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Does the U.S. extreme indicator matter in stock markets? International evidence

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Abstract

We propose a new predictor—the innovation in the daily return minimum in the U.S. stock market (ΔMIN^{US})—for predicting international stock market returns. Using monthly data for a wide range of 17 MSCI international stock markets during the period spanning over half a century from January 1972 to July 2022, we find that ΔMIN^{US} have strong predictive power for returns in most international stock markets:ΔMIN^{US} negatively predicts the next-month stock market returns. The results remain robust after controlling for a number of macroeconomic predictors and conducting subsample and panel data analyses, indicating that ΔMIN^{US} has significant predictive power and it outperforms other variables in international markets. Notably, ΔMIN^{US} demonstrates excellent predictive power even during the periods driven by financial upheavals (e.g., Global Financial Crisis and European Sovereign Debt Crisis). Both panel regressions and out-of-sample tests also support the robust predictive performance of ΔMIN^{US}. The predictive power, however, disappears during the non-financial crisis caused by COVID-19 pandemic, which is originated from the health sector rather than the financial sector. The results provide a new perspective on U.S. extreme indicator in stock market return predictability.

Keywords: Return predictability, Innovation in extreme minimum, International stock markets, Financial crisis

JEL Classification: C53, G12, G15

Introduction

Stock markets provide firms an effective channel to raise funds for both current operations and future developments, whilst investors have opportunities to obtain high returns from the markets. Since stock markets are replete with risks and opportunities, stock return predictability remains an area of active research in the field of finance. With the increase in global trade and cross-regional capital flows, international markets have become more interconnected than ever; see Singh (2007, 2016a) for the surveys. It is, therefore, crucial to go beyond narrow single market predictability, and examine the inter-market relationship in international stock markets. Many researchers in the past have claimed that the financial markets are not perfectly efficient and that investors are not rational, by showing that the stock trend is predictable (Poterba and Summers 1988; Fama and French 1992; Campbell et al. 1997; Bae et al. 2003; Hood and Malik 2013;

Barillas and Shanken 2018; Baker et al. 2020; Zerbib 2022). The literature documents many factors closely connected to stock markets, and among these, the factors related to risks are particularly important (see e.g., Bali et al. 2011; Chiang and Hughen 2017; Nartea et al. 2017; Baker et al. 2020; Huang et al. 2022). This is because the relationship between risk and returns is studied by almost every participant in the stock market—the trade-off between risk and returns is fundamental in investments.

A variety of risk-related factors have been used in stock return prediction, and researchers have achieved good prediction results; these factors include market beta, leverage, liquidity effect, momentum, volatilities, spread, and some macroeconomic variables (Rapach et al. 2005; Gharghori et al. 2009; Bali et al. 2011; Huang et al. 2012; Chung and Kim 2017; Nartea et al. 2017; Herrera and Clements 2018; Bogousslavsky 2021; Borup and Schütte 2022; Liu and Matthies 2022). Among these, extreme value factors seem to be able to better explain the risks in the stock market. The proposition of extreme value theory (EVT) makes it possible to analyse extreme returns. The EVT is a branch of statistics that addresses extreme deviations from the mean of a probability distribution (Singh et al. 2013; Jin and Sui 2022; Jin and Sui 2022). Longin (1996) and Embrechts et al. (1999) introduced it to financial studies. The EVT indicates that the extreme historical patterns can be considered as "shock" factors, and the "shock" tends to have strong predictive power for the future stock prices, especially during market turbulences (e.g., Huang et al. 2012; Corradin and Maddaloni 2020; Liu and Matthies 2022).

The extreme patterns of the historical returns, as the special states of volatilities, are directly linked with tail risks and returns, and thus they can be considered as the primary factor in predicting future returns. The empirical studies have supported this hypothesis in many international stock markets (Bae et al. 2003; Muchnik et al. 2009; Boyer et al. 2010; Bali et al. 2011; Annaert et al. 2013; Barberis et al. 2016; Jiang et al. 2018; Baker et al. 2020; Bogousslavsky 2021). Bali et al. (2011) and Kelly and Jiang (2014), considering different fluctuations of stock prices, split the extreme value into two indicators: the maximum (MAX) and the minimum (MIN) of daily stock returns in the past month. They reveal a significantly negative relationship between MAX and the expected stock returns. The extreme indicators used by Jiang et al. (2018) also exhibit short-term predictive power. However, Forand and DeRubeis (2014) and Nartea et al. (2017) question the significant results of the extreme indicators, as they cannot find robust evidence for the predictive power of these indicators in many other stock markets.

Under the internationally integrated financial environment, the shift of certain factors in the U.S. stock market can be used as predictive factors for the performance of the international stock markets. The market anomalies or the "shock" identified in the U.S. stock market can be observed in the stock markets of other countries (Jegadeesh and Titman 1993; Fama and French 1996; Rouwenhorst 1999; Grundy and Martin 2001; Titman et al. 2004; Bali et al. 2011; Kelly and Jiang 2014; Corradin and Maddaloni 2020; Xu et al. 2023). Researchers have discovered the lead-lag relationship between the U.S. stock market and the international stock markets. Rapach et al. (2013) show that the lagged U.S. returns are a useful prediction tool for the returns in other industrialised countries. In fact, these lagged U.S. returns perform better in predicting stock returns than the countries' own nominal interest rates and dividend yields. However, Siliverstovs (2017) tests the robustness of the U.S. indicators in different phases of the business cycle (recession and expansion) and finds that the Rapach et al. (2013) results are fragile. He finds that the predictive power of lagged U.S. return is significant only during the recession phase of the business cycle.

The synchronised movements theory also supports the predictability in international stock markets. In the highly integrated world economy with more potent channels of transmission, the effectiveness of coordination has become increasingly more relevant (Akın and Kose 2008). With the rise in direct and indirect linkages from the increasingly tight connection among financial markets, the global equity correction shows significant synchronisation (Otto et al. 2001). The previous research also argued that the economic shock plays an important role in shaping international volatility. Common international shocks, common transmission channels, and country-specific shocks form the synergy of economic cycles in international financial markets. One of the main channels for these shocks is the spill-over effect that spreads through international trade. The U.S. is the world's largest trading exporter, and shocks originating from its market can widely spread to the international market and lead to synchronised periodic fluctuations in market capitalisations across different financial markets in the world (Norrbin and Schlagenhauf 1996; Otto et al. 2001; Beltratti and Morana 2010; Yetman 2011; Singh 2016b; Mikhaylov et al. 2022; Wen et al. 2022; Moiseev et al. 2023). The international markets, therefore, show predictability under such conditions.

Yetman (2011) argues that higher frequency business cycles are strongly synchronised during recession periods, but typical "decoupling" could occur during low frequency business cycles. Therefore, the predictability of international financial markets should be strong during recession periods, such as global financial crisis (GFC), but weak during decoupling period, such as the COVID-19 pandemic period, when most countries introduced ubiquitous lockdowns and restrictive measures around the world.

This study aims to extend previous research (Bali et al. 2011; Rapach et al. 2013; Barberis et al. 2016; Ghosh et al. 2017; Jiang et al. 2018; Bogousslavsky 2021; Liu and Matthies 2022) and provide a new perspective on the use of extreme measure factor of the U.S. market to predict future stock returns in other international markets. Unlike previous studies, we focus on the change in expansion or contraction of the extreme minimum return (the extreme loss) of the daily closing price of the stock index in each month, which is the price difference in the daily return minimum, and we denote it as ΔMIN. We use this innovation of the extreme minimum in the U.S. stock market (ΔMIN^{US}) as an indicator to predict future returns in the international stock markets.

The framework of behavioural finance theory suggests that the stock market is replete with irrational investors (Berardi 2022). The investment patterns in the markets tend to exhibit loss aversion rather than risk aversion. The changes in extreme losses, therefore, can affect investment decisions more than other extreme factors, and also impact future stock returns. The investors are biased towards the possibility of extreme stock market conditions (Forand and DeRubeis 2014; Bakshi et al. 2018). Under such scenarios, investors' irrationality will lead to lower-level diversification of portfolios to obtain skewed returns. In the international financial markets, due to the leadership of the U.S. stock market, when the extreme losses of the U.S. stock market expand (ΔMIN^{US} decreases), then there is an occurrence of a loss signal, and the risk-averse investors prefer to transfer assets to other valuable portfolios during a recession to hedge risks (Hood and Malik

2013; Berardi 2022). The short-term capital transfers (capital flight) may occur between international stock markets to avoid potential losses.

The investors' pessimistic sentiments and herding behaviour in the wake of imperfect (asymmetric) information induce more and more irrational cross-market investors to begin selling U.S. stocks and turning to invest in other stock markets, driving up the prices in other stock markets in the short-term horizon. Therefore, theoretically there should be a significant negative correlation between ΔMIN^{US} and future stock returns in non-U.S. stock markets. However, because of the leadership of the U.S. stock market in the international stock markets, its economic downturn will also gradually spread to other markets and cause their stock prices to fall. Thus, from a longer-term perspective, the trend of the U.S. stock market and other stock markets should be similar. Therefore, $\Delta MIN^{US}$is expected to have weak predictive power in the longer-term horizons.

The study focusses on three empirical questions: Does ΔMIN^{US} have robust predictive power in international stock markets? Does ΔMIN^{US} outperform other macroeconomic control variables in international stock markets? What is the relationship between ΔMIN^{US} and stock market returns during economic recessions—both NBER-based and major recession periods? These research questions form the basis of the hypotheses tested in the empirical section.

The empirical results suggest that ΔMIN^{US} has strong predictive power for stock market returns in most international stock markets:ΔMIN^{US} negatively predicts the next-month stock market return. The results remain robust after (i) controlling for a number of macroeconomic predictors, (ii) conducting panel data analysis, and (iii) performing robustness checks. Notably,ΔMIN^{US} demonstrates excellent predictive power even during the times of financial upheavals (Global Financial Crisis and European Sovereign Debt Crisis). The predictive power, however, disappears during the unprecedented non-financial crisis caused by COVID-19 pandemic.

Our study contributes to the existing body of literature on two counts. First, previous studies have focused mainly on the extreme value of individual stocks, and especially in the U.S. stock market. Our study extends the analysis to stock market index predictions, and covers a comprehensively wider set of 17 developed stock markets and historically a longer period of time spanning over half a century from January 1972 (1972:01) to July 2022 (2022:07). The study follows time-series approach and takes a country-by-country account of the evidence. The findings based on our comprehensive coverage in terms of both space and time could be generalised to represent the behaviour of international financial markets. Second, the previous research has used the extreme indicators in level, whether MIN or MAX, and the predictive power of these indicators for stock market returns remains controversial (Rapach et al. 2013; Nartea et al. 2017; Huang et al. 2022). This study extends previous research and proposes a novel indicator, ΔMIN^{US}, which not only shows strong predictive power in international stock markets but also outperforms other extreme indicators.

The remainder of this study is organised as follows. Section "Data and model specification" discusses the data and methodology used in the study. Section "Empirical analysis" reports and analyses the empirical results. Section "Conclusions" concludes the study. The research process of the study is summarised in terms of a self-explanatory visualisation (Fig. 1).

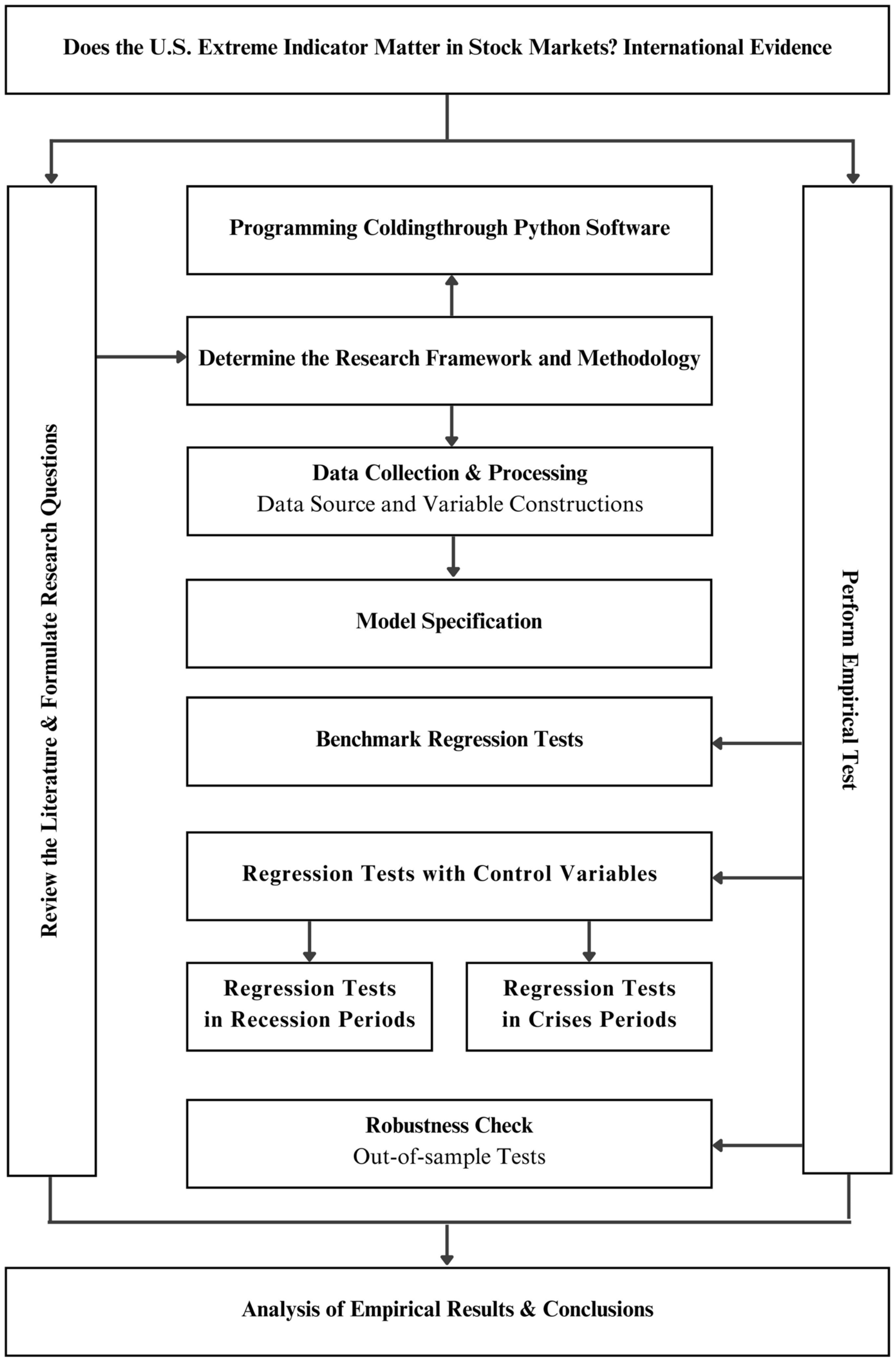

Fig. 1 Research Process

Data and model specification

Data description

The study covers the sample span of more than 50 years from January 1972 (1972:01) to July 2022 (2022:07) to comprehensively capture the long-term trend in the international stock markets—the year 1972:01 is the starting point for the Morgan Stanley Capital

International Standard Country (MSCI) index in most countries in the DataStream. Since one of the objectives of the study is to test the predictive power of extreme indicators in economic turmoil periods, the overall sample period is sub-divided into the sets of both NBER-based U.S. recession periods and the major recession periods. The data for the NBER-based U.S. recession periods are sourced from the Federal Reserve Economic Data (FRED) website; the recession period is represented by "1", and by "0" otherwise. The major recession periods include: (1) the period of Asian financial crisis (AFC), which extended from June 1997 to December 1999; (2) the period of global financial crisis (GFC), which extended from June 2007 to July 2009; (3) the period of European Sovereign Debt Crisis (ESDC), which stretched from the beginning of 2009 to the end of 2013; and (4) the period of COVID-19 pandemic which stretched from December 2019 to July 2022. The ESDC period is chosen to examine the impact of economic turmoil on the stock markets, especially the European markets.

To conduct the analysis of the relationship between the extreme returns and the future stock market returns, this study uses the data on MSCI Indexes for a comprehensive set of 17 stock markets of the industrialised countries. The MSCI Indexes are widely used by researchers in analysing the international stock return predictability. Apart from its ease of access, the MSCI is a reliable index for conducting comparative analysis. The data on MSCI are sourced from Refinitiv DataStream.

Rapach et al. (2005, 2013) use data on the stock markets of 10 countries in their sample and these markets include Australia, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, and the United Kingdom. Some studies have included a different set of 7 stock markets in their samples and these markets include Austria, Belgium, Denmark, Hong Kong, Norway, Singapore and Spain (e.g., Annaert et al. 2013; Walkshausl 2014). Unlike these studies, this study conducts an encompassing analysis and covers a comprehensive set of 17 stock markets of the MSCI developed countries and a longer time span of 50 years. Besides, this study also uses the overall MSCI World stock index, which can reflect the general situation of international stock markets. We also consider MSCI indexes for 17 other markets, including 5 MSCI young developed markets and 12 MSCI developing markets, which have data available over a time span of 30 years for robustness check.

The monthly log stock returns are used as the dependent variable for regression testing. The stock returns are calculated by summing log daily returns of the MSCI indexes in each market; denominated in both U.S. dollars and local currencies. Previous research uses the extreme indicators as the independent variable (Bali et al. 2011; Rapach et al. 2013; Barberis et al. 2016; Ghosh et al. 2017; Jiang et al. 2018; Barro and Liao 2021; Bogousslavsky 2021; Liu and Matthies 2022). The extreme value takes the highest or the lowest daily stock return of the MSCI index in every month in each market. This study extends the previous research and instead uses the innovation (first-level difference) of negative extreme return. These are defined as follows.

$$MIN_t^m = minimum(0, \forall R_{d,t}) \tag{1}$$

$$\Delta MIN_t^m = MIN_t^m - MIN_{t-1}^m \tag{2}$$

Table 1 Descriptive statistics of key variables [monthly returns of MSCI market indexes]

Market	Mean	Std	Median	Min	Max	25%	75%	Skewness	Kurtosis	ρ_1
Dependent variable: Stock return by market										
Australia	0.75	7.06	1.15	−58.90	22.72	−2.60	4.83	−1.58	10.09	0.00
Austria	0.57	7.22	0.86	−46.27	27.81	−2.63	4.46	−0.91	6.15	0.15
Belgium	0.76	6.08	1.31	−45.50	23.72	−2.36	4.31	−1.10	7.51	0.16
Canada	0.71	5.71	0.99	−31.39	19.28	−2.12	4.08	−0.90	3.70	0.04
Denmark	1.06	5.61	1.41	−29.67	22.12	−2.26	4.49	−0.49	2.23	0.05
France	0.79	6.45	1.15	−26.38	23.77	−2.77	4.90	−0.43	1.60	0.07
Germany	0.73	6.35	1.14	−27.91	21.26	−2.63	4.79	−0.64	1.84	0.02
Hong Kong	0.94	9.31	0.99	−56.98	63.05	−3.09	5.63	−0.50	8.31	0.09
Italy	0.46	7.38	0.82	−26.92	27.00	−3.79	5.15	−0.19	0.84	0.04
Japan	0.66	5.82	0.71	−21.55	21.72	−2.70	4.20	−0.01	0.89	0.10
Netherlands	0.97	5.60	1.33	−28.92	22.85	−1.62	4.35	−0.80	2.65	0.02
Norway	0.76	7.81	1.07	−40.59	22.67	−3.85	5.77	−0.78	3.05	0.12
Singapore	0.72	7.96	0.97	−53.34	42.70	−2.62	4.74	−0.49	6.13	0.10
Spain	0.59	6.87	0.86	−31.89	25.88	−3.19	4.67	−0.44	2.26	0.05
Sweden	0.99	6.82	1.25	−31.00	22.70	−2.71	5.18	−0.46	1.53	0.05
Switzerland	0.89	5.10	1.14	−19.40	21.98	−1.68	3.97	−0.39	1.42	0.06
United Kingdom	0.69	6.00	0.91	−24.25	44.73	−2.45	3.92	0.32	5.90	0.07
MSCI World	0.77	4.32	1.21	−20.99	13.73	−1.59	3.22	−0.76	2.19	0.07
Predictor										
ΔMIN^{US}	0.00	1.73	−0.01	−18.61	20.88	−0.55	0.55	0.96	58.43	−0.44

(1): "Std" refers to the standard deviation. (2): "25% and 75%" stand for the percentiles of the statistics. (3): ΔMIN^{US} stands for the innovation in the daily return minimum in the U.S. stock market. (4): ρ_1 is the first-order autocorrelation coefficient

where MIN_t^m refers to the negative extreme returns of market m at month t; $\forall R_{d,t}$ refers to every daily stock return in month t. ΔMIN_t^m refers to the innovation of negative extreme return at month t.

We follow Xu et al. (2023) to examine the effects of several other macroeconomic factors on stock returns, such as the ratio of dividend to stock price (DP), rate of inflation (IFL), 1-month Treasury bill rate (TB), money supply (M3) and crude oil price (OIL), and compare their predictive power with ΔMIN_t^{US}. Plugging multi-indicators as control variables can also alleviate the model mis-specification bias and enhance the explanatory power of the model.

The descriptive statistics of the monthly log returns of each stock market (18 dependent variables) and the key independent variable, ΔMIN_t^{US}, are reported in Table 1. The table shows that the mean values of dependent variables are smaller than their median values, and the values of the skewness are mostly less than zero, indicating that the stock market returns are skewed to the left (except for the United Kingdom, which has a positive skewness), with long or fat tails. However, the independent variables are skewed to the right. Therefore, the assumption of the efficient market hypothesis (EMH) is considered invalid, as none of the stock returns are normally distributed. The standard deviations are relatively high, which indicates that the variables spread widely from the mean. The pairwise correlation of stock market returns and the U.S. extreme indicator suggests that ΔMIN^{US} is negatively correlated with all the selected stock returns in international markets (see Table 2).

Table 2 Pairwise Correlation of stock market returns and the U.S. Extreme Indicator

Market	AUST	ASTR	BELG	CNDA	DNMK	FRNC	GERM	HGKG	ITAL	JPAN	NETH	NWAY	SING	SPAN	SWDN	SWIT	UTDK	WRLD	ΔMIN^{US}
AUST	1																		
ASTR	0.45	1																	
BELG	0.50	0.64	1																
CNDA	0.68	0.50	0.54	1															
DNMK	0.44	0.53	0.63	0.51	1														
FRNC	0.53	0.61	0.73	0.59	0.57	1													
GERM	0.50	0.69	0.72	0.55	0.62	0.76	1												
HGKG	0.48	0.35	0.39	0.46	0.36	0.39	0.41	1											
ITAL	0.42	0.53	0.57	0.48	0.50	0.64	0.60	0.31	1										
JPAN	0.39	0.39	0.45	0.40	0.44	0.47	0.45	0.37	0.43	1									
NETH	0.56	0.64	0.78	0.65	0.66	0.76	0.80	0.48	0.59	0.49	1								
NWAY	0.59	0.57	0.65	0.64	0.57	0.63	0.59	0.39	0.49	0.35	0.67	1							
SING	0.57	0.42	0.47	0.56	0.44	0.45	0.46	0.63	0.36	0.43	0.54	0.50	1						
SPAN	0.51	0.57	0.59	0.50	0.52	0.63	0.63	0.37	0.62	0.45	0.63	0.52	0.40	1					
SWDN	0.54	0.52	0.59	0.58	0.59	0.61	0.68	0.41	0.55	0.46	0.69	0.60	0.50	0.60	1				
SWIT	0.52	0.58	0.69	0.54	0.60	0.70	0.73	0.41	0.52	0.47	0.76	0.57	0.47	0.53	0.61	1			
UTDK	0.58	0.50	0.64	0.62	0.53	0.67	0.59	0.47	0.52	0.44	0.71	0.59	0.56	0.54	0.57	0.64	1		
WRLD	0.68	0.59	0.73	0.79	0.65	0.76	0.75	0.52	0.61	0.69	0.83	0.67	0.64	0.66	0.73	0.74	0.76	1	
ΔMIN^{US}	−0.07	−0.15	−0.09	−0.13	−0.04	−0.06	−0.11	−0.09	−0.04	−0.07	−0.14	−0.13	−0.08	−0.08	−0.10	−0.10	−0.14	−0.11	1

AUST, Australia; ASTR, Austria; BELG, Belgium; CNDA, Canada; DNMK, Denmark; FRNC, France; GERM, Germany; HGKG, Hong Kong; ITAL, Italy; JPAN, Japan; NETH, the Netherlands; NWAY, Norway; SING, Singapore; SPAN, Spain; SWDN, Sweden; SWIT, Switzerland; UTDK, the United Kingdom; WRLD, World

Model specification

Previous research has examined the relationship between the U.S. extreme indicator in level and stock market returns (Bali et al. 2011; Rapach et al. 2013; Barberis et al. 2016; Ghosh et al. 2017; Jiang et al. 2018; Barro and Liao 2021; Bogousslavsky 2021; Liu and Matthies 2022). This study extends the previous research and instead uses the novel indicator to predict the subsequent stock returns. The benchmark prediction model is specified as follows.

$$R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_2 \Delta MIN_{t-1}^{US} + \varepsilon_{i,t} \quad (3)$$

where α refers to the constant term;β_1 and β_2 refer to the parameters of the associated variables; $R_{i,t-1}$ denotes lagged own returns of the countries; ΔMIN_{t-1}^{US} denotes the innovation of extreme indicators of the U.S. market at month $t-1$; and $\varepsilon_{i,t}$ represents an error term.

Model (3) is extended to control for the effects of alternatively the (i) macroeconomic factors and (ii) economic recessions on stock market returns. Model (3) augmented to control for the effects of macroeconomic factors is specified as follows.

$$R_{i,t} = \alpha + \beta_2 \Delta MIN_{t-1}^{US} + \beta_X X_{t-1} + \varepsilon_{i,t} \quad (4)$$

where X_{t-1} denotes a vector of control variables in period *t-1*; β_X is a vector of the parameters of the control variables, including $R_{i,t-1}$, TB, DP and OIL.

Model (3) augmented with a slope dummy to capture the effects of economic recessions on stock market returns is specified as follows.

$$R_{i,t} = \alpha + \beta_2 \Delta MIN_{t-1}^{US} + \beta_D D_0 \times \Delta MIN_{t-1}^{US} + \varepsilon_{i,t} \quad (5)$$

where D_0 represents a dummy variable, which takes value "1" in the recession period, and value "0" otherwise. β_D is the coefficient of the interaction variable.

Model (5) is estimated separately for the NBER-based recession periods and for the major recession periods, such as AFC, GFC and ESDC, and the COVID-19 pandemic, to have a comprehensive account of the evidence.

We use Python software to develop programming code for data processing and model estimation. Specifically, we organise and analyse the time-series data through Python libraries, such as Numpy and Pandas. We also use the Matplotlib library to visualise the test results.

Empirical analysis

The U.S. extreme indicator – the benchmark model

Previous studies have shown that the U.S. stock market demonstrates a lead-lag relationship with other stock markets, and they have claimed that the extreme shocks occurred in the U.S. market also affect other markets (Rapach et al. 2013; Nyberg and Ponka 2016; Ghosh et al. 2017; Shue and Townsend 2021; Huang et al. 2022). Our study uses ΔMIN^{US} as an indicator to predict future returns in the international stock markets.

Table 3 shows the results of regression testing for 17 developed markets, in addition to the World market. It shows that ΔMIN^{US} has strong predictive power in 10 markets,

Table 3 Predictive Test Results with the U.S. Extreme Indicator

Market	Constant	$R_{i,t-1}$	ΔMIN^{US}	Adj-R^2(%)
Australia	0.008***	− 0.030	− 0.346	0.28
	(2.70)	(− 0.58)	(− 1.56)	
Austria	0.005	0.124	− 0.498**	3.29
	(1.51)	(1.61)	(− 2.01)	
Belgium	0.006**	0.139**	− 0.180	2.31
	(2.26)	(1.98)	(− 1.03)	
Canada	0.007***	− 0.004	− 0.432***	1.35
	(2.77)	(− 0.07)	(− 2.82)	
Denmark	0.010***	0.043	− 0.110	0.04
	(3.60)	(0.66)	(− 0.65)	
France	0.007***	0.051	− 0.172	0.27
	(2.60)	(1.06)	(− 0.90)	
Germany	0.007***	− 0.010	− 0.401**	0.81
	(2.63)	(− 0.23)	(− 2.55)	
Hong Kong	0.009**	0.069	− 0.363**	0.84
	(2.47)	(1.72)	(− 2.10)	
Italy	0.005	0.038	− 0.128	− 0.05
	(1.45)	(0.73)	(− 0.58)	
Japan	0.006**	0.088	− 0.195	0.94
	(2.37)	(1.62)	(− 1.12)	
Netherlands	0.010***	− 0.019	− 0.463***	1.60
	(3.75)	(− 0.35)	(− 3.73)	
Norway	0.007**	0.086	− 0.498***	2.13
	(2.07)	(1.26)	(− 2.96)	
Singapore	0.006**	0.082	− 0.236	0.89
	(2.04)	(1.49)	(− 1.01)	
Spain	0.006**	0.030	− 0.275	0.35
	(2.00)	(0.60)	(− 1.29)	
Sweden	0.010***	0.030	− 0.372**	0.79
	(3.16)	(0.67)	(− 2.14)	
Switzerland	0.008***	0.032	− 0.265**	0.72
	(4.04)	(0.81)	(− 2.18)	
United Kingdom	0.007***	0.039	− 0.437***	1.68
	(2.64)	(0.67)	(− 4.00)	
MSCI World	0.007***	0.040	− 0.229**	0.92
	(3.71)	(0.75)	(− 2.07)	

(1): $R_{i,t-1}$ refers to the own past return of the markets. (2): ΔMIN^{US} refers to the extreme minimum innovation of the U.S. stock market. (3) Figures in parentheses are *t*-values. (4) *** and ** indicate statistical significance at 1% and 5% level, respectively

including Austria, Canada, Germany, Hong Kong, the Netherlands, Norway, Sweden, Switzerland, the United Kingdom and the overall World market. The coefficients of the ΔMIN^{US} for the above markets are significant at the 5% level, with R-squared statistics of more than 0.5%. The coefficients of ΔMIN^{US}, β_2, are negative for all the 18 selected markets, which indicates an explicit negative relationship. The U.S. extreme negative returns thus show a good predictive ability in international stock markets. The coefficients of their own past returns (R_{t-1}) are insignificant for the stock markets of all the countries, except for Belgium. This shows that in the international stock markets,

ΔMIN^{US} can significantly influence other stock markets and take a dominant position, and its influence is even stronger than the trend of other markets themselves.

We also conduct the similar regression tests in 17 other stock markets (including young developed markets and developing markets), the results are shown in Table 9 of the "Appendix". We find that the significance of ΔMIN^{US} disappears in almost all these markets. This may be due to the unique characteristics and less integration of these markets with the U.S. market. The previous studies reported that the connection of the U.S. and Asian stock markets may not be as strong as perceived. Liu and Pan (1997) report that the U.S. has been influential in transmitting the returns and volatilities in the Asian region, but this transmission is unstable and is affected by the contagion effect. Ng (2000) suggests that the regional spill-overs from Japan are more significant than the global spill-overs from the U.S. market. Moreover, the relatively shorter time span of the regressions may also be the reason why the predictive power of the U.S. extreme indicator is not statistically significant in these markets.

We also test the correlation between each market's own extreme minimum innovation (ΔMIN^{own}) and future returns. We find that ΔMIN^{own} have predictive power only in few markets, and it does not outperform the own past return. So ΔMIN^{own}, as the indicator, is not as good as ΔMIN^{US} in predicting returns in international stock markets.[1] Moreover, when it comes to the longer-term time-horizons, including 3-month, 6-month, 12-month and 24-month horizons, the predictive ability of the extreme indicators (both the ΔMIN^{US} and ΔMIN^{own}) does not show the signs of persistence. It means that extreme indicators are different from some other traditional forecasting indicators in that they have significant predictive power only in short horizons, and they cannot affect the stock market in the long run.[2] These results are similar to those obtained in previous studies (Jiang et al. 2018; Bena et al. 2022; Johnson et al. 2022).

The U.S. extreme indicator and the control variables

The results of the regressions with additional control variables (including R^{own}, TB, DP and OIL) are reported in Table 4. The table provides the coefficients and *t*-statistics for both ΔMIN^{US} and control variables, along with adjusted R-squared values. The results demonstrate that the coefficients of ΔMIN^{US} barely change and they remain significant across 10 markets. This indicates that ΔMIN^{US} remains robust in the international stock markets, even with the control variables included in the model. While R^{own}, TB and OIL have limited correlations in few markets, there is insufficient evidence that these indicators correlate with international stock returns, and therefore they have weaker predictive power than ΔMIN^{US}. The coefficient of DP is also significant in 10 markets, suggesting this to be a good predictor in international stock markets.

The comparison suggests that the model with control variables has stronger explanatory power, as the adjusted R^2 values are generally higher (see Table 4), as compared to the model without control variables (Table 3). This indicates that the addition of control

[1] The test results are reported in Table 10 of "Appendix".

[2] Persistent predictors such as dividend yield (Fama & French 1988) tend to have strong predictive power over long-horizon returns. By contrast, ΔMIN^{US} has a relatively low autocorrelation coefficient. Like technical trading indicators, it is a short-term indicator, thus playing no role in long-horizon return predictability. The longer-term horizons tests results are not reported, but are available upon request.

Table 4 Predictive Test Results with the U.S. Extreme Indicator and Control Variables

Market	Constant	ΔMIN^{US}	$R_{i,t-1}$	TB	DP	OIL	Adj-R^2(%)
Australia	−0.00	−0.33	−0.04	−0.02	0.52*	0.01	0.20
	(−0.03)	(−1.50)	(−0.70)	(−1.29)	(1.84)	(0.43)	
Austria	0.00	−0.50**	0.13*	−0.01	0.26	−0.02	2.95
	(0.02)	(−1.98)	(1.71)	(−0.39)	(0.92)	(−0.53)	
Belgium	−0.00	−0.18	0.14*	−0.02	0.64**	−0.02	2.70
	(−0.82)	(−1.02)	(1.89)	(−1.38)	(2.50)	(−0.75)	
Canada	0.00	−0.42***	−0.01	−0.01	0.32	0.01	1.09
	(0.21)	(−2.73)	(−0.13)	(−0.67)	(0.93)	(0.31)	
Denmark	0.01	−0.11	0.05	−0.01	0.21	−0.01	−0.33
	(1.35)	(−0.64)	(0.70)	(−0.71)	(0.84)	(−0.38)	
France	−0.00	−0.17	0.05	−0.02	0.59*	−0.01	0.44
	(−0.46)	(−0.86)	(1.07)	(−1.09)	(1.81)	(−0.52)	
Germany	−0.00	−0.43**	−0.01	−0.01	0.49	−0.05*	1.52
	(−0.38)	(−2.57)	(−0.11)	(−0.74)	(1.58)	(−1.94)	
Hong Kong	−0.00	−0.37**	0.07*	−0.02	0.63	−0.02	0.75
	(−0.19)	(−2.07)	(1.68)	(−1.12)	(1.29)	(−0.63)	
Italy	−0.00	−0.18	0.05	0.00	0.19	−0.07*	0.73
	(−0.06)	(−0.74)	(0.94)	(0.01)	(0.56)	(−1.86)	
Japan	−0.01	−0.19	0.08	−0.02**	0.80***	−0.01	1.78
	(−1.28)	(−1.04)	(1.45)	(−2.12)	(2.78)	(−0.33)	
Netherlands	−0.00	−0.47***	−0.01	−0.02	0.64**	−0.03*	2.59
	(−0.44)	(−3.70)	(−0.25)	(−1.19)	(2.54)	(−1.76)	
Norway	0.00	−0.50***	0.09	−0.00	0.10	−0.02	1.70
	(0.58)	(−3.00)	(1.35)	(−0.00)	(0.27)	(−0.52)	
Singapore	−0.01	−0.23	0.08	−0.03	0.80*	−0.01	1.13
	(−0.83)	(−0.97)	(1.39)	(−1.40)	(1.91)	(−0.45)	
Spain	0.01	−0.31	0.03	0.02	−0.32	−0.03	0.29
	(1.36)	(−1.41)	(0.57)	(1.08)	(−0.92)	(−1.07)	
Sweden	−0.00	−0.40**	0.04	−0.01	0.52	−0.05	1.37
	(−0.10)	(−2.33)	(0.81)	(−0.61)	(1.18)	(−1.33)	
Switzerland	0.00	−0.27**	0.03	−0.02	0.45*	−0.02	1.04
	(0.39)	(−2.19)	(0.80)	(−1.33)	(1.84)	(−1.23)	
United Kingdom	−0.01	−0.43***	0.04	−0.01	0.66**	−0.00	2.15
	(−1.29)	(−3.99)	(0.60)	(−1.21)	(2.41)	(−0.16)	
MSCI World	−0.00	−0.23**	0.04	−0.02	0.52**	−0.02	1.87
	(−0.39)	(−2.07)	(0.81)	(−1.58)	(2.45)	(−1.28)	

(1): ΔMIN^{US} refers to the extreme minimum innovation of the U.S. stock market. (2): $R_{i,t-1}$ refers to the own past return of the markets respectively. (3): TB refers to the prices of one-month Treasury bill. (4): DP refers to the ratio of dividend to stock price. (5): Oil refers to the crude oil price. (6) Figures in parentheses are *t*-values. (7) ***, ** and * indicate statistical significance at 1%, 5% and 10% level, respectively

variables significantly improves the goodness-of-fit of the model. The coefficients of all constants in 17 markets are reduced and have insignificant *t*-statistics (Table 4).

The U.S. extreme indicator and the recession periods

The extreme value theory suggests that the extreme factors tend to be more important, with the occurrence of extreme economic conditions (Lettau 2003; Barberis and Huang 2008; Colacito et al. 2021; Perotti and Rola-Janicka 2022). We draw on these studies and examine the predictive power of extreme indicators during recession periods. We augment the benchmark regression model (3) with a slope dummy to control for the effects of recession periods, and we specify this as model (5). We estimate model (5) separately for the NBER-based recession periods as well as for the major recession periods, such as AFC, GFC, ESDC and the COVID-19 pandemic.

NBER-based recession periods

Table 5 reports the results of the regression model (5) estimated for the NBER-based recession periods. Surprisingly, unlike the conclusions of previous studies, ΔMIN^{US} does not exhibit a significant predictive ability during recession periods. The coefficient of the slope dummy for recession is not significant even at the 10% level in all selected markets. However, the coefficient of ΔMIN^{US} remains significant in several markets even after plugging the dummy variable in the regressions. This indicates that the predictive power of ΔMIN^{US} is significant whether in recession periods or other periods in international stock markets. Therefore, unlike some other indicators that have predictive power only during recession periods (e.g., Ghosh et al. 2017; Wen and Li 2020; Colacito et al. 2021; Bena et al. 2022; Borup and Schütte 2022), ΔMIN^{US} shows strong predictive power not only during recession periods, but also during the whole sample period of 50 years.

Major crises periods

After testing the predictive power of ΔMIN^{US} during the NBER-based recession periods, we extend the analysis and dig deeper into sub-sample tests, using the extreme episodes of financial upheavals, such as AFC, GFC and ESDC, and the COVID-19 pandemic. These crises are documented to have significant influence on the global economy (Ghosh et al. 2017; Colacito et al. 2021; Augustin et al. 2022). The results of the model estimated for these extreme episodes of financial upheavals and COVID-19 pandemic are reported in Table 6. These results demonstrate the superior predictive power of ΔMIN^{US} during the GFC (July 2007 to June 2009) for all the international stock markets. The coefficient of the U.S. extreme indictor is significant in all the 17 markets, indicating that the predictive performance of ΔMIN^{US} in the period of the GFC exceeds its performance in the full-sample period.

During the GFC period, the R^2 of the model estimated using ΔMIN^{US} as the predictor is higher than 10% in 16 of the 18 markets, stronger than in other periods. For investigating why the ΔMIN^{US} has such extreme strong predictive performance in GFC, we trace the trend of ΔMIN^{US} and three representative stock markets (including Hong Kong, the United Kingdom and World indexes) in the GFC period (Fig. 2). It can be observed from Fig. 2 that there are similar trends in these markets, and this may be due to the synchronised movements occurring in international stock markets. By contrast, ΔMIN^{US} shows an obvious opposite trend, which presents a strong negative correlation between ΔMIN^{US} and international stock markets. As mentioned earlier, the U.S. market has a leading position in the international stock markets and the information shock of U.S. market spreads and affects other markets, thus indicating the forecasting ability

Table 5 Predictive test results with the U.S. extreme indicator [under NBER-based recession periods]

Market	Constant	ΔMIN^{US}	Dummy × ΔMIN^{US}	Adj-R^2(%)
Australia	0.007***	− 0.227	− 0.448	0.37
	(2.71)	(− 1.05)	(− 0.44)	
Austria	0.006	− 0.537**	− 0.469	1.98
	(1.59)	(− 2.01)	(− 0.35)	
Belgium	0.007**	− 0.172	− 0.975	1.57
	(2.54)	(− 1.51)	(− 0.82)	
Canada	0.007***	− 0.375***	− 0.331	1.48
	(2.92)	(− 3.04)	(− 0.37)	
Denmark	0.010***	− 0.023	− 0.763	0.61
	(3.98)	(− 0.18)	(− 1.05)	
France	0.008***	− 0.146	− 0.500	0.28
	(2.69)	(− 0.83)	(− 0.71)	
Germany	0.007***	− 0.299**	− 0.576	1.14
	(2.63)	(− 2.20)	(− 0.74)	
Hong Kong	0.009**	− 0.398***	− 0.383	0.46
	(2.48)	(− 2.69)	(− 0.38)	
Italy	0.005	− 0.025	− 0.875	0.38
	(1.43)	(− 0.14)	(− 1.25)	
Japan	0.006**	− 0.155	− 0.552	0.55
	(2.37)	(− 1.00)	(− 0.98)	
Netherlands	0.009***	− 0.354***	− 0.572	1.99
	(4.01)	(− 3.67)	(− 0.73)	
Norway	0.008**	− 0.547***	− 0.348	1.53
	(2.17)	(− 3.76)	(− 0.33)	
Singapore	0.007**	− 0.241	− 0.758	0.65
	(2.02)	(− 1.26)	(− 0.69)	
Spain	0.006**	− 0.183	− 0.784	0.79
	(1.97)	(− 1.17)	(− 0.99)	
Sweden	0.010***	− 0.271	− 0.819	1.28
	(3.26)	(− 1.56)	(− 0.92)	
Switzerland	0.009***	− 0.247***	− 0.253	0.72
	(4.08)	(− 2.23)	(− 0.52)	
United Kingdom	0.007***	− 0.420***	− 0.339	1.67
	(2.67)	(− 4.52)	(− 0.48)	
MSCI World	0.008***	− 0.209***	− 0.348	1.05
	(4.01)	(− 2.34)	(− 0.53)	

(1): ΔMIN^{US} refers to the extreme minimum innovation of the U.S. stock market. (2) : $R_{i,t-1}$ refers to the own past return of the markets respectively. (3): Dummy refers to the dummy variable that stands for the recession periods. (4) Figures in parentheses are *t*-values. (5) *** and ** indicate statistical significance at 1% and 5% level, respectively

of ΔMIN^{US}. Rapach et al. (2013) note that at the extreme moment in history, such as the GFC, the impact of information shocks will be amplified, thereby improving the predictive ability of ΔMIN^{US} in the international stock markets.

We also follow Augustin et al. (2022) and Bena et al. (2022) and conduct another sub-sample regression for the period of the European Sovereign Debt Crisis (ESDC), which was also quite widespread globally, especially in the European region, from the beginning of 2009 to the end of 2013. The ESDC is considered as the important catastrophic event that have global influences (Chaplinsky and Haushalter 2010; Ari 2014;

Table 6 Predictive test results with the U.S. extreme indicator [under extreme recessionary conditions]

Country	AFC [1997:06–1999:12]		GFC [2007:07 to 2009:06]		ESDC [2009:01 to 2013:12]		COVID [2019:12 to 2022:07]	
	ΔMIN^{US}	Adj-R^2 (%)	ΔMIN^{US}	Adj-R^2 (%)	ΔMIN^{US}	Adj-R^2 (%)	ΔMIN^{US}	Adj-R^2 (%)
Australia	− 0.166	− 3.28	− 3.086***	29.18	− 2.256***	17.27	− 0.121	− 3.30
	(− 0.77)		(− 6.73)		(− 3.23)		(− 0.40)	
Austria	1.421***	11.94	− 3.723***	18.56	− 2.887***	18.40	− 0.529	− 1.85
	(− 2.96)		(− 2.97)		(− 4.09)		(− 1.04)	
Belgium	− 0.477	0.01	− 3.674***	26.86	− 1.218**	6.66	− 0.173	− 3.02
	(− 1.41)		(− 3.30)		(− 2.14)		(− 0.69)	
Canada	− 0.548**	− 1.22	− 2.476**	17.36	− 1.456*	15.26	− 0.117	− 3.25
	(− 2.12)		(− 2.46)		(− 1.81)		(− 0.48)	
Denmark	− 0.914**	− 6.30	− 2.044**	11.77	− 1.662***	11.50	− 0.116	− 3.12
	(− 2.38)		(− 2.18)		(− 3.61)		(− 0.50)	
France	− 0.673	2.13	− 2.190***	18.94	− 2.016**	13.08	− 0.522***	0.49
	(− 1.08)		(− 3.46)		(− 2.44)		(− 2.60)	
Germany	− 0.110	− 3.50	− 2.260***	15.34	− 1.811**	9.70	− 0.579*	1.09
	(− 0.30)		(− 3.10)		(− 2.08)		(− 1.66)	
Hong Kong	0.261	− 3.40	− 1.886***	10.24	− 1.746*	16.91	0.175	− 2.65
	(0.33)		(− 3.04)		(− 1.90)		(0.54)	
Italy	− 0.833*	1.75	− 2.092***	14.23	− 2.309***	9.98	− 0.703***	1.73
	(− 1.86)		(− 2.70)		(− 3.49)		(− 3.38)	
Japan	− 0.684	0.46	− 1.229**	8.94	− 0.417	− 0.35	− 0.445**	2.72
	(− 0.97)		(− 2.21)		(− 1.41)		(− 1.99)	
Netherlands	− 0.384	− 1.80	− 2.199**	15.77	− 1.329**	6.35	− 0.292	− 2.14
	(− 0.83)		(− 2.55)		(− 1.96)		(− 1.34)	
Norway	− 1.145**	2.91	− 2.971**	11.65	− 2.552***	16.80	− 0.267	− 2.65
	(− 2.08)		(− 2.48)		(− 3.24)		(− 0.88)	
Singapore	1.019	− 0.86	− 2.665***	17.55	− 1.595**	12.50	0.031	− 3.43
	(1.04)		(− 2.76)		(− 2.07)		(0.12)	
Spain	− 0.378	− 2.60	− 2.805***	24.99	− 1.975***	6.03	− 0.608***	0.71
	(− 0.51)		(− 4.08)		(− 2.85)		(− 3.01)	
Sweden	− 0.231	− 3.15	− 2.736***	21.85	− 1.796**	9.90	− 0.352	− 1.78
	(− 0.28)		(− 4.81)		(− 1.97)		(− 1.55)	
Switzerland	− 0.778	3.17	− 1.093**	6.63	− 1.144*	8.25	− 0.202	− 2.17
	(− 1.01)		(− 2.54)		(− 1.82)		(− 0.96)	
United Kingdom	− 0.431	− 1.61	− 1.547***	11.79	− 1.317**	10.27	− 0.293	− 1.80
	(− 1.48)		(− 2.73)		(− 2.28)		(− 1.22)	
MSCI World	− 0.146	− 3.19	− 1.659***	16.17	− 1.290**	14.00	− 0.163	− 2.89
	(− 0.42)		(− 2.79)		(− 2.39)		(− 0.66)	

Notes: (1): ΔMIN^{US} refers to the extreme minimum innovation of the U.S. stock market. (2): AFC refers to the sample period of June 1997 to December 1999 (Asian Financial Crisis). (3): GFC refers to the sample period of July 2007 to June 2009 (Global Financial Crisis). (4): ESDC refers to the sample period of January 2009 to December 2013 (European Sovereign Debt Crisis). (5): COVID refers to the sample period of December 2019 to July 2022, that COVID-19 crisis originates as a health shock. (6) Figures in parentheses are *t*-values. (7) ***, ** and * indicate statistical significance at 1%, 5% and 10% level, respectively

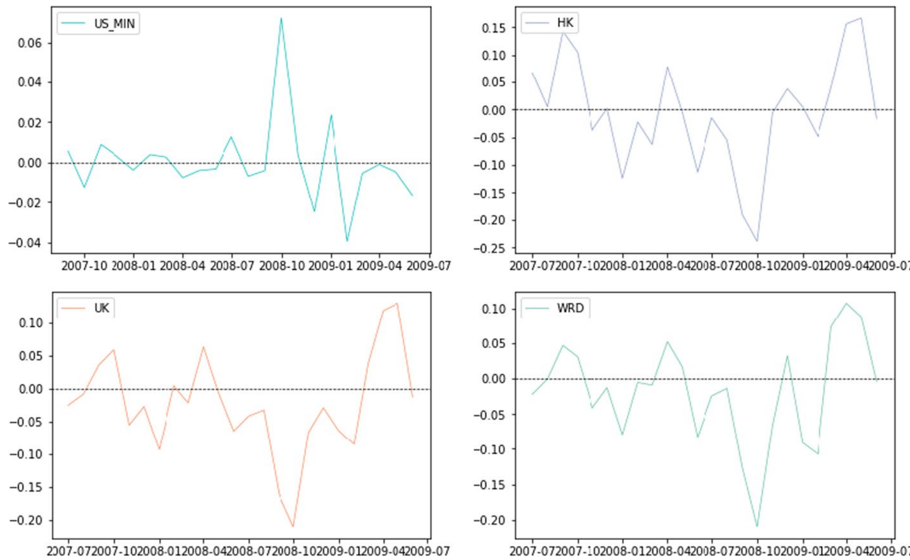

Fig. 2 U.S. Extreme Indicator and Stock Returns in GFC period

Barro and Liao 2021). The test results are similar to those in the GFC period, where ΔMIN^{US} still has robust predictive ability, especially in the European countries. The results even show a slightly higher adjusted-R^2 than in the GFC period. The coefficient of ΔMIN^{US} is not significant only in the case of Japan, which may be because the Japanese market is not directly affected by the ESDC.

In the sub-sample period of COVID-19 (December 2019 to July 2022), different from the above results, ΔMIN^{US} shows significant results only in four (France, Italy, Japan and Spain) out of 17 markets. And these results are quite intuitive. The global financial crises can be understood as the result of the frictions in financial sector. By contrast, the COVID-19 crisis originated as a health sector shock, different from previous financial and economic crises, which created enormous uncertainty for financial markets for an extended period of time (Bao and Huang 2021).

During the COVID-19 pandemic, the government interventions effectively curbed the spread of the virus in the world. The stock market and even all the international financial markets are affected by such government-control (Papanikolaou et al. 2021). The central banks, such as the U.S. Federal Reserve, have actively intervened in the market through monetary easing, slashing interest rates, and introducing large-scale supportive financing programs to improve liquidity to stimulate the economic activities and avoid a full-scale financial crisis (Eichenbaum et al. 2021). However, the interventions during COVID-19 further increased the central banks' footprints in the markets; these patterns may lead to many suspecting that there is a disconnection between financial markets and the real economy. Therefore, there is a lack of correlation between a large number of indicators in financial markets and economic trends in the COVID-19 period. This implies that it is difficult to conduct asset pricing tests without considering the role played by the central banks.

Under the traditional financial crisis, the flow of capital between international financial markets is unrestricted. During the COVID-19 pandemic, the connection between the country markets has weakened or even been interrupted, resulting in the breakdown of the lead-lag relationship in international markets, which makes it more difficult to predict stock returns using cross-market variables. Many studies have reported poor results in examining stock return predictability in the COVID-19 period (e.g., Augustin et al. 2022; Wen et al. 2022). The sub-sample analysis undertaken for the period of the AFC (June 1997 to December 1999) suggests that the predictive ability of ΔMIN^{US} seems weaker, as compared to its predictive ability during the GFC and the ESDC each (Table 6). The main drivers of the AFC of 1997 seem to have been the problems of the Asian markets' input-oriented developmentalism as well as the ineffective state intervention, and these are not directly related to the role of the U.S.

We follow Augustin et al. (2022) and further test the predictive ability of ΔMIN^{US} in 17 other markets during the sub-sample periods of AFC, GFC, ESDC and COVID-19. The results suggest that the predictive performance of ΔMIN^{US} is similar to that in the developed markets. During GFC, ΔMIN^{US} demonstrates strong predictive ability in most of the markets, while during ESGC it shows weak predictive ability. This may be because most selected markets are from the Asian rather than from the European region.[3] Second, we do the sub-sample tests in four additional recession periods. The results suggest that the predictive power of ΔMIN^{US} is still significant in the international stock markets during the oil shock recession period, the world debt crisis period, and the Nordic banking crisis period; it is insignificant only during the Dot-com bubble period (see "Appendix" Table 12). The Dot-com bubble crisis is driven by the internet industry, which only affects the relevant sectors in the U.S. stock markets – it does not have a serious impact on the international financial markets.

We also perform two common sub-sample tests to further assess the robustness of our results. We split the entire time span into two periods—first period stretches from January 1972 to December 1999 and the second period spans from the new millennium January 2000 to July 2022. The results remain similar to those obtained for (i) the NBER-based recession periods and (ii) the extreme episodes of financial upheavals, such as AFC, GFC and ESDC, and the COVID-19 pandemic periods. These results reinforce the robust predictive ability of ΔMIN^{US}.[4]

Robustness check

In the international stock markets, stock returns not only have serial-correlations in time-series, but also have inter-market correlations. The significant results obtained from time-series analysis may be insufficient to support the strong predictive power of ΔMIN^{US} without considering the inter-market influences in multiple stock markets. We extend the analysis further and estimate panel regressions to control for both cross-sectional and time effects, and test the robustness of ΔMIN^{US}. The panel data analysis is useful to analyse two-dimensional (cross-sectional and longitudinal) effects and it can improve estimation efficiency and inference power, compared to one-dimensional time-series or cross-sectional regressions. We consider 5 panel regression methods: fixed

[3] The corresponding sub-sample test results for the other markets are reported in Table 11 of "Appendix".

[4] The corresponding common sub-sample test results are not reported for brevity, but are available upon request.

Table 7 Panel regression results with the U.S. extreme indicator

Method	**Dependent variables:** $R_i, i = 1, \cdots, 17$					
	Predictor	**Predictor with control variables**				
	ΔMIN^{US}	ΔMIN^{US}	$R_{i,t-1}$	**TB**	**DP**	**OIL**
Fixed Effects (S.E. clustered by market)	− 0.303*** (− 9.34)	− 0.249*** (− 8.42)	0.083*** (7.74)	− 0.072*** (− 3.18)	0.371*** (5.99)	− 0.037*** (− 6.90)
Random Effects (S.E. clustered by market)	− 0.303*** (− 9.34)	− 0.250*** (− 8.39)	0.083*** (7.77)	− 0.072*** (− 3.19)	0.371*** (5.99)	− 0.037*** (− 6.10)
Pooled OLS (Fixed market dummies, S.E. clustered by market)	− 0.303*** (− 9.34)	− 0.250*** (− 8.41)	0.083*** (7.73)	− 0.072*** (− 3.18)	0.371*** (5.98)	− 0.037*** (− 6.90)
Pooled OLS (Fixed year dummies, S.E. clustered by month)	− 0.265*** (− 2.65)	− 0.230** (− 2.23)	0.027 (1.01)	− 0.038* (− 1.84)	3.128*** (3.31)	− 0.027 (− 1.36)
Pooled OLS (S.E. clustered by both market and month)	− 0.303** (− 2.50)	− 0.249** (− 2.33)	0.083*** (3.00)	− 0.072 (− 0.83)	0.367* (1.84)	− 0.037** (− 2.16)

(1) S.E. stands for standard errors. (2) Figures in parentheses are *t*-values. (3) The World market is excluded in the panel regressions. (4) ***, ** and * indicate statistical significance at 1%, 5% and 10% level, respectively

effects model, random effects model, pooled Ordinary Least Squares (OLS) with fixed market dummies, pooled OLS with fixed year dummies, and pooled OLS with standard errors clustered by both market and month following Petersen (2009).

The results of the (i) model with a single predictor, ΔMIN^{US}, and the (ii) model with additional control variables, including R^{own}, TB, DP and OIL, are reported in Table 7. These results show that the coefficient of ΔMIN^{US} is significant in all 5 panel tests, indicating that ΔMIN^{US} has robust predictive power in international stock markets, even after considering the correlations both over time and across markets. After plugging four control variables in the model, ΔMIN^{US} remains significant and its *t*-statistic is above 1.96 in all 5 regressions. Some of the other control variables, however, do not show the same level of significance in all the panel regressions. Therefore, ΔMIN^{US} outperforms other indicators as a predictor in panel regressions as well, again verifying its robustness.

For the rigour of testing, we use the out-of-sample R-squared (R^2_{os}) statistic of Welch and Goyal (2008) to perform the out-of-sample test (OOS) on ΔMIN^{US} and examine whether the predictors have robust predictive performance. The OOS prediction test is computed as follows.

$$R^2_{os} = 1 - \frac{\sum_{K=1}^{(1/2)T} \left(r^e_{(1/2)T+K} - r{1}^e_{(1/2)T+K}\right)^2}{\sum_{K=1}^{(1/2)T} \left(r^e_{(1/2)T+K} - r{2}^e_{(1/2)T+K}\right)^2} \tag{6}$$

where R^2_{os} is the out-of-sample R-squared; T is the total period, counted in months; K is the monthly number for out-of-sample testing; r is the in-sample forecast of stock returns within a certain month span (window), r_1 is the out-of-sample forecast of stock returns in the remaining time period, and r_2 is the arithmetic average of stock returns. The study uses two kinds of OOS tests, fixed rolling window test and expanding window test.

Table 8 Out-of-sample test results with the U.S. extreme indicator

Market	Expanding Window				Rolling Window			
	R^2_{OS} (%)	*P* Val	R^2_{OS} (%)	*P* Val	R^2_{OS} (%)	*P* Val	R^2_{OS} (%)	*P* Val
	240-month		300-month		240-month		300-month	
Australia	0.68	0.14	0.68	0.45	− 0.51	0.19	− 1.51	0.41
Austria	2.27	0.04	2.27	0.08	1.54	0.07	− 0.35	0.14
Belgium	0.70	0.09	0.70	0.12	− 1.67	0.15	− 1.58	0.31
Canada	1.29	0.11	1.29	0.09	− 0.72	0.20	− 0.12	0.20
Denmark	− 0.18	0.41	− 0.18	0.41	− 1.08	0.39	− 1.89	0.26
France	0.38	0.11	0.38	0.08	0.36	0.08	− 0.72	0.31
Germany	0.88	0.08	0.88	0.16	− 0.43	0.26	0.42	0.15
Hong Kong	0.16	0.21	0.16	0.05	− 1.39	0.41	− 0.76	0.37
Italy	− 0.21	0.37	− 0.21	0.08	0.50	0.05	− 0.60	0.33
Japan	0.73	0.07	0.73	0.43	0.24	0.13	0.22	0.13
Netherlands	0.94	0.11	0.94	0.08	− 1.00	0.31	0.25	0.17
Norway	1.91	0.04	1.91	0.03	− 0.15	0.07	1.15	0.05
Singapore	0.48	0.16	0.48	0.30	− 1.81	0.34	− 0.99	0.45
Spain	0.61	0.03	0.61	0.22	0.08	0.06	0.27	0.07
Sweden	0.35	0.17	0.35	0.35	− 0.81	0.41	0.09	0.22
Switzerland	1.00	0.07	1.00	0.07	0.15	0.15	0.13	0.14
United Kingdom	1.91	0.04	1.91	0.03	0.44	0.06	1.20	0.05
MSCI World	0.86	0.04	0.86	0.18	− 1.18	0.36	− 0.36	0.31

(1) R^2_{OS} refers to the out-of-sample R-Squared of the tests. (2) *P* Val is the probability under the assumption of no effect (null hypothesis)

The window selection of OOS should follow the criteria that the window span selection should be long enough to include enough initial data to get a reliable regression estimate. According to Welch and Goyal (2008), OOS tests, especially long-time span OOS tests, usually need to start after 20 years of data (240-month window), or choose half of the entire sample time span as the window for testing. Since the time span of our study is 50 years (600 months), it is appropriate to use 240-month and 300-month window in the OOS tests. We, therefore, perform the OOS tests of ΔMIN^{US}, including 240- and 300-month expanding windows and rolling windows, and the test results are reported in Table 8.

The OOS results of expanding windows show that the U.S. extreme indicator demonstrates strong out-of-sample predictive power in both 240-month and 300-month windows. Its $\mathrm{R}^2_{\mathrm{os}}$ is positive in 16 of the 18 developed markets and is significant at the 10% level in 9 markets. This significant result is consistent with and even stronger than the in-sample test results (Table 3), verifying the robustness of ΔMIN^{US}. The rolling window OOS results, although, are weaker than those in the expanding window, they still show positive $\mathrm{R}^2_{\mathrm{os}}$ in most markets, indicating that the predictive performance of ΔMIN^{US} are higher than the historical average level over the past 50 years in international markets.

Conclusions

This study has investigated the relationship between the extreme indicators and stock market returns for a comprehensive set of 17 advanced international stock markets using monthly data for half a century from 1972:01 to 2022:07. The sample span includes the sets of both NBER-based economic recessions and several extreme episodes of financial upheavals, such as AFC, GFC and ESDC, and the COVID-19 pandemic periods. The study proposes a novel extreme value indicator, the innovation in the daily return minimum in the U.S. stock market (ΔMIN^{US}), to predict future returns in international stock markets. We conduct a series of investigations on the relationship between ΔMIN^{US} and the international stock market returns. We find that ΔMIN^{US} has a significant negative correlation with returns in most stock markets. The results remain robust after controlling for a number of macroeconomic predictors and conducting subsample and panel data analyses. The predictive power of ΔMIN^{US} remains strong and it outperforms other variables in the international markets.

The results obtained from the model augmented with a slope dummy to capture the effects of economic recession suggest that the dummy variable has insignificant correlation with stock returns, indicating the weak predictive power of ΔMIN^{US} during recessions. However, ΔMIN^{US} remains significantly correlated with stock returns and it outperforms the recession dummy. ΔMIN^{US} shows very strong predictive power for international stock returns even during the periods driven by extreme financial upheavals such as the GFC and the ESDC. The significance of ΔMIN^{US}, however, disappears during the COVID-19 pandemic period. This could be ascribed to the unique nature of the COVID-19 pandemic, which stemmed from the health sector, as compared to financial crises which originated from the financial sector. We conduct the robustness checks by using both (1) panel regressions to consider inter-market correlations in the international stock return prediction and (2) out-of-sample tests to estimate the predictive performance of the indicator. Both sets of results successfully verify the robustness of ΔMIN^{US}.

The findings of the study have important implications for the researchers, the policy makers, and the finance practitioners. The results provide a new perspective on the U.S. extreme indicator in stock market return predictability. The ΔMIN^{US} outperforms other extreme indicators in predicting stock prices in international stock markets, and it should be considered as an important factor in the asset pricing and risk management. The study also shows the significance of the U.S. stock market in the non-U.S. stock markets.

Appendix

See Tables 9, 10, 11 and 12.

Table 9 Predictive test results with the U.S. extreme indicator—other markets

Market	Constant	$R_{i,t-1}$	ΔMIN^{US}	Adj-R^2(%)
Argentina	0.006	0.021	− 0.412	0.12
	(1.28)	(0.48)	(− 1.29)	
Chile	0.006**	0.050	− 0.071	0.00
	(2.38)	(0.70)	(− 0.36)	
China	0.000	0.087*	− 0.133	0.62
	(0.16)	(1.71)	(− 0.70)	
Ireland	0.002	0.077	− 0.221*	1.04
	(0.80)	(0.75)	(− 1.73)	
Finland	0.004	0.150***	− 0.096	2.10
	(1.40)	(3.34)	(− 0.61)	
Greece	0.001	0.126**	− 0.189	1.56
	(0.45)	(2.28)	(− 0.94)	
Indonesia	0.004	0.161***	− 0.530	3.46
	(1.02)	(2.86)	(− 1.38)	
Jordan	0.001	0.126**	− 0.166	1.63
	(0.38)	(2.12)	(− 1.31)	
Korean	0.003	0.037	− 0.256	0.18
	(1.00)	(0.64)	(− 1.23)	
Malaysia	0.003	0.145*	− 0.178	2.24
	(0.99)	(1.83)	(− 1.28)	
Mexico	0.007**	0.082	− 0.094	0.49
	(2.28)	(1.18)	(− 0.41)	
New Zealand	0.003	− 0.019	− 0.299*	0.58
	(1.54)	(− 0.36)	(− 1.89)	
Philippines	0.003	0.156***	− 0.165	2.47
	(1.02)	(3.09)	(− 0.94)	
Portugal	0.001	0.075	− 0.272	1.17
	(0.65)	(1.54)	(− 1.52)	
Taiwan	0.004	0.103*	− 0.020	0.76
	(1.18)	(1.80)	(− 0.11)	
Thailand	0.004	0.045	− 0.215	0.14
	(1.09)	(0.76)	(− 0.82)	
Türkiye	0.003	0.074	− 0.374	0.55
	(0.54)	(1.37)	(− 1.27)	

(1): $R_{i,t-1}$ refers to the own past return of the markets respectively. (2): ΔMIN^{US} refers to the extreme minimum innovation of the U.S. stock market. (3) Figures in parentheses are t-values. (4) *** and ** indicate statistical significance at 1% and 5% level, respectively

Table 10 Predictive test results with the own market extreme indicator

Market	Constant	$R_{i,t-1}$	ΔMIN^{own}	Adj-R^2(%)
Australia	0.006*	0.018	0.172	0.04
	(1.90)	(0.35)	(0.89)	
Austria	0.006	0.143*	− 0.130	− 0.06
	(1.48)	(1.95)	(− 0.39)	
Belgium	0.006**	0.156**	− 0.362	0.70
	(2.08)	(2.08)	(− 0.90)	
Canada	0.007**	0.033	0.016	− 0.16
	(2.52)	(0.69)	(0.06)	
Denmark	0.010***	0.053	− 0.254	0.25
	(3.69)	(0.85)	(− 1.13)	
France	0.008***	0.055	0.071	0.14
	(2.76)	(1.08)	(0.37)	
Germany	0.009***	0.002	0.091	− 0.12
	(3.09)	(0.04)	(0.48)	
Hong Kong	0.009**	0.085**	− 0.151	0.02
	(2.39)	(2.10)	(− 1.03)	
Italy	0.005	0.039	− 0.024	− 0.16
	(1.60)	(0.75)	(− 0.16)	
Japan	0.005**	0.103*	− 0.005	− 0.17
	(2.08)	(1.89)	(− 0.03)	
Netherlands	0.011***	0.003	− 0.026	0.64
	(4.06)	(0.05)	(− 0.10)	
Norway	0.009**	0.091	− 0.348	− 0.15
	(2.40)	(1.45)	(− 1.44)	
Singapore	0.005	0.110*	− 0.057	0.16
	(1.62)	(1.90)	(− 0.38)	
Spain	0.005*	0.053	0.102	− 0.11
	(1.80)	(1.04)	(0.82)	
Sweden	0.010***	0.045	0.053	− 0.08
	(3.30)	(0.96)	(0.24)	
Switzerland	0.010***	0.036	− 0.037	− 0.11
	(4.59)	(0.92)	(− 0.20)	
United Kingdom	0.008***	0.059	0.098	0.03
	(3.02)	(0.99)	(0.41)	
MSCI World	0.009***	0.006	− 0.132	− 0.16
	(3.60)	(0.11)	(− 0.59)	

(1): $R_{i,t-1}$ refers to the own past return of the markets respectively. (2): ΔMIN^{own} refers to the extreme minimum innovation of the own stock market. (3) Figures in parentheses are *t*-values. (4) *** and ** indicate statistical significance at 1% and 5% level, respectively

Table 11 Predictive test results with the U.S. extreme indicator- developing markets [under extreme recessionary conditions]

Country	AFC [1997:06–1999:12]		GFC [2007:07 to 2009:06]		ESDC [2009:01 to 2013:12]		COVID [2019:12 to 2022:07]	
	ΔMIN^{US}	Adj-R^2 (%)	ΔMIN^{US}	Adj-R^2 (%)	ΔMIN^{US}	Adj-R^2 (%)	ΔMIN^{US}	Adj-R^2 (%)
Argentina	0.683	− 2.12	− 4.521***	29.27	− 1.426	1.41	− 0.667	− 1.57
	(1.55)		(− 2.82)		(− 1.37)		(− 1.57)	
Chile	− 0.093	− 3.54	− 2.356***	21.64	− 2.271***	20.29	0.694**	− 0.19
	(− 0.37)		(− 3.00)		(− 2.66)		(2.03)	
China	1.176	− 1.82	− 2.641***	10.95	− 1.410	7.41	0.246	− 2.12
	(0.82)		(− 6.59)		(− 1.45)		(1.44)	
Ireland	− 0.303***	2.39	− 1.923***	8.53	− 0.947	1.40	− 0.293	− 2.31
	(− 2.62)		(− 2.64)		(− 0.96)		(− 1.31)	
Finland	− 0.019	− 3.57	− 1.075	− 1.39	− 1.040	0.89	− 0.458	− 0.04
	(− 0.03)		(− 1.43)		(− 0.74)		(− 1.51)	
Greece	0.009	− 2.13	− 2.997*	13.30	− 1.674	1.15	− 0.442	0.49
	(0.02)		(− 1.96)		(− 1.45)		(− 1.46)	
Indonesia	− 2.098	− 1.03	− 4.793***	31.93	− 0.438	− 1.22	− 0.124	− 3.31
	(− 0.71)		(− 4.02)		(− 0.59)		(− 0.41)	
Jordan	− 0.097	− 3.32	− 1.733**	10.77	− 0.282	− 0.88	0.085	− 3.40
	(− 0.51)		(− 2.42)		(− 0.69)		(0.46)	
Korean	− 0.762	− 2.53	− 2.383**	9.02	− 0.877	0.47	− 0.125	− 3.24
	(− 0.53)		(− 2.39)		(− 0.71)		(− 0.41)	
Malaysia	− 0.941	− 2.43	− 1.862***	20.66	− 0.916	6.07	0.018	− 3.44
	(− 1.28)		(− 5.65)		(− 1.43)		(0.10)	
Mexico	0.690	− 2.45	− 3.071***	27.85	− 0.686	0.32	− 0.570*	− 0.72
	(1.28)		(− 3.04)		(− 0.56)		(− 1.81)	
New Zealand	− 0.441	− 3.54	− 2.022***	12.54	− 0.764	1.07	0.096	− 3.31
	(− 0.61)		(− 3.57)		(− 1.16)		(0.43)	
Philippines	− 0.125	− 0.86	− 2.275***	19.92	− 0.556	− 0.40	− 0.137	− 3.21
	(− 0.11)		(− 4.10)		(− 0.80)		(− 0.61)	
Portugal	− 0.930	3.00	− 2.680***	27.17	− 1.019	2.10	− 0.686***	6.59
	(− 0.96)		(− 3.86)		(− 1.44)		(− 3.21)	
Taiwan	0.594	− 2.43	− 2.352***	15.23	− 1.500***	8.41	0.482*	0.02
	(1.30)		(− 9.81)		(− 3.70)		(1.78)	
Thailand	1.733*	− 0.98	− 4.087***	40.74	− 0.947	1.30	0.152	− 3.19
	(1.81)		(− 4.49)		(− 0.87)		(0.57)	
Türkiye	− 2.341**	2.69	− 3.270***	11.54	− 0.005	− 1.75	− 0.805*	1.23
	(− 2.47)		(− 3.44)		(− 0.01)		(− 1.83)	

(1): ΔMIN^{US} refers to the extreme minimum innovation of the U.S. stock market. (2): AFC refers to the sample period of June 1997 to December 1999 (Asian Financial Crisis). (3): GFC refers to the sample period of July 2007 to June 2009 (Global Financial Crisis). (4): ESDC refers to the sample period of January 2009 to December 2013 (European Sovereign Debt Crisis). (5): COVID refers to the sample period of December 2019 to July 2022, that COVID-19 crisis originates as a health shock. (6) Figures in parentheses are *t*-values. (7) ***, ** and * indicate statistical significance at 1%, 5% and 10% level, respectively

Table 12 Predictive test results with the U.S. extreme indicator [under extreme recessionary conditions]

Country	OS [1973:10 to 1974:03]		WDC [1982:08 to 1989:12]		NBC [1991:01 to 1993:12]		DCB [2000:03 to 2002:10]	
	ΔMIN^{US}	Adj-R^2 (%)	ΔMIN^{US}	Adj-R^2 (%)	ΔMIN^{US}	Adj-R^2 (%)	ΔMIN^{US}	Adj-R^2 (%)
Australia	−0.838	−3.25	0.013	−1.16	−0.995*	0.96	0.084	−3.40
	(−0.25)		(0.11)		(−1.67)		(0.08)	
Austria	−4.069***	7.49	−0.254*	0.55	−1.122	0.19	−0.423	−1.70
	(−3.46)		(−1.65)		(−1.44)		(−0.87)	
Belgium	−2.194**	25.21	−0.014	−1.16	−1.705***	15.94	−0.357	−2.61
	(−2.34)		(−0.16)		(−4.04)		(−1.09)	
Canada	−0.866	−3.08	−0.307***	2.83	−0.176	−2.77	−0.350	−2.79
	(−0.79)		(−4.90)		(−0.30)		(−0.36)	
Denmark	1.469	−2.99	−0.091*	0.93	−1.302**	2.64	1.006**	3.43
	(1.49)		(−1.93)		(−2.02)		(2.57)	
France	−1.414	−3.10	0.080	−1.00	−1.322***	4.51	0.947	1.72
	(−0.79)		(0.61)		(−3.52)		(1.29)	
Germany	−6.776***	16.07	−0.246**	2.10	−1.287***	3.80	0.539	−2.44
	(−5.29)		(−2.09)		(−3.47)		(0.74)	
Hong Kong	−6.055**	6.67	−0.297***	3.61	−0.712	−1.98	−1.103	1.08
	(−2.38)		(−3.45)		(−0.62)		(−1.30)	
Italy	−6.805*	6.34	0.259**	2.16	0.023	−3.03	0.890	2.08
	(−1.96)		(2.29)		(0.02)		(1.24)	
Japan	−4.067***	2.77	0.047	−1.10	−1.702**	2.03	0.019	−3.45
	(−5.07)		(0.46)		(−2.19)		(0.03)	
Netherlands	−1.635	−2.99	−0.402***	5.28	−1.253***	7.67	0.497	−2.19
	(−0.96)		(−7.23)		(−3.79)		(0.74)	
Norway	−2.438**	21.08	−0.526***	3.58	−1.998***	4.37	0.287	−2.87
	(−2.13)		(−4.07)		(−3.08)		(0.46)	
Singapore	−4.610**	4.24	−0.067	−1.09	−0.721	−0.79	−1.379	0.17
	(−2.24)		(−0.41)		(−1.07)		(−1.03)	
Spain	−1.054	−3.08	−0.104	−0.92	−1.888***	4.65	0.645	−1.32
	(−0.98)		(−0.91)		(−3.53)		(0.74)	
Sweden	−4.794***	3.37	−0.305*	1.11	−1.337*	1.26	1.436	1.91@@
	(−4.54)		(−1.87)		(−1.95)		(1.09)	
Switzerland	−5.147***	8.46	−0.130*	0.55	−1.010***	2.15	0.569	−0.08
	(−4.26)		(−1.73)		(−2.79)		(1.37)	
United Kingdom	3.613	−1.96	−0.368***	2.61	−1.321***	3.98	0.304	−2.18
	(1.22)		(−5.72)		(−3.76)		(0.56)	
MSCI World	0.706	−3.19	−0.310***	3.50	−1.361***	18.73	0.262	−2.83
	(0.90)		(−3.28)		(−3.80)		(0.39)	

(1): ΔMIN^{US} refers to the extreme minimum innovation of the U.S. stock market. (2): OS refers to the sample period of October 1973 to March 1974 (Oil shock recession period). (3): WDC refers to the sample period of August 1982 to December 1989 (World Debt Crisis). (4): NBC refers to the sample period of January 1991 to December 1992 (Nordic Banking Crisis). (5): DCB refers to the sample period of March 2000 to October 2002 (the Dot-com Bubble Crisis). (6) Figures in parentheses are *t*-values. (7) ***, ** and * indicate statistical significance at 1%, 5% and 10% level, respectively

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Author contributions

XJ comes up with the topic, reviews the literature, designs the research framework and conduct preliminary tests. DX conducts extensive tests, verifies the feasibility of the research and writes the manuscript. BL constructs the methodology, writes the programs for empirical tests and supervises the research project. TS contributes to the interpretation and analysis of results and supervises the research project. All the authors have read and approved the final manuscript.

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References

Akın Ç, Kose MA (2008) Changing nature of north-south linkages: stylized facts and explanations. J Asian Econ 19(1):1–28
Annaert J, Ceuster M, Verstegen K (2013) Are extreme returns priced in the stock market? European evidence. J Bank Finance 37(9):3401–3411
Ari A (2014) The European debt crisis: causes, consequences, measures and remedies. Cambridge Scholars Publishing, Newcastle
Augustin P, Sokolovski V, Subrahmanyam M, Tomio D (2022) In sickness and in debt: the COVID-19 impact on sovereign credit risk. J Financ Econ 143(3):1251–1274
Bae K, Karolyi GA, Stulz RM (2003) A new approach to measuring financial contagion. Rev Financ Stud 16(3):717–763
Baker S, Bloom N, Davis S, Kost K, Sammon M, Viratyosin T (2020) The unprecedented stock market reaction to COVID-19. Rev Asset Pricing Stud 10(4):742–758
Bakshi G, Cerrato M, Crosby J (2018) Implications of incomplete markets for international economies. Rev Financ Stud 31(10):4017–4062
Bali TG, Cakici N, Whitelaw RF (2011) Maxing out: stocks as lotteries and the cross-section of expected returns. J Financ Econ 99(2):427–446
Bao Z, Huang D (2021) Shadow banking in a crisis: evidence from fintech during covid-19. J Financ Quant Anal 56(7):2320–2320
Barberis N, Huang M (2008) Stocks as lotteries: the implications of probability weighting for security prices. Am Econ Rev 98(5):2066–2100
Barberis N, Mukherjee A, Wang B (2016) Prospect theory and stock returns: an empirical test. Rev Financ Stud 29(11):3068–3107
Barillas F, Shanken J (2018) Comparing asset pricing models. J Financ 73(2):715–754
Barro RJ, Liao GY (2021) Rare disaster probability and options pricing. J Financ Econ 139(3):750–769
Beltratti A, Morana C (2010) International house prices and macroeconomic fluctuations. J Bank Finance 34(3):533–545
Bena J, Dinc S, Erel I (2022) The international propagation of economic downturns through multinational companies: the real economy channel. J Financ Econ 146(1):277–304
Berardi M (2022) Uncertainty and sentiments in asset prices. J Econ Behav Organ 202:498–498
Bogousslavsky V (2021) The cross-section of intraday and overnight returns. J Financ Econ 141(1):172–194
Borup D, Schütte ECM (2022) Asset pricing with data revisions. J Financ Mark 59:100620
Boyer B, Mitton T, Vorkink K (2010) Expected idiosyncratic skewness. Rev Financ Stud 23(1):169–202
Campbell JY, Lo AW, Mackinlay AC (1997) The econometrics of financial markets. Princeton University Press, Princeton
Chaplinsky S, Haushalter D (2010) Financing under extreme risk: contract terms and returns to private investments in public equity. Rev Financ Stud 23(7):2789–2820
Chiang IE, Hughen WK (2017) Do oil futures prices predict stock returns? J Bank Finance 79:129–141
Chung Y, Kim S (2017) Extreme returns and herding of trade imbalances. Rev Finance 21(6):2379–2399
Colacito R, Riddiough SJ, Sarnode L (2021) Business cycles and currency returns. J Financ Econ 137(3):659–678
Corradin S, Maddaloni A (2020) The importance of being special: repo markets during the crisis. J Financ Econ 137(2):392–429
Eichenbaum MS, Rebelo S, Trabandt M, Koijen R (2021) The macroeconomics of epidemics. Rev Financ Stud 34(11):5149–5187
Embrechts P, Resnick S, Samorodnitsky G (1999) Extreme value theory as a risk management tool. N Am Actuarial J 3(2):30–41
Fama EF, French KR (1988) Dividend yields and expected stock returns. J Financ Econ 22(1):3–25
Fama EF, French KR (1992) The cross-section of expected stock returns. J Finance 47(2):427–465
Fama E, French K (1996) Multifactor explanations of asset pricing anomalies. J Finance 51(1):55–84

Forand N, DeRubeis R (2014) Extreme response style and symptom return after depression treatment: the role of positive extreme responding. J Consult Clin Psychol 82(3):500–509
Gharghori P, Lee R, Veeraraghavan M (2009) Anomalies and stock returns: Australian evidence. Account Finance 49(3):555–576
Ghosh A, Julliard C, Taylor AP (2017) What is the consumption-CAPM missing? An information-theoretic framework for the analysis of asset pricing models. Rev Financ Stud 30(2):442–504
Grundy B, Martin J (2001) Understanding the nature of the risks and the source of the rewards to momentum investing. Rev Financ Stud 14(1):29–78
Herrera R, Clements AE (2018) Point process models for extreme returns: harnessing implied volatility. J Bank Finance 88:161–175
Hood M, Malik F (2013) Is gold the best hedge and a safe haven under changing stock market volatility? Rev Financ Econ 22(2):47–47
Huang W, Liu Q, Ghon Rhee S, Wu F (2012) Extreme downside risk and expected stock returns. J Bank Finance 36(5):1492–1502
Huang S, Lee C, Song Y, Xiang H (2022) A frog in every pan: Information discreteness and the lead-lag returns puzzle. J Financ Econ 145(2):83–102
Jegadeesh N, Titman S (1993) Returns to buying winners and selling losers: implications for stock market efficiency. J Finance 48(1):65–91
Jiang Z, Wang G, Canabarro A, Podobnik B, Xie C, Stanley H, Zhou W (2018) Short term prediction of extreme returns based on the recurrence interval analysis. Quant Finance 18(3):353–370
Jin LJ, Sui P (2022) Asset pricing with return extrapolation. J Financ Econ 145(2):273–295
Johnson JA, Medeiros MC, Paye BS (2022) Jumps in stock prices: new insights from old data. J Financ Mark 60:100708
Kelly B, Jiang H (2014) Tail risk and asset prices. Rev Financ Stud 27(10):2841–2871
Lettau M (2003) Inspecting the mechanism: closed-form solutions for asset prices in real business cycle models. Econ J 113(489):550–575
Liu YA, Pan M-S (1997) Mean and volatility spillover effects in the U.S. and Pacific-Basin stock markets. Multinational Finance J 1(1):47–62
Liu YK, Matthies B (2022) Long-run risk: is it there? J Financ 77(3):1587–1633
Longin F (1996) The asymptotic distribution of extreme stock market returns. J Bus 69(3):383–408
Mikhaylov A, Bhatti IM, Dinçer H, Yüksel S (2022) Integrated decision recommendation system using iteration-enhanced collaborative filtering, golden cut bipolar for analyzing the risk-based oil market spillovers. Comput Econ 1–34.
Moiseev N, Mikhaylov A, Dinçer H, Yüksel S (2023). Market capitalization shock effects on open innovation models in e-commerce: golden cut q-rung orthopair fuzzy multicriteria decision-making analysis. Financ Innov 9(1)
Muchnik L, Bunde A, Havlin S (2009) Long term memory in extreme returns of financial time series. Physica A 388(19):4145–4150
Nartea GV, Kong D, Wu J (2017) Do extreme returns matter in emerging markets? Evidence from the Chinese stock market. J Bank Finance 76:189–197
Ng A (2000) Volatility spillover effects from Japan and the U.S. to the pacific-basin. J Int Money Finance 19(2):207–233
Norrbin SC, Schlagenhauf DE (1996) The role of international factors in the business cycle: a multi-country study. J Int Econ 40(1–2):75–85
Nyberg H, Ponka H (2016) International sign predictability of stock returns: the role of the United States. Econ Model 58:323–338
Papanikolaou D, Schmidt LDW, Pontiff J (2021) Working remotely and the supply-side impact of covid-19. Rev Asset Pricing Stud 12(1):53–111
Petersen MA (2009) Estimating standard errors in finance panel data sets: comparing approaches. Rev Financ Stud 22(1):435–480
Perotti E, Rola-Janicka M (2022) The good, the bad, and the missed boom. Rev Financ Stud 35(11):5025–5056
Poterba J, Summers L (1988) Mean reversion in stock prices. J Financ Econ 22(1):27–59
Otto G, Voss G, Willard L (2001) Empirical results| RDP 2001–05: Understanding OECD output correlations. Reserve Bank of Australia Research Discussion Papers.
Rapach DE, Strauss JK, Zhou G (2013) International stock return predictability: what is the role of the United States? Journal of Finance 68(4):1633–1662
Rapach DE, Wohar ME, Rangvid J (2005) Macro variables and international stock return predictability. Int J Forecast 21(1):137–166
Rouwenhorst K (1999) Local return factors and turnover in emerging stock markets. J Finance 54(4):1439–1464
Shue K, Townsend RR (2021) Can the market multiply and divide? Non-proportional thinking in financial markets. J Financ 76(5):2307–2357
Siliverstovs B (2017) International stock return predictability: on the role of the United States in bad and good times. Appl Econ Lett 24(11):771–773
Singh A, Allen D, Robert P (2013) Extreme market risk and extreme value theory. Math Comput Simul 94:310–328
Singh T (2007) Intertemporal optimizing models of trade and current account balance: a survey. J Econ Surv 21(1):25–64
Singh T (2016a) Rhetorics of saving-investment correlations and the international mobility of capital: a survey. J Int Trade Econ Dev Int Comp Rev 25(5):636–690
Singh T (2016b) International mobility of capital in the United States: robust evidence from time-series tests. J Time Series Econom 8(2):193–249
Titman S, Wei K, Xie F (2004) Capital investments and stock returns. J Financ Quant Anal 39(4):677–700
Walkshausl C (2014) The MAX effect: European evidence. J Bank Finance 42(1):1–10
Welch I, Goyal A (2008) A comprehensive look at the empirical performance of equity premium prediction. Rev Financ Stud 21(4):1455–1508
Wen Y, Li B (2020) Lagged country returns and international stock return predictability during business cycle recession periods. Appl Econ 52(46):5005–5019

Wen Y, Li B, Chen X, Singh T (2022) Spillover effects of the US stock market and the predictability of returns: international evidence based on daily data. Appl Econ (forthcoming)
Xu D, Li B, Singh T (2023) Does gold–platinum price ratio predict stock returns? International evidence. Int J Managerial Finance 19(2):308–330
Yetman J (2011) Exporting recessions: international links and the business cycle. Econ Lett 110(1):12–14
Zerbib OD (2022) A sustainable capital asset pricing model (S-CAPM): evidence from environmental integration and sin stock exclusion. Rev Finance 26(6):1345–1388

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