Measuring Time-Varying Disaster Risk: An Empirical Analysis of Dark Matter in Asset Prices[*]

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Abstract

To confront the challenge that disaster risk is "dark matter" in finance, we construct an objective measure of disaster risk, which is able to predict half of GDP crashes in a sample of 20 advanced economies between 1870 and 2021. Despite this significant predictability, we find no supportive, *and often contradictory*, evidence of higher predicted disaster risk being associated with a higher equity premium, volatility, or dividend/price ratio of the equity market index; higher corporate bond spreads, or higher term spreads. Our results suggest that the subjective disaster risk mirrored by asset prices lags objective disaster risk by two years.

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Since the influential work of Rietz (1988) and Barro (2006, 2009), disaster risk has been employed to understand a wide range of phenomena and puzzles in finance and macroeconomics. In these models, fear of rare but disastrous events, such as natural disasters, wars, and financial crises, may have profound effects on agents' asset valuations and investment decisions and thereby the real economy. Gabaix (2012) and Wachter (2013) model time-varying disaster risk as a key mechanism driving time-varying asset risk premiums, which helps explain several puzzles in asset markets, such as the excess volatility puzzle, the predictability of equity market returns by price-dividend ratios, the cross-sectional predictability of stock returns, and the term spread puzzle. Gourio (2013) argues that time-varying disaster risk helps to explain the level, volatility, and cyclicality of credit spreads. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) and Farhi and Gabaix (2016) use time-varying disaster risk to explain returns to currency carry trades and exchange rate dynamics. Furthermore, Gourio (2012) argues that disaster risk affects not only asset prices but also employment, output, and investment in the macroeconomy. Campbell (2017) devotes a separate section in his textbook on asset pricing to cover time-varying disaster risk.

However, this research agenda confronts a challenge that disaster risk is difficult to measure due to its very nature of being rare. As a result, some even venture to call disaster risk "dark matter" in economic models (e.g., Chen, Dou, and Kogan 2019). So far, the literature has relied on indirect measures of disaster risk from asset prices, such as from option prices (e.g., Bollerslev and Todorov 2011) and the cross-section of asset returns (e.g., Kelly and Jiang 2014). As these measures are not directly related to the actual occurrence of disaster events, they may capture investors' subjective rather than objective disaster risk or other factors unrelated to disaster risk. The lack of direct disaster risk measures has also given rise to an opposite view that financial markets may neglect disaster risk. Gennaioli, Shleifer, and Vishny (2013) argue that the neglect of tail risks by investors was a key mechanism driving the rapid expansion of shadow banking in the run-up to the 2007-08 financial crisis. Baron and Xiong (2017) find that bank credit expansions predict significantly higher crash risk of the bank equity index, and yet, despite the increased crash risk, credit expansions are associated with lower, rather than higher, risk premiums in bank equity returns. Similarly, Muir (2017) shows that during wars—the most severe disasters, as measured by consumption declines—there are small increases in risk premiums compared to during recessions and financial crises.

In this paper, we overcome this challenge by constructing a direct measure of disaster risk. Following Barro and Ursúa (2008), we use GDP crashes as an indicator of economic disasters. In place of their definition of a GDP crash episode as a peak-to-trough cumulative decline in real GDP per capita of -9.5% or more, we define a GDP crash as an annual episode that occurs in year t if GDP growth from year t-1 to year t is below the 2nd percentile of its historical distribution over all countries from year t-50 to year t.[1] We face a trade-off in the choice of the percentile threshold for defining GDP crashes. Choosing a more stringent cutoff would allow us to concentrate on fewer and more extreme disasters, at the expense of increasing the difficulty of capturing disaster risk with finite historical data and limiting its explanatory power for empirical dynamics in asset price. This trade-off is consistent with the notion of Chen, Dou and Kogan (2019) that the model's irrefutability rises as the disaster probability drops. The 2nd percentile threshold strikes a reasonable balance between capturing sufficiently severe GDP disasters and maximizing statistical power, and results in a sample of economic disasters comparable in magnitude to the set highlighted by Barro and Ursúa (2008).

Our measure of disaster risk builds on the recent literature that shows credit expansions have strong predictive power for subsequent banking crises, economic recessions, and low GDP growth tail events (e.g., Schularick and Taylor 2012, Mian, Sufi, and Verner 2017, Adrian, Grinberg, Liang, Malik, and Yu 2021, Baron, Verner, and Xiong 2021). Specifically, we follow Greenwood, Hanson, Shleifer, and Sørensen (2022), whose main focus is to predict financial crises by using a credit boom indicator, an equity market boom indicator, and their interaction as predictors of GDP crashes. Our sample covers 20 advanced economies from 1870 to 2021 and excludes the two world wars periods. Our regression analysis shows that the joint effect of a credit boom and market boom provides particularly strong predictability for GDP crashes in the future 2-4 year horizon. Conditional on both a credit boom and market boom, the probability of a GDP crash occurring in 2-4 years is 16.3%, more than double the unconditional probability of 6.0%. This significant predictability allows us to construct an objective measure of heightened disaster risk associated with credit booms and asset market booms—the Disaster Index.

[1] Unlike the Barro and Ursúa (2008) definition, this definition does not require future information to designate disasters (as it is not based on peak-to-trough declines) and accounts for the pronounced decreasing trend in GDP volatility throughout the 20th century.

By design, the Disaster Index is an incomplete measure of disaster risk as it is not intended to capture contractions in real GDP associated with other types of disasters such as wars and natural disasters. Nevertheless, the Disaster Index is able to capture a substantial fraction of realized GDP crashes—the index is in the top quintile three years prior to *half* of realized GDP crashes (24 out of the 47 crashes in our sample) while maintaining a reasonable 17% false positive rate.

Our objective Disaster Index allows us to systematically examine how time-varying disaster risk affects asset prices. As a disaster event disrupts aggregate consumption, the key insight of the consumption-based asset pricing models of time-varying disaster risk (e.g., Gabaix 2012 and Wachter 2013) is that time-varying disaster risk leads to a time-varying disaster risk premium. In contrast to this key prediction, we find that the Disaster Index *negatively*, rather than positively, predicts future returns of the market index and portfolios of value and growth stocks. Conditional on a one percentage point increase in the Disaster Index, the subsequent three-year log excess return of the market index is 2.7 percentage points lower than average within the full-sample period of 1870-2021 and 2.4 lower than average when restricting to the post-1950 sub-period.

Through the disaster risk premium channel, existing models have also highlighted several other asset pricing effects of time-varying disaster risk: an increase in disaster risk can drive up equity market volatility (e.g., Wachter 2013), corporate credit spreads (e.g., Gabaix 2012 and Gourio 2013), the nominal term spread (e.g., Gabaix 2012 and Tsai 2013), and the dividend yield of the equity market (e.g., Gabaix 2012 and Wachter 2013). We test these model implications by estimating univariate regressions of the Disaster Index with outcome variables, such as equity market volatility, corporate credit spreads, the nominal term spread, and the dividend yield of the equity market. We find no supportive, and often contradictory, evidence. First, the Disaster Index is negatively correlated with the volatility of the equity market index. Second, a rise in the Disaster Index is associated with a narrowing, rather than a widening, of corporate credit spreads and the nominal term spread. Specifically, a one percentage point increase in the Disaster Index corresponds to an average drop in the corporate credit spread index by 3.0 and 4.8 basis points over the subsample periods 1996-2005 and 2006-2021, respectively, and an average drop in the term spread by 18.4 and 9.4 basis points over the 1996-2005 and 2006-2021 periods, respectively. Third, a one percentage point rise in the Disaster Index is associated with a fall, rather than a rise, in the dividend/price and earning/price ratios of the aggregate market index in the range of 0.11 to 0.13 percentage points.

Taken together, our analysis suggests that the objective disaster risk measured by the Disaster Index may not be systematically incorporated by asset prices. This does not imply that disaster risk is irrelevant to asset prices. The challenge of measuring the time variation in disaster risk for econometricians also mirrors the challenge of making real-time financial decisions faced by market participants. Their decisions ultimately reflect subjective perceptions of disaster risk. Our findings highlight a potential gap between objective disaster risk captured by the Disaster Index and the subjective disaster risk mirrored by asset prices. Interestingly, our analysis suggests that the subjective disaster risk—reflected by equity market volatility, corporate credit spreads, the nominal term spread and equity dividend yield—lags objective disaster risk by approximately two years. We argue that our evidence is consistent with an alternative view in which many GDP disasters are endogenous and happen *precisely when* asset markets neglect risk, allowing banking crisis disasters (comprising roughly half of historical GDP disasters) to happen.

One may argue that the disaster risk captured by our Disaster Index is inherently different from other types of disasters, such as wars and natural disasters. As these other disasters are likely exogenous to the behaviors of asset market participants, their risks might be easier for market participants to assess and thus more relevant to time-varying disaster risk models.[2] If so, we would expect that the risk premiums reflected by asset prices show stronger predictability for GDP crashes that are unpredicted by the Disaster Index than those that are predicted, and similarly stronger predictability for GDP crashes unrelated to banking crises than for those related. However, this is not what we find. We plot the four risk premium measures (equity market volatility, corporate credit spreads, the nominal term spread, and equity dividend yield) around GDP crashes that are "unpredicted" versus "predicted" (based on our Disaster Index). We also decompose GDP crashes by disaster category (banking crisis, war, natural disaster or epidemic, and other). There is no evidence of the four risk premium measures offering stronger predictability for unpredicted disasters than for predicted ones or stronger predictability of disasters unrelated to banking crises than of those related. Thus, even though our Disaster Index by design tends to measure disaster risk related to banking crises, our finding that asset prices only slowly incorporate objective disaster risk is likely to hold for other types of disaster risk.

[2] One cannot argue, in defense of time-varying risk models, that the risks associated with non-banking disasters are even harder to assess, as such an argument reinforces dark matter concerns. If these types of disasters are inherently less predictable, then time-variations in such disaster risks will be less likely to influence financial markets, countering the relevance of time-varying disaster risk models for asset prices.

This paper contributes to the literature of time-varying disaster risk not only by constructing a large historical sample of economic disasters across 20 advanced countries but also decomposing these realized disasters into different categories. This sample facilitate a systematic analysis of asset pricing implications of time-varying disaster risk. Our analysis highlights several insights. First, one cannot simply treat economic disasters as exogenous to the financial system. In particular, our analysis highlights that half of the realized economic disasters in our sample are preceded with lower risk premiums in asset markets, possibly due to banks' credit expansions when banks neglect disaster risk (Gennaioli, Shleifer, and Vishny 2013; Baron and Xiong 2017) or have elevated risk appetite (Muir 2019; Krishnamurthy and Li 2020).

Second, there is a significant gap between objective disaster risk and the subjective disaster risk mirrored by asset prices. Thus, our results caution that indirect measures of time-varying disaster risk through asset prices, which are often used as warning signs of financial instability and disaster risk, may not reflect objective disaster risk. In this sense, our analysis also reinforces the concern of Chen, Dou and Kogan (2019) regarding risk premiums attributed to risks that are difficult to measure.

The rest of the paper proceeds as follows. Section I describes the data used for this empirical study. Section II constructs the Disaster Index and verifies its strong predictability for GDP crashes. Section III uses the Disaster Index to test various asset pricing implications of time-varying disaster risk models. Section IV provides additional analyses to compare risk premiums in asset prices around different types of realized disasters and to highlight that the subjective disaster risk mirrored by asset prices lags objective disaster risk. Section V concludes.

I. Data

This section describes how we construct the data. The variables form an unbalanced country panel across 20 developed economies over the period 1870-2021 at an annual frequency (with a year end of December 31). For asset returns, we gather the following variables: equity market index returns and the returns of equity portfolios sorted by book-to-market, dividend-to-price, and earning-to-price ratios constructed in the spirit of Fama and French (1993) for domestic stocks within each country. We also use the following country-level variables: growth in real GDP per capita, bank credit expansion, equity market volatility, a corporate bond spread index, the term spread, the inflation rate, and the dividend-to-price and earnings-to-price ratios of the broad equity market index. We describe in detail how each of these variables is constructed below, and we present summary statistics.

A. Data construction

Equity index returns

Equity returns of the broad equity market index for each country are expressed as log excess total returns. The excess total return is defined as the price return plus the dividend return of a broad equity market index minus the short-term government interest rate. For historical periods in which the short-term interest rate is unavailable, we use real total returns (price return plus dividend return minus the CPI inflation rate) in place of excess total returns. All data for this variable (price returns, dividend yields, short-term interest rates, and inflation) are taken from Baron, Verner, and Xiong (2021) for the period 1870 to 2016 and extended to the end of 2021 using the same data sources and methodology as detailed in their data appendix.

Equity factor portfolio returns

We use annual returns of country portfolios formed on the book-to-market, dividend-to-price, and earnings-to-price ratios in the Kenneth French Data Library (2021). We use this source for our primary analysis for two reasons: first, because it is a widely used and established source in empirical asset pricing, and second, because compared to an alternative approach described below that is based on data from Datastream and Worldscope, it provides slightly more coverage of 19 advanced economies: coverage begins in 1952 for the United States, 1975 for 12 countries, in 1977 for one country, and around 1990 for five countries.

For robustness, we also construct a second alternative dataset of annual factor portfolio returns using the international individual stock data from Thomson Reuters Datastream linked with their financial statement data from Worldscope. To construct annual factor portfolio returns, stocks are sorted at the start of each calendar year based on their book-to-market, dividend-to-price, or earnings-to-price ratios as of the previous year's December end. The monthly individual stock returns come adjusted for corporate actions (i.e., dividend payouts, stock splits, stock repurchases). If a sorting ratio is missing for a given stock-year, that stock is omitted in sorts of that ratio for that year. This alternative dataset begins in 1983 for ten countries and expands around 1990 for the remaining ten countries.[3]

Portfolios constructed by both methods are in local currency units, weighted by constituent market capitalization, and sorted annually at the start of each calendar year. Value portfolios (High) consist of firms in the top 30 percent of a ratio, and growth portfolios (Low) consist of firms in the bottom 30 percent.[4] The value and growth portfolio returns are log excess total returns at the annual level, and the value-minus-growth (High-minus-Low) spread portfolio return is based on the log of the value-minus-growth portfolio's annual total return.

Real GDP per capita

For real GDP per capita, we take the real GDP data from Baron, Verner, Xiong (2021) and divide by the population from Jordà, Schularick, and Taylor (2017) (with a few additions of real GDP per capita series from Jordà, Schularick, and Taylor (2017)). Coverage from these datasets begins in 1870 for most of the 20 countries and ends in 2016. We extend this series to the end of 2021 using nominal GDP and population figures published by the Organisation for Economic Co-operation and Development (OECD) and inflation published by Global Financial Data (GFD). Unless otherwise specified, the terms "GDP" and "GDP growth" are used in the remainder of this paper as shorthands for real GDP per capita and the one-year log change in real GDP per capita, respectively.

Bank credit expansion

Annual data for each country is taken from Baron, Verner, and Xiong (2021) and supplemented by recent Bank of International Settlements (BIS) data for the period 2017-2021. Credit Expansion, following the definition from Baron and Xiong (2017), is the annualized three-

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[3] For this alternative dataset, we have applied four additional filters to ensure data quality as recommended by the empirical literature using Datastream and Worldscope, such as Ince and Porter (2006). First, we restrict the dataset to domestic firms actively listed on primary exchanges and exclude firms marked by Worldscope as investment offices, unit investment trusts, real estate investment trusts, and "investors not classified." Second, because Datastream rounds the price index to the nearest 0.01, we drop observations with an unadjusted price below the 5th percentile of the country-month distribution to remove possibly erroneous returns for low-priced or low liquidity stocks. Third, we remove firms with a price of above one million in domestic currency units, or any observations with a monthly return of above 300% that is reversed in the subsequent month. Lastly, we remove observations with a monthly return outside of the country's 0.1 to 99.9 percentile range.

[4] The results reported in this paper are robust to alternative portfolio construction methods, such as the use of equal weighting, 10 or 20 percent (rather than 30 percent) cutoffs, and updating of portfolio constituents on July 1 of each year.

year change in the ratio of bank credit-to-GDP, where bank credit is defined as all credit granted by banking institutions to households and private domestic nonfinancial firms within that country.

Corporate credit spreads

The corporate credit spread index is defined as the yield of a corporate bond index for a given country minus the yield of a government bond index of similar duration. The data predominantly draws from ICE's Bank of America Global Corporate Index published by Bloomberg, supplemented by other sources (e.g., the *Economist* corporate bond index). Sources are detailed in Appendix Table B1.[5] Note that, although we have some data covering the 1980s for several countries, we present results based on the 1996-2021 sample only, as corporate bond indices are generally unreliable for many countries before 1996; in addition, we are only able to control for changes in the effective duration and the credit rating (AAA, AA, A, and BBB) of the bond index with the Bloomberg published data starting in 1996.

Other variables

Equity market volatility is computed as the annualized standard deviation of daily price returns of the broad equity market index, using the same index for each country as described earlier). Weekly or monthly price returns are used for historical periods when daily price returns are unavailable. The term spread (long-term government yield minus short-term government yield), inflation rate, and dividend-to-price and earning-to-price ratios of the broad equity market index are taken from Baron, Verner, and Xiong (2021) and extended to the end of 2021 based on their same methodology and data sources.

B. Summary statistics

Table 1 presents summary statistics of variables used in subsequent regressions. For the log excess total returns of the equity market index ("Market"), GDP growth, and bank credit expansion,

[5] As described by ICE, the corporate bond index constituents are grouped on the country level for each year from 1996 to 2021 on the last Friday of December (to avoid potential biases from rebalancing of constituents on the last calendar day of the month), and the country of a given bond is based on the physical location of the issuer's operating headquarters (as the bond may be issued in the currency of another country). The index only includes publicly issued, investment grade corporate debt. Qualifying securities satisfy a minimum size requirement, have a rating at or above BBB-equivalent issued by Moody's, S&P or Fitch, a fixed coupon schedule, and a minimum 18-month maturity at issuance. Qualifying currencies and their respective minimum size requirements (in local currency terms) are: Australian dollar 100 million; Canadian dollar 100 million; Swiss franc 100 million; Danish krone 1 billion; Euro 250 million; Japanese yen 20 billion; British pound 100 million; and US dollar 250 million.

the statistics in Table 1 are based on the full sample of country-year observations across 20 countries, 1870-2021. We exclude the periods around the two world wars (1914-1919, and 1939-1948) in these statistics and subsequent regression analysis. For equity factor returns, equity market volatility, corporate credit spreads, the term spread, and the dividend-to price and earnings-to-price ratios of the market index, the statistics in Table 1 are computed over the period 1950-2021, which is the sample period used for subsequent regression analysis on these variables.

We first note some stylized facts regarding equity returns. The mean log excess return of the broad market equity index is 3.4%. The value portfolios (High) sorted on B/P, D/P, and E/P have mean returns of 6.5%, 6.8%, 7.1% respectively, which are higher than the mean returns of the growth (Low) portfolios (4.3%, 4.0%, 3.9% respectively). Note the mean return of the value-minus-growth (High-minus-Low) spread portfolios does not correspond to the mean return of the High portfolio minus the mean return of the Low portfolio due to the use of log returns.

We next examine summary statistics for real GDP growth, which has a mean of 2.1%. Given that this paper focuses on GDP crashes based on the tail values of GDP growth (as explained in the following section), we report that the 5th percentile is -3.3%, and the 1st percentile is -8.7%.

Bank credit expansion has a mean value of 1.1 percentage points, which can vary as high as 5.8 (95th percentile) and as low as -3.1 (5th percentile) percentage points in a given year. We also report summary statistics for equity market volatility (mean=15.2%, s.d.=9.6%), credit spreads (mean=1.225%, s.d.=0.91%), the term spread (mean=1.028%, s.d.=1.82%), the dividend-to-price ratio (mean=3.8%, s.d.=1.9%), and the earnings-to-price ratio (mean=7.2%, s.d.=3.3%).

II. Construction of a GDP Disaster Index

A. GDP crashes as an indicator of disasters

Following Barro and Ursúa (2008), we use GDP crashes as an indicator of economic disasters. Specifically, Barro and Ursúa (2008) define a GDP crash episode as a peak-to-trough cumulative decline in GDP of -9.5% or more. This definition has two weaknesses. First, because identifying peak and trough episodes requires the full path of the GDP, it may be infeasible to determine whether a country in a given year is in a GDP crash without future information. This issue makes it difficult to use this definition to carry out predictive analysis of GDP crashes. Second, reported real GDP volatility has decreased markedly over the course of the twentieth century, which may be due either to improved economic resilience or extensive measurement error in historical GDP statistics (as argued by Romer 1989 and Watson 1994). Consequently, a constant cutoff of 9.5% for all years leads to a substantially smaller number of economic disasters after 1950.

To address these issues, we define a GDP crash as an annual episode that occurs in year t if GDP growth from year t-1 to year t is below the 2nd percentile of its historical distribution over all countries from year t-50 to year t.[6] This definition does not use future information and accounts for the decreasing trend in the GDP volatility. While we focus our attention on GDP crashes to align with the rare disaster literature's notion of disasters, we also build for some additional analyses an equity "market crash" indicator, which takes the value of one when the log excess return of the equity market index is below -30% in a particular year.

In Table 2, we present the frequency and severity of GDP crashes in 20 advanced economies over the period 1870-2021. We also present statistics for the associated peak-to-trough GDP declines surrounding annual GDP crashes to facilitate comparison with the chronology of Barro and Ursúa (2008).[7] We tabulate statistics for crash episodes separately over the pre-1950 subperiod (1870-1949) and the post-1950 subperiod (1950-2021), the latter of which we emphasize in our subsequent regression study on asset prices. The analysis in Table 2, as in the regression analysis in Section III, excludes episodes around World Wars I and II (specifically the years 1914-1919 and 1939-1948).[8]

We first focus on annual GDP crashes, our main definition of a real economic disaster. (In the rest of the paper, the term "GDP crashes" refers to annual GDP crash episodes rather than peak-to-trough episodes, unless "peak-to-trough" is specifically stated.) Table 2 reports that the frequency of experiencing a GDP crash in a particular year is 2.3%, with an average severity of -9.1%. However, for the post-1950 subperiod, the frequency drops to 1.8% and the severity drops to -5.9%. In the subsequent section of the paper, our regression analysis is based on the "included in regressions" GDP crashes listed in Table 2, which comprise 47 episodes (21 of the 35 episodes

[6] In using the past distributions from all countries to calculate the cutoff for a GDP crash (in contrast to having country-specific GDP cutoffs), we implicitly assume that GDP crashes of a given magnitude have similar asset pricing implications across all countries. This is consistent with the fixed cutoff across all countries of -9.5% for peak-to-trough GDP drop used by Barro and Ursúa (2008) to define disasters.

[7] We present a list of all individual GDP crashes under both definitions in Appendix Table A1.

[8] The two world war periods have limited or unreliable data for credit expansion and asset prices in many countries, due to stock market closures, high inflation, and other major disruptions. We analyze the many war-related GDP disaster during these periods separately in Section IV.

from the 1870-1949 subperiod and all 26 episodes from the post-1950 subperiod) and occur with a frequency of 2.3% and an average severity of -8.5%.[9] Even though we use the 2nd percentile of the historical distribution of GDP growth in the past 50 years, the pronounced downward trend in the GDP growth volatility has nevertheless made the realized frequency of GDP disasters visibly lower than 2% in the post-war period.

Note that we face a trade-off in choosing the cutoff of the 2nd percentile in defining a GDP crash. Choosing a lower cutoff makes a realized GDP crash more severe, but the lower frequency also makes the disaster risk harder to capture with the finite historical data and thus the "dark matter" concerns of such disaster risk being irrefutable more serious (as in Chen, Dou, and Kogan, 2019). Given that a cutoff of the 2nd percentile leads to a frequency of less 2% for GDP crashes in the post-1950 subperiod, further lowering the cutoff would make GDP crashes so rare that their predictability becomes irrefutable using standard confidence levels.

In order to facilitate comparisons with peak-to-trough disaster episodes from Barro and Ursúa (2008), we next define "BXY peak-to-trough episodes" as the peak-to-trough cumulative GDP declines surrounding the above-defined annual GDP crash episodes (which may encompass multiple annual GDP crash episodes). There are 53 BXY peak-to-trough episodes over the entire sample period, with a frequency of 4.5% that a country is currently in the midst of such an episode and with an average peak-to-trough severity of -12.6%. In the post-1950 subperiod (1950-2021), there are 24 such BXY peak-to-trough episodes, with a 3.3% frequency that a country is in the midst of one and with an average severity of -7.2%. In contrast, there are a total of 34 Barro-Ursúa episodes over the 1870-2021 sample (excluding the world war periods) with a frequency of 4.3% and peak-to-trough severity of -16.3%. For the post-1950 subperiod, there are 6 Barro-Ursúa episodes with a frequency of 1.5% and average severity of -11.0%. Barro-Ursúa episodes last longer than BXY peak-to-trough episodes, with a duration of 3.4 years over the 1870-2021 sample (versus 2.3 years).

Overall, BXY peak-to-trough episodes are of similar frequency as Barro-Ursúa disasters, and while slightly less in magnitude, still reasonably severe.

[9] "Included in regressions" refers to the subset of GDP crashes included in the estimation of Equation (1) in Table 3 (i.e. the subsample with non-missing data for the future GDP crash indicator, the Market Boom indicator, and the Credit Boom indicator).

The last five rows of Table 2 provide a decomposition of BXY disasters by disaster category (banking crisis, war, natural disaster or epidemic, and other).[10] We return to this decomposition by disaster category in Section IV, where we will analyze risk premium measures around these various types of disasters. For now, we highlight a few facts from Table 2. Focusing on the peak-to-trough declines which combine successive GDP crashes into unique episodes, and also re-including the WWI/WWII periods (1914-1919 and 1939-1948), first we see that banking crises are the most common type of historical GDP disaster in advanced economies (29 out of 76 events). Second, we see that "war disasters" are the most severe type in magnitude, with an associated average peak-to-trough GDP decline of -36% (compared to the average decline across all types of -20%). Third, there are, surprisingly, no natural disasters or epidemics causing GDP disasters over the 1870-2021 period in our sample of 20 advanced economies, except for the 2020 COVID pandemic-related GDP crashes, which account for all nine episodes in this category.

B. Probit estimation to forecast GDP crashes

In this section, we build the GDP Disaster Index by using a probit regression to predict the occurrence of a future GDP crash. We build on the extensive literature that shows that credit expansion provides strong predictive power for subsequent financial crises and economic downturns (e.g., Schularick and Taylor 2012, Mian, Sufi, and Verner 2017, Baron and Xiong 2017, Adrian et al. 2021, Baron, Verner, and Xiong 2021, and Greenwood et al. 2022). In particular, our approach follows that of Greenwood et al. (2022) who combine rapid credit expansion and asset price growth to jointly predict future banking crises and crashes in real GDP. They show that if a country is in the "red-zone" (credit expansion is in the top quintile of its historical distribution *and* three-year growth in equity prices is in the top tercile), the probability of entering into a financial crisis is 13% within one year and grows to 45% for the 4-year horizon (significantly higher than the unconditional crisis probability of 4%). They further find that conditional on being in the "red-zone", the probability of experiencing GDP growth below -2% within 3 to 4 years is markedly elevated compared to median GDP growth.

[10] Table A1 lists the full categorization of all individual GDP disasters. "Other" is a residual category and mainly comprises deep macroeconomic crises (e.g., a sharp export decline in Australia in 1881-1882, hyperinflation in Germany in 1922-1923, monetary tightening in Canada in 1990-1992).

For the probit analysis in this subsection and the construction of the Disaster Index in the next subsection, we need to define the indicator variables *Credit Boom*$_{i,t}$ and *Market Boom*$_{i,t}$ (corresponding to the broad equity market) in our context. The indicator variable *Credit Boom*$_{i,t}$ equals one for country i in year t if the variable bank credit expansion in the top quintile of the distribution for the full panel (i.e. all countries since 1870) up to year t. The *Market Boom*$_{i,t}$ indicator variable equals one for country i in year t if the country's past three-year log excess return of the market index is in the top tercile of the distribution for the full panel up to year t. The definitions of *Credit Boom*$_{i,t}$ and *Market Boom*$_{i,t}$ are identical to those of Greenwood et al. (2022) in the sense that the thresholding percentiles are the same (i.e., top quintile for credit booms, top tercile for market booms) and based on the distribution for the full panel, yet with the difference that we only use past information up to each point in time to prevent look-ahead bias in our forecasts. We require at least 30 observations of credit expansion (market returns) in the full panel to calculate the credit boom (market boom) indicator.

Before estimating the probit and Disaster Index, we start by presenting Figure 1, which helps to visualize the predictability of future GDP or equity market crashes at various horizons following the joint occurrence of both a credit boom and market boom. Panel A plots the observed probability of a GDP crash from t=-5 to t=+5 conditional on both *Credit Boom*$_{i,t}$ and *Market Boom*$_{i,t}$ equaling one at time t=0, comparing it with the baseline probability of a GDP crash during "normal times" (1.96%), represented by a horizontal dashed line. "Normal times" are defined as years when the country has not experienced the joint occurrence of a credit boom or market boom within a five-year window. Panel B is an analogous plot of the probability of an equity market crash from t=-5 to t=+5, conditional on both *Credit Boom*$_{i,t}$ and *Market Boom*$_{i,t}$ equaling one at time t=0.

In Panel A, at t=2, t=3, and t=4, the GDP crash probability is significantly elevated relative to "normal times", with probabilities of 4.28%, 7.57%, and 6.52% respectively, compared to 1.96% during "normal times". However, in the first year immediately following the joint credit boom and market boom (t=1), the country has an observed GDP crash probability of zero, as it takes time—a period of at least one year—for credit booms to go bust, even though the probability of a market crash is already elevated in the first year as shown by Panel B.

As a result of this finding that the predictability is highest in the 2 to 4-year-ahead horizons, we focus on these horizons in the subsequent probit analysis and Disaster Index construction. We consider the following probit regression, which predicts GDP crashes over a future 2-to-4-year horizon using *Credit Boom*$_{i,t}$, *Market Boom*$_{i,t}$, and their interaction as predictor variables:

$$\begin{aligned} &P\left(\Delta GDP_{i,t+2} < q_{t,0.02} \text{ or } \Delta GDP_{i,t+3} < q_{t,0.02} \text{ or } \Delta GDP_{i,t+4} < q_{t,0.02}\right) \qquad (1) \\ &\qquad = \Phi(\alpha_0 + \beta_1 (Credit\ Boom)_{i,t} + \beta_2 (Market\ Boom)_{i,t} \\ &\qquad\qquad + \beta_3 (Credit\ Boom)_{i,t} \times (Market\ Boom)_{i,t}) \end{aligned}$$

where $\Delta\text{GDP}_{i,t}$ denotes log growth in GDP from t-1 to t for country i, and $q_{t,0.02}$ is the 2nd percentile of the distribution of $\Delta\text{GDP}_{i,t}$ for all countries from year t-50 to year t. The probit regression thus estimates the conditional probability that a GDP crash occurs in *any* of the following years—2, 3, or 4—ahead. We skip the first year ahead because, as indicated by Figure 1, when this probit regression is estimated for GDP crashes in each future year individually, the probability of a crash is lower for one year ahead because the cycle takes time to turn; the probability is higher for horizons of two to four years. Equation (1) is estimated over the full sample of 20 economies over 1870-2021 (excluding the world war years of 1914-1919 and 1939-1948). We estimate the probit using standard errors that are double clustered on time and country to account for possible autocorrelation within each country and possible correlations across countries at each point in time.[11]

Table 3 reports the marginal effects of the three main predictor variables: the credit boom indicator, the market boom indicator, and their joint effect. In the univariate regressions in columns (1) and (2), we observe that a credit boom predicts a 3.2% increase in the probability of a GDP crash in 2-4 years, whereas the predictability of market booms is 4.5%. Column (3) reports similar coefficients from a bivariate specification. Column (4) also includes their interaction, which is the strongest predictor of the three, in terms of statistical significance and magnitude of the marginal effect, with a future GDP crash probability of 16.3% if both a credit boom and market boom are observed. Compared to the unconditional probability of a GDP crash in 2-4 years of 6.0%, this is more than doubling in crash risk.

[11] Note that Driscoll-Kraay standard errors, which we use in the rest of the paper, which also account for cross-autocorrelations, cannot be employed in a probit framework. We find similar results to those in Table 3 when we recast Equation (1) as a linear probability model and use Driscoll-Kraay standard errors with 6 lags.

Column (5) shows that a specification with just the interaction term has approximately the same level of predictability as the fully specified regression, in terms of both the magnitude of the sum of marginal effects (8.4% vs. 7.7%) and the pseudo R-squared (4.0% vs. 3.5%), suggesting that it is largely the interaction term of the credit boom and market boom indicators that predicts GDP crash risk. In specifications (6) and (7), we add the contemporaneous value and two lags of GDP growth, to which the results are robust.

These findings suggest that the interaction of rapid credit booms and asset price run-ups signal a risk build-up for relevant economic disasters in the medium run in the form of a GDP crash in 2-4 years. The joint occurrence of a rapid credit boom and an asset market boom has substantially stronger predictive power than a credit boom or an asset market boom alone because their joint occurrence is a sharp reflection of widespread exuberance in an economy that has led to not only rising asset prices but also an expansion of leverage in the economy, which can directly trigger both financial and economic instability when the boom goes bust. A credit boom in the absence of sharply rising asset prices may simply reflect financial deepening, while rising asset prices in the absence of a credit boom may well reflect positive economic fundamentals.

Our findings are consistent with those of Greenwood et al. (2022) who find that the joint occurrence of a credit boom and market boom forecast an increased probability of a banking crisis starting at the 1-year horizon (13.3%) and growing to 48.0% for the 4-year horizon. The elevated probability of a GDP crash following the joint occurrence of a credit boom and market boom is perhaps not surprising given that a sharp decline in GDP tends to be a product of a banking crisis. Greenwood et al. (2022) also find, similar to us, that there is a near-zero probability of real GDP growth below -2% within one year after a joint boom but that this probability jumps to 14.7% for a -2% real GDP crash in year two and climbs up to 40% for a 2 to 4-year horizon.

C. The Disaster Index

Given the strong in-sample predictability of the credit and market boom indicators for GDP crashes at future-2-to-4-year horizons, we next construct an out-of-sample measure of disaster risk, the "Disaster Index". We again estimate Equation (1) but now in a one-step-ahead rolling framework, using the regression specification from column (5) of Table 3. As before, this estimation is done over the full sample of 20 economies over 1870-2021 (excluding the periods around the world wars of 1914-1919 and 1939-1948). For each year *t*, we estimate the regression using data available from 1870 to year *t* and denote the predicted value as the Disaster Index. To calculate the Disaster Index, we require at least ten country-year observations where the GDP crash indicator, the credit boom indicator, and the market boom indicator are non-missing; thus, for countries with complete data going back to 1870, the Disaster Index starts in 1879.

The Disaster Index represents the probability of the occurrence of a GDP crash in the subsequent two to four years and thus captures the time-varying probability of a disaster in an economy adopted by Wachter (2013) to model time-varying disaster risk.[12] Figure 2 plots the Disaster Index for all 20 countries individually over the postwar subperiod of 1950-2021, which is the period in which we focus our asset pricing tests. In this subperiod, there are 1413 observation for the Disaster Index with a mean value of 5.0% and a standard deviation of 2.2%. The minimum value over our sample is 3.1%, and the maximum is 16.3%. The 25th percentile value is 3.7% and the 75th percentile value is 5.6%. The Disaster Index is quite volatile within countries. In Finland, for instance, the Disaster Index peaks in 1988, 2000, and 2007 with values of 8.2%, 6.3%, and 15.8% respectively. In the first and third instance, GDP crashes occur in the following two to four years (in 1991-1992 and 2009, both attributable to banking crises).

By construction, variation in the Disaster Index reflects both variation in the joint credit boom and market boom indicator over time and variation from a rolling estimate of the probit coefficients in Equation (1). The latter represents the econometrician's learning over time about the occurrence of disaster risk in the absence of the changes in the predicting variables of a particular country. Weitzman (2007) has developed a Bayesian framework to highlight the importance of learning in analyzing disaster risk. Even though we do not adopt a Bayesian learning framework, the rolling regressions provide a convenient approach to capture the realistic learning by economic agents over time. Such learning is reflected by the pronounced downward trend in the Disaster Index from 1950 up to the Global Financial Crisis, as seen in Figure 2, across all countries. In our regression sample, the unconditional probability of a GDP crash has declined over the course of the twentieth century: the probability of a GDP crash pre-1950 is 2.7% vis-à-vis a post-1950 crash probability of 1.8%, even though credit booms and equity market booms have not become less frequent. The

[12] In a closely related study, Gabaix (2012) adopts a different approach of assuming a constant probability of a disaster but time-varying severity when a disaster hits an economy. Interestingly, as shown by Schularick and Taylor (2012) and Baron, Verner, and Xiong (2021), credit expansion not only predicts the occurrence of a banking crisis but also the severity of the subsequent economic downturn. Thus, the two variables we use to predict the probability of a disaster may also predict the severity of the disaster. Nevertheless, for simplicity, we focus on the time-varying probability as the key source of time-varying disaster risk in our analysis.

"spikes" in the Disaster Index in Figure 2 represent observations in which both the credit and market boom indicators equal one.[13]

We use only two variables—*Credit Boom*$_{i,t}$ and *Market Boom*$_{i,t}$—to construct the Disaster Index. Even though these variables, to our best knowledge, have the most robust predictive power for subsequent financial crises and economic downturns, one could potentially include other variables to further improve the predictive power of the Disaster Index. We choose not to do so because adding more predictors, while improving in-sample explanatory power, often reduces out-of-sample predictive power.[14] By using these two predictors, the Disaster Index is designed to capture one particular type of disaster risk that is associated with financial and economic instability brought by exuberant booms in credit and equity markets, while generally failing to signal other types of disaster risks such as natural disasters or the onset of wars. Thus, the Disaster Index is an incomplete measure of the actual disaster risk in an economy. Nevertheless, we will show that it is able to capture a substantial fraction of historical GDP disasters in the data.

We verify that the Disaster Index indeed serves as a reasonable measure of GDP crash risk in three ways. First, we show that its level leading up to the year of a GDP crash is significantly elevated. Second, we show that approximately half of all GDP crashes are correctly predicted by the Disaster Index, in the sense that half of crashes are preceded by a Disaster Index value in the top quintile three years before the crash. Third, our evaluation of the Disaster Index in terms of the statistical tradeoff between true positives (i.e., predicting a crash that indeed happens) versus false positives (i.e., predicting a crash that does not occur) shows that the Disaster Index is a robust predictor of GDP crashes with a strong signal-to-noise ratio.

For the first of these tests, we plot the average dynamics of the Disaster Index in the five years prior to realized GDP crashes in Figure 3 panel A to show that the Disaster Index is significantly elevated compared to baseline levels. Conditional on a GDP crash at time t=0, we find that on average the Disaster Index is significantly elevated in years t=-4, t=-3, and t=-2 with values 6.9%,

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[13] The decaying of the baseline probability over time does not affect the conclusions of this paper. In Appendix Table A2, we consider an alternative Disaster Index that is simply equal to the interaction term (i.e. this alternative Disaster Index simply equals one if a market boom and a credit boom occur jointly, zero otherwise), which, by construction, has no such time-variation in the baseline probability of a GDP disaster. The results from this alternative Disaster Index are similar to those reported in the main tables.

[14] The literature has made numerous efforts to use a wide range of variables and models to predict financial crises and economic downturns. See Fouliard, Howell, and Rey (2021) for a recent study that uses a meta-statistical approach to predict financial crises by aggregating multiple models.

8.5%, and 7.9% relative to the baseline value of 5.5% during years when the country has not experienced the joint occurrence of a credit boom or market boom in a five-year window. The Disaster Index is near baseline levels in years t=-5 and before.

For the second of these tests, we examine the distribution of the Disaster Index three years prior to a GDP crash in panels B through D of Figure 3. In particular, we define a GDP crash to occur in year t and examine the distribution of the Disaster Index in year t-3 in terms of its quintile based on the distribution across all countries up to year t. We find that half of all GDP crashes (24 of 47) are correctly predicted by the Disaster Index (in the sense that these crashes are preceded by a Disaster Index value in the top quintile, as measured three years before the crash). When we consider BXY peak-to-trough episodes, we find that 20 of the total 40 episodes are preceded by a Disaster Index in the top quintile three years prior, and for the 16 Barro-Ursúa episodes that overlap with our sample, 12 of them are preceded by a Disaster Index in the top quintile three years prior. Further, we find that GDP crashes correctly predicted by the Disaster Index tend to be more severe than those that are not: the annual severity of GDP crashes correctly predicted by the Disaster Index is -9.3% versus a severity of -7.5% for the crashes that are not, the severity of peak-to-trough episodes correctly predicted by the Disaster Index is -15.7% (versus -8.9% for the other episodes), and the severity of Barro-Ursúa episodes correctly predicted by the Disaster Index is -21.3% (versus -19.0% for the other episodes), all in untabulated results.

Third, we evaluate the Disaster Index in terms of the statistical tradeoff between true positives (i.e. predicting a crash that indeed happens) versus false positives (i.e. predicting a crash that actually does not occur). To operationalize this analysis, we first define an elevated crash risk indicator at the beginning of each year t denoted $\text{Elevated}_{i,t}$. We say that a country i is in elevated crash risk territory at the beginning of year t ($\text{Elevated}_{i,t} = 1$) if its Disaster Index is in the top quintile in year t-3 (based on the distribution for the full panel up to year t). We then examine whether elevated crash risk indicator equaling one (or zero) at the beginning of year t corresponds to the occurrence (or non-occurrence) of a GDP crash in year t. We exclude in this analysis any country-year observations that have missing Disaster Index values in the preceding three years.

For the 47 GDP crashes in our sample, 24 crashes are correctly predicted by the elevated crash risk indicator (that is, the country's elevated crash risk indicator switches on at the beginning of the year, and a crash occurs that year) and 23 crashes are not predicted (that is, the country's elevated crash risk indicator is not elevated at the beginning of the year, yet a crash occurs that year), corresponding to a true positive rate of 51%. For the 1,894 country-year observations corresponding to non-GDP crashes, we find 330 false positives (that is, the country's elevated crash risk indicator is on at the beginning of the year, yet a crash does not occur that year), corresponding to a false positive rate of 17%.

An alternative detection criterion (associating a positive prediction for a crash in year t with the Disaster Index exceeding the historical median in year t-2, t-3, or t-4) yields a true positive rate of 79% and a false positive rate of 25% for the sample of 47 GDP crashes, and a true positive rate of 96% and a false positive rate of 27% for the subsample of 26 post-1950 GDP crashes.

Taken together, the analysis in this section shows that our constructed Disaster Index is a strong out-of-sample predictor of GDP crash risk, which we use in the following section to conduct empirical tests on asset prices.

III. Asset Pricing Tests

In this section, we use the Disaster Index to test various implications from asset pricing models with time-varying disaster risk. These models build on Barro's (2006) model with constant disaster risk. A disaster is a random shock that substantially reduces aggregate consumption and thus creates an additional source of variation to the representative agent's stochastic discount factor, leading to a risk premium for the disaster risk. Consequently, this model generates a positive disaster risk premium for assets with a positive exposure to the disaster risk, such as equities, and reduces the risk-free rate, thus resolving both the equity premium puzzle and the risk-free rate puzzle. As reviewed by Tsai and Wachter (2015) and Campbell (2017), several studies have expanded Barro's model to incorporate time-varying disaster risks and explain a wide range of asset pricing phenomena, such as predictability of both equity market index returns and factor portfolio returns, time-varying equity market volatility, time-varying term spreads and credit spreads, and time-varying dividend-to-price ratios.

A. Time-varying equity risk premiums

If either the probability of a disaster, as modeled by Wachter (2013), or the severity of a disaster, as modeled by Gabaix (2012), fluctuates over time, the equilibrium disaster risk premium should also vary over time. Consequently, the representative agent prices assets that are exposed to the disaster risk based on the time-varying disaster risk premium. Such assets include both the equity market portfolio and factor portfolios. The presence of this time-varying disaster risk premium is also the key channel for several other asset pricing effects that we will later examine. Motivated by these models, we hypothesize that as the Disaster Index rises, the disaster risk premium is also increased, leading to higher expected returns of the equity market index and other factor portfolios:

Hypothesis 1: As the Disaster Index rises, the subsequent returns of the equity market index and of portfolios of value and growth stocks are higher.

To test this hypothesis, we estimate the following OLS panel regression for the cumulative returns in the subsequent one to five years:

$$r_{i,t\to t+h} = \alpha_i + \beta\ DisasterIndex_{i,t} + \epsilon_{i,t\to t+h}\ , \qquad (2)$$

where $r_{i,t\to t+h}$ denotes the log excess return from holding the portfolio from the beginning of year t to end of year $t + h$. To incorporate the notion that investors can base decisions only on past information, the Disaster Index uses only past information up to that point in time in all regressions. Following Baron and Xiong (2017), we add to the baseline specification several country-year control variables known to predict equity risk premiums: log(dividend/price) of the equity market index, the inflation rate, and the term spread.

In this and other OLS regression exercises that follow, we calculate standard errors based on Driscoll and Kraay (1998). In particular, we implement Driscoll-Kraay standard errors with an annual lag of *ceiling(*1.5 x *h)* for *h*-horizon predictive regressions and with an annual lag of 2 for contemporaneous regressions. Compared to standard errors double clustered on country and time, the advantage of using Driscoll-Kraay standard errors is that in addition to accounting for possible correlations of residuals across countries at each point in time and autocorrelation of residuals within each country, we correct for possible cross autocorrelation of residuals in the *t*-statistics.[15]

[15] We find in this and subsequent OLS regressions that standard errors double clustered on country and time actually tend to be slightly more conservative than our reported results based on Driscoll-Kraay standard errors.

Table 4 presents the estimated coefficients for the $\text{DisasterIndex}_{i,t}$ from Equation (2). The estimation is performed over the full sample (row 1: 1870-2021) and for two subsamples (row 2: 1970-1949, excluding the world war periods; rows 3-4: 1950-2021). For the "Market (1950-2021)" estimation and for all factor portfolios, the first row in each set of rows reports Equation (2) estimated without controls and the second row with controls. Contrary to the theoretical prediction that investors would demand a higher expected return in times of greater disaster risk, we observe in Table 4 lower future average returns for the equity market index at 1- to 5-year horizons. For example, over the 1950-2021 subsample, conditional on a one-percentage point increase in the Disaster Index, the subsequent cumulative three-year return of the market index is lower than its historical average by 2.4 percentage points.[16]

Next, we examine the returns of value and growth portfolios. As measures of "value" versus "growth" stocks, we focus specifically on the three equity factor portfolios sorted on the Book/Price (B/P), Dividend/Price (D/P), or Earning/Price (E/P) ratios within each country. Table 2 shows that the subsequent cumulative returns of the value and growth portfolios are all negatively and significantly associated with higher disaster risk across all horizons and across the three measures of value and growth stocks. Taken together, Table 2 shows that as the Disaster Index rises, the equity premium is lower, rather than higher, rejecting Hypothesis 1.

Gabaix (2012) also shows that time-varying disaster risk may help explain the value premium because value stocks are assumed to be more exposed to the disaster risk. Motivated by his analysis, we further examine the following hypothesis:

Hypothesis 2: As the Disaster Index rises, the subsequent returns of long-short spread portfolios of value and growth stocks are higher; furthermore, conditional on the occurrence of a disaster, the return of the value portfolio is lower than that of the growth portfolio.

[16] We also find that the contemporaneous equity market return is positive, also inconsistent with disaster risk models, though we do not include these results in the table, due to the inclusion of the market boom indicator in the construction of the Disaster Index. In general, GDP crashes tend to be preceded by an elevated probability of equity market booms in the preceding 1-4 years, as the probit regressions demonstrate, which is itself inconsistent with disaster risk models.

Table 4 shows null results from the regression specified in Equation (2) for the B/P- and D/P-based value-growth spread portfolios at horizons from 1 to 5 years.[17] For the B/P value-growth spread, the point estimates of the coefficients tend to be weakly negative and thus inconsistent in direction with predictions from theory, suggesting that the issue is not simply a lack of statistical power. In contrast, for the D/P and E/P-based value-growth spread, the coefficients are often positive and significant, consistent with theory. However, one must note that the positive coefficient point estimates for the D/P and E/P spread portfolios are due to more negative future mean returns of growth stocks relative to future mean returns of value stocks, rather than positive and higher future expected returns of value stocks as predicted by theory.[18]

Finally, we test the prediction that value stocks should experience a larger contemporaneous decline relative to growth stocks conditional on the occurrence of an economic disaster. To test this, Table 5 estimates the following regression using the three High-minus-Low spread portfolios conditional on a GDP crash (in panel A) or an equity market crash (panel B):

$$r_{i,t} = \alpha_i + \beta\, I\{Disaster\}_{i,t} + \epsilon_{i,t}. \qquad (3)$$

Using this regression to estimate the coefficient on the indicator variable is equivalent to computing average returns in years conditional on the occurrence of each type of economic disaster. The advantage of this approach is being able to use Driscoll-Kraay standard errors.

Table 5 shows results that are inconsistent with Hypothesis 2. Panel A shows that value stocks, defined based on book-to-market, dividend-to-price, or earnings-to-price, earn relatively higher returns (or more accurately, less-negative returns) than growth stocks, conditional on GDP crashes over the period 1950-2016. These results are large in magnitude and significant over this period: conditional on GDP crashes, B/P, D/P, and E/P-sorted long-short portfolio returns are sharply

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[17] Note that the coefficients of the High-minus-Low portfolios do not necessarily equal to the coefficients of the High portfolio minus the coefficients of the Low portfolio due to the use of log returns.

[18] Appendix Table A3 shows that the results in Table 4 are consistent with those based on our alternative dataset of equity factor returns that we construct with Datastream and Worldscope data from individual stocks. Using this alternative dataset, we also verify that the null or negative results for factor portfolio are robust to variations in the construction of equity factor returns: for example, sorting and calculating portfolio results using June 30 as the year end; equal-weighting portfolios instead of market-cap weighting; and using 10 or 20 percent cutoffs for portfolio formation (rather than 30). To further isolate that the effect is driven by a *rise* in the Disaster Index, we have also performed the same regressions and replaced the main predictor by max(DisasterIndex, mean), the Disaster Index left censored at the mean of its historical distribution over all countries. Again, we find similar results.

positive at 17.1%, 13.9%, and 24.6%, all significant at the 1% significance level (columns 1, 3, and 5).

However, adding the 2020 COVID-19-related GDP crashes of 2020 produces a different picture (columns 2, 4, and 6): the results are insignificant and close to zero over the period 1950-2021 (due to a sharp rise in growth stocks in 2020, though these circumstances may be unique to the nature of the COVID-19 macroeconomic shock). Regardless of whether one focuses on the period 1950-2016 or 1950-2021, there is no evidence to suggest a significantly negative coefficient, as predicted by Hypothesis 2. Panel B shows similar results conditional on an equity market crash: the point estimates are all positive, but none is significant. Taken together, these results are inconsistent with the assumption from theory that value stocks are more exposed than growth stocks to economic disasters, such as GDP crashes or equity market crashes.

B. Equity market volatility

Wachter (2013) highlights time-varying disaster risk as a novel mechanism to capture the dynamics of stock market volatility. In particular, she shows that under suitable model conditions, equity volatility is an increasing function of the time-varying disaster probability. Motivated by her analysis, we examine the following hypothesis:

Hypothesis 3: Equity market volatility is positively correlated with the Disaster Index.

To test this hypothesis, we present results of the following OLS panel regressions in Table 6:

$$\sigma_{i,t} = \alpha_i + \beta \; DisasterIndex_{i,t} + \epsilon_{i,t}, \qquad (4)$$

where $\sigma_{i,t}$ is the annualized daily volatility of the market equity index of country i in year *t*. To further examine whether the Disaster Index has an asymmetric effect when its value is above its normal level, we also present results from an alternative specification:

$$\sigma_{i,t} = \alpha_i + \beta \max\left(DisasterIndex_{i,t}, mean\right) + \epsilon_{i,t},$$

where $mean$ is the mean of $DisasterIndex_{i,t}$ in the historical data of country i up to year t.

Our results in Table 6 shows that the Disaster Index has a significantly negative correlation with market volatility in the full sample period of 1950-2021 (columns 1-2), which is inconsistent with Hypothesis 3. However, when looking at the asymmetric effect when the Disaster Index is above its mean (columns 3-4), the coefficient is also negative but insignificant. As it is possible that the market dynamics prior to the Global Financial Crisis differs from the dynamics during and after the crisis, we also perform the regression analysis over the subsample periods of 1950-2005 and 2006-2021 and find that the correlation between market volatility and the Disaster Index remains negative across both periods (columns 5-6, 9-10). However, for the specifications when the Disaster Index is above its historical mean (columns 7-8, 11-12), the point estimates are positive for the 1950-2006 period but negative for the 2006-2021 period. While the evidence in Table 6 is mixed, overall, there is no strong evidence to support Hypothesis 3 and some evidence inconsistent with it.

C. Corporate credit spreads

Gabaix (2012) and Gourio (2013) have shown theoretically that rare disasters can also help account for the puzzling size of the corporate credit spread relative to actual default risks. To the extent that firms' defaults risk is higher when a disaster hits the economy, the positive correlation leads to a higher credit premium when disaster risk is higher. This insight motivates us to examine the following hypothesis:

Hypothesis 4: Corporate credit spreads are positively correlated with the Disaster Index.

To test this hypothesis, we estimate the following OLS panel regression:

$$CreditSpread_{i,t} = \alpha_i + \beta\ DisasterIndex_{i,t} + \epsilon_{i,t}, \qquad (5)$$

or

$$CreditSpread_{i,t} = \alpha_i + \beta \max\left(DisasterIndex_{i,t}, mean\right) + \epsilon_{i,t}.$$

Table 7 shows that the correlation of the Disaster Index and the corporate credit spread index is negative, inconsistent with Hypothesis 4. Over the full sample period of 1996-2021, we find negative but insignificant coefficients. Splitting the full sample into the subsample periods of 1996-2005 and 2006-2021, a one percentage point increase in the Disaster Index is associated with 1.5 and 5.1 basis point decreases in the corporate credit spread, respectively (columns 5 and 9, without controls). The results are relatively unchanged in columns 7 and 11, which look only at increases in the Disaster Index above its historical mean. Controlling for inflation, the term spread, effective duration, and four variables reporting the share of bonds by credit rating in the index (AAA, AA, A, BBB, respectively), we find greater magnitude and statistical significance of the coefficients. The evidence strongly rejects Hypothesis 4.

D. Term spread

Gabaix (2012) and Tsai (2013) have also employed disaster risk to explain the commonly observed upward-sloping yield curve. When an economic disaster hits, inflation tends to rise and cause prices of nominal bonds to fall. As a result, investors need to demand a disaster premium for holding bonds, thus leading to a positive term spread. Tsai (2013) specifically shows that as the disaster probability rises, the term spread increases. Thus, we examine the following hypothesis:

Hypothesis 5: The nominal term spread (the long-term government bond yield minus the short-term bill yield) is positively correlated with the Disaster Index.

To test this hypothesis, we perform the following OLS panel regressions:

$$TermSpread_{i,t} = \alpha_i + \beta\ DisasterIndex_{i,t} + \epsilon_{i,t}, \tag{6}$$

or

$$TermSpread_{i,t} = \alpha_i + \beta \max\left(DisasterIndex_{i,t}, mean\right) + \epsilon_{i,t}.$$

Table 8 shows evidence inconsistent with Hypothesis 5. Over the full sample period of 1950-2021 and in the subsample period of 1950-2005, we find that the correlation between the Disaster Index and the term spread is insignificant. However, for the 2006-2021 subsample period (column 9), a one percentage point increase in the Disaster Index is associated with an 10-basis point decrease in the term spread. In addition, However, when looking at the asymmetric effect when the Disaster Index is above its historical mean (columns 3-4, 7-8, 11-12), a rise of one percentage point in the Disaster Index is associated with a 8.0 basis point decline in the term spread over the full sample period (column 3, significant at the 1% level). These findings are robust to the addition of inflation as a control variable.

E. Dividend/price ratio of market index

Lastly, an implication of both Gabaix (2012) and Wachter (2013) is that as disaster risk rises, the increased disaster risk premium reduces equity prices, thus increasing the dividend/price ratio of the equity market index. This insight motivates the following hypothesis:

Hypothesis 6: The dividend yield of the equity market index is positively correlated with the Disaster Index.

To test this hypothesis, we estimate the following OLS panel regressions:

$$Dividend/Price_{i,t} = \alpha_i + \beta\ DisasterIndex_{i,t} + \epsilon_{i,t}, \tag{7}$$

or

$$Dividend/Price_{i,t} = \alpha_i + \beta \max\left(DisasterIndex_{i,t}, mean\right) + \epsilon_{i,t}.$$

Table 9 reports results indicating either a negligibly positive or significantly negative correlation, inconsistent with Hypothesis 6. In particular, a one percentage point increase in the Disaster Index is associated with an insignificant change in the dividend/price ratio, and a decline in the earning/price ratio of 0.10 percentage points (in columns 1 and 5). In the specification when the Disaster Index is above its historical mean (columns 3-4, 7-8), we find that a one percentage point increase corresponds to statistically significant declines of 0.11% and 0.13% in the dividend/price and earning/price ratios respectively (columns 3 and 7). These results are robust to including controls (columns 2, 4, 6, and 8).

IV. Discussion and Additional Analyses

We have developed an objective disaster risk measure that forecasts GDP crashes that is based on economic and financial instability associated with rapid credit expansions and asset market booms. Despite this Disaster Index being incomplete by design, it is able to capture roughly half of GDP crashes in the historical data. In contrast to the positive disaster risk premiums predicted by the consumption-based asset pricing models with time-varying disaster risk, the Disaster Index negatively, rather than positively, predicts future returns of the equity market index and portfolios of value and growth stocks. Furthermore, in contrast to the model predictions of time-varying disaster risk leading to higher equity market volatility, larger corporate credit spreads, a larger nominal term spread, and higher dividend yield of the equity market, we find no evidence of the Disaster Index being positively correlated with these key asset pricing variables, and, in some specifications, even significantly negatively correlated with some of the variables.

The aforementioned models of time-varying disaster risk assume that the representative investor can directly observe fluctuations in disaster risks. This is a strong assumption. In contrast, the "dark matter" concerns of Chen, Dou and Kogan (2019) about the irrefutability of disaster risk with finite historical data underlie the difficulty of measuring fluctuations in disaster risks in real time. Our findings may reflect the notion that disaster risk is difficult for financial market participants to assess and, as a result, asset prices may not reflect objective time-varying disaster risk. The difficulty of assessing disaster risk could give rise to "this time is different" thinking highlighted by Reinhart and Rogoff (2009) regarding borrowers' and lenders' inability to fully comprehend rising financial risks during times of exuberant credit booms. Gennaioli, Shleifer and Vishny (2013) further argue that such neglect of disaster risk is a key driver of financial innovations that facilitate credit booms. Thus, our evidence, while inconsistent with time-varying disaster risk models, may reflect an alternative view in which many GDP disasters are endogenous and happen *precisely* when financial markets either neglect risk or have elevated risk appetite. This is likely the case for the banking crisis disasters, which comprise roughly half of historical GDP disasters outside the WW1/WW2 period in our sample.

One may argue that time-varying disaster risk models may still work for other categories of GDP disasters (e.g., natural disasters, epidemics). As these non-banking disasters are likely exogenous to the behaviors of asset market participants, it is possible that their risks are easier for asset market participants to assess, thus being more relevant for validating time-varying disaster risk models. However, one cannot argue, in defense of time-varying risk models, that the risks associated with non-banking disasters are even harder to assess. If these types of disasters are inherently less predictable, then time-variations in such disaster risks will be less likely to affect financial market prices, countering the relevance of time-varying disaster risk models for asset prices.

In this section, we further analyze whether asset prices better reflect these other types of disasters, such as those not predicted by our Disaster Index and those non-banking-crisis disasters. Specifically, we perform two additional analyses. First, we plot event studies of risk premium measures around historical GDP crashes to ask, at what future horizons do risk premiums in asset prices start to reflect future GDP disasters. Second, we decompose GDP crashes into those that, based on the Disaster Index, are "predicted" versus "unpredicted" to ask whether risk premiums in asset prices better reflect risks of the "unpredicted" GDP crashes; we also compare banking crisis related GDP crashes with other types (war, natural disaster or epidemic, etc.).

A. At what horizons do risk premiums reflect future GDP disasters?

As the Disaster Index forecasts GDP crashes over a future two- to four-year horizon, our analysis suggests that asset prices do not systematically incorporate the disaster risk predicted by the Disaster Index at such horizons. At what point then do asset markets first perceive GDP disasters? To answer this question, we plot event studies of four risk premium measures (equity market volatility, corporate credit spreads, the nominal term spread, and equity dividend yield) around all realized GDP crashes in our sample.

The results from this event study are plotted in Figure 4. The four risk premium measures (equity market volatility in panel A, corporate credit spreads in panel B, the nominal term spread in panel C, and equity dividend yield in panel D) are plotted in red from t=-5 to t=+5, where we define a GDP crash to occur at time t=0. To analyze changes relative to baseline levels, we de-mean each variable by its average level within each country during years outside of the t=-5 to t=+5 window, then average the levels across events to create the event studies. In each panel, we also plot in blue the Disaster Index to compare it to the risk premium measures.

In panel A, we find that market volatility stays at the baseline level from t=-5 to t=-2 before a sharp upward jump at t=-1. Similarly, credit spreads (panel B) are at baseline levels from t=-5 to t=-3, are slightly elevated at t=-2, but jump sharply upward at t=-1 and remain high for several years after the GDP crash. Similarly, the term spread (panel C) is below average until t=0, when it rises sharply. Dividend yield (panel D) is below average from t=-5 to t=-2 before a sharp upward jump at t=-1. Overall, we conclude that these risk premium measures are not generally elevated two to five years before the GDP crash but do tend to rise sharply one year before.

Thus, asset markets do anticipate GDP crashes, but only one year ahead on average. As shown by Baron, Verner and Xiong (2021), in historical banking crises, asset markets on average crash roughly one-year ahead of GDP crashes. Thus, the one-year ahead predictability of the four risk premium measures likely reflect the asset market crashes just before the realizations of economic disasters. The horizon of this predictability stands in contrast to the Disaster Index plotted in blue in each of the panels, which is elevated from t=-4 to -2 and peaks at t=-3. In all four panels, the risk premium measures appear to lag the objective Disaster Index by two to three years.

Our results do not imply that disaster risk is irrelevant for asset prices, but rather suggest that there is a gap between the disaster risk perceived by financial market participants and objective disaster risk captured by the Disaster Index. To the extent that disaster risk is rarely realized, subjective beliefs about disaster risk are difficult to empirically discipline with realizations of disaster risk and are thus likely to be influenced by various behavioral biases, such as overconfidence (Daniel, Hirshleifer and Subramanyam 1998; Odean 1998), representativeness (Barberis, Shleifer and Vishny 1998), and diagnostic expectations (Bordalo, Gennaioli, and Shleifer 2018), as well as non-Bayesian factors, such as personal experience (Malmendier and Nagel 2011). It remains an open empirical question how investors form their subjective beliefs about disaster risk.

Ideally, one might want to directly measure such subjective beliefs through surveys. However, existing surveys of expectations of financial analysts, professional economists, and households are mostly about the mean, rather than the tail distribution, of their beliefs. In the absence of a direct measure of subjective disaster risk, one must instead rely on indirect asset pricing measures to gain understanding about how subjective disaster risk as mirrored by asset prices may be related to objective disaster risk.

Figure 5 further explores these issues by plotting event studies of the same four risk premium measures around the years (t=0) in which the Disaster Index is elevated (i.e. in the top quintile, where the quintiles are determined based on the historical distribution of the Disaster Index across all countries up to each point in time). As in the case of Figure 4, we de-mean each variable by its average level within each country during years outside of the t=-5 to t=+5 window, then average the levels across events to create the event studies. Figure 5 shows that market volatility (panel A) is at or below the baseline in years t=-2 through t=+1, then rises significantly above the baseline at t=+2 and t=+3 before tapering off at time t=+4 and t=+5. Similarly, corporate credit spreads (panel B) are not significantly different from their baseline level in years t=-5 through t=+1 but then rise significantly in years t=+2 and t=+3. The term spread (panel C) is mostly not statistically distinguishable from the baseline, while the dividend yield of the market index (panel D) is significantly below the baseline in years t=-5 through t=0 and rises to the baseline in years t=+1 through t=+3. Figure 5 again suggests that asset prices do not reflect disaster risk right away (as indicated by the Disaster Index hitting the top quintile) but do so in a more gradual fashion over the subsequent years. This event study is further evidence that market participants' subjective perception of disaster risk lags objective disaster risk.[19]

B. "Predicted" vs. "unpredicted" disasters and disasters by category

In this subsection, we further explore the predictability of the four risk premium measures across different types of disasters. Our analysis has shown that the Disaster Index is able to capture roughly half of GDP crashes (24 out of the 47) and that when the Disaster Index is elevated, risk premiums are not elevated, and sometimes even below historical averages. But what about the GDP crashes that are *not predicted* by the Disaster Index? As we mentioned earlier, one may argue that those GDP crashes predicted by the Disaster Index might have occurred endogenously when asset market participants neglected the disaster risks. Thus, it is possible that risk premiums in asset prices might better reflect disaster risks associated with other types of disasters that are exogenous to the behaviors of asset market participants. This argument motivates us to examine event studies of the same four risk premium measures around "predicted" versus "unpredicted"

[19] An alternative to this event study also presents the same conclusion. We run the following panel regression:

$$Asset\ Price_{i,t} = \alpha_i + \sum_{h=0}^{5} \beta_h\ DisasterIndex_{i,t-h} + \epsilon_{i,t}, \qquad (8)$$

where $Asset\ Price_{i,t}$ is one of market volatility, corporate credit spreads, the term spread, or the dividend yield of the equity market index and report estimates from Equation (8) in Appendix Table A4, with the four columns corresponding to the four asset pricing variables. In all four columns, the coefficient on the contemporaneous value is significantly negative, as we have shown earlier. The F-test statistics show that the five lags are jointly statistically significant at the 1% level, and the sum of their coefficients suggests that the values of the Disaster Index in the five prior years have a net *positive* effect on each of the four asset price variables, controlling for the contemporaneous value of the Disaster Index.

GDP crashes based on the Disaster Index and around banking-crisis related versus other types of GDP crashes.

As defined earlier, a GDP crash is categorized as "predicted" if the Disaster Index is in the top quintile of its historical distribution three years prior to the crash, and as "unpredicted" otherwise. (GDP crashes for which the Disaster Index is not available, because of lack of market index or credit expansion data, are omitted.) Importantly, in all the analysis in this subsection, we re-include the WWI/WWII periods (1914-1919 and 1939-1948), which were excluded in earlier analyses, and we also make use of the full sample from 1870 to 2021 for all 20 countries as a further robustness exercise. Although there is limited data for the WWI/WWII periods, this analysis allows us to compare the war-related downturns during these periods to evaluate whether these GDP disasters conform with model predictions.

Table 10 summarizes the frequency and severity of peak-to-trough GDP crashes by disaster category (banking crisis, war, natural disaster or epidemic, and other),[20] and by predictability using the Disaster Index ("predicted", "unpredicted", "WWI/WWII period").[21] Most "predicted" disasters are banking crises (16 out of 20), while "unpredicted" disasters are roughly half banking crises and half natural disasters (10 and 8, respectively, out of 20). Interestingly, the GDP disasters associated with banking crises tend to be more severe if they are predicted (-15% decline for predicted ones versus -11% for unpredicted ones). "War disasters", on the other hand, almost all fall (22 out of 24) within the excluded WWI/WWII periods, though they are the most severe type in magnitude, with an associated average peak-to-trough GDP decline of -36% (compared to the average decline across all types of -20%).

Figure 6 plots event studies around GDP crashes similar to those in Figure 4 but decomposing GDP crashes into three mutually exclusive types: "predicted", "unpredicted", and those in the WWI/WWII periods. Interestingly, there is little difference between these three categories. For all three categories, the four risk premium measures (equity market volatility, corporate credit spreads, the nominal term spread, and equity dividend yield) show no evidence of being elevated more than one year ahead of either the "unpredicted" or war period GDP crashes. Thus, neither the

[20] "Other" is a residual category and mainly comprises deep macroeconomic crises (e.g., a sharp export decline in Australia in 1881-1882, hyperinflation in Germany in 1922-1923, monetary tightening in Canada in 1990-1992).

[21] Table A1 lists the full categorization of all individual GDP disasters by category type and by predictability.

“unpredicted” nor the WWI/WWII episodes display stronger predictability of the risk premium measures for the realizations of GDP crashes than the “predicted” episodes.

Figure 7 plots event studies similar to those in Figure 4 but decomposing GDP crashes into the four disaster categories (banking crisis, war, natural disaster or epidemic, and other). The four risk premium measures show no evidence of being elevated more than one year ahead of any of these four categories of GDP disasters, and the evidence for all four categories is consistent with what we have previously seen in Figure 4.

Taken together, the four risk premium measures displayed similar dynamics over the full sample (1870-2021), over the WWI/WWII periods, and across different categories of crises. There is no evidence of the four risk premium measures offering stronger predictability of unpredicted disasters by the Disaster Index than predicted ones and stronger predictability of non-banking disasters than banking crisis related disasters. Thus, even though our Disaster Index by design tends to measure disaster risk related to banking crises, our finding that asset prices only slowly incorporate objective disaster risk is likely to hold for other types of disaster risk.

V. Conclusion

We develop an objective disaster risk measure that forecasts GDP crashes, based on economic and financial instability associated with rapid credit expansions and asset market booms. Despite this Disaster Index being incomplete by design, it is able to capture half of GDP crashes in the historical data. In contrast to positive disaster risk premiums predicted by the consumption-based asset pricing models with time-varying disaster risk, the Disaster Index negatively, rather than positively, predicts future returns of the equity market index and portfolios of value and growth stocks. Furthermore, in contrast to the model predictions of time-varying disaster risk leading to higher equity market volatility, larger corporate credit spreads, a larger nominal term spread, and higher dividend yield of the equity market, we find no evidence of the Disaster Index being positively correlated with these key asset pricing variables, and, in some specifications, even significantly negatively correlated with some of the variables. Our analysis further suggests that market participants’ subjective perceptions of disaster risk incorporated into asset prices lag the objective disaster risk measured by the Disaster Index by two years.

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Table 1: Summary statistics

	N	Mean	Median	SD	1%	5%	10%	90%	95%	99%
Excess Return										
Market	1835	0.034	0.044	0.230	-0.624	-0.355	-0.246	0.290	0.371	0.625
High B/P	857	0.065	0.101	0.284	-0.799	-0.453	-0.275	0.370	0.453	0.641
Low B/P	857	0.043	0.079	0.247	-0.699	-0.418	-0.276	0.305	0.372	0.550
High-Low B/P	857	0.006	0.028	0.241	-0.758	-0.371	-0.255	0.250	0.331	0.532
High D/P	858	0.068	0.100	0.256	-0.797	-0.350	-0.225	0.328	0.447	0.573
Low D/P	858	0.040	0.073	0.261	-0.725	-0.459	-0.311	0.311	0.384	0.628
High-Low D/P	858	0.001	0.028	0.251	-0.926	-0.368	-0.222	0.242	0.301	0.443
High E/P	842	0.071	0.105	0.268	-0.681	-0.365	-0.221	0.334	0.415	0.650
Low E/P	842	0.039	0.076	0.254	-0.743	-0.439	-0.304	0.303	0.390	0.590
High-Low E/P	842	0.013	0.033	0.234	-0.663	-0.339	-0.218	0.236	0.305	0.499
GDP Growth	1835	0.021	0.022	0.034	-0.087	-0.033	-0.014	0.059	0.073	0.106
Credit Expansion	1835	0.011	0.010	0.029	-0.083	-0.031	-0.017	0.041	0.058	0.091
Market Volatility	1320	0.152	0.129	0.096	0.038	0.059	0.071	0.258	0.316	0.590
Credit Spread	514	1.225	1.020	0.914	0.230	0.380	0.480	2.030	3.000	4.900
Term Spread	1433	1.028	1.020	1.808	-4.019	-1.715	-0.702	2.860	3.475	6.485
Dividend/Price	1321	0.038	0.034	0.019	0.009	0.014	0.017	0.062	0.072	0.096
Earnings/Price	890	0.072	0.064	0.033	0.018	0.035	0.041	0.111	0.132	0.189

This table reports summary statistics from a panel data set of 20 countries covering the period 1870-2021. All observations are annual and at the country level. The first set of variables is as follows: the log excess returns of the market index; the high and low equity portfolios sorted on book-to-market (B/P), dividend-to-price (D/P), and earnings-to-price (E/P); and their corresponding high-minus-low spread portfolios. (Note that the mean returns of the spread portfolios do not correspond to the mean returns of the high portfolios minus the mean returns of the low portfolios due to the use of log returns.) The second set of variables is as follows: GDP Growth is the annual log change in real GDP per capita; Credit Expansion is the annualized three-year difference in the ratio of bank-credit-to-GDP; Market Volatility is the annualized standard deviation of daily returns (or, when not available historically, weekly or monthly returns) of the market index; Credit Spread is the yield (in %) of an investment grade corporate bond index minus the yield of a government bond index of similar duration; Term Spread is the ten-year government bond yield minus the three-month bill yield; and Dividend/Price and Earnings/Price are the ratios of the equity market index. The following variables are only reported over the period 1950-2021 due to data availability limitations: the sorted equity portfolio returns, Credit Spread, and Earnings/Price. For all variables, the world wars periods of 1914-1919 and 1939-1948 are excluded.

Table 2: Frequency and severity of GDP disasters: 1870-2021

	Annual definition			Peak-to-trough definition			
Disaster type	**N**	**Frequency**	**Severity**	**N**	**Frequency**	**Severity**	**Duration**
Baron, Xiong, Ye (BXY)	61	2.3%	-9.1%	53	4.5%	-12.6%	2.3
Also BU	32	1.2%	-10.8%	24	3.0%	-18.3%	3.4
Non-BU	29	1.1%	-7.2%	29	1.5%	-7.8%	1.4
1870-1949	35	2.7%	-11.5%	29	5.9%	-17.0%	2.6
1950-2021	26	1.8%	-5.9%	24	3.3%	-7.2%	2.0
Barro, Ursúa (BU)				34	4.3%	-16.3%	3.4
Non-BXY				10	1.3%	-11.4%	3.5
1870-1949				28	7.4%	-17.4%	3.4
1950-2021				6	1.5%	-11.0%	3.5
Included in regressions	47	2.3%	-8.5%	40	4.7%	-12.3%	2.4
Also BU	23	1.1%	-10.7%	16	3.1%	-20.7%	3.9
Non-BU	24	1.2%	-6.3%	24	1.6%	-6.7%	1.4
1870-1949	21	3.3%	-11.7%	16	7.8%	-19.9%	3.1
1950-2021	26	1.8%	-5.9%	24	3.4%	-7.2%	2.0
BXY (incl. WWI/WWII)	102	3.4%	-13.3%	76	7.0%	-19.5%	2.8
Banking crisis	35	1.2%	-8.8%	29	2.7%	-13.7%	2.8
Natural disaster	9	0.3%	-6.9%	9	0.3%	-7.2%	1.1
War	43	1.4%	-19.5%	24	3.1%	-35.9%	3.9
Other	15	0.5%	-10.0%	14	0.9%	-11.6%	1.9

This table tabulates the frequency and severity of GDP disasters across 20 countries, 1870-2021, according to the Baron, Xiong, Ye (BXY) definition and the Barro-Ursúa (BU) definition. The world war periods of 1914-1919 and 1939-1948 are excluded in calculating statistics in the first three subsections of this table (with disaster type labelled as "Baron, Xiong, Ye (BXY)", "Barro, Ursúa (BU)", "Included in regressions"), whereas the world war one (1914-1919) and world war two (1938-1948) periods are included in calculating statistics in the last subsection of this table (with disaster type labelled as "BXY (incl. WWI/WWII)"). Baron, Xiong, Ye (BXY) define annual "GDP crash" events as country-year observations in which real GDP per capita growth is below the 2nd percentile of its historical distribution over all countries from year $t-50$ to year t. BXY peak-to-trough events are defined as the peak-to-trough cumulative GDP declines surrounding the above-defined annual "GDP crash" events (which may encompass multiple annual "GDP crash" observations). Barro and Ursúa (BU) define a GDP disaster as a peak-to-trough cumulative decline in GDP of -9.5% or more. For 1870-2006, episodes are taken from Barro and Ursúa (2008), while BU episodes for 2007-2021 are identified using BU's definition and new data, since BU's data only covers up to 2008. "Included in regressions" refers to the subset of BXY events included in the estimation of Equation (1) in Table 3 (i.e. the subsample with non-missing data for the future GDP crash indicator, the Market Boom indicator, and the Credit Boom indicator). The frequency of annual episodes is computed as the total number of annual crash episodes divided by the total number of country-year observations, whereas the frequency of peak-to-trough episodes is the total number of country-year observations that fall within a peak-to-trough episode (exclusive of the peak year, inclusive of the trough year) divided by the total number of country-year observations. Duration refers to the average number of years of a peak-to-trough episode. For both BXY and BU events, the severity of GDP declines is computed using real GDP per capita data from the BXY dataset, in order to make consistent comparisons.

Table 3: Credit booms and market booms predict GDP crashes in the next 2 to 4 years

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Credit Boom	0.032		0.030	-0.007		-0.011	
	[1.50]		[1.56]	[-0.32]		[-0.54]	
Market Boom		0.045*	0.044*	0.022		0.030	
		[1.85]	[1.87]	[0.93]		[1.27]	
Interaction				0.068**	0.077***	0.078***	0.087***
				[2.48]	[2.70]	[2.96]	[3.10]
Observations	1835	1835	1835	1835	1835	1835	1835
Pseudo R^2	0.009	0.021	0.029	0.040	0.035	0.057	0.048
Sum of Marginal Effects	0.032	0.045	0.074	0.084	0.077	0.097	0.087
Controls	No	No	No	No	No	Yes	Yes
Conditional Probability	0.081	0.084	0.121	0.163	0.163	0.192	0.187
Baseline Probability	0.060	0.060	0.060	0.060	0.060	0.060	0.060

This table reports the marginal effects from the probit regression in Equation (1), which predicts the likelihood of an annual "GDP crash" event over the next 2 to 4 years, conditional on the following indicator variables. Credit Boom is an indicator variable that takes the value of one in year t if Credit Expansion is in the top quintile of the distribution for all countries up to year t. Similarly, Market Boom is an indicator variable that takes the value of one in year t if the past three-year cumulative log excess return of the market index is in the top tercile of the distribution for all countries up to year t. Interaction is an indicator variable that takes the value of one if both Credit Boom and Market Boom are one. The "Sum of Marginal Effects" reports the total effect of the predictor variables. Controls include the contemporaneous value and two lags of real GDP growth. The "conditional probability" is the predicted value from the regression, conditional on Credit Boom and Market Boom both equalling one. The "baseline probability" is the unconditional mean of the dependent variable over the regression sample. T-statistics are in brackets and correspond to standard errors double clustered on country and time. *, **, *** correspond to p-values less than 10%, 5%, 1%, respectively. Observations are across 20 economies, 1870 to 2021 (excluding the world war periods 1914-1919 and 1939-1948).

Table 4: Future equity returns conditional on the Disaster Index

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5
Market (1870-2021)	-1.210***	-2.319***	-2.674***	-2.830***	-2.876***
Market (1870-1949)	-1.090***	-2.376***	-2.722***	-2.497***	-1.918***
Market (1950-2021)	-1.248***	-2.301***	-2.434***	-2.560***	-2.708***
	-1.557***	-2.873***	-3.053***	-3.209***	-3.437***
High B/P	-2.449*	-4.104***	-4.523***	-5.187***	-5.863***
	-2.267*	-3.747***	-4.008***	-4.598***	-5.255***
Low B/P	-1.649*	-3.433***	-3.902***	-4.255***	-4.490***
	-1.493	-3.067***	-3.364***	-3.632***	-3.799***
High-Low B/P	-0.676	-0.331	-0.072	-0.186	-0.730
	-0.681	-0.407	-0.174	-0.386	-1.026
High D/P	-2.495**	-4.222***	-4.894***	-5.075***	-5.531***
	-2.327*	-3.912***	-4.460***	-4.631***	-5.045***
Low D/P	-2.147**	-3.949***	-4.183***	-4.646***	-5.089***
	-1.959*	-3.560***	-3.576***	-3.920***	-4.252***
High-Low D/P	-0.009	0.605	0.424	0.750	0.764
	-0.046	0.466	0.172	0.372	0.303
High E/P	-2.618**	-4.435***	-5.029***	-5.255***	-5.616***
	-2.410**	-4.000***	-4.437***	-4.607***	-4.913***
Low E/P	-1.808*	-3.794***	-4.450***	-5.190***	-6.095***
	-1.635	-3.392***	-3.814***	-4.432***	-5.242***
High-Low E/P	-0.424*	0.311	0.707	1.252***	1.803***
	-0.354	0.373	0.679	1.151***	1.672**

This table reports β coefficient estimates from Equation (2), a linear panel regression, which predicts future cumulative returns at h-year horizons ($h \in \{1, 2, 3, 4, 5\}$) conditional on the variable $\texttt{DisasterIndex}_{i,t}$, which is the Disaster Index computed only using past data from all countries up to time t. Each number in this table is from a separate estimation of Equation (2). The first row corresponds to estimates for the market index returns for the full panel (1870-2021, excluding the world war periods 1914-1919 and 1939-1948), the second row for the pre-1950 sample (1870-1949, excluding the world war periods 1914-1919 and 1939-1948), and the third row for the post-1950 panel (1950-2021). Starting with Row 3, the top line reports coefficient estimates without controls and the bottom line with the following controls: log(dividend/price) of the market index, inflation, and the term spread in each country. Rows 5 and after have factor portfolio returns as the dependent variable with data covering 1950-2021. Note that the coefficients of the high-minus-low portfolios do not equal to the coefficients of the high portfolio minus the coefficients of the low portfolio due to the use of log returns. T-statistics are in brackets and correspond to Driscoll-Kraay standard errors with lags = ceiling($1.5 \times h$). *, **, *** correspond to p-values less than 10%, 5%, 1%, respectively.

Table 5: Spread portfolio returns conditional on GDP crashes and market crashes

Panel A: GDP Crashes

	Book/Price		Dividend/Price		Earning/Price	
	(1) 1950-2016	(2) 1950-2021	(3) 1950-2016	(4) 1950-2021	(5) 1950-2016	(6) 1950-2021
$\mathbb{E}[r_{i,t} \mid \texttt{GDP Crash}_{i,t}]$	0.171***	0.034	0.139***	0.021	0.246***	0.100
	[3.09]	[0.25]	[3.55]	[0.18]	[5.67]	[0.73]
Number of Episodes	17	25	17	25	17	25
Adjusted R^2	0.009	0.000	0.006	0.000	0.021	0.004

Panel B: Market Crashes

	Book/Price		Dividend/Price		Earning/Price	
	(1) 1950-2016	(2) 1950-2021	(3) 1950-2016	(4) 1950-2021	(5) 1950-2016	(6) 1950-2021
$\mathbb{E}[r_{i,t} \mid \texttt{Market Crash}_{i,t}]$	0.021	0.021	0.060	0.060	0.039	0.039
	[0.71]	[0.71]	[1.41]	[1.41]	[0.78]	[0.78]
Number of Episodes	66	66	66	66	66	66
Adjusted R^2	0.000	0.000	0.003	0.005	0.000	0.001

This table reports the average contemporaneous returns of high-minus-low spread portfolios in year t conditional on GDP crashes (Panel A) or market crashes (Panel B) in year t, as estimated using Equation (3). T-statistics are in brackets and correspond to Driscoll-Kraay standard errors with two lags. *, **, *** correspond to p-values less than 10%, 5%, 1%, respectively. Observations are across 20 economies, 1950-2021.

Table 6: Market volatility conditional on the Disaster Index

	1950-2021				1950-2005				2006-2021			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\texttt{DisasterIndex}_{i,t}$	-0.413**	-0.403**			-0.664***	-0.369**			-0.478	-0.455		
	[-2.58]	[-2.52]			[-2.91]	[-2.03]			[-1.61]	[-1.65]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-0.022	-0.100			0.845	0.500			-0.496	-0.455
			[-0.11]	[-0.54]			[1.39]	[0.98]			[-1.56]	[-1.45]
Observations	1,320	1,320	1,320	1,320	1,001	1,001	1,001	1,001	319	319	319	319
Adjusted R^2	0.038	0.045	0.029	0.037	0.059	0.113	0.048	0.110	-0.004	0.192	-0.005	0.190
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

This table reports estimates from Equation (4), which analyzes how equity market volatility varies contemporaneously with the Disaster Index. Market Volatility is the annualized standard deviation of daily returns (or, when not available historically, weekly or monthly returns) of the market index. For the specifications in columns 3-4, 7-8, and 11-12, the predictor variable is replaced by the Disaster Index left-censored at the mean of its historical distribution over all countries up to that point in time. Control variables are: the log(dividend/price) of the market index, inflation, and the term spread of each country. T-statistics are in brackets and correspond to Driscoll-Kraay standard errors with two lags. *, **, *** correspond to p-values less than 10%, 5%, 1%, respectively. Results are estimated across 20 economies over the full sample period of 1950-2021 (columns 1-4) and over two subperiods: 1950-2005 (columns 5-8) and 2006-2021 (columns 9-12).

Table 7: Corporate credit spreads conditional on the Disaster Index

	1996-2021				1996-2005				2006-2021			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\texttt{DisasterIndex}_{i,t}$	-1.557	-3.201			-1.470	-3.926***			-5.076**	-5.173*		
	[-0.82]	[-1.54]			[-1.55]	[-3.30]			[-2.19]	[-2.11]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-2.907	-3.841			-2.971*	-6.348***			-4.750	-5.650**
			[-1.52]	[-1.60]			[-2.09]	[-3.97]			[-1.74]	[-2.18]
Observations	514	514	514	514	196	196	196	196	318	318	318	318
Adjusted R^2	0.028	0.413	0.032	0.415	0.220	0.454	0.223	0.458	0.076	0.453	0.069	0.454
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

This table reports estimates from Equation (5), which analyzes how the corporate credit spread index in each country varies contemporaneously with the Disaster Index. The corporate credit spread index is constructed as the yield of a country's corporate bond index minus the yield of a government bond index of similar duration. For the specifications in columns 3-4, 7-8, and 11-12, the predictor variable is replaced by the Disaster Index left-censored at the mean of its historical distribution over all countries up to that point in time. Control variables (all at the country level) are: inflation, the term spread, the average effective duration of the index, and four variables reporting the share of bonds by credit rating in the index (AAA, AA, A, BBB, respectively, weighted by the market value of corporate bonds). T-statistics are in brackets and correspond to Driscoll-Kraay standard errors with two lags. *, **, *** correspond to p-values less than 10%, 5%, 1%, respectively. Results are estimated across 20 economies over the full sample period of 1996-2021 (columns 1-4) and over two subperiods: 1996-2005 (columns 5-8) and 2006-2021 (columns 9-12).

Table 8: The term spread conditional on the Disaster Index

	1950-2021				1950-2005				2006-2021			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\texttt{DisasterIndex}_{i,t}$	-2.952	-4.139			3.940	2.326			-10.052***	-10.347***		
	[-0.84]	[-1.14]			[0.73]	[0.43]			[-3.13]	[-3.42]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-8.002***	-9.684***			-18.370***	-21.529***			-9.443**	-9.716**
			[-3.76]	[-4.26]			[-2.91]	[-3.80]			[-2.28]	[-2.55]
Observations	1,433	1,433	1,433	1,433	1,113	1,113	1,113	1,113	320	320	320	320
Adjusted R^2	0.092	0.117	0.096	0.122	0.107	0.122	0.111	0.128	0.251	0.252	0.238	0.238
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

This table reports estimates from Equation (6), which analyzes how the term spread in each country varies contemporaneously with the Disaster Index. The term spread is defined as the long-term government bond yield minus the short-term government bill yield. For the specifications in columns 3-4, 7-8, and 11-12, the predictor variable is replaced by the Disaster Index left-censored at the mean of its historical distribution over all countries up to that point in time. The only control variable is inflation. T-statistics are in brackets and correspond to Driscoll-Kraay standard errors with two lags. *, **, *** correspond to p-values less than 10%, 5%, 1%, respectively. Results are estimated across 20 economies over the full sample period of 1950-2021 (columns 1-4) and over two subperiods: 1950-2005 (columns 5-8) and 2006-2021 (columns 9-12).

Table 9: Dividend/price and earnings/price of the market index conditional on the Disaster Index

	Dividend/Price of Market Index				Earnings/Price of Market Index			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\texttt{DisasterIndex}_{i,t}$	0.046	0.044			-0.098**	-0.104**		
	[0.59]	[0.55]			[-2.50]	[-2.40]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-0.107***	-0.115***			-0.127**	-0.134**
			[-2.97]	[-3.05]			[-2.23]	[-2.15]
Observations	1,321	1,321	1,321	1,321	890	890	890	890
Adjusted R^2	0.173	0.177	0.180	0.185	0.113	0.113	0.114	0.114
Controls	No	Yes	No	Yes	No	Yes	No	Yes

This table reports estimates from Equation (7), which analyzes how the dividend/price and earnings/price ratios of the market index in each country vary contemporaneously with the Disaster Index. For the specifications in columns 3-4 and 7-8, the predictor variable is replaced by the Disaster Index left-censored at the mean of its historical distribution over all countries up to that point in time. The control variables are inflation and the term spread. T-statistics are in brackets and correspond to Driscoll-Kraay standard errors with two lags. *, **, *** correspond to p-values less than 10%, 5%, 1%, respectively. Results are estimated across 20 economies, 1950-2021.

Table 10: Frequency and severity of GDP disasters (peak-to-trough) by prediction and disaster category, 1870-2021

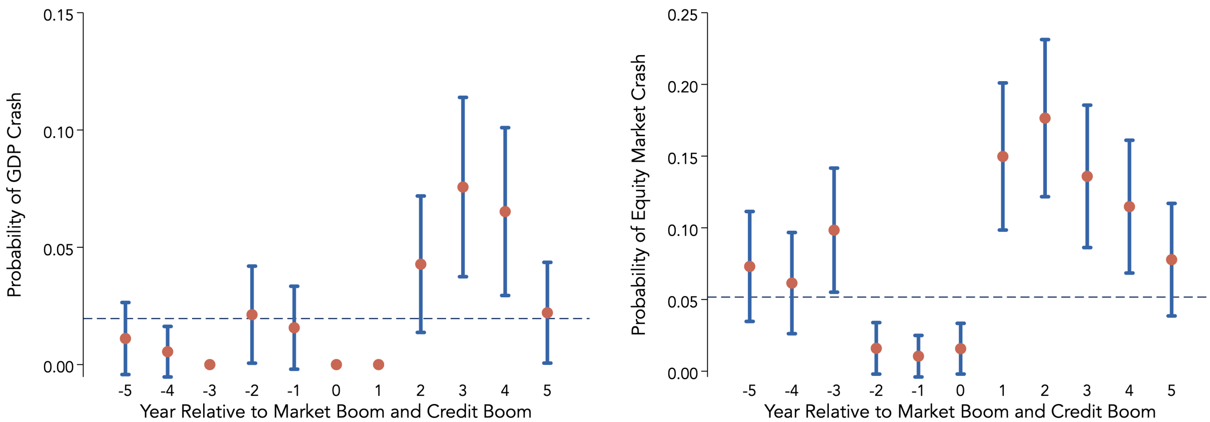
	Frequency					**Severity**				
	Banking crisis	Natural disaster	War	Other	Total	Banking crisis	Natural disaster	War	Other	Total
Predicted	16	1	2	1	20	-15%	-9%	-27%	-9%	-16%
Unpredicted	10	8	0	2	20	-11%	-7%		-7%	-9%
Disaster Index not available	3	0	0	10	13	-16%			-13%	-13%
Excluded WWI/II period	0	0	22	1	23			-37%	-12%	-36%
Total	29	9	24	14	76	-14%	-7%	-36%	-12%	-20%

This table tabulates the frequency and severity of GDP disasters (defined according to the BXY peak-to-trough definition) across 20 countries over the 1870-2021, decomposed by whether the GDP disaster is predicted by the Disaster Index and by category (banking crisis, natural disaster or epidemic, war, or other). A GDP disaster is defined as "predicted" by the Disaster Index if the Disaster Index is in the top quintile of its historical distribution three years prior to the first associated annual "GDP crash", and "unpredicted" otherwise. We also tabulate statistics of GDP disasters for which the Disaster Index is not available (that is, if either the Market Boom or the Credit Boom indicator is missing in year $t-3$ for a "GDP crash" occurring in year t) or that fall into the excluded world war periods of 1914-1919 and 1939-1948.

Figure 1: Realized probabilities of GDP crashes or market crashes around years with market booms and credit booms

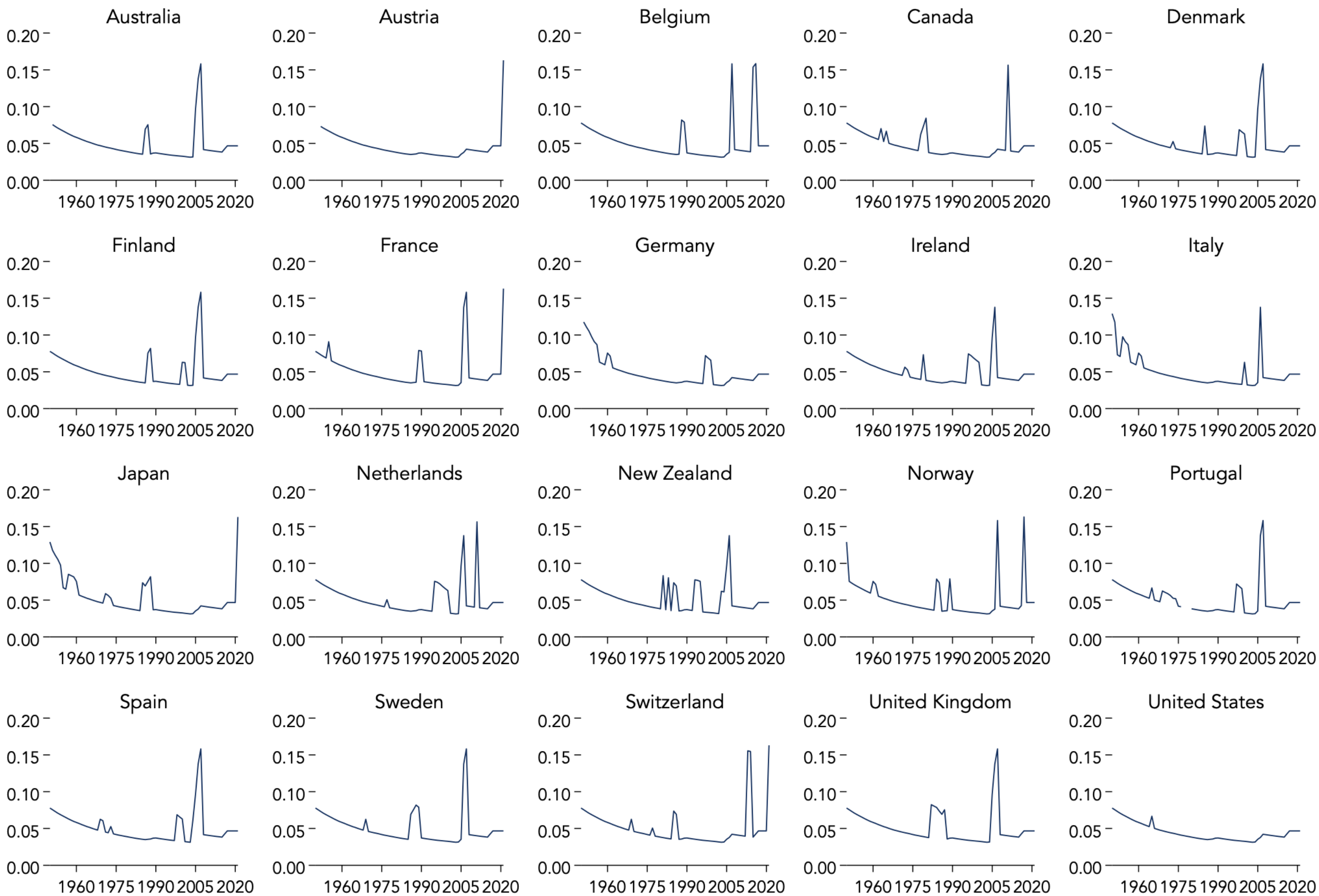
Panel A: GDP Crashes

Panel B: Market Crashes



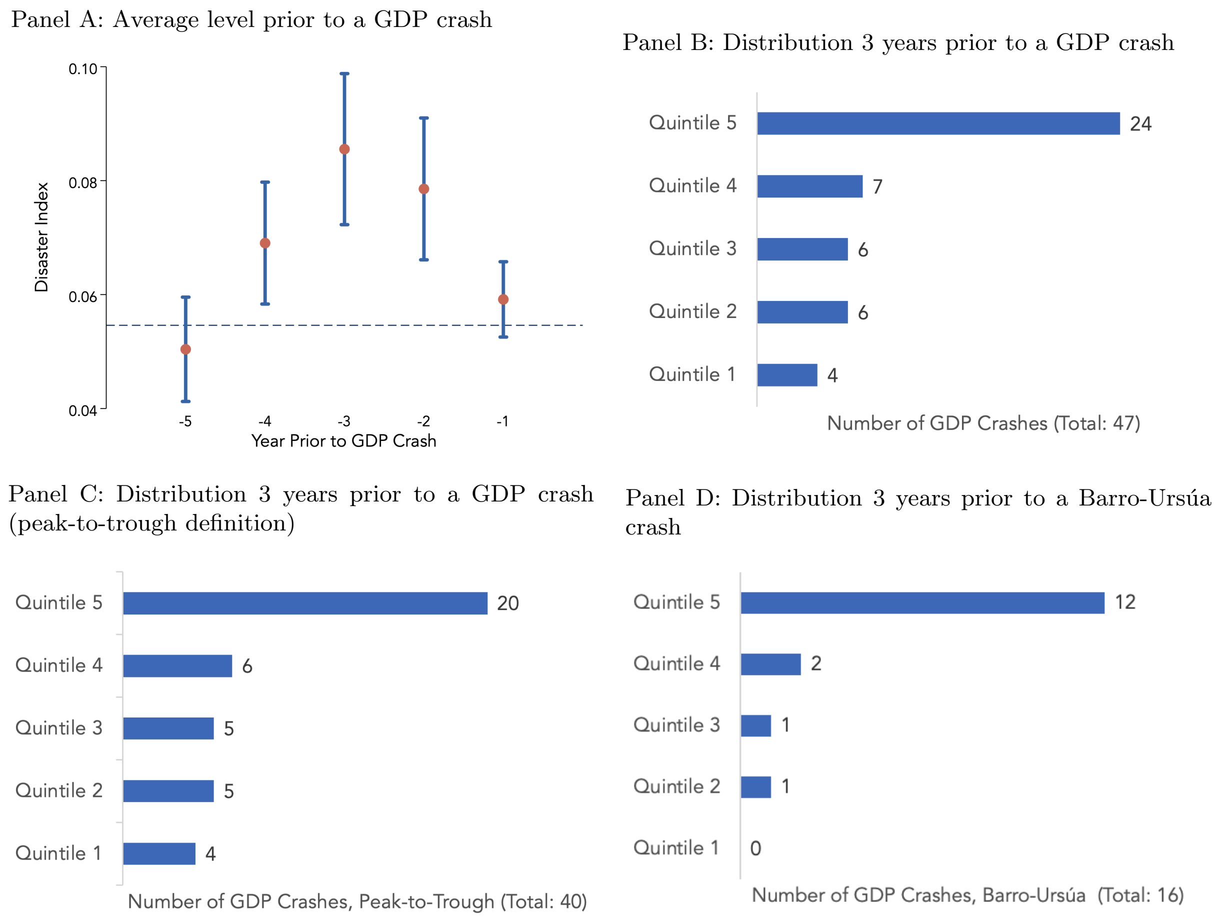
This figure presents the realized probabilities of GDP crashes (*Panel A*) and market crashes (*Panel B*) from $t = -5$ to $t = +5$ conditional on both Credit Boom and Market Boom equaling one at time $t = 0$. A country is defined to have a Credit Boom in year t if the variable Credit Expansion is in the top quintile of the distribution across all countries up to time t. A country is defined to have a Market Boom in year t if the log excess return of the equity market index is in the top tercile of the distribution across all countries up to time t. 95% confidence intervals are plotted based on Driscoll-Kraay standard errors with two lags. For comparison, the average crash probability during "normal times" (i.e. when the country has not experienced both a Credit Boom and a Market Boom together within a five-year window) is indicated by the dashed line. These event studies are constructed around 175 country-year observations with a joint Market Boom and Credit Boom, from a sample of 20 countries covering 1870-2021 (excluding the world war periods 1914-1919 and 1939-1948).

Figure 2: The Disaster Index across 20 economies, 1950-2021



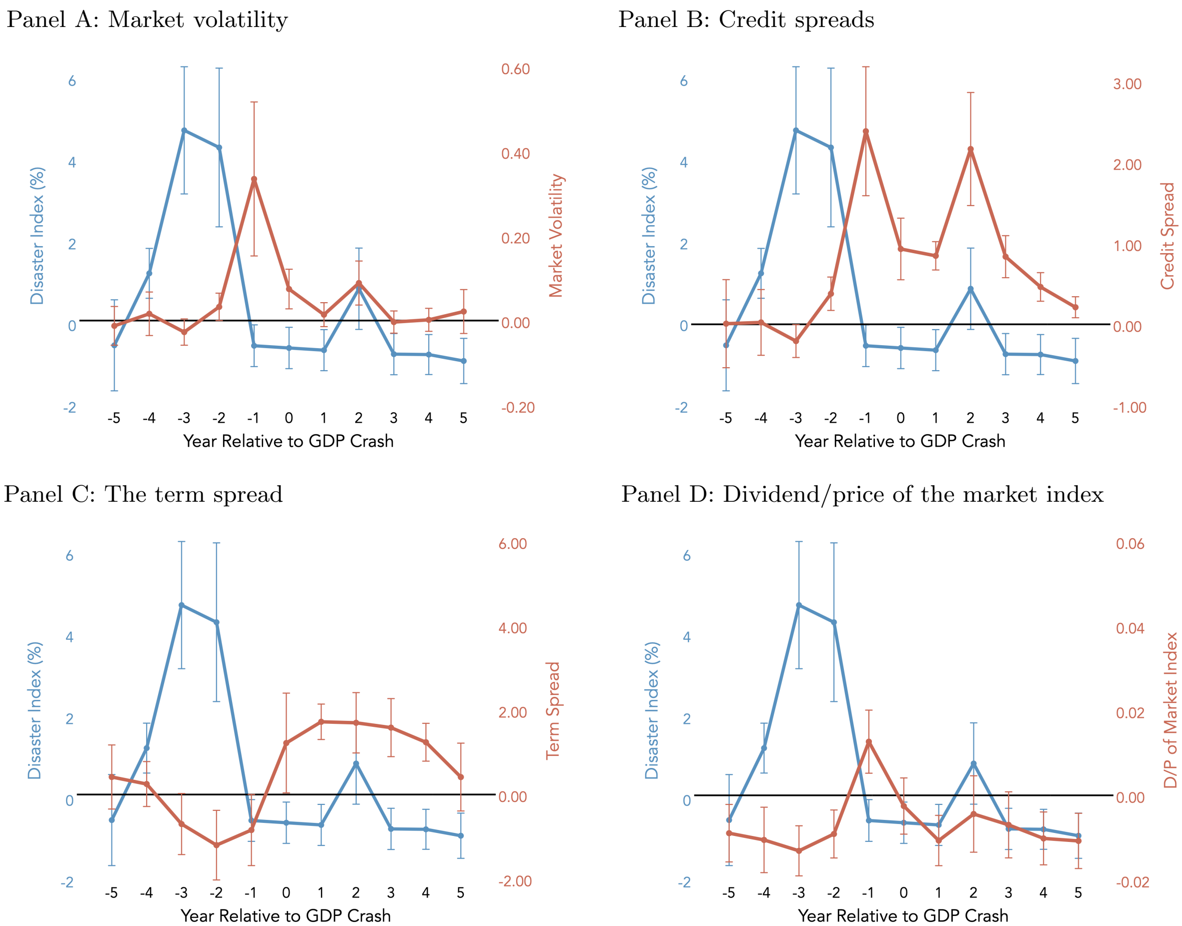
Observations: 1433. Mean: 0.050. Median: 0.043. SD: 0.022. Min: 0.031. Max: 0.163. 25%: 0.037. 75%: 0.056.

Figure 3: The Disaster Index prior to GDP crashes



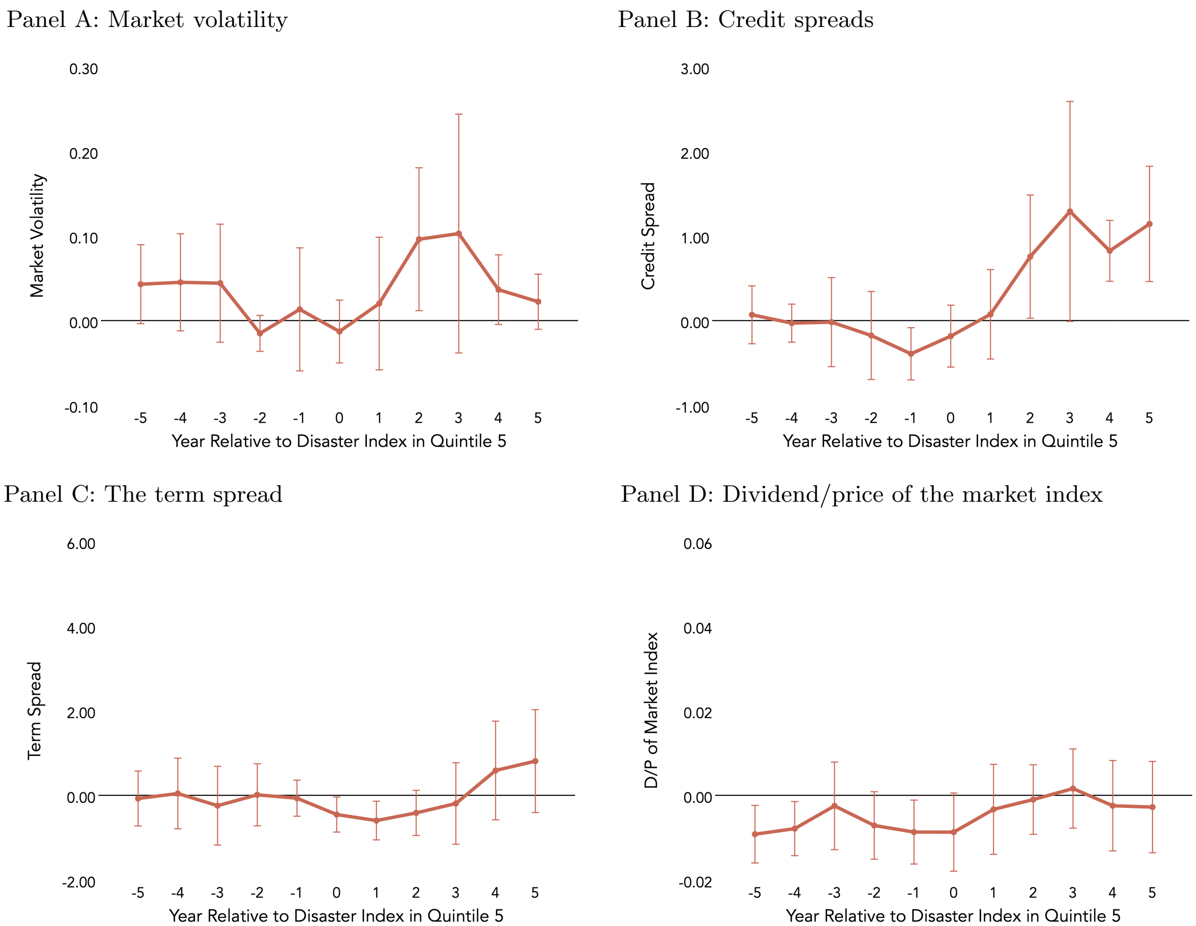
Panel A shows the average level of the Disaster Index from $t = -5$ to $t = -1$, conditional on a GDP crash at time $t = 0$. A GDP crash is defined to occur in year t if annual real GDP per capita growth is below the 2nd percentile of its historical distribution over all countries from year $t - 50$ to year t. 95% confidence intervals are plotted based on Driscoll-Kraay standard errors with two lags. For comparison, the average disaster index during "normal times" (i.e. outside a five-year window of a GDP crash) is indicated by the dashed line. *Panel B* plots the distribution of the Disaster Index three years before a GDP crash in terms of its quintiles, where the quintiles are defined based on the distribution of the Disaster Index across all countries up to year t. *Panel C* plots the distribution of the Disaster Index three years before a peak-to-trough GDP crash episode, where the three years is defined as prior to the peak year. *Panel D* plots the distribution of the Disaster index three years prior to a Barro-Ursúa GDP disaster. In all four panels, the world war periods of 1914-1919 and 1939-1948 are excluded, including all disaster episodes therein.

Figure 4: Risk premium measures around GDP crashes: an event study



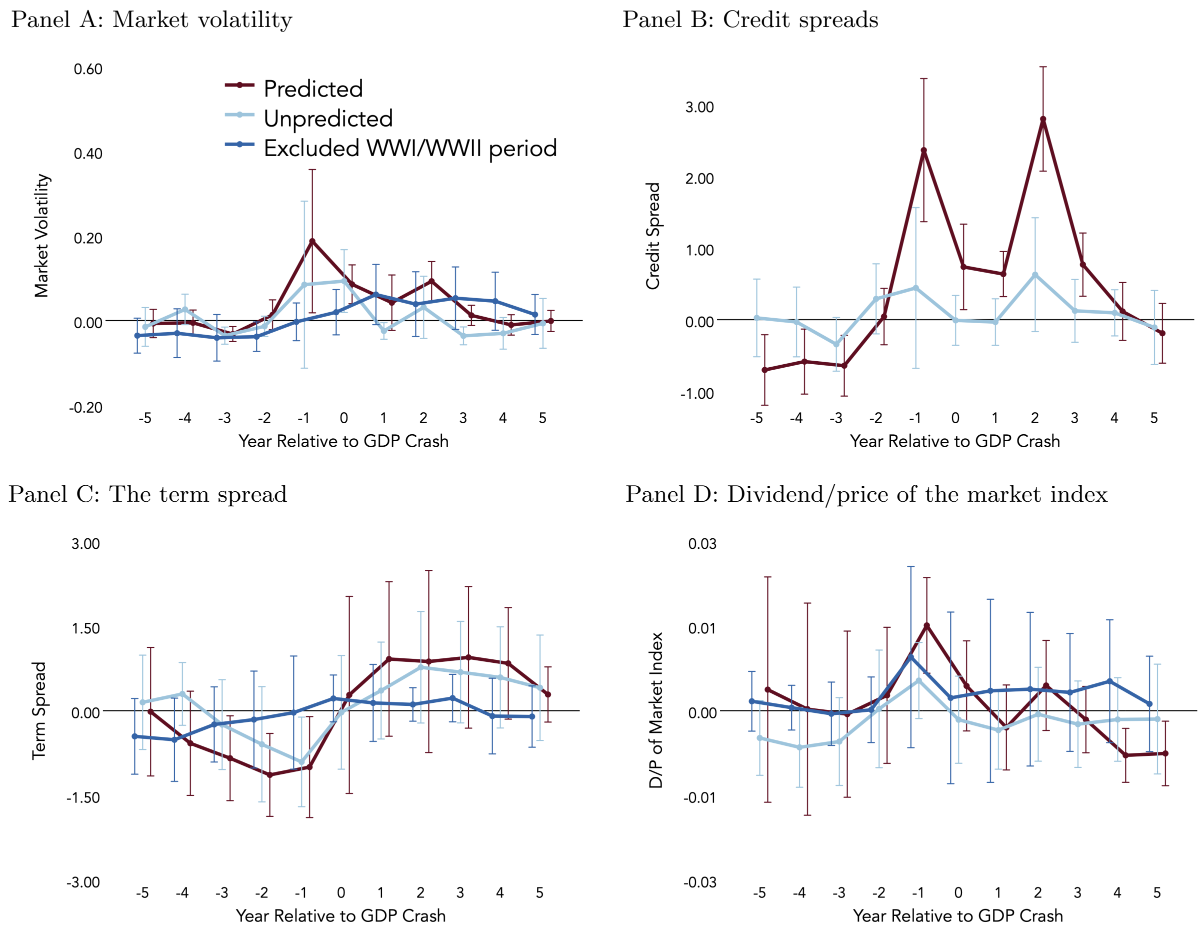
This figure presents the Disaster Index and the realized market volatility (*Panel A*), credit spreads (*Panel B*), the term spread (*Panel C*), and dividend/price ratio of the market index (*Panel D*) from $t = -5$ to $t = +5$, conditional on a GDP crash at time $t = 0$. Each variable is de-meaned by its average level during years outside of the $t = -5$ to $t = +5$ window within each country. 95% confidence intervals are plotted based on Driscoll-Kraay standard errors with two lags. These event studies are based on all BXY peak-to-trough GDP disaster episodes across 20 countries, 1950-2021.

Figure 5: Risk premium measures around years with the Disaster Index in quintile 5



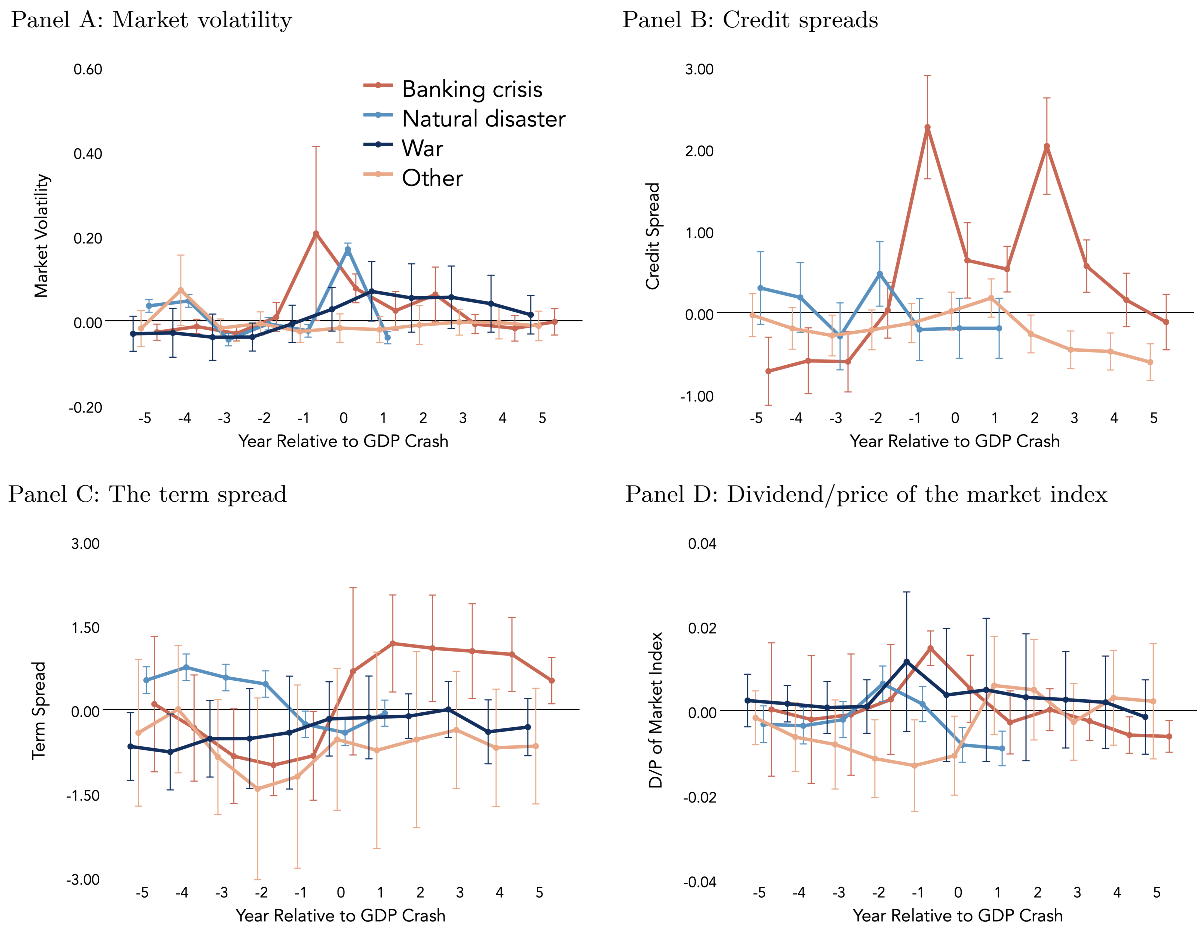
This figure presents the realized market volatility (*Panel A*), credit spreads (*Panel B*), the term spread (*Panel C*), and dividend/price ratio of the market index (*Panel D*) from $t = -5$ to $t = +5$, conditional on the Disaster Index being in quintile 5 at time $t = 0$, where the quintile is defined based on the historical distribution of the Disaster Index across all countries up to each point in time. Each variable is de-meaned by its average level during years outside of the $t = -5$ to $t = +5$ window within each country. 95% confidence intervals are plotted based on Driscoll-Kraay standard errors with two lags. These event studies are based on country-year observations across 20 countries, 1950-2021.

Figure 6: Risk premium measures around GDP crashes: predicted versus unpredicted crashes



This figure presents realized market volatility (*Panel A*), credit spreads (*Panel B*), the term spread (*Panel C*), and dividend/price ratio of the market index (*Panel D*) from $t = -5$ to $t = +5$, conditional on a GDP crash at time $t = 0$, decomposed by whether the GDP disaster is predicted by the Disaster Index. A GDP disaster is defined as "predicted" by the Disaster Index if the Disaster Index is in the top quintile of its historical distribution three years prior to the first associated annual "GDP crash", and "unpredicted" otherwise. We also separate out GDP disasters that fall into the world war periods of 1914-1919 and 1939-1948. (GDP disasters outside the world war years for which we have insufficient data to compute the Disaster Index are omitted from this figure, i.e. if either the Market Boom or the Credit Boom indicator is missing.) Each variable is de-meaned by its average level during years outside of the $t = -5$ to $t = +5$ window within each country. 95% confidence intervals are plotted based on Driscoll-Kraay standard errors with two lags. These event studies are constructed around all BXY peak-to-trough GDP disasters across 20 countries, 1870-2021. One series in *Panel B* is omitted due to lack of data.

Figure 7: Risk premium measures around GDP crashes: by disaster category



This figure presents realized market volatility (*Panel A*), credit spreads (*Panel B*), term spread (*Panel C*), and dividend/price ratio of the market index (*Panel D*) from $t = -5$ to $t = +5$, conditional on a GDP crash at time $t = 0$, decomposed by disaster category (banking crisis, natural disaster or epidemic, war, or other), which are categorized in Table A1. Each variable is de-meaned by its average level during years outside of the $t = -5$ to $t = +5$ window within each country. 95% confidence intervals are plotted based on Driscoll-Kraay standard errors with two lags. These event studies are constructed around all BXY peak-to-trough GDP disasters across 20 countries, 1870-2021. One series in *Panel B* is omitted due to lack of data.

Appendix

Table A1: The full sample of GDP disasters (BXY, BU, or both)

Country	Type	Category	Annual crash	Peak	Trough	Severity	Included	Prediction
Australia	BXY	Other	1882	1881	1882	-9.2%	Y	NP
Australia	Both	Banking crisis	1892,1893,1895	1889	1897	-29.9%	Y	NP
Australia	Both	Banking crisis	1930	1926	1933	-22.7%	Y	P
Austria	Both	War	1914,1915,1919	1912	1919	-37.6%		WWI/II
Austria	Both	Banking crisis	1932	1929	1933	-24.3%	Y	P
Austria	Both	War	1945	1944	1945	-87.9%		WWI/II
Austria	BXY	Banking crisis	2009	2008	2009	-4.1%	Y	NP
Austria	BXY	Natural disaster	2020	2019	2020	-6.5%	Y	NP
Belgium	Both	War	1917,1918	1913	1918	-34.9%		WWI/II
Belgium	BU	Banking crisis		1928	1934	-10.5%		
Belgium	Both	War	1940	1939	1943	-25.1%		WWI/II
Belgium	BXY	Natural disaster	2020	2019	2020	-5.7%	Y	NP
Canada	BU	Banking crisis		1874	1878	-12.3%		
Canada	BXY	Banking crisis	1908	1907	1908	-8.1%	Y	P
Canada	BXY	War	1914	1913	1914	-10.0%		WWI/II
Canada	Both	Banking crisis	1921	1917	1921	-24.7%	Y	NP
Canada	Both	Banking crisis	1931	1928	1933	-36.7%	Y	P
Canada	BXY	Banking crisis	1982	1981	1982	-4.4%	Y	NP
Canada	BXY	Other	1991	1989	1992	-5.2%	Y	NP
Canada	BXY	Banking crisis	2009	2007	2009	-5.6%	Y	NP
Canada	BXY	Natural disaster	2020	2019	2020	-6.5%	Y	NP
Denmark	Both	War	1915	1914	1918	-16.5%		WWI/II
Denmark	Both	War	1940,1941	1939	1941	-25.3%		WWI/II
Denmark	BXY	Banking crisis	2009	2007	2009	-6.3%	Y	P
Finland	BU	Other		1876	1881	-12.0%		
Finland	Both	War	1917,1918	1913	1918	-37.2%		WWI/II
Finland	Both	Banking crisis	1991,1992	1989	1993	-11.2%	Y	P
Finland	BXY	Banking crisis	2009	2008	2009	-8.7%	Y	P
France	Both	Other	1873,1876	1874	1879	-12.7%		DI N/A
France	BU	Banking crisis		1882	1885	-3.6%		
France	Both	War	1914,1917,1918	1912	1918	-34.9%		WWI/II
France	Both	War	1940-42,1944	1939	1944	-52.5%		WWI/II
France	BXY	Natural disaster	2020	2019	2020	-6.1%	Y	NP
Germany	Both	War	1914,1915,1917	1913	1919	-37.5%		WWI/II
Germany	Both	Other	1923	1922	1923	-14.7%		DI N/A
Germany	Both	Banking crisis	1931,1932	1928	1932	-29.3%	Y	P
Germany	Both	War	1945,1946	1943	1947	-108.5%		WWI/II
Germany	BXY	Banking crisis	2009	2008	2009	-5.5%	Y	NP
Ireland	Both	Banking crisis	2008,2009	2007	2009	-12.5%	Y	P
Italy	BU	Other		1918	1921	-8.4%		
Italy	Both	War	1943,1944,1945	1939	1945	-48.9%		WWI/II
Italy	Both	Banking crisis	2009	2007	2014	-11.2%	Y	P

Italy	BXY	Natural disaster	2020	2019	2020	-7.5%	Y	NP
Japan	BXY	Other	1899	1898	1899	-8.8%	Y	P
Japan	BXY	Banking crisis	1920	1919	1920	-7.5%	Y	NP
Japan	BXY	Banking crisis	1930	1929	1931	-9.8%	Y	NP
Japan	Both	War	1945	1940	1945	-70.5%		WWI/II
Japan	BXY	Banking crisis	2009	2007	2009	-6.3%	Y	NP
Netherlands	Both	War	1917,1918	1913	1918	-17.9%		WWI/II
Netherlands	BU	Banking crisis		1929	1934	-16.4%		
Netherlands	Both	War	1940,1942,1944	1939	1944	-58.2%		WWI/II
Netherlands	BXY	Banking crisis	2009	2008	2009	-4.3%	Y	P
New Zealand	Both	Other	1879	1878	1879	-17.9%		DI N/A
New Zealand	Both	Other	1908	1907	1909	-11.1%		DI N/A
New Zealand	BXY	Other	1921	1920	1922	-10.1%		DI N/A
New Zealand	Both	Other	1926	1925	1927	-11.9%		DI N/A
New Zealand	BXY	Banking crisis	1931	1929	1932	-18.4%		DI N/A
New Zealand	Both	Other	1948	1947	1948	-12.4%		WWI/II
New Zealand	BU	Other		1950	1951	-10.0%		
Norway	Both	War	1917	1916	1918	-15.3%		WWI/II
Norway	Both	Banking crisis	1921	1920	1921	-11.4%	Y	P
Norway	BXY	Natural disaster	2020	2018	2020	-8.8%	Y	P
Portugal	Both	Other	1928	1927	1928	-11.4%		DI N/A
Portugal	Both	War	1936	1934	1936	-15.2%	Y	P
Portugal	BXY	Natural disaster	2020	2019	2020	-7.0%	Y	NP
Spain	BXY	Other	1874	1873	1874	-8.7%		DI N/A
Spain	Both	Other	1896	1892	1896	-12.8%		DI N/A
Spain	BU	Banking crisis		1929	1933	-11.7%		
Spain	Both	War	1936,1937	1935	1938	-38.4%	Y	P
Spain	Both	Banking crisis	2009	2007	2013	-10.6%	Y	P
Spain	Both	Natural disaster	2020	2019	2020	-10.6%	Y	NP
Sweden	Both	War	1918	1916	1918	-13.7%		WWI/II
Sweden	BU	Banking crisis		1920	1921	-5.3%		
Sweden	BXY	Banking crisis	2009	2007	2009	-6.8%	Y	P
Switzerland	BXY	Banking crisis	1872	1871	1872	-12.2%		DI N/A
Switzerland	Both	Other	1877	1875	1877	-14.8%		DI N/A
Switzerland	Both	War	1918	1912	1919	-15.2%		WWI/II
Switzerland	BXY	Banking crisis	1921	1920	1921	-17.0%		DI N/A
UK	BU	Other		1918	1921	-24.1%		
UK	Both	War	1919	1918	1921	-19.5%		WWI/II
UK	BXY	Banking crisis	2009	2007	2009	-5.4%	Y	P
UK	BXY	Natural disaster	2020	2019	2020	-6.2%	Y	NP
US	Both	Banking crisis	1908	1907	1908	-10.7%	Y	NP
US	Both	War	1914	1913	1914	-9.9%		WWI/II
US	Both	Banking crisis	1930,1932	1929	1933	-32.3%	Y	P
US	Both	War	1946	1944	1947	-30.6%		WWI/II

This table lists the full sample of GDP disasters across 20 countries, 1870-2021. The list includes both Baron, Xiong, Ye (BXY) peak-to-trough GDP crashes (as defined in Table 2) and Barro and Ursúa (BU) peak-to-trough GDP disasters (as defined by Barro and Ursúa (2008)), which are specified in column 2. The disaster categorization is listed in column 3. The years of annual GDP crashes, around which BXY peak-to-trough GDP disasters are defined, are listed in column 4. For columns 5-7, the peak and trough years and the peak-to-trough severity are computed using real GDP per capita data from the BXY dataset. The "Included" column is marked with "Y" if the BXY episode is included in the estimation of Equation (1) (i.e. if there is non-missing data for the future GDP crash indicator, the Market Boom indicator, and the Credit Boom indicator, and if it falls outside the world war periods of 1914-1919 and 1939-1948). The "Prediction" column is marked with "P" if the BXY disaster is predicted by the Disaster Index (i.e. if the Disaster Index is in the top quintile of its historical distribution three years prior to the associated annual "GDP crash"), with "NP" if the disaster is not predicted by the Disaster Index, with "DI N/A" if the Disaster Index is not available due to missing data (that is, if either the Market Boom or the Credit Boom indicator is unavailable), or with "WWI/II" if the disaster falls into the world war periods of 1914-1919 and 1939-1948.

Table A2: An alternative one-stage approach, defining the Disaster Index as:
$\texttt{DisasterIndex}_{i,t} = 1(\texttt{MarketBoom}_{i,t} = 1 \text{ and } \texttt{CreditBoom}_{i,t} = 1)$

As a robustness test, we re-estimate Tables 4, 6, 7, 8, and 9 but with defining the Disaster Index as $\texttt{DisasterIndex}_{i,t} = 1(\texttt{MarketBoom}_{i,t} = 1 \text{ and } \texttt{CreditBoom}_{i,t} = 1)$, instead of estimating it from the first-stage probit regression in Table 3.

Panel A: Future equity returns

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5
Market (1870-2021)	-0.070*	-0.161***	-0.213***	-0.235***	-0.250***
Market (1870-1949)	-0.105***	-0.280***	-0.369***	-0.377***	-0.419***
Market (1950-2021)	-0.084**	-0.173***	-0.240***	-0.274***	-0.293**
	-0.064*	-0.140**	-0.197***	-0.223***	-0.238**
High B/P	-0.084	-0.179	-0.258**	-0.312***	-0.355***
	-0.051	-0.119	-0.185*	-0.231**	-0.261**
Low B/P	-0.111**	-0.265***	-0.391***	-0.465***	-0.511***
	-0.077*	-0.189***	-0.288***	-0.353***	-0.387***
High-Low B/P	0.030	0.095	0.157*	0.196*	0.198
	0.032	0.081	0.126	0.155*	0.157
High D/P	-0.091	-0.204*	-0.314***	-0.351***	-0.394***
	-0.063	-0.152	-0.248**	-0.284***	-0.317***
Low D/P	-0.138***	-0.298***	-0.413***	-0.495***	-0.543***
	-0.103*	-0.221***	-0.311***	-0.380***	-0.412***
High-Low D/P	0.060*	0.130*	0.154*	0.203**	0.212**
	0.056*	0.109*	0.124	0.162*	0.166*
High E/P	-0.123*	-0.250***	-0.359***	-0.394***	-0.432***
	-0.092	-0.186**	-0.278***	-0.306***	-0.333***
Low E/P	-0.099*	-0.271***	-0.402***	-0.490***	-0.568***
	-0.065	-0.195**	-0.298***	-0.372***	-0.439***
High-Low E/P	-0.015	0.051	0.088	0.143**	0.183***
	-0.010	0.051	0.081	0.131**	0.174***

Panel B: Equity volatility

	1950-2021		1950-2005		2006-2021	
	(1)	(2)	(3)	(4)	(5)	(6)
$\texttt{DisasterIndex}_{i,t}$	0.010	0.006	0.013	0.007	-0.065	-0.050
	[0.75]	[0.50]	[0.84]	[0.51]	[-1.62]	[-1.55]
Observations	1,320	1,320	1,001	1,001	319	319
Adjusted R^2	0.030	0.037	0.055	0.114	0.041	0.192
Controls	No	Yes	No	Yes	No	Yes

Panel C: Corporate credit spreads

	1996-2021		1996-2005		2006-2021	
	(1)	(2)	(3)	(4)	(5)	(6)
$\texttt{DisasterIndex}_{i,t}$	-0.439**	-0.439**	0.013	-0.090	-0.524*	-0.656**
	[-2.16]	[-2.30]	[0.14]	[-1.11]	[-1.85]	[-2.36]
Observations	514	514	196	196	318	318
Adjusted R^2	0.052	0.427	0.217	0.439	0.072	0.461
Controls	No	Yes	No	Yes	No	Yes

Panel D: Term spread

	1950-2021		1950-2005		2006-2021	
	(1)	(2)	(3)	(4)	(5)	(6)
$\texttt{DisasterIndex}_{i,t}$	-0.548***	-0.590***	-0.394**	-0.455***	-0.993**	-1.025**
	[-3.42]	[-3.70]	[-2.44]	[-3.04]	[-2.51]	[-2.80]
Observations	1,433	1,433	1,113	1,113	320	320
Adjusted R^2	0.099	0.125	0.110	0.127	0.241	0.241
Controls	No	Yes	No	Yes	No	Yes

Panel E: Dividend/price and earnings/price ratios of market index

	Dividend/Price of Market Index		Earnings/Price of Market Index	
	(1)	(2)	(3)	(4)
$\texttt{DisasterIndex}_{i,t}$	-0.006*	-0.005*	-0.009*	-0.009*
	[-1.99]	[-1.89]	[-1.87]	[-1.86]
Observations	1,320	1,320	889	889
Adjusted R^2	0.179	0.183	0.115	0.142
Controls	No	Yes	No	Yes

Table A3: Equity factor portfolios constructed using Datastream and Worldscope datasets

This table re-estimates Table 4 but using factor portfolios that we construct from the Datastream and Worldscope data sets (instead of using Kenneth French's factor portfolios).

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5
High B/P	-2.385*	-4.463***	-5.824***	-7.554***	-7.992***
	-2.105	-3.951***	-5.242***	-7.026***	-7.717***
Low B/P	-2.138*	-3.902***	-4.409***	-4.658***	-4.337***
	-1.690	-3.201***	-3.304***	-3.391**	-3.242**
High-Low B/P	0.063	-0.184	-1.105	-2.368	-2.900
	-0.141	-0.323	-1.540	-3.013*	-3.621*
High D/P	-2.289**	-4.613***	-5.230***	-5.596***	-5.523***
	-1.999*	-4.081***	-4.564***	-4.942***	-5.039***
Low D/P	-2.553*	-4.406***	-4.584***	-4.747***	-4.471***
	-2.193	-3.684***	-3.409***	-3.422***	-3.434***
High-Low D/P	0.122	-0.093	-0.209	-0.188	0.231
	0.137	-0.025	-0.332	-0.410	0.054
High E/P	-2.853*	-4.464***	-4.766***	-5.202***	-4.994***
	-2.516*	-4.002***	-4.085***	-4.582***	-4.518***
Low E/P	-2.987*	-5.108***	-6.535***	-7.453***	-7.558***
	-2.615*	-4.400***	-5.498***	-6.403***	-6.802***
High-Low E/P	0.438	1.119*	2.525***	3.546***	4.342***
	0.386	0.777	2.056**	3.036***	4.094***

Table A4: Market volatility, corporate credit spreads, the term spread, and dividend/price of the market index conditional on the contemporaneous value and five annual lags of the Disaster Index

	(1) Volatility	(2) Credit Spreads	(3) Term Spread	(4) Dividend/Price
Contemporaneous	-0.761**	-3.259**	-4.219*	-0.089**
	[-2.45]	[-2.17]	[-1.83]	[-2.02]
Lag 1	0.862*	7.993**	-4.097**	0.095**
	[1.71]	[2.61]	[-2.00]	[2.55]
Lag 2	0.541*	7.301**	2.041	0.068***
	[1.95]	[2.66]	[1.20]	[2.84]
Lag 3	-0.325*	0.604	-0.320	0.005
	[-1.87]	[0.86]	[-0.09]	[0.14]
Lag 4	-0.031	6.811***	4.952*	0.021
	[-0.14]	[2.72]	[1.71]	[0.86]
Lag 5	-0.551*	6.117***	7.345**	0.100**
	[-1.88]	[3.69]	[2.45]	[2.10]
Observations	1,324	712	1,328	1,248
Test for all lags = 0	17.168***	39.950***	5.058***	13.507***
Sum of lag coefficients	0.497**	28.827***	9.920***	0.288***
R^2	0.111	0.296	0.120	0.246
Model F-test statistic	62.748***	126.928***	83.782***	425.092***

This table reports estimates from Equation (8), which analyzes how market volatility (column 1), corporate credit spreads (column 2), the term spread (column 3), and dividend/price of the market index (column 4) in each country vary with the contemporaneous value and five annual lags of the Disaster Index. "Sum of Lag Coefficients" is the sum of the coefficients corresponding to lag terms 1 to 5. F-statistics for the joint significance of the lags and for the overall model are reported. T-statistics are in brackets and correspond to Driscoll-Kraay standard errors with eight lags. *, **, *** correspond to p-values less than 10%, 5%, 1%, respectively. Observations are across 20 economies, 1950-2021.

Appendix Table B1: Corporate Credit Spreads Construction Methodology

Country	Coverage	Source & Details
Australia	1996-2021	Bank of America Australia Corporate Index option adjusted spread over government bond (Bloomberg: AUC0)
Austria	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
Belgium	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
Canada	1996-2021	Bank of America Canada Corporate Index option adjusted spread over government bond (Bloomberg: F0C0)
Denmark	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
Finland	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
France	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
Germany	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
Ireland	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
Hong Kong	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
Israel	1999-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
Italy	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
Japan	1996-2003	12-year corporate bond yield minus 10-year Development Bank of Japan bond: Japan Securities Dealers Association
	2004-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
Netherlands	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
New Zealand	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
Norway	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
Portugal	1998-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
Singapore	1999-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
Spain	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
Sweden	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
Switzerland	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
United Kingdom	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)
United States	1996-2021	Bank of America Global Corporate Index option adjusted spread over government bond (Bloomberg: G0BC)