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

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January 2024

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 developed 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 a disconnect between objective disaster risk and subjective disaster risk as mirrored by asset prices.

* The authors would like to thank Hui Chen, Mete Kilic, Sam Hanson, Christian Heyerdahl-Larsen, Yueran Ma, Asaf Manela, Justin Murfin, Ivan Shaliastovich, Andrei Shleifer, and seminar participants at Boston College, Cambridge, Cheung Kong GSB, Cornell, Durham, Princeton, Reichman University, the University of Florida, the NBER Behavioral Finance meeting, SFS Cavalcade, the EFA annual meeting, and the AFA annual meeting for helpful comments and suggestions. Zhou Fan provided excellent research assistance.

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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 et al. (2011) and Farhi and Gabaix (2016) use time-varying disaster risk to explain the returns of 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.

One of the main attractions of these models is their potential to account for numerous asset pricing anomalies and risk premiums dynamics in a succinct and unified framework. At the same time, this research agenda confronts a challenge that these models are inherently difficult to empirically discipline and test due to disaster risk's very nature of being rare. Chen, Dou, and Kogan (2019) even venture to call disaster risk "dark matter" in economic models, arguing that models relying on sufficiently rare events may be inherently irrefutable with finite historical data.

Given these challenges, the empirical literature on disaster risk models has often relied on in-sample calibration or indirect measures extracted from asset prices. In-sample calibration methods, such as those employed by Gourio (2013), Nakamura et al. (2013), and Wachter (2013), use long-run consumption and asset price data to calibrate model parameters that can retrospectively fit historical data. However, these approaches can be vulnerable to the "fallacy of fit" critique of Kocherlakota (2007), since calibration approaches neither make out-of-sample forecasts of future disaster risk nor analyze the risk-return tradeoff faced by investors in real time. On the other hand, indirect measures of disaster risk derived from asset prices—for instance, from options or the cross-section of asset returns, as examined by Backus, Chernov, and Martin (2011), Bollerslev and Todorov (2011), and Kelly and Jiang (2014)—may not correspond to actual disaster occurrences.

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Instead, these measures might be driven by investors' subjective risk perceptions or other factors unrelated to actual disaster risk.

In this paper, we address these challenges by developing a method to directly forecast realized disaster risk, covering a sample of 20 developed countries from 1870 to 2021. Our approach uses data that was available historically to investors in real time and predicts economic disasters without depending on information that emerges in the future. Moreover, our approach is centered on anticipating disaster risk several years prior to the manifestation of disaster events, thereby testing model predictions during normal times before any initial tail events occur.

Following Barro and Ursúa (2008), we use GDP crashes as proxies of economic disasters. 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. The 2nd percentile threshold strikes a reasonable balance between capturing sufficiently severe GDP disasters and maximizing statistical power, resulting in a sample of economic disasters comparable in magnitude to the set highlighted by Barro and Ursúa (2008).[1]

Our measure of disaster risk builds on the recent literature that shows credit expansions have strong predictive power for subsequent banking crises and low GDP growth tail events (e.g., Schularick and Taylor 2012, Mian, Sufi, and Verner 2017, Adrian et al. 2022, Baron, Verner, and Xiong 2021). In particular, Greenwood et al. (2022) show that banking crises are predictable using a credit boom indicator, an equity market boom indicator, and their interaction term. Adopting a similar approach, our regression analysis shows that the joint effect of a rapid credit expansion and high past equity market returns provides particularly strong predictability for subsequent GDP crashes. Conditional on elevated credit expansion and past market returns, the probability of a GDP crash occurring in 2-4 years is 12.0%, close to double the unconditional probability of 6.2%.

This significant predictability allows us to construct an objective out-of-sample forecast of heightened future disaster risk associated with credit booms and asset market booms, which we

[1] Unlike Barro and Ursúa's (2008) definition of a GDP crash as a peak-to-trough decline in real GDP per capita of at least -9.5%, our definition does not require future information to designate disasters in real time (as it is not based on peak-to-trough declines) and accounts for the decreasing trend in GDP volatility since 1870, which is partly the result of measurement error in historical GDP statistics (Romer 1989, Watson 1994).

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call the Disaster Index. Our Disaster Index correctly forecast *half* of realized GDP crashes in the post-1950 out-of-sample testing period, while maintaining a reasonable 16.5% false positive rate.

In constructing the Disaster Index, we make a deliberate choice to omit forecasting one-year-ahead GDP crashes, opting instead to focus on the 2-to-4-year-ahead horizon. This choice is informed by the findings of Baron, Verner, and Xiong (2021), who demonstrate that banking crises, accounting for 40% of GDP disasters in our sample, often precede significant GDP downturns by one year, illustrating the real economy's delayed response to banking distress. Market indicators typically already reflect an ongoing banking crisis in the year before a GDP disaster, even though GDP itself reacts with a delay. This observation motivates us to bypass the immediate year preceding a crisis and focus on longer forecast horizons. This approach aligns with our broader aims of analyzing the anticipatory aspects of disaster risks prior to any initial realizations of tail events, consistent with Gabaix (2012) and Wachter (2013), who emphasize that a low probability of future disasters can drive risk premium dynamics even during normal times.

The Disaster Index enables us to systematically examine how time-varying disaster risk affects asset prices. As a disaster event disrupts aggregate consumption, the key insight of asset pricing models (e.g., Gabaix 2012, Wachter 2013) is that an increase in disaster risk leads to higher risk premiums and expected returns. In contrast to this prediction, our first main finding is 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 1.3 percentage points lower than average within the full-sample period of 1870-2021 and 1.5 percentage points lower than average when restricting to the post-1950 subperiod.

Existing models have also highlighted several other asset pricing effects of time-varying disaster risk: an increase in forecasted disaster risk can drive up equity market volatility (Wachter 2013), corporate credit spreads (Wachter 2013, Gourio 2013), the nominal term spread (Gabaix 2012, Tsai 2013), and the dividend-to-price of the equity market (Gabaix 2012, Wachter 2013). We test these model implications by estimating regressions of these outcome variables on the Disaster Index. We find no supportive, and often contradictory, evidence of these model predictions. First, the Disaster Index is negatively correlated with the volatility of the equity market

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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 2.6-basis-point (bp) drop in the corporate credit spread index and an average 0.9-bp drop in the term spread over the full-sample period of 1870-2021. Third, a one percentage point rise in the Disaster Index is associated with a negligible change (0.1 bps) in the dividend/price ratio and an average decline in the earning/price ratio of the aggregate market index by 7.8 bps.

Given that the Disaster Index tends, by design, to better forecast GDP disasters associated with banking crises and other macroeconomic crises and is not designed to forecast GDP disasters associated with wars and natural disasters, one may argue that our Disaster Index does not capture certain types of risks that 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 four risk premium measures (equity market volatility, corporate credit spreads, the nominal term spread, and equity dividend-to-price) 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 for disasters unrelated to banking crises than for those related. Thus, even though our Disaster Index by design tends to measure disaster risk related to banking crises, our main findings are likely to hold for other types of disaster risk.

Our focus on the anticipatory aspects of disaster risks, before there are realizations of initial tail events, also sets our work apart from other related studies that focus on important issues during and after tail events are realized, as substantial uncertainty remains about the duration, severity,

[2] One cannot argue, in defense of rational time-varying risk models, that wars and natural 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 influence financial markets, countering the relevance of time-varying disaster risk models for asset prices.

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and potential recovery of disasters even after their initial realization. For example, Ghaderi, Kilic, and Seo (2022) model a regime-switching process in the economy in which investors rationally learn that they are already in a disaster regime after observing realizations of tail events. Muir (2017) studies risk premiums conditional on the occurrence of financial crises (comparing them to wars and recessions). Pagano, Wagner, and Zechner (2023) study how stock returns vary in response to firms' exposures to the Covid-19 pandemic risk after its onset.

In contrast, we forecast future disasters at 2-to-4-year horizons to focus on the anticipatory aspects of disaster risks. This horizon choice also sharply differs from other papers that focus on shorter horizons. For example, a contemporaneous study by Marfè and Pénasse (2023) also develops an out-of-sample disaster risk measure for GDP disasters starting at the following *one year*. They find that this measure is positively correlated with risk premiums, consistent with time-varying disaster risk models. However, among their extensive set of predictors, two variables—a global recession indicator and a global war indicator—are most influential in predicting GDP disasters one year ahead. We view this as a post-hoc disaster prediction, emerging only after a significant event has already occurred. Instead, our choice of bypassing the immediate year preceding a crisis and focusing on longer forecast horizons results in markedly different conclusions from prior work using shorter forecast horizons.

In an additional analysis, we carefully analyze the role of forecast horizons. Our results suggest that financial markets do tend to positively price in disasters contemporaneously and at one-year future horizons (consistent with Marfè and Pénasse (2023)), but not at longer future horizons. This finding suggests that the "Minsky moment"—the point at which financial markets begin to factor in an impending economic disaster, leading asset prices to fall and risk premiums to spike—typically occurs roughly one year prior to the actual realization of a GDP crash.

The challenge of measuring time variation in disaster risk for econometricians, as highlighted by Chen, Dou and Kogan (2019), also mirrors the challenge of making real-time financial decisions faced by market participants. Their decisions ultimately reflect subjective perceptions of disaster risk. Our analysis reinforces the survey evidence provided by Giglio et al. (2021), who find that, in a survey of investors with investment accounts at Vanguard, expected stock market returns and subjective probability of rare disasters are negatively correlated both within and across

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investors. Their findings, like ours, raise doubt on whether asset prices accurately incorporate disaster risk in equilibrium.[3] Our findings are also related to Manela and Moreira (2017), who use Wall Street Journal articles since 1890 to construct a news-based disaster risk measure, reflecting subjective disaster concerns of the news media. While their measure positively predicts asset risk premiums, it is an open question to what extent subjective disaster risk measures such as these are correlated with objective disaster risk in a global sample.

Our analysis highlights several additional insights. First, our evidence supports an alternative view in which many GDP disasters are endogenous and happen precisely when banks or investors neglect disaster risk (Gennaioli, Shleifer, and Vishny 2013, Baron and Xiong 2017) or have elevated risk appetite (Krishnamurthy and Li 2020). Second, as there is a significant gap between objective disaster risk and subjective disaster risk mirrored by asset prices, our results caution that indirect measures of time-varying disaster risk from asset prices, which are often used as warning signs of financial instability, may not accurately forecast objective disaster risk.[4]

The rest of the paper proceeds as follows. Section I summarizes key features of existing time-varying disaster risk models and maps out their specific hypotheses that our paper aims to test. Section II describes the data. Section III constructs the Disaster Index and verifies its predictability for GDP crashes. Section IV uses the Disaster Index to test various asset pricing implications of time-varying disaster risk models. Section V provides additional analyses. Section VI concludes.

I. Empirical Design

The time-varying disaster risk literature typically models rare disasters as Poisson shocks to the representative agent's consumption process. For expositional purposes, we denote these Poisson shocks as $\nu_t = J_t 1_{N_t \neq N_{t-1}}$, where N_t follows a Poisson counting process and the arrival intensity of Poisson shocks, π_t, is a time-varying random process. The variable J_t is the impact of

[3] Our finding does not imply that all market participants neglect or misprice disaster risk. Chen, Joslin and Tran (2012) show theoretically that when investors hold heterogeneous beliefs about disaster risk, it may only take the presence of a small number of optimists in the economy to significantly reduce the disaster risk premium, causing the asset market equilibrium to deviate from that implied by models with a representative investor facing objective disaster risk.

[4] Consistent with this note of caution, Welch (2016) shows that investor perceptions of disaster risk, as measured by the cost of deep-out-of-money put options to protect against a stock market crash, spiked only in 2008 during the height of the financial crisis, and were generally low in other times.

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the disaster conditional on a disaster arriving. Gourio (2012) and Wachter (2013) concentrate on exploring the effects of π_t (the fluctuating disaster probability), whereas Gabaix (2012) develops a tractable approach to examine the impact of J_t. In this paper, we focus our empirical tests on the fluctuating disaster probability π_t, though we also perform analysis related to disaster severity J_t in Section V.C.

Models of time-varying disaster risk implicitly make two types of predictions about risk premium dynamics: prior to a disaster's initial unfolding (i.e., during "normal" times) and conditional on disaster realization. Our work's focus on the first type—the anticipatory aspects of disaster risks, before any realizations of tail events—sets our work apart from the other studies, such as Ghaderi, Kilic, and Seo (2022), who model a regime-switching process in an economy in which investors rationally learn that they are already in a disaster regime after observing realizations of tail events. Those papers explore important issues explaining why risk premiums spike conditional on disaster occurrence. However, these times after tail events are realized are only a small part of our data sample and involve different types of uncertainties than before the initial realization. In contrast, our work focuses on the longer-horizon anticipatory aspects of disaster risks and whether variations in the low likelihood of potential disasters can be a key driver of time-variation asset prices before any initial tail risk realizations.

Our paper also differs from prior empirical work by using an objective, real-time, and forward-looking measure of disaster risk. In contrast to calibration approaches (Gourio 2013, Nakamura et al. 2013, Wachter 2013, and Ghaderi, Kilic, and Seo 2022), which select model parameters that can retrospectively fit the data, our Disaster Index allows us to directly test the consistency of disaster risk models, incorporating the risk-return tradeoff faced by investors in real time. This approach leads us to conclusions that differ markedly from those reached through calibration methods.

We now discuss our conceptual approach to testing rational time-varying disaster risk models. The assumption of rational expectations is core to the purpose of these models, as their main appeal lies in providing a succinct and unified explanation for a wide range of asset pricing anomalies, without resorting to assumptions of more complex investor behaviors.

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We first start with the class of rational expectations models by Wachter (2013), Gabaix (2012), Tsai and Wachter (2015, 2016), and others, in which the representative investor directly observes the time-varying disaster risk probability π_t. We argue that in this class of models, the Disaster Index must theoretically predict future equity returns or risk premiums with a positive regression coefficient. To show this, in Appendix Section A, we first trace through prominent time-varying disaster risk models in the literature, demonstrating that they all predict a positive relationship between the time-varying disaster probability π_t and future equity returns or risk premiums. This relationship holds robustly across different asset classes and model refinements, such as persistent disasters with potential recoveries. Then, acknowledging that the disaster risk probability π_t is not directly measurable by the econometrician, we link the Disaster Index to these models, even though it not directly featured in them. We show that these models all imply a positive regression coefficient between risk premiums and the Disaster Index, which follows from the positive correlation between the Disaster Index and π_t, since the Disaster Index is a noisy but informative signal of π_t. Our analysis in Appendix Section A concludes that a key characteristic of these rational expectation models with time-varying disaster risk is the impossibility of the Disaster Index negatively predicting equity risk premiums or other risk premiums. Thus, a negative coefficient found in our empirical test would contradict these models.

We next turn to time-varying disaster risk models featuring rational learning or alternative belief formation processes, such as those of Collin-Dufresne, Johannes, and Lochstoer (2016), Ghaderi, Kilic, and Seo (2022), and Wachter and Zhu (2023). In Appendix Section B, we propose a framework for analyzing these types of models where the objective time-varying disaster probability π_t is not directly observable to the agents within the model. Instead, the representative investor has beliefs s_t about the time-varying disaster probability, which is derived from the investor's learning process. Both π_t and s_t remain unobservable to the econometrician, who only estimates the Disaster Index. Importantly, in our framework, we do not equate the Disaster Index with the agents' beliefs within a rational disaster risk model. We show that as long as the investor's subjective beliefs s_t are reasonably aligned with objective disaster probability π_t within the model, the Disaster Index must still predict the equity risk premium with a positive coefficient.

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Consequently, a negative coefficient found in our empirical analysis would suggest a "disconnect" between the subjective beliefs of investors and the objective disaster probability.[5]

II. Data

In this section, we describe in detail how each variable is constructed. We then present summary statistics. 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. We gather the following country-level variables: equity market index returns; 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; growth in real GDP per capita; bank credit expansion; equity market volatility; a corporate bond spread index; the term spread; and the dividend-to-price and earnings-to-price ratios of the broad equity market index.

A. Data construction

Equity index returns. Equity returns of the broad equity market index for each country are expressed as annual log excess total returns as of December 31. 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. Data for these variables (price returns, dividend-to-prices, short-term 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 listed 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 from the Kenneth French Data

[5] See Appendix Section B for full details of our framework. For models with learning or beliefs, we are formally testing the joint hypothesis that: 1) the model is true *and* 2) there is no "disconnect" between subjective beliefs and objective disaster probabilities within the model. By "disconnect", we mean a near-zero or negative correlation between subjective beliefs and objective disaster probabilities within the model. Thus, for any proposed model, a negative coefficient estimated from the data implies either: 1) a rejection of the model or 2) a "disconnect" between subjective beliefs and objective disaster probabilities within the model.

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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 developed 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 total returns come adjusted for corporate actions (e.g., stock splits). 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 other ten countries.[6]

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.[7] 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 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

[6] For this alternative dataset, we apply four additional filters to ensure data quality as recommended by Ince and Porter (2006) for Datastream and Worldscope. 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. 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.

[7] These equity factor portfolios are based on univariate valuation sorts, rather than on bivariate sorts by size and value. 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 each year.

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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 and inflation published by Global Financial Data. Unless otherwise specified, the terms “GDP” and “GDP growth” are used in this paper as shorthand 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 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 past three-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 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 Table B1.[8] Although we have limited 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, and also we only have data to control for changes in the effective duration and the credit rating of the bond index 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 minus short-term government yield) and

[8] 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, 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 another country’s currency). The index only includes publicly issued, investment grade corporate debt. Qualifying securities must be issued in one of eight major currencies, satisfy a minimum size requirement, and have a rating at or above BBB-equivalent, a fixed coupon schedule, and a minimum 18-month maturity at issuance.

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dividend-to-price and earnings-to-price ratios of the broad equity market index are from Baron, Verner, and Xiong (2021) and extended to the end of 2021 based on the same data sources.[9]

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, 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, 1939-1949) in these statistics and subsequent regression analysis.[10] For equity factor returns, equity market volatility, corporate credit spreads, the term spread, and dividend-to price and earnings-to-price ratios of the market index, the statistics are computed over 1950-2021 (or the subset for which data are available), which is the sample period used for subsequent regression analysis on these variables. The mean log excess return of the broad market equity index is 3.3%. The value portfolios (High) sorted on B/P, D/P, and E/P have mean returns of 6.4%, 6.8%, 7.1%, respectively, higher than the mean returns of the growth (Low) portfolios (4.3%, 4.0%, 3.9% respectively).[11]

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 -3.4%, 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 -3.0 (5th percentile) percentage points in a given year. We also report summary statistics for equity market volatility (mean=15.4%, s.d.=9.7%), credit spreads (mean=1.225%, s.d.=0.91%), the term spread (mean=1.008%, 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%).

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[9] We do not include any variable from options market, such as implied volatility and variance risk premiums, because options market data are only available for a few developed countries starting in the 1980s. This small sample makes it difficult to examine predictability for GDP disasters in our broader sample.

[10] 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 V.B.

[11] 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.

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III. 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. 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 is infeasible to determine in real time 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 since 1870, which may be due either to improved economic resilience or extensive measurement error in historical GDP statistics (the latter 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.[12] This definition results in a sample of episodes similar to Barro and Ursúa's (2008) in terms of incidence, frequency, and average severity, but 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 developed 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).[13] We tabulate statistics for crash episodes separately over the pre-1950 (1870-1949) and post-1950 subperiods (1950-2021), the latter of which we emphasize in our subsequent

[12] 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.

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

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regression study on asset prices. The analysis in Table 2, as in the regression analysis in Section IV, excludes episodes around World Wars I and II (in the years 1914-1919 and 1939-1949).

We first focus on annual GDP crashes, our main definition of a real economic disaster. (In the rest of the paper, the term "GDP crash" refers to an annual GDP crash episode rather than a peak-to-trough episode, 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 44 episodes (18 of the 44 episodes from the 1870-1949 subperiod and all 26 episodes from the post-1950 subperiod) and occur with a frequency of 2.2% and an average severity of -8.3%.[14] 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.

We face a trade-off in choosing the 2nd percentile cutoff in defining a GDP crash. Choosing a lower cutoff would allow us to concentrate on more extreme disasters, but the lower frequency also makes disaster risk harder to measure with the finite historical data and limits the statistical power for testing asset pricing theories. 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. 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 the models becomes irrefutable using standard confidence levels.

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,

[14] "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, Market Boom, and Credit Boom, variables which are defined in the subsequent section).

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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 six 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.

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). We return to this decomposition by disaster category in Section V, where we will analyze risk premium measures around these various types of disasters. For now, we highlight a few facts by focusing on the peak-to-trough declines and re-including the world war periods. First, we see that banking crises are the most common type of historical GDP disaster in developed economies (29 out of 76 peak-to-trough events). Second, "war disasters" are the most severe type in magnitude, with an associated average peak-to-trough GDP decline of -35.9% (compared to the average decline across all types of -19.5%). Third, there are, surprisingly, no natural disasters or epidemics causing GDP disasters over the 1870-2021 period in our sample of 20 developed 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. 2022, Greenwood et al. 2022). In particular, our approach is motivated by that of Greenwood et al. (2022) who combine rapid credit expansion and asset price growth to jointly

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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 past equity returns are in the top tercile), the probability of entering into a financial crisis is 13% within one year and grows to 45% for the 3-year horizon (significantly higher than the unconditional crisis probability of 4% per year). 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.

For the probit analysis in this subsection and the construction of the Disaster Index in the next subsection, we define two predictor variables, *Credit Boom*$_{i,t}$ and *Market Boom*$_{i,t}$. *Credit Boom*$_{i,t}$ is bank credit expansion for country i in year t, standardized using only past information until year t and then left censored at zero. *Market Boom*$_{i,t}$ is the past three-year cumulative log excess return of the market index for country i in year t, again standardized using only past information until year t and then left censored at zero.[15] Both variables are constructed from standardization up to each point in time based on the distribution for all countries. In contrast to Greenwood et al. (2022) who use discrete indicator variables, our variables capture the continuous variations in credit expansion and past market returns, which increases the statistical power of our constructed Disaster Index, even when *Credit Boom*$_{i,t}$ and *Market Boom*$_{i,t}$ are not beyond any artificially chosen cutoffs. Throughout the paper, when constructing variables, 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 *Credit Boom*$_{i,t}$ (*Market Boom*$_{i,t}$).

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 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*$_{i,t}$ being in the top quintile and top tercile respectively at time t=0, comparing it with the baseline probability of a GDP crash during "normal times" (1.97%), represented by a horizontal dashed line. (These

[15] The reason we left censor at zero is that the literature (e.g., Greenwood et al., 2022) has shown a nonlinearity: "booms" in credit growth and market returns predict banking crises and GDP disasters, while "slumps" (i.e., times when these variables are below their means) add little predictability. We add two tests, reported in Table A2, to justify our approach. Table A2, Panel A, re-estimates Table 3 but using linear predictors, rather than left-censored variables, to show that the main results of the paper are robust to not left censoring variables (though finds weaker disaster predictability, as expected). Panel B then demonstrates that the predictability of credit expansion and market returns for GDP crashes stems from "booms" (left-censored variables) rather than from "slumps" (right-censored variables).

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threshold definitions using quintiles and terciles are taken from Greenwood et al. (2022). Although we employ *Credit Boom*$_{i,t}$ and *Market Boom*$_{i,t}$ as continuous variables for most of our analysis, we occasionally use these thresholds to define "elevated" levels of these variables.) "Normal times" are defined as years when the country has not experienced the joint occurrence of a credit boom in the top quintile or market boom in the top tercile 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*$_{i,t}$ being in the top quintile and tercile respectively at 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 3.93%, 7.95%, and 6.29% respectively, compared to 1.97% during "normal times". However, at t=1, the country has an observed GDP crash probability of zero, as it takes time—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.

Since disaster predictability is absent at the 1-year horizon in Figure 1 but peaks at the 2- to 4-year horizons, we tailor our subsequent probit analysis and the Disaster Index to these specific horizons. This approach contrasts with other disaster prediction studies, such as Marfè and Pénasse (2023), which concentrate on one-year-ahead forecasts. Our analysis aims to forecast disaster risk before declines in fundamentals are detected, leading us to deliberately bypass the immediate year preceding a disaster and focus on the 2-to-4-year forecast horizon.

This logic follows from Baron, Verner, and Xiong (2021), who show that banking crises (which account for 40% of GDP disasters in our sample) often precede significant GDP downturns by one year, reflecting the delayed yet anticipated responses of the real economy to banking distress. The 2007-08 financial crisis exemplifies this pattern, with the stock market crash at the end of 2007 preceding the GDP crash by about a year. We therefore exclude the one-year-ahead prediction horizon, which is contrary to our objective, as outlined in Section I, of analyzing the anticipation of low-probability disasters before fundamentals rapidly deteriorate. We return to the issue of forecast horizons in Section V.A.

We thus 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 term:

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

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. Equation (1) is estimated over the full sample of 20 economies over 1870-2021 (excluding the world war years 1914-1919 and 1939-1949). We estimate the probit using standard errors that are double clustered on time and country to account for possible autocorrelation within each country and correlations across countries at each point in time.[16]

Table 3 reports the marginal effects of the three main predictor variables: *Credit Boom*$_{i,t}$, *Market Boom*$_{i,t}$, and their interaction term. In the univariate regressions in columns (1) and (2), we observe that conditional on credit expansion and past market returns above their historical mean, a one standard unit increase predicts a 3.2% increase in the probability of a GDP crash in 2-4 years, whereas a standard unit increase in past market returns predicts a 3.8% increase. Column (3) reports similar coefficients from a bivariate specification. Column (4) also includes their interaction term, which is the strongest predictor of the three, in terms of statistical significance and magnitude of the marginal effect. As calculated at the bottom of Table 3, the predicted GDP crash probability from this probit specification is 12.0% when credit expansion is in the top quintile and past market returns is in the top tercile. Compared to the unconditional probability of a GDP crash in 2-4 years of 6.2%, this is close to a doubling in crash risk.

Column (5) shows that a specification with just the interaction term has approximately the same predictability as the fully saturated regression, in terms of both the magnitude of the pseudo R-squared (6.6% vs. 6.2%) and the sum of marginal effects (5.4% vs. 3.9%), suggesting that it is largely the interaction term that predicts GDP crash risk. In specifications (6) and (7), we control for the contemporaneous value and two lags of GDP growth, to which the results are robust.

[16] In estimating the probit, we do not use Driscoll-Kraay standard errors, as we do for most other regressions in this paper in order to account for cross-autocorrelations, since it would be challenging to code in this setting. However, we find qualitatively similar results when we recast Equation (1) as a linear probability model and implement Driscoll-Kraay standard errors.

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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 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 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 forecasts not only an increased probability of a banking crisis but also an increased probability of real GDP growth being below -2% in subsequent years 2-4. However, in contrast to Greenwood et al. (2022) who use discrete indicator variables, our specification in Equation (1) captures the continuous variations in credit expansion and past market returns, which increases the statistical power of our Disaster Index to predict asset returns, even when $\textit{Credit Boom}_{i,t}$ and $\textit{Market Boom}_{i,t}$ are not beyond any artificially chosen cutoffs.[17]

C. The Disaster Index

Given the strong in-sample predictability in Table 3 of $\textit{Credit Boom}_{i,t}$ and $\textit{Market Boom}_{i,t}$ for GDP crashes at future 2-to-4-year horizons, we next construct an out-of-sample measure of disaster risk, which we call the "Disaster Index". We again estimate Equation (1) but now in a one-step-ahead rolling framework, with no look-ahead bias, 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 1939-1949). For each year t, we estimate the regression using data available from 1870 to year t for all countries and denote the predicted value for country i and year t as the Disaster Index. To avoid any potential

[17] Table A3 and Table A4 show that the paper's main findings are robust to two alternative specifications. Table A3 reports the paper's main results after standardizing credit expansion and past market index returns *country-by-country*. Table A4 presents the main regression results using the *indicator* predictor variables from Greenwood et al. (2022).

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look-ahead bias, all disaster forecasts throughout the paper are based on rolling probit regressions using data strictly from 1870 through year t to make disaster forecasts for year t+2 to t+4.[18] To calculate the Disaster Index, we require at least ten country-year observations where the GDP crash indicator and predictor variables of credit boom and market boom 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, as adopted by Wachter (2013) to model time-varying disaster risk.[19] Figure 2 plots the Disaster Index for all 20 countries individually over the postwar subperiod of 1950-2021, which is when we focus our asset pricing tests. In this subperiod, there are 1377 observations for the Disaster Index with a mean value of 5.9% and a standard deviation of 4.7%. The minimum value over our sample is 3.3%, and the maximum is 67.4%. The 25th percentile value is 3.9% and the 75th percentile value is 6.3%. The Disaster Index is quite volatile within countries. In Finland, for instance, the Disaster Index rises in 1988, 2000, and 2006. In the first and third of these instances, GDP crashes occur in the following two to four years (both attributable to banking crises).

By construction, variation in the Disaster Index reflects both variation in *Credit Boom*$_{i,t}$ and *Market Boom*$_{i,t}$ 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

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[18] For example, when making a forecast in the year 2000 for whether there will be a GDP crash in 2002, 2003, or 2004, the forecast is based on an estimated probit regression that uses all starting years up to and including 1996. This way, the last dependent variable in this regression is an indicator variable of a GDP crash in years 1998, 1999, or 2000, which is information that would be available to an investor in the year 2000.

[19] Gabaix (2012) adopts a different theoretical approach, assuming a constant disaster probability but of time-varying severity. Interestingly, as shown by Schularick and Taylor (2012) and Mian, Sufi, and Verner (2017), 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. We analyze whether asset prices reflect the time-varying *severity* of disaster risk in Section V.C.

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over time. Such learning is reflected by the pronounced downward trend in the baseline probability of 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 2.9% vis-à-vis a post-1950 crash probability of 1.8%, even though rapid credit expansions and equity market booms have not become less frequent.[20]

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.[21] 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 two ways. First, we show that its level leading up to the year of a GDP crash is significantly elevated. Second, we evaluate the Disaster Index in terms of the statistical tradeoff between true positives (i.e., predicting a GDP disaster that indeed happens) versus false positives (i.e., predicting a GDP disaster that does not occur) and show that the Disaster Index is a robust predictor of GDP disasters with a high signal-to-noise ratio. In particular, the Disaster Index can correctly forecast half of all GDP crashes in our sample, while achieving a reasonable 16.5% false positive rate.

[20] The decaying of the baseline probability over time does not affect the conclusions of this paper. In Table A5, we consider an alternative "zero-one" Disaster Index that is simply equal to one if both *Credit Boom*$_{i,t}$ is in the top quintile and *Market Boom*$_{i,t}$ is in the top tercile, zero otherwise, which, by construction, has no such time-variation in the baseline disaster probability. The results from this alternative analysis are qualitatively similar.

[21] 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.

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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 9.7%, 10.6%, and 7.8% relative to the baseline value of 6.1% 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 evaluate the Disaster Index as a forecaster of future GDP disasters in terms of the statistical tradeoff between true positives (i.e. predicting a GDP disaster that indeed happens) versus false positives (i.e. predicting a crash that actually does not occur) by plotting receiver operator characteristic (ROC) curves in panels B through D. To do so, we use the Disaster Index to forecast future GDP disasters over the period 1950-2021: specifically, for this ROC analysis, a GDP disaster in year t and country i is classified as "predicted" if the Disaster Index for that country in year t-3 is at or above the *p*th percentile of its historical distribution across all countries up to that point in time, and "not predicted" otherwise.

The ROC curve plots the true positive rate (TPR), defined as the fraction of actual GDP disasters that are correctly classified as "predicted", versus the false positive rate (FPR), defined as the fraction of non-GDP crashes that are incorrectly classified as "predicted", by allowing p to range from 0 to 100. As the prediction threshold p increases, the TPR decreases while the FPR also decreases; hence, there is a tradeoff. A better forecaster is one with a better tradeoff as p is varied (i.e. forms an ROC curve higher and to the left). This tradeoff is conventionally measured by the "area under the curve" (AUC) of the ROC plot, which can vary from 50% (a completely uninformative forecaster) to 100% (a perfect forecaster).

Panel B reports the ROC curve for the Disaster Index in predicting annual GDP crashes (AUC = 76%), panel C for predicting BXY peak-to-trough GDP crashes (AUC = 76%), and panel D for predicting Barro-Ursúa GDP disasters (AUC = 73%). In particular, panel B shows that the Disaster Index can achieve a 50% true positive rate over the period 1950-2021, while maintaining a reasonable 16.5% false positive rate.

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For the remainder of this paper, we call this point on the ROC curve, which is marked in red in panel B, the "Disaster Threshold". This threshold corresponds to the Disaster Index being at or above the *p*=48 percentile (relative to its historical distribution across all countries up until year t). While one could choose other thresholds *p*, the 50% TPR / 16.5% FPR point corresponds to similar values that Richter, Schularick, and Wachtel (2021) and Greenwood et al. (2022) argue are reasonable cutoffs that policymakers might adopt when trying to prevent a financial crisis. For the rest of the paper, our convention is to call an episode "predicted" and the Disaster Index "elevated", if the Disaster Index is above this "Disaster Threshold".

Specifically, using this threshold, for the 26 GDP crashes in our sample over the period 1950-2021, 13 crashes are correctly predicted by an elevated Disaster Index (TPR = 50%). For the 1,288 country-year observations corresponding to non-GDP crashes, we find 212 false positives (the Disaster Index is elevated at t-3, yet a crash does not occur in year t), corresponding to FPR = 16.5%. Taken together, the analysis in this section shows that our constructed Disaster Index is a useful out-of-sample predictor of GDP crash risk, which we use in the following section to conduct empirical tests on asset prices.

IV. Asset Pricing Tests

In this section, we use the Disaster Index to test various implications from asset pricing models with time-varying disaster risk. As discussed in Section I, these models generate a positive risk premium for assets with a positive exposure to the disaster risk. Furthermore, the literature has incorporated time-varying disaster risk to explain a wide range of asset pricing phenomena, such as 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. Specifically, the representative agent prices assets that are exposed to

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the time-varying disaster risk with a positive risk premium. Motivated by these models, we put forward the following hypothesis:

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 panel regression:

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

where $r_{i,t\to t+h}$ denotes the cumulative log excess return from holding the portfolio from the beginning of year t to end of year t+h. Equation (2) also includes country fixed effects, α_i. 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 at time t known to predict equity risk premiums: the log(dividend/price) of the equity market index, the inflation rate, and the term spread.

In all panel regressions throughout the paper (assuming the time dimension of the panel T is greater than 25), we implement Driscoll and Kraay (1998) standard errors with Kiefer-Vogelsang (2005) fixed-b critical values and bandwidth parameter of $ceiling(1.3\mathrm{T}^{1/2})$, using the rule-of-thumb recommended by Lazarus et al. (2018). Compared to standard errors double clustered on country and time (to which we resort for panel regressions in which $T < 25$), the advantage of using Driscoll-Kraay standard errors is that in addition to accounting for possible correlations of residuals across countries in each year and autocorrelation of residuals within each country, we also correct for possible cross-autocorrelation of residuals.[22]

[22] Given that $DisasterIndex_{i,t}$ is a "generated regressor", the standard errors in Tables 4-9 could potentially underestimate the true error, since they do not take into account uncertainty about the first-stage coefficients. To address this issue, in Table A7, we re-estimate all our main results (Tables 4-9) with bootstrapped *t*-statistics estimated by drawing bootstrap panel datasets that preserve the cross-sectional and time-series dependence and then estimating the both the first- and second-stage regressions within each bootstrap sample. The main results of the paper and their statistical significance are robust to this alternative approach. In fact, with bootstrapping, the *t*-statistics are often even larger than before. This is because, while accounting for the "generated regressor" decreases the *t*-statistic (since there is uncertainty about the first-stage coefficient estimates), block bootstrapping produces larger *t*-statistics than the Driscoll-Kraay (1998) approach, which perhaps is too conservative in its assumptions. These bootstrapping results additionally help alleviate concerns about the finite-sample performance of Driscoll-Kraay (1998) standard errors.

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Table 4 presents estimated β coefficients from Equation (2), with each value in the table corresponding to a separate regression, with future cumulative return horizons ranging from h=1 to 5.[23] 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 in rows 3-4 and for all subsequent rows, the first row in each set of rows reports β estimates from regressions 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 (i.e., β should be positive), Table 4 reports lower future average returns for the equity market index at 1- to 5-year horizons. For example, over the full sample period of 1870-2021, conditional on a one-percentage point increase in the Disaster Index, the subsequent cumulative two-year market index return is lower than its historical average by 0.873 percentage points.[24,25,26]

[23] 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 variable 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.

[24] In Table A8, we also test our estimated coefficients against the model-implied regression coefficients (H_A: $\beta = \beta_0 > 0$) from Appendix Section A (rather than against the null hypothesis H_0: $\beta = 0$). (Note that these model-implied regression coefficients correspond to regressions of risk premiums on the *true disaster probability* π_t in the model, not our constructed Disaster Index.) Panel A tests Hypotheses 1 and 2 and reports the *t*-statistics corresponding to H_A: $\beta = \beta_0 > 0$ (i.e., the model-implied predictions), which are all greater than 6, corresponding to rejections of the theoretical models at standard critical values. Panel B reports *t*-statistics corresponding to market volatility (1950-2021), the term spread (1950-2021), and D/P of the market index (1950-2021), for which we cannot (in Section IV.B, D, E) reject the null hypothesis (H_0: $\beta = 0$) corresponding to these measures, as the point estimates are generally close to zero and mixed in sign. However, when testing against the model-implied predictions (H_A: $\beta = \beta_0 > 0$), we can now reject H_A for all these risk premium measures at standard critical values. These tests strengthen our interpretation that the evidence is inconsistent with theoretical predictions of time-varying rare disaster models, as opposed to these models just being difficult to test due to sample size concerns associated with rare events.

[25] In Table A9, we report the distribution of returns conditional on both the Disaster Index exceeding the "Disaster Threshold" and whether a GDP crash is observed 2-4 years ahead. Table A9 shows that, conditional on the Disaster Index being elevated and a future disaster occurring, the average returns are highly negative and significant. Conditional on the Disaster Index being elevated and a future disaster *not* occurring, the coefficients are mixed in sign and not significantly different from zero. Our interpretation of these results is that the lower returns conditional on an elevated Disaster Index do not appear to be the result of another factor broadly lowering risk premiums, but rather a reflection of the unanticipated occurrence of the disaster (that causes the market to crash).

[26] To distinguish between global and domestic GDP disasters, we construct several proxies for a global disaster index, and then re-estimate in Table A10 the main results of the paper. In these regressions, we run a "horse race" between each of these global disaster index proxies and the variable "Domestic Disaster Index." Table A10 shows that the global disaster index contributes some explanatory power for future returns and risk premiums, jointly with the "Domestic Disaster Index", but the global disaster index coefficient is only significantly negative in certain

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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, respectively, on the Book/Price (B/P), Dividend/Price (D/P), or Earning/Price (E/P) ratios within each country. Table 4 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 4 shows that as the Disaster Index rises, the equity premium is lower, rather than higher, rejecting Hypothesis 1.

Gabaix (2012) and Tsai and Wachter (2016) also show theoretically 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 these analyses, we 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.

Table 4 shows supporting results from the regression specified in Equation (2) for the B/P-, D/P-, and E/P-based value-growth spread portfolios (rows 9-10, 15-16, 21-22) at horizons from 1 to 5 years.[27] The coefficients are positive and often significant, consistent with theory. However, these positive coefficients for the spread portfolios are mostly 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.[28]

Finally, we test the prediction that value stocks experience a larger contemporaneous decline relative to growth stocks conditional on the occurrence of an economic disaster, as predicted by

specifications and horizons. Overall, our interpretation is that both the domestic and global disaster indexes have negative coefficients, inconsistent with time-varying disaster risk models.

[27] 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.

[28] Table A6 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 results 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).

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theory. 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):

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

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 this prediction of larger contemporaneous declines for value stocks. 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 positive at 17.1%, 13.9%, and 24.6%, all significant at the 1% significance level (columns 1, 3, and 5). However, adding the 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). Panel B shows similar results conditional on an equity market crash: the point estimates are all positive, but only one is significant. Overall, these results from Table 5 are inconsistent with the assumption from theory that value stocks are more exposed than growth stocks, conditional on the occurrence of an economic disaster.

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 estimate the following panel regressions with country fixed effect:

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$$\sigma_{i,t} = \alpha_i + \beta\ DisasterIndex_{i,t} + \epsilon_{i,t} \tag{4}$$

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

where $\sigma_{i,t}$ is the annualized volatility of the market equity index of country i in year t. The second of these specifications examines whether the Disaster Index has an asymmetric effect when above its normal level, where $mean$ is the past mean of $DisasterIndex_{i,t}$ of country i until year t.

Table 6 mostly shows coefficient estimates that are not significantly different from zero. The Disaster Index has a negative but insignificant correlation with market volatility in the full sample period of 1950-2021 (columns 1-2). When looking at the asymmetric effect when the Disaster Index is above its mean (columns 3-4), the coefficient is positive but again 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 is positive and sometimes significant during 1950-2005 but negative and significant during 2006-2021 (columns 5-8, 9-12). While the evidence in Table 6 is mixed, overall, there is no strong evidence to support Hypothesis 3 and evidence over the period 2006-2021 is inconsistent with it.

C. Corporate credit spreads

Gabaix (2012), Gourio (2013), and Wachter (2013) show theoretically that fear of 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 higher credit spreads 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 panel regressions with country fixed effects:

$$CreditSpread_{i,t} = \alpha_i + \beta\ DisasterIndex_{i,t} + \epsilon_{i,t} \tag{5}$$

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

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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 significantly negative coefficients. However, the time span is limited (26 years) with the observations around the 2007-2008 financial crisis likely being influential. We thus split the full sample into two subsamples, 1996-2005 and 2006-2021, finding that a one percentage point increase in the Disaster Index is associated with 0.2- and 4.6-bp decreases (columns 5 and 9), respectively, in corporate credit spreads, with the coefficient for 1996-2005 being insignificant. The results are similar in columns 3, 7 and 11, which look only at increases in the Disaster Index above its historical mean. Controlling in the even-numbered columns for inflation, the term spread, the effective duration of the corporate bond index, and four variables reporting the share of bonds by credit rating in the index (AAA, AA, A, BBB), we find similar or slightly increased coefficient magnitudes. The evidence generally rejects Hypothesis 4, though we note the limited time sample results in the statistical significance being driven in large part by the 2007-2008 financial crisis.

D. Term spread

Gabaix (2012) and Tsai (2013) also employ 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 demand a disaster premium for holding nominal bonds, 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 estimate the following panel regressions with country fixed effects:

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

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

Table 8 shows evidence inconsistent with Hypothesis 5. Over the full sample period of 1950-2021, the correlation between the Disaster Index and the term spread is negative. The correlation is positive but insignificant for the 1950-2005 subsample period (column 5). For the 2006-2021

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subsample period (column 9), the correlation is significantly negative: a one percentage point increase in the Disaster Index is associated with a 5.8-bp decrease in the term spread. When looking at the asymmetric effect when the Disaster Index is above its historical mean (columns 3-4, 7-8, 11-12), the correlation is also significantly negative: a one percentage point rise in the Disaster Index is associated with a 1.5-bp decline in the term spread over the full sample period (column 3). These findings are robust to the addition of contemporaneous inflation as a control variable.[29]

E. Dividend/price ratio of market index

Both Gabaix (2012) and Wachter (2013) show theoretically 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-to-price and earnings-to-price ratios of the equity market index are positively correlated with the Disaster Index.

To test this hypothesis, we estimate the following panel regressions with country fixed effects:

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

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

Table 9 reports no evidence that supports Hypothesis 6. A one percentage point increase in the Disaster Index is associated with an insignificant decline in the dividend/price ratio (column 1) and a significant decline in the earning/price ratio of 7.8 bps (in column 5). In the specification when the Disaster Index is above its historical mean (columns 3-4, 7-8), a one percentage point increase corresponds to declines of 3.5 and 9.0 bps for the dividend/price and earnings/price ratios (columns 3 and 7). These results are robust to including controls (even-numbered columns).

[29] In our sample of developed countries, we find that both a higher Disaster Index and the occurrence of a GDP disaster predict average lower inflation by roughly two percentage points, contrary to the prediction of the Gabaix (2012) and Tsai (2013) models. This is partly since banking crises comprise 40% of GDP disasters, which are often followed by low inflation (e.g., following the 2007-8 financial crises) or deflation (e.g., during the Great Depression). Even after other types of GDP disasters, high inflation does not always occur: While COVID- and WWII-related GDP disasters were on average followed by higher inflation, many countries experienced deflation after WWI-era GDP disasters, when countries severely tightened monetary policy to achieve prewar gold parity. The Gabaix (2012) and Tsai (2013) predictions of higher inflation may apply to emerging market economies, though testing them in these settings is beyond the scope of this paper.

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V. Additional Analyses

In this section, we extend our analysis to address several remaining issues. We start by analyzing the issue of forecast horizons. As the Disaster Index in our main analysis forecasts GDP crashes over a future 2-4 year horizon, our analysis suggests that asset prices do not systematically incorporate the disaster risk predicted by the Disaster Index at such horizons. We thus ask, at what horizon do asset markets first perceive GDP disasters? Our analysis finds that asset markets do anticipate GDP crashes, but only up to around one year ahead.

Our second analysis addresses the following concern. Given that the Disaster Index tends, by design, to better forecast GDP disasters associated with banking crises and other macroeconomic crises and is not designed to forecast GDP disasters associated with wars and natural disasters, one may argue that time-varying disaster risk models may still work for GDP disasters that are not well forecasted by our Disaster Index. To address this issue, we decompose GDP crashes into those that, based on the Disaster Index, are "predicted" versus "unpredicted" (or those that are related to banking crises versus those that are not), and ask whether risk premiums in asset prices better reflect risks of the "unpredicted" or non-banking-crisis GDP crashes. We find no evidence of this.

Third, we address the issue of disaster severity. As our Disaster Index only measures time-varying *probability* of GDP crashes, we also examine whether asset prices reflect the time-varying *severity* of GDP crashes, as highlighted by Gabaix's (2012) model. Lastly, we analyze the over- or underreaction of stock prices conditional on the occurrence of a GDP crash.

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

We first plot event studies of four risk premium measures (equity market volatility, corporate credit spreads, the nominal term spread, and equity dividend-to-price) 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 volatility in panel A, corporate credit spreads in panel B, nominal term spread in panel C, and dividend-to-price in panel D) are plotted in red from t=-5 to t=+5, with t=0 defined as the year of the GDP crash. 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

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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 equity 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-to-price (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 reflects 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.

Our secondary analysis further elucidates the risk-return relationship over multiple future horizons. Table 10 examines several alternative disaster indexes, each forecasting specific horizons ranging from 1 to 5 years ahead, as per the following equations:

$$P\big(\Delta GDP_{i,t+h} < q_{t,0.02}\big) = \Phi[\alpha_0 + \beta_1 (Credit)_{i,t} + \beta_2 (Market)_{i,t} + \beta_3 (Interact.)_{i,t}] \quad \text{(8a)}$$

$$r_{i,t\to t+h} = \alpha_i + \beta\ AltDisasterIndex(h)_{i,t} + \epsilon_{i,t\to t+h} \quad \text{(8b)}$$

For instance, the first row of Table 10 illustrates the use of an alternative disaster index, derived from a first-stage regression (Equation 8a), that exclusively forecasts disasters one year ahead. Subsequently, in a second-stage regression (Equation 8b), this one-year-ahead disaster index is employed to predict market returns at various future horizons. Row 2 in Table 10 follows a similar methodology, but with the disaster index forecasting two years ahead. Rows 3 and 4 replicate this approach for 3- and 4-year-ahead horizons, respectively. Similar to our primary analysis in Section IV, these alternative disaster indexes are calculated using rolling probit regressions, using non-censored versions of credit growth, past returns, and their interaction term as predictors.

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Table 10 finds positive second-stage coefficients (consistent with Marfè and Pénasse 2023) for the one-year-ahead disaster index, but negative coefficients (consistent with our results in Section IV) for the two-, three-, and four-year ahead disaster indexes. The fact that the coefficient reverses sign between the 1- and 2-year ahead forecast horizons suggests that there is a "Minsky moment" roughly one year prior to the actual realization of a GDP crash. That is, financial markets tend to positively price in disaster risk contemporaneously and at one-year-ahead horizons, but not at longer future horizons before this "Minsky moment." This finding helps explain the divergent results between our paper and prior work that analyzes shorter forecast horizons.

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 half of GDP crashes (13 out of the 26) with a reasonable 16.5% false positive rate over the postwar period of 1950-2021, 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" 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 three years prior to the crash is above the "Disaster Threshold" defined in Section III.C, 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 the analysis of this subsection, we re-include the WWI/WWII periods (1914-1919 and 1939-1949), 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

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analysis allows us to compare the war-related downturns during these periods to evaluate whether these GDP disasters conform with model predictions.

Table 11 summarizes the frequency and severity of peak-to-trough GDP crashes by disaster category (banking crisis, war, natural disaster or epidemic, and other),[30] and by predictability using the Disaster Index ("predicted", "unpredicted", "WWI/WWII period"). Table A1 lists the full categorization of all individual GDP disasters by category type and by predictability. Most "predicted" disasters are banking crises (14 out of 18), while "unpredicted" disasters are roughly half banking crises and half natural disasters (9 and 8, respectively, out of 19). Interestingly, the GDP disasters associated with banking crises tend to be more severe if they are predicted (-15% decline for predicted ones versus -13% for unpredicted ones). War disasters, on the other hand, almost all (22 out of 23) fall 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%).[31]

Figure 5 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 in Figure 5. For all three categories, the four risk premium measures (equity volatility, corporate credit spreads, the nominal term spread, and equity dividend-to-price) show no evidence of being elevated more than one year ahead of either the "unpredicted" or war-period GDP crashes. Thus,

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[30] "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).

[31] Ferguson (2006) and Berkman, Jacobsen, and Lee (2011) are two related papers that provide divergent evidence on whether the anticipation of wars is reflected in asset prices. Ferguson (2006) provides evidence—broadly consistent with our conclusions—that British bond markets were repeatedly surprised by the outbreak of wars over the period 1843-1914 and that bond markets exhibited declining sensitivity to political events over this period. To bond market investors, the outbreak of WWI in August 1914 came as a "bolt from the blue" (Ferguson, 2006, p. 70): bond yields did not rise until July 30, 1914, even though, as Ferguson (2006) documents, to international observers in real time, the risk of a European-wide war was high and growing since the assassination of Franz Ferdinand in June 1914. In contrast, Berkman, Jacobsen, and Lee (2011) find that geopolitical crises around the world are priced into both U.S. and world stock markets, consistent with time-varying disaster risk models. Their paper analyzes a set of 447 geopolitical crises, which include both more minor events like a Peruvian helicopter getting shot down in 1981 in a border dispute with Ecuador to more major events like the Cuban Missile Crisis in 1962. This paper shows that such events lead to contemporaneous stock declines and increased stock volatility, D/P, and E/P. However, these crises do not predict higher future stock returns. One drawback of this paper is that these geopolitical crisis events are not shown to predict realized GDP disasters. An alternative interpretation of these results could be that investors dislike government policy uncertainty, as in Pastor and Veronesi (2012).

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neither the "unpredicted" nor the WWI/WWII episodes display stronger predictability of the risk premium measures for the realizations of GDP crashes than for the "predicted" episodes.

Figure 6 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 display 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 for unpredicted disasters by the Disaster Index than predicted ones and stronger predictability of non-banking-crisis disasters than banking-crisis-related ones. 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.

C. Do risk premiums predict disaster severity?

Disaster risk may vary over time along two dimensions—either in probability or severity of disaster shocks. Wachter (2013) models time-varying disaster risk as the predictability in the probability, while Gabaix (2012) highlights the predictability in the severity. Thus far, our analysis has focused on the Disaster Index based on the *probability* of GDP disasters. It is possible that asset prices may reflect a risk premium for time-varying severity of disaster risk, rather than time-varying probability. Given that it is challenging to directly construct a measure of time-varying severity of disaster risk, we instead adopt an indirect approach to examine the cross-sectional relationship between risk premiums embedded in asset prices and their predictability of the peak-to-trough severity of GDP crash episodes. We rely on a simple argument that if the risk premium is driven by time-varying severity of disaster risk, then there should be a positive correlation between the ex-ante risk premium and the ex-post realized magnitude of GDP crashes.

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Based on our entire sample starting in 1870, we group peak-to-trough GDP crashes into six global episodes: World War I, post-World War I, the Great Depression, World War II, the Global Financial Crisis, and the 2020 pandemic. We estimate the following regression:

$$Severity_{i,t} = \beta\ Risk\ Premium_{i,t-h} + \epsilon_{i,t}, \tag{10}$$

$Severity_{i,t}$ denotes the peak-to-trough decline of the GDP crash episode with GDP peak occurring at time t, and $Risk\ Premium_{i,t-h}$ is one of the following four risk premium measures: equity volatility, corporate credit spreads, the nominal term spread, and the equity dividend-to-price ratio.

Table A13 reports results from Equation (10), estimated either cross-sectionally within each of these six global episodes (columns 2-7) or pooling all six episodes and using a specification with episode fixed effects (column 1).[32] Across different risk premium measures, global episodes, and predictability horizons, Table A13 shows no systematic evidence of the ex-ante risk premium positively predicting the ex-post severity of GDP disasters, except for occasionally positive coefficients for the term spread and dividend-to-price ratio during the World War II and 2020 Pandemic episodes. The other significant coefficients are all negative, and most coefficients in Table A13 are not significantly different from zero. Taken together, Table A13 shows that the risk premium embedded in asset prices is unlikely to reflect time-varying severity of disaster risk.

D. Do stock prices over- or underreact to disaster occurrence?

Throughout most of the paper, we focus on the disaster risk probability confronting the representative investor prior to a disaster's initial occurrence. However, we briefly explore risk premium dynamics as the disaster is unfolding to distinguish between two classes of models to

[32] Each row in Table A13 corresponds to a different predictability horizon: risk premiums are variously measured at years t-3, t-2, and t-1 (rows 1-3), relative to GDP crash episodes with GDP peaks at time t. To mitigate potential biases associated with measuring risk premium at a particular point in time, Table A13 also examine two alternative specifications in rows 4 and 5:

$$Severity_{i,t} = \beta \min(Risk\ Premium_{i,t-5}, \dots\ , Risk\ Premium_{i,t-1}) + \epsilon_{i,t}$$
$$Severity_{i,t} = \beta \max\left(Risk\ Premium_{i,t-5}, \dots\ , Risk\ Premium_{i,t-1}\right) + \epsilon_{i,t}$$

where $\min(Risk\ Premium_{i,t-5}, \dots)$ or $\max(Risk\ Premium_{i,t-5}, \dots)$ are the minimum (maximum) risk premium value over years t-5 through t-1 within each country. The intuition of analyzing the minimum is to test whether unusually low risk premiums (i.e., the lowest point across years t-5 to t-1) predict more severe GDP disasters, consistent with the hypothesis that times of unusually low risk premiums contribute to future crises. The fact that the maximum also negatively predicts crisis is more surprising and shows that even the highest level of risk premiums in the run-up still does not correctly predict future disaster severity.

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explain those dynamics: those that invoke extrapolative expectations (e.g., Bordalo, Gennaioli and Shleifer 2018, Krishnamurthy and Li 2021, Maxted 2023) and those that invoke rational learning (e.g., Ghaderi, Kilic, and Seo 2022, Wachter and Zhu 2023). While there are exceptions to this categorization, models of extrapolative beliefs generally predict asset price overreaction upon disaster realization, as agents overreact to recent bad news. In contrast, several prominent models of rational learning generally predict asset price underreaction (e.g., Ghaderi, Kilic, and Seo 2022), as agents only slowly learn whether they are in a disaster regime and update their beliefs as successive bad news arrives.[33]

Table 12 analyzes whether the stock market over- or underreacts to the occurrence of a GDP disaster. Coefficient estimates are reported corresponding to the estimation of Equation (11) below, which regresses the market index excess return in year t ($r_{i,t}$) on last year's excess return ($r_{i,t-1}$), interacted with an indicator variable of whether year t is a GDP disaster ($Disaster_{i,t}$). The timing assumption inherent in Equation (11) is that the market crashes at t-1 in advance of the GDP disaster at t (as demonstrated in Section V.A for most historical disasters); thus, this table analyzes potential momentum or reversion in returns in year t, conditional on the return in year t-1.

$$r_{i,t} \;=\; \beta_1\, r_{i,t-1} \times \left(1 - Disaster_{i,t}\right) \;+\; \beta_2\, r_{i,t-1} \times \left(Disaster_{i,t}\right) \;+\; \epsilon_{i,t} \qquad (11)$$

Table 12 generally shows evidence consistent with overreaction (i.e., reversion) of stock returns conditional on disasters realizations. Column 2 reports estimates of the baseline specification for Equation (11) and finds reversion conditional on a GDP disaster. Column 3 shows this overreaction is primarily driven by reversion after negative returns during disasters. Columns 4-7 restrict the definition of GDP disasters to the four different types of disasters: banking crises,

[33] Models of overoptimistic beliefs before crises are difficult to distinguish empirically from a third class of models emphasizing intermediation frictions (e.g., He and Krishnamurthy 2012, Brunnermeier and Sannikov 2014). Both types of models generally predict low risk premiums before crises and high, overreacting risk premiums during crises. While it is beyond the scope of the current paper to distinguish these views, several recent papers take up this challenge. Baron and Xiong (2017) show that credit booms predict highly negative average bank returns, suggesting that bank equity investors do not anticipate crisis risk (in contrast to models of intermediation frictions, which predict a low but still positive risk premiums). Similarly, Krishnamurthy and Li (2021) test a model incorporating both intermediation frictions and time-varying sentiment and conclude that time-varying sentiment is needed to account for the observed "frothy" pre-crisis behavior.

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natural disasters, wars, and other. The results in these columns often show overreaction, except in the case of natural disasters, in which no over- or underreaction is detected.[34]

V. Conclusions

We have developed a Disaster Index as an objective measure for forecasting GDP crashes, based on economic and financial instability associated with rapid credit expansions and asset market booms. This index successfully forecasts half of the GDP crashes with a low false positive rate. Contrary to the positive disaster risk premiums predicted by asset pricing models with a representative investor and time-varying disaster risk, our Disaster Index negatively predicts future returns of the equity market index and portfolios of value and growth stocks. Furthermore, our findings challenge model predictions that time-varying disaster risk should be positively correlated with increased equity market volatility, larger corporate credit spreads, wider nominal term spreads, and higher equity dividend-to-price ratios. The Disaster Index is not positively correlated with these traditional asset pricing variables and, in many cases, is significantly negatively correlated.

These findings bring to light the challenge, as noted by Chen, Dou, and Kogan (2019), in reliably measuring fluctuations in disaster risks, especially given the limitations of finite historical data. This difficulty is echoed in our findings, suggesting that market participants may struggle to accurately assess disaster risk, potentially leading to asset prices that do not reflect objective, time-varying disaster risks. This misalignment might contribute to the "this time is different" thinking highlighted by Reinhart and Rogoff (2009), where borrowers and lenders fail to recognize rising financial risks during credit booms. Gennaioli, Shleifer and Vishny (2013) further highlight this neglect of disaster risk as a key driver of financial innovations that fuel credit expansions. Our results, though divergent from standard disaster risk models, could reflect an alternate perspective where many GDP disasters are endogenous, arising from financial markets that either overlook risk or exhibit heightened risk appetite. This is particularly relevant for banking crisis disasters, which constitute approximately 40% of the GDP disasters in our sample.

[34] Note that the overreaction cannot simply be explained by potential GDP recoveries (Nakamura et al. 2013), since investors should not be systematically surprised by recoveries in a rational model (i.e., asset prices should not be systematically predictable).

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Our results do not negate the influence of disaster risk on asset prices. Instead, they suggest a disconnect between the disaster risk perceived by market participants and the objective disaster risk captured by the Disaster Index. Given the rarity of actual disaster realization, subjective beliefs about disaster risk are hard to empirically validate and are thus likely shaped 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 as to how investors form their subjective beliefs about disaster risk.

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Table 1: Summary statistics

	N	Mean	Median	SD	1%	5%	10%	90%	95%	99%
Excess Return										
Market	1788	0.033	0.044	0.230	-0.637	-0.356	-0.249	0.289	0.370	0.625
High B/P	856	0.064	0.101	0.284	-0.799	-0.453	-0.275	0.370	0.453	0.641
Low B/P	856	0.043	0.079	0.248	-0.699	-0.418	-0.276	0.305	0.372	0.550
High-Low B/P	856	0.006	0.028	0.241	-0.758	-0.371	-0.255	0.250	0.331	0.532
High D/P	857	0.068	0.100	0.256	-0.797	-0.350	-0.225	0.328	0.447	0.573
Low D/P	857	0.040	0.073	0.261	-0.725	-0.459	-0.311	0.311	0.384	0.628
High-Low D/P	857	0.001	0.027	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	1788	0.021	0.022	0.033	-0.087	-0.034	-0.015	0.057	0.070	0.104
Credit Expansion	1788	0.011	0.010	0.030	-0.083	-0.030	-0.017	0.041	0.058	0.092
Market Volatility	1279	0.154	0.129	0.097	0.038	0.059	0.072	0.261	0.322	0.594
Credit Spread	514	1.225	1.020	0.914	0.230	0.380	0.480	2.030	3.000	4.900
Term Spread	1377	1.008	0.990	1.815	-4.291	-1.748	-0.727	2.850	3.461	6.629
Dividend/Price	1280	0.037	0.034	0.019	0.009	0.014	0.017	0.061	0.072	0.094
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 1939-1949 are excluded.

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

Disaster type	Annual definition N	Annual definition Frequency	Annual definition Severity	Peak-to-trough definition N	Peak-to-trough definition Frequency	Peak-to-trough definition Severity	Peak-to-trough definition 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	44	2.2%	-8.3%	37	4.4%	-12.1%	2.4
Also BU	21	1.0%	-10.5%	14	2.9%	-21.1%	4.1
Non-BU	23	1.1%	-6.2%	23	1.6%	-6.7%	1.4
1870-1949	18	2.9%	-11.8%	13	6.9%	-21.2%	3.3
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. 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. The world war periods of 1914-1919 and 1939-1949 are excluded in calculating statistics in the first three subsections of this table ("Baron, Xiong, Ye (BXY)", "Barro, Ursúa (BU)", "Included in regressions"), but included in the last subsection of this table ("BXY (incl. WWI/WWII)"). "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 of the future GDP crash indicator, $MarketBoom_{i,t}$, and $CreditBoom_{i,t}$). 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.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$CreditBoom_{i,t}$	0.032***		0.029***	0.012		0.010	
	[2.66]		[2.79]	[0.83]		[0.69]	
$MarketBoom_{i,t}$		0.038**	0.034**	0.017		0.025	
		[2.11]	[2.07]	[1.01]		[1.50]	
$Interaction_{i,t}$				0.025*	0.039***	0.027**	0.042***
				[1.92]	[2.87]	[2.17]	[3.04]
Observations	1788	1788	1788	1788	1788	1788	1788
Pseudo R^2	0.036	0.024	0.056	0.066	0.062	0.082	0.075
Sum of Marginal Effects	0.032	0.038	0.063	0.054	0.039	0.062	0.042
Controls	No	No	No	No	No	Yes	Yes
Conditional Probability	0.088	0.082	0.112	0.120	0.112	0.128	0.118
Baseline Probability	0.062	0.062	0.062	0.062	0.062	0.062	0.062

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 variables. $CreditBoom_{i,t}$ is Credit Expansion standardized using only past information at each point in time, then left censored at zero. Similarly, $MarketBoom_{i,t}$ is the past three-year cumulative log excess return of the market index standardized using only past information at each point in time, then left censored at zero. $Interaction_{i,t}$ is $CreditBoom_{i,t}$ multiplied by $MarketBoom_{i,t}$. 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 $CreditBoom_{i,t}$ and $MarketBoom_{i,t}$ being in their top quintile and tercile, respectively. 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 1939-1949).

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Table 4: Future equity returns conditional on the Disaster Index

	Controls?	Year 1 (1)	Year 2 (2)	Year 3 (3)	Year 4 (4)	Year 5 (5)
(1) Market (1870-2021)	No	-0.276*** [-2.60]	-0.873*** [-2.82]	-1.274*** [-2.76]	-1.386** [-2.14]	-1.455** [-1.97]
(2) Market (1870-1949)	No	-0.210** [-2.03]	-0.593*** [-3.13]	-0.924*** [-3.32]	-0.814** [-2.51]	-0.781** [-2.53]
(3) Market (1950-2021)	No	-0.248 [-1.60]	-0.980** [-2.02]	-1.451** [-1.99]	-1.665* [-1.77]	-1.764* [-1.70]
(4)	Yes	-0.279** [-2.19]	-1.033*** [-3.73]	-1.508*** [-3.39]	-1.720*** [-2.74]	-1.825*** [-2.58]
(5) High B/P	No	-0.316 [-1.38]	-1.480*** [-3.04]	-2.102*** [-5.38]	-2.320*** [-6.54]	-2.452*** [-5.14]
(6)	Yes	-0.071 [-0.31]	-1.072** [-2.28]	-1.625*** [-3.90]	-1.804*** [-5.06]	-1.828*** [-4.12]
(7) Low B/P	No	-0.463*** [-2.93]	-1.999*** [-7.80]	-3.031*** [-7.02]	-3.416*** [-4.49]	-3.346*** [-3.47]
(8)	Yes	-0.199 [-1.27]	-1.449*** [-6.66]	-2.303*** [-6.50]	-2.620*** [-3.93]	-2.458*** [-3.02]
(9) High-Low B/P	No	0.248 [0.92]	0.733 [1.45]	1.257*** [2.58]	1.523*** [2.62]	0.978 [0.90]
(10)	Yes	0.255 [0.99]	0.616 [1.28]	1.010** [2.05]	1.213** [2.17]	0.667 [0.65]
(11) High D/P	No	-0.380* [-1.67]	-1.913*** [-3.12]	-2.964*** [-5.23]	-3.249*** [-7.60]	-3.390*** [-6.50]
(12)	Yes	-0.173 [-0.80]	-1.565*** [-2.59]	-2.537*** [-4.31]	-2.816*** [-7.18]	-2.875*** [-6.17]
(13) Low D/P	No	-0.773*** [-6.00]	-2.265*** [-12.21]	-3.207*** [-9.23]	-3.644*** [-5.69]	-3.755*** [-4.99]
(14)	Yes	-0.504*** [-3.04]	-1.711*** [-8.01]	-2.493*** [-8.54]	-2.845*** [-4.93]	-2.846*** [-4.41]
(15) High-Low D/P	No	0.491** [2.36]	0.907** [1.97]	0.998* [1.79]	1.100 [1.63]	1.071 [1.33]
(16)	Yes	0.462** [2.56]	0.755* [1.80]	0.790 [1.51]	0.821 [1.26]	0.776 [1.01]

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	Controls?	Year 1 (1)	Year 2 (2)	Year 3 (3)	Year 4 (4)	Year 5 (5)
(17) High E/P	No	-0.557*** [-3.20]	-2.075*** [-4.14]	-2.988*** [-6.29]	-3.246*** [-8.49]	-3.438*** [-6.45]
(18)	Yes	-0.320** [-2.25]	-1.655*** [-3.44]	-2.466*** [-4.87]	-2.687*** [-7.75]	-2.805*** [-6.44]
(19) Low E/P	No	-0.338* [-1.71]	-1.741*** [-6.05]	-2.872*** [-10.05]	-3.512*** [-6.51]	-3.808*** [-5.62]
(20)	Yes	-0.078 [-0.34]	-1.190*** [-3.80]	-2.148*** [-8.18]	-2.704*** [-6.11]	-2.914*** [-5.37]
(21) High-Low E/P	No	-0.188* [-1.68]	0.109 [0.42]	0.502* [1.68]	0.848*** [2.59]	0.905** [2.11]
(22)	Yes	-0.165 [-1.42]	0.067 [0.26]	0.420 [1.37]	0.734** [2.11]	0.800* [1.75]

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 1939-1949), the second row for the pre-1950 sample (1870-1949, excluding the world war periods 1914-1919 and 1939-1949), 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 report results with 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 lag = 16 (rows 1), lag = 12 (row 2), and lag = 12 (row 3 onward) and Kiefer-Vogelsang fixed-b critical values. *, **, *** correspond to p-values less than 10%, 5%, 1%, respectively.

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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
	[3.11]	[0.27]	[7.28]	[0.22]	[10.79]	[0.83]
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
	[0.83]	[0.83]	[1.87]	[1.87]	[1.00]	[1.00]
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 12 lags and Kiefer-Vogelsang fixed-b critical values. *, **, *** correspond to p-values less than 10%, 5%, 1%, respectively. Observations are across 20 economies, 1950-2021.

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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)
$\texttt{DisasterIndex}_{i,t}$	-0.107	-0.110			0.017	0.055			-0.448	-0.427*		
	[-0.91]	[-0.93]			[0.25]	[1.01]			[-1.60]	[-1.86]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			0.086	0.063			0.191**	0.188**			-0.320***	-0.349**
			[0.80]	[0.73]			[2.63]	[2.62]			[-3.36]	[-2.58]
Observations	1,279	1,279	1,279	1,279	960	960	960	960	319	319	319	319
Adjusted R^2	0.032	0.038	0.030	0.036	0.044	0.112	0.054	0.118	0.000	0.195	-0.012	0.188
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 12 lags and Kiefer-Vogelsang fixed-b critical values (columns 1-8) or standard errors double clustered on country and time (columns 9-12, since $T \leq 25$). *, **, *** 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)
$\texttt{DisasterIndex}_{i,t}$	-2.596**	-2.597***			-0.192	-0.273			-4.580**	-4.575*		
	[-2.00]	[-3.01]			[-0.73]	[-1.16]			[-2.39]	[-2.05]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-2.502**	-2.532***			-0.244	-0.238			-3.598***	-4.463**
			[-2.24]	[-2.85]			[-0.95]	[-1.37]			[-4.10]	[-2.26]
Observations	514	514	514	514	196	196	196	196	318	318	318	318
Adjusted R^2	0.049	0.426	0.044	0.422	0.218	0.435	0.218	0.435	0.080	0.458	0.064	0.453
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 7 lags and Kiefer-Vogelsang fixed-b critical values (columns 1-4) or standard errors double clustered on country and time (columns 5-12, since $T \leq 25$). *, **, *** 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).

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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)
$\texttt{DisasterIndex}_{i,t}$	-0.949	-1.364			0.440	-0.417			-5.798***	-6.222***		
	[-0.65]	[-1.13]			[0.41]	[-0.43]			[-4.07]	[-3.33]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-1.478*	-1.846**			-0.726	-1.312*			-5.304***	-5.755***
			[-1.77]	[-2.35]			[-1.15]	[-1.95]			[-5.40]	[-3.27]
Observations	1,377	1,377	1,377	1,377	1,057	1,057	1,057	1,057	320	320	320	320
Adjusted R^2	0.088	0.122	0.088	0.123	0.103	0.126	0.103	0.127	0.222	0.223	0.215	0.215
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 lag = 12 (columns 1-4) or lag = 10 (columns 5-8) and Kiefer-Vogelsang fixed-b critical values, or standard errors double clustered on country and time (columns 9-12, since $T \leq 25$). *, **, *** 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)
$\texttt{DisasterIndex}_{i,t}$	0.000	-0.000			-0.078***	-0.080***		
	[0.01]	[-0.00]			[-5.63]	[-5.10]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-0.035	-0.037			-0.090***	-0.092***
			[-1.13]	[-1.16]			[-3.73]	[-3.64]
Observations	1,280	1,280	1,280	1,280	890	890	890	890
Adjusted R^2	0.186	0.192	0.192	0.198	0.119	0.119	0.120	0.120
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 12 lags and Kiefer-Vogelsang fixed-b critical values. *, **, *** correspond to p-values less than 10%, 5%, 1%, respectively. Results are estimated across 20 economies, 1950-2021.

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Table 10: Alternative disaster indexes forecasting at different horizons

Using the:	Market return$_{t,t+1}$ (1)	Market return$_{t,t+2}$ (2)	Market return$_{t,t+3}$ (3)	Market return$_{t,t+4}$ (4)	Market return$_{t,t+5}$ (5)	Volatility$_t$ (6)	Credit spread$_t$ (7)	Term spread$_t$ (8)	D/P$_t$ (9)	E/P$_t$ (10)
(1) 1-year-ahead disaster forecast	1.336**	3.433**	4.688	5.377	6.947**	-0.026	25.417**	5.899	0.498***	0.846***
	[2.22]	[2.11]	[1.51]	[1.52]	[2.11]	[-0.03]	[2.24]	[1.45]	[6.12]	[5.26]
(2) 2-year-ahead disaster forecast	-1.519*	-3.665**	-5.473***	-6.022***	-5.565**	-0.358	-0.911	-5.034	0.191	0.15
	[-1.90]	[-2.47]	[-3.12]	[-2.91]	[-2.44]	[-0.80]	[-0.29]	[-0.80]	[1.35]	[1.19]
(3) 3-year-ahead disaster forecast	-0.299*	-1.154**	-1.648**	-1.885*	-1.988*	-0.026	-2.982**	-1.278	-0.016	-0.098***
	[-1.83]	[-2.16]	[-2.09]	[-1.86]	[-1.82]	[-0.20]	[-2.05]	[-0.91]	[-0.40]	[-4.00]
(4) 4-year-ahead disaster forecast	-0.163	-0.764*	-1.081	-1.246	-1.316	0.04	-2.768*	-0.656	-0.011	-0.113***
	[-1.56]	[-1.74]	[-1.47]	[-1.25]	[-1.25]	[0.38]	[-1.80]	[-0.54]	[-0.29]	[-3.84]

This table reports estimates from Equation (8), which builds and analyzes alternative disaster indexes that forecast at different horizons. In the first row, for example, an alternative disaster index is first estimated that forecasts disasters at the *1-year-ahead horizon only*; then, in a second stage regression, this new one-year-ahead disaster index is used to predict market returns at future horizons (columns 1-5) or contemporaneous risk premium measures (columns 6-10). Row 2 is similar, except that the disaster index forecasts disasters at a 2-year-ahead horizon only, and rows 3 and 4 are analogous for 3- and 4-year-ahead horizons. As in our main analysis, these alternative disaster indexes are estimated as rolling probit regressions with three predictor variables: 3-year past market index returns, 3-year past change in bank credit-to-GDP, and their interaction term. (Unlike for the main Disaster Index earlier in the paper, past market returns and past change in bank credit-to-GDP are not left-censored at zero for these disaster indexes, to allow for the fact that market crashes and credit contractions do predict disasters at the one-year-ahead horizon.) The four alternative disaster indexes are plotted in Appendix Figure A1. This table stops at Row 4 because the 5-year-ahead disaster index (and beyond) have minimal forecasting power for future disasters, and thus second-stage regressions cannot be estimated.

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Table 11: 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	14	1	2	1	18	-15%	-9%	-27%	-9%	-15%
Unpredicted	9	8	0	2	19	-13%	-7%		-7%	-10%
Disaster Index not available	6	0	0	10	16	-15%			-13%	-14%
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 period 1870-2021, decomposed by disaster category (banking crisis, natural disaster or epidemic, war, or other) and 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 above the "Disaster Threshold" (as defined in Section II.C) three years prior to the first associated annual "GDP crash", and "unpredicted" otherwise. In the third and fourth rows, we also tabulate statistics of GDP disasters for which the Disaster Index is not available (i.e., if either $MarketBoom_{i,t}$ or $CreditBoom_{i,t}$ is missing in year $t-3$ for a "GDP crash" occurring in year t) or which occur within the excluded world war periods of 1914-1919 and 1939-1949.

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Table 12: Overreaction in stock prices conditional on the occurrence of GDP disasters

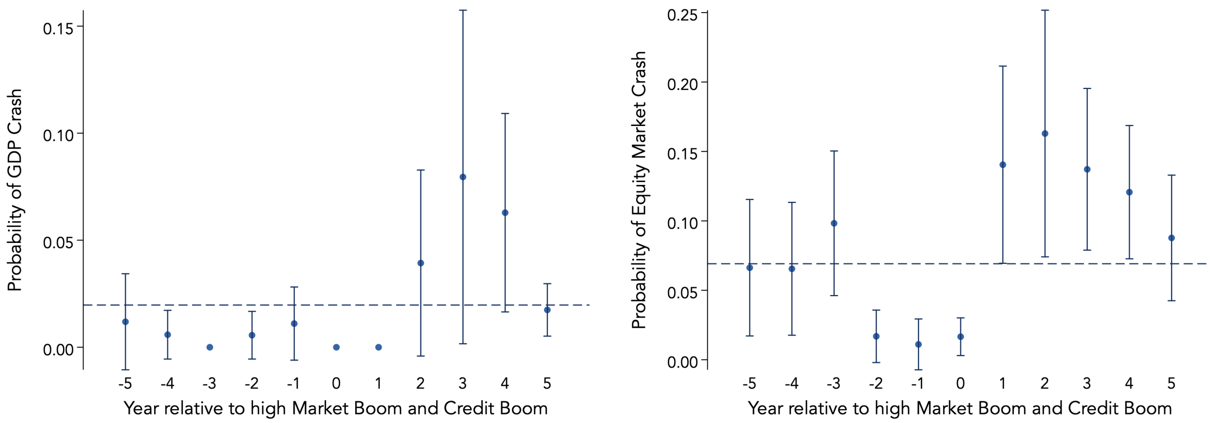
	All Types of Disasters			Banking Crises	Natural Disasters	Wars	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$r_{i,t-1}$	0.03						
	[1.29]						
$r_{i,t-1} \times (1 - Disaster_{i,t})$		0.04		0.04	0.03	0.04	0.03
		[1.59]		[1.41]	[1.34]	[1.38]	[1.32]
$r_{i,t-1} \times Disaster_{i,t}$		-0.26**		-0.90***	0.02	-0.34*	-0.33
		[-2.54]		[-3.79]	[0.04]	[-1.67]	[-1.33]
${r_{i,t-1}}^{--} \times (1 - Disaster_{i,t})$			0.09				
			[1.12]				
${r_{i,t-1}}^{++} \times (1 - Disaster_{i,t})$			0.02				
			[0.50]				
${r_{i,t-1}}^{--} \times Disaster_{i,t}$			-0.31*				
			[-2.02]				
${r_{i,t-1}}^{++} \times Disaster_{i,t}$			-0.16				
			[-0.99]				
$Disaster_{i,t}$		-0.03	-0.05	-0.32***	0.19***	0.03	-0.03
		[-0.66]	[-0.79]	[-3.33]	[8.05]	[0.38]	[-0.69]
Constant	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***
	[38.12]	[21.83]	[6.12]	[30.74]	[38.29]	[31.14]	[37.91]
Observations	2459	2459	2459	2459	2459	2459	2459
R^2	0.01	0.01	0.01	0.02	0.01	0.01	0.01

This table reports estimates from Equation (11) that analyzes whether the stock market over- or underreacts to the occurrence of a GDP disaster. The dependent variables in these regressions is the country's annual excess total return in year t of the broad market index, denoted $r_{i,t}$. The timing assumption inherent in Equation (11) is that the market crashes at $t-1$ in advance of the disaster at t (as previously demonstrated for most historical disasters); thus, this table analyzes potential momentum or reversion in returns in year t, conditional on the return in year $t-1$. The regressors are: $Disaster_{i,t}$, an indicator variable that takes the value of one, if country i has an annual GDP disaster in year t; $r_{i,t-1}$, the country's previous-year excess return. Columns 1-3 consider all disasters in the sample, whereas columns 4-7 restrict the definition of disasters to four different types. Columns 1 estimates persistence in returns across the entire sample, column 2 conditions the persistence on disaster versus non-disaster years, and column 3 further splits past-year returns into those that are positive or negative (${r_{i,t-1}}^{--} = \min(0, r_{i,t-1})$ and ${r_{i,t-1}}^{++} = \max(0, r_{i,t-1})$). All specifications use country fixed effects, and standard errors are clustered by country. Regressions are estimated over the entire sample, 1870-2021. Before 1920, real returns are not substituted for excess returns when the short-term interest rate is missing, since measurement error in inflation likely gives rise to false persistence in real returns. *, **, *** correspond to p-values less than 10%, 5%, 1%, respectively.

Figure 1: Realized probabilities of GDP 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 $CreditBoom_{i,t}$ and $MarketBoom_{i,t}$ being in the top quintile and top tercile respectively at time $t = 0$. 95% confidence intervals are plotted based on Driscoll-Kraay standard errors with 16 lags and Kiefer-Vogelsang fixed-b critical values. For comparison, the dashed line indicates the average crash probability during "normal times" (i.e., outside of all five-year windows when $CreditBoom_{i,t}$ and $MarketBoom_{i,t}$ are jointly in the top quintile and top tercile). The quintiles of $CreditBoom_{i,t}$ and the terciles of $MarketBoom_{i,t}$ are defined based on the distribution of these variables across all countries and only past information at each point in time. These event studies are constructed around 175 country-year observations with both $CreditBoom_{i,t}$ in the top quintile and $MarketBoom_{i,t}$ in the top tercile, from a sample of 20 countries covering 1870-2021 (excluding the world war periods 1914-1919 and 1939-1949).

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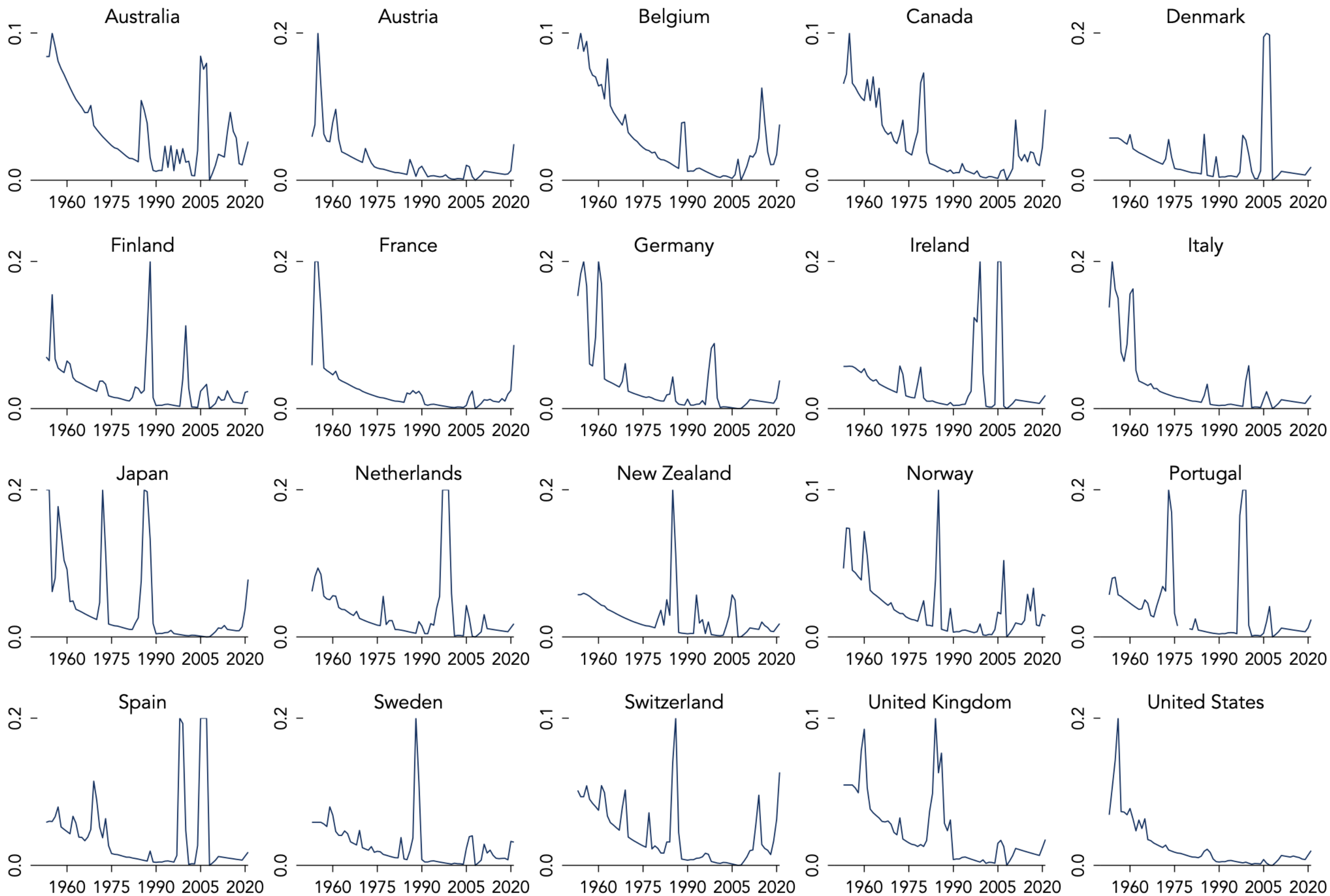
Figure 2: The Disaster Index across 20 economies, 1950-2021



Observations: 1377. Mean: 0.059. Median: 0.045. SD: 0.047. Min: 0.033. Max: 0.674. 25%: 0.039. 75%: 0.063.

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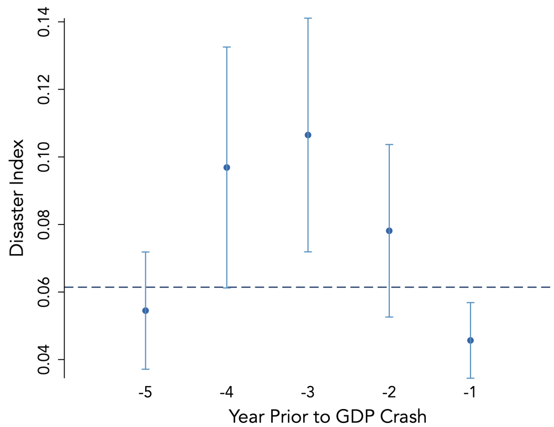
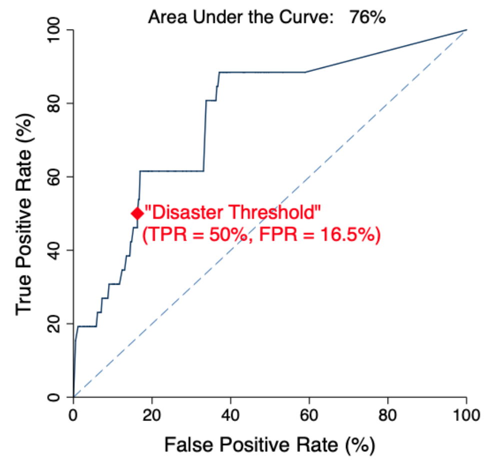
Figure 3: Sensitivity and specificity of the Disaster Index as a predictor of GDP disasters

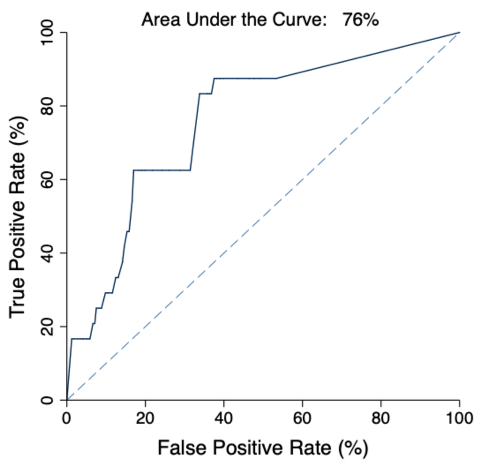
Panel A: Average level prior to a GDP crash



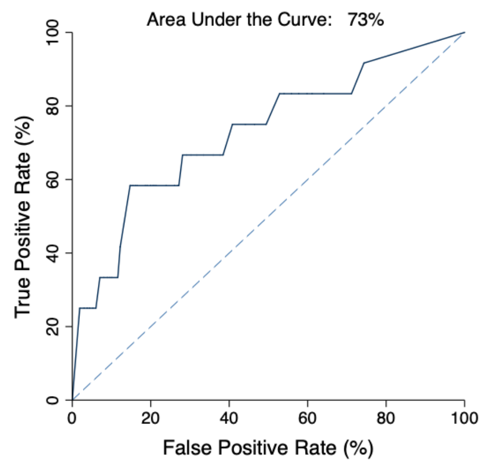
Panel B: ROC curve for annual GDP crashes



Panel C: ROC curve for BXY peak-to-trough GDP disasters



Panel D: ROC curve for Barro-Ursúa GDP disasters



Panel A plots the average level of the Disaster Index from $t = -5$ to -1 conditional on an annual GDP crash at time $t = 0$. 95% confidence intervals are plotted based on Driscoll-Kraay standard errors with 16 lags and Kiefer-Vogelsang fixed-b critical values. 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 receiver operator characteristic (ROC) curve to assess the accuracy of the Disaster Index to predict annual GDP crashes. In constructing the ROC curve, a GDP crash in year t is classified as "predicted" if the Disaster Index in year $t - 3$ is above the pth percentile of its historical distribution across all countries up to that point in time, and "not predicted" otherwise, where p is allowed to range from 0 and 100. The True Positive Rate (y-axis) is the percentage of GDP crashes that are correctly classified as "predicted". The False Positive Rate (x-axis) is the percentage of non-GDP crashes that are incorrectly classified as "predicted". Panel C replicates the ROC curve from Panel B but instead uses the first annual GDP crash associated with each BXY peak-to-trough GDP disasters as the event being predicted. Panel D replicates the ROC curve from Panel B but instead uses Barro-Ursúa GDP disasters as the event being predicted.

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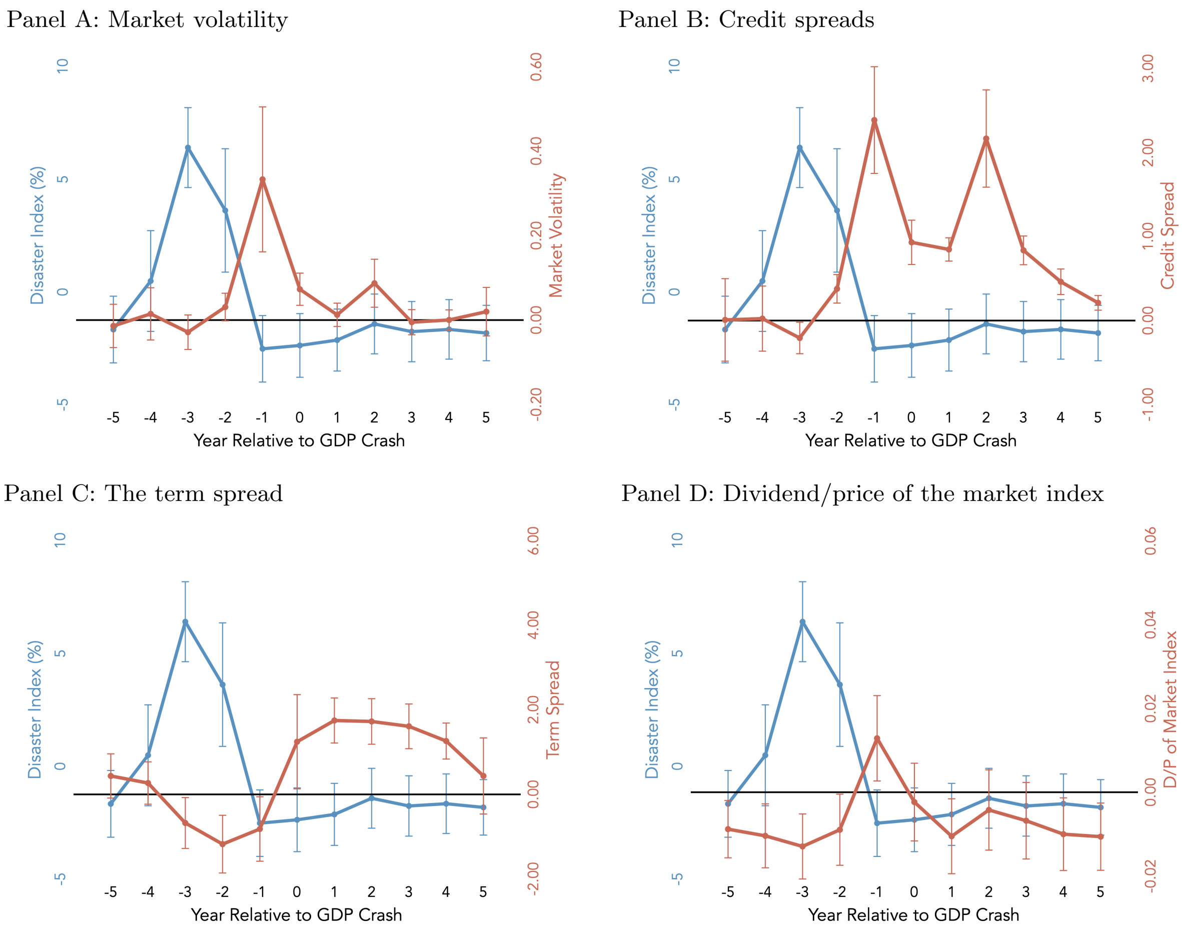
Figure 4: Risk premium measures around GDP crashes: an event study



This figure presents the Disaster Index (blue line) and realized market volatility (Panel A, red line), credit spreads (Panel B), the term spread (Panel C), and the 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 12 lags (for the Disaster Index, market volatility, term spread, and dividend/price ratio) or 7 lags (for credit spreads) and with Kiefer-Vogelsang fixed-b critical values. These event studies are based on all BXY peak-to-trough GDP disaster episodes across 20 countries, 1950-2021.

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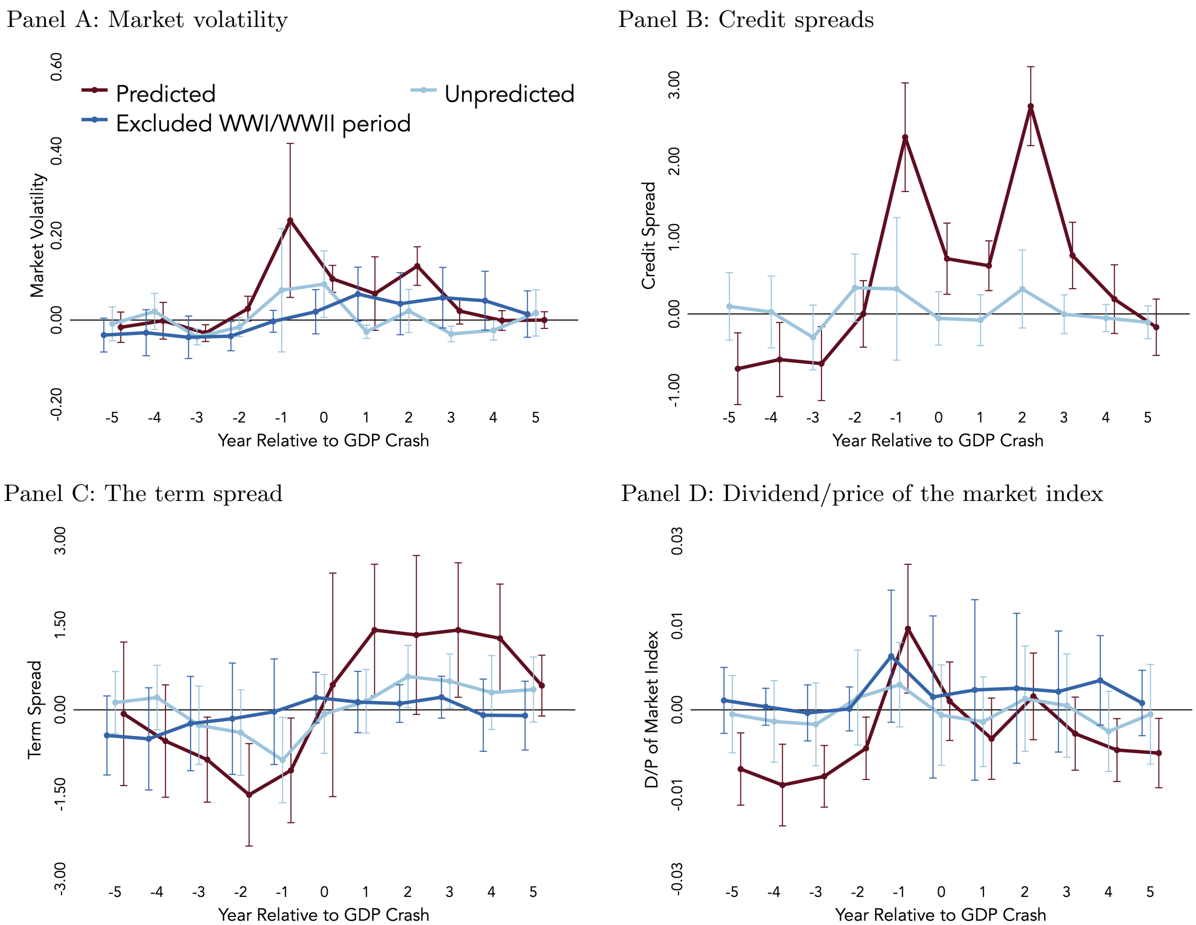
Figure 5: Risk premium measures around GDP crashes: predicted versus unpredicted crashes



This figure presents realized market volatility (Panel A), credit spreads (Panel B), the term spread (Panel C), and the 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 or not. A GDP disaster is defined as "predicted" by the Disaster Index if the Disaster Index is above the "Disaster Threshold" (as defined in Section II.C) 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 1939-1949. 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 $MarketBoom_{i,t}$ or $CreditBoom_{i,t}$ 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 12 lags (for the Disaster Index, market volatility, term spread, and dividend/price ratio) or 7 lags (for credit spreads) and with Kiefer-Vogelsang fixed-b critical values. 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.

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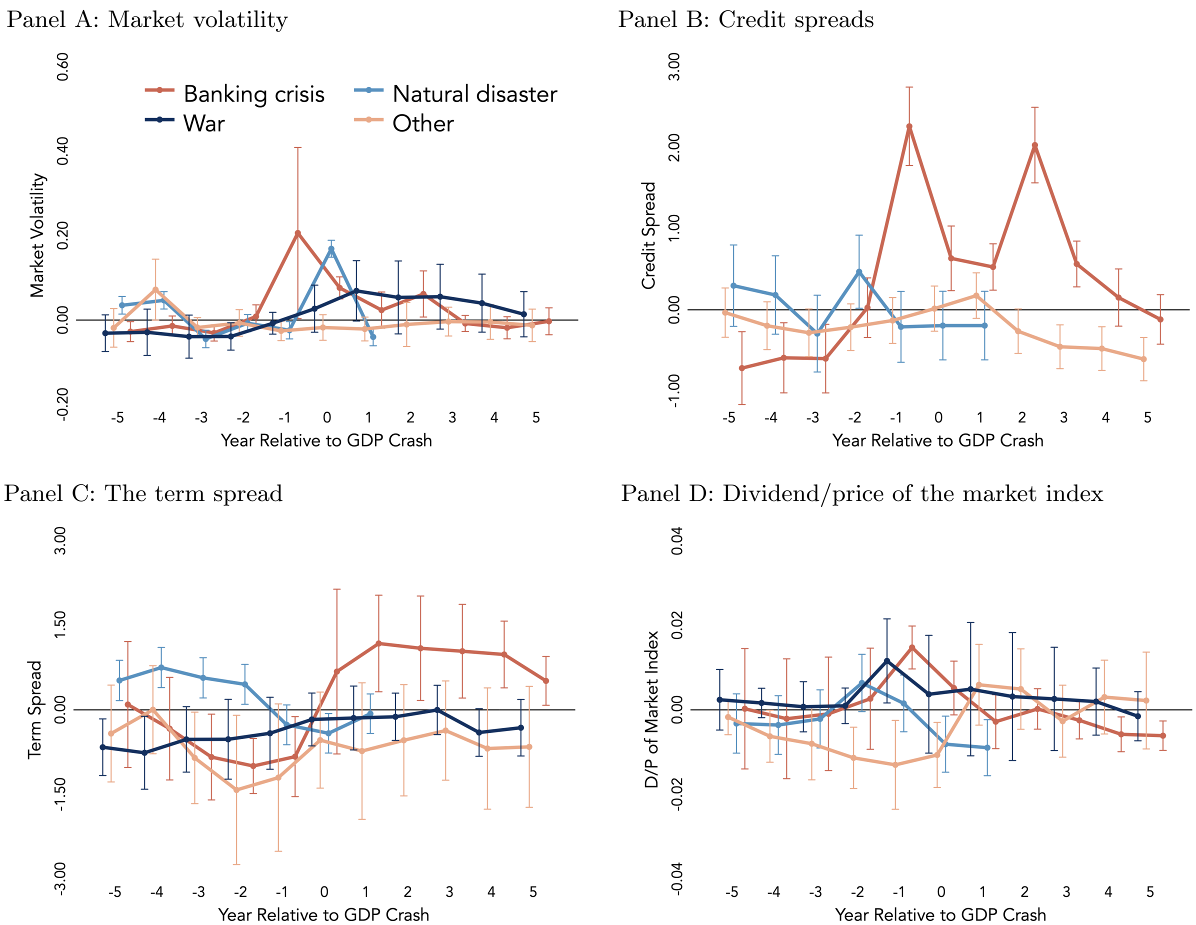
Figure 6: Risk premium measures around GDP crashes: by disaster category



This figure presents realized market volatility (Panel A), credit spreads (Panel B), the term spread (Panel C), and the 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 12 lags (for the Disaster Index, market volatility, term spread, and dividend/price ratio) or 7 lags (for credit spreads) and with Kiefer-Vogelsang fixed-b critical values. 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.

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Internet Appendix

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

Matthew Baron, Wei Xiong, and Zhijiang Ye

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A. Testing rational expectations models with the Disaster Index

We start by describing how we test specific models in the literature, such as Wachter (2013), Gabaix (2012), Tsai and Wachter (2015, 2016), and Marfè and Pénasse (2023), along with variations on these models, under the assumption of rational expectations. We show that *a robust feature of a broad range of these models* is that the Disaster Index must predict the equity risk premium with a positive coefficient. (One important issue that we will address is how the Disaster Index maps into these models, given that it does not directly appear in these models.) Thus, a negative coefficient estimate in our empirical test is a rejection of these models. Importantly, we also allow in this framework for a variety of asset classes and potential refinements of the models from the literature, which we show do not change the core prediction of a positive model-implied regression coefficient.

Aligning with standard practices in asset pricing research, we assume that investors process information rationally and form expectations about time-varying disaster probability π_t accordingly. The combination of rational beliefs with time-varying disaster risk is core to the purpose of these models, as their main appeal lies in their potential to provide a unified and succinct account for numerous asset pricing anomalies and the dynamics of risk premiums both during normal times and crises, circumventing the need to rely on more complicated theories of investor behavior and subjective beliefs.

We start by tracing through a variety of rational expectations models, extracting the model-implied coefficient estimates, all positive in magnitude. In these models—Wachter (2013), Gabaix (2012), Tsai and Wachter (2015, 2016), Marfè and Pénasse (2023), and others—the true time-varying disaster probability π_t is public information within these models and known perfectly by the representative investor (though not measurable by the econometrician). We first show that all these models imply a positive coefficient between the disaster probability π_t and risk premiums or future equity returns. This is true for our main asset pricing test with future stock index returns and HML portfolios (corresponding to Table 4) and for the tests with volatility, credit spreads, term spread, and D/P (corresponding to Tables 6-9).

We start with the regression of future excess equity index returns on the disaster probability π_t (analogous to Equation (2) that we estimate in the main paper). In Wachter's (2013) calibration,

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the regression coefficient is $\beta_0 = 2.0$ (taken from the slope of Figure 3 in her paper) for one-year-ahead excess returns. To generalize this prediction to other horizons, we follow the model of Marfè and Pénasse (2023), who log-linearized Wachter's (2013) model into a more tractable framework, though with slightly different calibration parameters. Marfè and Pénasse (2023) calculate a theoretical $\beta_0 = 1.68$ for one-year-ahead excess returns, 3.94 for three-year-ahead cumulative excess returns, and $\beta_0 = 5.31$ for five-year-ahead cumulative excess returns.[35]

In Appendix Section C, we reproduce Marfè and Pénasse (2023)'s log-linearized exposition of Wachter's (2013) model, along with the calibration assumptions from their paper, so the reader can see how these theoretical values for the regression coefficients β_0 are calculated. Their calibration assumes relatively standard parameter estimates from the disaster risk literature: a relative risk aversion parameter of 5, a mean disaster size of -9.9%, and a "leverage factor" of 2.6 (i.e., log dividends are assumed to fall by 2.6 times the fall in consumption), among other parameter choices. Any increase in these parameters would lead to a higher theoretical β_0, since worse disasters or higher risk aversion would make the representative agent more fearful of disasters and thus increase β_0. Therefore, we take the Marfè and Pénasse (2023) estimates as *lower bounds* on β_0. If we reject these lower values of β_0, then the other higher values (e.g., $\beta_0 = 2.0$ from Wachter (2013)) would also likewise be rejected.

The only class of model that might produce weaker, but still positive, estimates of β_0 is that of Nakamura et al. (2013) and Barro and Jin (2021), which allow for disasters to unfold over multiple years and consumption to partially recover in a subset of disasters. (These models, as written, have a constant disaster probability and are written to explain the unconditional equity premium. Our point in discussing them is that adapting these models to a rational time-varying disaster risk framework would not reverse the core logic of why time-varying disaster risk models fail.) Estimating these dynamics on historical macroeconomic data, Nakamura et al. (2013) show that these modifications reduce the equity premium (and thus the implied β_0) by a factor of ten,

[35] We take these theoretical values of the regression coefficients β_0 from the 2016 working paper version of Marfè and Pénasse (2023), since their 2023 version no longer calculates theoretical values for β_0. For purposes of empirically testing these model-implied coefficients (see Table A8), we interpolate to get values for the 2- and 4-year horizons of $\beta_0 = 2.81$ and $\beta_0 = 4.63$, respectively.

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relative to the baseline Reitz-Barro model with one-period permanent consumption drops. However, because this model no longer matches the average equity premium and other key facts of long-run data, they then reverse this drop in the equity premium and restore the original value by increasing the coefficient of relative risk aversion (CRRA) to 6.4 and the intertemporal elasticity of substitution (IES) to 2. Following the totality of Nakamura et al.'s (2013) approach, we thus leave the theoretical benchmark from Marfè and Pénasse (2023) unchanged at $\beta_0 = 1.68$, as otherwise—by allowing slowly unfolding disasters and recoveries but without modifying the CRRA and IES—the model would miss the unconditional equity premium and other key facts of long-run data by a factor of ten.

Similarly, we look for theoretical values of β_0 corresponding to the other asset classes and risk premiums. Appendix Section C reports methodological details for how these coefficient values are calculated and from which papers they are taken. To summarize all the model-implied predictions:

- Market portfolios at 1-, 2-, 3-, 4-, 5-year horizons: 1.68, 2.81, 3.94, 4.63, 5.31
- HML value portfolios at 1-year horizon, $\beta_0 = 1.7$ (Tsai and Wachter 2016)
- Stock volatility, $\beta_0 = 0.76$ (Marfè and Pénasse 2023)
- D/P, $\beta_0 = 1.19$ (Marfè and Pénasse 2023)
- Credit spreads, $\beta_0 = 0.087$ (Wachter 2013)
- Term spread, $\beta_0 = 1.7$ (Tsai 2013)

We next connect the Disaster Index to the models by showing that these models imply a positive regression coefficient between the Disaster Index and risk premiums, even though the Disaster Index does not directly feature in these models. We assume that the econometrician does not observe π_t (even though it is public information to agents in the model) and can only estimate the Disaster Index based on the data, which we further assume is a noisy signal of the true π_t. We show that, in these types of models and under these assumptions, it is impossible to have the Disaster Index negatively predict the equity risk premium or other risk premiums, and thus a negative coefficient estimate in our empirical test is a rejection of these model.

The econometrician can only observe the Disaster Index x_t, which we assume is positively correlated with, but not exactly equal to, π_t:

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$$\text{corr}(x_t, \pi_t) > 0 \tag{A.1}$$

A key prediction of all models in this class is that there is positive relationship between the equity premium and the time-varying disaster probability π_t:

$$\text{Equity premium} = \alpha_0 + \beta_0 \pi_t \tag{A.2}$$

For simplicity, Equation (A.2) is presented as linear, following Marfè and Pénasse's (2023) log-linearization of Wachter (2013), but the overall argument holds more generally as long as the equity premium is monotonically increasing in π_t, as in Wachter (2013), Gabaix (2012), and other models. It therefore follows from Equations (A.1) and (A.2) that, if these models are true, then x_t must also be positively correlated with the equity premium, since:

$$\text{corr}(x_t, \text{equity premium}_t) = \text{corr}(x_t, \alpha_0 + \beta_0 \pi_t) = \beta_0 \,\text{corr}(x_t, \pi_t) > 0 \tag{A.3}$$

If this relationship does not hold in the data, then the model is rejected. This argument similarly holds for other measures we test, such as the stock dividend-price ratio and volatility, because the theoretical models all predict positive relationships analogous to Equation (A.2).

B. Models with investor beliefs

We next relax the assumption of rational expectations, which allows us to consider the class of disaster risk models with rational learning or other belief formation processes, such as those by Collin-Dufresne, Johannes, and Lochstoer (2016), Ghaderi, Kilic, and Seo (2022), and Wachter and Zhu (2023), in addition to models with more general investor beliefs. In these models, we formally test the joint hypothesis that: 1) the model is true *and* 2) there is no "disconnect" between subjective beliefs and objective disaster probabilities within the model. By "disconnect", we mean a near-zero or negative correlation between subjective beliefs and objective disaster probabilities within the model, as we formalize and explain below. Thus, for any proposed model, a negative coefficient estimated from the data implies either: 1) a rejection of the model or 2) a "disconnect" between subjective beliefs and objective disaster probabilities within the model.

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Consider the following framework for testing a given model. In the class of models we are testing, the objective time-varying disaster probability π_t is unobservable to agents in the model (and also to the econometrician). Assume the representative investor has beliefs s_t about the time-varying disaster probability (which the econometrician cannot observe either) and that in the model *Equity Premium*$_t$ = $\alpha_0 + \beta_0\, s_t$, analogous to the formulation in Wachter (2013). Furthermore, assume that the joint hypothesis is true: specifically, that the correlation between the investor's beliefs s_t and the true disaster probability π_t must be sufficiently high: that is, $\text{corr}(s_t, \pi_t) > \rho_{\text{agent}}$, where $\rho_{\text{agent}} > 0$ is a constant that is the assumed lower bound on $\text{corr}(s_t, \pi_t)$. If the joint hypothesis is not true and the actual correlation between the agent's beliefs and the actual disaster probability is lower than this ρ_{agent}—in other words, either near zero or negatively correlated—we will say that there is a "disconnect" between subjective beliefs and objective disaster probabilities within the model. For the purposes of our empirical tests, $\text{corr}(s_t, \pi_t)$ is assumed to be bounded below by 0.65 (i.e., $\rho_{\text{agent}} = 0.65$), under our joint hypothesis that s_t and π_t are not too "disconnected." (Note that $\rho_{\text{agent}} = 0.65$ is chosen deliberately so that the resulting model-implied regression coefficient will be positive under this assumption, as we will see).

As before, we assume that the econometrician can only observe the Disaster Index x_t, a noisy but informative signal of the true underlying time-varying disaster probability π_t: i.e., $\text{corr}(x_t, \pi_t) > 0$. Based on all the above assumptions, we now argue that the Disaster Index x_t and the investor's beliefs s_t must be positively correlated: i.e., $\text{corr}(x_t, s_t) > 0$. The intuition is that if both processes x_t and s_t are decently precise signals of the true underlying disaster probability π_t, then they must be positively correlated with each other.[36] Mathematically, this follows from the following fact from probability theory, which says that $\text{corr}(x_t, s_t)$ is bounded between $[\text{corr}(x_t, \pi_t)\, \text{corr}(s_t, \pi_t) \pm (1-\text{corr}(x_t, \pi_t)^2)^{1/2}\, (1-\text{corr}(s_t, \pi_t)^2)^{1/2}]$. If $\text{corr}(x_t, \pi_t) \approx 0.77$, an estimate that is implied by

[36] Another way to get this result that the econometrician's signal x_t and the investor's beliefs must be positively correlated is to assume that the econometrician's signal takes the following form: $x_t = \pi_t + e_t$, where we assume $\text{corr}(e_t, \pi_t)=0$ and $\text{corr}(e_t, s_t - \pi_t) > 0$. (Intuitively, $\text{corr}(e_t, \pi_t)=0$ is an assumption that econometrician optimally extracts the signal from the data, and $\text{corr}(e_t, s_t - \pi_t) > 0$ is an assumption that the noise terms in the agent's and econometrician's signals are not negatively correlated.) However, these are strong assumptions about the functional form of the signals, so this is not our preferred route. If these assumptions hold, then one can see that $\text{corr}(x_t, s_t) > 0$, since $\text{cov}(x_t, s_t) = \text{cov}(\pi_t + e_t, s_t) = \text{cov}(s_t, \pi_t) + \text{cov}(e_t, s_t) > 0$.

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our empirical regression results in Table 3 (see calculations in the Appendix Section C for details), and $corr(s_t, \pi_t) > \rho_{agent} = 0.65$ by assumption, then:

$$
\begin{aligned}
corr(x_t, s_t) &\geq [corr(x_t, \pi_t)\, corr(s_t, \pi_t) - (1-corr(x_t, \pi_t)^2)^{1/2}\, (1-corr(s_t, \pi_t)^2)^{1/2}] \\
&> 0.77*0.65 - sqrt(0.41*0.58) = 0.013 > 0 \qquad \text{(A.4)}
\end{aligned}
$$

It then follows that:

$$corr(x_t, \text{equity premium}_t) = corr(x_t, \alpha_0 + \beta_0\, s_t) = \beta_0\, corr(x_t, s_t) > 0 \qquad \text{(A.5)}$$

Thus, if we find a negative coefficient in the data, our test implies either that: 1) the model is rejected or 2) there is a “disconnect” between subjective beliefs and objective disaster probabilities (i.e., the correlation is low or negative). As this extensive discussion above shows, we do not need to assume that the Disaster Index and agents’ beliefs in a rational disaster risk model are the same for this argument to work. Yet, a robust feature of these models remains that the Disaster Index must predict the equity risk premium with a positive coefficient under the assumptions of the joint hypothesis.

To see how one might employ our joint hypothesis, consider a proposed model in which behavioral biases or institutional frictions lead investors to have subjective beliefs that are uncorrelated (or negatively correlated) with *ex post* disaster realization frequencies. This might be, for example, a model of “this time is different” thinking in which investors hold the (incorrect) belief that financial regulation or assertive monetary policy in the post-1945 period have eliminated the possibility that credit booms and market booms lead to banking crises with severe GDP declines. Our empirical findings would not be inconsistent with such models. However, if one believes such a model provide the “correct” description of reality, then a negative estimated regression coefficient implies that there is a strong “disconnect” between subjective beliefs and objective disaster probabilities with this model.

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C. A log-linearized model of time-varying disaster risk

C.1. The baseline model

The following model is a log-linearized version of the model from Wachter (2013) and is taken directly from the exposition of Marfè and Pénasse (2023), whose setup and notation we reproduce below. Consider a pure-exchange economy with a representative investor with recursive Epstein-Zin-Weil preferences. For tractability, the elasticity of intertemporal substitution is set to one. As a result, the log value function of the representative investor normalized by consumption, denoted $V_t \equiv logV_t/C_t$, is given by:

$$V_t = \frac{\delta}{1-\gamma} log\mathbb{E}_t e^{(1-\gamma)(\Delta c_{t+1}+V_{t+1})} \tag{A.6}$$

where δ is the time discount factor, γ is the relative risk aversion, and $\Delta c_{t+1} = logC_{t+1}/C_t$ is consumption growth. The dynamics of consumption growth evolve according to:

$$\Delta c_t = \mu + \sigma\epsilon_t + v_t \tag{A.7}$$

where μ and σ are constants, ϵ_t is a standard normal random variable, and v_t is the "disaster" term, modeled as a compound Poisson shock: $v_t = J_t 1_{N_t \neq N_{t-1}}$. N_t is a Poisson counting process and the disaster event $N_t \neq N_{t-1}$ has size described by a random variable J_t, which has a time-invariant distribution that is independent from all other shocks in the model. J_t is governed by the moment generating function $Z(u) = \mathbb{E}_t[e^{uJ_t}]$. The intensity of disaster arrivals is time-varying and modeled by the following discretized square-root process:

$$\pi_t - \bar{\pi} = \rho(\pi_{t-1} - \bar{\pi}) + \nu\sqrt{\pi_{t-1}}u_t \tag{A.8}$$

where $\bar{\pi} > 0$, $0 < \rho < 1$, and $\nu > 0$ are constants and u_t is a standard normal random variable uncorrelated with ϵ_t. In the model, stocks pay dividends that are assumed to fall more than consumption: $\Delta d_{t+1} = \Phi\Delta c_{t+1}$, where $\Phi > 1$ is referred to as the "leverage factor".

We skip over the details of solving this model and jump to the main result. According to Marfè and Pénasse (2023), who solve for the equilibrium, the log equity premium is given by:

$$log\mathbb{E}_t\left[e^{r_r^{equity}}\right] - r_t^f = \gamma\Phi\sigma^2 + \left[(\gamma-1)k_1 p_\pi v_\pi \nu^2\right]\pi_t + \left[Z(\Phi) + Z(-\gamma) - Z(\Phi-\gamma) - 1\right]\pi_t \tag{A.9}$$

The parameters used in the above equation are summarized below. The parameters in bold are the specific values that we adopt.

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- γ = relative risk aversion coefficient = 3 (Wachter 2013), **5** (Marfè and Pénasse 2023), or 6 (Nakamura et al. 2013)

- Φ = "leverage factor" = **2.6** (Wachter 2013)

- σ = consumption volatility (in normal times outside of disasters) = 2.0% (Wachter 2013) or **2.8%** (Marfè and Pénasse 2023)

- $k_1 = e^{pd}/(1 + e^{pd})$, where $pd = log(P_t/D_t)$ is the log dividend-price ratio. Marfè and Pénasse (2023) call k_1 an "endogenous constant" in the model. We set $k_1 = 1/(1 + D_t/P_t) \approx (1 - D_t/P_t) \approx$ **0.95**, assuming a "constant" D/P ratio of 5%. Obviously, this ratio is not constant in the model but a function of π_t. However, in practice, variation in k_1 will be small, and k_1 will hover just under 1 and not contribute much quantitatively to variation in the second term of the equity premium.

- ν = the volatility of π_t = **0.24** (Marfè and Pénasse 2023). Wachter (2013) uses 0.067, but Marfè and Pénasse (2023) argue this is not consistent with the data.

- δ = time discount factor = 0.988 (Wachter 2013) or **0.99** (Marfè and Pénasse 2023).

- ρ = mean-reversion constant of π_t = 0.920 (Wachter 2013) or **0.75** (Marfè and Pénasse 2023)

- $Z(u) = \mathbb{E}_t[e^{uJ_t}]$, the moment generating function governing the time-invariant distribution of the disaster size J_t. Marfè and Pénasse (2023) use $Z(u) = \frac{1}{1+u\alpha}e^{-u\theta}$, where $\theta = 0.057$ and $\alpha = 0.042$. This results in a distribution of disaster magnitudes with a minimum disaster size of $-\theta = -5.7\%$ and a mean of $-(\theta + \alpha) = -9.9\%$.

- $p_\pi = \frac{1}{k_1^2\nu^2}\left[\Omega - \sqrt{\Omega^2 + 2k_1^2\nu^2\left[Z(1-\gamma) - Z(\Phi-\gamma)\right]}\right]$, a function of the parameters $k_1, \nu, v_\pi, \rho, \gamma, \Phi$, where $\Omega = 1 - (1-\gamma)k_1^2\nu^2 v_\pi \rho$.

- $v_\pi = \frac{-(1-\delta)(1-\gamma) - \sqrt{(1-\gamma)^2(1+\delta(\delta+2\delta\sigma^2-2) - 2\delta\sigma^2 Z(1-\gamma))}}{\delta(1-\gamma)^2\sigma^2}$, a function of the parameters $\delta, \gamma, \sigma, \Phi$.

C.2. Calibrating the model with parameters

Plugging in the parameter values above, the log equity premium is:

$$\begin{aligned} log\mathbb{E}_t\left[e^{r_r^{equity}}\right] - r_t^f &= \gamma\Phi\sigma^2 + \left[(\gamma-1)k_1 p_\pi v_\pi \nu^2\right]\pi_t + \left[Z(\Phi) + Z(-\gamma) - Z(\Phi-\gamma) - 1\right]\pi_t \\ &= 0.010 + 1.387\pi_t + 0.185\pi_t \end{aligned} \tag{A.10}$$

resulting in $\beta_0 = 1.387 + 0.185 = 1.57$.

Note that, in both Wachter (2013) and Marfè and Pénasse (2023), the parameters are essentially chosen to get β_0 in the range of 1 to 2, in order match the unconditional equity premium (estimates of which range from 4 to 7%). To see this, note that if the unconditional disaster probability ($\mathbb{E}\pi_t$) in the data is approximately 3%, then the unconditional equity premium, using Equation (A.10) is approximately $(1.0\% + \beta_0 * \mathbb{E}\pi_t) = 1.0\% + 1.57 * 3\% = 5.7\%$.

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We can try other calibrations. If the disasters are even more severe (let the mean disaster size increase from -9.9% to -11.5%, i.e., let $\theta = 0.68$), then $\beta_0 = 3.0$.

C.3. Coefficient predictions for other asset classes and risk premium measures

Stock market volatility. For stock market variance, the Wachter (2013) model predicts the following, according to the log-lineared exposition of Marfè and Pénasse (2023):

$$Equity\ variance_t = \Phi^2\sigma^2 + k_1^2 p_\pi^2 \nu^2 \pi_t + \Phi^2 \mathbb{E}_t(J_{t+1}^2)\pi_t \tag{A.11}$$

with $\mathbb{E}_t(J_{t+1}^2) = \frac{d^2 Z(u)}{du^2} \mid_{u=0} = 2\alpha^2 + \theta^2 + 2\alpha\theta$.

A linear approximation of $Equity\ volatility_t = \sqrt{Equity\ variance_t}$ around the approximate average disaster probability of $\bar{\pi} = 3\%$ yields a slope coefficient of $\frac{k_1^2 p_\pi^2 \nu^2 + \Phi^2 \mathbb{E}_t(J_{t+1}^2)}{2\sqrt{\Phi^2\sigma^2 + k_1^2 p_\pi^2 \nu^2 \bar{\pi} + \Phi^2 \mathbb{E}_t(J_{t+1}^2)\bar{\pi}}} = 0.76$. Similarly, in Figure 4 of Wachter (2013), the slope of the tangent line around $\bar{\pi} = 3\%$ is approximately 1.8. For a lower average disaster probability, the slope is higher, due to the concavity of the square root function. Thus, we take 0.76 as a lower bound on the coefficient for our empirical tests.

HML portfolios. Tsai and Wachter (2016) construct a model in which time-varying rare disasters give rise to a value premium. (This model is more complicated than the baseline model from Wachter (2013), so we do not attempt to reproduce the model in closed form here.) The calibrated model results from Tsai and Wachter (2016) for the value-growth spread are shown in their paper's Figure 2, Panel A. In this figure, the slope of the tangent line around $\bar{\pi} = 3\%$ is β_0 =1.7, which is the predicted coefficient that we use in our tests. Their model is based on the book-to-market definition of the value premium. We assume the same coefficient for spread portfolios formed on dividend-to-price and earnings-to-price.

Dividend yield. For the dividend yield, the Wachter (2013) model predicts the following, according to the log-lineared exposition of Marfè and Pénasse (2023):

$$d_t/P_t = e^{-p_0 + p_\pi \pi_t} \approx 1 - p_0 - p_\pi \pi_t \tag{A.12}$$

where $p_0 = log(k_1) - log(1 - k_1) - p_\pi \bar{\pi}$ and p_π is given above. This yields a slope of $-p_\pi$ = 1.19.

Credit spreads. For credit spreads, Wachter's (2013) model predicts the following excess return for a risky bond (modified to allow for an arbitrary loss rate conditional on default):

$$r_t^B - r_t^f = q\left[Z(\Phi) + Z(-\gamma) - Z(\Phi - \gamma) - 1\right]\pi_t \tag{A.13}$$

The assumption in the model is that the bond is an overnight interest-bearing claim that has a probability of default

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q if a disaster realization occurs (with percentage loss in default equal to the fall in consumption) and 0 otherwise. Calibrating this model with $q = 0.19$ (calculated as the average corporate bond default rate averaged across the five worst crises in US history since 1866, from Giesecke, Longstaff, Schaefer, and Strebulaev (2010)) and $\Phi = 10$ (which implies a 35% recovery rate for a -10% consumption disaster and a 10% recovery rate for a -20% consumption disaster), we get a predicted coefficient of $\beta_0 = 0.087$.

Term spread. Tsai (2013) constructs a model in which there are two types of time-varying disaster risk: real disaster risk (as considered in Wachter (2013)) and inflation disaster risk, which gives rise to a nominal bond term premium. Figure 5 from Tsai (2013) plots results from a calibrated model for the return premium of five-year nominal government bond over the risk-free rate. In this figure, the slope is approximately $\beta_0 = 1.7$, which is the predicted coefficient that we use in our tests. (For longer-maturity bonds, the slope would be higher, according to Tsai (2013), so $\beta_0 = 1.7$ represents a conservative lower bound for our tests.

D. Additional mathematical details

In this section, we explain some final mathematical details related to mapping the Disaster Index into a general framework of time-varying disaster risk with learning or subjective beliefs. As explained previously, we assume that the econometrician observes a noisy signal x_t (i.e., the "Disaster Index") of the true time-varying disaster probability π_t and that $corr(x_t, \pi_t) > 0$. We then test models under the assumption that the correlation between the investor's beliefs s_t and the true disaster probability π_t must sufficiently high: that is, $corr(s_t, \pi_t) > \rho_{agent}$, where $\rho_{agent} > 0$ is assumed to be 0.65. If this is not the case, then we say that there is a "disconnect" between subjective beliefs and objective disaster probabilities. More precisely, we are testing the joint hypothesis that the model is true AND $corr(s_t, \pi_t) > \rho_{agent}$. If we find a negative coefficient in the data, then our test implies either that the model is rejected OR that there is a disconnect between objective and subjective beliefs.

Based on all the above assumptions, we now argue that the Disaster Index x_t and the investor's beliefs must be positively correlated: i.e., $corr(x_t, s_t) > 0$. The intuition is that if both signals are decently precise signals of the underlying disaster probability t, then they must be positively correlated with each other.

In Appendix Section B, we showed that $corr(x_t, \pi_t) > 0$ and $corr(s_t, \pi_t) > \rho_{agent}$ imply $corr(x_t, s_t) > 0$ if the first two correlations are sufficiently high. This follows from the mathematical formula that says that $corr(x_t, s_t)$ is bounded between $corr(x_t, \pi_t)corr(s_t, \pi_t) \pm \sqrt{(1 - corr(x_t, \pi_t)^2)(1 - corr(s_t, \pi_t)^2)}$.

$corr(s_t, \pi_t) > \rho_{agent}$ is high by assumption. What about the level of $corr(x_t, \pi_t)$? We can estimate a reasonable value for this based on our data. Similar to the probit regressions in Table 3 of the main paper, we can estimate a linear regression model that regresses observed disaster outcomes over the next 2-4 year horizons on $Interaction_{i,t}$ (essentially, our Disaster Index x_t), which estimates an $R^2 = corr(1_{disaster(t=2,3,4)}, Interaction_{i,t})^2 = 0.070$. However,

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since $1_{disaster(t=2,3,4)}$ is an indicator variable of realized disasters and not the underlying time-varying probability of $\pi_{i,t}$ (unobserved and corresponding to the model we are testing), we need to use $corr(1_{disaster(t=2,3,4)}, x_t)$ to produce an estimate of $corr(\pi_{i,t}, x_t)$. Since the observed realized disasters $1_{disaster(t=2,3,4)}$ are realized Bernoulli observations that equal 1 with probability $\pi_{i,t}$ and 0 with probability $(1 - \pi_{i,t})$, it follows (assuming $\bar{\pi} = 4\%$ and $\rho = 0.90$, both roughly estimated from our data) that:

$$\begin{aligned} corr(x_t, \pi_t) &= \frac{\sigma_{realized\ disasters}}{\sigma_\pi} corr(1_{disaster(t=2,3,4)}, x_t) \\ &= \frac{\sqrt{(1-\bar{\pi})\bar{\pi} + \frac{\nu^2}{2(1-\rho)}}}{\sqrt{(1-\bar{\pi})\bar{\pi}}} corr(1_{disaster(t=2,3,4)}, x_t) \\ &= \frac{\sqrt{0.0384+0.288}}{\sqrt{0.0384}} * \sqrt{R^2} \\ &= 2.915 * \sqrt{R^2} \\ &= 2.915 * \sqrt{0.07} = 0.771 \end{aligned}$$

Intuitively, these calculations are saying that the Disaster Index x_t is a lot more correlated with the true unobservable process π_t than with the realized disaster indicator $1_{disaster(t=2,3,4)}$, because the realized disaster indicator takes on the values of 0 and 1 (which are very volatile), whereas the true unobservable process π_t is the less-volatile "average" of the realizations. The equality in the first row follows because $corr(x_t, \pi_t) = \frac{cov(\pi_{i,t}, DisasterIndex_{i,t})}{\sigma_\pi \sigma_{DI}} = \frac{cov(1_{disaster(t=2,3,4)}, DisasterIndex_{i,t})}{\sigma_\pi \sigma_{DI}} = \frac{\sigma_{realized\ disasters}}{\sigma_\pi} corr(1_{disaster(t=2,3,4)}, x_t)$.

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

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. The type is 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, $MarketBoom_{i,t}$, and $CreditBoom_{i,t}$, and if it falls outside the world war periods of 1914-1919 and 1939-1949). The "Prediction" column is marked with "P" if the BXY disaster is predicted by the Disaster Index (i.e., if the Disaster Index is above the "Disaster Threshold" (as defined in Section II.C) 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 (i.e., if either $MarketBoom_{i,t}$ or $CreditBoom_{i,t}$ is unavailable), with "WWI/II" if the disaster falls into the world war periods of 1914-1919 and 1939-1949, and blank if it is not a BXY disaster.

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	NP
Austria	Both	War	1914,1915,1919	1912	1919	-37.6%		WWI/II
Austria	Both	Banking crisis	1932	1929	1933	-24.3%	Y	NP
Austria	Both	War	1945	1944	1945	-87.9%		WWI/II
Austria	BXY	Banking crisis	2009	2008	2009	-4.1%	Y	P
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%		DI N/A
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

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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%		DI N/A
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%		DI N/A
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%		

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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

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Table A2: Predictability of credit expansion and market returns for GDP crashes stems from credit booms and market booms

This table demonstrates that the predictability of credit expansion and market returns for GDP crashes stems from "booms" (left-censored variables) rather than from "slumps" (right-censored variables). We start, in Panel A, by re-estimating Table 3 but using *linear* predictors, rather than left-censored variables, to first show that the main result of the paper are robust to not left-censoring variables. The linear predictors are the past three-year change in credit-to-GDP (i.e., "Credit Expansion") and the past three-year cumulative log excess return of the market index (i.e., "Market Return"), both standardized using only past information at each point in time, along with their interaction term. In Panel B, we re-estimate Table 3 using as predictors both the left-censored and right-censored versions of the above variables, as well as their interaction terms. As defined previously, $CreditBoom_{i,t}$ is the past three-year credit-to-GDP change standardized using only past information at each point in time and then left-censored at zero, while $CreditSlump_{i,t}$ is the same standardized variable but right-censored at zero. Similarly, $MarketBoom_{i,t}$ is the past three-year cumulative log excess return of the market index standardized using only past information at each point in time and then left-censored at zero, while $MarketSlump_{i,t}$ is the same standardized variable but right-censored at zero.

Panel A: Credit expansion and market returns predict GDP crashes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$CreditExpansion_{i,t}$	0.019*		0.018**	0.008		0.008	
	[1.84]		[1.96]	[0.77]		[0.82]	
$MarketReturn_{i,t}$		0.025*	0.024*	0.016		0.025*	
		[1.88]	[1.94]	[1.34]		[1.95]	
$Interaction_{i,t}$				0.020**	0.027***	0.020***	0.029***
				[2.25]	[3.09]	[2.60]	[3.37]
Observations	1788	1788	1788	1788	1788	1788	1788
Pseudo R^2	0.023	0.024	0.046	0.066	0.053	0.089	0.063
Controls	No	No	No	No	No	Yes	Yes

Panel B: Credit booms and market booms predict GDP crashes, whereas credit slumps and market slumps do not

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$CreditBoom_{i,t}$	0.034***		0.031***	0.016		0.014	
	[2.75]		[2.89]	[1.09]		[0.98]	
$CreditSlump_{i,t}$	-0.009		-0.007	-0.004		-0.003	
	[-0.66]		[-0.47]	[-0.29]		[-0.21]	
$MarketBoom_{i,t}$		0.033**	0.028*	0.012		0.018	
		[2.00]	[1.80]	[0.80]		[1.21]	
$MarketSlump_{i,t}$		0.013	0.016	0.020		0.033	
		[0.59]	[0.73]	[0.83]		[1.34]	
$CreditBoom_{i,t} \times MarketBoom_{i,t}$				0.023*	0.039***	0.025**	0.042***
				[1.80]	[2.91]	[2.02]	[3.08]
$CreditSlump_{i,t} \times MarketSlump_{i,t}$				0.018*	0.001	0.019*	-0.005
				[1.74]	[0.09]	[1.77]	[-0.34]
Observations	1788	1788	1788	1788	1788	1788	1788
Pseudo R^2	0.037	0.026	0.059	0.070	0.062	0.090	0.075
Controls	No	No	No	No	No	Yes	Yes

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Table A3: An alternative Disaster Index constructed by standardizing predictor variables *country-by-country*

As a robustness test, we re-estimate our main results after re-defining the predictor variables $CreditBoom_{i,t}$ and $MarketBoom_{i,t}$ as the past three-year credit-to-GDP change and past three-year cumulative market log excess returns *standardized country-by-country*. As before, these predictor variables use only past information at each point in time in their construction and standardization and are then left-censored at 0. With these new predictor variables standardized country-by-country, we then re-estimate Tables 3-6 and 7-9 in Panels B-F, respectively.

Panel A: Credit booms and market booms predict GDP crashes in the next 2 to 4 years

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$CreditBoom_{i,t}$	0.031***		0.028***	0.017		0.016	
	[2.59]		[2.66]	[1.19]		[1.12]	
$MarketBoom_{i,t}$		0.030*	0.025	0.013		0.021	
		[1.79]	[1.63]	[0.77]		[1.30]	
$Interaction_{i,t}$				0.014	0.027***	0.015*	0.030***
				[1.53]	[2.66]	[1.72]	[2.96]
Observations	1720	1720	1720	1720	1720	1720	1720
Pseudo R^2	0.038	0.018	0.051	0.055	0.050	0.073	0.066
Sum of Marginal Effects	0.031	0.030	0.053	0.044	0.027	0.052	0.030
Controls	No	No	No	No	No	Yes	Yes
Conditional Probability	0.092	0.077	0.115	0.117	0.107	0.127	0.114
Baseline Probability	0.060	0.060	0.060	0.060	0.060	0.060	0.060

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Panel B: Future equity returns

	Controls?	Year 1 (1)	Year 2 (2)	Year 3 (3)	Year 4 (4)	Year 5 (5)
(1) Market (1870-2021)	No	-0.234** [-2.45]	-0.747*** [-2.94]	-1.005** [-2.48]	-1.152** [-2.08]	-1.344** [-2.14]
(2) Market (1870-1949)	No	-0.088 [-0.51]	-0.458* [-1.88]	-0.593*** [-3.64]	-0.450** [-2.20]	-0.456 [-1.58]
(3) Market (1950-2021)	No	-0.148 [-0.98]	-0.889 [-1.52]	-1.335 [-1.40]	-1.591 [-1.35]	-1.829 [-1.39]
(4)	Yes	-0.265** [-1.98]	-1.100*** [-3.26]	-1.578** [-2.37]	-1.845** [-2.17]	-2.108** [-2.30]
(5) High B/P	No	-0.262 [-0.93]	-1.576** [-2.03]	-2.304*** [-2.67]	-2.350*** [-3.07]	-2.319** [-2.30]
(6)	Yes	0.036 [0.14]	-1.074* [-1.66]	-1.691** [-2.19]	-1.664** [-2.46]	-1.509* [-1.73]
(7) Low B/P	No	-0.432** [-2.24]	-2.348*** [-5.96]	-3.830*** [-6.35]	-4.272*** [-4.95]	-4.126*** [-4.00]
(8)	Yes	-0.122 [-0.56]	-1.702*** [-5.98]	-2.956*** [-7.15]	-3.292*** [-4.72]	-3.037*** [-3.72]
(9) High-Low B/P	No	0.304 [0.92]	1.117* [1.71]	2.043*** [3.16]	2.632*** [3.55]	2.150 [1.62]
(10)	Yes	0.316 [1.00]	0.991 [1.57]	1.770*** [2.68]	2.271*** [3.13]	1.780 [1.43]
(11) High D/P	No	-0.205 [-0.71]	-1.892* [-1.95]	-3.246*** [-2.78]	-3.451*** [-3.63]	-3.520*** [-3.16]
(12)	Yes	0.056 [0.23]	-1.439* [-1.65]	-2.671** [-2.44]	-2.854*** [-3.38]	-2.827*** [-2.85]
(13) Low D/P	No	-0.924*** [-5.00]	-2.913*** [-6.76]	-4.229*** [-6.49]	-4.663*** [-5.93]	-4.635*** [-5.43]
(14)	Yes	-0.599*** [-3.61]	-2.246*** [-7.70]	-3.345*** [-7.23]	-3.654*** [-5.93]	-3.488*** [-5.48]
(15) High-Low D/P	No	0.790** [2.48]	1.639*** [2.59]	1.977** [2.57]	2.165** [2.56]	2.047** [2.14]
(16)	Yes	0.752*** [2.66]	1.454** [2.48]	1.717** [2.35]	1.799** [2.22]	1.639* [1.83]
(17) High E/P	No	-0.420* [-1.85]	-2.233*** [-2.80]	-3.558*** [-3.54]	-3.788*** [-4.24]	-3.832*** [-3.42]
(18)	Yes	-0.119 [-0.77]	-1.691** [-2.55]	-2.868*** [-3.14]	-3.030*** [-3.96]	-2.978*** [-3.12]
(19) Low E/P	No	-0.187 [-0.79]	-2.022*** [-4.49]	-3.675*** [-6.39]	-4.488*** [-6.35]	-4.719*** [-5.66]
(20)	Yes	0.121 [0.47]	-1.369*** [-3.53]	-2.790*** [-6.80]	-3.469*** [-6.82]	-3.581*** [-5.91]
(21) High-Low E/P	No	-0.169 [-1.05]	0.348 [1.00]	0.928** [2.42]	1.426*** [3.72]	1.511*** [2.63]
(22)	Yes	-0.123 [-0.73]	0.326 [0.86]	0.849** [1.98]	1.296*** [2.93]	1.378** [2.17]

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Panel C: Equity volatility

	1950-2021				1950-2005				2006-2021			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\texttt{DisasterIndex}_{i,t}$	-0.292**	-0.291*			-0.140***	-0.073			-1.064	-0.901		
	[-2.18]	[-1.89]			[-2.62]	[-0.85]			[-1.28]	[-1.60]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			0.001	-0.030			0.102	0.098			-0.619***	-0.603**
			[0.01]	[-0.30]			[0.75]	[0.73]			[-2.98]	[-2.82]
Observations	1,279	1,279	1,279	1,279	960	960	960	960	319	319	319	319
Adjusted R^2	0.040	0.045	0.029	0.035	0.047	0.112	0.045	0.112	0.015	0.201	-0.012	0.186
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Panel D: Corporate credit spreads

	1996-2021				1996-2005				2006-2021			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\texttt{DisasterIndex}_{i,t}$	-5.239*	-4.989***			-0.318	-0.529			-9.874*	-7.838*		
	[-1.89]	[-3.36]			[-0.40]	[-0.61]			[-1.80]	[-2.01]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-5.394**	-5.108***			-0.307	-0.314			-6.768***	-7.775**
			[-2.31]	[-3.11]			[-0.37]	[-0.45]			[-3.91]	[-2.35]
Observations	514	514	514	514	196	196	196	196	318	318	318	318
Adjusted R^2	0.052	0.427	0.046	0.421	0.218	0.435	0.218	0.434	0.093	0.455	0.063	0.448
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

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Panel E: Term spread

	1950-2021				1950-2005				2006-2021			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\texttt{DisasterIndex}_{i,t}$	-1.409	-1.884			0.690	-0.335			-10.277***	-10.893***		
	[-0.60]	[-1.00]			[0.40]	[-0.22]			[-3.58]	[-3.32]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-2.722*	-3.030**			-0.929	-1.613*			-9.781***	-10.604***
			[-1.65]	[-2.19]			[-0.99]	[-1.84]			[-6.48]	[-3.47]
Observations	1,377	1,377	1,377	1,377	1,057	1,057	1,057	1,057	320	320	320	320
Adjusted R^2	0.088	0.123	0.089	0.124	0.103	0.126	0.103	0.127	0.221	0.220	0.213	0.212
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

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

	Dividend/Price of Market Index				Earnings/Price of Market Index			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\texttt{DisasterIndex}_{i,t}$	0.003	0.002			-0.161***	-0.164***		
	[0.05]	[0.04]			[-7.44]	[-7.17]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-0.062	-0.064			-0.204***	-0.207***
			[-1.35]	[-1.39]			[-3.60]	[-3.64]
Observations	1,280	1,280	1,280	1,280	890	890	890	890
Adjusted R^2	0.186	0.192	0.194	0.200	0.121	0.121	0.122	0.122
Controls	No	Yes	No	Yes	No	Yes	No	Yes

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Table A4: An alternative Disaster Index constructed using indicator variables following Greenwood et al. (2022)

As a robustness test, we re-estimate our main results after re-defining $CreditBoom_{i,t}$ and $MarketBoom_{i,t}$ as indicators variables, following Greenwood et al. (2022). Specifically, $CreditBoom_{i,t}$ is re-defined as $1[CreditBoom_{i,t}]$, an indicator variable that takes the value of one in year t if the past three-year credit-to-GDP change is in the top quintile of the distribution for all countries up to year t. Similarly, $MarketBoom_{i,t}$ is re-defined as $1[MarketBoom_{i,t}]$, an indicator variable that takes the value of one in year t if the past three-year cumulative market log excess return is in the top tercile of the distribution for all countries up to year t. $Interaction_{i,t}$ is an indicator variable that takes the value of one if both $1[CreditBoom_{i,t}]$ and $1[MarketBoom_{i,t}]$ are one. With these new predictor variables constructed following Greenwood et al. (2022), we then re-estimate Table 3 in Panel A. (Note that, in Panel A, the "Conditional Probability" is calculated as the predicted value from the regression, conditional on $1[CreditBoom_{i,t}]$ and $1[MarketBoom_{i,t}]$ both equalling one.) We then re-estimate Tables 4, 6, 7, 8, and 9 in Panels B-F using the new Disaster Index constructed from these indicator variables.

Panel A: Credit booms and market booms predict GDP crashes in the next 2 to 4 years

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$1[CreditBoom_{i,t}]$	0.032		0.031	-0.007		-0.011	
	[1.51]		[1.58]	[-0.34]		[-0.54]	
$1[MarketBoom_{i,t}]$		0.046*	0.045*	0.023		0.031	
		[1.88]	[1.91]	[0.95]		[1.29]	
$Interaction_{i,t}$				0.070**	0.080***	0.079***	0.089***
				[2.57]	[2.75]	[2.98]	[3.12]
Observations	1816	1816	1816	1816	1816	1816	1816
Pseudo R^2	0.009	0.022	0.030	0.042	0.037	0.058	0.048
Sum of Marginal Effects	0.032	0.046	0.076	0.086	0.080	0.099	0.089
Controls	No	No	No	No	No	Yes	Yes
Conditional Probability	0.082	0.085	0.122	0.166	0.166	0.196	0.191
Baseline Probability	0.061	0.061	0.061	0.061	0.061	0.061	0.061

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Panel B: Future equity returns

	Controls?	Year 1 (1)	Year 2 (2)	Year 3 (3)	Year 4 (4)	Year 5 (5)
(1) Market (1870-2021)	No	-0.166	-0.579	-0.803	-0.931	-1.241
		[-0.41]	[-0.69]	[-0.68]	[-0.62]	[-0.71]
(2) Market (1870-1949)	No	0.262	0.131	0.060	0.002	-0.345
		[0.77]	[0.21]	[0.09]	[0.00]	[-0.84]
(3) Market (1950-2021)	No	0.045	-0.304	-0.414	-0.383	-0.461
		[0.06]	[-0.19]	[-0.19]	[-0.13]	[-0.14]
(4)	Yes	-0.504	-1.324	-1.661	-1.835	-2.099
		[-1.08]	[-1.14]	[-0.91]	[-0.78]	[-0.76]
(5) High B/P	No	-0.499	-1.460	-2.217**	-2.623**	-3.140*
		[-0.95]	[-1.53]	[-2.12]	[-2.09]	[-1.93]
(6)	Yes	-0.212	-0.955	-1.609**	-1.993*	-2.313*
		[-0.45]	[-1.27]	[-2.04]	[-1.94]	[-1.74]
(7) Low B/P	No	-0.894***	-2.917***	-4.278***	-5.043**	-6.009***
		[-3.20]	[-3.40]	[-2.71]	[-2.50]	[-2.66]
(8)	Yes	-0.571***	-2.246***	-3.412***	-4.155***	-4.904***
		[-2.98]	[-4.41]	[-2.91]	[-2.62]	[-2.76]
(9) High-Low B/P	No	0.428	1.479**	2.169**	2.744**	3.235**
		[0.95]	[2.26]	[2.40]	[2.17]	[2.26]
(10)	Yes	0.406	1.309**	1.889**	2.430**	2.910**
		[0.92]	[2.09]	[2.39]	[2.20]	[2.27]
(11) High D/P	No	-0.509	-1.770*	-2.925**	-3.246**	-3.975**
		[-0.81]	[-1.92]	[-2.52]	[-2.50]	[-2.46]
(12)	Yes	-0.255	-1.320*	-2.371***	-2.705***	-3.250***
		[-0.43]	[-1.87]	[-2.79]	[-2.79]	[-2.63]
(13) Low D/P	No	-1.170***	-3.043***	-4.017**	-4.758**	-5.732**
		[-2.95]	[-2.74]	[-2.11]	[-2.03]	[-2.33]
(14)	Yes	-0.839***	-2.378***	-3.146**	-3.833*	-4.535**
		[-2.86]	[-3.00]	[-2.05]	[-1.94]	[-2.17]
(15) High-Low D/P	No	0.843	1.768*	1.729	2.187	2.373
		[1.10]	[1.94]	[1.33]	[1.40]	[1.55]
(16)	Yes	0.800	1.599*	1.490	1.903	2.076
		[1.09]	[1.90]	[1.19]	[1.24]	[1.36]
(17) High E/P	No	-0.893*	-2.291**	-3.396**	-3.519*	-4.008*
		[-1.68]	[-2.08]	[-2.11]	[-1.91]	[-1.77]
(18)	Yes	-0.590	-1.734**	-2.698**	-2.823*	-3.124
		[-1.64]	[-2.15]	[-2.03]	[-1.80]	[-1.64]
(19) Low E/P	No	-0.536*	-2.544***	-3.874**	-4.774**	-6.187***
		[-1.68]	[-2.60]	[-2.49]	[-2.54]	[-3.09]
(20)	Yes	-0.200	-1.833***	-2.933**	-3.790**	-4.961***
		[-0.65]	[-2.72]	[-2.51]	[-2.57]	[-3.13]
(21) High-Low E/P	No	-0.223	0.551	0.791	1.489**	2.353***
		[-0.57]	[1.11]	[1.23]	[1.99]	[2.92]
(22)	Yes	-0.210	0.470	0.640	1.308*	2.177***
		[-0.55]	[0.89]	[0.99]	[1.82]	[2.76]

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Panel C: Equity volatility

	1950-2021				1950-2005				2006-2021			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\texttt{DisasterIndex}_{i,t}$	-0.755***	-0.703**			-0.629***	-0.336***			-0.839	-0.651		
	[-2.88]	[-2.20]			[-4.19]	[-3.67]			[-1.21]	[-1.39]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			0.131	0.075			0.829*	0.773*			-0.492	-0.422
			[0.49]	[0.33]			[1.84]	[1.74]			[-1.26]	[-1.20]
Observations	1,320	1,320	1,320	1,320	1,001	1,001	1,001	1,001	319	319	319	319
Adjusted R^2	0.055	0.059	0.029	0.037	0.064	0.114	0.050	0.113	0.004	0.193	-0.015	0.182
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Panel D: Corporate credit spreads

	1996-2021				1996-2005				2006-2021			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\texttt{DisasterIndex}_{i,t}$	-3.414	-3.560**			0.943	-0.758			-5.915	-2.849		
	[-1.21]	[-2.03]			[0.25]	[-0.25]			[-1.37]	[-1.54]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-2.627	-2.379*			3.695	0.529			-3.173	-1.453
			[-1.52]	[-1.81]			[0.51]	[0.10]			[-1.59]	[-1.30]
Observations	514	514	514	514	196	196	196	196	318	318	318	318
Adjusted R^2	0.032	0.410	0.028	0.406	0.218	0.434	0.221	0.434	0.065	0.434	0.051	0.430
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Panel E: Term spread

	1950-2021				1950-2005				2006-2021			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\texttt{DisasterIndex}_{i,t}$	0.474	0.272			5.081	3.783			-4.310	-4.367		
	[0.10]	[0.07]			[1.03]	[0.86]			[-1.23]	[-1.31]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-6.991	-8.403*			-16.775***	-19.653***			-2.827	-2.889
			[-1.62]	[-1.89]			[-3.34]	[-4.97]			[-1.03]	[-1.16]
Observations	1,433	1,433	1,433	1,433	1,113	1,113	1,113	1,113	320	320	320	320
Adjusted R^2	0.090	0.114	0.092	0.117	0.109	0.123	0.110	0.127	0.201	0.199	0.198	0.196
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

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

	Dividend/Price of Market Index				Earnings/Price of Market Index			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\texttt{DisasterIndex}_{i,t}$	0.146*	0.148*			-0.115**	-0.117**		
	[1.67]	[1.68]			[-2.22]	[-2.12]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-0.055	-0.061			-0.218	-0.221
			[-0.59]	[-0.64]			[-1.48]	[-1.47]
Observations	1,321	1,321	1,321	1,321	890	890	890	890
Adjusted R^2	0.196	0.201	0.172	0.176	0.112	0.112	0.116	0.116
Controls	No	Yes	No	Yes	No	Yes	No	Yes

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Table A5: An alternative “zero-one” Disaster Index

As a robustness test, we re-estimate our main results after re-defining the Disaster Index as:

$$\texttt{DisasterIndex}_{i,t} = 1[\texttt{MarketBoom}_{i,t} \texttt{ in Top Tercile AND CreditBoom}_{i,t} \texttt{ in Top Quintile}],$$

instead of estimating the Disaster Index from a first-stage probit regression. Specifically, this new Disaster Index equals one if $\texttt{MarketBoom}_{i,t}$ is in the top tercile of the distribution for all countries up to year t *and* $\texttt{CreditBoom}_{i,t}$ is in the top quintile of the distribution for all countries up to year t, and is zero otherwise. Using this new “zero-one” Disaster Index, we then re-estimate Tables 4, 6, 7, 8, and 9 in Panels A-E. In addition to reporting these new regression results, Panel A also decomposes the returns conditional on whether $\texttt{DisasterIndex}_{i,t} = 1$ and $\texttt{DisasterIndex}_{i,t} = 0$, where $\texttt{DisasterIndex}_{i,t}$ is the new “zero-one” Disaster Index. The mean, standard deviation, and number of observations (N) of the conditional returns are reported. Note that, just for this Panel A, regressions do not use country fixed effects, so that the regression coefficient estimates (reported in the first row of each block) exactly match the differences of the means conditional on $\texttt{DisasterIndex}_{i,t} = 1$ and $\texttt{DisasterIndex}_{i,t} = 0$.

Panel A: Future equity returns

	Controls?	Year 1 (1)	Year 2 (2)	Year 3 (3)	Year 4 (4)	Year 5 (5)
(1) Market (1870-2021)	No	-0.070**	-0.163***	-0.217***	-0.240**	-0.251**
		[-2.47]	[-2.78]	[-2.68]	[-2.48]	[-2.34]
Conditional on $\texttt{DisasterIndex}_{i,t} = 1$:						
$\mathbb{E}[r_{i,t\to t+h}]$		-0.030	-0.079	-0.091	-0.077	-0.054
$\mathbb{SD}[r_{i,t\to t+h}]$		0.282	0.409	0.451	0.499	0.536
N		184	184	181	179	175
Conditional on $\texttt{DisasterIndex}_{i,t} = 0$:						
$\mathbb{E}[r_{i,t\to t+h}]$		0.040***	0.084***	0.126***	0.163***	0.197***
$\mathbb{SD}[r_{i,t\to t+h}]$		0.217	0.312	0.375	0.424	0.457
N		1,847	1,792	1,740	1,686	1,634
(2) Market (1870-1949)	No	-0.089***	-0.233***	-0.303***	-0.311***	-0.324***
		[-4.76]	[-6.92]	[-5.02]	[-3.73]	[-4.20]
Conditional on $\texttt{DisasterIndex}_{i,t} = 1$:						
$\mathbb{E}[r_{i,t\to t+h}]$		-0.080***	-0.203***	-0.251***	-0.242***	-0.242***
$\mathbb{SD}[r_{i,t\to t+h}]$		0.179	0.374	0.426	0.503	0.518
N		31	31	29	28	26
Conditional on $\texttt{DisasterIndex}_{i,t} = 0$:						
$\mathbb{E}[r_{i,t\to t+h}]$		0.009	0.031*	0.052**	0.069**	0.082**
$\mathbb{SD}[r_{i,t\to t+h}]$		0.181	0.275	0.341	0.386	0.414
N		588	554	522	488	455
(3) Market (1950-2021)	No	-0.080**	-0.171**	-0.238***	-0.271**	-0.286**
		[-2.25]	[-2.38]	[-2.61]	[-2.55]	[-2.39]
Conditional on $\texttt{DisasterIndex}_{i,t} = 1$:						
$\mathbb{E}[r_{i,t\to t+h}]$		-0.025	-0.061	-0.075	-0.064	-0.037
$\mathbb{SD}[r_{i,t\to t+h}]$		0.300	0.405	0.442	0.482	0.531
N		145	145	145	145	144
Conditional on $\texttt{DisasterIndex}_{i,t} = 0$:						
$\mathbb{E}[r_{i,t\to t+h}]$		0.056***	0.111***	0.163***	0.207***	0.249***
$\mathbb{SD}[r_{i,t\to t+h}]$		0.230	0.322	0.378	0.425	0.458
N		1,156	1,136	1,116	1,096	1,077
(4) Market (1950-2021)	Yes	-0.063*	-0.143**	-0.201**	-0.228**	-0.239**
		[-1.82]	[-2.11]	[-2.33]	[-2.23]	[-2.03]

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	Controls?	Year 1 (1)	Year 2 (2)	Year 3 (3)	Year 4 (4)	Year 5 (5)
(5) High B/P	No	-0.083	-0.185**	-0.262***	-0.308***	-0.344***
		[-1.36]	[-1.98]	[-3.27]	[-3.95]	[-3.89]
(6)	Yes	-0.066	-0.153*	-0.222***	-0.265***	-0.301***
		[-1.18]	[-1.84]	[-3.23]	[-4.09]	[-4.04]
(7) Low B/P	No	-0.102***	-0.257***	-0.373***	-0.439***	-0.470***
		[-3.01]	[-5.07]	[-8.89]	[-14.77]	[-10.91]
(8)	Yes	-0.083***	-0.213***	-0.313***	-0.373***	-0.401***
		[-2.61]	[-4.92]	[-9.47]	[-13.82]	[-9.79]
(9) High-Low B/P	No	0.018	0.070	0.116*	0.147*	0.133
		[0.50]	[1.20]	[1.95]	[1.89]	[1.24]
(10)	Yes	0.015	0.055	0.092	0.115	0.095
		[0.43]	[0.97]	[1.60]	[1.53]	[0.92]
(11) High D/P	No	-0.089	-0.209**	-0.316***	-0.348***	-0.387***
		[-1.31]	[-2.13]	[-3.22]	[-4.31]	[-5.31]
(12)	Yes	-0.073	-0.180**	-0.278***	-0.310***	-0.347***
		[-1.14]	[-1.98]	[-3.07]	[-4.24]	[-5.35]
(13) Low D/P	No	-0.130***	-0.290***	-0.396***	-0.470***	-0.504***
		[-3.12]	[-4.68]	[-7.34]	[-12.45]	[-12.48]
(14)	Yes	-0.109***	-0.248***	-0.338***	-0.404***	-0.432***
		[-2.75]	[-4.42]	[-7.36]	[-11.40]	[-10.38]
(15) High-Low D/P	No	0.055	0.120***	0.139**	0.187***	0.192**
		[1.43]	[2.66]	[2.26]	[2.66]	[2.50]
(16)	Yes	0.052	0.109**	0.122*	0.161**	0.161**
		[1.43]	[2.42]	[1.92]	[2.15]	[1.99]
(17) High E/P	No	-0.121***	-0.255***	-0.363***	-0.392***	-0.424***
		[-2.61]	[-4.10]	[-6.81]	[-10.05]	[-10.37]
(18)	Yes	-0.102**	-0.216***	-0.312***	-0.337***	-0.366***
		[-2.42]	[-3.91]	[-6.29]	[-9.09]	[-9.77]
(19) Low E/P	No	-0.092**	-0.266***	-0.390***	-0.474***	-0.539***
		[-1.96]	[-3.74]	[-6.13]	[-9.99]	[-11.24]
(20)	Yes	-0.073	-0.224***	-0.331***	-0.408***	-0.468***
		[-1.59]	[-3.35]	[-5.60]	[-8.95]	[-9.37]
(21) High-Low E/P	No	-0.021	0.037	0.069	0.126***	0.159***
		[-1.27]	[1.05]	[1.49]	[2.85]	[3.31]
(22)	Yes	-0.018	0.038	0.063	0.116***	0.148***
		[-1.09]	[1.02]	[1.40]	[2.69]	[2.91]

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Panel B: Equity volatility

	1950-2021		1950-2005		2006-2021	
	(1)	(2)	(3)	(4)	(5)	(6)
$\texttt{DisasterIndex}_{i,t}$	0.009	0.005	0.012	0.006	-0.009	-0.009
	[0.64]	[0.44]	[0.70]	[0.37]	[-0.30]	[-0.30]
Observations	1,320	1,320	1,081	1,081	239	239
Adjusted R^2	0.029	0.037	0.026	0.034	0.040	0.050
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
	[-2.10]	[-3.38]	[0.08]	[-0.63]	[-1.82]	[-1.60]
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)
$\texttt{DisasterIndex}_{i,t}$	-0.550***	-0.591***	-0.393***	-0.453***	-0.993**	-1.025**
	[-2.87]	[-3.22]	[-2.59]	[-3.42]	[-2.87]	[-2.88]
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	-0.006*	-0.009*	-0.009*
	[-1.57]	[-1.67]	[-1.92]	[-1.89]
Observations	1,321	1,321	890	890
Adjusted R^2	0.179	0.185	0.115	0.116
Controls	No	Yes	No	Yes

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Table A6: 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).

	Controls?	Year 1 (1)	Year 2 (2)	Year 3 (3)	Year 4 (4)	Year 5 (5)
(1) High B/P	No	-0.252 [-0.84]	-1.196** [-2.07]	-2.225*** [-3.31]	-3.041*** [-5.56]	-3.208*** [-6.25]
(2)	Yes	-0.052 [-0.16]	-0.847 [-1.47]	-1.915*** [-2.85]	-2.730*** [-4.81]	-2.864*** [-4.79]
(3) Low B/P	No	-0.150 [-0.67]	-1.300*** [-3.08]	-2.377*** [-5.58]	-3.176*** [-5.92]	-3.259*** [-4.96]
(4)	Yes	0.246 [1.29]	-0.492 [-1.33]	-1.277*** [-3.04]	-1.895*** [-3.17]	-1.900*** [-2.98]
(5) High-Low B/P	No	0.021 [0.08]	0.368 [0.83]	0.368 [0.71]	0.303 [0.38]	0.242 [0.24]
(6)	Yes	-0.149 [-0.60]	-0.030 [-0.07]	-0.295 [-0.57]	-0.495 [-0.60]	-0.575 [-0.55]
(7) High D/P	No	-0.233 [-1.13]	-1.441*** [-2.87]	-2.072*** [-3.97]	-1.948*** [-5.58]	-1.770*** [-5.19]
(8)	Yes	0.004 [0.02]	-1.003** [-2.20]	-1.617*** [-3.25]	-1.451*** [-4.58]	-1.298*** [-3.62]
(9) Low D/P	No	-0.387 [-1.59]	-1.842*** [-4.81]	-3.090*** [-7.10]	-3.730*** [-5.61]	-3.796*** [-5.27]
(10)	Yes	0.057 [0.31]	-0.893*** [-2.70]	-1.925*** [-5.03]	-2.470*** [-4.15]	-2.535*** [-4.23]
(11) High-Low D/P	No	0.212 [0.68]	1.010** [2.38]	2.025*** [3.72]	2.625*** [2.82]	2.929** [2.41]
(12)	Yes	-0.027 [-0.10]	0.544 [1.44]	1.393*** [3.53]	1.953*** [2.69]	2.189** [2.30]
(13) High E/P	No	-0.174 [-0.61]	-0.971* [-1.83]	-1.525*** [-3.21]	-2.322*** [-8.79]	-2.665*** [-10.29]
(14)	Yes	0.158 [0.67]	-0.405 [-0.81]	-0.919* [-1.91]	-1.731*** [-5.97]	-2.092*** [-8.47]
(15) Low E/P	No	-0.502** [-2.18]	-1.808*** [-4.24]	-3.294*** [-6.36]	-4.253*** [-10.25]	-4.458*** [-8.08]
(16)	Yes	-0.134 [-0.68]	-1.029*** [-2.85]	-2.382*** [-5.11]	-3.374*** [-8.20]	-3.615*** [-6.72]
(17) High-Low E/P	No	0.315 [1.49]	1.019*** [3.16]	2.007*** [7.64]	2.380*** [5.12]	2.492*** [2.75]
(18)	Yes	0.329 [1.32]	0.954** [2.56]	2.011*** [6.30]	2.518*** [7.80]	2.702*** [3.70]

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Table A7: Adjusted standard errors for "generated regressors" using bootstrapping

This table re-estimates Tables 4-9 with bootstrapped t-statistics estimated by drawing bootstrap panel datasets that preserve the cross-sectional and time-series dependence and then estimating the two-step procedure within each bootstrap sample.

Panel A: Future equity returns

	Controls?	Year 1 (1)	Year 2 (2)	Year 3 (3)	Year 4 (4)	Year 5 (5)
(1) Market (1870-2021)	No	-0.276***	-0.873***	-1.274***	-1.386***	-1.455***
		[-6.72]	[-7.02]	[-5.81]	[-4.97]	[-4.94]
(2) Market (1870-1949)	No	-0.210*	-0.593**	-0.924***	-0.814***	-0.781***
		[-1.74]	[-2.31]	[-3.08]	[-2.72]	[-2.58]
(3) Market (1950-2021)	No	-0.248***	-0.980***	-1.451***	-1.665***	-1.764***
		[-4.78]	[-5.22]	[-4.83]	[-4.58]	[-4.59]
(4)	Yes	-0.279***	-1.033***	-1.508***	-1.720***	-1.825***
		[-4.05]	[-5.31]	[-5.00]	[-4.66]	[-4.51]
(5) High B/P	No	-0.316***	-1.480***	-2.102***	-2.320***	-2.452***
		[-3.29]	[-3.74]	[-3.81]	[-3.90]	[-3.87]
(6)	Yes	-0.071	-1.072***	-1.625***	-1.804***	-1.828***
		[-0.78]	[-3.36]	[-3.59]	[-3.71]	[-3.57]
(7) Low B/P	No	-0.463***	-1.999***	-3.031***	-3.416***	-3.346***
		[-3.21]	[-3.45]	[-3.40]	[-3.28]	[-3.14]
(8)	Yes	-0.199*	-1.449***	-2.303***	-2.620***	-2.458***
		[-1.86]	[-3.24]	[-3.21]	[-3.03]	[-2.81]
(9) High-Low B/P	No	0.248**	0.733***	1.257***	1.523***	0.978
		[2.21]	[2.60]	[2.84]	[2.66]	[1.53]
(10)	Yes	0.255**	0.616**	1.010***	1.213**	0.667
		[2.21]	[2.54]	[2.75]	[2.42]	[1.12]
(11) High D/P	No	-0.380***	-1.913***	-2.964***	-3.249***	-3.390***
		[-3.03]	[-3.71]	[-3.65]	[-3.69]	[-3.65]
(12)	Yes	-0.173	-1.565***	-2.537***	-2.816***	-2.875***
		[-1.37]	[-3.42]	[-3.46]	[-3.53]	[-3.47]
(13) Low D/P	No	-0.773***	-2.265***	-3.207***	-3.644***	-3.755***
		[-3.63]	[-3.60]	[-3.54]	[-3.41]	[-3.34]
(14)	Yes	-0.504***	-1.711***	-2.493***	-2.845***	-2.846***
		[-3.39]	[-3.49]	[-3.43]	[-3.23]	[-3.08]
(15) High-Low D/P	No	0.491**	0.907**	0.998*	1.100*	1.071
		[2.43]	[2.23]	[1.89]	[1.76]	[1.59]
(16)	Yes	0.462**	0.755**	0.790	0.821	0.776
		[2.38]	[2.01]	[1.62]	[1.43]	[1.21]
(17) High E/P	No	-0.557***	-2.075***	-2.988***	-3.246***	-3.438***
		[-3.71]	[-3.73]	[-3.79]	[-3.96]	[-4.08]
(18)	Yes	-0.320**	-1.655***	-2.466***	-2.687***	-2.805***
		[-2.49]	[-3.41]	[-3.56]	[-3.76]	[-3.90]
(19) Low E/P	No	-0.338***	-1.741***	-2.872***	-3.512***	-3.808***
		[-3.23]	[-3.69]	[-3.61]	[-3.57]	[-3.50]
(20)	Yes	-0.078	-1.190***	-2.148***	-2.704***	-2.914***
		[-0.79]	[-3.38]	[-3.43]	[-3.35]	[-3.22]
(21) High-Low E/P	No	-0.188*	0.109	0.502*	0.848**	0.905**
		[-1.93]	[0.56]	[1.65]	[2.21]	[1.98]
(22)	Yes	-0.165*	0.067	0.420	0.734**	0.800*
		[-1.71]	[0.36]	[1.48]	[2.04]	[1.74]

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Panel B: Equity volatility

	1950-2021				1950-2005				2006-2021			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\texttt{DisasterIndex}_{i,t}$	-0.107	-0.110*			0.017	0.055			-0.448	-0.427*		
	[-1.53]	[-1.75]			[0.34]	[1.54]			[-1.64]	[-1.78]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			0.086*	0.063			0.221***	0.188***			-0.320*	-0.349*
			[1.85]	[1.35]			[3.87]	[2.89]			[-1.68]	[-1.69]
Observations	1,279	1,279	1,279	1,279	960	960	960	960	319	319	319	319
Adjusted R^2	0.032	0.038	0.030	0.036	0.044	0.112	0.054	0.118	0.000	0.195	-0.012	0.188
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Panel C: Corporate credit spreads

	1996-2021				1996-2005				2006-2021			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\texttt{DisasterIndex}_{i,t}$	-2.596***	-2.597***			-0.192*	-0.273*			-4.580*	-4.575***		
	[-2.66]	[-3.13]			[-1.70]	[-1.69]			[-1.82]	[-2.64]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-2.502**	-2.532***			-0.244	-0.238			-3.598*	-4.463**
			[-2.43]	[-2.69]			[-1.64]	[-1.61]			[-1.81]	[-2.16]
Observations	514	514	514	514	196	196	196	196	318	318	318	318
Adjusted R^2	0.049	0.426	0.044	0.422	0.218	0.435	0.218	0.435	0.080	0.458	0.064	0.453
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

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Panel D: Term spread

	1950-2021				1950-2005				2006-2021			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\texttt{DisasterIndex}_{i,t}$	-0.949	-1.364**			0.440	-0.417			-5.798**	-6.222**		
	[-1.22]	[-2.03]			[0.52]	[-0.62]			[-2.23]	[-2.27]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-1.478**	-1.846***			-0.726	-1.312***			-5.304*	-5.755*
			[-2.49]	[-3.45]			[-1.37]	[-3.08]			[-1.89]	[-1.93]
Observations	1,377	1,377	1,377	1,377	1,057	1,057	1,057	1,057	320	320	320	320
Adjusted R^2	0.088	0.122	0.088	0.123	0.103	0.126	0.103	0.127	0.222	0.223	0.215	0.215
Controls	No	Yes	No	Yes	No	Yes	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)	(5)	(6)	(7)	(8)
$\texttt{DisasterIndex}_{i,t}$	0.000	-0.000			-0.078***	-0.080***		
	[0.02]	[-0.00]			[-4.34]	[-4.49]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-0.035**	-0.037**			-0.090**	-0.092**
			[-2.10]	[-2.25]			[-2.34]	[-2.34]
Observations	1,280	1,280	1,280	1,280	890	890	890	890
Adjusted R^2	0.186	0.192	0.192	0.198	0.119	0.119	0.120	0.120
Controls	No	Yes	No	Yes	No	Yes	No	Yes

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Table A8: Testing regression coefficients against model-implied predictions

This table re-estimates Table 4 (in Panel A) and coefficients from Tables 6-9 (in Panel B) but tests the regression coefficients against model-implied predictions. In each set of results, the first two rows reproduce the original coefficient estimates and t-statistics under the null hypothesis $H_0 : \beta = 0$; the third row lists out the alternative hypothesis, $H_A : \beta = \beta_0 > 0$ (i.e., the model-implied prediction); and the fourth row reports the t-statistics corresponding to H_A.

Panel A: Future market index returns

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5
(1) Market (1870-2021)					
$\hat{\beta}$	-0.276***	-0.873***	-1.274***	-1.386**	-1.455**
t-stat for $H_0 : \beta = 0$	[-2.60]	[-2.82]	[-2.76]	[-2.14]	[-1.97]
$\boldsymbol{H_A : \beta = \beta_0 > 0}$	$\boldsymbol{\beta_0 = 1.68}$	$\boldsymbol{\beta_0 = 2.81}$	$\boldsymbol{\beta_0 = 3.94}$	$\boldsymbol{\beta_0 = 4.63}$	$\boldsymbol{\beta_0 = 5.31}$
t-stat for H_A	**[-18.42]**	**[-11.88]**	**[-11.29]**	**[-9.30]**	**[-9.15]**
(2) Market (1870-1949)					
$\hat{\beta}$	-0.210**	-0.593***	-0.924***	-0.814**	-0.781**
t-stat for $H_0 : \beta = 0$	[-2.03]	[-3.13]	[-3.32]	[-2.51]	[-2.53]
$\boldsymbol{H_A : \beta = \beta_0 > 0}$	$\boldsymbol{\beta_0 = 1.68}$	$\boldsymbol{\beta_0 = 2.81}$	$\boldsymbol{\beta_0 = 3.94}$	$\boldsymbol{\beta_0 = 4.63}$	$\boldsymbol{\beta_0 = 5.31}$
t-stat for H_A	**[-18.25]**	**[-17.95]**	**[-17.45]**	**[-16.79]**	**[-19.70]**
(3) Market (1950-2021)					
$\hat{\beta}$	-0.248	-0.980**	-1.451**	-1.665*	-1.764*
t-stat for $H_0 : \beta = 0$	[-1.60]	[-2.02]	[-1.99]	[-1.77]	[-1.70]
$\boldsymbol{H_A : \beta = \beta_0 > 0}$	$\boldsymbol{\beta_0 = 1.68}$	$\boldsymbol{\beta_0 = 2.81}$	$\boldsymbol{\beta_0 = 3.94}$	$\boldsymbol{\beta_0 = 4.63}$	$\boldsymbol{\beta_0 = 5.31}$
t-stat for H_A	**[-12.44]**	**[-7.83]**	**[-7.38]**	**[-6.69]**	**[-6.80]**
(4) Market (1950-2021) with controls					
$\hat{\beta}$	-0.279**	-1.033***	-1.508***	-1.720***	-1.825***
t-stat for $H_0 : \beta = 0$	[-2.19]	[-3.73]	[-3.39]	[-2.74]	[-2.58]
$\boldsymbol{H_A : \beta = \beta_0 > 0}$	$\boldsymbol{\beta_0 = 1.68}$	$\boldsymbol{\beta_0 = 2.81}$	$\boldsymbol{\beta_0 = 3.94}$	$\boldsymbol{\beta_0 = 4.63}$	$\boldsymbol{\beta_0 = 5.31}$
t-stat for H_A	**[-15.40]**	**[-13.88]**	**[-12.26]**	**[-10.12]**	**[-10.09]**

Panel B: Factor portfolio returns and risk-premium measures

	High-Low B/M $r_{t,t+1}$	High-Low D/P $r_{t,t+1}$	High-Low E/P $r_{t,t+1}$	Volatility$_t$	Credit spread$_t$	Term spread$_t$	D/P$_t$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\hat{\beta}$	0.248	0.491	-0.188	-0.107	-2.596	-0.949	0.000
t-stat for $H_0 : \beta = 0$	[0.92]	[2.36]	[-1.68]	[-0.91]	[-2.00]	[-0.65]	[0.01]
$\boldsymbol{H_A : \beta = \beta_0 > 0}$	$\boldsymbol{\beta_0 = 1.70}$	$\boldsymbol{\beta_0 = 1.70}$	$\boldsymbol{\beta_0 = 1.70}$	$\boldsymbol{\beta_0 = 0.76}$	$\boldsymbol{\beta = 0.087}$	$\boldsymbol{\beta_0 = 1.70}$	$\boldsymbol{\beta_0 = 1.19}$
t-stat for H_A	**[-5.38]*** **	**[-5.82]*** **	**[-16.84]*** **	**[-7.39]*** **	**[-2.06]** **	**[-1.81]* **	**[-33.05]*** **

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Table A9: Future equity returns conditional on a future disaster occurring or not

This table re-estimates Table 4 but conditioning on the Disaster Index being elevated AND a future disaster occurring or not. The Disaster Index ($\texttt{DI}_{i,t}$) is considered to be "elevated" at time t when $\texttt{DI}_{i,t} \geq \texttt{DisasterThreshold}$, with the Disaster Threshold defined in Section II.C. $\texttt{Future Disaster}_{t+2\to4}$ is an indicator variable that equals one if there is a disaster in that country during the next two to four years, and zero otherwise. As conditioning on a future disaster requires future information, the purpose of this analysis is to assess retrospectively how the *ex post* distribution of returns depends on whether a disaster is realized or not.

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5
(1) Market (1870-2021):					
Conditional on $\texttt{DI}_{i,t} \geq \texttt{DisasterThreshold}$ and Future Disaster$_{t+2\to4}$					
$\mathbb{E}[r_{i,t\to t+h}]$	-0.043	-0.169***	-0.345***	-0.475***	-0.461***
$\mathbb{SD}[r_{i,t\to t+h}]$	0.031	0.047	0.069	0.114	0.117
N	190	141	106	71	67
Conditional on $\texttt{DI}_{i,t} \geq \texttt{DisasterThreshold}$ and NO Future Disaster$_{t+2\to4}$					
$\mathbb{E}[r_{i,t\to t+h}]$	-0.005	-0.021	-0.051	-0.077	-0.114**
$\mathbb{SD}[r_{i,t\to t+h}]$	0.020	0.033	0.040	0.049	0.056
N	1,183	1,181	1,179	1,177	1,139
(2) Market (1870-1949):					
Conditional on $\texttt{DI}_{i,t} \geq \texttt{DisasterThreshold}$ and Future Disaster$_{t+2\to4}$					
$\mathbb{E}[r_{i,t\to t+h}]$	-0.046***	-0.139***	-0.241***	-0.383***	-0.323***
$\mathbb{SD}[r_{i,t\to t+h}]$	0.016	0.026	0.036	0.048	0.053
N	164	128	94	60	58
Conditional on $\texttt{DI}_{i,t} \geq \texttt{DisasterThreshold}$ and NO Future Disaster$_{t+2\to4}$					
$\mathbb{E}[r_{i,t\to t+h}]$	0.017	0.040	0.058	0.067	0.070
$\mathbb{SD}[r_{i,t\to t+h}]$	0.016	0.028	0.036	0.044	0.052
N	660	658	656	654	620
(3) Market (1950-2021):					
Conditional on $\texttt{DI}_{i,t} \geq \texttt{DisasterThreshold}$ and Future Disaster$_{t+2\to4}$					
$\mathbb{E}[r_{i,t\to t+h}]$	0.126***	0.003	-0.522**	-0.457***	-0.467***
$\mathbb{SD}[r_{i,t\to t+h}]$	0.029	0.089	0.220	0.146	0.078
N	26	13	12	11	9
Conditional on $\texttt{DI}_{i,t} \geq \texttt{DisasterThreshold}$ and NO Future Disaster$_{t+2\to4}$					
$\mathbb{E}[r_{i,t\to t+h}]$	0.018	0.015	-0.003	-0.015	-0.042
$\mathbb{SD}[r_{i,t\to t+h}]$	0.025	0.042	0.054	0.072	0.084
N	523	523	523	523	519
(4) Market (1950-2021) with controls:					
Conditional on $\texttt{DI}_{i,t} \geq \texttt{DisasterThreshold}$ and Future Disaster$_{t+2\to4}$					
$\mathbb{E}[r_{i,t\to t+h}]$	0.128***	0.006	-0.520**	-0.458***	-0.470***
$\mathbb{SD}[r_{i,t\to t+h}]$	0.029	0.089	0.222	0.146	0.076
N	26	13	12	11	9
Conditional on $\texttt{DI}_{i,t} \geq \texttt{DisasterThreshold}$ and NO Future Disaster$_{t+2\to4}$					
$\mathbb{E}[r_{i,t\to t+h}]$	0.019	0.011	-0.025	-0.052	-0.085
$\mathbb{SD}[r_{i,t\to t+h}]$	0.025	0.040	0.043	0.054	0.070
N	374	374	374	374	371

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Table A10: Global vs. Domestic Disaster Indexes

To distinguish between global and domestic GDP disasters, we construct several proxies for a global disaster index and re-estimate Table 4 (in Panel A) and Tables 6-9 (in Panel B) for each of them. The variable "Domestic Disaster Index" is the same country-specific disaster index as before. The three proxies for a global disaster index are: "Global Average DI" (an average across all countries' disaster indexes), "Global DI 75th Percentile" (the 75th percentile across all countries' disaster indexes), and the first two principal components across all countries' disaster indexes. The results corresponding to Table 4 are reported in Panel A. In Panel B, we re-estimate columns (1) and (2) in Table 6-8 and columns (1), (2), (5), and (6) in Table 9 using this new "Global Disaster Index," comparing it to the "Domestic Disaster Index" from the main analysis.

Panel A: Future equity index returns, 1950-2021

	Year 1		Year 2		Year 3		Year 4		Year 5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Domestic Disaster Index	-0.248***	-0.182*	-0.503***	-0.392***	-0.597**	-0.460***	-0.661	-0.512*	-0.744*	-0.588**
	[-2.64]	[-1.77]	[-2.92]	[-4.79]	[-2.10]	[-2.78]	[-1.60]	[-1.79]	[-1.71]	[-1.99]
Global Average DI	-0.001	-0.422	-2.068	-2.813**	-3.723	-4.638**	-4.410	-5.407**	-4.495	-5.573**
	[-0.00]	[-0.67]	[-0.97]	[-2.09]	[-1.19]	[-2.15]	[-1.25]	[-2.12]	[-1.22]	[-2.10]
Observations	1,260	1,260	1,240	1,240	1,220	1,220	1,200	1,200	1,180	1,180
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

	Year 1		Year 2		Year 3		Year 4		Year 5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Domestic Disaster Index	-0.127	-0.055	-0.486	-0.364	-0.679*	-0.529**	-0.970*	-0.812**	-1.033*	-0.867**
	[-1.34]	[-0.65]	[-1.53]	[-1.57]	[-1.73]	[-2.03]	[-1.87]	[-2.31]	[-1.96]	[-2.46]
Global DI 75th Percentile	-0.557	-1.045**	-2.276	-3.127**	-3.580	-4.617*	-3.245	-4.332	-3.424	-4.594*
	[-0.71]	[-2.20]	[-1.23]	[-2.58]	[-1.13]	[-1.92]	[-0.93]	[-1.61]	[-1.01]	[-1.77]
Observations	1,260	1,260	1,240	1,240	1,220	1,220	1,200	1,200	1,180	1,180
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

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	Year 1		Year 2		Year 3		Year 4		Year 5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Domestic Disaster Index	-0.164*	-0.059	-0.454**	-0.285**	-0.657**	-0.469**	-0.886**	-0.674**	-0.905**	-0.675**
	[-1.77]	[-0.56]	[-2.20]	[-2.16]	[-2.14]	[-2.46]	[-1.98]	[-2.31]	[-1.97]	[-2.38]
Principal Component 1	0.000	-0.007	-0.005	-0.017*	-0.006	-0.020*	-0.005	-0.021	-0.008	-0.026
	[0.04]	[-1.53]	[-0.50]	[-1.84]	[-0.50]	[-1.66]	[-0.33]	[-1.42]	[-0.41]	[-1.36]
Principal Component 2	-0.010	-0.005	-0.046***	-0.037***	-0.075***	-0.065***	-0.077***	-0.065***	-0.077***	-0.063***
	[-1.09]	[-0.54]	[-3.27]	[-2.70]	[-7.64]	[-6.90]	[-6.77]	[-5.65]	[-7.83]	[-6.01]
Observations	1,203	1,203	1,183	1,183	1,163	1,163	1,143	1,143	1,123	1,123
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Risk premium measures, 1950-2021

	Volatility		Credit Spreads		Term Spread		Dividend/Price		Earnings/Price	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Domestic Disaster Index	0.071	0.066	-0.866**	-1.265**	-1.085*	-0.984*	-0.014	-0.015	-0.042***	-0.044***
	[1.39]	[1.25]	[-2.21]	[-2.13]	[-1.69]	[-1.65]	[-0.79]	[-0.86]	[-3.03]	[-3.03]
Global Average DI	-0.773*	-0.774	-11.368*	-11.376***	0.569	-1.613	0.062	0.064	-0.234**	-0.245**
	[-1.70]	[-1.57]	[-1.73]	[-2.83]	[0.08]	[-0.27]	[0.72]	[0.71]	[-2.52]	[-2.50]
Observations	1,279	1,279	514	514	1,377	1,377	1,280	1,280	890	890
Adjusted R^2	0.054	0.059	0.104	0.468	0.087	0.122	0.189	0.195	0.130	0.132
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

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	Volatility		Credit Spreads		Term Spread		Dividend/Price		Earnings/Price	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Domestic Disaster Index	0.048	0.043	-1.236***	-1.455**	-1.120*	-1.043**	-0.012	-0.013	-0.039**	-0.040**
	[0.99]	[0.96]	[-3.43]	[-2.49]	[-1.93]	[-2.09]	[-0.60]	[-0.66]	[-2.13]	[-2.16]
Global DI 75th Percentile	-0.715**	-0.719*	-11.550	-13.067***	0.757	-1.440	0.059	0.062	-0.325***	-0.341***
	[-2.00]	[-1.75]	[-1.20]	[-2.67]	[0.12]	[-0.27]	[0.77]	[0.79]	[-2.72]	[-2.69]
Observations	1,279	1,279	514	514	1,377	1,377	1,280	1,280	890	890
Adjusted R^2	0.051	0.057	0.089	0.467	0.087	0.122	0.189	0.195	0.137	0.139
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

	Volatility		Credit Spreads		Term Spread		Dividend/Price		Earnings/Price	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Domestic Disaster Index	0.142***	0.145***	-0.988**	-1.205**	-1.087	-0.994	-0.020	-0.021	-0.053***	-0.054***
	[3.38]	[5.00]	[-2.04]	[-2.20]	[-1.61]	[-1.56]	[-1.07]	[-1.14]	[-3.14]	[-3.13]
Principal Component 1	-0.010***	-0.011***	-0.084	-0.082	0.010	0.002	0.002***	0.002***	0.002	0.001
	[-3.65]	[-2.63]	[-0.58]	[-1.23]	[0.23]	[0.06]	[4.51]	[4.76]	[0.71]	[0.64]
Principal Component 2	0.000	0.000	-0.066***	-0.082***	-0.035	-0.057	-0.002***	-0.002***	-0.002*	-0.002*
	[0.07]	[0.07]	[-3.14]	[-4.26]	[-0.61]	[-1.08]	[-5.16]	[-5.05]	[-1.90]	[-1.94]
Observations	1,222	1,222	514	514	1,320	1,320	1,223	1,223	851	851
Adjusted R^2	0.099	0.099	0.101	0.482	0.086	0.115	0.278	0.282	0.138	0.138
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

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Table A11: Government bond yields conditional on the Disaster Index

This table reports coefficient estimates of a regression analyzing the relationship between the contemporaneous government bond yield in a given country and the Disaster Index. The long-term government bond yield is the yield-to-maturity of a 10-year government bond, whereas the short-term government bond yield typically represents the yield-to-maturity of a 3-month treasury bill. 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 time t. The control variables are inflation and the log excess return of the equity market index from $t-1$ to t. T-statistics are in brackets and correspond to Driscoll-Kraay standard errors with lag = 12 and Kiefer-Vogelsang fixed-b critical values. *, **, *** correspond to p-values less than 10%, 5%, 1%, respectively. Results are estimated across 20 economies over the full sample period of 1870-2021 (Panel A), 1870-1949 (Panel B), or 1950-2021 (Panel C).

Panel A: Full sample, 1870-2021

	Short-term Gov't Bond Yield				Long-term Gov't Bond Yield			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\texttt{DisasterIndex}_{i,t}$	-0.030	0.009			-0.047	-0.017		
	[-0.47]	[0.18]			[-0.82]	[-0.42]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-0.004	0.013			-0.012	-0.003
			[-0.13]	[0.59]			[-0.41]	[-0.14]
Observations	1,919	1,919	1,919	1,919	1,960	1,960	1,960	1,960
Adjusted R^2	0.062	0.361	0.060	0.361	0.070	0.370	0.065	0.370
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: 1870-1949

	Short-term Gov't Bond Yield				Long-term Gov't Bond Yield			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\texttt{DisasterIndex}_{i,t}$	-0.000	0.006			0.005	0.006		
	[-0.01]	[0.57]			[0.94]	[1.18]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			0.022	0.026**			0.016**	0.018**
			[1.58]	[2.00]			[2.36]	[2.50]
Observations	542	542	542	542	583	583	583	583
Adjusted R^2	0.564	0.595	0.567	0.599	0.490	0.491	0.495	0.496
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Panel C: 1950-2021

	Short-term Gov't Bond Yield				Long-term Gov't Bond Yield			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\texttt{DisasterIndex}_{i,t}$	-0.035	0.005			-0.044	-0.015		
	[-0.45]	[0.11]			[-0.65]	[-0.34]		
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$			-0.019	0.016			-0.033	-0.007
			[-0.41]	[0.71]			[-0.81]	[-0.31]
Observations	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377
Adjusted R^2	0.056	0.501	0.055	0.502	0.070	0.492	0.068	0.491
Controls	No	Yes	No	Yes	No	Yes	No	Yes

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Table A12: Currency returns conditional on the Disaster Index

This table reports results of a regression of the change in the exchange rate of a country (relative to the USD) on the Disaster Index. More specifically, the dependent variable in the regression is: in Panel A, the contemporaneous one-year-change ($t-1$ to t) in the exchange rate (relative to the USD); and, in Panels B-D, the future t to $t+1$, $t+2$, or $t+3$ change in the exchange rate, respectively. Higher coefficient estimates correspond to a currency appreciation (relative to the USD). $\texttt{Interest diff}_{i,t}$ is the interest rate differential, defined as the short-term interest rate of country i minus the U.S. short-term interest rate. For the specifications in columns 4-6, the predictor variable is replaced by the Disaster Index left-censored at the mean of its historical distribution over all countries up to time t. The control variables are inflation, the log excess return of the equity market index from $t-1$ to t, and the dividend yield of the market index. T-statistics are in brackets and correspond to Driscoll-Kraay standard errors with lag = 12 and Kiefer-Vogelsang fixed-b critical values. *, **, *** correspond to p-values less than 10%, 5%, 1%, respectively. Results are estimated across 19 economies (20 economies excluding the U.S.) over the full sample period of 1870-2021.

Panel A: Currency change$_{t-1,t}$ (relative to USD)

	(1)	(2)	(3)	(4)	(5)	(6)
$\texttt{DisasterIndex}_{i,t}$	0.016	0.018	0.021			
	[0.18]	[0.20]	[0.25]			
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$				0.018	0.022	0.019
				[0.23]	[0.27]	[0.28]
$\texttt{Interest diff}_{i,t}$		0.099	0.224		0.100	0.224
		[0.46]	[0.77]		[0.46]	[0.77]
Observations	1,072	1,072	1,072	1,072	1,072	1,072
Adjusted R^2	-0.001	-0.002	0.018	-0.001	-0.002	0.018
Controls	No	No	Yes	No	No	Yes

Panel B: Currency change$_{t,t+1}$

$\texttt{DisasterIndex}_{i,t}$	-0.011	-0.007	-0.003			
	[-0.10]	[-0.06]	[-0.04]			
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$				-0.017	-0.010	-0.025
				[-0.15]	[-0.08]	[-0.24]
$\texttt{Interest diff}_{i,t}$		0.205	0.331		0.205	0.330
		[0.89]	[1.08]		[0.89]	[1.08]
Observations	1,055	1,055	1,055	1,055	1,055	1,055
Adjusted R^2	-0.001	0.001	0.016	-0.001	0.001	0.016
Controls	No	No	Yes	No	No	Yes

Panel C: Currency change$_{t,t+2}$

$\texttt{DisasterIndex}_{i,t}$	-0.038	-0.026	-0.031			
	[-0.22]	[-0.15]	[-0.23]			
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$				-0.066	-0.046	-0.092
				[-0.36]	[-0.26]	[-0.55]
$\texttt{Interest diff}_{i,t}$		0.512	0.781		0.510	0.778
		[1.18]	[1.36]		[1.18]	[1.35]
Observations	1,038	1,038	1,038	1,038	1,038	1,038
Adjusted R^2	0.010	0.016	0.041	0.010	0.016	0.041
Controls	No	No	Yes	No	No	Yes

Panel D: Currency change$_{t,t+3}$

$\texttt{DisasterIndex}_{i,t}$	-0.060	-0.045	-0.058			
	[-0.38]	[-0.27]	[-0.42]			
$\texttt{max}(\texttt{DisasterIndex}_{i,t}, \texttt{mean})$				-0.089	-0.066	-0.135
				[-0.53]	[-0.39]	[-0.82]
$\texttt{Interest diff}_{i,t}$		0.544	0.895		0.542	0.890
		[0.87]	[1.15]		[0.86]	[1.14]
Observations	1,021	1,021	1,021	1,021	1,021	1,021
Adjusted R^2	0.023	0.028	0.054	0.023	0.028	0.055
Controls	No	No	Yes	No	No	Yes

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Table A13: Do risk premiums predict disaster severity?

This table reports estimates from Equation (10), $Severity_{i,t} = \beta Risk\ Premium_{i,t-h} + \epsilon_{i,t}$, which analyzes how each of the four risk premium measures predicts the peak-to-trough severity of GDP crashes. $Severity_{i,t}$ denotes the peak-to-trough decline of the GDP crash episode with GDP peak occurring at time t. $Risk\ Premium_{i,t-h}$ is the risk premium measure at year $t-h$, de-meaned by its average level during years outside of the $t-5$ to $t+5$ window within each country. The four risk premium measures are market volatility (Panel A), corporate credit spreads (Panel B), the term spread (Panel C), and the dividend-to-price ratio of the market index (Panel D). Each cell in the table reports a β estimate from a separate regression. Each row corresponds to a different predictability horizon: risk premiums are variously measured at years $t-3$ (row 1), $t-2$ (row 2), $t-1$ (row 3), and its minimum (row 4) or maximum (row 5) over years $t-5$ through $t-1$, relative to GDP crash episodes with GDP peaks occurring at time t. As for the columns, peak-to-trough GDP crashes have been grouped into six global episodes (columns 2-7), where the regression is estimated cross-sectionally within each of these six global episodes. For each country, up to one peak-to-trough GDP crash episode is included within any particular global episode (if a country has more than one GDP crash that occur during a global episode, the earliest GDP crash is included). Column 1 then pools all observations from all six global episodes into a single regression with episode fixed effects. Blank cells indicate insufficient data. "World War I" corresponds to GDP crash episodes with GDP peaks between 1912-18, "Post World War I" between 1919-20, "Great Depression" between 1928-29, "World War II" between 1939-40, "Global Financial Crisis" between 2007-08, and "2020 Pandemic" in 2019. These six global episodes are chosen as they involve at least three countries. GDP crashes that do not fall within one of these six episodes are excluded from this analysis. Robust T-statistics are in brackets. *, **, *** correspond to p-values less than 10%, 5%, 1%, respectively.

Panel A: Market volatility

	All episodes (1)	World War I (2)	Post World War I (3)	Great Depression (4)	World War II (5)	Global Fin. Crisis (6)	2020 Pandemic (7)
Volatility_{t-3}	0.011	-0.895	-0.579**	0.327	0.017	-0.240	0.205
	[0.04]	[-0.70]	[-7.49]	[0.79]	[0.03]	[-1.12]	[1.10]
Volatility_{t-2}	-0.171	-0.608	-0.795	0.472	-0.451	-0.071	0.126
	[-0.50]	[-0.58]	[-2.17]	[0.87]	[-0.52]	[-0.28]	[1.54]
Volatility_{t-1}	-0.157	-2.932***	0.341	0.491	-1.155	-0.163**	-0.137
	[-0.68]	[-3.69]	[0.94]	[1.27]	[-0.90]	[-3.09]	[-1.26]
$\text{Min}(\text{Vol}_{t-5}, \ldots, \text{Vol}_{t-1})$	-0.478	-1.138	0.049	0.627	-2.516**	-0.108	-0.090
	[-0.94]	[-0.69]	[0.08]	[1.13]	[-4.19]	[-0.33]	[-0.65]
$\text{Max}(\text{Vol}_{t-5}, \ldots, \text{Vol}_{t-1})$	-0.129	-1.641	-0.506	0.360	-0.287	-0.035	0.321
	[-0.39]	[-1.43]	[-0.55]	[0.80]	[-0.40]	[-0.19]	[1.53]
Number of episodes	47	10	4	6	6	12	9

Panel B: Credit spreads

	All episodes (1)	World War I (2)	Post World War I (3)	Great Depression (4)	World War II (5)	Global Fin. Crisis (6)	2020 Pandemic (7)
$\text{CreditSpread}_{t-3}$	-0.040**					-0.067***	-0.020
	[-2.61]					[-3.74]	[-1.37]
$\text{CreditSpread}_{t-2}$	-0.036**					-0.056**	-0.018
	[-2.86]					[-2.95]	[-1.31]
$\text{CreditSpread}_{t-1}$	-0.024**					-0.034	-0.016*
	[-2.38]					[-1.61]	[-2.04]
$\text{Min}(\text{CS}_{t-5}, \ldots, \text{CS}_{t-1})$	-0.041***					-0.068***	-0.020
	[-3.17]					[-3.47]	[-1.52]
$\text{Max}(\text{CS}_{t-5}, \ldots, \text{CS}_{t-1})$	-0.033***					-0.044**	-0.022*
	[-3.12]					[-2.43]	[-1.90]
Number of episodes	21	0	0	0	0	12	9

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Panel C: The term spread

	All episodes (1)	World War I (2)	Post World War I (3)	Great Depression (4)	World War II (5)	Global Fin. Crisis (6)	2020 Pandemic (7)
TermSpread_{t-3}	0.017	-0.036		-0.001	0.039*	0.003	0.008
	[1.08]	[-0.73]		[-0.03]	[2.43]	[0.58]	[1.42]
TermSpread_{t-2}	0.015	-0.042		0.001	0.035**	0.001	0.011*
	[1.12]	[-1.69]		[0.04]	[2.95]	[0.28]	[2.01]
TermSpread_{t-1}	-0.012	-0.068**	-0.038	-0.033	0.032	0.002	0.010*
	[-1.03]	[-3.17]	[-0.66]	[-1.20]	[0.41]	[0.32]	[1.93]
$\text{Min}(\text{TS}_{t-5}, \ldots, \text{TS}_{t-1})$	0.000	-0.050*	0.002	-0.028	0.053	0.002	0.015*
	[0.00]	[-1.81]	[0.05]	[-0.45]	[1.11]	[0.38]	[2.24]
$\text{Max}(\text{TS}_{t-5}, \ldots, \text{TS}_{t-1})$	0.023	-0.038	-0.047**	0.007	0.046**	-0.000	0.009
	[1.64]	[-0.91]	[-17.95]	[0.21]	[4.03]	[-0.01]	[1.83]
Number of episodes	47	12	3	5	6	12	9

Panel D: Dividend/price of the market index

	All episodes (1)	World War I (2)	Post World War I (3)	Great Depression (4)	World War II (5)	Global Fin. Crisis (6)	2020 Pandemic (7)
D/P_{t-3}	-0.183	-5.309	0.194	-3.563	13.913	0.117	0.082
	[-0.43]	[-2.00]	[1.75]	[-1.21]	[1.23]	[0.08]	[0.17]
D/P_{t-2}	-1.529	-5.424	0.068	-4.660*	-6.810	-0.084	-0.053
	[-1.43]	[-1.79]	[0.25]	[-2.36]	[-1.76]	[-0.06]	[-0.15]
D/P_{t-1}	-1.477*	-1.069	-0.025	-4.847	-7.159	-0.888	-0.260
	[-1.80]	[-1.01]	[-0.10]	[-1.73]	[-2.36]	[-0.54]	[-0.68]
$\text{Min}(\text{D/P}_{t-5}, \ldots, \text{D/P}_{t-1})$	-0.000	-1.319	0.544	-3.792	17.903**	-0.302	0.183
	[-0.00]	[-0.39]	[1.02]	[-1.98]	[6.10]	[-0.19]	[0.39]
$\text{Max}(\text{D/P}_{t-5}, \ldots, \text{D/P}_{t-1})$	-1.085	-1.928	-0.080	-3.143	-7.715	0.000	-0.041
	[-1.53]	[-1.63]	[-0.27]	[-1.36]	[-2.22]	[0.00]	[-0.09]
Number of episodes	42	7	4	6	4	12	9

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Table A14: Do risk premiums predict disaster severity? Analysis including countries without GDP disasters

This table re-estimates Table A13, but includes *all countries* within each global episode for which risk premium and GDP data are available, regardless of whether that country experienced a GDP disaster. For countries that do not experience any GDP decline at all during the global episode, the peak-to-trough GDP severity is coded as zero.

Panel A: Market volatility

	All episodes (1)	World War I (2)	Post World War I (3)	Great Depression (4)	World War II (5)	Global Financial Crisis (6)	2020 Pandemic (7)
Volatility_{t-3}	0.354	0.625	-0.184	0.421	0.680	-0.159	-0.105
	[1.38]	[0.90]	[-0.82]	[1.51]	[1.30]	[-1.00]	[-0.46]
Volatility_{t-2}	-0.076	-0.123	0.142	0.126	-0.180	-0.104	-0.162
	[-0.28]	[-0.20]	[0.35]	[0.39]	[-0.35]	[-0.44]	[-0.74]
Volatility_{t-1}	-0.123	-1.558	0.000	0.802***	-0.726	-0.092	-0.502**
	[-0.49]	[-1.37]	[0.00]	[3.95]	[-0.98]	[-1.21]	[-2.63]
$\text{Min}(\text{Vol}_{t-5}, \ldots, \text{Vol}_{t-1})$	-0.093	-0.269	-0.071	0.846**	-0.981	-0.119	-0.396**
	[-0.29]	[-0.33]	[-0.37]	[2.33]	[-0.73]	[-0.41]	[-2.31]
$\text{Max}(\text{Vol}_{t-5}, \ldots, \text{Vol}_{t-1})$	-0.013	-1.343	0.022	0.069	-0.028	0.094	-0.142
	[-0.06]	[-1.29]	[0.08]	[0.22]	[-0.06]	[0.84]	[-0.55]
Number of episodes	106	14	13	19	20	20	20

Panel B: Credit spreads

	All episodes (1)	World War I (2)	Post World War I (3)	Great Depression (4)	World War II (5)	Global Financial Crisis (6)	2020 Pandemic (7)
$\text{CreditSpread}_{t-3}$	-0.007					-0.022	0.002
	[-0.47]					[-1.02]	[0.13]
$\text{CreditSpread}_{t-2}$	-0.011					-0.014	-0.009
	[-0.79]					[-0.72]	[-0.44]
$\text{CreditSpread}_{t-1}$	0.001					-0.008	0.006
	[0.07]					[-0.44]	[0.43]
$\text{Min}(\text{CS}_{t-5}, \ldots, \text{CS}_{t-1})$	-0.010					-0.018	-0.003
	[-0.70]					[-0.89]	[-0.16]
$\text{Max}(\text{CS}_{t-5}, \ldots, \text{CS}_{t-1})$	-0.004					-0.020	0.007
	[-0.28]					[-0.96]	[0.44]
Number of episodes	40	0	0	0	0	20	20

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Panel C: The term spread

	All episodes (1)	World War I (2)	Post World War I (3)	Great Depression (4)	World War II (5)	Global Financial Crisis (6)	2020 Pandemic (7)
TermSpread_{t-3}	0.019	-0.034	-0.003	0.003	0.046	0.004	0.012
	[0.94]	[-0.83]	[-0.13]	[0.20]	[1.44]	[0.92]	[1.58]
TermSpread_{t-2}	0.022	-0.016	-0.008	0.008	0.048*	0.003	0.012
	[1.12]	[-0.47]	[-0.33]	[0.42]	[1.81]	[0.69]	[1.28]
TermSpread_{t-1}	-0.017	-0.019	-0.008	-0.029	-0.032	0.002	0.010
	[-1.57]	[-0.57]	[-0.40]	[-1.49]	[-0.92]	[0.46]	[1.10]
$\text{Min}(\text{TS}_{t-5}, ... ,\text{TS}_{t-1})$	0.002	-0.018	0.002	-0.009	0.017	0.002	0.010
	[0.12]	[-0.61]	[0.21]	[-0.44]	[0.38]	[0.49]	[0.92]
$\text{Max}(\text{TS}_{t-5}, ... ,\text{TS}_{t-1})$	0.026	-0.037	0.006	0.007	0.053**	0.003	0.011
	[1.50]	[-1.09]	[0.92]	[0.30]	[2.54]	[0.53]	[1.43]
Number of episodes	110	17	14	19	20	20	20

Panel D: Dividend/price of the market index

	All episodes (1)	World War I (2)	Post World War I (3)	Great Depression (4)	World War II (5)	Global Financial Crisis (6)	2020 Pandemic (7)
D/P_{t-3}	0.568	1.163	0.525***	-1.762	8.495	-0.085	0.752
	[1.58]	[0.44]	[5.09]	[-1.31]	[1.26]	[-0.09]	[1.69]
D/P_{t-2}	0.259	0.982	0.991***	-2.381**	1.605	-0.152	1.031**
	[0.52]	[0.35]	[3.75]	[-2.49]	[0.64]	[-0.15]	[2.47]
D/P_{t-1}	0.376	0.772	0.987***	-1.964*	2.339	-0.194	0.901***
	[0.80]	[0.60]	[3.19]	[-1.83]	[0.82]	[-0.19]	[2.95]
$\text{Min}(\text{D/P}_{t-5}, ... ,\text{D/P}_{t-1})$	0.962	3.302	1.389***	-2.329*	9.646	-0.142	0.992**
	[1.38]	[1.04]	[3.34]	[-1.77]	[1.56]	[-0.13]	[2.54]
$\text{Max}(\text{D/P}_{t-5}, ... ,\text{D/P}_{t-1})$	0.369	0.078	0.700***	-1.254	1.177	-0.027	1.124***
	[1.00]	[0.06]	[3.66]	[-0.88]	[0.44]	[-0.03]	[3.27]
Number of episodes	95	11	12	17	15	20	20

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Figure A1: Disaster indexes with alternative forecast horizons

This figure plots event studies of the alternative disaster indexes used in Table 10. The event studies are created by averaging these alternative disaster indexes across all disasters in the sample. Each of the alternative disaster indexes is created by estimating the first stage of Equation (8), a rolling probit regression that forecasts disasters at future h-year-ahead horizon (h = 1, 2, 3, or 4). Unlike the main Disaster Index that forecasts disasters at joint 2, 3, or 4-year future horizons, these alternative disaster indexes only consider a single-year h-year-ahead horizon. These disaster indexes are created as the predicted values estimated from rolling probit regressions, similar to the main Disaster Index. The probit uses the three predictor variables: the three-year-past market return, the three-year-past change in bank credit-to-GDP, and their interaction. (Unlike with the main Disaster Index, past market returns and the past change in bank credit-to-GDP are not left-censored at zero, to allow for the fact that market crashes and credit contractions do predict disasters at the one-year-ahead horizon.) These event studies are marked with a diamond at the year corresponding to the horizon h. For example, the 1-year-ahead disaster index (thick black line) has a diamond marker at t = -1, the horizon at which it is "intended" to forecast the disaster at time 0. The dotted horizontal line represents the unconditional likelihood of a disaster in a given year in our sample.

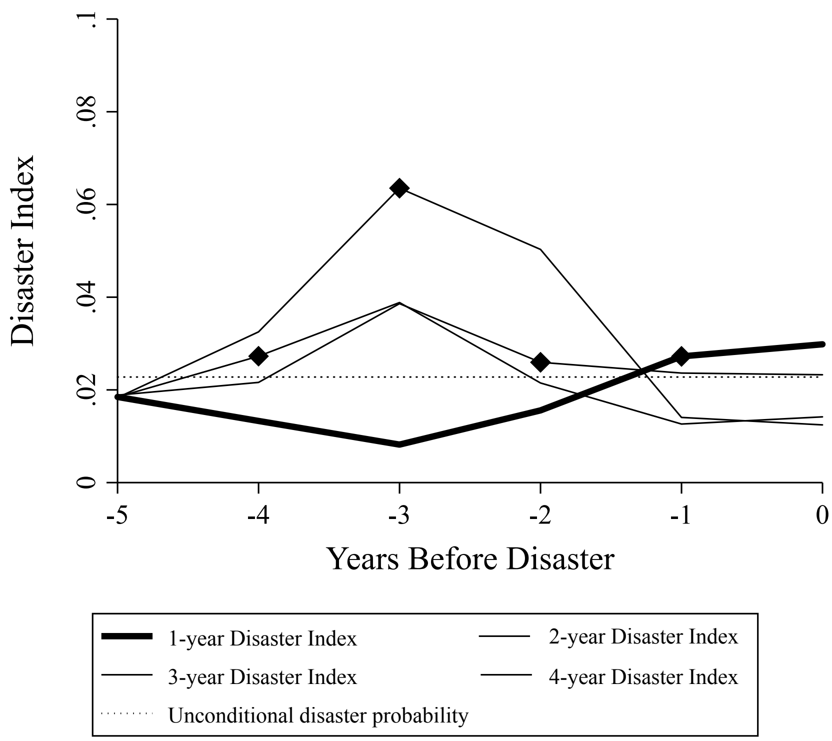

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Table B1: Data sources for corporate credit spread indexes

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)

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