5 CLIMATE CHANGE

APRIL 2020—GLOBAL FINANCIAL STABILITY REPORT

PHYSICAL RISK AND EQUITY PRICES—ONLINE ANNEXES 5.1–5.7

CONTENTS

Online Annex 5.1. Data Sources, Climate Science Overview, Descriptive Statistics

Online Annex Table 5.1.1 Data Sources

Variable	Description	Source
Macroeconomic Variables		
Real Gross Domestic Product	Gross domestic product, constant prices in national currency	IMF, World Economic Outlook
Nominal Gross Domestic Product	Gross domestic product, current prices in national currency	IMF, World Economic Outlook
Nominal Gross Domestic Product, World	Gross domestic product, world, current prices in US dollars	IMF, World Economic Outlook
Gross Domestic Productor Deflator	Gross domestic product, current prices in national currency	IMF, World Economic Outlook
Consumer Price Index	Consumer price index, percent	IMF, World Economic Outlook
Nominal Private Consumption Expenditure	Private consumption expenditure, current prices	IMF, World Economic Outlook
Real Private Consumption Expenditure	Private consumption expenditure, constant prices	IMF, World Economic Outlook
Short-Term Nominal Interest Rate	Three-month treasury bill or interbank rate	Refinitiv Datastream; and Haver Analytics
Long-Term Government Bond Yield	Ten-year government bond yield	Refinitiv Datastream; and Haver Analytics
Government Debt	Public debt, percent of GDP	IMF, World Economic Outlook
Demographic Variables		
Population	Total population in millions	IMF, World Economic Outlook
Population, gridded	Grid-level population estimates for the year 2000	NASA Socioeconomic Data and Applications Center (SEDAC)
Aggregate Financial Variables		
Market Capitalization	Market values calculated from the constituents of the sector/market lists (US dollars). Index market value on Refinitiv Datastream is the sum of share price multiplied by the number of ordinary shares in issue for each index constituent. The amount in issue is updated whenever new tranches of stock are issued or after a capital change.	Refinitiv Datastream

Online Annex Table 5.1.1 Data Sources (continued)

Stock Market Price Index	The price as a percentage of its value on the base date, adjusted for capital changes. Sector and market aggregations are weighted by market value and are calculated using a representative list of shares.	Refinitiv Datastream
Price-to-Earnings Ratio	Derived by dividing total market value by total earnings, thus providing an earnings-weighted average of the price-earnings ratios of the constituents.	Refinitiv Datastream
Total Return Index	The return index for a sector or market expresses the theoretical growth in value of a share holding over a specified period, assuming that dividends are re-invested to purchase additional units of the stock. The calculation method used is determined by the source index agency.	Refinitiv Datastream
Dividend Yield	The dividend yield for an index is the total dividend amount for the index, expressed as a percentage of the total market value for the constituents of that index.	Refinitiv Datastream
Firm-level Variables		
Book Value per Share	Represents the book value (proportioned common equity divided by outstanding shares) of a company.	Refinitiv Datastream
Market Capitalization	Represents the current total market value of a company based on current price and current shares outstanding (US dollars).	Refinitiv Datastream
Stock Price	The most recent closing price of a company within the last sixty days available in the database (local currency).	Refinitiv Datastream
Total Return Index	The return index for a stock expresses the theoretical growth in value of a share holding over a specified period, assuming that dividends are re-invested to purchase additional units of the stock. The calculation method used is determined by the source index agency.	Refinitiv Datastream
Price-to-Book Ratio	The ratio of market price to book value per share of a company.	Refinitiv Datastream

Online Annex Table 5.1.1 Data Sources (continued)

Climate Variables		
Observed temperature and precipitation, gridded	Grid-level monthly temperature and precipitation time-series data from 1900 to 2017.	University of Delaware, Department of Geography
Projected temperature and precipitation	Model projections of future temperature and precipitation under different Representative Concentration Pathways (RCPs) by economy.	Koninklijk Nederlands Meteorologisch Instituut (KNMI), Climate Change Atlas
Δ Extreme heat	Number of Days with Dangerous Heat (Heat Index > 35°C). Anomaly to the baseline period of 1986-2005.	World Bank Group, Climate Change Knowledge Portal
Δ Extreme precipitation	Average count of days per month or year with at least 50mm of daily rainfall. Anomaly to the baseline period of 1986-2005.	World Bank Group, Climate Change Knowledge Portal
Δ Heatwave probability	The daily probability of observing such a heat wave, which is a 3 or more-day sequence where the daily temperature is above the long-term 95th percentile of daily mean temperature. Anomaly to the baseline period of 1986-2005.	World Bank Group, Climate Change Knowledge Portal
Δ Drought likelihood	Annual probability of experiencing at least severe drought conditions (Standardized Precipitation Evapotranspiration Index <-2). Anomaly to the baseline period of 1986-2005.	World Bank Group, Climate Change Knowledge Portal
Climate Change Related Indices		
Climate Change Hazard Index	Defined as 10 minus the Verisk Maplecroft Climate Change Exposure Index. The index assesses the degree to which economies are exposed to the physical impacts of climate extremes and future changes in climate over the next three decades. Ranges from low risk = 0 to high risk =10.	Verisk Maplecroft
Sea level rise index	Defined as 10 minus Verisk Maplecroft Sea Level Rise index. Ranges from low risk = 0 to high risk =10. The Sea Level Rise Index quantifies the physical threat of inundation of coastal areas due to projected sea level rise between the present and end-century.	Verisk Maplecroft

Online Annex Table 5.1.1 Data Sources (continued)

Climate Change Adaptive Capacity Index	The Climate Change Adaptive Capacity Index assesses the present abilities of an economy's institutions, economy and society to adjust to, or take advantage of, existing or anticipated stresses resulting from climate change. (ranges from 0 = low adaptive capacity to 10 = high adaptive capacity).	Verisk Maplecroft
Climate Change Sensitivity Index	Defined as 10 minus Verisk Maplecroft Climate Change Sensitivity Index: The Index assesses the susceptibility to the impacts of extreme climate related events and projected climate change. Sensitivity is a function of a population's existing physical, social and livelihood circumstances, with the index examining aspects of sensitivity related to health, poverty, knowledge, infrastructure, conflict, agriculture, and population and resource pressure. (ranges from 0 = low risk to 10 = high risk).	Verisk Maplecroft
Climate Change Physical risk index	Defined as 10 minus Verisk Maplecroft Climate Change Vulnerability index. Ranges from low risk = 0 to high risk =10. The index evaluates the susceptibility of human populations to the impacts of climate extremes and changes in climate over the next three decades. It combines exposure to climate extremes and change with the current human sensitivity to those climate stressors and the capacity of the economy to adapt to the impacts of climate change.	Verisk Maplecroft

Disaster Variables

The data on climatic disasters are sourced from the EM-DAT database. All recorded disasters conform to at least one of the following three criteria: 10 or more deaths; 100 or more people affected; the declaration of a state of emergency and/or a call for international assistance.
Non-climatic disasters such as geophysical disasters (e.g. earthquakes, volcanic activity), biological disasters (e.g. epidemics), extra-terrestrial disasters, and technological disasters (e.g. industrial accidents) are excluded from the analysis.
Reported damages from disasters are measured imperfectly and generally cover only direct costs from damages to physical assets, crops and livestock. Indirect costs from the disruption of economic activity (including through supply chain effects) are not directly observable and are generally excluded. Furthermore, costs associated with vulnerability reduction, such as investments in infrastructure and research and development for risk reduction, which materialize with a lag and are not necessarily be incurred at the location of the disaster, are not considered.

Disaster damages	The amount of damage to property, crops, and livestock in US$ ('000). For each disaster, the figure corresponds to the total damage value over the full duration of the event.	EM-DAT: The Emergency Events Database

Online Annex Table 5.1.1 Data Sources (continued)

Large disaster	A disaster is defined as "large" if the rate of affected population is greater than 0.5 percent, or damages are greater than 0.05 percent of GDP.	EM-DAT; IMF staff calculations
Bond Market Data (Online Box 5.4)		
Spread to benchmark	Spread between coupon rate of security and US Treasury or Benchmark (bps)	Dealogic
Maturity	Years to maturity	Dealogic
Size	Deal Value (Face) in USD	Dealogic
VIX	CBOE Volatility Index	Refinitiv Datastream
CAT Bond Data (Online Box 5.3)		
CAT Bond Issuance Volume	Face value in USD for bonds issued between 1997 and 2019	Dealogic, Bloomberg and Artemis
CAT Bond Original Maturity	Maturity measured as the difference between the pricing and the final maturity dates	Dealogic, Bloomberg and Artemis
CAT Bond Spreads	Floater spread from quoted benchmark rate	Dealogic, Bloomberg and Lane Financial
CAT Bond Expected Loss	Annualized expected loss based on actuarial model	Lane Financial
CAT Bond Hurricane Exposure	Dummy variable denoting whether a bond is exposed to risk from hurricanes, windstorms, typhoons and other tropical storms based on tranche notes and perils covered	Dealogic and Artemis
Other Indicators		
Worldwide Governance Indicators	An indicator that reports on six dimensions of governance for over 200 economies and territories over the period 1996 to 2018.	World Bank Group
Insurance penetration	Reported insurance premium volume as percent GDP	World Bank Group, Global Financial Development Database
Sovereign Rating	Annual average of foreign currency long-term sovereign debt ratings by Moody's, Standard & Poor's, and Fitch Ratings	Kose and others 2017 (World Bank Group, fall 2019 version)
Assets Held by Sustainable Equity Funds	Fund size in USD of all equity funds labeled as "Sustainable Investment – Environmental"	Morningstar

Online Annex Table 5.1.2. Sample Economies, and Time Period
(Percent)

Economy	Period	Economy	Period
Advanced Economies		**Emerging Market and Developing Economies**	
Australia	1973–2019	Argentina	1988–2019
Austria	1973–2019	Bahrain	2003–2019
Belgium	1973–2019	Brazil	1994–2019
Canada	1973–2019	Bulgaria	2000–2019
Cyprus	1992–2019	Chile	1989–2019
Czech Republic	1995–2019	China	1993–2019
Denmark	1973–2019	Colombia	1992–2019
Estonia	1997–2019	Croatia	2005–2019
Finland	1988–2019	Egypt	1996–2019
France	1973–2019	Hungary	1991–2019
Germany	1973–2019	India	1990–2019
Greece	1988–2019	Indonesia	1990–2019
Hong Kong SAR	1973–2019	Jordan	2006–2019
Ireland	1973–2019	Kuwait	2003–2019
Israel	1993–2019	Malaysia	1986–2019
Italy	1973–2019	Mexico	1988–2019
Japan	1973–2019	Morocco	1994–2019
Korea	1987–2019	Nigeria	2009–2019
Lithuania	1998–2019	Oman	2005–2019
Luxembourg	1992–2019	Pakistan	1992–2019
Malta	2000–2019	Peru	1994–2019
Netherlands	1980–2019	Philippines	1987–2019
New Zealand	1988–2019	Poland	1994–2019
Norway	1980–2019	Qatar	2003–2019
Portugal	1990–2019	Romania	1996–2019
Singapore	1973–2019	Russia	1998–2019
Slovak Republic	2006–2019	Saudi Arabia	2005–2019
Slovenia	1998–2019	South Africa	1973–2019
Spain	1987–2019	Sri Lanka	1987–2019
Sweden	1982–2019	Thailand	1987–2019
Switzerland	1973–2019	Turkey	1988–2019
Taiwan Province of China	1987–2019	United Arab Emirates	2003–2019
United Kingdom	1970–2019	Venezuela	2012–2019
United States	1973–2019	Vietnam	2007–2019

Online Annex Table 5.1.3. Climate Change Scenarios and Past Changes in Extreme Weather Events (IPCC 2014)

Climate Scenarios

The Representative Concentration Pathways (RCPs) describe four different 21st century pathways of greenhouse gas (GHG) emissions. RCPs are labeled by the radiative forcing (in W/m2) that will occur in 2100.

Emission scenario	Likely Increase of Global Mean Surface Temperature by the End of the 21st Century (2081–2100) relative to 1986–2005
RCP 2.6	0.3°C to 1.7°C.
RCP 4.5	1.1°C to 2.6°C.
RCP 6.0	1.4°C to 3.1°C.
RCP 8.5	2.6°C to 4.8°C.

Past Change in Extreme Weather Events

Weather Extreme	Observed Past Changes	Human Contribution
Warmer (and/or fewer cold) days and nights	• Very likely increase (decrease) in frequency over most land areas	• Very likely
Heat Waves	• Medium confidence in increase on global scale • Likely increase in large parts of Europe, Asia, and Australia	• Likely
Heavy Precipitation	• Likely increases over more land areas than decreases	• Medium confidence
River Floods	• Limited to medium evidence for changes in frequency of river floods at the regional level • Low confidence for sign of change of river floods at the global level	• Low confidence
Drought	• Low confidence in change on a global level	• Low confidence
Tropical Cyclones	• Low confidence in increase in activity (intensity and frequency) on timescales of 100 years • Virtually certain increase in activity in North Atlantic since 1970	• Low confidence
Sea-levels	• Likely increase since 1970	• Likely

Sources: IPCC (2014) and Bouwer (2019).

Online Annex Table 5.1.4. Sample Economies—Largest Climatic Disasters

Country	Year	Disaster Type	Disaster Name	Damage-to-GDP Ratio (percent)	Damage insured (percent)	Duration	Number of Deaths	Number of Affected	Market Return (T-5 to T+20; percent)
Advanced Economies									
Australia	1981	Drought		3.2		2 years		80,000	-6.9
Czech Republic	1997	Flood	1997 Central European flood	3.0	17	~ 1 month	29	102,107	5.0
Czech Republic	2002	Flood	2002 European floods	2.9	50	~ 1 month	18	200,000	-1.5
Spain	1983	Flood		2.3		< 1 month	45	506,000	
Denmark	1999	Storm	Anatol	1.5	81	< 1 month	7		3.6
Austria	2002	Flood	2002 European floods	1.1	17	< 1 month	9	60,000	0.4
Canada	1976	Drought		1.1		4 years	0		0.03
Portugal	2003	Wildfire		1.0		2 months	14	150,000	2.5
Greece	1990	Drought		1.0		~ 1 month			6.7
United States	2005	Storm	Hurricane Katrina	1.0	48	~ 1 month	1833	500,000	-0.4
Emerging Market and Developing Economies									
Thailand	2011	Flood	2011 Thailand floods	10.1	25	5 months	813	9,500,000	-6.5
Oman	2007	Storm	Cyclone Gonu	9.3	16.7	< 1 month	76	20,000	4.4
Jordan	1992	Cold wave		7.4		< 1 month	15		
Pakistan	2010	Flood	2010 Pakistan floods	5.4	1.1	< 1 month	1985	20,359,496	-6.5
Peru	1983	Landslide		5.2		~ 1 month	364	700,000	
Philippines	2013	Storm	Typhoon Haiyan (Yolanda)	3.7	7	< 1 month	7354	16,106,870	-8.1
Venezuela	1999	Flood	Vargas tragedy	3.2	12.7	~ 1 month	30000	483,635	6.1
Indonesia	1997	Wildfire		3.1		~ 1 month	240	32,070	7.4
Vietnam	2015	Drought		3.1		1 year		1,750,000	-3.1
China	1998	Flood	Yangtze river flood	2.9	1.0	2 months	3656	239,000,000	-32.9

Sources: EM-DAT; Refinitiv Datastream; and IMF staff calculations.
Note: Missing cells = N/A.

Online Annex 5.2. Large Climatic Disasters and Equity Returns

A standard event study methodology is used to examine the effects of large climatic disasters on equity returns, with a particular focus on the banking and non-life insurance sectors. The analysis also examines how the aggregate stock market and the real sector (industrial sector) stocks react to climatic disasters.

Cumulative Average Abnormal Returns (CAARs) around Disasters

1. Expected returns are estimated for each economy and each sector in an economy based on a pre-event estimation window that starts 12 months before a disaster occurs and ends one month before the disaster.[1] For the excess stock return (excess of the risk-free rate) $r^e_{i,c,t}$ in economy *c* and day *t* of each stock index $i \in$ {Market, Banks, Non-life Insurance, Industrial}, the following global factor model is estimated for all disasters:

$$r^e_{i,c,t} = \alpha_i + \beta^{global}_{i,c} \cdot r^e_{global,t} + \epsilon_{i,c,t}$$

where $r^e_{global,t}$ is the excess return for the global stock index (in excess of the risk-free rate of the U.S.), and $\beta^{global}_{i,c}$ is the loading on the global factor. Estimation is conducted at the daily frequency. Returns are calculated using the Stock Market Price Index.

2. For each disaster, using the estimated coefficient $\widehat{\beta^{global}_{i,c}}$, the expected return for time τ after the disaster is estimated to be $E\left(r^e_{i,c,\tau}\right) = \widehat{\beta^{global}_{i,c}} \cdot r^e_{global,\tau}$ and abnormal return for time τ is $AR\left(r^e_{i,c,\tau}\right) = r^e_{i,c,\tau} - E\left(r^e_{i,c,\tau}\right)$. The cumulative abnormal return (*CAR*) is computed by summing up the abnormal returns starting 21 trading days before the start date of the disaster up to 60 trading days after the disaster start date. The cumulative average abnormal return (CAAR) is the average of the CARs across all disasters in the sample.

Regression Analysis of Equity Market Reaction to Large Disasters

To analyze whether economy characteristics affect the equity market reaction to disasters, the following model is estimated:

$$CAR40_{i,c,d} = \mu_i + \gamma_{1,i} Char_{c,d} + \gamma_{2,i} X_d + \epsilon_{i,c,d}$$

where $CAR40_{i,c,d}$ is the 40-trading-day cumulative abnormal returns for Index $i \in$ {Market, Banks, Non-life Insurance, Industrial} in economy *c* after disaster *d*. $Char_{c,d}$ includes economy characteristics in the disaster economy *c* at the time of disaster *d*, including insurance penetration (ratio of total non-life insurance premiums to GDP, one year lagged), and sovereign financial strength (sovereign bond rating on a scale from 1 to 21, 21 being the highest, and one year lagged). X_d controls for the economic damage to GDP ratio for disaster *d*.

To examine whether economy characteristics play a role in determining the downside risk to CARs after disasters, the following quantile regression is estimated:

$$CAR40^q_{i,c,d} = \mu^q_i + \gamma^q_{1,i} Char_{c,d} + \gamma^q_{2,i} X_d + \epsilon^q_{i,c,d}$$

[1]Note: Only disasters for which precise start dates are available are included in the analysis.

where q is the 10^{th} percentile, capturing the left tail of the distribution of cumulative abnormal returns.

Robustness Analysis

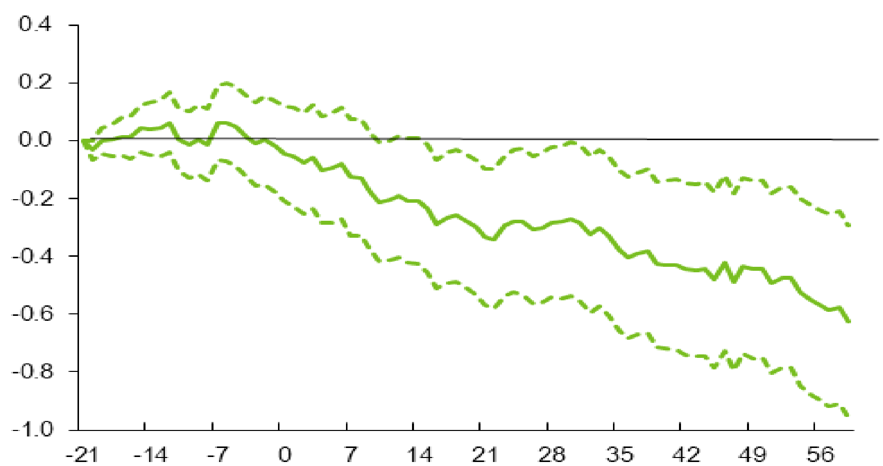
Results remain broadly unchanged for the following robustness checks:

1. To account for business cycle effects and government policy responses, the change in the short-term interest rate (3-month government bond yield) relative to the end of the previous year or the change in the long-term interest rate (10-year government bond yield) relative to the end of the previous year, has been added as an additional control variable.
2. To account for the fact that some disasters such as storms and floods may have more acute effects than other disasters such as droughts and wildfires, the sample is restricted to storms and floods only.

To better understand the role of re-insurers and the global spillovers of disasters, the CAAR analysis is repeated with all globally listed re-insurance companies and all disasters in the sample. Cumulative average abnormal returns are negative and significant as can be seen in Online Annex Figure 5.2.1

Online Annex Figure 5.2.1. Cumulative Average Abnormal Returns for Global Reinsurance Sector

Sample Economies, Reinsurance Sector: Cumulative Average Abnormal Returns (CAAR) Around Large Disasters, 90 Percent Confidence Interval
(Percent)



Sources: Refinitiv Datastream and IMF staff estimates.
Note: This figure plots the cumulative average abnormal returns (CAARs) for the global reinsurance sector during the trading days around large climatic disasters. The global reinsurance sector return is simple average of daily returns of all publicly-traded reinsurance companies globally. Abnormal returns are computed based on a single global factor model and estimation uses historical data one year before each disaster. The x-axis is trading days and time 0 is the start day of disasters. Dashed lines are the 90th percent confidence intervals.

Online Annex 5.3. The Pricing of Physical Risk: Cross-Economy Evidence

Empirical Approach

Using cross-sectional regressions and economy-level measures of predicted changes in hazard occurrence, the following equation is estimated:

$$Valuation_c = \alpha + \beta Hazard_c + \gamma\, Valuation\ Controls_c + \epsilon_c \qquad (1)$$

where *c* is economy; $Valuation_c$ is either the log of the price-earnings ratio, of the market-to-book ratio or of the price-to-dividends ratio; $Hazard_c$ is a measure of predicted change in climatic hazard occurrence.[1] $Valuation\ Controls_c$ are proxies for expected future earnings growth, the equity risk premium, and the risk-free interest rate, as in IMF (2019).

Valuation metrics[2]	Climatic Hazard Indicators	Valuation Controls
• Log of Price-to-Earnings per Share Ratio (P/EPS) • Log of Price-to-Book per Share Ratio (P/BPS) • Log of Price-to-Dividend per Share Ratio (P/Div)	• Measures of future changes in hazard occurrence (Maplecroft indicators, World Bank indicators)	• mean annual growth of earning per share (past 5 years) • standard deviation of annual growth of earnings per share (past 5 years) • 3-month govt. bond yield

The estimations are repeated for each of four different representative concentration pathways (RCPs): RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5. The sample of economies with available data includes 50 economies in total.

To assess the impact of climate change sensitivity and climate change adaptive capacity, Equation (1) is then augmented as follows:

$$\begin{aligned} Valuation_c = \beta_0 + \beta_1 Hazard_c + \beta_2\, \mathbb{1}\{High\}_c + \beta_3 Hazard_c \mathrm{X}\, \mathbb{1}\{High\}_c \\ + \beta_4 Valuation\ Controls_c + \epsilon_c \end{aligned} \qquad (2)$$

where $\mathbb{1}\{High\}_c$ is an indicator variable equal to one when the Climate Change Sensitivity Index or the Climate Change Adaptive Capacity Index is above the median of the cross-economy distribution.

[1]The climate hazard risks considered are ΔExtreme heat, ΔExtreme precipitation, ΔHeatwave probability, ΔDrought likelihood, Sea level rise index, Climate Change Hazard Index (See Online Annex Table 5.1.1 for data sources and definitions).

[2]Average of monthly observations in 2019.

Robustness Analysis

To control for additional factors that could influence the relationship between future climate hazards and current market valuations, a range of robustness checks have been performed:

- The price-to-book and price-to-dividend ratios have been used as alternative measures of market valuations
- To control for the aggregate state of the economy regressions have been performed using yearly averages of the market valuation metrics as well as averages over longer periods of time (e.g. 5-10 years).
- Possible confounding effects due to the economic and financial cycle have been formally examined by augmenting the baseline specification with the credit-to-GDP gap and Output gap measures. Confounding due to political risk and fiscal capacity have been tested by including interaction terms of the climatic hazard indicators with sovereign ratings. Transition risk proxies have been added as control variables.
- Different projection horizons of the climatic hazard indicators have been used.

The results are robust to these additional tests.

Moreover, there is no change in the pricing of climate change physical risk over time, and no difference in pricing in economies with higher levels of attention to climate change (measured using the Google search index for the topic "climate change" or with the share of sustainable fund investors relative to total market capitalization).

One potential reason for the lack of significance in the pricing of equities might be related to how different agents in the economy trade off immediate costs and uncertain future costs that occur in the very long run. Agents with lower discount rates are also more sensitive to developments expected several years in the future. To test this hypothesis, cross-sectional regressions for different sectors, including the banking sector, insurance, industrials, real estate and utilities were estimated. In line with the previous intuition, insurances and industrials show some degree of pricing of the Climatic Hazard Risk and future Heat Wave likelihoods. The results however do not hold once controls for the financial cycle are included in the baseline specification. The results from the specification with adaptive climate capacity and climate change sensitivity remain unchanged.

ONLINE ANNEX 5.4. TEMPERATURE SENSITIVITY AND PREDICTABLE EQUITY RETURNS

Empirical Approach

This annex summarizes the empirical approach used to calculate the abnormal returns from a portfolio invested in stocks with a high temperature sensitivity.[1]

The 27 economies in the analysis are selected based on the criterion that they have at least 50 listed firms in the first month of 1998. The regressions are conducted based on the same sample period 1993-2017 for all economies.[2]

The analysis follows the two-stage regression approach of Kumar, Xin, and Zhang (2019) and uses the *asreg* command in STATA:

Stage 1: The temperature anomaly is defined as the difference between the current temperature and the average temperature over the past 30 years in the same month. For each month t, the excess return of each firm *i* in economy *c* is regressed on the excess market return and on the temperature anomaly using a rolling window of 5 years (60 months):

$$r_{i,c,t} - r_{f,t} = \alpha_{i,c} + \beta_{i,c}\left(r_{mkt,c,t} - r_{f,t}\right) + \theta_{i,c} TemperatureAnomaly_{c,t} + \epsilon_{i,c,t}, \quad (1)$$

where $r_{i,c,t}$ is firm *i*'s monthly equity return in US dollars, $r_{f,t}$ is the 3-month U.S. treasury yield, $r_{mkt,c,t}$ is monthly market returns in economy *c* in U.S. dollars, and $\theta_{i,c}$ captures the sensitivity of firm *i*'s return to the temperature anomaly in the 5-year window up to month t. Returns are calculated using the Total Return Index. $\theta_{i,c}$ is time-varying since the equation is estimated using rolling windows. The key variable of interest, temperature sensitivity $\theta_{i,c}^{T}$ is the absolute value of $\theta_{i,c}$.

Stage 2: Firms within the same economy are ranked by their temperature sensitivity to the temperature anomaly $\theta_{i,c}^{T}$ in each month and then grouped into quintiles (5 bins), with the top quintile consisting of firms with the highest temperature sensitivity. A dummy variable $HighTS_{i,c,t}$ is created which is equal to 1 if firm *i* belongs to the top quintile in month *t*. The high temperature sensitivity dummy $HighTS_{i,c,t}$ is then used in the following cross-sectional regressions (run for each month *t*):

$$r_{i,c,t+1} - r_{f,t+1} = \mu_{c,t} + \lambda_{c,t} HighTS_{i,c,t} + \gamma'_{c,t} X_{i,c,t} + \xi_{i,c,t+1}, \quad (2)$$

where $X_{i,c,t}$ is the vector of each firm's exposure to three Fama-French factors (excess market returns, the small-minus-big factor, and the high-minus-low factor). The variable of interest is $\hat{\lambda}_c = \left(\sum_{t=1}^{240} \lambda_{c,t}\right)/240$, an

[1] For example, Feng and Peng (forthcoming) show that food sector stock returns may be affected by temperature.

[2] The same pattern of mispricing across economies is present even after allowing earlier starting months for economies that have data for at least 50 listed firms before 1998m1.

average of estimated parameter $\lambda_{c,t}$ over the period 1998m1 to 2017m12. If $\hat{\lambda}_c$ is significantly negative, stocks highly sensitive to temperature anomalies earn abnormal lower returns, indicating mispricing.[3]

Robustness Analysis

To control for any other potential risk exposure three additional standard risk factors are included when estimating equation 2: RMW (robustness minus weak), CMA (conservative minus aggressive) and MOM (momentum).[4]

In addition, following Kumar and others (2019) three additional firm-level characteristics are included in the Fama-Macbeth cross-sectional regressions: lagged firm returns, firm market cap, and firm book-to-market.

With all variables included, the pricing anomaly remains.

[3]Same as the Fama-Macbeth test, the t-statistics are calculated using Newey-West adjusted standard errors with 3-month lags.

[4]RMV and CMA are based on the 5-factor model by Fama and French (2015). MOM is based on Carhart (1997).

Online Annex 5.5. The Pricing of Hurricane and Storm Risk in the Catastrophe Bond Market

Data on 778 catastrophe (CAT) bonds issued between 1997 and 2018, including their spreads, expected losses, maturity, and triggers is obtained from Tomunen (2019). Bonds related to mortgage risk are excluded since the focus is on natural disasters. The final sample comprises 656 observations. Bonds are classified depending on whether they are exposed to hurricane and storm risk (including European Windstorms and Pacific Typhoons) or not. OLS regressions based on the following model are performed:

$$\begin{aligned} Spread_{b,t} &= \beta_0 + \beta_1 ExpectedLoss_{b,t} + \beta_2 Hurricane\ Exposure_{b,t} + \beta_3\ USExposure_{b,t} \\ &+ \beta_4\ Maturity_{b,t} + \beta_5\ \log\left(AmountIssued_{b,t}\right) + \beta_6 TriggerType_{b,t} + \mu_t + \epsilon_{b,t} \end{aligned} \tag{1}$$

$Spread_{b,t}$ is the spread over the floating benchmark quoted of bond b issued on day t and is measured in basis points. $ExpectedLoss_{b,t}$ is measured in percentage points, and is the annualized expected loss given the underlying actuarial risk model. $Hurricane\ Exposure_{b,t}$ and $USExposure_{b,t}$ are dummy variables indicating whether the bonds are exposed to hurricane and storm risk and risk in the U.S. respectively. $Maturity_{b,t}$ is the maturity at issuance of the bond in years. $AmountIssued_{b,t}$ is the total face value in U.S. dollars of the bond. $TriggerType_{b,t}$ is a set of dummy variables describing the type of trigger of the bond, including Parametric, Industry Loss Index, Modelled Loss, Indemnity and Multiple Triggers. μ_t are year fixed effects. The coefficient of interest is β_2.

Online Annex 5.6. Long-Run Risk Model with Climatic Disasters

The model builds on the long-run risk (LRR) framework of Bansal and Yaron (2004). It features Epstein and Zin (1989) recursive preferences, a preference for early resolution of uncertainty, and persistent consumption growth shocks. To account for the potentially severe consequences of climate change, temperature-induced very large climatic disasters that affect consumption growth are introduced in the framework, similarly to Barro (2009), Wachter and others (2015) and Bansal and others (2019). In this framework, temperature provides information about the probability of future very large climatic disasters. The main components of the models are described below:

Representative Agent Preferences

The representative LRR agent has recursive Epstein and Zin (1989) preferences, as expressed by the following utility function:

$$\mathrm{U_t} = \left[(1-\delta)\,\mathrm{C_t}^{\frac{1-\gamma}{\theta}} + \delta\left(E_t\left[U_{t+1}^{1-\gamma}\right]\right)^{\frac{1}{\theta}}\right]^{\frac{\theta}{1-\gamma}}, \tag{1}$$

where C_t is consumption at time t, δ reflects the agent's time preference, γ is the coefficient of risk aversion, and $\theta = (1-\gamma)/(1-\frac{1}{\psi})$ where ψ is the elasticity of intertemporal substitution (IES). Utility maximization is subject to the following budget constraint:

$$\mathrm{W_{t+1}} = (W_t - C_t)\,R_{C,t+1} \tag{2}$$

Where W_t is wealth and $R_{C,t}$ is the return on all invested wealth.

Consumption and Dividends Dynamics:

$$\begin{aligned}
\Delta c_{t+1} &= \mu_c + x_t + \sigma_t \eta_{t+1} - D_{t+1} \\
x_{t+1} &= \rho x_t + \varphi_e \sigma_t e_{t+1} \\
\sigma_{t+1}^2 &= \overline{\sigma^2} + v\left(\sigma^2 - \overline{\sigma^2}\right) + \sigma_w w_{t+1} \\
\Delta d_{t+1} &= \mu_d + \phi_d x_t + \varphi_d \sigma_t u_{t+1}
\end{aligned} \tag{3}$$

where Δc_{t+1} and Δd_{t+1} are the growth rate of consumption and dividends, respectively; μ_c is a positive drift parameter; and x_t is a small but persistent component that captures long run risks in consumption growth. As in the long run risk literature, $\mu_c + x_t$ is the conditional expectation of consumption growth. Volatility of consumption and dividends are driven by a common time-varying component, σ_t . D_{t+1} is a drop in consumption growth due to temperature-induced very large disasters. In addition, the shocks η, e, w and u are assumed to be i.i.d normal and orthogonal to each other.

Model Solutions

The log of the intertemporal marginal rate of substitution (IMRS) can be defined as:

$$m_{t+1} = \theta \, log\delta - \frac{\theta}{\psi} \, \Delta c_{t+1} + (\theta - 1) r_{c,t+1} \tag{4}$$

In order to characterize the intertemporal marginal rate of substitution, one needs to solve for the unobservable return on the consumption claim. Using the linear approximations suggested by Campbell and Shiller (1988), the log return of the endogenously determined aggregate wealth portfolio r_c and the log return of the market portfolio r_m, which constitutes a claim to the dividend stream, can be defined as follows:

$$\mathrm{r}_{\mathrm{c,t+1}} = k_0 + k_1 z_{t+1} - z_t + \Delta c_{t+1} \tag{5}$$

$$r_{m,t+1} = k_{0,m} + k_{1,m} z_{m,t} - z_{m,t} + \Delta d_{t+1} \tag{6}$$

where z denotes the log price-consumption ratio, z_m is the log price-dividend ratio and k_* are approximating constants which depend on the unknown mean of z. Accordingly, z is found by numerically solving a fixed-point problem. In so doing, the risk premium for the market asset is then determined by the covariation of the return innovation with the innovation into the pricing kernel:

$$\mathrm{E}_{\mathrm{t}}\left[r_{m,t+1} - r_{f,t}\right] + 0.5\sigma^2_{t,r_j} = -Cov_t\left(m_{t+1} - E_t(m_{t+1}), r_{m,t+1} - E_t\left(r_{m,t+1}\right)\right) \tag{7}$$

Model Estimation and Calibration

The LRR model, as described above, implies a vector stochastic process for consumption and dividend growth (macro variables), as well as a vector stochastic process for the return of the market portfolio, the risk-free rate, and the price-dividend ratio (financial variables) which depend on the following set of parameters:

$$\Theta = \{ \underbrace{\gamma, \psi, \delta,}_{\text{Preferences}} \quad \underbrace{\mu_c, \rho, \varphi_e, \sigma^2, \nu, \sigma_w, \mu_d, \phi_d, \varphi_d,}_{\text{Cash flows}} \quad \underbrace{h}_{\text{Time Aggregation}} \} \tag{8}$$

Acknowledging the inherently recursive structure of the LRR model and the challenge posed by the presence of two latent processes, the estimation of the macro parameters is performed using an auxiliary model based on a generalized method of moments-type criterion, which isolates the estimation of the macroeconomic dynamics from that of preferences[1]. In order to do so, a simulation of LRR model-implied data is required to perform the indirect inference estimation. Draws from standard normally distributed random variables are used to obtain realizations of the innovations of the shocks for the macro variables, while the probability of climatic disasters is mapped to the current level of temperature in the simulation. The appropriate time series length for the

[1]Preference parameters are assumed exogenous and their parametrization follows the asset pricing literature.

simulations is then determined by the number of observations, the sampling frequency of the empirical data, the assumed decision frequency of the investor, as well as the length of the projected climate scenario (available until 2100). To overcome possible bias due to small sample dataset the estimation approach is replicated using bootstrap simulations. Given the significant uncertainty surrounding future temperature projections, three main climatic scenarios are considered: RCP 2.6, RCP 6.0 and RCP 8.5. Risk premia reported in the Chapter are estimated using the average, the 5th percentile and the 95th percentile of the temperature projections obtained from the ensemble of models included in the fifth phase of the Coupled Model Intercomparison Project (CMIP5) for each one of the scenarios. These are then compared to a counterfactual scenario with no future climate risk and the market-implied risk premia based on a standard discounted cash-flow valuation model. [2] Details of the calibration of the frequency and size of the disasters are provided below.

Calibration of the Impact of Very Large Climatic Disasters

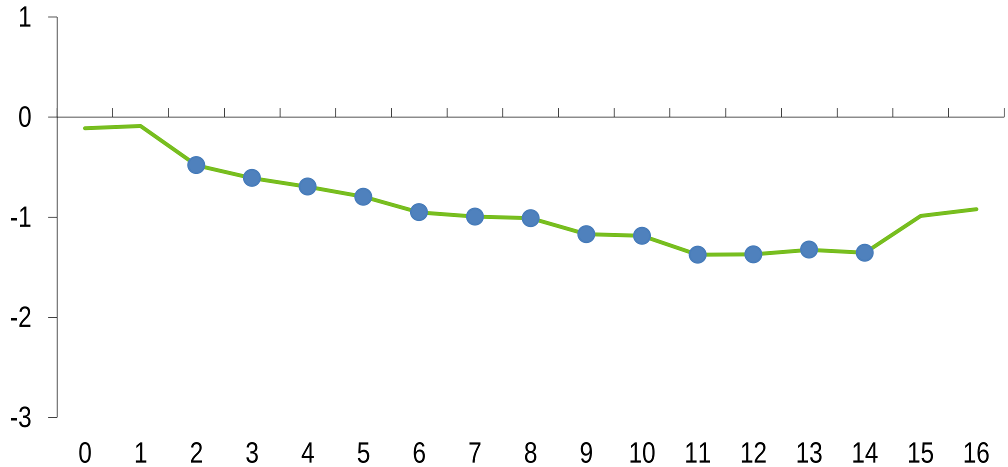
Based on the same sample of the Chapter, the effect of very large disasters on consumption growth is calibrated using the local projections method (Jorda, 2005) with the following specification:

$$y_{c,t+h} - y_{c,t-1} = \beta_0^h + \beta_1^h \mathbb{1}\{Disaster\}_{c,t} + \beta_2^h X_{c,t} + \theta_c + \theta_t + \epsilon_{c,t}^h \tag{9}$$

where *c* is an economy, *t* is a quarter, *h* is a positive integer between 0 and 16, the dependent variable is the log difference in real consumption per capita between time *t-1* to *t+h;* and $\mathbb{1}\{Disaster\}_{c,t}$ is an indicator variable that takes value equal to 1 if economy *c* was hit by a very large disaster in quarter *t*. Economy fixed effects θ_c and quarter fixed effects, θ_t, are included to capture long run differences in growth across economies and the impact of global shocks that are common to all economies in the sample. The residual term $\epsilon_{c,t}^h$ corresponds to an error term that is assumed i.i.d. Net official development assistance and official aid received (percent of GDP) is added as an additional control to the specification ($X_{c,t}$), as in Raddatz (2009). The sample period starts in 1975. The impact of disasters is calibrated based on the estimates for very large disasters reported (β_1^h) in Online Annex Figure 5.6.1.

[2] Implied methods used for the calculations of the equity risk premiums are derived from the standard dividend discount model (DDM) by inverting the discounted cash-flow valuation formulas. Specifically, the market implied equity risk premium is computed as the difference between the 18 months ahead forecasts of earnings per share-to-price ratio and the 10-year government bond yield (inflation adjusted). The measure is then averaged over the last 15 years.

Online Annex Figure 5.6.1. Impact of Very Large Disasters on Consumption
(Deviation from no-disaster scenario, percent)



Sources: EM-DAT, Haver; and IMF staff calculations.
Notes: The figure reports the estimated coefficients measuring the impact of disasters on real per capita consumption. Estimations are based on local projections (Jorda, 2005). The Indicator dummy used in the estimation is equal to one if a very large disaster occurred at time t. A disaster is defined as very large if the ratio of affected population to total population the ratio of deaths to total population, or the damage-to-GDP ratio, are above the 95th percentile of the historical distribution. Blue dots indicate that the coefficients are statistically significant at the 10 percent level or lower.

Calibration of the Likelihood of Climatic Disasters

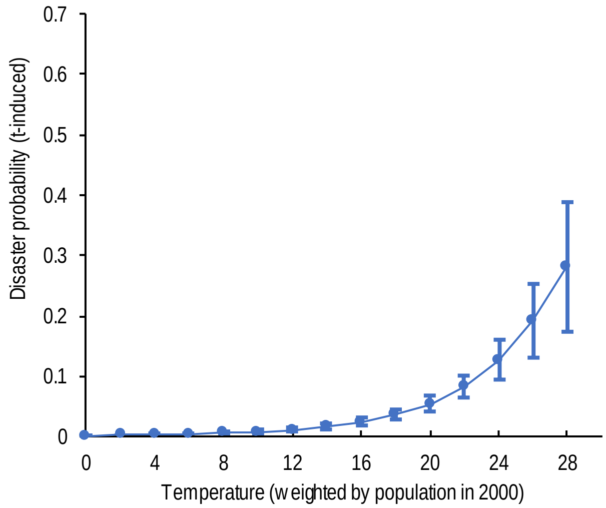
The relationship between temperature and the occurrence of disasters is calibrated using the following panel logit model:

$$\Pr\left(Disaster_{c,t} = 1\right) = \Phi(f(T_{c,t}) + f(P_{c,t}) + \theta_c + \epsilon_{c,t}) \qquad (10)$$

where c is economy, t is a quarter, $f(T_{c,t})$ is a quadratic function of temperature, $f(P_{c,t})$ is a quadratic function of precipitations, θ_c are economy fixed effects and $\epsilon_{c,t}$ is the error term. The model is also tested for each disaster type separately. To facilitate the mapping between the temperature level and the likelihood of climatic disasters, the disaster probability calibration is performed only using wildfires, droughts and heat waves events, as arguably these are the most likely to be directly linked to temperature rises. The category of climatic disasters based on these events is then defined, as "T-Induced". The estimates are robust to different fixed effects structures and to the inclusion of economy specific time trends. Within the model simulation, the logit-implied probabilities are scaled by the number of very large T-induced disasters over the total number of T-induced disasters observed in the EM-DAT database, to match the calibration of the size of disasters in the previous section. The (marginal) implied quarterly probability of all T-Induced disasters at different level of temperature is reported in Online Annex Figure 5.6.2.

Online Annex Figure 5.6.2. Model implied Quarterly Probability of ("T-Induced") Disasters

(Probability)



Sources: EM-DAT; University of Delaware (Department of Geography); and IMF staff calculations.
Notes: The figure reports the marginal quarterly probability of all temperature induced ("T-induced") disasters for different levels of temperature. T-induced disasters refer to Heat Waves, Wildfires and Droughts. Vertical lines delineate the 95 percent confidence bounds around the point estimates.

Online Annex 5.7. The Pricing of Physical Risk into Sovereign Bonds

Results are based on the following baseline specification:

$$\begin{aligned} Bond\ Spread\ at\ issuance_{b,c,t} = \alpha_{c,t} + \beta_1\ Climate_c + \beta_2\ longterm_{b,c,t} + \\ \beta_3\ Climate_c X\ longterm_{b,c,t} + \beta_4\ Controls_{b,c,t} + \epsilon_{b,c,t}, \end{aligned} \quad (1)$$

where b is bond, c is economy, and t is year. $Bond\ Spread\ at\ issuance_{b,c,t}$ is the spread between the coupon rate of the security and the US Treasury or another Benchmark bond, and is measured in basis points. Long-term is a dummy for bonds with maturities after 2040. Control variables are log of issue size, log of maturity, VIX, and sovereign credit rating. $\alpha_{c,t}$ are economy-year fixed effects

There is no perfect single measure of climate change physical risk available – one that considers changes in hazard frequency and intensity, and also changes in exposure and vulnerability. The analysis uses the same measures of climate change physical risk as the main text of the Chapter:

$Climate_c$ is one of the following seven variables:

1. projected change in the number of extreme heat days
2. projected change in the number of extreme precipitation days
3. projected change in heatwave likelihood
4. projected change in drought likelihood
5. Sea Level Rise Index
6. Climate Change Hazard Index
7. Climate Change Physical Risk Index

The coefficient of interest is β_3.

Projected changes in climate hazard variables (i.e. variables 1-4) are available for four different projection horizons up to the year 2100, and for four different emission scenarios. The analysis concentrates on the horizon 2020–39 and emission scenario RCP 8.5, but results are robust to other horizons/scenarios.

The sample includes 41,211 bonds, issued in 121 economies. 94 percent of the bonds are issued by advanced economies, and 54 percent by the United States alone. The results are robust to excluding the United States from the sample and to excluding economies not included in the analysis discussed in the main text of the chapter.

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