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. Natural disasters' intensity is measured through an original set of geophysical indicators for a sample of 88 countries over 1996-2016. Using local projections, we show that, following storms, the EFP significantly drops (rises) when macroprudential regulation is stringent (lax). These results support the hypothesis that regulated financial systems could foster favorable financing conditions to replace the destroyed capital with a more productive one. Macroprudential stringency seems less crucial in case of floods, whose predictability may prompt self-discipline.

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1 Introduction

While the adverse real economic effects of climate change are now widely admitted, 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. Rather recently, the latter have motivated the implementation of (macro)prudential (MP) measures. While, so 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 to 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 pre-requisite for our empirical analysis. Hence, as a first step of our investigation, we highlight different channels through which NDs may generate financial stress: high probability of negative wealth effects, deterioration of banks' and borrowers' balance sheets, increase in credit and sovereign risks. The transmission and amplification of NDs effects through these mechanisms might be nonetheless 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 too leveraged, any shock on (collateralized) financial or real assets might be smoother compared to 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 national macroprudential framework, we use the local projections (LPs) 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. An original NDs dataset is constructed: NDs are gauged by meteorological intensity, collected from different sources stemming from meteorological stations and satellites. We focus on two types of NDs in particular, 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 hit areas. Intensity of flooding is measured in terms of 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 NDs indicators we build. Furthermore, they are augmented by the density of population, in order 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 issue. Finally, our measure of prudential stringency refers to the number of macroprudential instruments that have been actually activated in each country. This "extensity" measure of stringency is based on the recent

[1] To the best of our knowledge macroprudential frameworks had never been officially developed to tackle climate-related financial risks. Initiatives intended to take better account of climate risks for 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.

[2] At the opposite, chronic global risks like rising sea levels and increasing temperatures have a real and financial impact that is much more gradual over time.

integrated Macroprudential Policy (iMaPP) database, which provides a comprehensive coverage in terms of macroprudential instruments, countries, and time periods.

Our results, based on a panel of 88 countries over 1996-2016, show that storms, while affecting only one or several regions within a country, significantly impact the EFP at the national level, 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 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 an overall large 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. At the opposite, a small country with a stringent macroprudential framework could benefit from a decrease in the EFP of about 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 the destroyed capital with a more productive one. 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 are not conclusive regarding the financial effects of flooding. 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 been distant from each other until now: the impact of natural disasters and the benefits of macroprudential policy. On the one hand, there is a rich literature dealing with the impact of NDs on the real sector of the economy[3]. While the negative economic effects of catastrophes seem to increase over time (Klomp and Valckx, 2014), some structural features like 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 banks' performances 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). At the opposite, others emphasize the existence of a Schumpeterian creative destruction effect in affected regions, with recovery lending[4] 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 deals with the growing literature on the macroeconomic effects 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),

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

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

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 a ND can cause financial stress. Second, we propose a quantitative macroeconomic evaluation of the effects of NDs on 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, as far as we know, we are the first to consider the 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 is 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

Our empirical approach aims at assessing the overall financial effect of NDs. We do not seek to identify the contribution of any particular transmission channel: as there are multiple channels, with a varying importance in time and across countries, it is extremely difficult to assess in an international setting, which channel might dominate. Yet, 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, and in particular the 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 each other. 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 as they demand for bank loans. At the same time, the shock induced by the ND generates more information asymmetry. This implies higher agency premiums through the financial accelerator mechanism (Bernanke et al.,

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

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 of firms' debt service capability. This entails higher credit risk.

(3) By lowering the actual and expected profitability of firms, ND may cause a fall 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 the economic activity increases non-performing loans (Klomp, 2014; Dafermos et al., 2018). Meanwhile, banks may suffer from missing savings and immediate withdrawals of deposits used to replace lost physical assets and afford medical care (Brei et al., 2019). Given maturity mismatch, this worsens the 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 a 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, a ND can be viewed 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, to the reconstruction of public infrastructures, medical purposes, as well as to the bail out of insolvent banks (Lamperti et al., 2019). Since tax revenue jointly decreases, public debt increases, as well as 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 would have to be bailed out by the government. This worsens sovereign distress even further.

These five key transmission channels predict an increase in bank lending rates in the wake of a ND, particularly due to an increase in agency and risk premium.[10]

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[6] This 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).

[7] Baker 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.

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

[9] As 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 find that an increase in climate risk is associated with an increase in issuance costs of municipal bonds.

[10] The results are rather mixed in the literature regarding credit volume. 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 a 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.,

Further, we analyze how this increase in financial stress can be mitigated by the macroprudential regulation. To do this 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 the past decades, through the implementation of quantitative restrictions on borrowing, like 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 intend to protect the 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 cycle, in mitigating asset prices fluctuations, and in reducing bank risk.[13]

Overall, a 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 on (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 impact 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 condition are tightened, 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 a ND.

Finally, macroprudential regulation may even prompt an easing of credit conditions in the wake of a ND. Indeed, a sound financial system may support the short-run recovery, by reducing the procyclicality of lending standards, by reducing uncertainty and by 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 inherent higher 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 the macroprudential regulation.

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).

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

[12] See for instance Farhi and Werning (2016); Korinek and Simsek (2016); Bianchi and Mendoza (2018) that theoretically demonstrate the efficiency of macroprudential regulation.

[13] See for example the evidence provided by Vandenbussche et al. (2015), Jiménez et al. (2017), Altunbas et al. (2018), Akinci and Olmstead-Rumsey (2018) and Araujo et al. (2020), while considering 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 to a storm or to a flood. We thus are able to capture different disaster types and their potential heteroegenous effects on financial stability. More precisely, $D_{i,t}^{d}$ is defined as a continuous variable representing the physical intensity, or exposure, related to a natural disaster d, with $D_{i,t}^{d} > 0$ if a disaster d occurs and $D_{i,t}^{d} = 0$ otherwise. Once controlled for the geographical position and the size of the country i, which can influence the occurrence and the 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 $Y_{i,t}$ 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

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

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

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

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 through country fixed effects. This corresponds to the Conditional Independence Assumption (CIA): conditionally on a set of covariates the potential outcomes are independent from 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 be different in intensity over time, it is interesting to assess the ATE at different successive horizons, corresponding to quarters in our case. The ATE of a 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 $h = 0, 1, 2, \ldots, H$, such that:

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

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

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

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

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

Then, we denote $P_{i,t-1}$ 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 $Y_{i,t+h}$, conditionally on the macroprudential environment is gauged with the following interactive model:

$$Y_{i,t+h} - Y_{i,t-1} = \alpha_{i,h} + \beta_h D^d_{i,t} + \gamma_h \left[D^d_{i,t} \times P_{i,t-1}\right] + \omega_h P_{i,t-1} + \theta_h Z_{i,t} + \varepsilon_{i,t+h} \tag{6}$$

As before, we can note that $\mathbb{E}_t\left(Y_{i,t+h} - Y_{i,t-1} | D^d_{i,t} = 0, Z_{i,t}\right) = \alpha_{i,h} + \omega_h \mathbb{E}_t\left(P_{i,t-1} | D^d_{i,t} = 0, Z_{i,t}\right)$, while $\mathbb{E}_t\left(Y_{i,t+h} - Y_{i,t-1} | D^d_{i,t} > 0, Z_{i,t}\right) = \alpha_{i,h} + \beta_h D^d_{i,t} + \gamma_h \mathbb{E}_t\left(P_{i,t-1} | D^d_{i,t} > 0, Z_{i,t}\right) D^d_{i,t} + \omega_h \mathbb{E}_t\left(P_{i,t-1} | D^d_{i,t} > 0, Z_{i,t}\right)$. As macroprudential frameworks are primarily established to deal with the resilience to financial imbalances and economic shocks, we can reasonably assume that having a stringent macroprudential framework or not is independent from the occurrence of a ND in time t. For instance, the recommendations of the Basel Committee on Banking Supervision since the 1980s have been primarily motivated 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 examine how including climate risks in the banking stress tests[14], albeit without reforming the macroprudential framework. This implies that $\mathbb{E}_t\left(P_{i,t-1} | D^d_{i,t} > 0, Z_{i,t}\right) D^d_{i,t} = \mathbb{E}_t\left(P_{i,t-1} | D^d_{i,t} = 0, Z_{i,t}\right) D^d_{i,t} = P_{i,t-1}$.[15] Hence, the ATE derived from equation (6), designing the impact of natural disasters on Y at quarters h, conditionally on the stringency of the macroprudential regulation, is equal to:

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

Finally, we add L lags of the dependent variable as well as a set of one year (four quarters) lagged control variables ($X_{i,t-4}$) capturing macroeconomic and financial characteristics (see details in the next section). In addition, time fixed effects (τ^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 of 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 of the external finance premium that would be unrelated to any natural disaster. Hence, the model actually estimated is the following

$$\begin{aligned} Y_{i,t+h} - Y_{i,t-1} = \alpha_{i,h} + \beta_h D^d_{i,t} + \gamma_h \left[D^d_{i,t} \times P_{i,t-1}\right] + \omega_h P_{i,t-1} + \sum_{l=1}^{L} \rho_h \Delta Y_{i,t-l} \\ + \theta_h X_{i,t-4} + \sum_{j=1}^{h-1} \delta_h D^d_{i,t+h-j} + \sum_{j=1}^{h-1} \eta_h C_{i,t+h-j} + \tau_{h,t} + \varepsilon_{i,t+h}, \end{aligned} \tag{8}$$

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

[14] For example, the Network of central banks and supervisors for Greening the Financial System (NGFS), which partly aims at integrating climate-related risks into supervision and financial stability monitoring, has been created very recently, in December 2017.

[15] To ensure this hypothesis we will consider as 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 for dealing with potential nonlinearities (Jordà, 2005). Such nonlinearities are possible in our case, as there might be a time of adjustment before the shock is translated to 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, whose high dimensionality 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, whose specification errors can get accumulated 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 disasters data

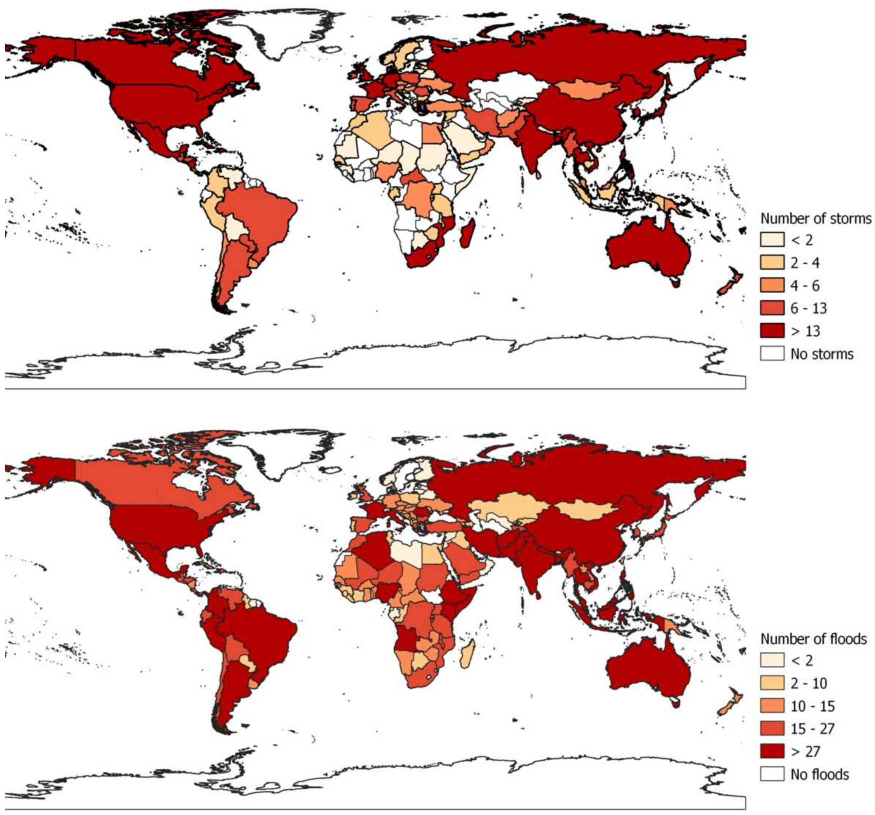
This subsection presents our two new country-level quarterly indexes of NDs. In this setting, it is important to note that three concomitant elements make a geophysical event a ND: *hazard*, *exposure* and *vulnerability* (Yonson et al., 2018). As defined by the Intergovernmental Panel on Climate Change (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 while investigating the economic and financial effects of a 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 the quantity of precipitation, can be considered 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). From 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 too restrictive with regard to the three abovementioned components. In particular, it could lead to considering many insignificant climate events. However, a relevant identification strategy requires somewhat large shocks.

Against this background, we develop and use a new dataset of NDs (i) whose types, locations, and dates are first identified with the EM-DAT database, and (ii) that are gauged by meteorological intensity measures. 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 considering hazards related to a certain threshold of vulnerability. Moreover, through this approach, we avoid any endogeneity problem, as the geophysical intensity of natural events 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]

More precisely, 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 like 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., density of the population), and thus creating a new index, and (iv) by building quarterly indicators, not annual ones. Figure 1 depicts the geographical distribution of storms and floods. We observe that all continents and countries were hit by at least one disaster from 1996-2016.

Figure 1: Total number of storms and floods over 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. 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 Administration (NOAA), and the Global Surface Summary of Day (GSOD). We select the maximum

[16] In any case, if one were to neglect some events whose consequences would have been mitigated by macroprudential policy, our estimates would underestimate the true effects of macroprudential policy. Overconservative estimates are preferable to the opposite.

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 the regional level, not at the national level: this is done for accuracy purposes, as floods are highly localized. More precisely, as data are provided in millimeters for 0.5 latitude and longitude degree grid nodes (i.e., over an area of approximately 55m^2), 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 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 (noted τ_i, expressed in $1000\,\text{km}^2$). This normalization is justified as 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:

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

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 a ND). This Augmented IGI (labeled AIGI) measures the *potential* impact of a natural hazard exogenous to financial stability. It reads:

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

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 very populated areas affected by disasters, India is included in the second percentile of affected countries if the measure of intensity is the 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 1996-2016 in our sample of 88 countries. 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. At the opposite, the strongest hurricane reaches 300 km/h. The average flood 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				
	IGI	0.8	3.3	0.0	49.4	859	0.0004	0.6392	0.1924
	AIGI	6.8	69.4	0.0	1836.9				
Flood	Geophysical intensity[b]	166.8	174.9	0.2	1541.1				
	IGI	0.8	1.9	0.0	31.5	1262	0.0001	0.5920	0.1109
	AIGI	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 exposed in Appendix D), countries (134 countries), and time spans (from 1990 to 2016). In particular, it delivers information on the tightening, unchanging or loosening of each macroprudential instrument from quarter to quarter. Nevertheless, the initial value of each instrument and the amplitude of their 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 the 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 stringency of macroprudential frameworks is the cumulative number of macroprudential instruments actually used in each country since 1990. It represents a measure of *extensity* of the implementation of macroprudential policy (Aizenman et al., 2020): the higher the number of available instruments, the stronger the macroprudential requirements.

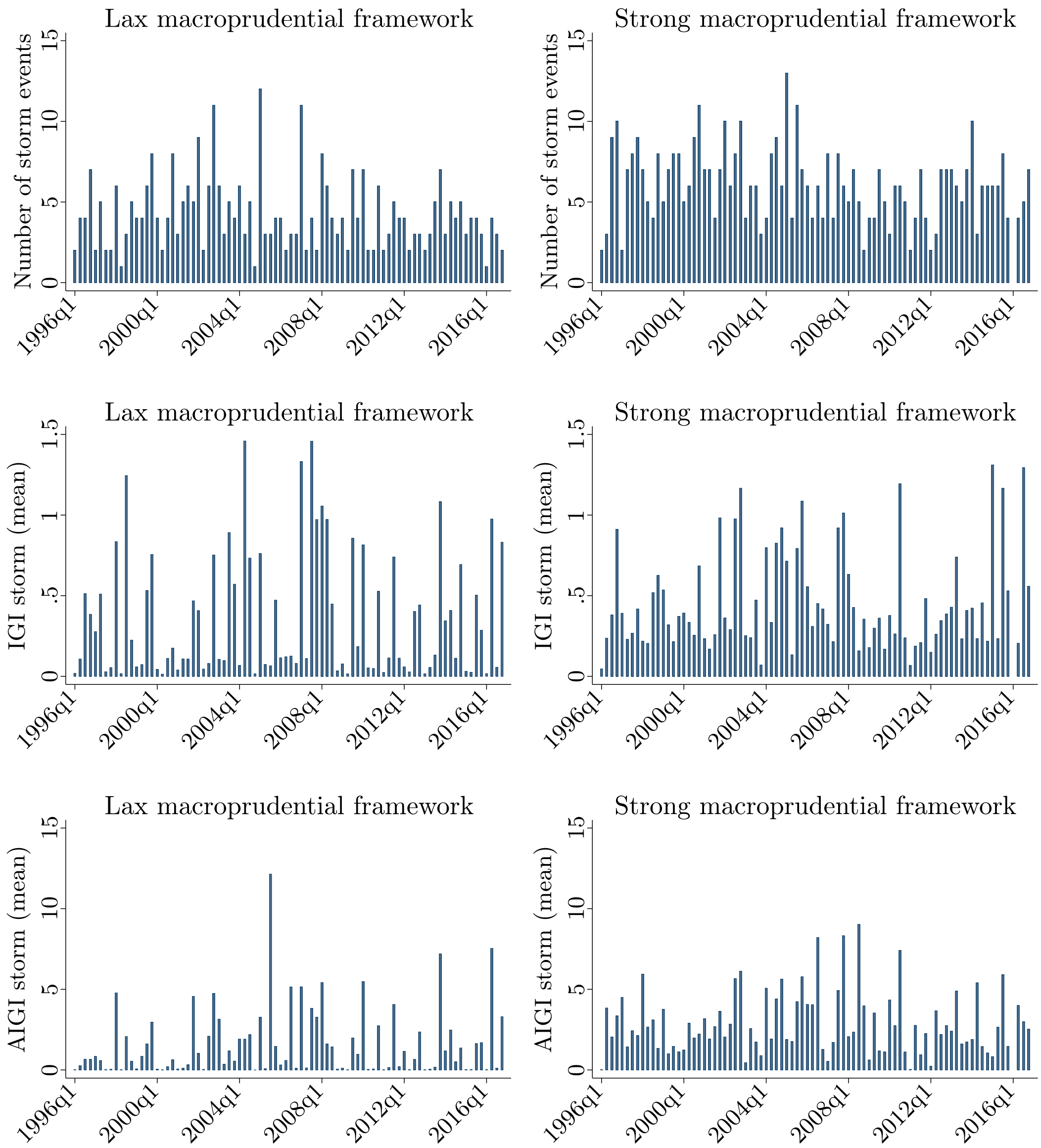
Countries are differentiated according to whether their macroprudential policy framework is stringent ($P = 1$ in Eq. 8) or lax ($P = 0$). At each quarter t, a country i is considered to have a strong (lax) macroprudential framework if it has implemented at least (less than) two instruments, which is the median number of instruments implemented over the whole period while 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 $\boldsymbol{P}$. In addition, for 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 1996-2016, 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.

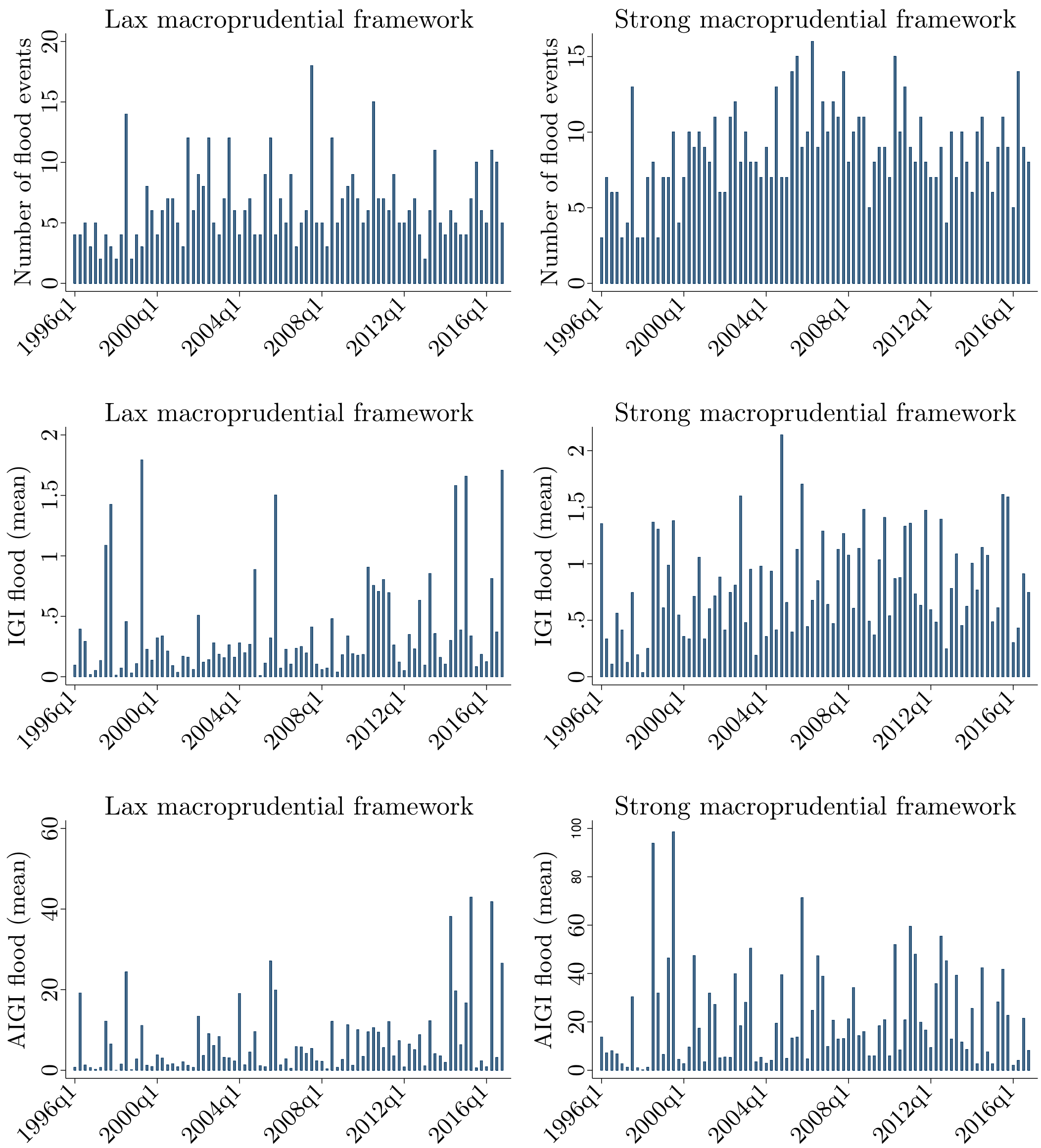
[17]The null hypothesis of equal means in the two groups is never rejected except for the IGI flood, which is higher for the group of strong macroprudential frameworks. However, this is not truly an issue in our setting, which precisely aims to test macroprudential policies' ability to ensure the financial sector's resilience to 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 concern lax (strong) macroprudential countries. Plots in the first row represent the number of storms. Plots in the second row refer to the mean IGI for storms. Plots in the third row represent the mean AIGI for storms. The top 1%, or the most intense disasters are excluded from these plots for clarity of representation. These extreme cases are equally distributed over 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 concern lax (strong) macroprudential countries. Plots in the first row represent the number of floods. Plots in the second row refer to the mean IGI for floods. Plots in the third row represent the mean AIGI for floods. Source: Authors' calculations.

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 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, which are listed in Appendix G.

Next, we consider a set of control variables that are likely to explain the EFP. This concerns some traditional financial characteristics, such as bank concentration and credit-to-GDP ratio. The occurrence of banking crisis 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 terms of information asymmetry and 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.

5 Results

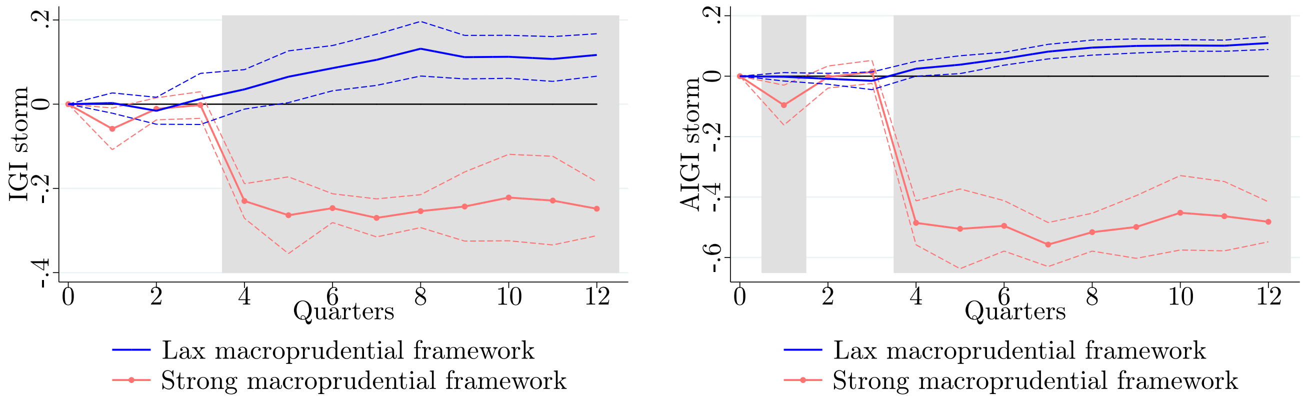
Our empirical investigation is based on a quarterly sample of 88 countries over the period 1996-2016. The impact of NDs on the EFP is gauged by local projections from $h = 1$ to 12 quarters after the initial shock, conditional on the degree of stringency of the macroprudential framework (lax *vs* strong), 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 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. More precisely, we observe that the EFP starts increasing significantly five quarters after the shock on 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, to assess the damages and to evaluate the needs. Moreover, compensation, if any, is not immediate. This obviously influences the time frame for reconstruction projects and hence for their financing. Berg and Schrader (2012) for example also find a delay in loan application for enterprises after NDs.

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 statistically different. The drop of the EFP, in the case of a strong macroprudential context, can be explained by the Schumpeterian creative destruction process. Indeed, the destruction of capital stock may provide incentives to re-invest in more productive one (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 having 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 on AIGI. Hence, credit conditions tighten following a ND, as found e.g., by Hosono et al. (2016), but not in those countries that are expected to have a sounder financial system as a consequence of a strong macroprudential framework.[18]

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



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

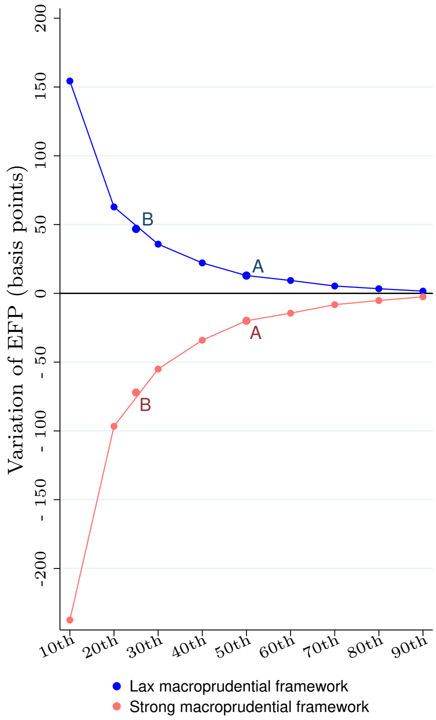
To better capture the amplitude of the EFP reaction, we can represent the estimated impact of NDs conditional on the surface area of a country and on the density of population in the affected areas. For illustration purposes, we point out the response of the EFP two years ($h = 8$) after a storm equivalent to hurricane Katrina. Moreover, we focus on two types of countries: a median size country called "A" (e.g., like United-Kingdom) and a country "B" corresponding to the first quartile in the distribution of countries' areas (e.g., like Lithuania). According to Figure 5, in the case of a lax macroprudential framework, countries A and B would suffer a raise of their EFP of about 12.94 and 46.85 basis points, respectively. At the opposite, on the case of a strong macroprudential framework, such a storm would cause a decrease in EFP of 19.91 bps in country A and 72.08 bps in country B.[19] Although not necessarily dramatic, such 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 very biggest countries). 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 high effects in the long run.

Next, the AIGI allows to assess a possible agglomeration effect, by evaluating the marginal effect

[18]Figure H.1 in Appendix H shows the response of 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.

[19]Figure 5 represents $\widehat{\mathcal{R}}_{P,IGI}(8) \times \frac{IGI_{t=1}}{\sigma_{IGI}}$ for each percentiles 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 on IGI. σ_{IGI} stands for the standard deviation of IGI over 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 percentiles of population density, with σ_{AIGI}=26.66.

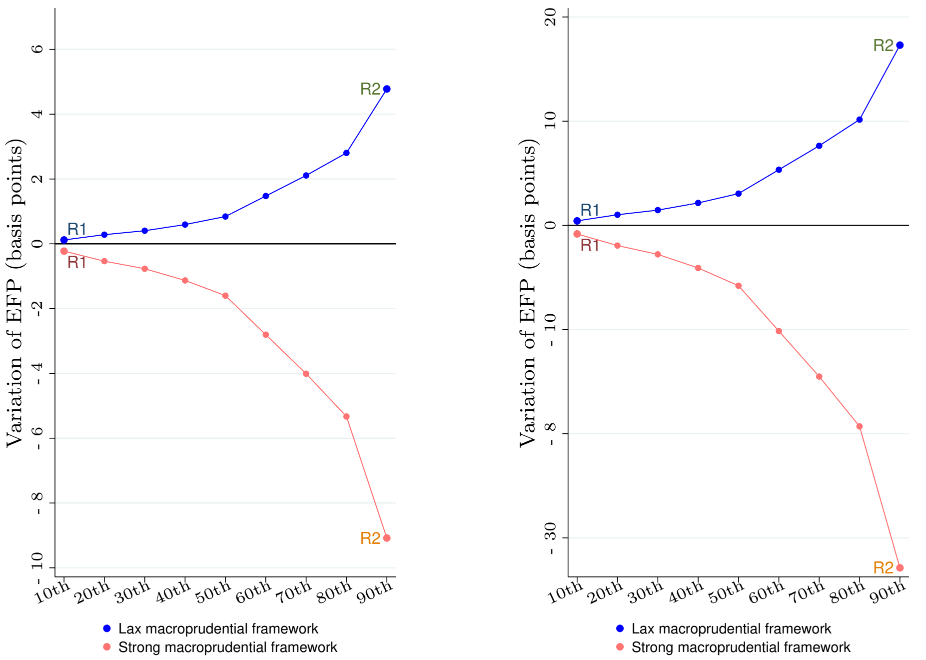
Figure 5: Reaction of EFP to IGI-storms as a function of country area (h=8)



Note: This figure represents the variation of 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 country area. “A” and “B” refer to countries corresponding to the second and first quartile in the distribution of countries’ areas, respectively.

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

(a) Country A (size = median) (b) Country B (size = first quartile)



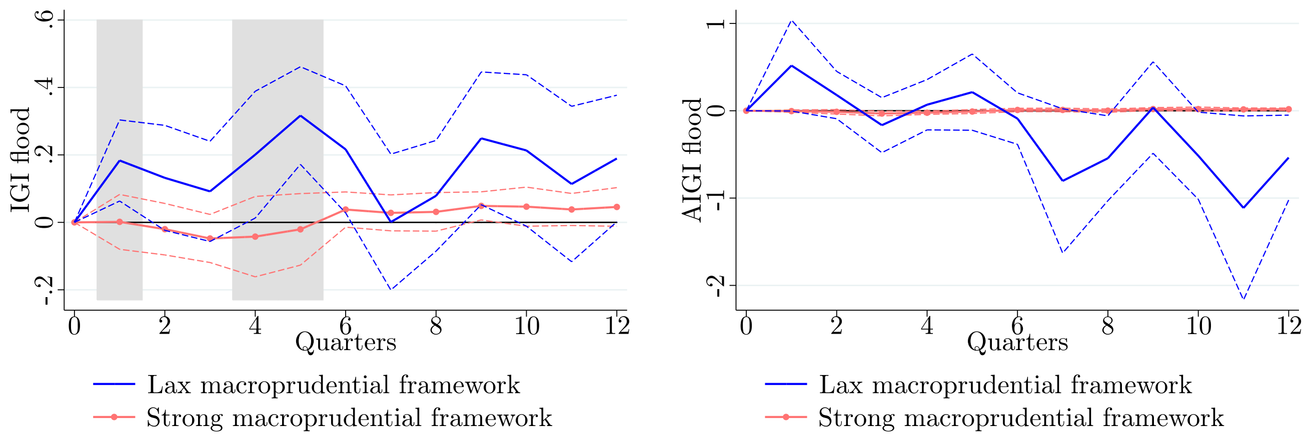
Note: This figure represents the variation of the External Finance Premium (EFP) two years after a Katrina-like storm, depending on country area and population density conditional on the stringency of the macroprudential framework. The x-axis corresponds to the percentiles of population density. The 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 percentile of density distribution, respectively.

of the density of population in the specific regions hit by shocks, for a given country size. Figure 6 provides an illustrative insight of the EFP response, two years after a Katrina-like shock, depending on whether the latter hits a more or less populated region. For the sake of the analysis, let us imagine an underpopulated region, corresponding to the 10th percentile of density distribution, i.e. 15.99 inhab/km^2 ("region 1", or "R1" Figure 6) and a highly populated region, corresponding to the 90th percentile of density distribution, i.e. 619,77 inhab/km^2 ("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 hits 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 hits the highly populated region in country A. This gain would reach 32.07 bps in country B. Even if these examples only concern the response at the 8-quarter horizon to a one-shot shock, the main lesson from the AIGI is that density of population does not appear that crucial for the macroeconomic impact of a storm, compared to country size.

5.2 Floods

Figure 7 shows the response of 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 each other, except for 3 quarters (See the grey 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 for storms.[20]

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



Note: This figure represents the response of the External Finance Premium (EFP) to a one standard deviation shock to (A)IGI-floods, for lax *vs* strong macroprudential framework, over horizons from 1 to 12 quarters. Dotted lines correspond to confidence bands at 90%. Shaded areas mean 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

[20]Figure H.2 in Appendix H shows the response of EFP irrespective of the extensity of the macroprudential policy. The results are not clear-cut neither. Moreover, given inconclusive results, we choose not to represent further the effects of flooding as a function of country area and population density.

floods do not depend on the specific way we measure NDs intensity, nor on the database we use, neither on the type of floods we consider. To do this, 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 hit by this ND). Second, we construct our flood-related indexes using an alternative database on rainfalls (i.e. from the Global Precipitation Climatology Centre). Third, we differentiate the results according to the types of floods (flash flood, riverine flood) identified in line with the EM-DAT classification. The results obtained in the three cases are similar to the ones of the initial setting: they do not suggest clear-cut conclusions concerning the role of macroprudential policies in mitigating floods effects on the financial stability. All these additional results are available upon request.

This apparent insignificant financial impact of floods, even conditional on the extensity of macroprudential policy, has several potential explanations. First, flood-prone areas are usually easily identifiable (along costs and rivers). Therefore it is possible to anticipate a disaster and circumvent its financial impact through greater discipline, like risk abstinence and damages insurance. Garbarino and Guin (2021) shows that, consistent with the valuation of the amenity of being close to water, borrowers living near flood-risk areas have relatively higher incomes and display lower loan-to-value ratios than borrowers living further away. Not only do they have a lower than average credit risk, but they can afford to take out insurance policies. Second, Faiella and Natoli (2018) provide another possible explanation by showing that lending to non-financial firms (especially to small and medium enterprises, which are less prone to purchase an insurance policy) is negatively correlated with their flood risk exposure. Hence, banks tend to be less exposed to this disaster. Note that, like floods, earthquakes also occur in areas that are fairly well identified beforehand. In this respect, Garmaise and Moscowitz (2009) find that the likelihood that a property gets financed through bank debt is reduced in earthquake-prone areas, especially when the catastrophe insurance market is poorly developed. In this line, Bos and Li (2017) show that banks that faced strong earthquakes experiences reduce their exposure to real estate and are 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 so far the analysis was based on the comparison of 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 interactive variable $P_{i,t-1}$ in Eq. (8) now represents the number of instruments in a 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 EFP (i.e. β_h in Eq 6) and for its effects in interaction 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 to IGI-storms triggers an increase in the EFP of about 29 bps, on average from 5 to 12 quarters after the shock, the implementation of an additional instrument significantly mitigates this tightening by about 20 bps. The interaction term is also significant with AIGI-storms from 5 to 12 quarters after the shock. In this case, having adopted an additional instrument reduces the impact of a one standard deviation to AIGI by 40 bps on average (against an average raise of 47 bps of the EFP as a direct impact of the AIGI shock).

In contrast, as previously found, the direct effect of IGI-flood 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.

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$_t$	-0.00	-0.04	0.00	0.11	0.19*	0.25***	0.36***	0.37***	0.29***	0.28***	0.27**	0.29***
	(0.05)	(0.05)	(0.07)	(0.09)	(0.10)	(0.08)	(0.08)	(0.08)	(0.10)	(0.10)	(0.11)	(0.11)
IGI Storm$_t$ × Number of instrument$_{t-1}$	-0.01	0.02	-0.00	-0.13*	-0.18**	-0.21***	-0.29***	-0.28***	-0.23***	-0.22**	-0.21**	-0.23**
	(0.03)	(0.03)	(0.04)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.08)	(0.09)	(0.10)	(0.09)
AIGI Storm$_t$	0.03	-0.02	-0.07	0.33*	0.37**	0.43**	0.58***	0.55***	0.50**	0.45*	0.49**	0.51***
	(0.06)	(0.04)	(0.05)	(0.17)	(0.17)	(0.17)	(0.15)	(0.15)	(0.21)	(0.23)	(0.20)	(0.18)
AIGI Storm$_t$ × Number of instrument$_{t-1}$	-0.04	0.01	0.05	-0.32*	-0.35**	-0.39**	-0.51***	-0.47***	-0.42**	-0.37*	-0.41**	-0.42**
	(0.06)	(0.03)	(0.04)	(0.16)	(0.16)	(0.16)	(0.15)	(0.14)	(0.20)	(0.21)	(0.19)	(0.17)
IGI Flood$_t$	0.09*	0.03	-0.03	0.06	0.17**	0.15*	0.01	0.04	0.18**	0.14	0.10	0.14*
	(0.05)	(0.05)	(0.07)	(0.08)	(0.08)	(0.09)	(0.09)	(0.07)	(0.09)	(0.10)	(0.10)	(0.08)
IGI Flood$_t$ × Number of instrument$_{t-1}$	-0.02*	-0.01	-0.00	-0.02	-0.05***	-0.03	0.00	0.00	-0.03	-0.02	-0.02	-0.03
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
AIGI Flood$_t$	0.04	-0.01	-0.05	-0.01	0.05	0.01	-0.05	-0.05	0.02	-0.12	-0.16	-0.12
	(0.03)	(0.04)	(0.06)	(0.05)	(0.05)	(0.07)	(0.10)	(0.08)	(0.10)	(0.09)	(0.16)	(0.13)
AIGI Flood$_t$ × Number of instrument$_{t-1}$	-0.02	0.00	0.01	-0.00	-0.02	0.00	0.03	0.02	0.00	0.07	0.09	0.07
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(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 FE. Standard errors in parentheses are corrected for heteroskedasticity and clustered at the country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 a reverse causality bias, we re-estimate the impact of NDs on the EFP by excluding cases where the extensity of the macroprudential framework was changed over a three-year period following a ND. This concerns 22 storms and 35 floods in our initial sample.

Figure H.3 in Appendix H shows that the estimates when excluding countries that changed the extensity group in the wake of a storm are highly similar to the baseline results. Concerning floods, Figure H.4 shows that the results are not really impacted either, as we still do not find clear-cut significant differences between lax and restrictive countries (only for IGI with $h = 4, 5$).

6.2 Robustness to alternative mitigating factors

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

Several potential shock absorbers are successively considered, following the broad literature on the economic impact of NDs. First, we add an interaction implying 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 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 a NDs' absorber. In this case, X is a dummy variable that is equal to one once a country has adopter IT, and zero otherwise. Moreover, in line with Ramcharan (2007), we consider the nature of the exchange rate regime by adding an interaction term that is based on the *de facto* exchange rate classification provided by Ilzetzki et al. (2017). Additionally, we take into account 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 in the analysis and check if the dampening effects of macroprudential policies still hold in the presence of budget balance 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 that is equal to one when a country follows a fiscal rule, and 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 horizon of 1, 4, 8 and 12 quarters. The first part of the table deals with IGI, while the second part concerns AIGI, for storms. It appears that the attenuating effect of stringent macroprudential framework holds even when we include other potential 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 raw labelled "All"). This means that the beneficial effects of macroprudential policies that we have found so far in the case of storm are really due to the properties of this policy *per se*, and not to other factors that our measure of macroprudential stringency might have proxied.

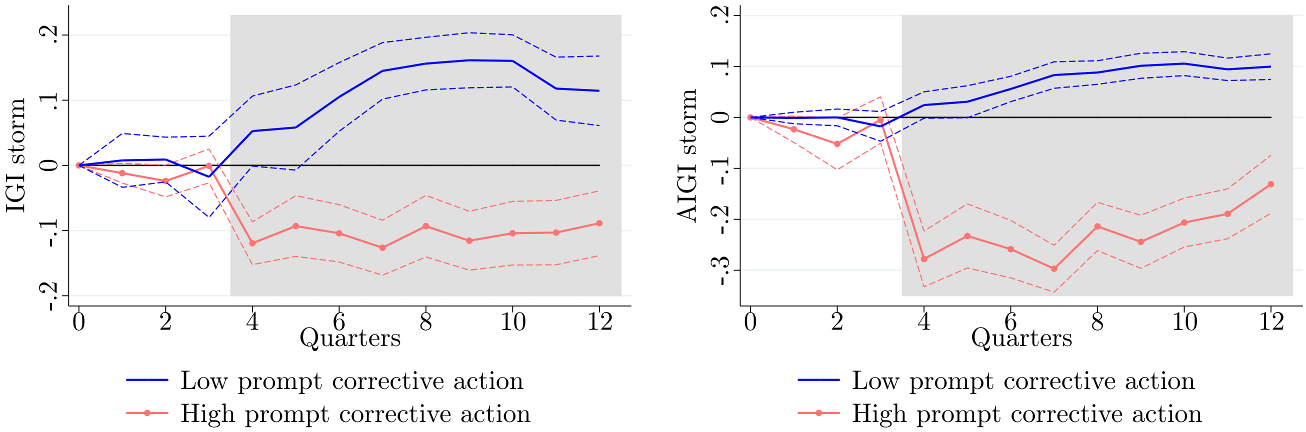
Results for floods are reported in H.2 in Appendix H. In the few cases where it is significant (i.e. for $h = 1$), the dampening effect of macroprudential policy is also robust to the inclusion of other mitigating factors.

6.3 Impact of *ex post* prudential action

Macroprudential policies can be viewed as *ex ante* prudential measures: thus, we check now whether the effect of NDs on credit conditions is mitigated by the *ex post* reaction of the regulator. 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 pre-determined levels of bank solvency deterioration. Hence, $P_{i,t} = 1$ for countries that have a high *prompt corrective action* index (PCA), i.e. that is higher than the median value of PCA in the sample over the full period of analysis. Otherwise $P_{i,t} = 0$ (i.e. low PCA).

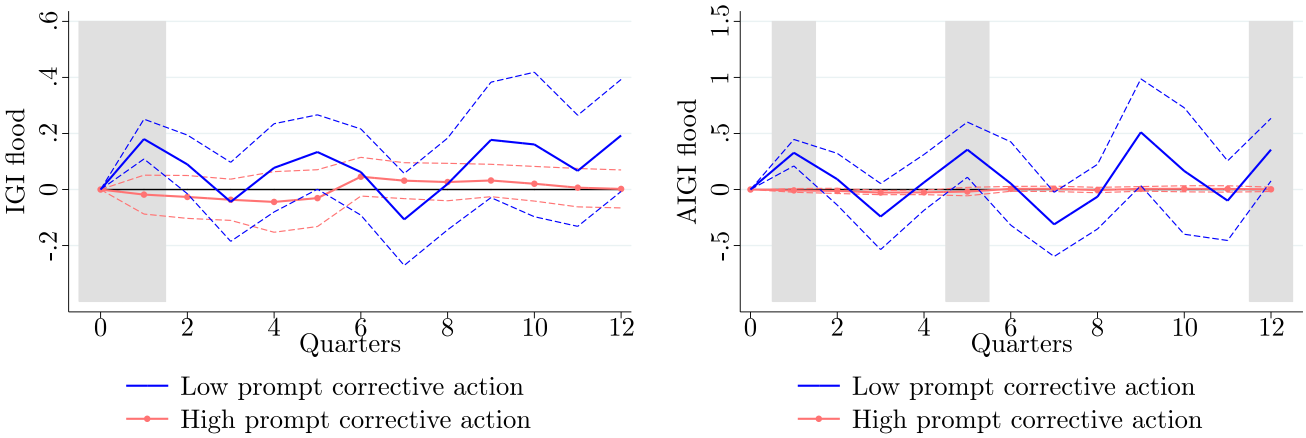
Figure 8 shows that *ex post* prudential actions significantly mitigate the impact of storms on the EFP, like macroprudential measures do (with similar amplitude). Figure 9 shows that the restrictive effect of flooding on EFP is reduced by PCA immediately, in the quarter following the shock. However, 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 8: Response of EFP to storms conditional on prompt corrective action



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

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



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

7 Focus on the recent period and on income country groups

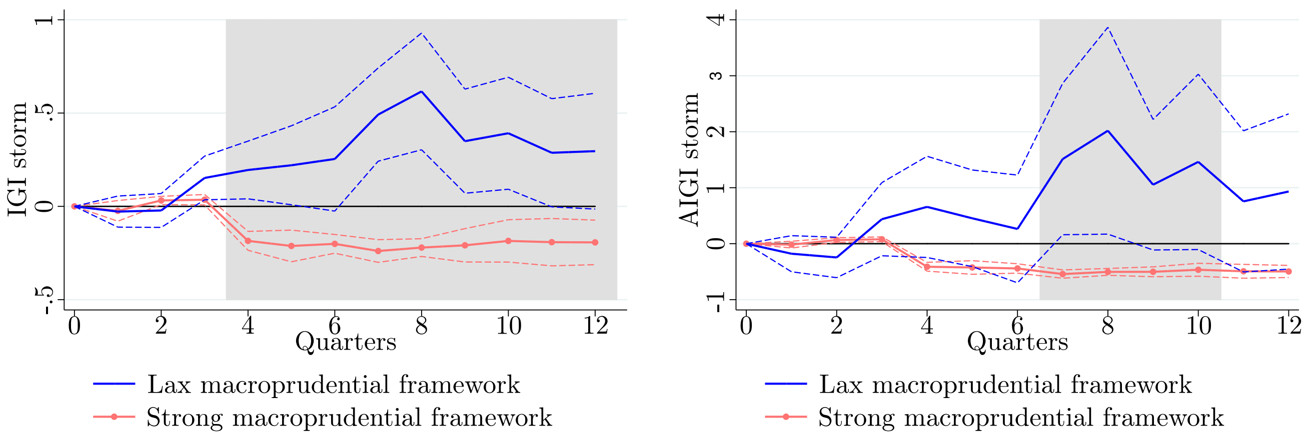
7.1 Recent period: 2006-2016

Since the 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 is available, i.e 2006-2016 (the second decade of our sample).[21]

[21] We could also run regressions over the first decade (1996-2006) only, for a comparison purpose: however this seems less relevant as macroprudential policy was still in its infancy before the Great Financial Crisis.

We notice in Figure 10 that for IGI-storms the differential effect between the two country-groups remains significant (after 4 quarters), with a significant increase in EFP for countries that have a lax macroprudential framework (excepted for $h = 6$). For AIGI-storms, the results are slightly different than 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 storms damages, even in the most recent period.

Figure 10: Response of EFP to storms - recent period



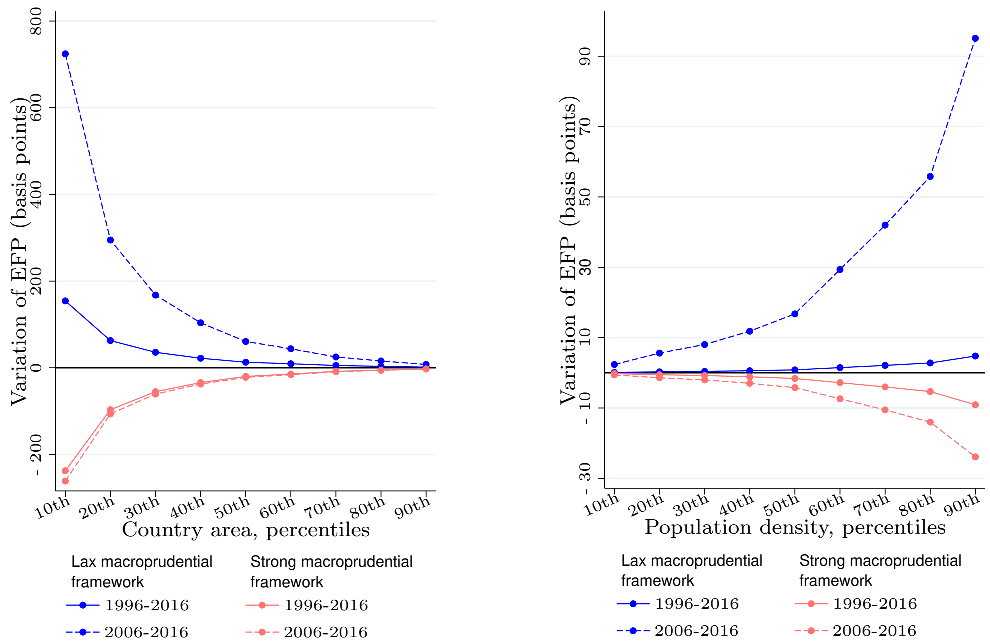
Note: This figure represents the response of the External Finance Premium (EFP) to a one standard deviation shock to (A)IGI-storms, for lax *vs* strong macroprudential framework, over horizons from 1 to 12 quarters. Dotted lines correspond to confidence bands at 90%. Shaded areas mean that the interaction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

Figure 11 aims 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* over the most recent decade (dashed lines). The left-hand side plot deals with IGI-storms. We can observe that the decrease in EFP when 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 with the estimate obtained over the whole 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 AIGI, and depending on the population density in affected areas. Once again, we can 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 higher than the estimated hike found over the full period. Similarly, but to a lesser extent, the EFP decreases barely more in the case of stringent macroprudential framework over the second decade than over the full sample.

Finally, the results obtained for floods over 2006-2016 are presented in Figure 12. It appears that the effects of flooding are not significant overall, regardless of macroprudential policy extensity, similarly to the estimates obtained over the entire period.

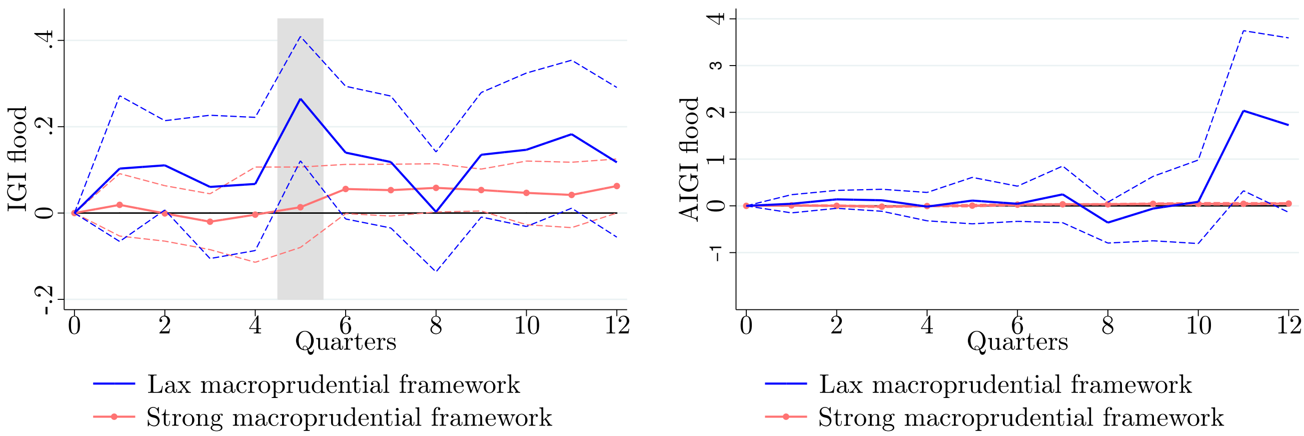
Figure 11: Reaction of EFP as a function of country area, population density and estimation period (h=8)

(a) Function of country size (b) Function of population density



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

Figure 12: Response of 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-floods, for lax *vs* strong macroprudential framework, over horizons from 1 to 12 quarters. Dotted lines correspond to confidence bands at 90%. Shaded areas mean that the interaction term is significantly different from zero at 5% confidence level. Estimation period: 2006-2016.

7.2 Heterogeneity by country income

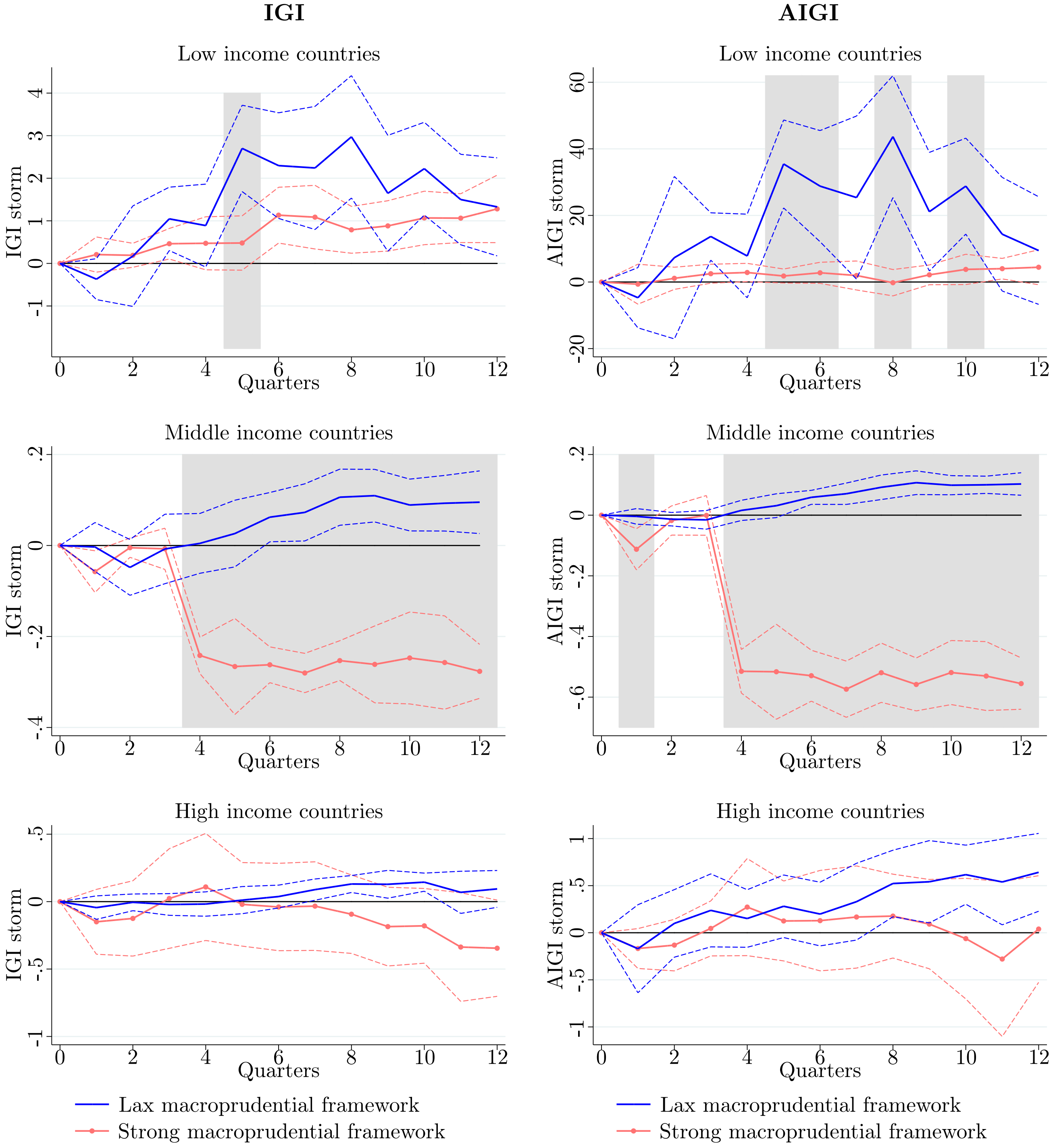
We now assess whether the impact of NDs and the dampening effect of macroprudential policy depend on the level of economic development. To this end, our sample is split into three groups of countries, following the World Bank classification: low income (10 countries), middle income (43) and high income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

Figure 13 shows that, in the case of lax macroprudential policy, EFP significantly increases in the wake of a storm in low and middle-income countries, but not in the high-income countries. In these most developed countries, the EFP does not significantly change either 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 EFP is sometimes significantly different between the two groups of macroprudential stringency (for $h = 5, 6, 8, 10$). Finally, only in middle-income countries does a strong macroprudential setting significantly lowers the EFP post-storm. Thus, it is mainly for these countries that the responses of EFP are significantly different depending on the extensity of the macroprudential framework.

Therefore, the patterns of local projections represented in Figure 13 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 a more productive capital. Precisely, 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 an 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. And as shown before, the smaller the country is 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. At the opposite, possibly because of there is no expected technological leap, high-income countries with stringent macroprudential policy do not significantly benefit from a cut in EFP. Indeed, since the damaged capital might have been already 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 an insufficient absorptive capacity (Crespo Cuaresma et al., 2008).

Finally, Figure H.5 in the Appendix H shows that the 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, although 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. Splitting the sample does not shed new light on the lack of macroprudential effect on financial stress, following floods.

Figure 13: Response of 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-storms in the first column of plots and to a one standard deviation shock to AIGI-storms shock 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 mean that the interaction term is significantly different from zero at 5% confidence level.

8 Conclusion

Natural disasters (NDs) can impact the financial sector, with potential consequences ranging from surges in premiums to financial crises. In the same time, although independently, macroprudential policies have been developed to address financial instability. Against this background, our paper aims at empirically investigating 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 1996-2016, and relies on original indicators of 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 country size distribution) with a lax macroprudential framework would suffer of an increase 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 impact in the long run. Importantly, we find that this impact gets worst 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 about 67 bps, two years after a Category 5 hurricane.

A key reason for the benefits of a strong macroprudential framework is that an initially sound financial environment fosters favorable financing conditions to replace destroyed capital by 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 drop 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 riversides 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 a strong macroprudential regulation improves countries' ability to better cope with the financial impact of NDs. Certainly, macroprudential policy by itself cannot solve the natural disasters problems, strongly related to climate change issue. However, by containing the financial impact of NDs, it 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 the transition to a low-carbon economy.

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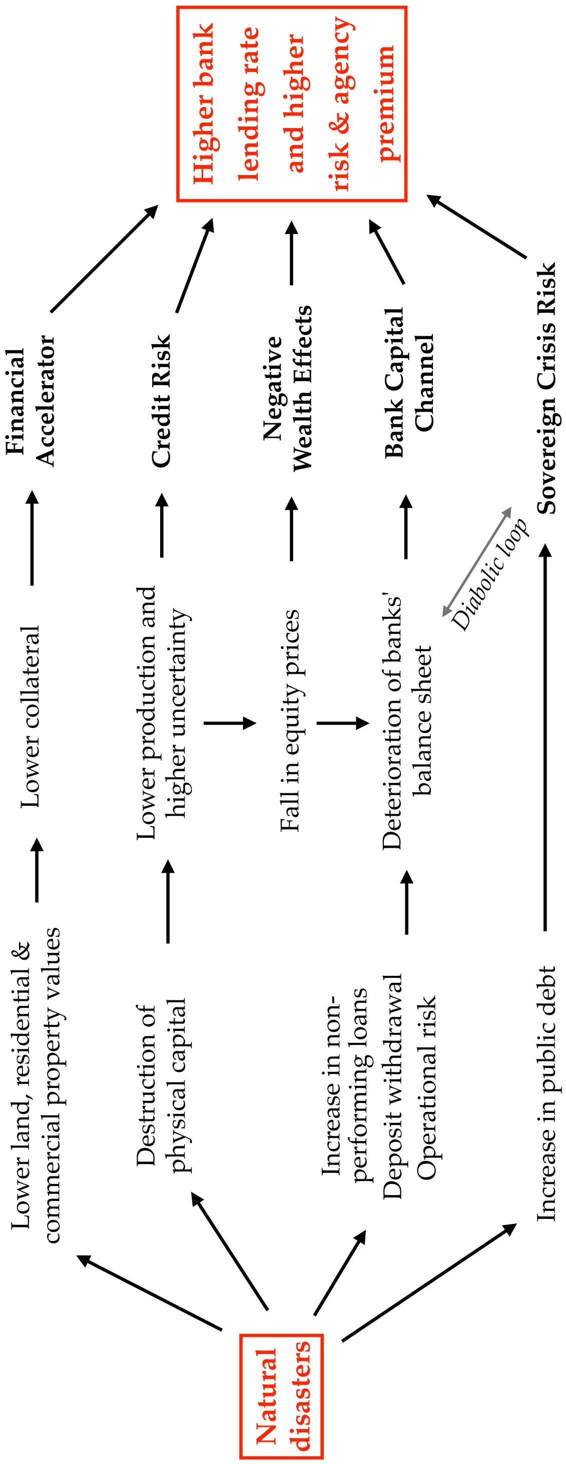
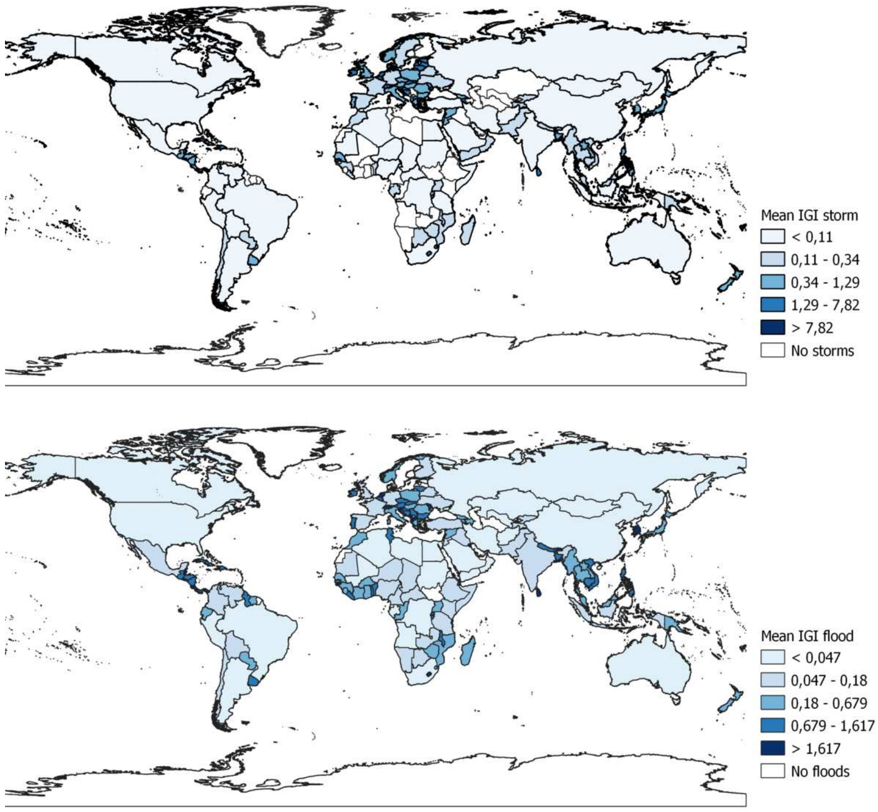
A Transmission channels of natural disasters on credit conditions



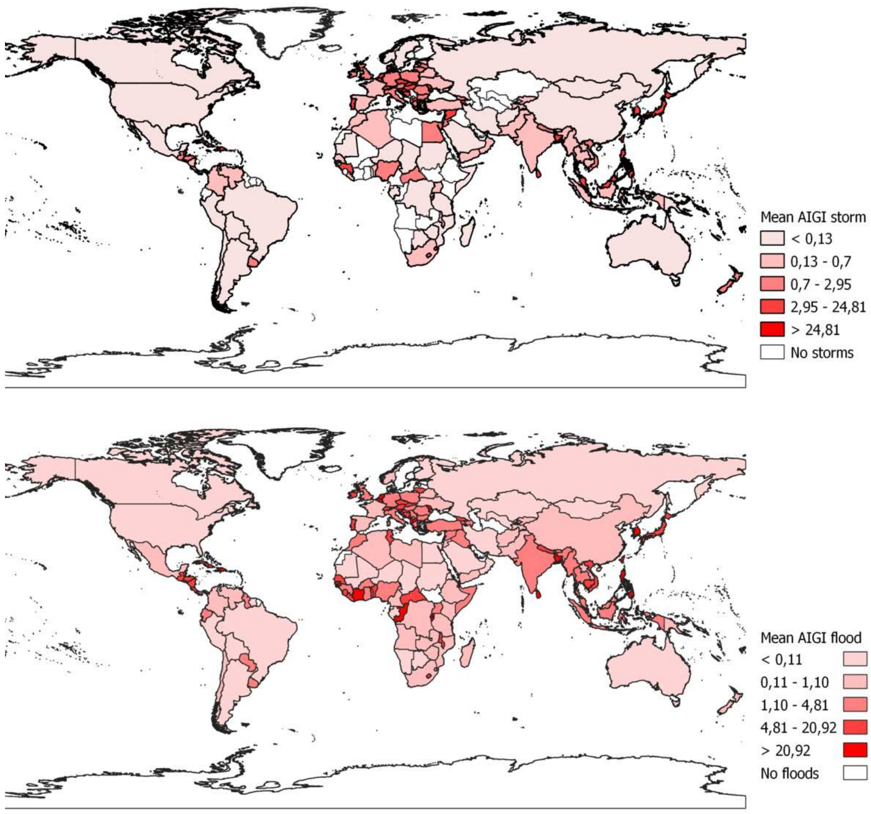
B World mean values of IGI, AIGI and EFP over 1996-2016

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



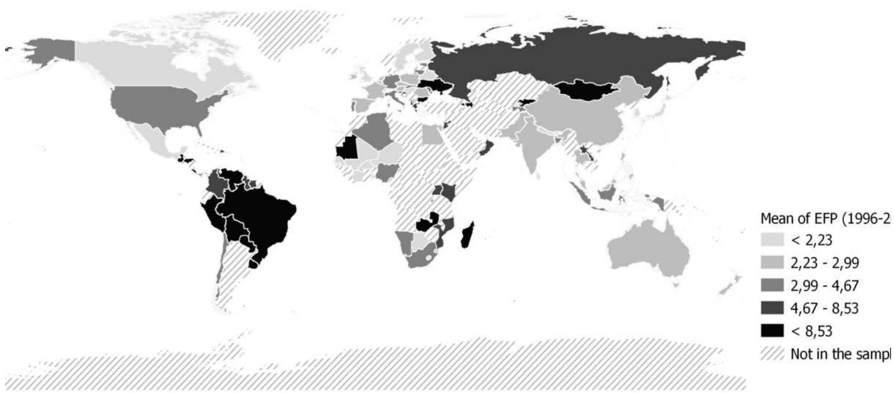
Note: The legend is determined by the percentiles of the distribution (20th, 40th, 60th, 80th).

Figure B.2: World mean value of AIGI over 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 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 hitting 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 the QGIS software to compute the density of population at the first administrative level area. This is done in line with the maps from GADM (3.6 version) 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-year 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 make the hypothesis of an exponential growth of population in between the 5-year database.

In general, in EM-DAT all the information for disasters location is available at the first administrative level. However, when it 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 hitting "North Portugal": Viana Do Castelo, Braga, Porto, Vila Real, 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 Macroprudential Policy (iMaPP) Database - details

Table D.1: Macroprudential 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 or the policy rate is considered if the 3-month money market rate data are not available. Source: IMF - IFS.
- **Extensity 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 intervention. 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 calculated from 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 gain, 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: Ilzetzki 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

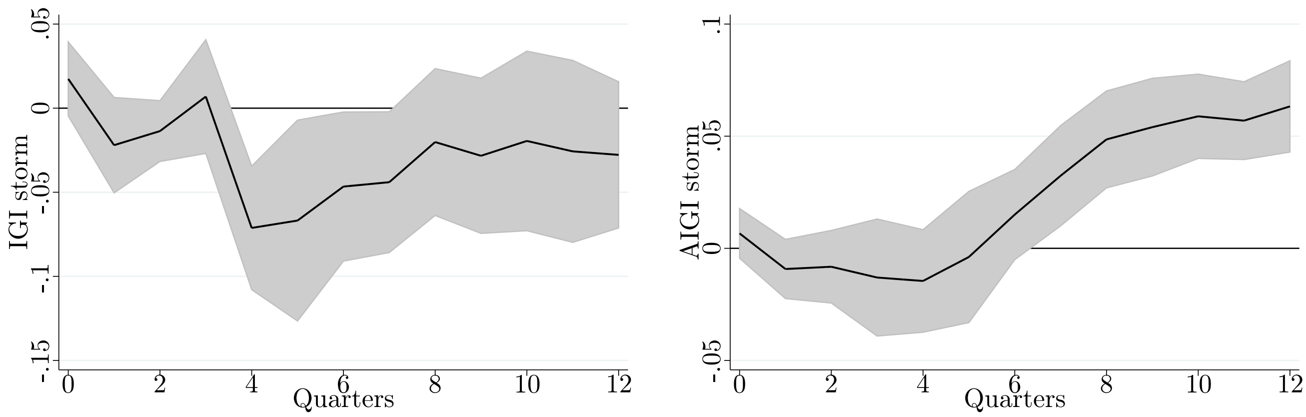
Table G.1: List of Countries

Countries		
Albania	(Guatemala)	Nigeria
Algeria	(Guyana)	Oman
Armenia	Honduras	Pakistan
Australia	Hungary	(Panama)
Austria	India	Paraguay
Azerbaijan	Indonesia	Peru
Bahrain	Ireland	Philippines
Bangladesh	Italy	Poland
Belarus	*Jamaica*	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
China	Lithuania	(Suriname)
Colombia	(Madagascar)	Sweden
Coasta Rica	Malaysia	Tajikistan
Ivory Coast	Mali	Thailand
Croatia	*Mauritania*	Togo
Cyprus	Mauritius	Trinidad & Tobago
Czech Republic	Mexico	Uganda
Dominican Republic	Moldova	*Ukraine*
(Egypt)	*Mongolia*	United Kingdom
Estonia	*Mozambique*	United States
Finland	(Namibia)	Uruguay
France	*Nepal*	(Venezuela)
Gambia	Netherlands	*Zambia*
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 1996-2016.

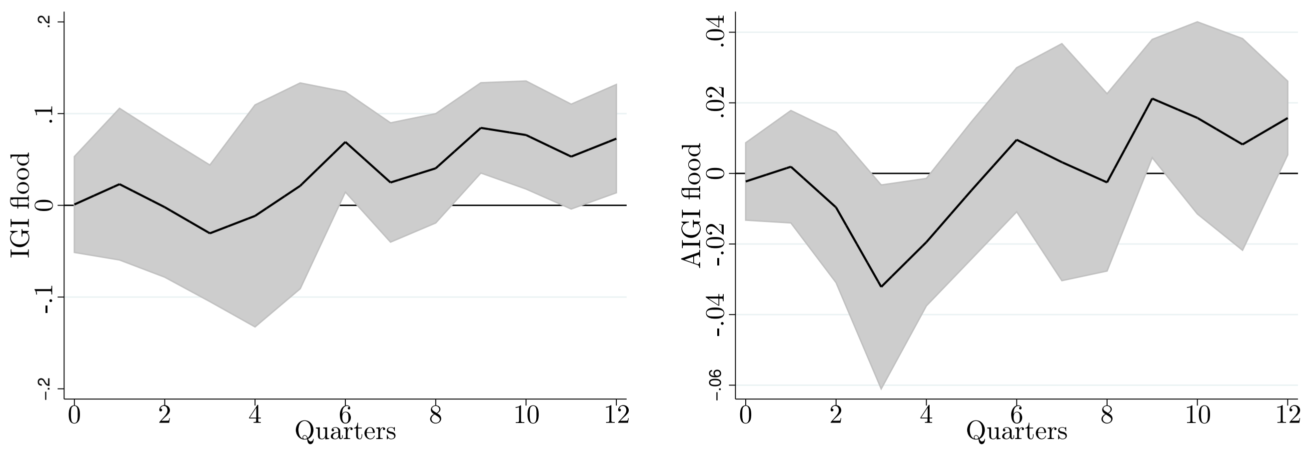
H Additional results and robustness checks

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



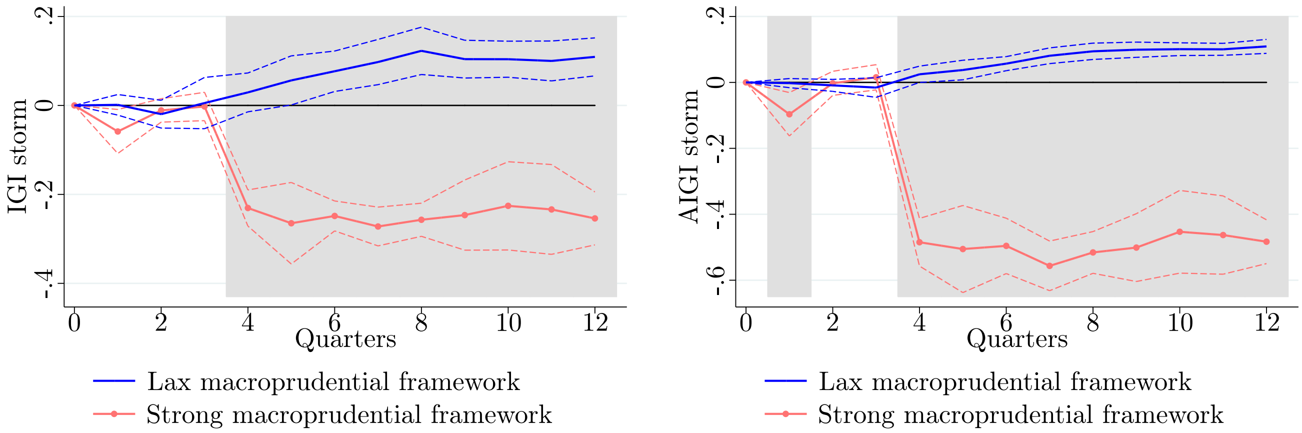
Note: This figure represents the response of the External Finance Premium (EFP) to a one standard deviation shock to (A)IGI-storms, over horizons from 1 to 12 quarters. Shaded areas correspond to confidence bands at 90%.

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



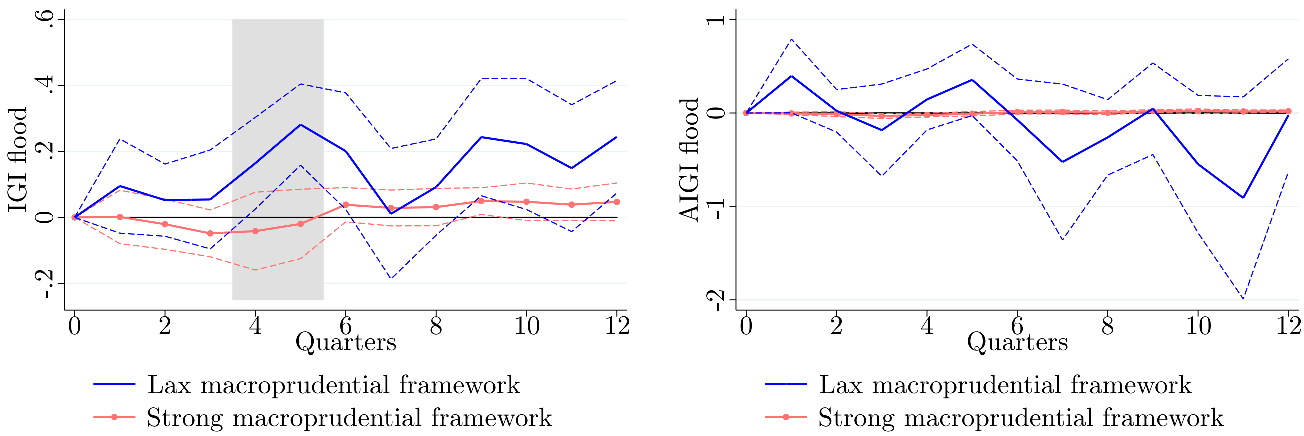
Note: This figure represents the response of the External Finance Premium (EFP) to a one standard deviation shock to (A)IGI-floods, over horizons from 1 to 12 quarters. Shaded areas correspond to confidence bands at 90%.

Figure H.3: Response of 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 mean that the interaction term is significantly different from zero at 5% confidence level.

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

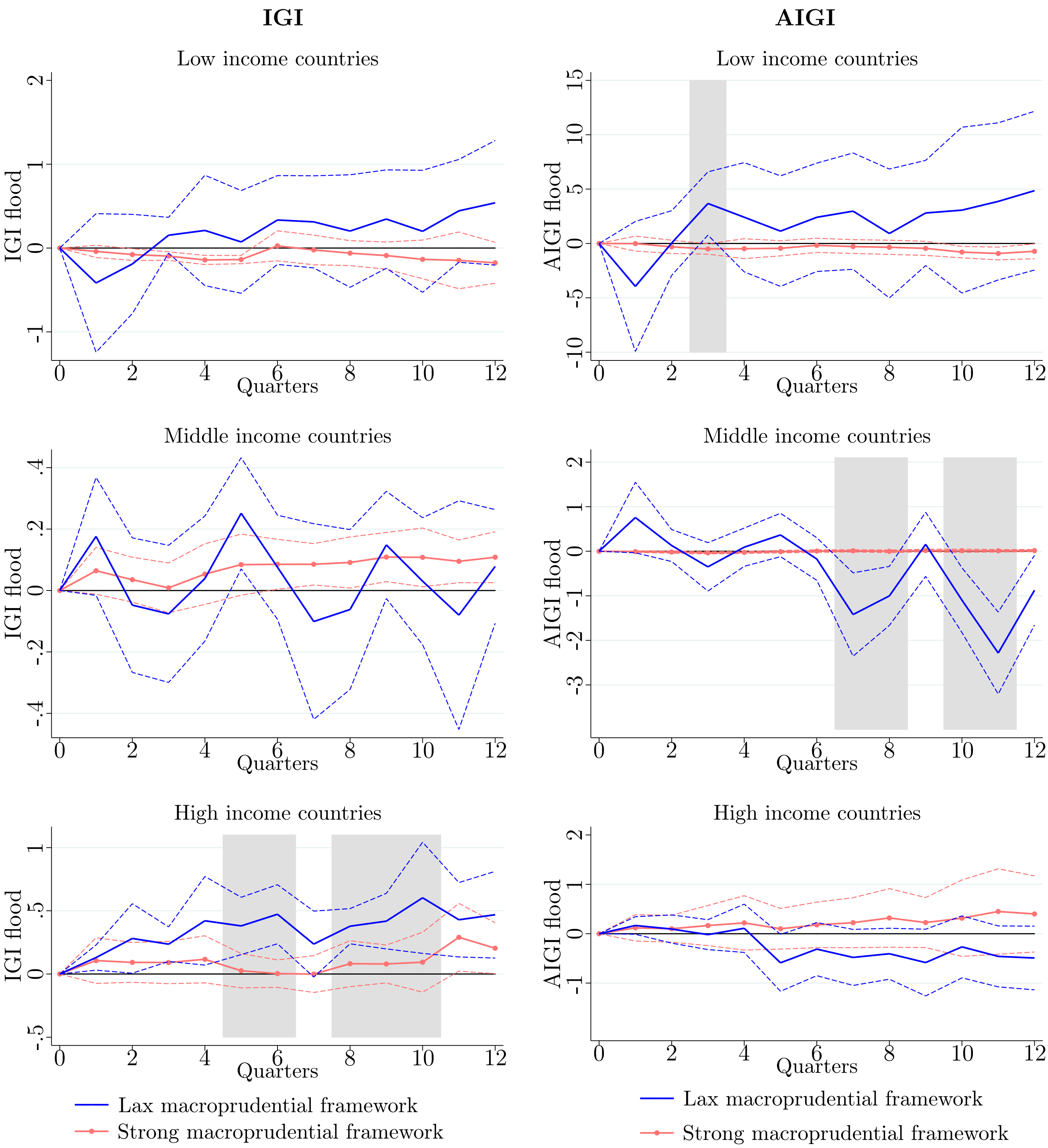
Note: This table reports the estimated value of the interaction term of the geophysical intensity of storms (A)IGI and the dummy variable that represents the stringency of macroprudential framework when adding other potential mitigating factors in interaction with (A)IGI. These other shock absorbers 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 FE. 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**	-0.29**	-0.10	-0.18
	(0.09)	(0.14)	(0.10)	(0.12)
GDP per capita	-0.20**	-0.26**	-0.10	-0.18
	(0.08)	(0.12)	(0.09)	(0.12)
Polity2	-0.19**	-0.25*	-0.13	-0.21
	(0.09)	(0.13)	(0.10)	(0.13)
Control of corruption	-0.22***	-0.29***	-0.13	-0.19*
	(0.08)	(0.10)	(0.08)	(0.11)
Inflation targeting	-0.24***	-0.32**	-0.12	-0.20
	(0.09)	(0.15)	(0.12)	(0.14)
FX regime	-0.18**	-0.21	-0.09	-0.16
	(0.09)	(0.14)	(0.11)	(0.12)
Financial markets depth	-0.21**	-0.27**	-0.09	-0.16
	(0.09)	(0.11)	(0.09)	(0.11)
Budget balance rule	-0.21**	-0.27**	-0.09	-0.16
	(0.09)	(0.11)	(0.09)	(0.11)
All	-0.21**	-0.29**	-0.15	-0.20
	(0.09)	(0.14)	(0.11)	(0.14)
AIGI Flood	Quarter 1	Quarter 4	Quarter 8	Quarter 12
Baseline	-0.68*	-0.27	0.36	0.42
	(0.37)	(0.29)	(0.31)	(0.34)
Log GDP per capita	-0.68*	-0.30	0.32	0.47
	(0.37)	(0.32)	(0.28)	(0.36)
Polity2	-0.72*	-0.36	0.23	0.36
	(0.36)	(0.31)	(0.29)	(0.33)
Control of corruption	-0.67*	-0.32	0.32	0.48
	(0.37)	(0.32)	(0.28)	(0.35)
Inflation targeting	-0.75**	-0.36	0.29	0.35
	(0.34)	(0.31)	(0.37)	(0.38)
FX regime	-0.80***	-0.52**	0.13	0.06
	(0.29)	(0.23)	(0.42)	(0.44)
Financial markets depth	-0.69*	-0.21	0.37	0.35
	(0.36)	(0.30)	(0.33)	(0.35)
Budget Balance Rule	-0.61	-0.19	0.47	0.54
	(0.37)	(0.29)	(0.31)	(0.33)
All	-0.92***	-0.53	-0.17	0.01
	(0.25)	(0.32)	(0.53)	(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 FE. 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 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-floods 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 mean that the interaction term is significantly different from zero at 5% confidence level.