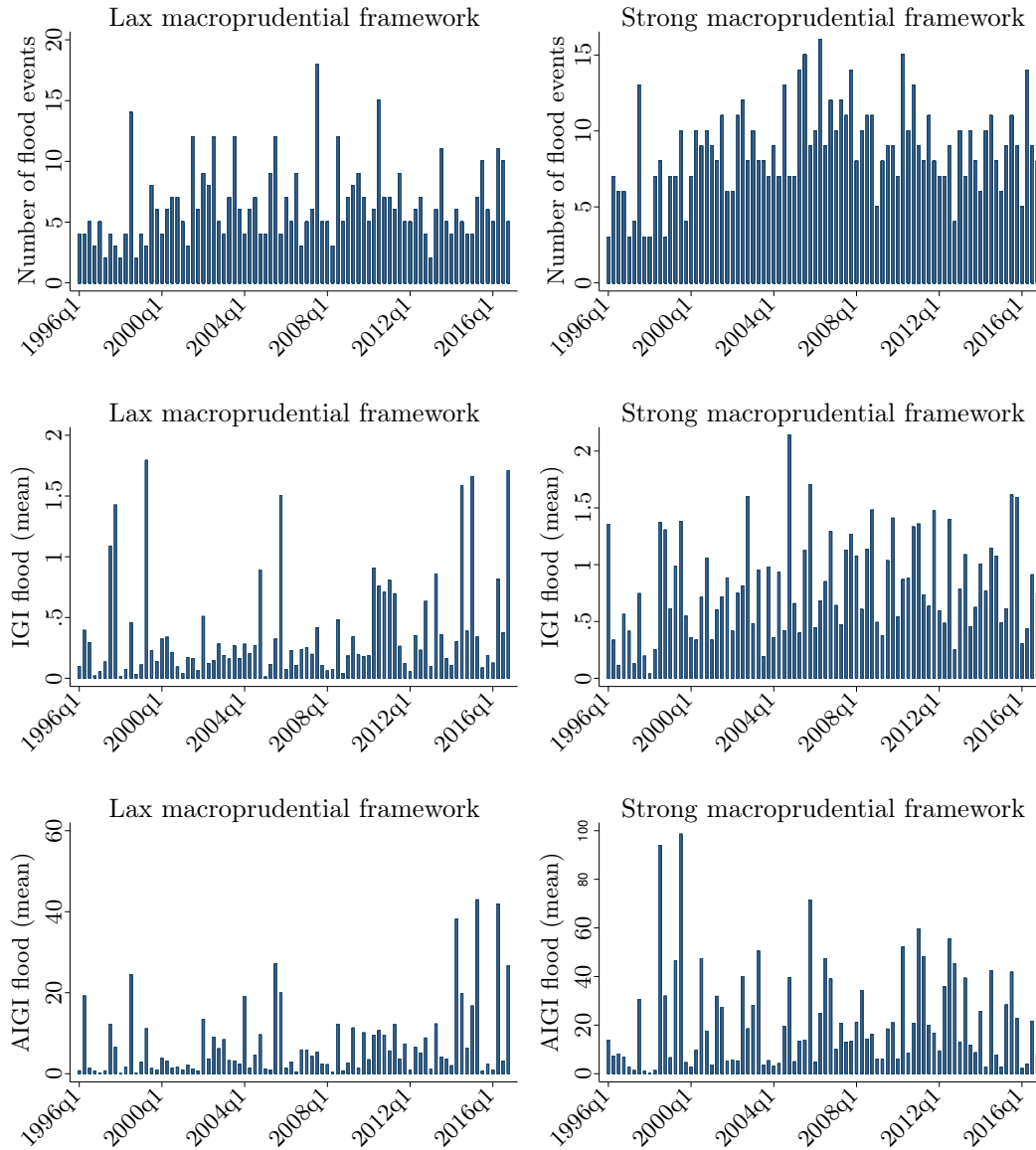
¹⁷The null hypothesis of equal means in the two groups is never rejected except for the IGI flood, which is higher for the strong macroprudential framework group. However, this is not truly an issue in our setting, as we specifically seek to test the ability of macroprudential policies to ensure the financial sector's resilience in the face of NDs that are possibly important.

Figure 2: Distribution of storms in countries with lax *vs.* strong macroprudential policies



Note: The x-axis corresponds to the time period in quarters. The left-hand (right-hand) side plots depict lax (strong) macroprudential countries. Plots in the first row represent the number of storms. Plots in the second row refer to the mean IGI-storm. Plots in the third row represent the mean AIGI-storm. The top 1%, or the most intense disasters are excluded from these plots for clarity of representation. These extreme cases are equally distributed between the lax and strong frameworks.
Source: Authors' calculations.

Figure 3: Distribution of floods in countries with lax *vs.* strong macroprudential policies



Note: The x-axis corresponds to the time period in quarters. The left-hand (right-hand) side plots depict lax (strong) macroprudential countries. Plots in the first row represent the number of floods. Plots in the second row refer to the mean IGI-flood. Plots in the third row represent the mean AIGI-flood.
 Source: Authors' calculations.

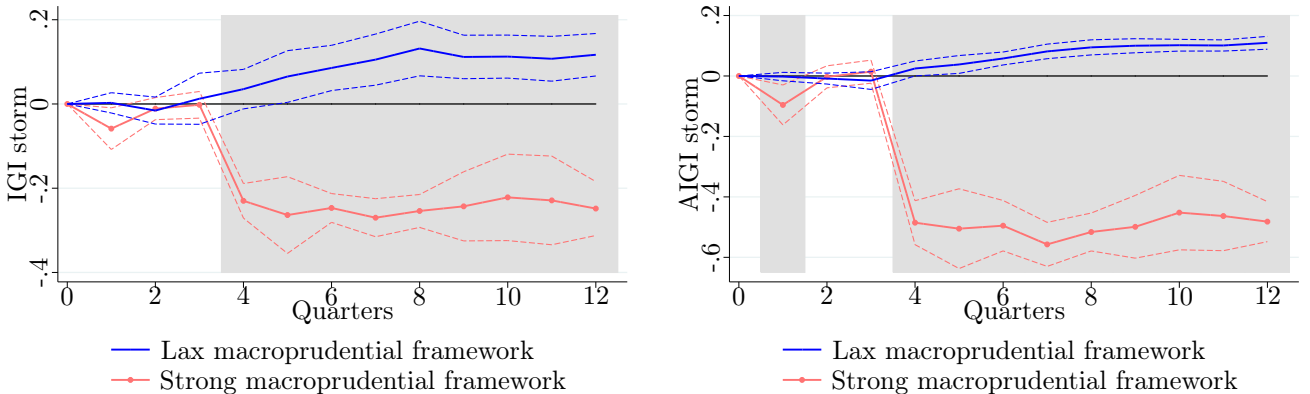
5 Results

Our empirical investigation is based on a sample of 88 countries over the period 1996-2016, at a quarterly frequency. The impact of NDs on the EFP is gauged by local projections from $h = 1$ to 12 quarters after the initial shock, conditional on the degree of stringency of the macroprudential framework (lax *vs.* strong), following equations (7) and (8). We first present the results obtained with storms. Then, we show the results obtained for floods. Finally, we assess the marginal effect of implementing additional macroprudential instruments, for the two types of catastrophes.

5.1 Storms

Figure 4 presents the response of the EFP to a one-standard-deviation shock to IGI (left plot) and AIGI (right plot), according to local projections, from 1 to 12 quarters after a storm. It shows that this response significantly depends on the stringency of the macroprudential framework. Specifically, we observe that the EFP starts significantly increasing five quarters after the shock to IGI in the case of a lax macroprudential framework (blue line). Credit conditions then continue to tighten for a long time after the storm. The delayed reaction of the EFP, which starts moving after one year, may be the consequence of the time needed to collect information, assess damages and evaluate needs. Moreover, compensation, if any, is not immediate. This obviously influences the timeframe for reconstruction projects and hence for their financing. For example, [Berg and Schrader \(2012\)](#) also find a delay in loan applications for enterprises after NDs.

Figure 4: Response of the EFP to storms conditional on the stringency of the macroprudential framework



Note: This figure represents the external finance premium (EFP) response to a one-standard-deviation shock to (A)IGI storms, for a lax *vs.* a strong macroprudential framework, over horizons from 1 to 12 quarters. Dotted lines correspond to confidence bands at 90%. Shaded areas indicate that the interaction term is significantly different from zero at the 5% confidence level.

On the contrary, the EFP decreases durably in countries with a strong macroprudential framework (red line). The shaded areas indicate that the difference between the two responses is significantly different. In a strong macroprudential context, the Schumpeterian creative destruction process can explain the drop in EFP. Indeed, the destruction of capital stock may provide incentives to re-invest in a more productive capital ([Crespo Cuaresma et al., 2008](#); [Leiter et al., 2009](#); [Cavallo et al., 2013](#); [Klomp, 2017](#)). This creates opportunities for financing productive projects with low risk (past capital has proven its usefulness). Therefore, credit conditions may be eased, especially in the case of strong banking competition. The pattern is the same in the case of a shock to AIGI. Hence, credit conditions

tighten following an ND, as found by, e.g., [Hosono et al. \(2016\)](#), but not in those countries that are expected to have a more sound financial system as a consequence of a strong macroprudential framework.¹⁸

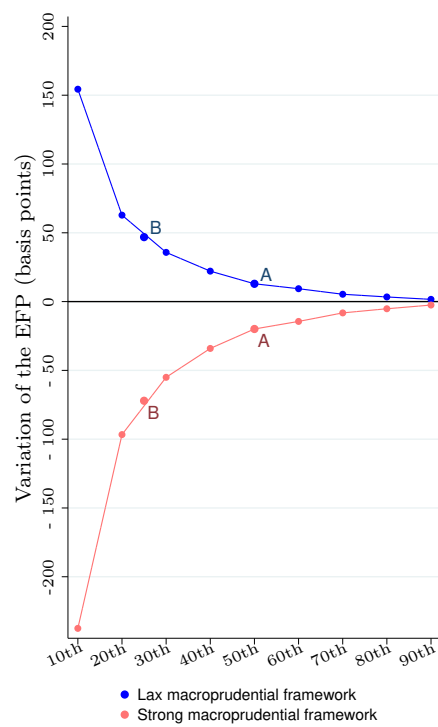
To better capture the amplitude of the EFP reaction, we can represent the estimated impact of NDs conditional on the country’s surface area and the density of the population in the affected areas. For illustration purposes, we highlight the response of the EFP two years ($h = 8$) after a storm equivalent to hurricane Katrina. Moreover, we focus on two types of countries: a median-size country called “A” (e.g., the United Kingdom) and a country called “B” corresponding to the first quartile in the distribution of countries’ areas (e.g., Lithuania). According to [Figure 5](#), in the case of a lax macroprudential framework, countries A and B would suffer an increase in their EFP of approximately 12.94 and 46.85 basis points, respectively. Conversely, in the case of a strong macroprudential framework, such a storm would entail a 19.91 bps decrease in country A and a 72.08 bps decrease in country B.¹⁹ Although not necessarily dramatic, this magnitude is convincing. In particular, this shows that localized shocks have a clear impact at the macroeconomic level in general (except in the case of the largest countries). Note that this example only considers the impact of a one-shot shock at a specific horizon (2 years after the shock). According to [Figure 4](#), the impact of a one-shot shock lasts for more than three years. In addition, other storms may occur in this time period. This implies potentially large effects in the long run.

Next, the AIGI allows us to assess a possible agglomeration effect by evaluating the marginal effect of population density in the specific regions impacted by shocks for a given country size. [Figure 6](#) provides illustrative insight into the EFP response two years after a Katrina-like shock, depending on whether the latter impacts a more or less populated region. For the sake of the analysis, let us imagine an underpopulated region, corresponding to the 10th percentile of the density distribution, i.e., 15.99 inhab/km² (“region 1”, or “R1” [Figure 6](#)) and a highly populated region, corresponding to the 90th percentile of the density distribution, i.e., 619,77 inhab/km² (“region 2” or R2). In the case of a lax macroprudential framework, the increase in the EFP at the national level of a median-size country (country A) would be 4.23 bps higher if the hurricane occurs in region 2 rather than in region 1. In the smaller country B, the global impact on the EFP would be 16.87 bps larger if the storm affects region 2 rather than region 1. In the case of a stringent macroprudential framework, the EFP would decrease by 8.85 bps more if the storm impacts the highly populated region in country A. This gain would reach 32.07 bps in country B. Although these examples only concern the response at the 8-quarter horizon to a one-shot shock, the main lesson from the AIGI is that population density does not appear to be particularly crucial for the macroeconomic impact of a storm compared to country size.

¹⁸Figure [H.1](#) in [Appendix H](#) shows the response of the EFP irrespective of the stringency of the macroprudential framework. The patterns suggest that it is worth considering interactions with macroprudential regulation to assess the financial effects of NDs.

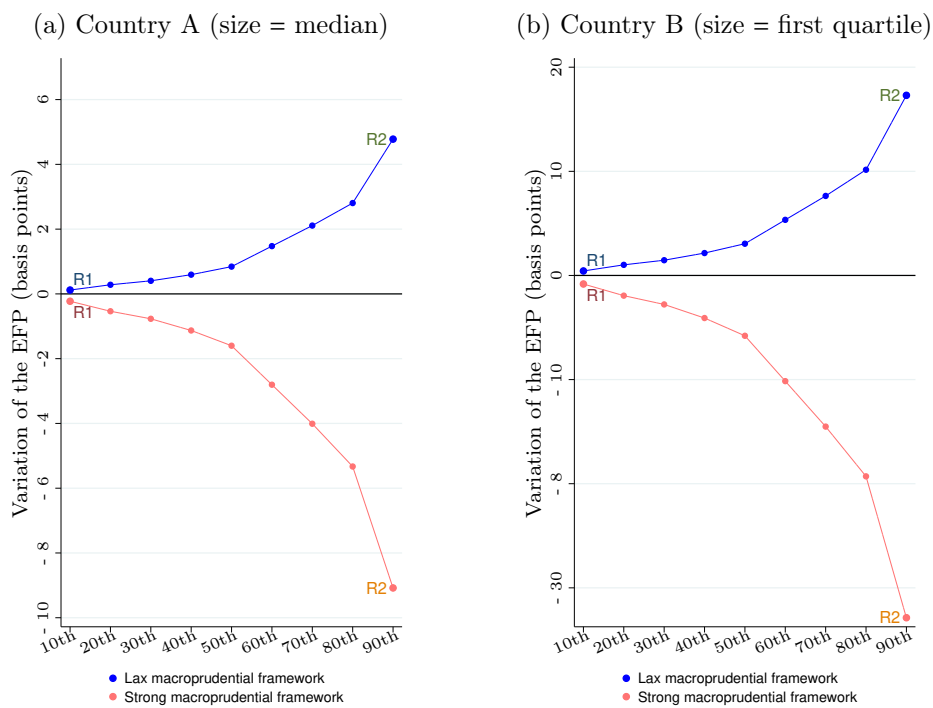
¹⁹Figure [5](#) represents $\widehat{\mathcal{R}}_{P,IGI}(8) \times \frac{IGI_{t=1}}{\sigma_{IGI}}$ for each percentile of country area (x-axis). $\widehat{\mathcal{R}}_{P,IGI}(h)$ is defined by [Eq. \(7\)](#) and estimated following [Eq. \(8\)](#). Its estimate is presented in the left plot of [Figure 4](#). We focus on its value eight quarter after a shock to IGI . σ_{IGI} denotes the standard deviation of IGI over the period 1996-2016 (equal to 1.18). Following the same approach, [Figure 6](#) represents $\widehat{\mathcal{R}}_{P,AIGI}(8) \times \frac{AIGI_{t=1}}{\sigma_{AIGI}}$ for each percentile of population density, with $\sigma_{AIGI}=26.66$.

Figure 5: Reaction of the EFP to IGI storms as a function of country area (h=8 quarters)



Note: This figure represents the variation in the external finance premium (EFP) two years after a Katrina-like storm, according to the estimates based on IGI, depending on the size of a country and on the stringency of the macroprudential framework. The x-axis represents percentiles of the country's area. "A" and "B" refer to countries corresponding to the second and first quartiles in the distribution of country areas, respectively.

Figure 6: Reaction of the EFP to AIGI storms as a function of the country’s area and population density (h=8 quarters)

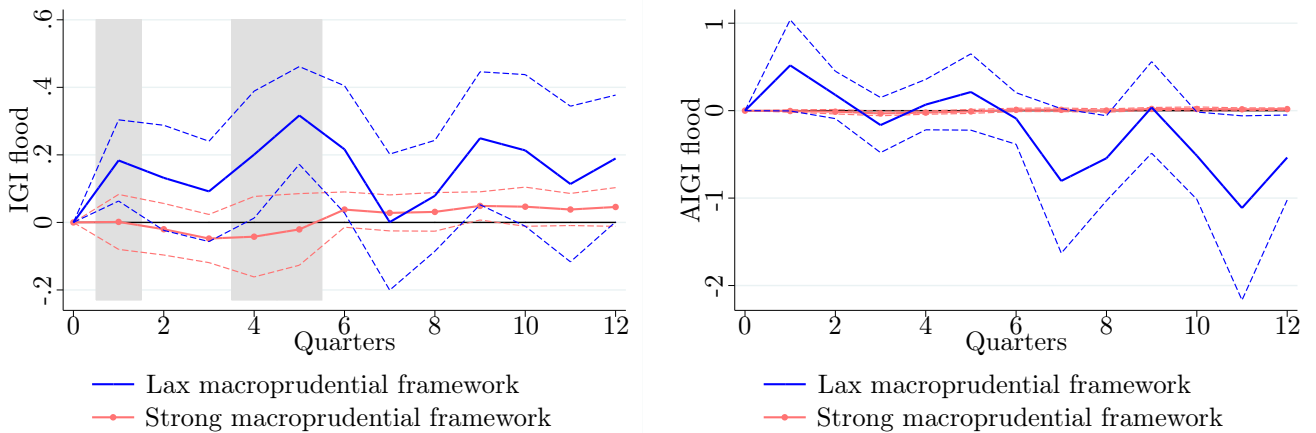


Note: This figure represents the variation in the external finance premium (EFP) two years after a Katrina-like storm, depending on the country’s area and population density conditional on the stringency of the macroprudential framework. The x-axis corresponds to the percentiles of population density. The left-hand plot refers to a median-size country (“country A”). The right-hand plot refers to a smaller country, with a size corresponding to the first quartile (“country B”). “R1” and “R2” refer to regions corresponding to the 10th and 90th percentiles of the density distribution, respectively.

5.2 Floods

Figure 7 shows the response of the EFP to a one-standard-deviation shock to IGI (left plot) and AIGI (right panel), following local projections from 1 to 12 quarters after a flood event. According to IGI, flooding seems to significantly raise the EFP if the macroprudential framework is lax (blue line), especially in the short-run (for $h = 1, 4$ and 5 quarters) and for $h = 9$ quarters. In contrast, floods do not affect the EFP in the case of strong macroprudential policy (red line). However, the two conditional effects are not significantly different from one another, except at 3 quarters (see the gray areas for $h = 1, 4, 5$). According to AIGI, the EFP does not respond differently to a strict or to a lax macroprudential framework at any point. Hence, the results for floods are less clear-cut than those for storms.²⁰

Figure 7: Response of the EFP to floods conditional on the stringency of the macroprudential framework



Note: This figure represents the external finance premium (EFP) response to a one-standard-deviation shock to (A)IGI-flood for lax *vs.* strong macroprudential frameworks over horizons from 1 to 12 quarters. Dotted lines correspond to confidence bands at 90%. Shaded areas indicate that the interaction term is significantly different from zero at the 5% confidence level.

We conduct further investigations to ensure that our non-statically-significant results concerning floods do not depend on the specific way we measure ND intensity, the database we use, or the type of floods we consider. To do so, first, we recompute our intensity index based on the deviation from the long-term average rainfall of the entire country affected by floods (instead of the region impacted by this ND). Second, we construct our flood-related indexes using an alternative database on rainfall (i.e., from the Global Precipitation Climatology Centre). Third, we differentiate the results according to the flood type (flash flood, riverine flood) identified in line with the EM-DAT classification. The results obtained in the three cases are similar to those from the initial setting: they do not suggest clear-cut conclusions concerning the role of macroprudential policies in mitigating flood effects on financial stability. All these additional results are available upon request.

This apparently insignificant financial impact of floods, even conditional on the extensity of macroprudential policy, has several potential explanations. First, rainfall may not necessarily translate into floods at the location where it happens. Second, flood-prone areas are usually easily identifiable (along coasts and rivers). Therefore, it is possible to anticipate a disaster and circumvent its financial impact through greater discipline, such as risk abstinence and damage insurance. [Garbarino and Guin \(2021\)](#)

²⁰Figure H.2 in Appendix H shows the EFP response irrespective of the extensity of macroprudential policy. These results are also not clear-cut. Moreover, given the inconclusive results, we choose not to further present the effects of flooding as a function of the country's area and population density.

show that, consistent with the valuation of the amenity of being close to water, borrowers living near flood prone areas have relatively higher incomes and display lower loan-to-value ratios than borrowers living farther away. Not only do they have below-average credit risk, but they can also afford to take out insurance policies. Third, [Faiella and Natoli \(2018\)](#) provide another possible explanation by showing that lending to nonfinancial firms (especially small and medium enterprises, which are less likely to purchase an insurance policy) is negatively correlated with their flood risk exposure. Hence, banks tend to be less exposed to this type of disaster. Note that, like floods, earthquakes occur in areas that are fairly well aware of the potential for these events. In this respect, [Garmaise and Moscovitz \(2009\)](#) find that the likelihood that a property is financed through bank debt is reduced in earthquake-prone areas, especially when the catastrophic insurance market is poorly developed. Along this line, [Bos and Li \(2017\)](#) show that banks that face strong earthquake experiences reduced their exposure to real estate and were more likely to lend to high-income borrowers.

Overall, this suggests that coping strategies are developed in areas identified as risky (at the microeconomic level). As a consequence, macroprudential policy is less decisive in this context.

5.3 Marginal effects of the number of macroprudential instruments

While the analysis thus far has been based on comparing two groups of countries, according to their macroprudential framework extensity (lax *vs.* strong), we now focus on the effect of adding a macroprudential instrument, regardless of the initial number of instruments. To this end, the macroprudential context $P_{i,t-1}$ in Eq. (8) now represents the number of instruments in country i at time $t - 1$.

For the sake of parsimony, Table 2 only reports the coefficients estimated for the direct effect of a geophysical shock on the EFP (i.e., β_h in Eq 6) and its effects when interacting with the number of instruments (i.e., $\gamma_h P_{i,t-1}$) for horizons of 1 to 12 quarters. While a one-standard-deviation increase in IGI-storm triggers an increase in the EFP of approximately 29 bps, on average from 5 to 12 quarters after the shock, the implementation of an additional instrument significantly mitigates this tightening by approximately 20 bps. The interaction term is also significant with AIGI-storm from 5 to 12 quarters after the shock. In this case, having adopted an additional instrument reduces the impact of a one-standard-deviation increase in AIGI by 40 bps on average (against an average increase of 47 bps in the EFP as a direct impact of the AIGI shock).

In contrast, as previously found, the direct effect of IGI floods is rarely significant (except for horizons of 5, 6, 9, and 12 quarters). Moreover, the marginal impact of having one additional macroprudential instrument (interaction term) is never significant (except for $h = 5$) in the case of flooding.

6 Robustness checks

6.1 Reverse causality check

As underlined in Section 3, our strategy relies on the assumption that the stringency of the macroprudential framework does not depend on the occurrence of NDs. To check that our results do not suffer from reverse causality bias, we re-estimate the impact of NDs on the EFP by excluding cases in which the extensity of the macroprudential framework changed the three years following an ND. This concerns 22 storms and 35 floods in our initial sample.

Figure H.3 in Appendix H shows that when excluding countries, their estimates that changed their

extensity group in the wake of a storm are highly similar to the baseline results. Concerning floods, Figure H.4 shows that these results are also not notably impacted, as we still do not find clear-cut significant differences between lax and restrictive countries (only for IGI with $h = 4, 5$).

Table 2: Effects of natural disasters conditional on the number of macroprudential instruments

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
IGI Storm _{<i>t</i>}	-0.00 (0.05)	-0.04 (0.05)	0.00 (0.07)	0.11 (0.09)	0.19* (0.10)	0.25*** (0.08)	0.36*** (0.08)	0.37*** (0.08)	0.29*** (0.10)	0.28*** (0.10)	0.27** (0.11)	0.29*** (0.11)
IGI Storm _{<i>t</i>} × Number of instrument _{<i>t-1</i>}	-0.01 (0.03)	0.02 (0.03)	-0.00 (0.04)	-0.13* (0.07)	-0.18** (0.07)	-0.21*** (0.06)	-0.29*** (0.06)	-0.28*** (0.06)	-0.23*** (0.08)	-0.22** (0.09)	-0.21** (0.10)	-0.23** (0.09)
AI GI Storm _{<i>t</i>}	0.03 (0.06)	-0.02 (0.04)	-0.07 (0.05)	0.33* (0.17)	0.37** (0.17)	0.43** (0.17)	0.58*** (0.15)	0.55*** (0.15)	0.50** (0.21)	0.45* (0.23)	0.49** (0.20)	0.51*** (0.18)
AI GI Storm _{<i>t</i>} × Number of instrument _{<i>t-1</i>}	-0.04 (0.06)	0.01 (0.03)	0.05 (0.04)	-0.32* (0.16)	-0.35** (0.16)	-0.39** (0.16)	-0.51*** (0.15)	-0.47*** (0.14)	-0.42** (0.20)	-0.37* (0.21)	-0.41** (0.19)	-0.42** (0.17)
IGI Flood _{<i>t</i>}	0.09* (0.05)	0.03 (0.05)	-0.03 (0.07)	0.06 (0.08)	0.17** (0.08)	0.15* (0.09)	0.01 (0.09)	0.04 (0.07)	0.18** (0.09)	0.14 (0.10)	0.10 (0.10)	0.14* (0.08)
IGI Flood _{<i>t</i>} × Number of instrument _{<i>t-1</i>}	-0.02* (0.01)	-0.01 (0.01)	-0.00 (0.02)	-0.02 (0.02)	-0.05*** (0.02)	-0.03 (0.02)	0.00 (0.02)	0.00 (0.02)	-0.03 (0.02)	-0.02 (0.03)	-0.02 (0.03)	-0.03 (0.03)
AI GI Flood _{<i>t</i>}	0.04 (0.03)	-0.01 (0.04)	-0.05 (0.06)	-0.01 (0.05)	0.05 (0.05)	0.01 (0.07)	-0.05 (0.10)	-0.05 (0.08)	0.02 (0.10)	-0.12 (0.09)	-0.16 (0.16)	-0.12 (0.13)
AI GI Flood _{<i>t</i>} × Number of instrument _{<i>t-1</i>}	-0.02 (0.02)	0.00 (0.02)	0.01 (0.02)	-0.00 (0.02)	-0.02 (0.02)	0.00 (0.03)	0.03 (0.04)	0.02 (0.04)	0.00 (0.05)	0.07 (0.04)	0.09 (0.07)	0.07 (0.06)

Note: This table represents the direct impact of a one-standard-deviation shock to (A)IGI (storms, floods) and its indirect impacts in interaction with the number of macroprudential instruments. Columns correspond to the horizons h . All regressions include control variables (see Section 4.3) as well as time and country FEs. Standard errors in parentheses are corrected for heteroskedasticity and clustered at the country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.2 Robustness to alternative mitigating factors

We test whether the attenuating effects of macroprudential policies are robust to the inclusion of alternative possible mitigating factors. This means that an interaction term $\chi_h(D_{i,t}^d \times X_{i,t-1})$ is included in Equation (8), with X designating a possible mitigating factor, in addition to the interaction term representing macroprudential extensity $\gamma_h(D_{i,t}^d \times P_{i,t-1})$.

Several potential shock absorbers are successively considered, following the broad literature on the economic impact of NDs. First, we add an interaction capturing the logarithm of GDP per capita as the level of development may affect the capacity of a country to cope with NDs (Noy, 2009; Felbermayr and Groschl, 2014; Loayza et al., 2012). Next, as the effects of NDs may be alleviated when institutions are strong (Noy, 2009; Acevedo et al., 2019), we include an interaction with variables that account for the quality of institutions: polity2 and the control of corruption index. We also consider whether countries have an inflation targeting (IT) regime, in line with Fratzscher et al. (2020), who find that this monetary policy arrangement acts as an ND absorber. In this case, X is a dummy variable that is equal to one once a country has adopted IT, zero otherwise. Moreover, in line with Ramcharan (2007), we consider the nature of the exchange rate regime by adding an interaction term based on the *de facto* exchange rate classification provided by Ilzetzi et al. (2017). Additionally, we account for the role of financial development, which can be a determinant of the impact of NDs, as reported by Botzen et al. (2019) in their literature review. Financial development is measured through the financial markets

depth (FMD) index provided by the IMF. Finally, we go deeper into the analysis and assess whether the dampening effects of macroprudential policies still hold in the presence of balanced budget rules. By enhancing discipline and credibility, fiscal rules can help to reduce the impact of (financial) shocks (Levieuge et al., 2021). X is a dummy variable equal to one when a country follows a fiscal rule, zero otherwise. Further details on these data are provided in Appendix E.

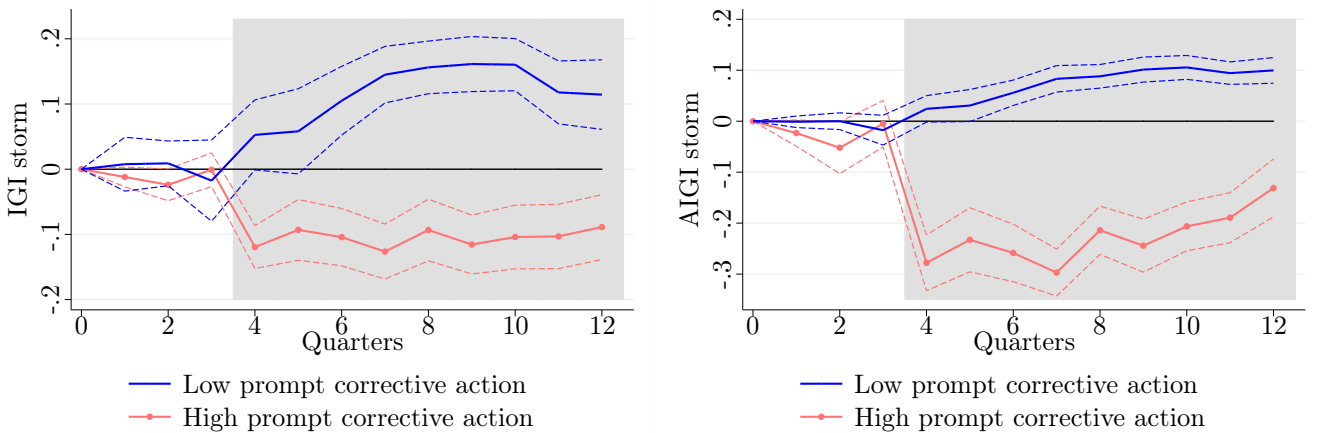
Table H.1 in Appendix H reports the dampening effects of macroprudential extensity, i.e., γ_h , while these potential shock absorbers X are also in interaction with NDs. The impact is reported for horizons of 1, 4, 8, and 12 quarters. The first part of the table addresses IGI, while the second part concerns AIGI for storms. It appears that the attenuating effect of stringer macroprudential framework holds even when we include other potentially mitigating factors, both for IGI and AIGI shocks. The magnitude of the effect does not seem to be affected either, even when all the alternative shock absorbers are simultaneously included in the regression (last row labeled “All”). This means that the beneficial effects of macroprudential policies that we have found thus far in the case of storms are truly due to the properties of this policy *per se*, not to other factors for which our measure of macroprudential stringency might have proxied.

The results for floods are reported in H.2 in Appendix H. In the few cases where it is significant (i.e., for $h = 1$), the dampening effect of macroprudential policy is also robust to the inclusion of other mitigating factors.

6.3 Impact of *ex-post* prudential action

Macroprudential policies can be viewed as *ex-ante* prudential measures: thus, we now check whether the *ex-post* reaction of the regulator mitigates an NDs’ effect on credit conditions. To this end, we consider the *prompt corrective action* index provided by Barth et al. (2013) as a key explanatory variable. This index measures whether supervisors have the requisite and appropriate powers to take automatic enforcement actions based on predetermined levels of bank solvency deterioration. Hence, $P_{i,t} = 1$ for countries that have a high *prompt corrective action* index (PCA), i.e., higher than the median value of PCA in the sample over the full analysis period. Otherwise, $P_{i,t} = 0$ (i.e., low PCA).

Figure 8: Response of the EFP to storms conditional on prompt corrective action

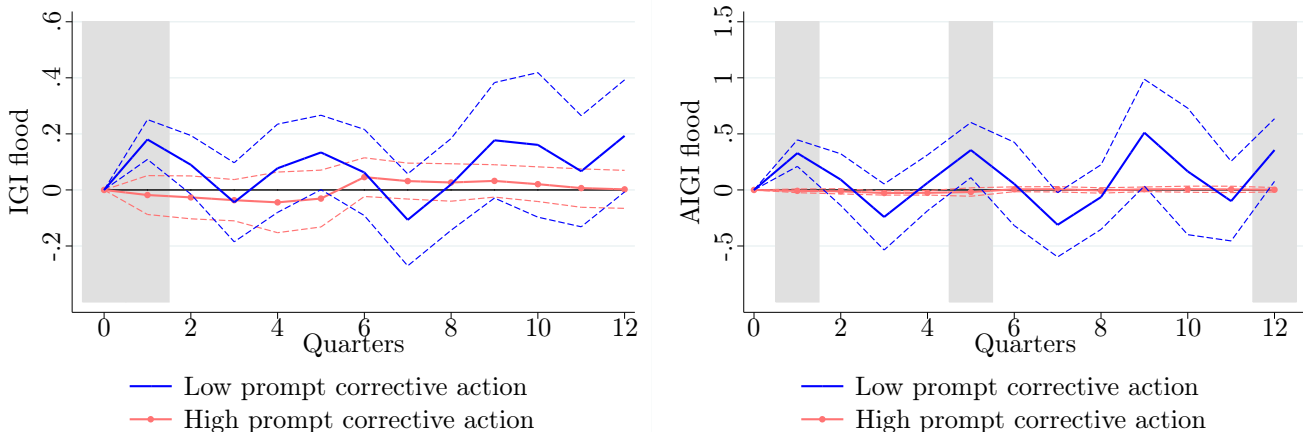


Note: This figure represents the external finance premium (EFP) response to a one-standard-deviation shock to (A)IGI storms for low *vs.* high levels of *prompt corrective action* over horizons from 1 to 12 quarters. Dotted lines correspond to confidence bands at 90%. Shaded areas indicate that the interaction term is significantly different from zero at the 5% confidence level.

Figure 8 shows that *ex-post* prudential actions significantly mitigate the impact of storms on the

EFP, as it was the case with macroprudential measures (similar amplitude). Figure 9 shows that the restrictive effect of flooding on the EFP is immediately reduced by PCA in the quarter following the shock. However, for all other horizons, ex-post prudential actions do not alter the financial impacts of floods. This confirms the previous results and interpretations. As flood risk is fairly well identified and anticipated, self-discipline may render prudential requirements (*ex-ante*) and support (*ex-post*) less crucial if the risk occurs. In contrast, the financial impact of storms is sensitive to both *ex-ante* and *ex-post* measures.

Figure 9: Response of the EFP to floods conditional on prompt corrective action



Note: This figure represents the external finance premium (EFP) response to a one-standard-deviation shock to (A)IGI floods for low *vs.* high levels of *prompt corrective action* over horizons from 1 to 12 quarters. Dotted lines correspond to confidence bands at 90%. Shaded areas indicate that the interaction term is significantly different from zero at the 5% confidence level.

7 Focus on the recent period and on income-based country groups

7.1 Recent period: 2006-2016

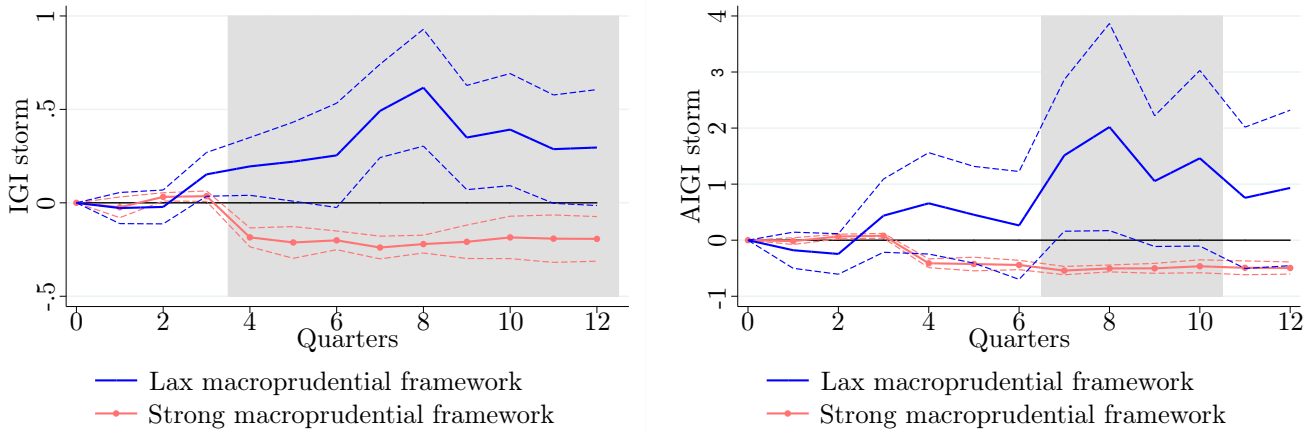
Since macroprudential policy has been designed and used rather recently, and since the intensity and frequency of natural disasters are increasing, it is worth focusing on the most recent period for which data are available, i.e., 2006-2016 (the second decade of our sample).²¹

We note from Figure 10 that for IGI-storm the differential effect between the two country groups remains significant (after 4 quarters), with a significant increase in the EFP for countries that have a lax macroprudential framework (except for $h = 6$). For AIGI-storm, the results are slightly different from those obtained over the full period. While there is still a significant, albeit small, decrease in the EFP in countries with a strong macroprudential setting, the tightening of credit conditions is only significant in Q7 and Q8 in those countries that have a lax macroprudential framework. However, the differential effect is still significant, although over a shorter time span (from $h = 7$ to 11). Thus, it seems that the extensity of the prudential framework helps to financially cope with storm damages, even in the most recent period.

The aim of Figure 11 is to compare the amplitude of the effects of a Katrina-like storm, 2 years after the shock, estimated over the full period (solid lines) *vs.* that over the most recent decade (dashed lines). The left-hand side plot concerns IGI-storm. We observe that the decrease in the EFP when

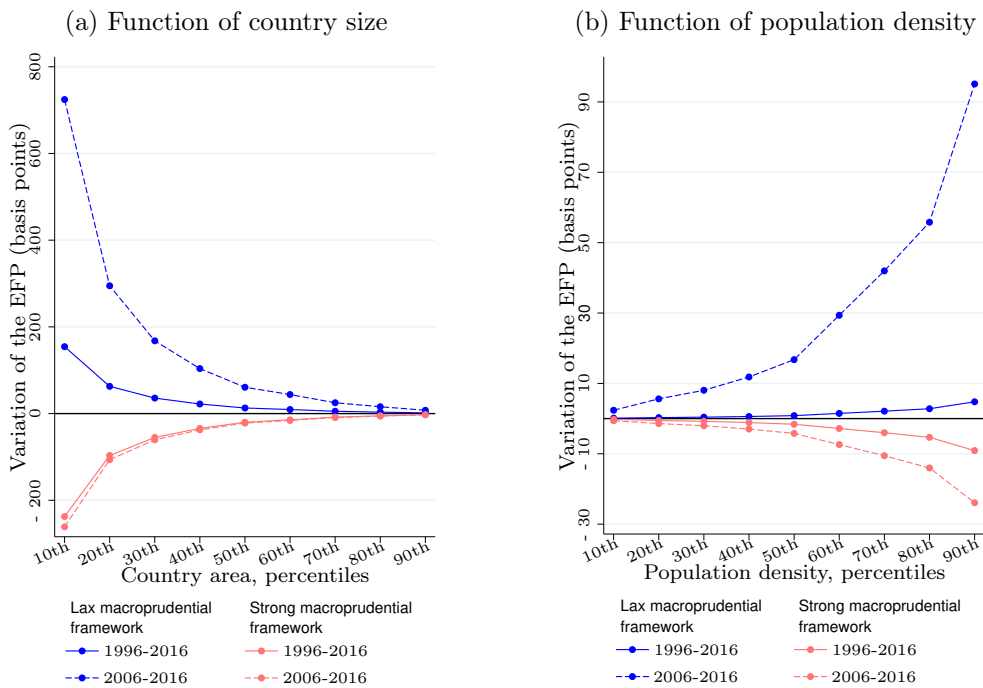
²¹We could also run regressions over the first decade (1996-2006) only for comparison purposes; however, this seems less relevant because macroprudential policy was still in its infancy before the Global Financial Crisis.

Figure 10: Response of the EFP to storms - recent period



Note: This figure represents the response of the external finance premium (EFP) to a one-standard-deviation shock to (A)IGI-storm, for a lax *vs.* strong macroprudential framework, over horizons from 1 to 12 quarters. Dotted lines correspond to confidence bands at 90%. Shaded areas indicate that the interaction term is significantly different from zero at the 5% confidence level. Estimation period: 2006-2016.

Figure 11: Reaction of the EFP as a function of country area, population density and estimation period (h=8 quarters)



Note: The left-hand side plot represents the variation in the external finance premium (EFP) two years after a Katrina-like storm, according to the estimates based on the IGI, and depending on the size of the country. The x-axis represents the percentiles of country area. The right-hand side plot represents the estimated variation in the EFP based on the AIGI for a median-sized country, and depending on the population density in affected areas. The x-axis represents the percentiles of population density.

the macroprudential framework is stringent does not seem to be sensitive to the estimation period. In contrast, in the case of lax policy setting, the rise in the premium is much higher in the recent period. For example, the surge in premium is nearly 5 times higher for a median-sized country. The difference from the estimate obtained over the full period can reach more than 5 percentage points for a small country belonging to the first decile. The right-hand side plot represents the impact of a Katrina-like storm on a median-sized country, according to the estimates obtained with the AIGI, and depending on the population density in affected areas. Once again, we observe that the increase in the EFP in lax countries is dramatically higher over the recent period than over the full sample. For example, for a country with a median population density, the estimated rise in EFP over the past decade is almost 19 times larger than the estimated increase found over the full period. Similarly, but to a lesser extent, the EFP decreases slightly more in the case of a stringent macroprudential framework over the second decade than over the full sample.

Finally, the results obtained for floods over the period 2006-2016 are presented in Figure H.5 in Appendix H. It appears that the effects of flooding are not significant overall, regardless of macroprudential policy extensity, similar to the estimates obtained over the entire period.

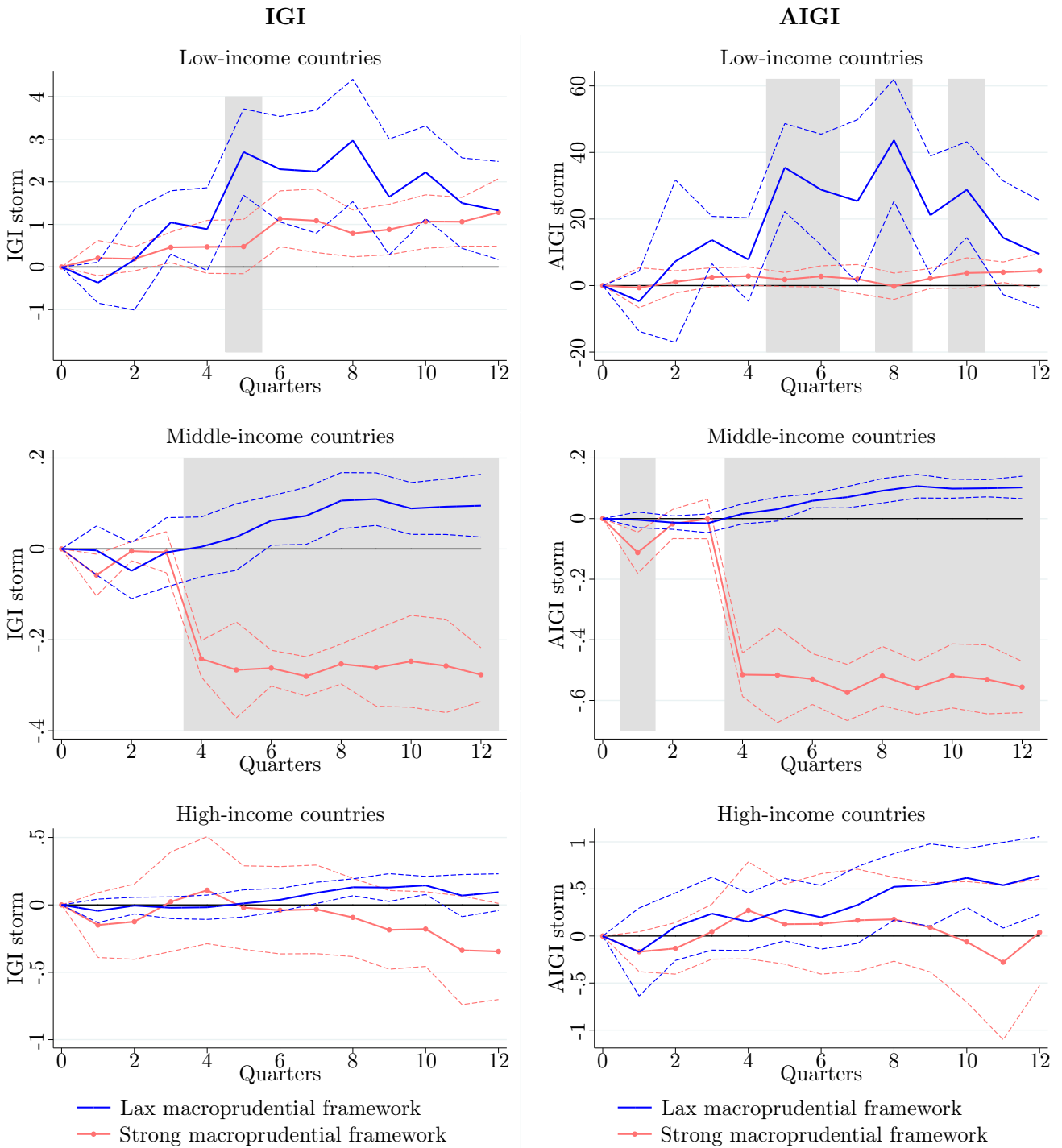
7.2 Heterogeneity by country income

We now assess whether the impact of NDs and the dampening effect of macroprudential policy depend on the level of economic development. To this end, we divide our sample into three groups of countries, following the World Bank classification: low-income (10 countries), middle-income (43) and high-income countries (35).

Figure 12 shows that, in the case of lax macroprudential policy, the EFP significantly increases in the wake of a storm in low- and middle-income countries but not in high-income countries. In these most developed countries, the EFP also does not significantly change when the macroprudential framework is stringent. The findings are less clear-cut for low-income countries. On the one hand, the results with IGI suggest that an extensive macroprudential policy does not prevent the premium from rising. On the other hand, the results based on AIGI indicate that a stringent setting ensures that the premium does not increase; in this case, the response of the EFP is sometimes significantly different between the two groups with different macroprudential stringency (for $h = 5, 6, 8, 10$). Finally, only in middle-income countries a strong macroprudential setting significantly does lower the EFP post-storm. Thus, it is mainly for these countries that the responses of the EFP differ significantly depending on the extensity of the macroprudential framework.

Therefore, the patterns of local projections represented in Figure 12 suggest that the baseline results are driven by middle-income countries. This is perfectly consistent with our interpretation based on the fact that the destruction of capital provides an incentive to reinvest in more productive capital. Specifically, middle-income countries can be presumed to have the required absorption capacity to fully exploit new facilities. This creates opportunities for financing productive replacement projects (Cavallo et al., 2013; Klomp, 2017), which do not involve a high level of risk for lenders. Indeed, if the destroyed capital must be replaced, it is because it has a proven utility. Moreover, the replacement investment is not necessarily a breakthrough innovation, but maybe already proven equipment. Thus, there is no reason for the premium associated with replacement capital funding to increase. Accordingly, a sound financial system, supported by a rigorous macroprudential framework, is likely to offer favorable financing conditions. Moreover, middle-income countries are the ones that attract large international capital flows (Hannan, 2018). The presence of a strong macroprudential regulation in these countries

Figure 12: Response of the EFP to storms depending on country income level



Note: This figure represents the response of the external finance premium (EFP) to a one-standard-deviation shock to IGI-storm in the first column of plots and to a one-standard-deviation shock to AIGI-storm in the second column of plots, for a lax *vs.* strong macroprudential framework, over horizons from 1 to 12 quarters, depending on country income level. Dotted lines correspond to confidence bands at 90%. Shaded areas indicate that the interaction term is significantly different from zero at the 5% confidence level.

might (i) make them less exposed to sudden stops (Bergant et al., 2020) following a shock as a ND and (ii) even attract further foreign capitals (Cortés and Strahan, 2017) due to the perspective of higher profit opportunities. Furthermore, as shown previously, the smaller the country and/or the more densely populated the area affected by a disaster is, the more the aggregate financing conditions at the country level are driven by the easing of the EFP for replacement investments. However, possibly because there is no expected technological leap, high-income countries with stringent macroprudential policy do not significantly benefit from a decline in the EFP. Indeed, since the damaged capital might have already been highly productive, the introduction of new (replacement) capital after a disaster may generate few marginal gains. Finally, from this perspective, the failure of macroprudential policy to have a mitigating effect in low-income countries may be the result of insufficient absorptive capacity (Crespo Cuaresma et al., 2008).

Finally, Figure H.6 in Appendix H shows that macroprudential policy extensity does not significantly influence the impact of flooding in any country group. Eventually, an effect of the macroprudential framework may be observed in high-income countries when considering IGI and in middle-income countries when considering AIGI, albeit with too much volatility for this result to be conclusive. Thus, the conditional impact of floods does not seem to depend on the level of development. Dividing the sample does not shed new light on the lack of a macroprudential effect on financial stress following floods.

8 Conclusion

Natural disasters (NDs) can impact the financial sector, with potential consequences ranging from surges in premiums to financial crises. Moreover, although independently, macroprudential policies have been developed to address financial instability. Against this background, the aim of our paper is to empirically gauge the impact of natural disasters on financial conditions, conditional on the degree of stringency of the macroprudential framework. In line with the literature on financial frictions and crises, financial conditions are measured by the external finance premium (EFP). Our investigation is based on a local projection (LP) methodology for a panel of 88 countries over the period 1996-2016 and relies on original indicators of the geophysical intensity of storms and floods.

Our results show that storms, although affecting only a part of the territory, have a significant macroeconomic impact on financial conditions. This impact may be negative or positive, depending on the stringency of the macroprudential framework. According to our estimates, a relatively small country (corresponding to the first quartile of the country size distribution) with a lax macroprudential framework would suffer of an increase in the domestic EFP of 44 basis points (bps) two years after a Katrina-like hurricane. This deterioration in financing conditions persists beyond 3 years, which suggests a large impact in the medium-long run. Importantly, we find that this impact is more severe if evaluated over the recent period: the estimated hike reaches 219 bps when considering only the second decade of the sample. In contrast, a small country with a stringent macroprudential framework could benefit from a decrease in the EFP of approximately 67 bps two years after a category 5 hurricane.

A key explanation for the benefits of a strong macroprudential framework is that an initially sound financial environment fosters favorable financing conditions to replace destroyed capital with more productive capital. Further investigation shows that it is especially the category of middle-income countries that benefits from stringent macroprudential policies; in fact, these countries can be presumed to have sufficient absorption capacity to fully exploit new facilities. In contrast, we find that credit

conditions worsen in low-income countries, following storms, irrespective of the degree of stringency of their macroprudential framework. Similarly, high-income countries with stringent macroprudential policy do not significantly benefit from a decline in the EFP, possibly because no technological leap is expected. Nonetheless, they are subject to a worsening of financing conditions in the case of a loose macroprudential framework. These findings are robust to different econometric specifications and alternative measures of macroprudential regulation.

The results are not conclusive regarding the financial effects of flooding. As they are more geographically isolated (along rivers and coasts), floods are more foreseeable. This may induce spontaneous discipline and greater insurance coverage, as highlighted by some recent studies. Hence, this could render macroprudential measures less crucial. As an extension, this plausible hypothesis would deserve to be checked with micro-banking and insurance data.

Finally, our results show that strong macroprudential regulation improves countries' ability to better cope with the financial impact of NDs. Certainly, macroprudential policy by itself cannot solve problems arising from natural disasters which are strongly related to climate change. However, by containing the financial impact of NDs, macroprudential regulation can help to save resources that are needed to finance the energy transition. Otherwise, major financial shocks might occur and require a bailout that could overshadow other economic policy objectives, including the objective of transitioning to a low-carbon economy.

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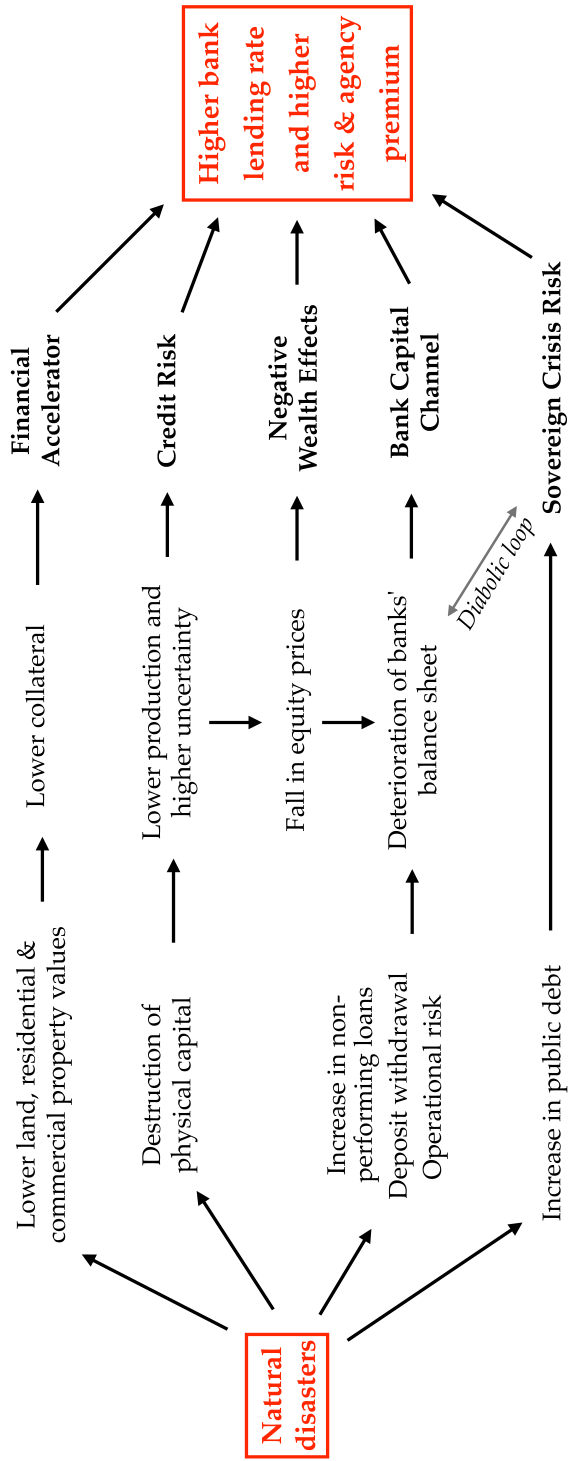
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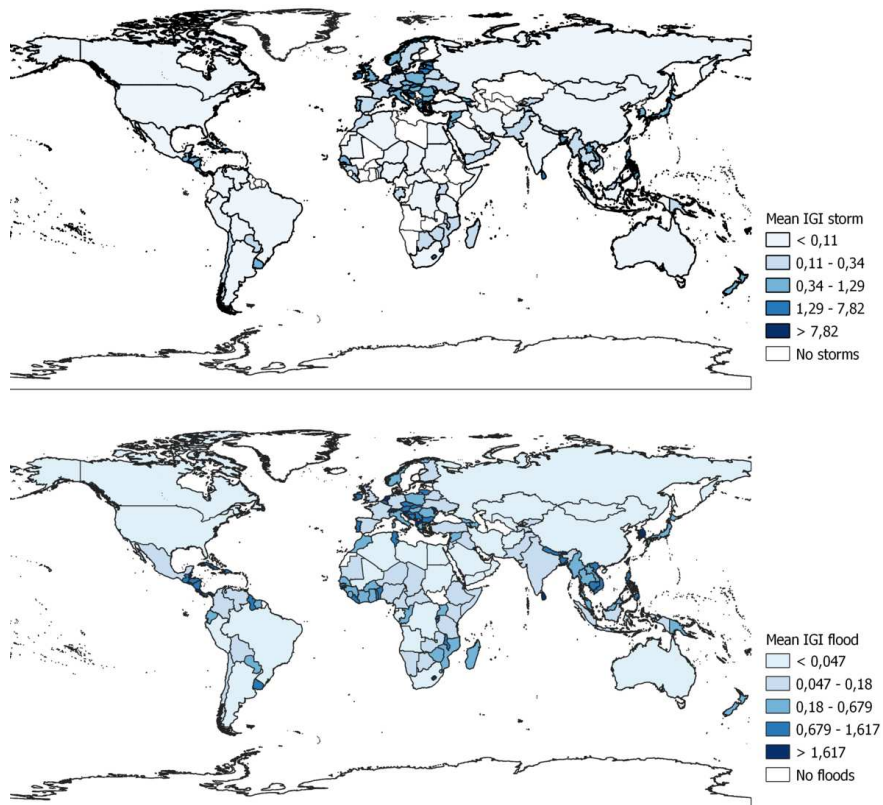
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A Transmission channels of natural disasters on credit conditions



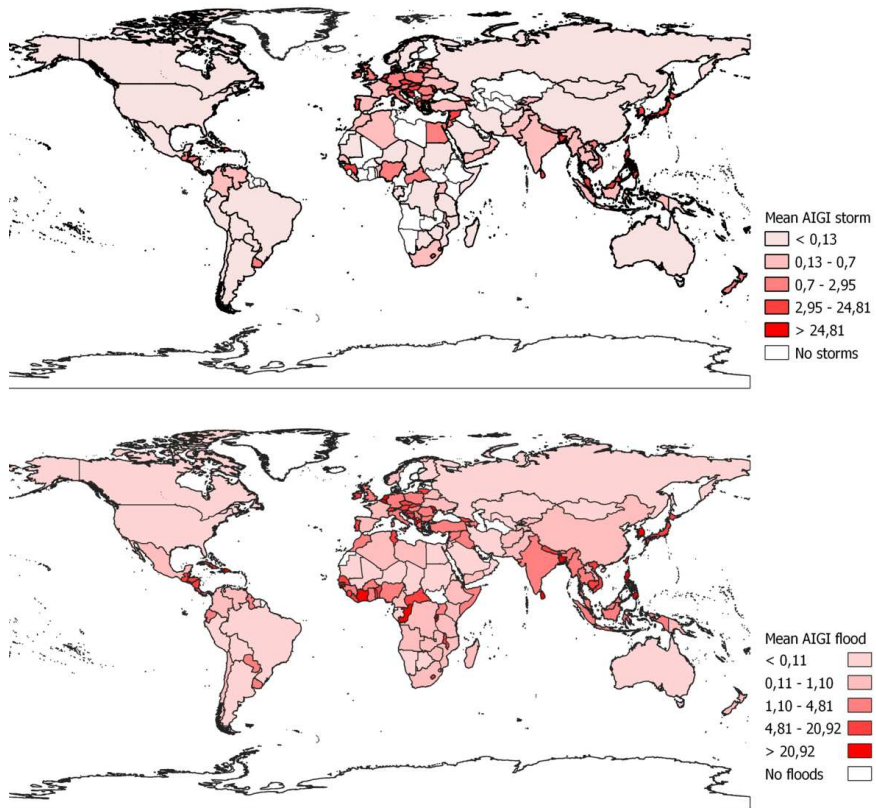
B World mean values of IGI, AIGI and EFP over the period 1996-2016

Figure B.1: World mean value of IGI over the period 1996-2016



Note: The legend is determined by the percentiles of the distribution (20th, 40th, 60th, 80th).

Figure B.2: World mean value of AIGI over the period 1996-2016



Note: The legend is determined by the percentiles of the distribution (20th, 40th, 60th, 80th).

Figure B.3: World mean value of the EFP over the period 1996-2016



Note: EFP = external finance premium. The legend is determined by the percentiles of the distribution (20th, 40th, 60th, 80th).

C Additional information on the database on natural disasters

On EM-DAT The Emergency Disasters Database (EM-DAT) supported by the Centre for Research on the Epidemiology of Disasters (CRED) covers most of the disasters registered at world level. To be considered in the EM-DAT database, a disaster has to fulfil at least one of the following criteria : (1) 10 or more people are reported killed, (2) 100 or more people are reported affected, (3) a declaration of a state of emergency was issued (4) and/or there is a call for international assistance.

Link to EM-DAT data: <https://www.emdat.be/>

On GSOD Global Surface Summary of Day (GSOD) measures the wind speed from over 9000 worldwide stations. GSOD uses daily summaries of hourly observations contained in the Integrated Surface Data (ISD). If information on timing is incomplete with regard to the initial information provided by EM-DAT (e.g., the month and the year are available but the day is missing) we consider the highest value of the wind speed recorded during the relevant month.

Link to GSOD data: <https://www.ncei.noaa.gov>

On the geophysical intensity of floods The geophysical intensity of floods impacting several regions within a country is computed as the maximum of the monthly rainfall deviation among the affected territorial units. Moreover, for events lasting more than one month, intensity is computed as the maximum of the monthly deviations over the duration of the event.

On matching population density with location information Information on the affected regions is based on EM-DAT. Further, we use QGIS software to compute the population density at the first administrative level area. This is done in line with the maps from GADM (version 3.6) and the information from the UN WPP-adjusted population count rasters (Gridded Population of the World - GPW) collection provided by the Center for International Earth Science Information Network (CIESIN). Information is available every 5 years and consists of estimates of human population (number of persons per pixel), consistent with national censuses and population registers with respect to the relative spatial distribution. We hypothesize exponential population growth in between the 5-year database updates.

In general, all the disaster location information in EM-DAT is available at the first administrative level. However, when this is not the case we aggregate data at the first administrative level if they are only available initially at the second administrative or municipal levels. Moreover, if according to EM-DAT, an event spreads over a large area that includes several regions defined at the first administrative level, we associate the available information to each of these regions. For example, all the following regions are supposed to be concerned by an event affecting “North Portugal”: Viana Do Castelo, Braga, Porto, Vila Real, and Braganca. Finally, if initial information related to the location of the disaster is available only at country level and not at regional level in EM-DAT, we construct the measure of exposure by considering the mean of population density within the country.

Link to GADM maps: <https://gadm.org/>

Link to UN WPP-adjusted population count rasters: <https://sedac.ciesin.columbia.edu>

D Integrated Macprudential Policy (iMaPP) Database - details

Table D.1: Macprudential instruments in iMaPP dataset: definitions

Instrument	Definition
CCB	A requirement for banks to maintain a countercyclical capital buffer. Implementations at 0% are not considered as a tightening in dummy-type indicators.
Conservation	Requirements for banks to maintain a capital conservation buffer, including the one established under Basel III.
Capital	Capital requirements for banks, which include risk weights, systemic risk buffers, and minimum capital requirements. Countercyclical capital buffers and capital conservation buffers are captured in their sheets respectively and thus not included here. Subcategories of capital measures are also provided, classifying them into household sector targeted (HH), corporate sector targeted (Corp), broad-based (Gen), and FX-loan targeted (FX) measures.
LVR	A limit on leverage of banks, calculated by dividing a measure of capital by the bank’s non-risk-weighted exposures (e.g., Basel III leverage ratio).
LLP	Loan loss provision requirements for macroprudential purposes, which include dynamic provisioning and sectoral provisions (e.g. housing loans).
LCG	Limits on growth or the volume of aggregate credit, the household-sector credit, or the corporate-sector credit by banks, and penalties for high credit growth. Subcategories of limits to credit growth are also provided, classifying them into household sector targeted (HH), corporate sector targeted (Corp), and broad-based (Gen) measures.
LoanR	Loan restrictions that are more tailored than those captured in “LCG”. They include loan limits and prohibitions, which may be conditioned on loan characteristics (e.g., the maturity, the size, the LTV ratio and the type of interest rate of loans), bank characteristics (e.g., mortgage banks), and other factors. Subcategories of loan restrictions are also provided, classifying them into household sector targeted (HH), and corporate sector targeted (Corp) measures. Restrictions on foreign currency lending are captured in “LFC”.
LFC	Limits on foreign currency (FC) lending, and rules or recommendations on FC loans.
LTV	Limits to the loan-to-value ratios, including those mostly targeted at housing loans, but also includes those targeted at automobile loans, and commercial real estate loans.
DSTI	Limits to the debt-service-to-income ratio and the loan-to-income ratio, which restrict the size of debt services or debt relative to income. They include those targeted at housing loans, consumer loans, and commercial real estate loans.
Tax	Taxes and levies applied to specified transactions, assets, or liabilities, which include stamp duties, and capital gain taxes.
Liquidity	Measures taken to mitigate systemic liquidity and funding risks, including minimum requirements for liquidity coverage ratios, liquid asset ratios, net stable funding ratios, core funding ratios and external debt restrictions that do not distinguish currencies.
LTD	Limits to the loan-to-deposit (LTD) ratio and penalties for high LTD ratios.
LFX	Limits on net or gross open foreign exchange (FX) positions, limits on FX exposures and FX funding, and currency mismatch regulations.
RR	Reserve requirements (domestic or foreign currency) for macroprudential purposes. Please note that this category may currently include those for monetary policy as distinguishing those for macroprudential or monetary policy purposes is often not clear-cut. A subcategory of reserve requirements is provided for those differentiated by currency (FCD), as they are typically used for macroprudential purposes.
SIFI	Measures taken to mitigate risks from global and domestic systemically important financial institutions (SIFIs), which include capital and liquidity surcharges.
Other	Macroprudential measures not captured in the above categories—e.g., stress testing, restrictions on profit distribution, and structural measures (e.g., limits on exposures between financial institutions).

Source: Alam, Z., Alter, M. A., Eiseman, J., Gelos, M. R., Kang, M. H., Narita, M. M., ... & Wang, N. (2019). Digging deeper—Evidence on the effects of macroprudential policies from a new database. International Monetary Fund.

E Our variables: further details

- **External finance premium.** Difference between the bank lending rate (all maturities) and the 3-month money market rate. The discount rate or the policy rate is considered if the 3-month money market rate data are not available. Source: IMF - IFS.
- **Extensivity of macroprudential framework.** Number of macroprudential instruments that have been activated in a country. Source: [Alam et al. \(2019\)](#).
- **Prompt corrective action** A discrete variable measuring whether a law establishes predetermined levels of bank solvency deterioration that force automatic actions, such as government interventions. It ranges from 0 to 6, with a higher value indicating more promptness in responding to problems. The database contains five surveys (1999, 2003, 2007, 2011 and 2019). To conserve the panel structure of our data, we consider time span according to the description of the authors. The first survey for the years 1990-2000, the second survey for the years 2001-2003, the third survey for the years 2004-2007, the fourth survey for years 2008-2011 and the fifth survey for the years 2012-2016. Source: [Barth et al. \(2013\)](#).
- **Banking concentration.** Assets of the three largest commercial banks as a share of total commercial banking assets. Total assets include total earning assets, cash and due from banks, foreclosed real estate, fixed assets, goodwill, other intangibles, current tax assets, deferred tax assets, discontinued operations and other assets. Source: World Bank - Global Financial Development.
- **Credit-to-GDP ratio.** Ratio of bank loans to the private sector on GDP at current prices. When necessary, a linear interpolation was implemented to have a GDP at quarterly frequency. Source: IFM-IFS (line 22d, FOSAOP), World Bank - World Development Indicators.
- **Annual growth of real GDP.** Growth of real GDP (in constant US\$). Source: World Bank - World Development Indicators.
- **GDP per capita.** Logarithmic transformation of GDP per capita (in constant US\$). Source: World Bank - World Development Indicators.
- **Inflation.** Index computed as the growth of Consumer Price Index (CPI). Source: IMF - International Financial Statistics.
- **The Chinn-Ito index.** Index measuring a country's degree of capital account openness. Source: [Chinn and Ito \(2006\)](#).
- **Polity2.** The Polity2 score ranges from +10 (strongly democratic) to -10 (strongly autocratic). Source: Polity5 Project, Political Regime Characteristics and Transitions, 1800-2018.
- **Baking Crisis.** Dummy variable equal to 1 when a country is in a situation of financial crisis at time t and 0 otherwise. Source: [Laeven and Valencia \(2020\)](#).
- **Control of corruption** Perceptions of the extent to which public power is exercised for private gains, including petty and grand forms of corruption. The indicator lies between -2.5 and 2.5. Source: World Bank - Worldwide Governance Indicators.
- **Inflation targeting.** Dummy variable equal to 1 once a country has adopted inflation targeting (0 otherwise). Source: [Roger \(2009\)](#); [Schmidt-Hebbel and Carrasco \(2016\)](#); [Adler et al. \(2020\)](#).
- **FX regime.** De facto exchange rate arrangement classification, set from 1 (fixed) to 6 (more flexible). Source: [Iizetzki et al. \(2017\)](#).
- **Financial markets depth index.** Composite index that compiles data on stock market capitalization to GDP, stocks traded to GDP, international debt securities of government to GDP, and total debt securities of financial and non-financial corporations to GDP. Source: IMF - Financial Development Index Database.
- **Budget Balance Rule.** Dummy variable that is equal to 1 if fiscal policy operates under a budget balance rule in a country i at time t (0 otherwise). Source: [Lledó et al. \(2017\)](#).

F Descriptive statistics

Table F.1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Change in spread ($h=1$)	-0.06	3.43	-55.17	59.58	5433
Change in spread ($h=6$)	-0.08	4.5	-54.43	61.54	4986
Change in spread ($h=12$)	-0.19	4.76	-52.73	57.57	4461
IGI Storm	0.09	1.18	0	49.36	5526
AIGI Storm	0.88	26.65	0	1836.88	5526
IGI Flood	0.14	0.87	0	31.55	5526
AIGI Flood	5.22	96.06	0	6769.45	5526
Number of instruments (dummy)	0.61	0.49	0	1	5526
Prompt corrective action (dummy)	0.55	0.5	0	1	4745
Banking concentration	66.09	18.63	20.19	100	5494
Credit-to-GDP ratio (%)	51.98	42.12	2.13	267.64	5484
GDP growth (%)	0.91	0.94	-4.17	8.62	5526
Logarithm of GDP per capita	8.80	1.44	5.39	11.11	5526
Inflation	1.22	2.02	-12.99	28.21	5522
Chinn-Ito index	0.83	1.52	-1.92	2.35	5526
Polity2	5.93	5.39	-9	10	5526
Banking crisis	0.07	0.26	0	1	5526
Control of corruption	0.15	1	-1.5	2.46	4927
Inflation targeting (dummy)	0.24	0.43	0	1	5526
Exchange rate regime	2.07	1.04	1	6	5524
Financial markets depth	0.31	0.3	0	0.99	5526
Budget balance rule in place (dummy)	1	0	1	1	2377

Table F.2: Cross-correlation table

Variables	Change in spread ($h=6$)	Logarithm of GDP per capita	Polity2	Banking concentration	Credit-to-GDP ratio	Chinn-Ito index	Inflation	GDP growth
Change in spread ($h=6$)	1.000							
Logarithm of GDP per capita	-0.004	1.000						
Polity2	-0.045	0.397	1.000					
Banking concentration	0.034	-0.079	-0.157	1.000				
Credit-to-GDP ratio	0.076	-0.023	-0.121	0.051	1.000			
Chinn-Ito index	-0.009	0.604	0.299	0.020	-0.074	1.000		
Inflation	0.025	-0.097	-0.061	0.018	0.186	-0.129	1.000	
GDP growth	-0.043	-0.250	-0.180	0.029	0.034	-0.154	-0.027	1.000

G Country list

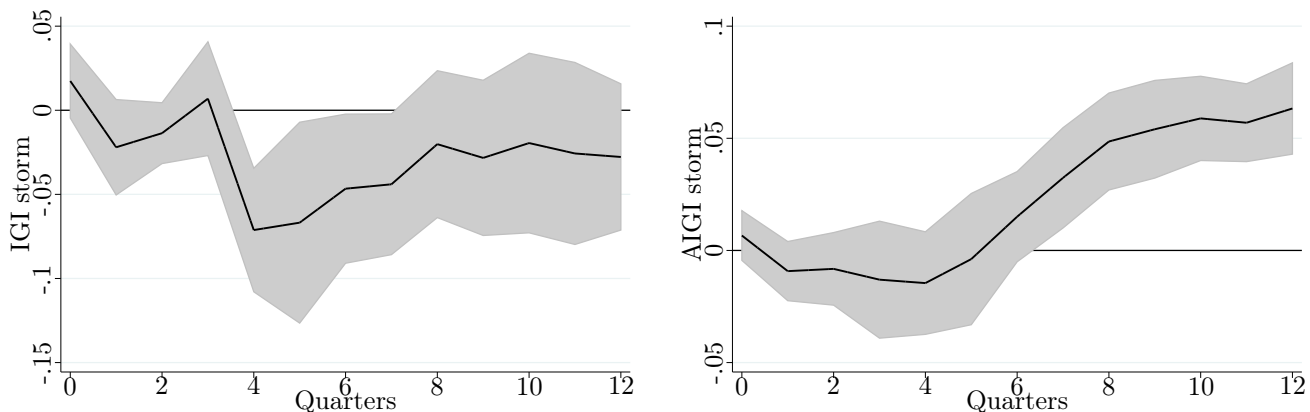
Table G.1: List of Countries

Countries		
<i>Albania</i>	(Guatemala)	Nigeria
<i>Algeria</i>	(Guyana)	Oman
Armenia	Honduras	Pakistan
Australia	Hungary	(Panama)
Austria	India	Paraguay
<i>Azerbaijan</i>	Indonesia	Peru
Bahrain	Ireland	Philippines
Bangladesh	Italy	Poland
Belarus	<i>Jamaica</i>	Portugal
Belgium	Japan	Romania
(Bolivia)	Jordan	Russia
Botswana	Kenya	Senegal
Brazil	Korea	Singapore
Bulgaria	Kuwait	Slovak Republic
Burkina Faso	Kyrgyz Republic	Slovenia
Burundi	Laos	South Africa
Canada	Lebanon	Spain
Chile	Lesotho	Sri Lanka
<i>China</i>	Lithuania	(Suriname)
Colombia	(Madagascar)	Sweden
Coasta Rica	Malaysia	Tajikistan
Ivory Coast	Mali	Thailand
Croatia	<i>Mauritania</i>	Togo
Cyprus	Mauritius	Trinidad & Tobago
Czech Republic	Mexico	Uganda
<i>Dominican Republic</i>	Moldova	<i>Ukraine</i>
(Egypt)	<i>Mongolia</i>	United Kingdom
Estonia	<i>Mozambique</i>	United States
Finland	(Namibia)	Uruguay
France	<i>Nepal</i>	(Venezuela)
Gambia	Netherlands	<i>Zambia</i>
Germany	New Zealand	
Greece	Niger	

Countries in italics correspond to those that are considered in the baseline estimates but not in the robustness estimates with the “prompt corrective action” measure as interactive variable. Countries in brackets are those that are considered in these robustness estimates, but not in the baseline estimates. The sample size is governed by data availability concerning EFP. We keep in our sample countries for which we have at least 50% of consecutive observations over the period 1996-2016.

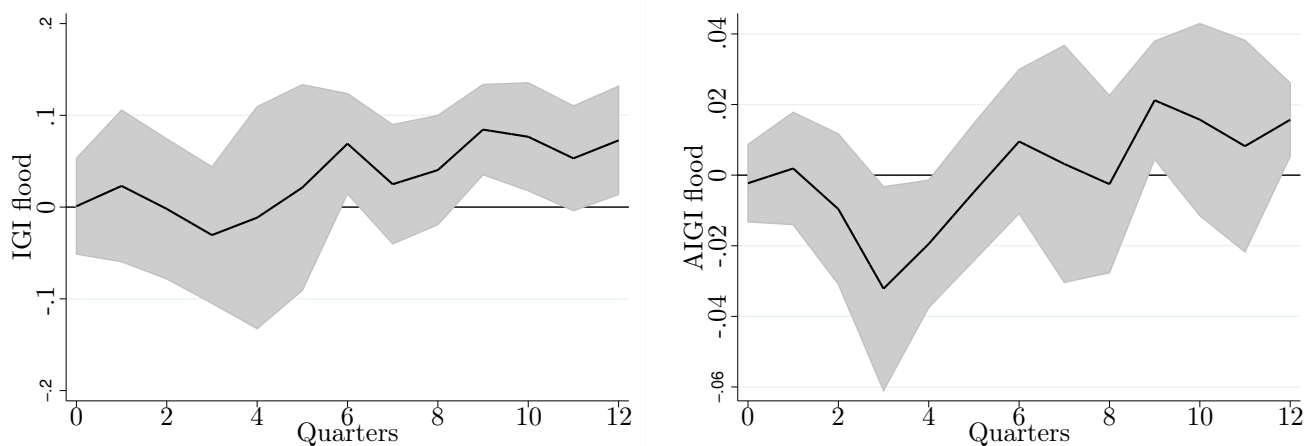
H Additional results and robustness checks

Figure H.1: Response of the EFP to storms (no interaction with macroprudential framework)



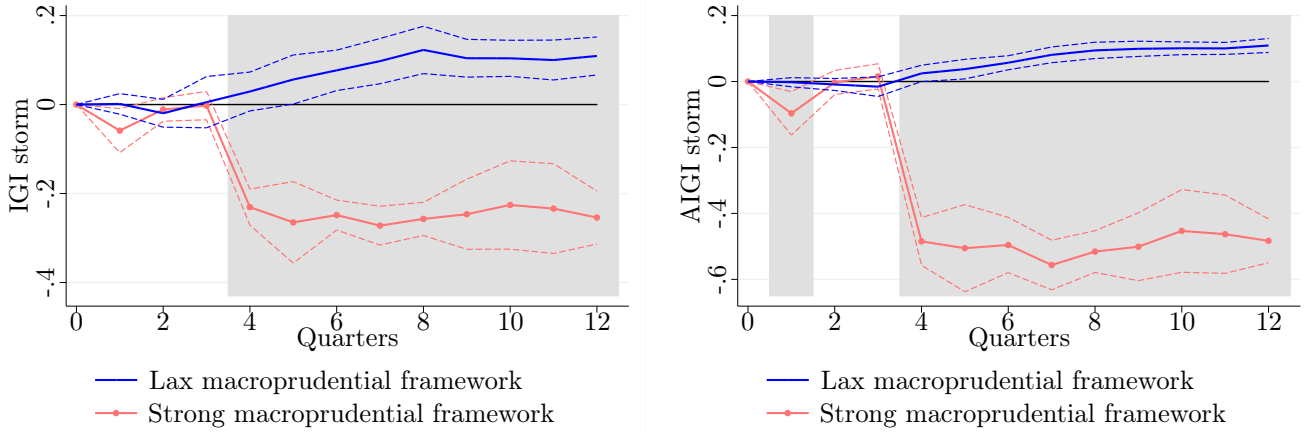
Note: This figure represents the response of the external finance premium (EFP) to a one-standard-deviation shock to (A)IGI-storm, over horizons from 1 to 12 quarters. Shaded areas correspond to confidence bands at 90%.

Figure H.2: Response of the EFP to floods (no interaction with macroprudential framework)



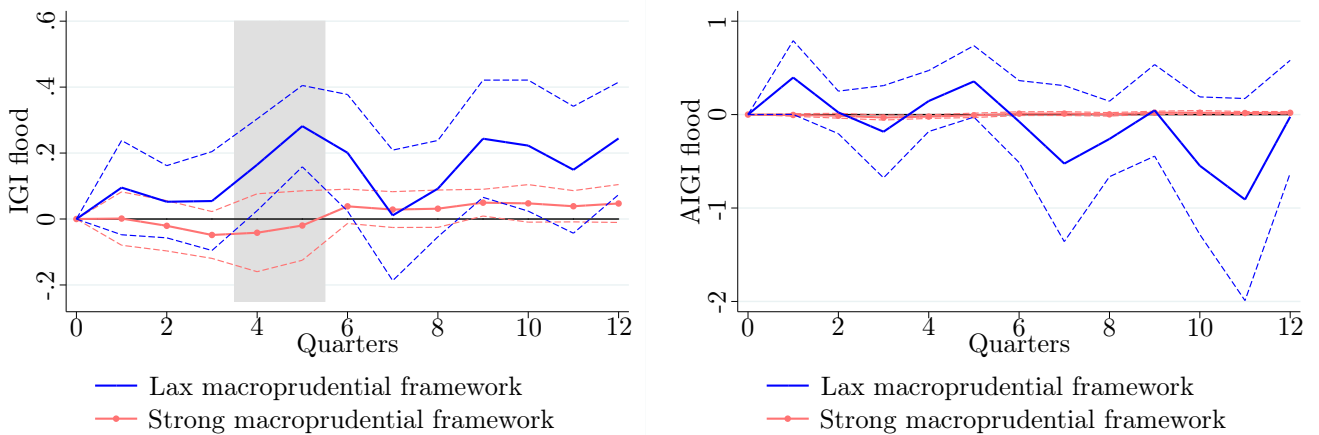
Note: This figure represents the response of the external finance premium (EFP) to a one-standard-deviation shock to (A)IGI-flood, over horizons from 1 to 12 quarters. Shaded areas correspond to confidence bands at 90%.

Figure H.3: Response of the EFP to storms - reverse causality checks



Note: This figure represents the response of the external finance premium (EFP) to a one-standard-deviation shock to (A)IGI, for lax *vs.* strong macroprudential framework, over horizons from 1 to 12 quarters. Dotted lines correspond to confidence bands at 90%. Shaded areas indicate that the interaction term is significantly different from zero at the 5% confidence level.

Figure H.4: Response of the EFP to floods - reverse causality checks



Note: This figure represents the response of the external finance premium (EFP) to a one-standard-deviation shock to (A)IGI, for lax *vs.* strong macroprudential framework, over horizons from 1 to 12 quarters. Dotted lines correspond to confidence bands at 90%. Shaded areas indicate that the interaction term is significantly different from zero at the 5% confidence level.

Table H.1: Storms: The effects of macroprudential policies while adding other shock absorbers

IGI Storm	Quarter 1	Quarter 4	Quarter 8	Quarter 12
Baseline	-0.06* (0.03)	-0.26*** (0.03)	-0.39*** (0.04)	-0.36*** (0.04)
GDP per capita	-0.06* (0.04)	-0.26*** (0.03)	-0.39*** (0.04)	-0.36*** (0.04)
Polity2	-0.06* (0.03)	-0.28*** (0.03)	-0.40*** (0.05)	-0.38*** (0.04)
Control of corruption	-0.07** (0.03)	-0.28*** (0.04)	-0.39*** (0.05)	-0.39*** (0.04)
Inflation targeting	-0.06* (0.03)	-0.26*** (0.03)	-0.38*** (0.04)	-0.36*** (0.04)
FX regime	-0.06* (0.04)	-0.26*** (0.03)	-0.38*** (0.04)	-0.38*** (0.04)
Financial markets depth	-0.03 (0.03)	-0.26*** (0.04)	-0.40*** (0.05)	-0.37*** (0.04)
Budget balance rule	-0.05* (0.03)	-0.26*** (0.04)	-0.38*** (0.04)	-0.35*** (0.04)
All	-0.01 (0.09)	-0.26*** (0.08)	-0.40*** (0.08)	-0.45*** (0.10)
AIGI Storm	Quarter 1	Quarter 4	Quarter 8	Quarter 12
Baseline	-0.09** (0.04)	-0.51*** (0.05)	-0.61*** (0.05)	-0.59*** (0.04)
GDP per capita	-0.05 (0.07)	-0.54*** (0.06)	-0.65*** (0.06)	-0.63*** (0.09)
Polity2	-0.12** (0.06)	-0.54*** (0.04)	-0.60*** (0.05)	-0.58*** (0.05)
Control of corruption	-0.11*** (0.04)	-0.50*** (0.05)	-0.58*** (0.05)	-0.57*** (0.05)
Inflation targeting	-0.09** (0.04)	-0.51*** (0.05)	-0.61*** (0.05)	-0.60*** (0.04)
FX regime	-0.09** (0.04)	-0.51*** (0.05)	-0.60*** (0.05)	-0.58*** (0.04)
Financial markets depth	-0.02 (0.07)	-0.54*** (0.09)	-0.77*** (0.08)	-0.77*** (0.11)
Budget balance rule	-0.09** (0.04)	-0.51*** (0.04)	-0.61*** (0.05)	-0.58*** (0.05)
All	0.11 (0.17)	-0.34* (0.19)	-0.59*** (0.16)	-0.80*** (0.22)
Number of observations	5436	5166	4813	4465

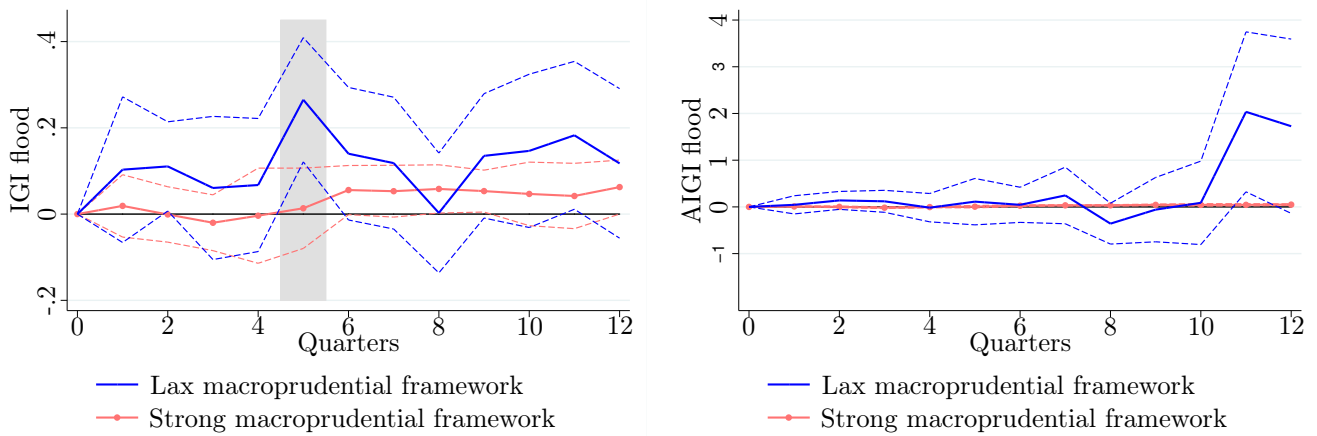
Note: This table reports the estimated value of the interaction term of the geophysical intensity of storms (A)IGI and the dummy variable that represents the stringency of macroprudential framework when adding other potential mitigating factors in interaction with (A)IGI. These other shock absorbers are labelled in the first column. The dependent variable is the external finance premium (EFP). All regressions include control variables (see Section 4.3) as well as time and country FEs. Standard errors in parentheses are corrected for heteroskedasticity and clustered at the country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table H.2: Floods: The effects of macroprudential policies while adding other shock absorbers

IGI Flood	Quarter 1	Quarter 4	Quarter 8	Quarter 12
Baseline	-0.22** (0.09)	-0.29** (0.14)	-0.10 (0.10)	-0.18 (0.12)
GDP per capita	-0.20** (0.08)	-0.26** (0.12)	-0.10 (0.09)	-0.18 (0.12)
Polity2	-0.19** (0.09)	-0.25* (0.13)	-0.13 (0.10)	-0.21 (0.13)
Control of corruption	-0.22*** (0.08)	-0.29*** (0.10)	-0.13 (0.08)	-0.19* (0.11)
Inflation targeting	-0.24*** (0.09)	-0.32** (0.15)	-0.12 (0.12)	-0.20 (0.14)
FX regime	-0.18** (0.09)	-0.21 (0.14)	-0.09 (0.11)	-0.16 (0.12)
Financial markets depth	-0.21** (0.09)	-0.27** (0.11)	-0.09 (0.09)	-0.16 (0.11)
Budget balance rule	-0.21** (0.09)	-0.27** (0.11)	-0.09 (0.09)	-0.16 (0.11)
All	-0.21** (0.09)	-0.29** (0.14)	-0.15 (0.11)	-0.20 (0.14)
AIGI Flood	Quarter 1	Quarter 4	Quarter 8	Quarter 12
Baseline	-0.68* (0.37)	-0.27 (0.29)	0.36 (0.31)	0.42 (0.34)
Log GDP per capita	-0.68* (0.37)	-0.30 (0.32)	0.32 (0.28)	0.47 (0.36)
Polity2	-0.72* (0.36)	-0.36 (0.31)	0.23 (0.29)	0.36 (0.33)
Control of corruption	-0.67* (0.37)	-0.32 (0.32)	0.32 (0.28)	0.48 (0.35)
Inflation targeting	-0.75** (0.34)	-0.36 (0.31)	0.29 (0.37)	0.35 (0.38)
FX regime	-0.80*** (0.29)	-0.52** (0.23)	0.13 (0.42)	0.06 (0.44)
Financial markets depth	-0.69* (0.36)	-0.21 (0.30)	0.37 (0.33)	0.35 (0.35)
Budget Balance Rule	-0.61 (0.37)	-0.19 (0.29)	0.47 (0.31)	0.54 (0.33)
All	-0.92*** (0.25)	-0.53 (0.32)	-0.17 (0.53)	0.01 (0.65)
Number of observations	5436	5166	4813	4465

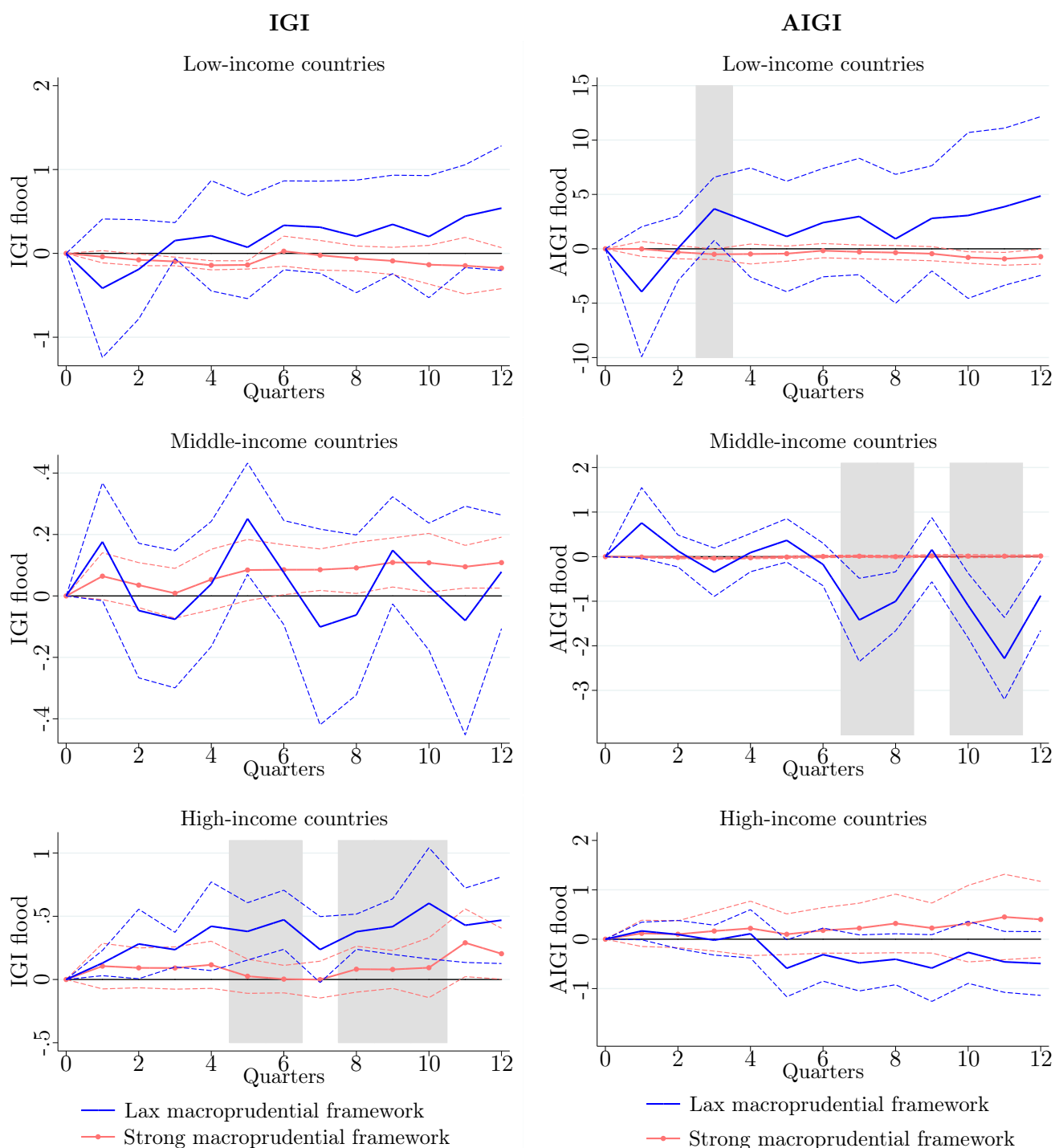
Note: The table reports the estimated value of the interaction term of the geophysical intensity of floods (A)IGI and the dummy variable that represents the stringency of macroprudential framework when adding other potential mitigating factors in interaction with (A)IGI. These other shock absorbers are labelled in the first column. The dependent variable is the external finance premium (EFP). All regressions include control variables (see Section 4.3) as well as time and country FEs. Standard errors in parentheses are corrected for heteroskedasticity and clustered at the country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure H.5: Response of the EFP to floods - recent period



Note: This figure represents the response of the external finance premium (EFP) to a one-standard-deviation shock to (A)IGI-flood, for a lax *vs.* strong macroprudential framework, over horizons from 1 to 12 quarters. Dotted lines correspond to confidence bands at 90%. Shaded areas indicate that the interaction term is significantly different from zero at the 5% confidence level. Estimation period: 2006-2016.

Figure H.6: Response of the EFP to floods depending on country income level



Note: This figure represents the response of the external finance premium (EFP) to a one-standard-deviation shock to IGI-flood in the first column of plots and to a one-standard-deviation shock to AIGI-flood in the second column of plots, for lax *vs.* strong macroprudential framework, over horizons from 1 to 12 quarters, depending on country income level. Dotted lines correspond to confidence bands at 90%. Shaded areas indicate that the interaction term is significantly different from zero at the 5% confidence level.