Risk Aversion Propagation: Evidence from Financial Markets and Controlled Experiments *

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Abstract

We study risk aversion (RA) propagation from US to several major developed economies. Using daily financial market and news data, we identify US RA events and show that the international pass-through of US high RA events is significantly higher (61%) than that of US low RA events (43%), suggesting asymmetric US risk aversion propagation. In our lab experiment, non-US subjects when primed with a US financial bust shock exhibited asymmetrically more negative emotion and higher risk aversion. The foreign nature of bust shocks may change emotions more than that of boom shocks, which explains 20% of the RA propagation asymmetry in our experiment.

Keywords: risk aversion, propagation, emotions, animal spirits, controlled experiment, VIX, variance risk premium, uncertainty, international comovement

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"With such contagion around the world, ... is there any reason to doubt that contagion of stories has economic significance, or that there could be world-wide fluctuations in animal spirits?"

— George Akerlof and Robert Shiller, *Animal Spirits (2010)*

1. Introduction

While the time variation in investor risk appetite is widely examined,[1] there is scant research on how investor risk appetite may respond in an international context. Despite several obvious empirical identification challenges (e.g., country-level risk aversion measurement, lack of narratives), recent equilibrium frameworks have demonstrated that comoving country risk aversion is potentially important in explaining international comovements of utility growth and asset returns (e.g., Stathopoulos (2017); Xu (2019)) and global financial cycle (e.g., Miranda-Agrippino and Rey (2020); Bekaert, Hoerova, and Xu (2021)).

In this paper, we aim to address this knowledge gap by studying how non-US risk aversion in several major developed economies responds to US risk aversion events. We use financial market and news data (2000-2017) to establish the potential propagation patterns while addressing several empirical challenges in the first part of the paper, and then conduct two controlled experiments to examine testable mechanisms in the second part of the paper. Our main findings are two fold. First, we identify a significantly higher international pass-through of US high risk aversion events (61%) than that of US low risk aversion events (43%), suggesting asymmetric US risk aversion propagation. Second, in our main experiment, non-US subjects when primed with a US stock market bust shock exhibited asymmetrically lower positive emotion, higher negative emotion and higher risk aversion than those primed with a US boom shock. While the psychological link between emotions and risk aversion has been well discussed (Lopes (1987); Loewenstein (2000); Kuhnen and Knutson (2005); Kuhnen and Knutson (2011); among many others), we are among the first to establish that the *foreign* nature of bust or negative shocks may change emotions more than that of boom or positive shocks, hence resulting in asymmetric risk aversion propagation. Compared to other testable but insignificant channels such as beliefs

[1] For instance, Campbell and Cochrane (1999) and its recent variants construct structural asset pricing models to examine the effect of time-varying risk aversion on asset prices; Bakshi and Madan (2006) among many others examine this question using option prices. Since the global financial crisis, there is renewed interest in understanding the dynamics of investor risk aversion; Cohn, Engelmann, Fehr, and Maréchal (2015) and Guiso, Sapienza, and Zingales (2018) use tools of experiments and surveys, while Pflueger, Siriwardane, and Sunderam (2020) and Bekaert, Engstrom, and Xu (Forthcoming) explore a wide range of financial and economic data.

about fundamental spillovers, such an emotion-related mechanism significantly explained 20% of the propagation asymmetry in our experiment.

We provide more details next. In the first part of the paper, we provide daily-frequency evidence of how non-US risk aversion changes in response to US risk aversion events. We first need to construct US risk aversion shock proxies, and there are four challenges: (1) time-varying country-level risk aversion is hard to measure; (2) risk aversion, a price-of-risk variable, likely comoves with other fundamental risk variables, such as uncertainty, an amount-of-risk variable; (3) significant changes in the US risk aversion could be caused by events originated from at other countries; (4) the literature has not agreed on a comprehensive list of pure risk aversion events for us to use directly.

To address these challenges, our approach starts with a parsimonious financial market proxy for risk aversion: variance risk premium (henceforth, VRP), or the difference between the squared implied volatility index and an estimate of the conditional variance ("uncertainty") of the stock market. This empirical proxy is particularly suitable for our research for two reasons. First, conceptually, recent research has shown robust evidence on the positive relation between VRP and demanded risk compensations in the US and around the world (e.g., Bollerslev, Tauchen, and Zhou (2009) and see Zhou (2018) for a detailed summary), and some papers have explicitly or suggestively linked the changes in investor risk aversion with VRP in equilibrium frameworks (e.g., Bakshi and Madan (2006), Todorov (2010), Bollerslev, Gibson, and Zhou (2011), Bekaert and Hoerova (2014), Martin (2017), Bekaert, Engstrom, and Xu (Forthcoming)). The second reason is that VRP can be constructed for several major economies at the daily frequency, given the availability of volatility indices and return data. Lakonishok, Lee, Pearson, and Poteshman (2007) document that variance swap markets are driven mostly by domestic investors/accounts, which makes it plausible to interpret risk measures derived from these markets as representative for a particular country. We consider the following six countries as our "non-US" country set given data availability: Switzerland, Germany, France, Japan, the Netherlands, and the United Kingdom.

Next, we define country daily risk aversion (RA) *shocks* as abnormal changes after projecting country risk aversion onto a moving-average term and a collection of past local fundamental variables; country uncertainty (UC) shocks are obtained in a similar way. Finally, we use a comprehensive global news database to systematically keep track of one major negative and one major positive news of the day and their country origins, given coverage and sentiment metrics. Put the financial market and news data together, our US "high RA" ("low RA") event dates are identified when (a) US risk aversion shocks are abnormally high (low) but US uncertainty shocks are within a normal range – this is to address the comoving risk variable concern – and (b) the identified negative (positive) news of the day originates from US – this is to address the origin concern.

One advantage of our approach is to systematically obtain potential narratives of US risk aversion or uncertainty events, whereas extant literature typically studies one narrative at a time.[2] Out of the identified 146 US risk aversion events and 77 uncertainty events between 2000 and 2017, we find that business and economy news more likely result in extreme changes in the expectation of future market fluctuations (uncertainty), while politics and society news more likely result in extreme changes in attitude toward risk (risk aversion).

Our main event study analysis consists of two parts. First, we use abnormal US risk aversion changes as the response variable to provide an economic baseline of identified US events. We show that US risk aversion abnormally and significantly increases (decreases) by 59.2% (-62.6%), compared to its historical level, on our selection of high-RA (low-RA) event dates; both numbers are statistically close in absolute term. Second, on the foreign responses to US risk aversion events, we find that international risk aversion, on average, abnormally and significantly increases (decreases) by 36.8% (-26.9%), compared to a country's own historical risk aversion level, on US high-RA (low-RA) event dates. The pass-through levels of high and low US risk aversion events – 61% and 43%, respectively – are statistically significantly different from each other, documenting an *asymmetric* US risk aversion propagation. Our main empirical result is robust to various news categories, country compositions, and exclusions of 2008 crisis period or stock market jump days.

While financial market and news data allow us to examine US risk aversion propagation in a real and aggregate context, it is not an ideal context to examine the underlying mechanisms given the simultaneously changing and complex market conditions. In the second part of the paper, we design two experiments to explore potential mechanisms for asymmetric risk aversion propagation that are testable in a controlled setting. We first validate the risk aversion interpretation of our US treatment shocks on US participants in Study 1, and then examine

[2]For instance, Campbell and Cochrane (1999) study how consumption shocks may affect risk aversion; Brandt and Wang (2003) inflation shocks; Brunnermeier and Nagel (2008) wealth shocks; Bassi, Colacito, and Fulghieri (2013) weather risk; Wang and Young (2020) terrorist shocks; Guiso, Sapienza, and Zingales (2018) economic crisis; and so on.

how non-US participants' risk aversion respond to US risk aversion shocks in Study 2. We exploit the priming method (commonly used in Psychology and increasingly used in Finance and Economics) to stimulate the propagation of risk aversion. We conclude by discussing the link to the first part of the paper.

On our treatment shocks, we follow Cohn, Engelmann, Fehr, and Maréchal (2015) and prime participants with a fictive financial boom (continuously increasing price with stable fluctuations) or a bust scenario (continuously decreasing price with stable fluctuations). Different from Cohn, Engelmann, Fehr, and Maréchal (2015) who study risk aversion cyclicality, we are interested in the (a)symmetry of risk aversion shock propagation, and therefore we design our control groups with non-RA scenarios (stable price with increasing or decreasing fluctuations). In all treatment and control groups, participants were instructed to write a timed (5 min) diary about the scenario randomly assigned to them as the priming procedure (Lu, Lee, Gino, and Galinsky (2018)).

One advantage of a controlled experimental setting is that risk aversion can be clearly elicited and assessed. Among the set of elicitation methods summarized in Charness, Gneezy, and Imas (2013), we follow Gneezy and Potters (1997) and Cohn, Engelmann, Fehr, and Maréchal (2015) to directly measure participants' risk aversion from their investment decision in a risky project with a positive expected return (to incentivize) and explicitly specified probabilities and payoffs (to rule out the potential impact of expectation, ambiguity, subject uncertainty and so on). As a useful instrument for capturing treatment effects, the relative simplicity of this method, combined with the fact it can be implemented with one trial and basic experimental tools, also makes it suitable for assessing risk attitudes in the field (Charness, Gneezy, and Imas (2013)). Given our research question, our experiments need non-US participants from several major economies; however, this potentially introduces risk aversion heterogeneity to begin with given their different local macro environments, culturally-driven risk tolerance levels (Hofstede (2011), Gandelman and Hernández-Murillo (2015), Rieger, Wang, and Hens (2015), Falk, Becker, Dohmen, Enke, Huffman, and Sunde (2018)), or persistent individual-level differences (Jiang, Peng, and Yan (2020)). To control for unknown built-in risk aversion heterogeneity, we instructed participants to make a baseline investment decision of the same investment task before the experimental manipulation, and the pre-priming investment level is used as a control variable in our analysis.

In Study 1, we find that risky investment levels of US participants in the US bust (boom) groups were significantly lower (higher) than those in the US control groups, with similar magnitude, which validates the effectiveness and interpretation of our priming treatment shocks and provides a baseline magnitude to measure the pass-through for non-US participants in Study 2. In Study 2, we find that non-US participants when primed with a US bust shock exhibited asymmetrically lower risky investment level (higher risk aversion) than those primed with a US boom shock. Taken together, the bust shock pass-through is significantly higher than the boom shock pass-through, which is consistent with our previous financial market evidence of asymmetric US risk aversion propagation.

To explore the underlying mechanisms for asymmetric US risk aversion shock propagation, we hypothesize and examine two testable channels: the fundamental spillover channel and the non-fundamental channel. One hypothesis is that non-US investors update their beliefs about their own-country fundamentals given a US boom or bust condition; the foreign nature of US bust shocks may trigger more "pessimistic bias", and the induced pessimism could result in further decreases in non-US investors' risky investment choices. We find little evidence of such a channel as belief updating appeared statistically symmetric.

Our second hypothesis, the non-fundamental channel, is motivated from extant evidence on the links between psychological forces (such as emotions) and investors' attitude towards risk (Kuhnen and Knutson (2005)). That is, the US shocks could also *directly* affect the risk aversion of non-US investors through affecting their emotional states; hence, the foreign nature of the shocks may trigger more negative emotions in the US bust treatment, hence leading to asymmetric risk aversion responses. To test this hypothesis, we obtained participants' post-priming emotional states, using the following eight dimensions (Watson, Clark, and Tellegen (1988); Lu, Lee, Gino, and Galinsky (2018)): positive (enthusiastic, excited, happy, relaxed) and negative (distressed, irritable, nervous, scared). We also construct a measure of general emotion as the difference between positivity and negativity. We find that non-US participants when primed with a US bust shock exhibited asymmetrically lower positive emotion, higher negative emotion and higher risk aversion than those primed with a US boom shock. Finally, we conduct a mediation analysis and show that close to 20% of the excessive high RA response in our study can be explained by emotion, providing supportive evidence for the non-fundamental mechanism posited above.

While the psychological link between emotions and risk aversion has been well examined and documented (Lopes (1987); Loewenstein (2000); Kuhnen and Knutson (2005); Kuhnen and

Knutson (2011); Cohn, Engelmann, Fehr, and Maréchal (2015), among many others), there is little direct discussion on how and why "foreign" nature of negative events may amplify emotional states and hence risk aversion. One plausible reason is familiarity: people are more afraid of an unfamiliar (foreign) negative shock or challenge than a familiar (domestic) one (see e.g., Cao, Han, Hirshleifer, and Zhang (2011) and Kenning, Mohr, Erk, Walter, and Plassmann (2006)).

The significant mediating effect of emotions is potentially consistent with our financial market evidence. We conduct a Jackknife exercise of our event study, dropping one country at a time, and then recalculate the non-US response asymmetry. We find that United Kingdom, France, and the Netherlands contribute more to the asymmetric responses than Switzerland, Japan and Germany. Meanwhile, the Gallup's Well-Being Index survey shows that United Kingdom, France and The Netherlands (among the six countries we consider in this research) have higher percentages of adults who report experiencing emotions on a daily basis. There is a potential link between the financial market and experimental evidence on emotions being a mechanism for the asymmetric propagation.

Our research contributes to several strands of the literature. Our **empirical findings** speak to the international asset pricing literature in three fold. First, our main empirical finding is that there exhibits an excessive international risk premium comovement on extreme US high risk aversion event days. The high RA shock pass-through is about 50% higher than the low RA shock pass-through. These qualitative and quantitative results provide potential testable hypotheses for modeling risk aversion processes in international models involving multiple country agents.

Second, our empirical findings potentially relate to several international financial market phenomena that we do not fully understand yet. We discuss two below. Various papers have documented excessive international stock return comovement during global stock market downturns that are not necessarily correlated with business cycles; such a phenomenon, which has obvious investment implications, is typically referred to as asymmetric return comovement (see e.g. Cappiello, Engle, and Sheppard (2006), Li (2014)). Recent papers have argued that the asymmetric nature of a "global" risk aversion state variable (e.g. higher chance for extreme increases than decreases), in theory, could contribute to asymmetric international return comovement (see e.g. Martin (2013) and Xu (2019)). Our research provides one empirical explanation for why global risk aversion can indeed be asymmetric, through asymmetric risk aversion propagation when a bad shock materializes in the US. Our work also relates to the burgeoning literature examining the existence of a world-wide risk aversion (e.g., Miranda-Agrippino and Rey (2020), Bekaert, Hoerova, and Xu (2021), Karolyi, Lee, and Van Dijk (2012) and so on). Our evidence shows that local shocks could transmit internationally by influencing global risk aversion.

Third, by utilizing both news and financial market data in our shock identification procedure, we are among the first to suggest narratives for spikes in VIX, VRP, or stock market uncertainty in a systematic and easily replicable way. Relatedly, Baker, Bloom, Davis, and Sammon (2020) examine narratives of major stock-market jumps (i.e., first moment), whereas we focus on the narratives of major changes in risk variables (i.e., higher moments). It is noteworthy that both papers, with completely different methodologies, find multiple consistent results (as expected); for instance, policy events reduce stock market uncertainty and generally produce positive jumps to the market. Both papers advocate for the importance of narratives, in line of Shiller (2017).

Our **experimental findings** on the mechanisms of the asymmetric risk aversion propagation phenomenon potentially relate to a growing behavioral literature on the role of immediate emotions (or, more broadly, visceral factors) in risk taking and other economic behaviors (see e.g. Loewenstein (2000), Hirshleifer and Shumway (2003), Kuhnen and Knutson (2005), Callen, Isaqzadeh, Long, and Sprenger (2014), Cohn, Engelmann, Fehr, and Maréchal (2015), Andrade, Odean, and Lin (2016), Guiso, Sapienza, and Zingales (2018), Wang and Young (2020), among many others). First, broadly, our evidence supports the risk-as-feelings perspective as proposed by Loewenstein, Weber, Hsee, and Welch (2001), as opposed to the fully cognitive and consequentialist perspective. Our research demonstrates the value of collecting information on emotional reactions to risks, which is called for as a routine practice in Loewenstein, Weber, Hsee, and Welch (2001); meanwhile, the Psychology literature has matured in measuring emotions, and we chose an eight-item approach (Watson, Clark, and Tellegen (1988)) given our interest in both positive and negative feelings.

Second, while the behavioral literature has shown that emotions play an important role in the level of risk aversion (Kuhnen and Knutson (2005)) and the countercyclicality of risk aversion (Cohn, Engelmann, Fehr, and Maréchal (2015)), our paper joins this research agenda and provides new evidence about the role of emotions in the international transmission of risk attitude across countries, highlighting a "cross-country" perspective. In our evidence, a non-trivial part of asymmetric risk aversion propagation was explained through the asymmetric emotional responses when non-US participants were primed with a foreign negative (bust) shock compared to a foreign positive (boom) shock. Overall, while the existing literature typically examines international comovement through the lens of macro and aggregate factors, our research aims to offer a micro and behavioral perspective on how investors risk appetite may respond in an international context.

The remainder of the paper is organized as follows. Section 2 discusses our approach of obtaining potential US risk aversion events. Section 3 conducts the event study analysis. Section 4 presents our experimental findings, and concluding remarks are in Section 5.

2. Risk Aversion Events

In the first part of the paper, we provide daily-frequency evidence of how non-US risk aversion responds to US risk aversion events, using financial market and news data and the event study methodology. In this section, we identify extreme US risk aversion events to be used in our event studies in Section 3, after addressing the four challenges mentioned in the Introduction: measurement, comoving risk variables, country origin, and narrative validation. Specifically, Section 2.1 motivates and constructs our measures of aggregate market risk aversion (RA) and RA shocks for the US and six other major developed economies. Sections 2.2 and 2.3 explain our US risk aversion event identification methodology.

2.1. Measures of risk aversion and risk aversion shocks

2.1.1. Motivation

It is commonly agreed that time-varying aggregate risk aversion is difficult to measure, and the asset pricing literature has proposed several empirical candidates. One group of candidates exploits the close connection between risk aversion and the curvature of per period utility function of the representative agent. A prominent class of consumption-based asset pricing models features habit-type utility functions as in Campbell and Cochrane (1999), and hypothesizes that the time variation in risk aversion is likely driven by current and past real economic shocks, such as consumption growth, and should exhibit countercyclical and persistent behaviors. Following these theoretical suggestions, Wachter (2006) proxies time-varying aggregate risk aversion using the minus summation of past inflation-adjusted consumption growth innovations. However, such consumption-based risk aversion measure is not suitable for our research for two reasons: one, it is not empirically straightforward to obtain daily measures of consumption;[3] and two, recent papers using various methodologies have shown evidence that investor risk aversion might be more actively changing than what we typically model in theories (see Cohn, Engelmann, Fehr, and Maréchal (2015) using an experiment, Martin (2017) using option market data, Wang and Young (2020) using mutual fund flows, Pflueger, Siriwardane, and Sunderam (2020) through stylized models and so on). On the other hand, Bekaert, Engstrom, and Xu (Forthcoming) in fact provide a daily financial proxy to aggregate risk aversion, that is consistent with dynamics of asset moments of major risky asset prices and equilibrium implications of a dynamic no-arbitrage asset pricing framework with power utility. However, applying their framework and estimation strategy to other countries is non-trivial, given data availability of some of their estimation inputs and assumptions of fundamental process remodeling for non-US economies. As a result, extant utility-based risk aversion measures are not suitable in our research.

As a result, we choose a simple empirical candidate, variance risk premium (VRP) as our empirical proxy for time-varying risk aversion. Following the literature, it is typically defined as the difference between the squared implied-volatility index with country market index as the underlying asset and an estimate of the conditional variance of the market (or a proxy for "uncertainty"). Consider US as an example. The VIX index is the implied option volatility of the S&P500 index for contracts with a maturity of one month (22 trading days), and the difference between the squared VIX and expected future market variance over the next month is the compensation demanded by variance sellers in a variance swap contract for giving up their hedging position.

Such an empirical proxy is suitable for our research for two reasons. Conceptually, recent research has shown empirical evidence on the potentially close relation between VRP and risk compensations demanded in various asset markets, in both the US and other countries (Bollerslev, Tauchen, and Zhou (2009) and a voluminous literature; see Zhou (2018) for a detailed summary). Moreover, some papers have explicitly or suggestively linked the changes in risk aversion with VRP in general equilibrium frameworks (e.g., Bakshi and Madan (2006), Todorov (2010), Bollerslev, Gibson, and Zhou (2011), Bekaert and Hoerova (2014), Martin (2017), Bekaert, Engstrom, and Xu (Forthcoming)). Intuitively, during bad times, investors

[3] Although the National Income and Product Accounts also releases a monthly consumption series, this series is ex-post smoothed and has been often used with precaution in the asset pricing literature; see detailed discussions in Duffee (2005), Bekaert and Engstrom (2017), and Xu (2021).

exhibiting higher risk aversion would expect a higher risk compensation demanded for giving up the hedging position, i.e. a higher VRP.[4] Overall, we are not the first to use VRP as an empirical proxy for financial-market aggregate risk aversion in the macroeconomics and finance literature (see e.g. Bekaert, Hoerova, and Lo Duca (2013) and Miranda-Agrippino and Rey (2020)). Adding to its potentially close economic relation with risk aversion, the second advantage of using country VRP as our empirical proxy for country risk aversion is that VRP can be easily constructed for several major countries at the daily frequency, given the availability of implied volatility indices and return data (see Appendix Table A1 for a summary). Also, given that variance swap markets are highly liquid but heavily segmented across countries (Lakonishok, Lee, Pearson, and Poteshman (2007)), it is plausible to interpret country VRP as a country-level risk aversion of investors for the corresponding country.[5] Taken together, our non-US countries of interest consist of Switzerland (CH), Germany (DE), France (FR), Japan (JP), the Netherlands (NL), and the United Kingdom (UK).[6]

We then define country risk aversion *shocks* as the abnormal changes in country VRP compared to a reduced-form projection from moving-average and business cycle variables. We explain the data and estimation in details next.

2.1.2. Data and Estimation

For each country i on day t, the squared implied-volatility index of the country stock market index for contracts with a maturity of 22 trading days (denoted as $IV_{i,t}$) is decomposed into an expected realized variance component measured over the next 22 trading days under the

[4]It is admitted that the interpretation of VRP is an ongoing debate, and the literature has explored other potential explanations of VRP using equilibrium frameworks without time-varying risk aversion or power utility, for instance, volatility of volatility in a recursive preference and long-run risk paradigm. Some recent papers have examined the relative importance of "vol of vol" and "risk aversion" in explaining the dynamics of VRP using pure empirical frameworks, and find that they may both matter; for instance, Londono and Xu (2021) use a GMM framework to show that 60% of US VRP is likely explained by pure risk aversion variability (cleansed from fundamental exposures) while 40% by uncertainty-related state variables. We further address this point in Section 2.2 using our event selection procedure.

[5]Particularly, among few research on option market participation, Lakonishok, Lee, Pearson, and Poteshman (2007) document option market activity using trading data at the Chicago Board Options Exchange (CBOE), and find that "foreign" broker-dealer accounts – belonging to the "other public customers" category – share a very small fraction and are dropped in their main analysis. As a result, it is plausible to view risk measures derived from these markets as representative for a particular country.

[6]This non-US country list accounts for around 20% of the world GDP (while US accounts for around 24%) and around 21% of the world total market capitalization (US, around 36%), according to the World Bank and the World Federation of Exchanges. These statistics suggest that our country list is economically and financially representative.

physical expectation, $E_t\left[RV^{(22)}_{i,t+22}\right]$, and a variance risk premium component, $VRP_{i,t}$:

$$IV_{i,t} = \underbrace{E_t\left[RV^{(22)}_{i,t+22}\right]}_{Uncertainty\ \text{“}UC\text{”}} + \underbrace{VRP_{i,t}}_{Risk\ aversion\ \text{“}RA\text{”}}. \tag{1}$$

The physical expected variance is our proxy for the country stock market uncertainty (UC). We use a popular long-memory model to forecast future 22-day realized variance for performance and simplicity purposes (as also used in Corsi (2009), Bollerslev and Todorov (2011), Andersen, Bollerslev, and Diebold (2010); Bekaert and Hoerova (2014), Liu, Patton, and Sheppard (2015), Bekaert, Hoerova, and Xu (2021) among many others):[7]

$$E_t\left[RV^{(22)}_{i,t+22}\right] = \widehat{\alpha}_i + \widehat{\beta^m}_i RV^{(22)}_{i,t} + \widehat{\beta^w}_i RV^{(5)}_{i,t} + \widehat{\beta^d}_i RV_{i,t} + \widehat{\gamma}_i IV_{i,t}, \tag{2}$$

where $RV^{(22)}_{i,t}$ denotes cumulative realized variances from day $t-21$ to t; $RV^{(5)}_{i,t}$ and $RV_{i,t}$ denote weekly and daily realized variances till day t, respectively. We obtain daily implied volatility indices from DataStream and daily realized variance data from Oxford-Man Institute using 5-min returns. We scale all variance variables to monthly decimal-squared for interpretation purpose. Our sample is from February 15, 2000 to December 29, 2017.

Table 1 provides the full-sample summary statistics of daily risk aversion (RA) and stock market uncertainty (UC), cross-country correlations of RA and UC, and within-country correlation between RA and UC. Three observations are worth mentioning. Consistent with the literature, both risk aversion and uncertainty are right-skewed; second, physical stock market uncertainty explains a slightly higher fraction of the implied volatility-squared (e.g., about 59% for US); third, we observe a high level of correlations across countries for both risk variables (>0.7), which indeed justifies the comoving risk variables challenge as mentioned before and our fixes (in shock construction next and event selection in Section 2.2).

We then obtain the abnormal changes in country risk aversion as country risk aversion shocks:

$$\underbrace{VRP_{i,t}}_{Risk\ aversion\ \text{“}RA\text{”}} = \underbrace{\alpha_i + \beta_i \times MA(n)_{i,t-n,t-1} + \boldsymbol{\gamma_i} \times \boldsymbol{Z_{i,t-1}}}_{Expected} + \underbrace{\varepsilon_{i,t}}_{RA\ shock}, \tag{3}$$

[7]There is a voluminous literature on realized variance forecasting in order to obtain the conditional variance. Researchers typically find that the resulting expectations are highly correlated using one method versus the other (e.g. Bekaert and Hoerova (2014), Liu, Patton, and Sheppard (2015).

where $MA(n)_{i,t-n,t-1} = \frac{1}{n}\sum_{\nu=1}^{n} VRP_{i,t-\nu}$ is a n-day moving average from t-n to t-1 and we consider $n \in \{30, 60, 90, 120\}$; $\boldsymbol{Z_{i,t-1}}$ denotes a collection of the last available, standardized monthly or quarterly first-differences in country business condition variables such as dividend yield, nominal rate, and term spread (source: FRED and DataStream).[8] Finally, we allow β_i and γ_is to have a recession value and a non-recession value, or $\beta_{i,t-1} = \beta_{i,0} + \beta_{i,1} \times I_{rece.,i,t-1}$ where $I_{rece.,i,t-1}$ denotes a country recession indicator (source: OECD, for cross-country consistency). For each country, all models are estimated using the longest daily sample, and model selection is based on the goodness of fit criteria (BIC). We conduct the same analysis with country daily stock market uncertainty to obtain country "UC shock." We relegate model selection details and benchmark model coefficient estimates to our Online Appendix. In general, loading coefficients and signs are consistent with the literature; for instance, an inverting term structure predicts higher risk aversion and market risk (uncertainty) in the future, and models with coefficient instability statistically dominate those without.

Table 2 summarizes country risk aversion and uncertainty shocks. The main observation is that, from Panel E, the cross-country correlations of risk aversion shocks, the cross-country correlations of uncertainty shocks, and the within-country correlation between risk aversion and uncertainty shocks are all lower, compared to those using the *raw* measures (Table 1). This observation is not surprising because a meaningful portion of risk variable dynamics is likely driven by persistence and changing fundamental conditions which also comove across countries. Time series evidence of US (international) shocks are shown in Figure 1 (Figures 2 and 3).

2.2. Identification of US Risk Aversion Events

To identify US risk aversion events (both high and low RA events), it is perhaps intuitive to simply use extreme values in the US risk aversion shocks (constructed from Section 2.1). However, other country events could also cause extreme fluctuations in US risk aversion, which makes these events not "from US." Moreover, changes in risk aversion could comove with changes in other countercyclical risk premium variables (such as uncertainty), as seen in Table 2, which makes these events not "pure." These two concerns remain to be resolved.

We propose a "news-integrated" methodology to potentially address these concerns. In Step

[8]Using first differences helps circumvent collinearity issues with the moving average term in this projection model. In unreported results, we have also considered including past US business condition variables, which could cause obvious collinearity issues with local country business condition variables; regardless of statistical concerns, daily country shocks with or without US variables are highly correlated (>0.95).

1, we use a comprehensive news database RavenPack to select one positive and one negative global news of the day, given coverage and sentiment metrics; the advantage of using a comprehensive news aggregator is that they already keep track of the origin of the news. In Step 2, we keep those "US" news days with extreme (high / low) US RA shocks but normal US UC shocks as our selections of US (high / low) RA events. To be more specific, we sort the US RA and UC shock series (constructed from Section 2.1) into 3 bins each: (1) those with magnitude greater than 90th percentile of the full sample or "High", (2) between 10th and 90th or "Normal", and (3) less than 10th or "Low". We then group dates with high (low) RA shocks but normal UC shocks as the high (low) RA event type; high and low UC event types can be obtained similarly:

Event Type:	**1.High RA**	**2.Low RA**	**3.High UC**	**4.Low UC**
RA Shock:	>90th	<10th	Normal	Normal
UC Shock:	Normal	Normal	>90th	<10th

This step further addresses the comoving risk variable concern, and teases out the part of VRP shocks that may come from "volatility of volatility" without complicating the system, which comoves positively with volatility itself as often found in empirical evidence (e.g., Segal, Shaliastovich, and Yaron (2015)). The third use of this step is to ensure that we are not picking up crisis periods because they are often accompanied by extreme RA and UC shocks (as we observe in our data). Finally, in Step 3, we use the news coverage metrics to help identify post-event dates among consecutive extreme risk reaction dates that are picked out from Step 2. We relegate detailed step-by-step event selection procedures to Appendix II.

2.3. Event Summary and Potential Narratives

Table 3 shows the event distribution over time, and across the final four event types, (1) High RA, (2) Low RA, (3) High UC and (4) Low UC. We include parallel analysis using UC groups for comparison and benchmark purposes throughout the paper. Using our methodology which aims to address the aforementioned four challenges, We identify a total of 146 US risk aversion events (high RA: 86; low RA: 60) and 77 US uncertainty events (high UC: 30; low UC: 47) from 2000 to 2017. These events appear quite equally distributed over time with no spikes during the 2006-2011 interval, which is expected as cyclical events likely show both heightened RA and UC.

One advantage of our approach is that it suggests potential event narratives in a relatively systematic way, while the current literature typically examines the effect of one event type of interest on time-varying aggregate risk aversion (see e.g. Brunnermeier and Nagel (2008) studying wealth fluctuations; Bassi, Colacito, and Fulghieri (2013), weather risk; Wang and Young (2020), terrorist shocks; Guiso, Sapienza, and Zingales (2018), economic shocks; and so on). Table 4 summarizes our suggestive narratives of each event type, given RavenPack (primary source) and Wall Street Journals (verification by four independent research assistants). For consistency, we adopt RavenPack's five news categorizations: Business, Economy, Environment, Politics, and Society. Appendix Table A2 provides more details regarding subcategories.

Economy news share the largest fraction in both RA and UC event groups, which is expected given that over 60% of the total news articles in the Global Macro-Dow Jones edition of RavenPack correspond to "Economy." Therefore, we focus on comparing the fractions of the same news category *across* each event type. We observe that Business and Economy news more likely result in extreme changes in the expectation of future market volatility (or uncertainty), while Politics and Society news more likely result in extreme changes in risk premiums and attitude. Moreover, Society news (war conflicts, accidents, shootings, crimes) mostly appear in the high RA event list. This finding is intuitive and consistent with Wang and Young (2020), as such events – e.g. multiple war declarations (2001-2009), the Washington D.C. metro collision (2009/6/22), the Philadelphia building collapse (2013/6/5) and the Orlando shooting (2016/6/12) – likely triggered negative emotions, fear and anxiety. We also find that Politics news (government announcements, elections, legislation) often appear in the low RA event list, boosting investor risk appetite; for instance, our evidence suggests that market risk appetite was likely high on the election result dates of the 2000/2004/2016 US Presidential Elections, which is consistent with the literature (e.g., Goodell and Vähämaa (2013), Pantzalis, Stangeland, and Turtle (2000)).[9] Environmental news likely increase both risk and risk aversion.

3. Event Study

In our event study analysis, we study the US domestic responses to the high or low US RA event groups in Section 3.1 to provide a baseline economic magnitude, and then the average

[9]To be precise, according to our calculation, the market on the 2000 election day and the day after exhibited high anxiety (>90th percentile) and low uncertainty (<10th percentile). On November 17, 2000, "the Florida Supreme Court late Friday forbade Secretary of State Katherine Harris from certifying a winner until the court issues a decision on manual recounts of ballots" (`https://www.wsj.com/articles/SB974470432386371285?mod=searchresults&page=1&pos=17`), and that "result" day is selected in our "low RA" event list. The 2008 US Presidential election date is sorted into the low RA-low UC bin, and hence it does not fit the (pure) low RA event list that we want to study in this paper.

foreign responses in Section 3.2, followed by a series of robustness results in Section 3.3. The ratio of foreign to domestic responses, or pass-through, constitutes our measure of "risk aversion propagation." We similarly obtain a measure of "uncertainty propagation" for comparison purpose.

3.1. Domestic responses: economic magnitudes of chosen events

For each event horizon from Day -30 to Day 30 and for each event type, we construct the average US abnormal risk aversion shocks across events scaled by the sample average of US risk aversion (VRP):

$$\frac{E\left[\varepsilon_{US,z}|z \in EventDates\right]}{E\left[VRP_{US,t}|t \in \{1, ..., T\}\right]},$$

where ε_{US} denotes the risk aversion shock obtained from Equation (3).

From the first two panels of Table 5, US risk aversion abnormally and significantly increases (decreases) by 59.2% (-62.6%) on a high-RA (low-RA) event date, denoted by "[0, 0]", compared to its historical risk aversion level; the magnitudes of these two numbers are statistically close. This result suggests that our selected US high and low RA events have symmetric effects on domestic risk aversion, which serves as an economic benchmark for foreign responses later. Figure 4 is the corresponding event study plot, with solid lines indicating the responses and dashed lines the 95% confidence intervals. Until Day -3, responses are indifferent from zero. As we trace the horizon further back, the pattern appears noisier. There also appears to be a quick ramp-up a couple days before the events, which is mostly from the Economy news category. Appendix Table A4 shows the Economy and Non-Economy results separately, and the ramp-up disappears when we only consider Non-Economy events, which is intuitive given some unexpected nature. Column "[1, 3]" in Table 5 then shows that, within three days after a RA event, the abnormal percentage changes drop by half to 35.3% (high RA) and -37.6% (low RA), and the post-event responses to a high RA event in particular decay to zero within less than a week on average.

Next, we find that the response magnitudes and patterns of abnormal uncertainty on UC event dates are quite different from those of abnormal risk aversion on RA event dates, which in turn supports our efforts to separate the price- versus quantity-of-risk events using statistical model and news data. According to the third and fourth panels of Table 5, US uncertainty abnormally and significantly changes by a magnitude of 60%–70% on an UC event date. The pre- and post-event magnitudes, unlike those of RA events (above), exhibit significantly more persistence. This observation can be partly explained by our discussion from Section 2.3 that fundamental news more likely change belief about future stock-volatility (uncertainty). As seen in our evidence (Table 4), more than 86% of our selected extreme top/bottom 10% UC days are explained by fundamental news categories, Business and Economy, which is also consistent with Baker, Bloom, Davis, and Sammon (2020) who focus on macro and policy events.[10]

The slightly different news category composition in each event type is not the only reason why RA and UC domestic event study results appear different. Appendix Table A4 shows robustness of response magnitude using only Economy news in each event type. Therefore, it is plausible that certain economic news may trigger RA or UC responses differently. Through the lens of our research, Economy news in our RA event lists typically feature phrases/subtopics such as "consumption", "consumer confidence" and "jobless claims", while Economy news in our UC event lists typically feature phases such as "recession guidance", "economy slowdown" and "domestic product." Of course, while we try to link extreme changes in RA or UC to major news of the day according to news coverage and sentiment metrics, one can never be 100% sure about the news assignments. We hope that this evidence may be suggestive and useful for future research and modeling assumptions.

Finally, we conduct a validation analysis and examine the average abnormal risk aversion (uncertainty) during UC (RA) events, or "cross responses." Given our efforts to separate RA and UC using statistical model and news selection procedures (see Section 2), we indeed find evidence that cross responses are statistically significantly weaker than direct responses (see Appendix Table A3, Panel B).

3.2. Foreign responses: evidence of propagation

We use a similar event study approach to examine international risk aversion propagation. For each event horizon from Day -30 to Day 30 and for each event type, we calculate the average country abnormal risk aversion across event days scaled by the sample average of country risk

[10] In particular, we find that Economy news show the highest fraction in the low UC event list (see Table 4). This result is consistent with Baker, Bloom, Davis, and Sammon (2020) where they use different methodology and show that "policy events (particularly monetary policy) reduce future stock-volatility." See other details in Appendix Table A2.

aversion, and then obtain a cross-country average:

$$\frac{1}{C}\sum_{i=1}^{C}\frac{E\left[\varepsilon_{i,z}|z\in EventDates\right]}{E\left[VRP_{i,t}|t\in\{1,...,T\}\right]},$$

where ε_i denotes the risk aversion shock as obtained from the country-level regression Equation (3), $E\left[VRP_{i,t}|t\in\{1,...,T\}\right]$ denotes the sample average of country VRP, and C indicates the total number of countries-of-interest, 6, given the data availability as explained in Section 2.1.

Table 6 presents our main foreign response results. International risk aversion, on average, abnormally and significantly increases (decreases) by 36.8% (-26.9%) compared to country's own historical risk aversion level on a high (low) US RA event date. The magnitude of the average abnormal change on a low-RA event date is significantly lower than that on a high-RA event date, given a 10% significance test. Figure 5 displays the propagation pattern (left: US high-RA event list; right: US low-RA event list).[11] Foreign responses exhibit overall similar patterns as domestic responses. It is interesting to observe that the average abnormal international risk aversion responses remain relatively persistent on Day 1, and part of that is likely due to time-zone differences.[12]

We formalize our pass-through results next. We define a "pass-through" level as the ratio of foreign responses to domestic responses given an event type on the event date [0,0]. Table 7 reports the bootstrapped estimates and standard errors of the international pass-through levels for each event type, and conducts the corresponding equality tests. The first column uses all chosen events. The pass-through levels of US risk aversion events are significantly different: The high RA event type exhibits an average pass-through around 61% (Bootstrapped standard error=3%), while the low RA event type 43% (Bootstrapped standard error=5%); their pass-through levels are statistically significant different from each other (t=3.18***), with the high RA pass-through being stronger. This constitutes our main empirical finding of asymmetric risk aversion pass-through.

[11] Appendix Figures A1 and A2 provide detailed country-level propagation patterns.

[12] US is the last major country to open the stock market on the same day; if a US event occurs after 11:30 am Eastern Time on day t, all foreign stock markets (considered in our paper) have closed, and the US news would enter these markets' $t+1$ information set. It is not straightforward how to universally correct for the time zone difference, which hence suggests that our pass-through result is conservative.

3.3. Robustness

We conduct a series of robustness checks of our main result, examining the roles of news categories, 2008-09 crisis period, country composition and discussing an alternative explanation.

Subsamples: news categories and 2008-09 crisis period. We examine whether our results are driven by one particular news category or one particular period of time. Robustness set "(2)" in Table 7 demonstrates that keeping Economy news only in both high and low RA event groups still renders significant asymmetry in the international pass-through. Section 3.1 briefly touches on our observation that certain economic news may trigger RA or UC responses differently. Similarly, robustness set (4) shows robustness after dropping the events during the 2008-09 periods.

Country "jackknife" exercise. In robustness set (3), we drop one country at a time and re-examine the pass-through (a)symmetry. While the symmetry tests are all rejected, dropping United Kingdom, France or the Netherlands appears to weaken the asymmetry differences more than dropping Switzerland, Japan or Germany. This suggests that the underlying mechanisms of asymmetric risk aversion propagation may relate to some different features of these two groups of countries. We return to this evidence towards the end of our experimental evidence.

Alternative explanation. Changes in volatility indices are typically found to have a high correlation with stock price changes in time series (e.g. R-squared around 60-70% for US). Therefore, one alternative story may be that non-US risk aversion simply responds to US stock market jumps rather than US risk aversion events. To address this concern, we exclude major US stock market jump dates (as identified in Baker, Bloom, Davis, and Sammon (2020) and downloadable at `www.stockmarketjumps.com`) that overlap with our event choices: 8 out of 86 high RA events, 10 out of 60 low RA events, 8 out of 30 high UC events and 0 out of 47 low UC events. Robustness set (5) shows that the asymmetry magnitude decreases only a little and their equity test is still statistically rejected at a 1% significance test.

Finally, as before, we obtain the UC counterpart result as a validation exercise for our RA event selection. The second halves of Tables 6 and 7 show that the pass-through levels of US high and low UC shocks are 30% (Bootstrapped standard error=6%) and 39% (Bootstrapped standard error=5%), respectively; and both UC shock pass-through levels are robustly indifferent from each other across all robustness sets. Other details are relegated to Appendix Tables A4 and A5.

4. Experimental Evidence and Mechanisms

While financial market and news data help us study US risk aversion propagation in a real and aggregate context, it is not an ideal context to examine the underlying mechanisms, given the simultaneously changing and complex market and economic conditions. As a result, in the second part of the paper, we design two controlled experiments to explore some potential and testable mechanisms for the asymmetric non-US responses to US risk aversion events in a controlled setting. We exploit the priming method (commonly used in Psychology and increasingly used in Finance and Economics) to stimulate the propagation of risk aversion. Section 4.1 outlines the key elements of our experiments. Section 4.2 tests our main empirical result in a controlled experimental setting. Section 4.3 explores potential mechanisms and Section 4.4 discusses links to our empirical part of the paper.

4.1. Participants, Manipulation, Risk Aversion Measure

Each of our experiments consists of five parts in the following order: icebreaker questions, baseline investment task, priming (experimental manipulation), outcome measure, and demographic information and survey feedback.

Participants. We implemented our experiments through an online crowd-sourcing platform, CloudResearch (formerly known as TurkPrime), which offers the option of locating high-quality participants from a variety of developed countries (Litman and Robinson (2020); Chinco, Hartzmark, and Sussman (Forthcoming); Bergman, Chinco, Hartzmark, and Sussman (2020)). We aimed to recruit 400-500 US participants for our benchmark study and 250-270 non-US participants for our propagation study; we explain the two studies later in Section 4.2. Participants qualified for our studies only if they were fluent in English. We excluded participants who failed to answer any financial literacy questions correctly,[13] failed the attention check question, correctly guessed the purpose of the study, or failed to follow the instruction during the priming procedure. A total of exactly 700 participants across our two studies (average: 32% female, age 30-40, annual income \$50,000-\$70,000; see detailed descriptive statistics in Appendix Table A6) successfully participated in exchange of a baseline compensation of \$2 each for finishing the 20-min survey and a possible dollar bonus gained from their investment task (see details

[13] We adopted the same financial literacy questions from Cohn, Engelmann, Fehr, and Maréchal (2015); see their online appendix.

below).

Although our participants were not recruited as financial professionals, we seemed to be able to reach a sample who were sufficiently sophisticated in financial decisions. For example, in our financial literacy question screening, our international (non-US) participants on average answered 53% of financial literacy questions correctly (Appendix Table A6), which is comparable to the accuracy rate 67% for Swiss financial professionals surveyed by Cohn, Engelmann, Fehr, and Maréchal (2015). In addition, 93% of our international (non-US) participants self reported that they make final decisions on their investments instead of fully relying on financial advisors. Finally, Appendix Figure A3 shows that our international (non-US) participants exhibited similar country decomposition as our empirical analysis. According to self-reported answers, 85.6% of them have never been to the US, and on average, only 29.4% of their financial investments are linked to US assets.

Experimental manipulation. Following Cohn, Engelmann, Fehr, and Maréchal (2015), our experimental stimuli of risk aversion (RA) shocks are fictive financial bust and boom scenarios of continuing decreasing and increasing price with stable fluctuations, respectively, as shown in the top two plots of Figure 6. We opt for such bust and boom scenarios in our research for several reasons:

First, extant research such as Cohn, Engelmann, Fehr, and Maréchal (2015) has demonstrated that this pair of scenarios can stimulate statistically significant risk aversion responses. Second, different from their work (which compares bust scenario to boom scenario only), we are interested in the (a)symmetry of risk aversion shock propagation, and therefore we also need to design a control group. These fictive RA scenarios allow us to design clean non-RA scenarios as shocks to our control group: stable price with increasing or decreasing fluctuations, as shown in the bottom two plots of Figure 6. Notice that these non-RA scenarios conveniently provide the "Uncertainty" analogy to the first part of our paper, while the RA scenarios keep the price fluctuations the same. Third, real-event pictures or video clips (e.g., violence and trauma as in Callen, Isaqzadeh, Long, and Sprenger (2014)) as experimental stimuli to participants' risk aversion are likely associated with measurement and identification problems; moreover, finding comparable counterparts down this road as our control group can be difficult. Fourth, our empirical robustness tests (Table 7) show that asymmetric risk aversion propagation exists within the Economy event group, which should support the "bust/boom" scenarios here.

Participants were randomly assigned to one of the four scenarios (two RA and two non-RA scenarios as displayed in Figure 6). As our priming method, participants were instructed to spend at least 5 minutes writing a detailed diary about the scenario presented to them. For example, for non-US participants seeing a continuing boom scenario of US stock price, we would ask "*Imagine you are an investor, describe (1) what might be causing the continuing boom in the US stock market? (2) what might happen to your current country's stock market today and in the future? (3) how would the continuing boom in the US stock market change your financial portfolio and investment decision?*" To manage participants' attention, we displayed the price movements with animated videos. This diary writing approach is a common priming method in Psychology and behavioral economics (e.g. Lu, Lee, Gino, and Galinsky (2018), D'Acunto (2018)).[14]

Risk aversion measure. We follow Gneezy and Potters (1997) and Cohn, Engelmann, Fehr, and Maréchal (2015) to measure participants' risk aversion from their risk taking decision in an investment task. In our investment task, each participant was endowed with an initial portfolio funding of 1000 experimental currencies and need to decide how much to invest in a risky asset, using a simple slide bar; the remaining amount was automatically invested in a safe asset with a zero interest rate. The probabilities and payoffs are explicitly specified. The risky asset had a known 50% success rate; if the investment was a success, participants would earn 2.5 times of the risky investment amount; if the investment was not a success, they would lose the risky investment amount.[15] Participants were aware that there was a moderate chance (one in ten) of earning one percent of their realized final portfolio value as dollar bonuses at the end of the survey, which could range from $0 to $25. We include a screenshot of the investment task in the Appendix III. Our main outcome measure is the "post-priming" risky investment level, which has a negative relationship with risk aversion.

[14] We thought about leaving our control group with a simple blank page rather than uncertainty scenarios. However, uncertainty priming is still more suitable. First, it is an ongoing debate in Psychology whether a blank control is an appropriate control condition (Dien, Franklin, and May (2006), Rossell and Nobre (2004)). Second, it is possible that the time participants spend on writing something down (regardless of the scenarios) may lead to increasing commitment to the survey (Staw (1981)) and result in better sample quality. Third, the empirical part of our paper also compares risk aversion against uncertainty, throughout, for validation purpose.

[15] Cohn, Engelmann, Fehr, and Maréchal (2015) also conduct an ambiguity task where participants did not know the precise probabilities, and measure participants' risk aversion by controlling for their expectations. They found similar inferences on participants' risk aversion between the risk task (with explicitly specified probabilities) and the ambiguity task (without explicitly specified probabilities).

Control variables and randomization check. Our research requires both US and non-US participants, and therefore, we should be aware that participants could join the internet survey with heterogeneous risk aversion levels for various reasons: one, they might be currently experiencing different physical, local macro or personal environments; and two, papers have documented different culturally-driven risk avoidance levels across countries (see e.g. Hofstede (2011), Gandelman and Hernández-Murillo (2015), Rieger, Wang, and Hens (2015), Falk, Becker, Dohmen, Enke, Huffman, and Sunde (2018)). It would be challenging to resolve these potential heterogeneities by simply adding country fixed effects. As a result, we instructed participants to make a baseline investment decision of the same investment task before the experimental manipulation.[16] We also confirm that participants were randomly assigned to treatment/control groups and studies (see Appendix Tables A6 and A7). In our regressions, the pre-priming risky investment level, demographic information (income, age, financial literacy, gender) and country dummies are our control variables.

4.2. Treatment Validation and Experimental Evidence of Asymmetric Propagation

We first validate our priming scenarios in Study 1 (US participants responding to US shocks, or denoted as "US/US") in Section 4.2.1, and then examine our main empirical finding of asymmetric US risk aversion propagation in Study 2 (non-US participants responding to US shocks, or denoted as "US/NUS") in Section 4.2.2. Participants from both studies received the same experimental manipulation, and the only difference is their current residence country.[17]

4.2.1. Responses of US risk aversion to US shocks

In Study 1, we analyze how US participants' risky investment level responded to US bust and boom scenarios, compared to those in the control group. The first set of bars in Figure 7, Panel A, displays the average changes in risky asset investment before and after the priming. We find that US participants in Study 1 reduced their risky investment (or risk aversion $\uparrow$) when primed with the bust scenario (gray bar), while they increased their risky investment (or risk

[16] We also use this information to further identify participants who slided bars from one extreme to the other extreme (i.e. with risky investment changes being 1000 or -1000 before and after the priming) as problematic participants.

[17] We used the "Worker Requirement/Location" feature at CloudResearch to find our non-US participants. We were also able to cross validate their self-reported country information in our survey which included questions on both residence and birth countries.

aversion ↓) when primed with the boom scenario (white bar). Both responses were statistically different from zero. In contrast, US participants' risk aversion did not seem to respond to our non-RA or uncertainty priming. From Panel B of Figure 7, US participants when primed with uncertainty scenarios exhibited no significant changes in their risky investment decision. This evidence supports the "risk aversion" interpretation of the bust/boom scenarios and validates the control group with uncertainty scenarios. Henceforth, we also refer to the bust (boom) treatment as the "High RA" ("Low RA") treatment.

We formalize this result in the following regression framework:

$$Y_i = \beta_0 + \beta_1 I_{HighRA,i} + \beta_2 I_{LowRA,i} + \boldsymbol{\gamma}' \boldsymbol{X_i} + \varepsilon_i, \tag{4}$$

where Y_i represents the post-priming risky investment level; $I_{HighRA,i}$ ($I_{LowRA,i}$) represents a dummy variable which equals to 1 if the subject is from the bust/high RA (boom/low RA) treatment group; $\boldsymbol{X_i}$ represents a collection of control variables mentioned above (pre-priming risky investment level, individual income, age, gender, financial literacy and country dummies). Consistent with Figure 7, Regressions (1) and (2) of Table 8 show that, relative to the control group, risky investment level is significantly lower in the high RA treatment by 40.19 ($SE =$ 17.30) experimental currencies and significantly higher in the low RA treatment by 50.51 ($SE =$ 17.23).

4.2.2. Responses of non-US risk aversion to US shocks

In Study 2, we examine how non-US participants' risky investment level responded to US boom and bust scenarios, compared to those in the control group. We filter out non-US participants who could not correctly choose what pattern of US stock price in their assigned scenario when asked later in an attention check question. From the bars on the right hand side of Figure 7, Panel A, risk aversion of non-US participants compared to the control group increased (decreased) significantly when they were primed with the US bust/high RA (boom/low RA) scenario, suggesting effectively risk aversion propagation. On the other hand, from Panel B, there were no significant changes in non-US participants' risk aversion when primed with US uncertainty scenarios. In terms of magnitudes, the pass-through level – the ratio of foreign responses to domestic responses – almost doubled for the bust group compared to the boom group, which is potentially consistent with our findings in Section 3.

Tables 8 and 9 formalize this asymmetric propagation result. Relative to the control group, non-US participants when primed with a US high (low) RA treatment exhibited significantly lower (higher) post-priming risky investment level by 85.29 with $SE = 22.42$ (58.55 with $SE = 22.43$). To test the statistical significance of the asymmetry, we use two tests to compare the pass-through level of the high US RA treatment ($85.29/40.19 = 2.12$) with that of the low US RA treatment ($58.55/50.51 = 1.16$). Panel A of Table 9 shows that the high RA pass-through is statistically different from 1 ($p - value = 0.036$) while the low RA pass-through is statistically close to 1 ($p - value = 0.70$). The asymmetry is also supported by the two-way factorial ANOVA test as shown in Panel B, which rejects the null that treatments in both Studies 1 and 2 exhibited same effects on the risky investment changes.

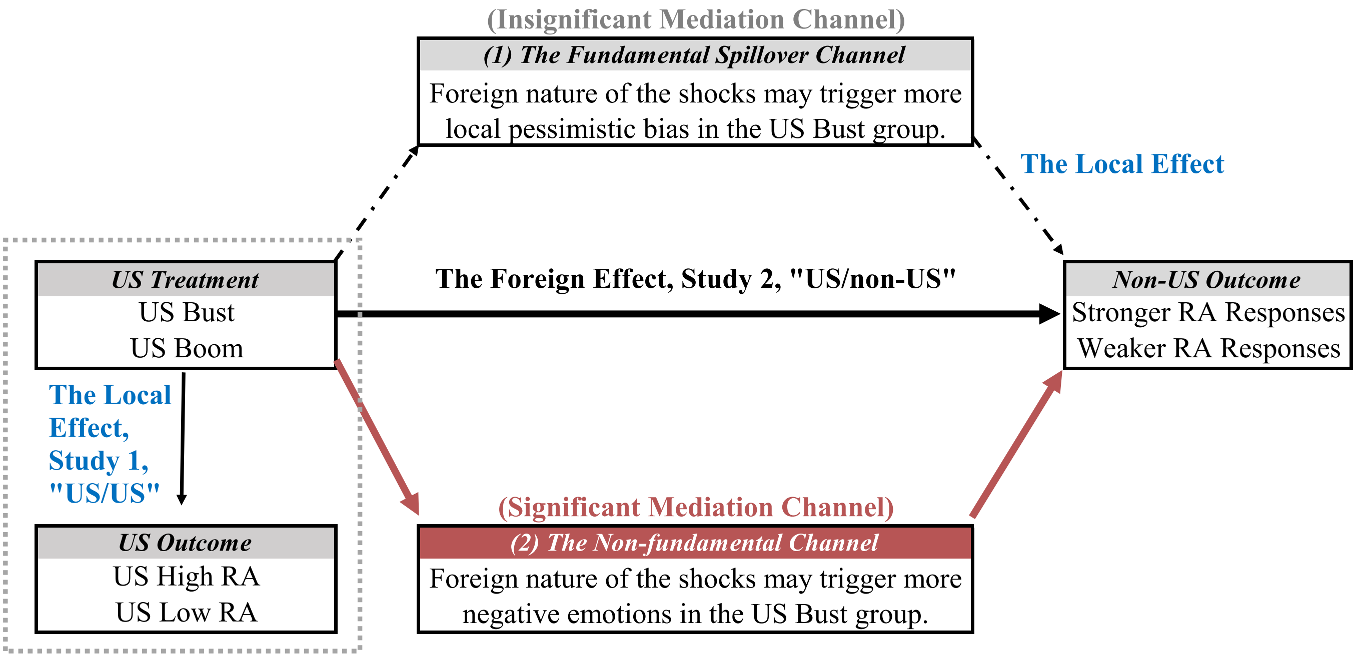
4.3. Testable Mechanisms

To explore the potential underlying mechanisms for the asymmetric non-US responses to the US risk aversion shocks in our study, we hypothesize and examine the following two general channels:

(1) The *fundamental spillover* channel. The US shocks may affect non-US investors' risky investment decision *indirectly* by first affecting their beliefs about their own country fundamentals. Since the foreign nature of US bust shocks may trigger "pessimistic bias" in non-US investors' belief updating about their own country fundamentals, the induced pessimism could result in further decreases in non-US investors' risky investment choices. We examine this hypothesis in Section 4.3.1.

(2) The *non-fundamental* channel. Alternatively, given extant evidence on the links between psychological forces (such as emotions) and investors' attitude towards risk (Kuhnen and Knutson (2005)), the US shocks could also *directly* affect the risk aversion of non-US investors through affecting their emotional states. In particular, the foreign nature of the shocks may trigger more negative emotions in the US bust group, hence leading to asymmetric risk aversion responses. We examine this hypothesis in Section 4.3.2.

The diagram below summarizes our studies and channels, along with a preview of our results which we elaborate next:



4.3.1. The fundamental spillover channel

Kuhnen (2015) documents that investors exhibit pessimism bias and update beliefs to a larger extent to negative shocks than to positive shocks. Suppose that a French investor sees continuing bust in the US stock market; she may have a stronger belief about a similar bust in the French stock market, and hence the induced higher pessimism bias could result in asymmetric changes in her risky investment decision. This example illustrates a potential fundamental channel in the asymmetric non-US investment changes in the US bust treatment group in our study.

To test this hypothesis, we elicited non-US participants' beliefs about how their own country stock prices would behave given a US scenario at the end of Study 2. They were given three choices: *Increase*, *Stay the same*, or *Decrease*.[18] Using a similar specification as Equation (4), we regress non-US participants' beliefs about an increasing local price and beliefs about a decreasing local price on the high and low RA treatment indicators along with our standard set of control variables (individual income, age, financial literacy, gender, and country effects). We split up the belief-question variable into two categorical variables, rather than a 1/0/-1 variable, to indeed allow for a less restrictive analysis and observe the (a)symmetric belief updating more

[18] As mentioned earlier, an attention check question was inserted in this part of the survey as well. That is, we asked the participants to choose what pattern of US stock price they were observing in their assigned scenario (which was shown again on top of the same page as the question). We excluded participants who failed to identify the correct pattern (e.g., "Increase" or "Stay the same" was chosen while this participant was in the bust group).

accurately.

Regressions (5)–(6) in Table 10 demonstrate that non-US participants updated their beliefs about their own country stock prices significantly, in the same direction as the US scenarios, and rather symmetrically.[19] Given the magnitude of the coefficients, there was a 57.6% (54%+3.6%) higher chance that non-US participants receiving a US bust shock believed that their local price would decrease than those receiving a US boom shock. Similarly, there was a 52.9% (42.5%+10.4%) higher chance that non-US participants receiving a US boom shock believed that their local price would increase than those receiving a US bust shock. It is interesting that our sample also exhibited some but statistically insignificant mean-reverting beliefs. In summary, the belief updating responses were quite symmetric between groups, suggesting that such a fundamental-spillover channel was less likely the underlying mechanism triggering an excessive non-US risk aversion response to US bust/high RA shocks in our study.

4.3.2. The non-fundamental channel

Loewenstein (2000) argues that emotions (or more broadly, a wide range of visceral factors) play an important role in people's bargaining behavior, intertemporal choice, and decision-making. Moreover, recent experimental evidence shows that general emotional states can affect the level of risk aversion (Kuhnen and Knutson (2005); Kuhnen and Knutson (2011)) and explain countercyclical risk aversion (Cohn, Engelmann, Fehr, and Maréchal (2015)). Recent empirical evidence using surveys (Guiso, Sapienza, and Zingales (2018)) and fund flows (Wang and Young (2020)) support the particular role of negative emotions (fear, anxiety, scare) in explaining the higher risk aversion during local economic or warfare crises. Beyond behavioral evidence and settings, Bekaert, Engstrom, and Xu (Forthcoming) filter a time-varying US risk aversion from a wide range of risky asset prices, macro data and a no-arbitrage asset pricing framework, and they claim that risk aversion should be "moodier" than what standard asset pricing models typically assume in order to explain the observed risky asset price behavior, particularly the higher moments. Similar conclusion is suggested in Pflueger, Siriwardane, and Sunderam (2020).

As a result, we hypothesize that the US shocks could directly affect the risk aversion of non-US investors through affecting their emotional states. In particular, the foreign nature of

[19] Previous literature has documented both symmetric (e.g., Hartzmark, Hirshman, and Imas (2021)) and asymmetric (e.g., Da, Huang, and Jin (2021)) belief updating to positive vs. negative signals in different contexts.

bust or negative shocks may change emotions more than that of boom or positive shocks, hence resulting in asymmetric risk aversion propagation.

We obtained participants' positive and negative emotional states using the following eight dimensions (Watson, Clark, and Tellegen (1988); Lu, Lee, Gino, and Galinsky (2018)): enthusiastic, excited, happy, relaxed, distressed, irritable, nervous, scared (1 = not at all, 5 = very much). The eight items were placed soon after the diary priming part, on the same page as they choose the post-priming investment decision, but before the final portfolio value reveal. The order of the eight items was randomized. We aggregate ratings of enthusiastic, excited, happy, and relaxed as a measure of positive emotion (Cronbach's $\alpha = 0.7313$) and ratings of distressed, irritable, nervous, and scared as a measure of negative emotion ($\alpha = 0.8123$). We also construct a measure of general emotion as the difference between positive and negative emotion (e.g., Schimmack, Radhakrishnan, Oishi, Dzokoto, and Ahadi (2002)); a higher general emotion means more positivity and less negativity.

Regressions (7)–(9) in Table 10 show that non-US participants receiving the US bust (high RA) shock exhibited significantly less positive and more negative emotions than those in the control group. Non-US participants' general emotion in the US bust group significantly decreased by -0.722 ($SE = 0.201$), which is contributed by the decreases in their positive emotion, -0.375 ($SE = 0.124$) and the increases in their negative emotion, 0.347 ($SE = 0.130$). The correlation between positive and negative emotions is -0.353 ($p - value < 0.01$). On the other hand, the coefficients of the US boom (low RA) group dummy show expected signs but are statistically insignificant. Taken together, our result suggests that, for non-US participants, the foreign bust shock triggered larger changes in both positive and negative emotions than the foreign boom shock. This result is robust after including various demographic variables (age, income, gender, financial literacy) and country fixed effects.

4.3.3. Mediation Analysis

In this section, we follow Cohn, Engelmann, Fehr, and Maréchal (2015) and conduct mediation analysis (Baron and Kenny (1986)) to evaluate whether the fundamental spillover and the non-fundamental emotion channels are significant mechanisms for the asymmetric US risk aversion propagation. We first examine whether the two channels are related to risky investment decisions by replacing the treatment dummies with our mediating variables. From the first two columns of Table 11, we find an insignificant relationship between investment decisions and belief updating; to the contrary, the relationship between investment decisions and general emotional states is much stronger and statistically different from zero with an expected positive coefficient, 26.22 (SE = 7.47). That is, a generally more positive or less negative emotional state is associated with larger risky investment.

Results so far show that the specific priming of US bust and boom shocks – which we label as RA shocks – caused significant changes in both local fundamental belief updating and emotional states (Table 10); however, it is likely the emotional states that contributed to changes in risky investment decisions. To study the extent to which the treatment effect is mediated by emotional states, we estimate a regression model where we simultaneously include treatment dummies and our measure of general emotion. Our main results are reported in Regression (13) of Table 11, and Regression (12) simply copies over our benchmark specification from Table 8. We find that the magnitude of the "High RA Treatment" dummy coefficient drops after controlling for general emotion, from -85.29 (SE = 22.42) to -74.47 (SE = 22.93). In contrast, that of the "Low RA Treatment" dummy coefficient does not change much, from 58.55 (SE = 22.43) to 54.47 (SE = 22.38). The coefficient and significance for general emotion drop as expected.

We next quantify to what extent general emotion mediated the excessive high RA response among non-US participants. We find that there is a 45.7% excessive high RA response compared to its low RA response in the benchmark regression, and the asymmetry drops to 36.7% after adding general emotion in Regression (13). Building on Judd and Kenny (1981)'s expression for mediating effects, we conclude that 19.6% of the excessive high RA response can be explained by general emotion. The mathematical expression is summarized as follows:

$$1 - \underbrace{\frac{|\beta_{1,\text{With Emotion}}| - |\beta_{2,\text{With Emotion}}|}{|\beta_{2,\text{With Emotion}}|}}_{\substack{\textit{Excessive High RA propagation after} \\ \textit{controlling for general emotion}}} \Big/ \underbrace{\frac{|\beta_1| - |\beta_2|}{|\beta_2|}}_{\substack{\textit{Excessive} \\ \textit{High RA} \\ \textit{Propagation}}} = 19.60\%$$

General emotion uses information from both positive and negative emotions. A natural next question is whether the mediation effect of general emotion comes from both positive and negative emotions or only one of the two. From Regressions (14)-(15) of Table 11, both emotions exhibited statistically strong associations with risky investment decisions. Regressions (16)-(17) shows that the mediation effects of positive and negative emotions, when added separately into the main specification, were 12.8% and 8.3%, respectively. It is noteworthy that the sum of these two mediation effects is quite close to the mediation effect of general emotion. Our measured emotion variables do not fully mediate the treatment coefficient asymmetry. Nevertheless, our core contribution is to provide specific evidence that an "emotion"-related non-fundamental channel played a significant role in explaining some excessive high RA propagation.

Taken together, our results suggest that foreign shocks from US could directly affect the non-US participants' risk aversion through affecting their emotional states. The foreign nature of bust or negative shocks may change emotions – positive emotion decreases and negative emotion increases – *more* than that of boom or positive shocks, hence resulting in asymmetric risk aversion propagation in our study. While the psychological link between emotions and risk aversion has been well examined and documented (Lopes (1987); Loewenstein (2000); Kuhnen and Knutson (2005); Kuhnen and Knutson (2011); Cohn, Engelmann, Fehr, and Maréchal (2015), among many others), there is little direct evidence on how risk aversion may transmit across subjects. Regarding how and why "foreign" nature of RA events potentially amplifies changes in emotional states and risk aversion, one theory we have in mind is lack of familiarity due to geographical, economic, or social distances. Psychology literature has documented that people fear more about an unfamiliar (e.g., foreign) negative shock or challenge than a familiar (e.g., domestic) one, such as Cao, Han, Hirshleifer, and Zhang (2011) on investment decisions, Scovel (1978) and MacIntyre, Noels, and Clément (1997) on language learning, and so on. More related to our paper, Kenning, Mohr, Erk, Walter, and Plassmann (2006) find that, when (German investors) making a decision about foreign investment (in US), subjects revealed a significant correlation between activities within the amygdala-hippocampal regions of the brain (related to negative emotional processing such as fear) and their general risk aversion; as a result, the authors interpret the home-bias investment phenomenon with the additional fear triggered by the possibility of investing in foreign assets.

Of course, we interpret the responses of non-US risk aversion to US shocks as responses to "foreign" shocks, to draw a parallel with the "domestic" responses in our Study 1. While this interpretation is valid and self-contained within our studies, we are aware that US is often perceived as one of the most important foreign countries to most population in the world (Pew Research Center; Wike, Poushter, Fetterolf, and Schumacher (2020)). The asymmetry we document in both financial-market and experimental evidence triggered by US shocks is likely on the larger side of the spectrum.

4.4. Link to the Financial Market Evidence in Section 3

The significant mediating effect of emotions – general, positive and negative emotions – may also partially explain the heterogeneous asymmetric propagation across countries that we document at the end of Section 3, or Robustness set (3) of Table 7. There, we find that leaving out United Kingdom, France, or The Netherlands weakens the magnitude of asymmetric propagation more than leaving out Switzerland, Japan or Germany does. According to Gallup's Well-Being Index surveys, there are large variations in individual emotional states across countries, which can be explained by cultural, religious, and other factors. Specifically, when we focus on the countries in our research, United Kingdom, France and The Netherlands all have higher percentages of adults who report experiencing emotions like "enjoyment", "sadness", "worry" on daily basis than Switzerland, Japan and Germany do.[20] Individuals who are more likely to experience emotional changes may also show higher potency of being influenced by external factors, such as foreign negative shocks in our context; if so, we would indeed expect the asymmetric risk aversion responses of United Kingdom, France and The Netherlands to be stronger than those of Switzerland, Japan and Germany. As a result, the Gallup evidence, together with our financial market evidence, is potentially consistent with our mediation analysis, suggesting that emotions may well be a relevant mediating channel to explain the asymmetric risk aversion propagation.

5. Conclusion

Our paper studies how non-US risk aversion (RA) responds to US risk aversion events using both financial market data and controlled experiments. First, we obtain US risk aversion shocks using financial market data and news data to identify US risk aversion events using a novel news-integrated approach. Our approach aims to address several empirical challenges: measurement of country daily risk aversion, comoving risk premium variables (uncertainty), the US origination of events, and event narratives. We find that, from 2000 to 2017, international pass-through of US high RA shocks (61%) is significantly higher than that of US low RA shocks (43%). While financial market and actual news data offer an aggregate and real-life view of this new

[20]Gallup measures daily emotions in more than 150 countries and areas by asking residents whether they experienced different emotions a lot the previous day. Using data from 2009 to 2020, we obtain the average percentage of individuals who experience "enjoyment", "sadness", and "worry" in these six countries: (1) United Kingdom (38.67%); (2) The Netherlands (37.70%); (3) France (37.67%); (4) Germany (36.92%); (5) Switzerland (36.70%); (6) Japan (31.81%).

phenomenon, we conducted two subsequent experiments to explore the underlying mechanisms of asymmetric US risk aversion propagation in a controlled way. We exploited the priming method to stimulate the propagation of risk aversion, and obtained our main outcome measure, participants' risk aversion, from an established investment task with explicitly specified payoff and probabilities. Our studies included a total of 700 US and non-US participants. We show that the US shocks could directly affect non-US participants' risk aversion through affecting their emotional states; the foreign nature of high RA or bust shocks may change emotions – positive emotion decreases and negative emotion increases – more than that of low RA or boom shocks, hence resulting in asymmetric risk aversion propagation. Our mediation analysis shows that 19.6% of the propagation asymmetry can be explained by this general emotion channel (12.8% if using the positive emotion dimension only, and 8.3% if using the negative emotion dimension only). Hence, joining the recent growing experimental evidence of how emotion affects risk aversion (e.g., the level effect as in Kuhnen and Knutson (2005) and the cyclical effect as in Cohn, Engelmann, Fehr, and Maréchal (2015)), our research suggests a cross-subject "propagation" effect such that an emotion-related non-fundamental channel may play an important role in explaining the excessive risk aversion propagation in times of bad domestic shocks.

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Table 1: Empirical measures of daily country risk aversion and uncertainty

This table reports summary statistics of daily risk aversion and uncertainty measures proxied by daily country variance risk premium (VRP) and stock market conditional variance (PVAR), respectively. Country VRPs are calculated as the difference between implied volatility index-squared (source: DataStream) and conditional variance of country market index returns, defined as the expectation of future 22-trading day realized variances. The realized variance forecasting model uses a variant of the Corsi (2009) HAR model:

$$E_t\left[RV_{t+22}^{(22)}\right] = \hat{\alpha} + \hat{\beta^m} RV_t^{(22)} + \hat{\beta^w} RV_t^{(5)} + \hat{\beta^d} RV_t + \hat{\gamma} IV_t,$$

where $RV_{t+22}^{(22)} = \sum_{i=1}^{22} RV_{t+i}$ denotes realized variances of market returns from Day $t+1$ to $t+22$; $RV_t^{(22)}$, $RV_t^{(5)}$ and RV_t denote monthly, weekly and daily realized variances till Day t, respectively; IV_t denotes the square of implied option volatility of the market index for contracts with a maturity of one month (22 trading days) on Day t. Countries that we consider are Switzerland (CH), Germany (DE), France (FR), Japan (JP), Netherlands (NL), United Kingdom (UK), and United States (US). The conditional variance estimation is conducted at the country level and uses the longest data available. Panels A and B provides the summary statistics (unit: monthly decimal-squared). Panels C, D and E use overlapping sample is from February 15, 2000 to December 29, 2017 (4089 trading days). Correlation with Japan corrects for non-synchronous trading (i.e., correlating Japan's $t+1$ with US' t).

	CH	DE	FR	JP	NL	UK	US
Panel A: Summary statistics of country risk aversion							
Mean	0.00162	0.00158	0.00194	0.00300	0.00254	0.00115	0.00164
SD	0.00226	0.00183	0.00215	0.00415	0.00332	0.00165	0.00183
Skew	5.00666	3.20986	3.12173	4.85857	3.15222	3.75294	3.71164
q90	0.00356	0.00358	0.00425	0.00578	0.00569	0.00275	0.00334
Panel B: Summary statistics of country stock market uncertainty							
Mean	0.00187	0.00387	0.00303	0.00285	0.00260	0.00263	0.00229
SD	0.00178	0.00368	0.00263	0.00164	0.00256	0.00259	0.00315
Skew	4.32086	3.47935	3.81662	5.60349	3.56641	4.77869	6.19883
q90	0.00351	0.00765	0.00574	0.00406	0.00502	0.00500	0.00431
Panel C: Correlation between country risk aversion							
CH	1.00	0.94	0.89	0.81	0.93	0.92	0.75
DE		1.00	0.94	0.71	0.96	0.92	0.79
FR			1.00	0.67	0.93	0.90	0.77
JP				1.00	0.74	0.76	0.72
NL					1.00	0.92	0.79
UK						1.00	0.85
US							1.00
Panel D: Correlation between country stock market uncertainty							
CH	1.00	0.94	0.96	0.74	0.96	0.95	0.89
DE		1.00	0.96	0.67	0.96	0.92	0.82
FR			1.00	0.69	0.97	0.96	0.88
JP				1.00	0.68	0.76	0.82
NL					1.00	0.95	0.85
UK						1.00	0.93
US							1.00
Panel E: Correlation between risk aversion and uncertainty							
	0.9347	0.9514	0.8942	0.8677	0.9389	0.8832	0.6414

Table 2: Empirical measures of daily country risk aversion and uncertainty shocks

This table summarizes the daily country risk aversion and uncertainty shocks, defined as risk aversion and uncertainty (see Table 1) *minus* their respective expected components (see Tables OA.3 and OA.4, respectively, in the Online Appendix). Panels A and B provide the summary statistics (unit: monthly decimal-squared). Panels C, D and E use overlapping sample is from February 15, 2000 to December 29, 2017 (4089 trading days). Correlation with Japan corrects for non-synchronous trading (i.e., correlating Japan's $t+1$ with US' t).

	CH	DE	FR	JP	NL	UK	US
Panel A: Summary statistics of country abnormal risk aversion							
Mean	0	0	0	0	0	0	0
SD	0.00112	0.00081	0.00106	0.00221	0.00132	0.00083	0.00104
Skew	8.46681	4.50419	2.80500	5.22980	2.86773	3.40364	4.25003
q90	0.00063	0.00054	0.00085	0.00141	0.00095	0.00061	0.00071
Panel B: Summary statistics of country abnormal uncertainty							
Mean	0	0	0	0	0	0	0
SD	0.00092	0.00179	0.00138	0.00095	0.00129	0.00135	0.00157
Skew	5.89208	5.28330	5.95595	3.72805	4.20556	7.18659	6.99260
q90	0.00048	0.00110	0.00087	0.00057	0.00083	0.00079	0.00085
Panel C: Correlation between country abnormal risk aversion							
CH	1.00	0.84	0.67	0.54	0.73	0.65	0.41
DE		1.00	0.74	0.58	0.76	0.71	0.54
FR			1.00	0.45	0.74	0.66	0.48
JP				1.00	0.53	0.48	0.37
NL					1.00	0.72	0.45
UK						1.00	0.61
US							1.00
Panel D: Correlation between country abnormal uncertainty							
CH	1.00	0.84	0.84	0.46	0.83	0.82	0.76
DE		1.00	0.89	0.58	0.86	0.84	0.77
FR			1.00	0.49	0.93	0.91	0.81
JP				1.00	0.43	0.48	0.52
NL					1.00	0.89	0.77
UK						1.00	0.81
US							1.00
Panel E: Correlation between risk aversion and uncertainty							
	0.7538	0.7805	0.6494	0.7262	0.7636	0.6108	0.1397

Table 3: Event summary by year and type

This table reports the numbers of events over time and across the four event types. See Section 2 for the detailed event selection procedure.

Event Type:	***Total RA***	***Total UC***	***1.High RA***	***2.Low RA***	***3.High UC***	***4.Low UC***
RA shock:			*>90th*	*<10th*	*Normal*	*Normal*
UC shock:			*Normal*	*Normal*	*>90th*	*<10th*
2000-2005	51	26	33	18	16	10
2006-2011	51	23	23	28	13	10
2011-2017	44	28	30	14	1	27
Total	146	77	86	60	30	47

Table 4: Event summary by news category

This table presents potential narratives of the identified abnormal RA and UC event dates. We use RavenPack's 5 general news categorizations: Business, Economy, Environment, Politics, and Society. See Section 2 and Appendix II for the detailed event selection procedure. The table below also reports the fraction of each news category in each event type. Here are some key examples of news in each category according to RavenPack's Taxonomy and UserGuide 4.0 (see more details in Table A2):

- Business: acquisitions-mergers, credit grading, earnings, incident, market, oil, regulatory
- Economy: consumer, domestic-product, employment, interest-rate, trade balance-of-payments, production
- Environment: natural-disaster
- Politics: elections, foreign-relation, government, legislation
- Society: accidents-with-deaths, crime, legal, war-conflict/security

Highlighted numbers indicate the event type in which this news category is mentioned the most (not enough data for Environment).

Event Type:	***Total RA***	***Total UC***	***1.High RA***	***2.Low RA***	***3.High UC***	***4.Low UC***
Business (*% of Total*)	19 (*13.0%*)	15 (*19.5%*)	13 (*15.1%*)	6 (*10.0%*)	8 (*26.7%*)	7 (*14.9%*)
Economy	85 (*58.2%*)	51 (*66.2%*)	46 (*53.5%*)	39 (*65.0%*)	18 (*60.0%*)	33 (*70.2%*)
Environment	2 (*1.4%*)	1 (*1.3%*)	2 (*2.3%*)	0 (*0.0%*)	1 (*3.3%*)	0 (*0.0%*)
Politics	17 (*11.6%*)	6 (*7.8%*)	4 (*4.7%*)	13 (*21.7%*)	0 (*0.0%*)	6 (*12.8%*)
Society	23 (*15.8%*)	4 (*5.2%*)	21 (*24.4%*)	2 (*3.3%*)	3 (*10.0%*)	1 (*2.1%*)
Total	146	77	86	60	30	47

Table 5: Event study: Domestic responses

This table reports the average abnormal changes in US risk aversion/uncertainty before, during, and after the US events, scaled by the average level of risk aversion/uncertainty during the sample period. The first row shows the day interval (e.g., [-30, -11] indicates 30 to 11 trading days before the event or news day, and [0,0] indicates the event day). For instance, 0.592 means that the abnormal changes in US risk aversion on identified high RA dates are on average 59.2% higher than a sample average level of risk aversion. Block bootstrapped standard errors are reported in parentheses. Bold (italic) values indicate that a coefficient is significant at the 1% (5%) significance level. Other details can be found in Section 3.1.

[-30, -11]	[-10, -4]	[-3, -1]	[0, 0]	[1, 3]	[4, 10]	[11, 30]
News: 1. High RA; Response: Abnormal RA						
-0.0330	0.0425	**0.1435**	**0.5920**	**0.3532**	0.0516	-0.0496
(0.0253)	(0.0264)	(0.0286)	(0.0186)	(0.0386)	(0.0394)	(0.0310)
News: 2. Low RA; Response: Abnormal RA						
0.1103	0.0233	**-0.1518**	**-0.6263**	**-0.3762**	**-0.2286**	*-0.0583*
(0.0483)	(0.0652)	(0.0437)	(0.0444)	(0.0316)	(0.0422)	(0.0281)
News: 3. High UC; Response: Abnormal UC						
0.1091	*0.2517*	**0.4178**	**0.6943**	**0.5993**	**0.4467**	**0.2759**
(0.1040)	(0.1130)	(0.0696)	(0.0534)	(0.0874)	(0.0795)	(0.0978)
News: 4. Low UC; Response: Abnormal UC						
0.0088	**-0.3392**	**-0.5115**	**-0.6191**	**-0.5388**	**-0.3964**	*-0.1491*
(0.0875)	(0.0944)	(0.0501)	(0.0328)	(0.0474)	(0.0531)	(0.0693)

Table 6: Event study: Foreign responses

This table reports the average scaled abnormal changes in country risk aversion or uncertainty across the six non-US countries before, during, and after the interested US events; see detailed construction in Section 3.2; see other notation details in Table 5.

[-30, -11]	[-10, -4]	[-3, -1]	[0, 0]	[1, 3]	[4, 10]	[11, 30]
News: 1. High RA; Response: Abnormal Non-US RA						
-0.0357	0.0960	**0.1822**	**0.3681**	**0.3678**	**0.1825**	0.0443
(0.0435)	(0.0511)	(0.0476)	(0.0500)	(0.0567)	(0.0655)	(0.0785)
News: 2. Low RA; Response: Abnormal Non-US RA						
0.0854	-0.0565	-0.1331	**-0.2687**	**-0.2714**	**-0.2648**	-0.0799
(0.0951)	(0.0815)	(0.0682)	(0.0673)	(0.0601)	(0.0684)	(0.0563)
News: 3. High UC; Response: Abnormal Non-US UC						
0.0210	0.1493	0.1445	**0.2116**	*0.2568*	*0.2125*	0.0718
(0.0665)	(0.1056)	(0.0833)	(0.0806)	(0.1001)	(0.0996)	(0.1004)
News: 4. Low UC; Response: Abnormal Non-US UC						
0.0364	*-0.1238*	**-0.2001**	**-0.2390**	**-0.2423**	**-0.1776**	*-0.0917*
(0.0632)	(0.0511)	(0.0411)	(0.0369)	(0.0393)	(0.0432)	(0.0371)

Table 7: Pass-through asymmetry and robustness

This table presents pass-through measures, tests of asymmetry, and various robustness tests. **Pass-through** is calculated as the ratio of foreign responses to domestic responses on US event days "[0,0]"; pass-through estimates and standard errors shown in this table are obtained from 1000 times of bootstrapping. **The equality test** tests the equality between the "high" RA pass-through and the "low" RA pass-through, followed by its significance (*, **, and *** indicate significance at the 10%, 5%, and 1% significance level, respectively); hence, this test can be interpreted as asymmetry test; in the second half of the table, similar tests are conducted for UC. **Columns:** **Robustness set (1)** uses the full event sample as in Tables 5 and 6, or our main specification. **Robustness set (2)** conducts the same analysis considering economy news only and non-economy news only. **Robustness set (3)** drops one international country at a time. **Robustness set (4)** drops the 2008-09 period. **Robustness set (5)** drops US event days that overlap with Baker, Bloom, Davis, and Sammon (2020)'s stock market jump days. All detailed domestic and foreign response estimates for (2) – (5) are provided in the Appendix Tables A4 and A5.

	(1)	***(2) News category***		***(3) Jackknife country set***						***(4) Time***	***(5) Mechanism***
	Main	Econ	Non-Econ	No CH	No DE	No FR	No JP	No NL	No UK	Non-crisis	Non-jumps
News: 1. High RA	**0.6123**	**0.6213**	**0.6017**	**0.6336**	**0.6192**	**0.5982**	**0.6354**	**0.6275**	**0.5521**	**0.6225**	**0.6104**
	(0.0322)	(0.0455)	(0.0467)	(0.0351)	(0.0355)	(0.0352)	(0.0346)	(0.0374)	(0.0313)	(0.0374)	(0.0332)
News: 2. Low RA	**0.4259**	**0.4341**	**0.4077**	**0.3932**	**0.4156**	**0.4404**	**0.4470**	**0.4673**	**0.3919**	**0.3760**	**0.4676**
	(0.0489)	(0.0561)	(0.0856)	(0.0532)	(0.0521)	(0.0521)	(0.0519)	(0.0548)	(0.0525)	(0.0558)	(0.0382)
Equality test (t stats):	3.1820	2.5899	1.9899	3.7730	3.2306	2.5084	3.0206	2.4147	2.6199	3.6702	2.8212
Significance:	***	***	**	***	***	**	***	**	***	***	***
News: 3. High UC	**0.2973**	**0.2598**	**0.3875**	**0.2872**	**0.2706**	**0.3030**	**0.3426**	**0.2896**	**0.2730**	**0.3635**	**0.3984**
	(0.0641)	(0.0554)	(0.0804)	(0.0459)	(0.0478)	(0.0474)	(0.0472)	(0.0495)	(0.0482)	(0.0564)	(0.0530)
News: 4. Low UC	**0.3906**	**0.3657**	**0.4292**	**0.3858**	**0.3988**	**0.3795**	**0.4083**	**0.3827**	**0.3808**	**0.3951**	**0.3906**
	(0.0531)	(0.0568)	(0.0734)	(0.0460)	(0.0459)	(0.0449)	(0.0444)	(0.0435)	(0.0445)	(0.0343)	(0.0335)
Equality test (t stats):	-1.1202	-1.3356	-0.3822	-1.5158	-1.9350	-1.1705	-1.0136	-1.4118	-1.6421	-0.4781	0.1248
Significance:											

Table 8: Main asymmetry results in experiments

This table shows the effects of treatments on US participants' risky investment level (which is interpreted as the inverse risk aversion in our research) in Regressions (1)–(2) and on non-US participants' risky investment level in Regressions (3)–(4). The regression framework is as follows:

$$Y_i = \beta_0 + \beta_1 I_{HighRA,i} + \beta_2 I_{LowRA,i} + \boldsymbol{\gamma}'\boldsymbol{X_i} + \varepsilon_i,$$

where Y_i represents the post-priming risky investment level; $I_{HighRA,i}$ ($I_{LowRA,i}$) represents a dummy variable which equals to 1 if the subject is from the bust/high RA (boom/low RA) treatment group; $\boldsymbol{X_i}$ represents a collection of control variables (pre-priming risky investment level, individual income, age, gender, financial literacy and country fixed effects). The standard errors are in parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dep. Var:	***Post-priming Inv. Level***			
Exp. Sample:	***Study 1, "US/US"***		***Study 2, "US/NUS"***	
Shock:	***US***		***US***	
Participants:	***US***		***Non-US***	
High RA Treatment	**-39.77****	**-40.19****	**-88.17*****	**-85.29*****
	(17.276)	(17.296)	(21.196)	(22.418)
Low RA Treatment	**53.70*****	**50.51*****	**54.74****	**58.55*****
	(17.160)	(17.230)	(21.528)	(22.433)
Pre-priming Inv. Level	**0.855*****	**0.860*****	**0.843*****	**0.849*****
	(0.027)	(0.028)	(0.035)	(0.037)
Income control	N	Y	N	Y
Age control	N	Y	N	Y
Financial literacy	N	Y	N	Y
Gender	N	Y	N	Y
Country effect	N	Y	N	Y
Observations	457	457	243	243
R-squared	0.692	0.697	0.717	0.734
Adjusted R-squared	0.690	0.692	0.714	0.708

Table 9: Asymmetry tests

This table complements Table 8 in providing formal tests of (a)symmetric non-US responses. Panel A uses non-linear tests and coefficient estimates from Regressions (2) and (4) to test whether responses in Study 2 (the foreign effect) is significantly larger than those in Study 1 (the domestic effect). Panel B uses the two-way factorial Analysis of Variance (ANOVA) test (Afifi and Azen (2014)) to examine individual factor effects and combined interaction effects on investment changes (for simplicity, post-priming minus pre-priming investment levels). There are two factors: Group (Treatment High RA, Treatment Low RA, and control groups) and Study (Study 1, the domestic effect, and Study 2, the foreign effect); the interaction effect of whether group effects in one study are on average significantly different from those in the other study is of interest (highlighted in grey). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Pass-through Asymmetry Tests from Table 8					
High RA treatment H_0: Coeff. in Study 2 / Coeff. in Study 1 = 1					
$\chi^2(1)$:	**4.41****				
$p-value$:	0.0356				
Low RA treatment H_0: Coeff. in Study 2 / Coeff. in Study 1 = 1					
$\chi^2(1)$:	0.15				
$p-value$:	0.697				
Panel B: Two-way ANOVA using investment change					
Source	***Partial SS***	***df***	***MS***	***F***	***Prob>F***
Model	1.55E+06	5	3.11E+05	**13.64*****	0
- Group	1.39E+06	2	6.97E+05	**30.58*****	0
- Study	6.85E+04	1	6.85E+04	**3.01***	0.0834
- Group×Study	1.09E+05	2	5.46E+04	**2.4***	0.0919
Residual	1.58E+07	694	2.28E+04		
Total	1.74E+07	699	2.48E+04		

Table 10: Mediators

This table presents the effects of treatments on mediators in Study 2: belief updating and emotion channels. Regressions (5)-(6) test non-US participants' beliefs about changes in local market prices after seeing the US price movements; non-US participants were shown three choices: increase, stay the same or decrease. "Belief about local price ↑" is 1 if they chose the option "Increase" (0 otherwise); "Belief about local price ↓" is 1 if they chose the option "Decrease" (0 otherwise). Regressions (7)-(9) test non-US participants' emotional states: (a) General emotion is positive emotion minus negative emotion, (b) Positive emotion, and (c) Negative emotion, separately. Positive emotion is the average rating of enthusiastic, excited, happy, and relaxed (1=not at all; 5=very much); negative emotion is the average rating of distressed, irritable, nervous, and scared (1=not at all; 5=very much). The 8 emotional states are based on the Positive and Negative Affect Schedule (PANAS) (Watson, Clark, and Tellegen (1988); Lu, Lee, Gino, and Galinsky (2018)). The standard errors are in parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(5)	(6)	(7)	(8)	(9)
Dep. Var:	***Belief about local price ↑***	***Belief about local price ↓***	***General Emotion***	***Positive Emotion***	***Negative Emotion***
High RA Treatment	-0.104	**0.540*****	**-0.722*****	**-0.375*****	**0.347*****
	(0.064)	(0.068)	(0.201)	(0.124)	(0.130)
Low RA Treatment	**0.425*****	-0.0361	0.287	0.197	-0.0901
	(0.064)	(0.068)	(0.201)	(0.124)	(0.130)
Income control	Y	Y	Y	Y	Y
Age control	Y	Y	Y	Y	Y
Financial literacy	Y	Y	Y	Y	Y
Gender	Y	Y	Y	Y	Y
Country effect	Y	Y	Y	Y	Y
Observations	243	243	243	243	243
R-squared	0.294	0.350	0.275	0.222	0.209
Adjusted R-squared	0.227	0.288	0.206	0.148	0.134

Table 11: Mediation analysis

This table presents the mediation analysis. The dependent variable is the post-priming risky investment (inverse risk aversion). Independent variables include indicators for high and low RA treatment dummies, mediators, and our standard set of controls (pre-priming investment level, income, age, financial literacy, gender, country effect). The five mediators are discussed in Table 10. Coefficient asymmetry is measured as "|High RA Treatment|/|Low RA Treatment|-1". Mediation effect is the percent drop in coefficient asymmetry *after* adding effective mediators. Regression (12) is our benchmark regression (i.e., (4) from Table 8). The standard errors are in parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(10)	(11)	(12)	(13)
Dep. Var:		***Post-priming Inv. Level***		
High RA Treatment			**-85.29*** **	**-74.47*** **
			(22.418)	(22.931)
Low RA Treatment			**58.55*** **	**54.47** **
			(22.433)	(22.380)
1. Belief about local price ↑	9.487			
	(27.580)			
2. Belief about local price ↓	-30.88			
	(25.257)			
3. General Emotion		**26.22*** **		**14.76** **
		(7.467)		(7.454)
Pre-priming Inv. Level	**0.848*** **	**0.841*** **	**0.849*** **	**0.846*** **
	(0.040)	(0.039)	(0.037)	(0.037)
Controls	Y	Y	Y	Y
Observations	243	243	243	243
Adjusted R-squared	0.667	0.666	0.680	0.708
Coefficient Asymmetry	-	-	0.457	0.367
Mediation Effect	-	-	-	19.6%

	(14)	(15)	(16)	(17)
Dep. Var:		***Post-priming Inv. Level***		
High RA Treatment			**-74.62*** **	**-81.81*** **
			(22.679)	(22.792)
Low RA Treatment			**53.36** **	**57.66** **
			(22.330)	(22.470)
4. Positive Emotion	**44.80*** **		**27.70** **	
	(12.156)		(12.023)	
5. Negative Emotion		**-23.64* **		-9.980
		(12.061)		(11.604)
Pre-priming Inv. Level	**0.841*** **	**0.843*** **	**0.843*** **	**0.849*** **
	(0.035)	(0.035)	(0.037)	(0.037)
Controls	Y	Y	Y	Y
Observations	243	243	243	243
Adjusted R-squared	0.715	0.714	0.713	0.707
Coefficient Asymmetry	-	-	0.398	0.419
Mediation Effect	-	-	12.8%	8.3%

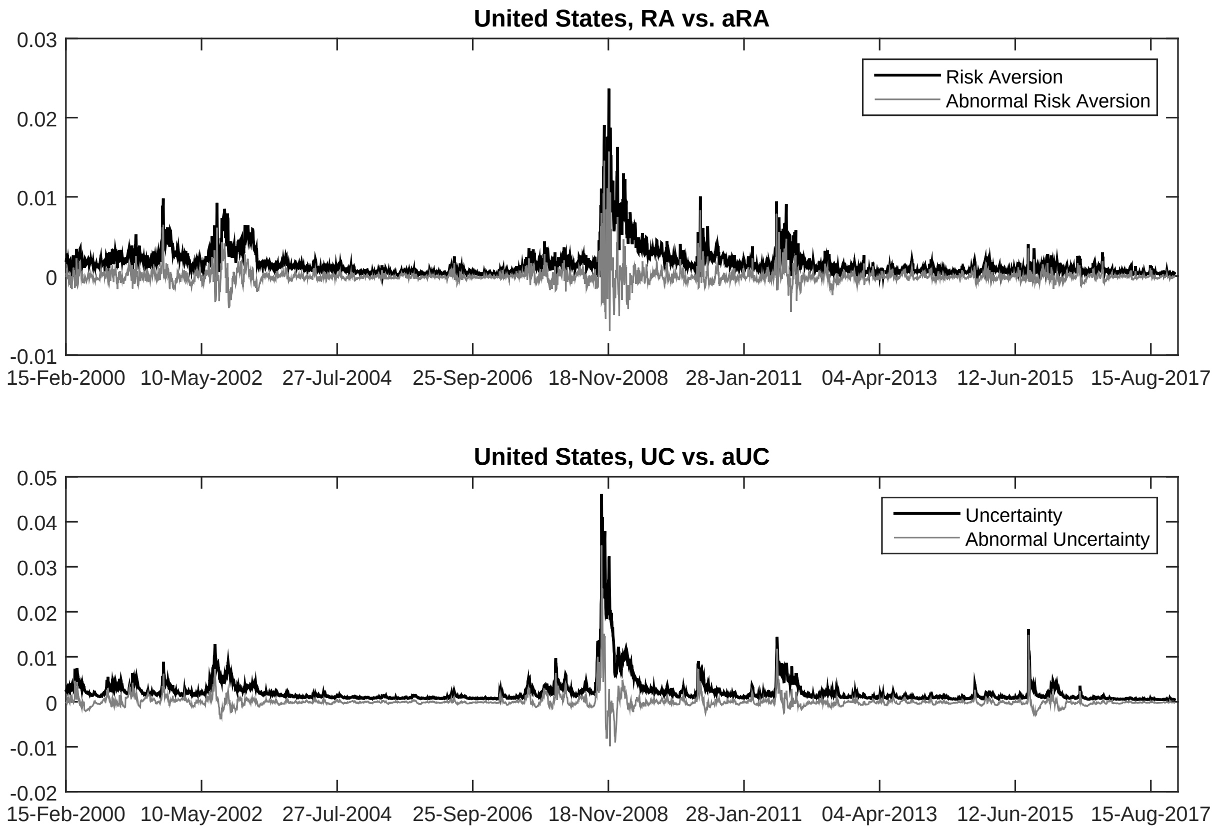


Figure 1: Time variation in US risk aversion, abnormal risk aversion (top plot), uncertainty, and abnormal uncertainty (bottom plot) in the final overlapping sample from 2000 to 2017.

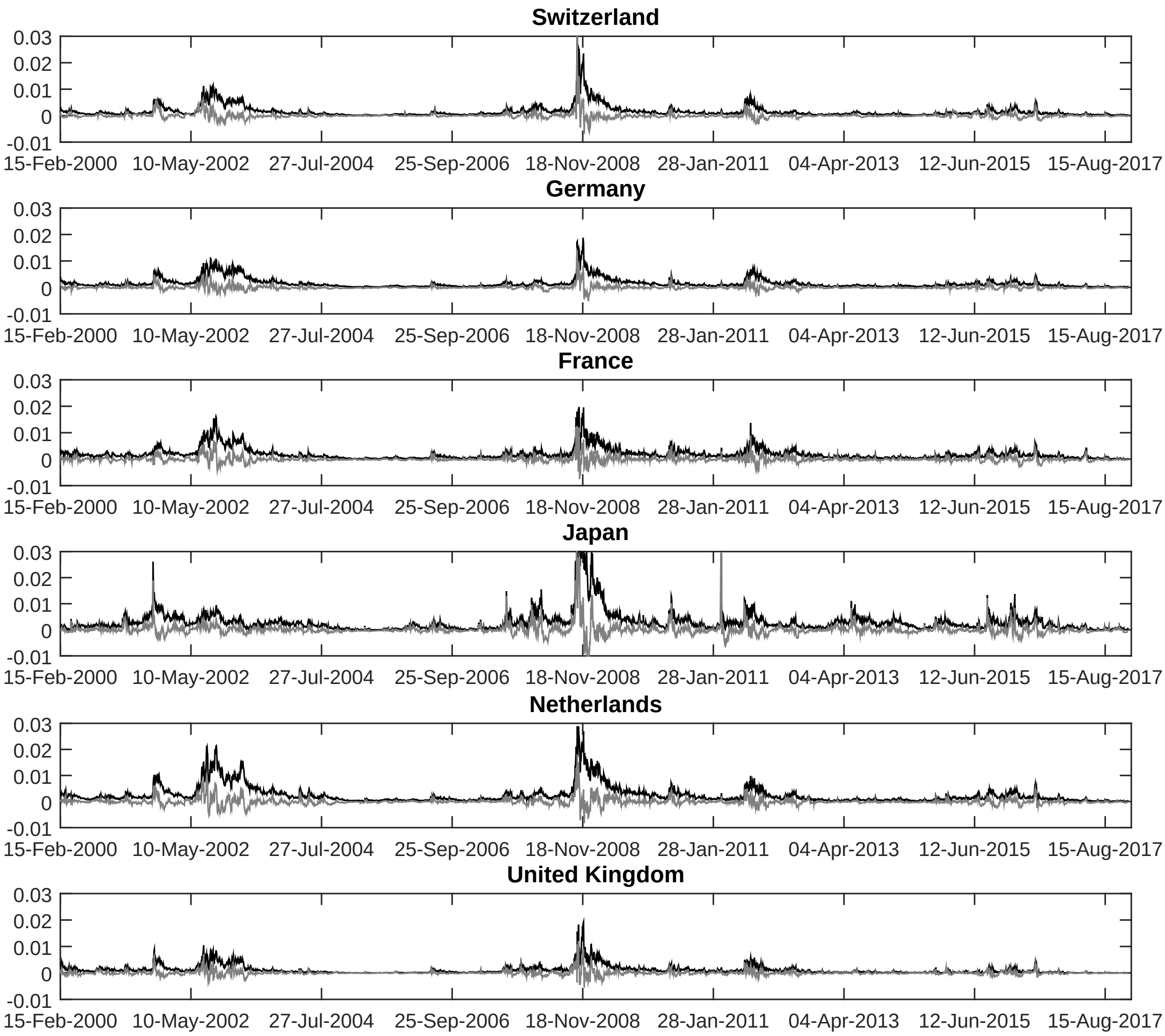


Figure 2: Time variation in international risk aversion (black) and abnormal risk aversion (gray) in the final overlapping sample from 2000 to 2017.

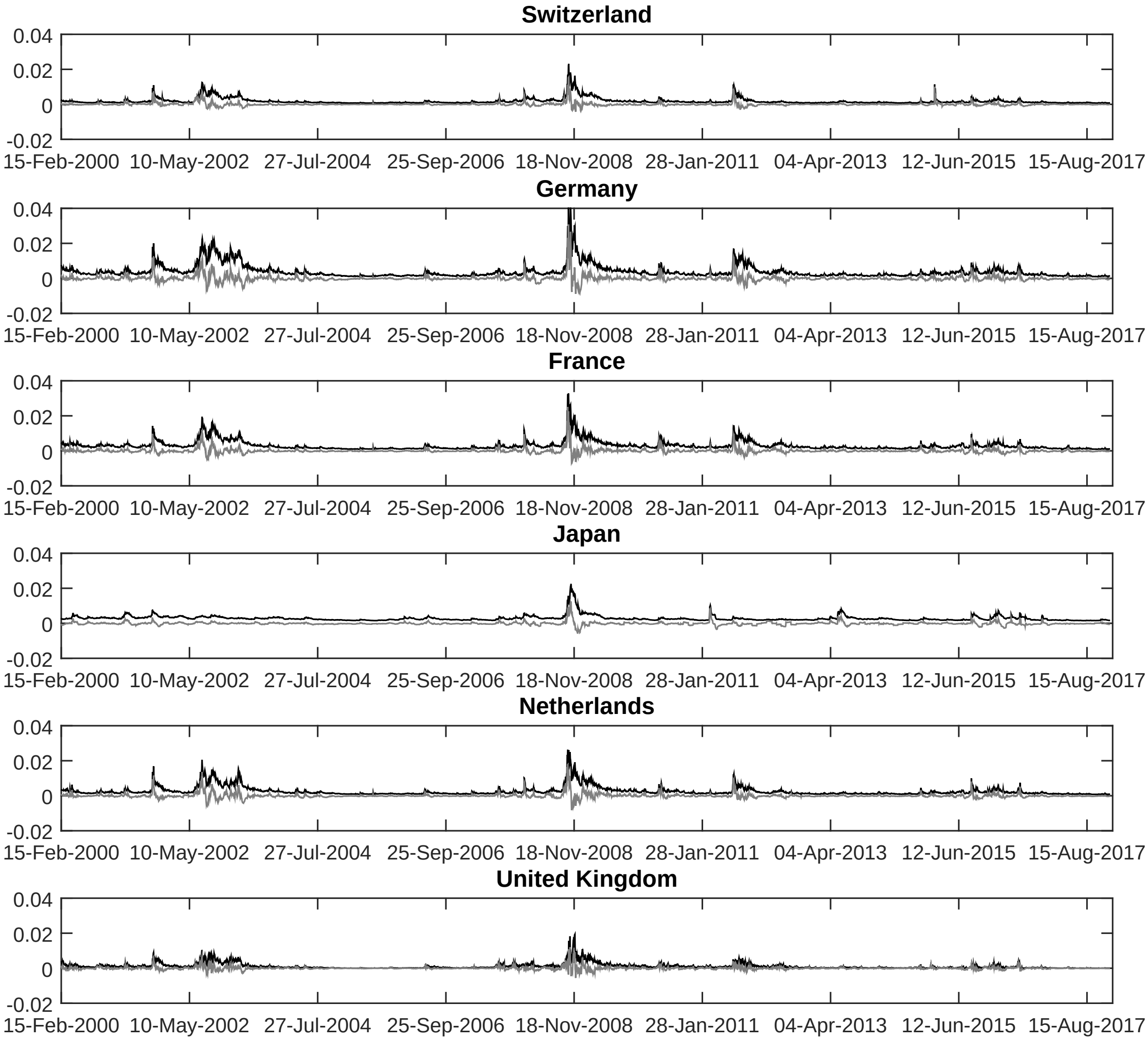


Figure 3: Time variation in international uncertainty (black) and abnormal uncertainty (gray) in the final overlapping sample from 2000 to 2017.

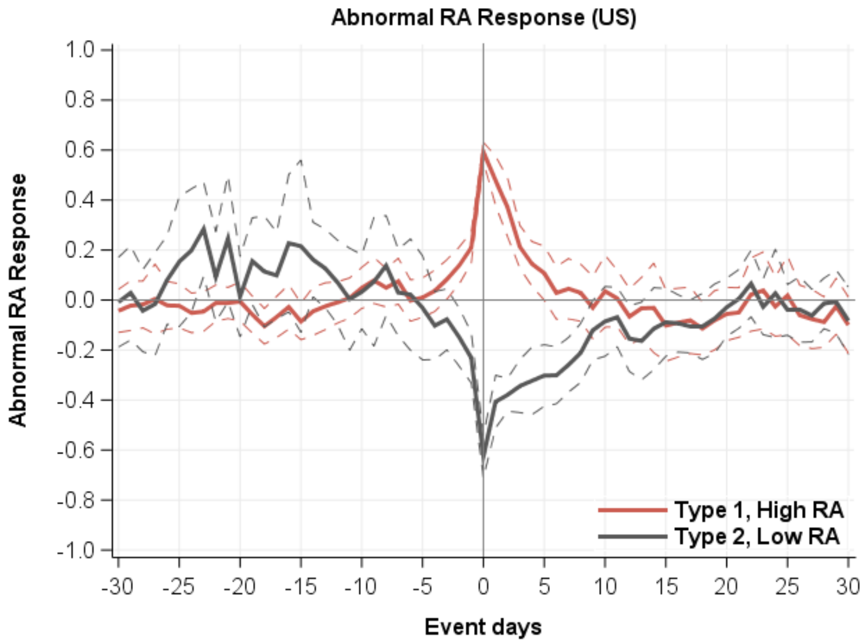


Figure 4: Event study: Abnormal US risk aversion responses to US RA shocks

This plot shows the average abnormal changes in US risk aversion (RA), scaled by the average level of risk aversion during the sample period, for Type 1 "High RA" (red) and Type 2 "Low RA" (black) risk aversion events. The dashed lines indicate 95% confidence intervals.

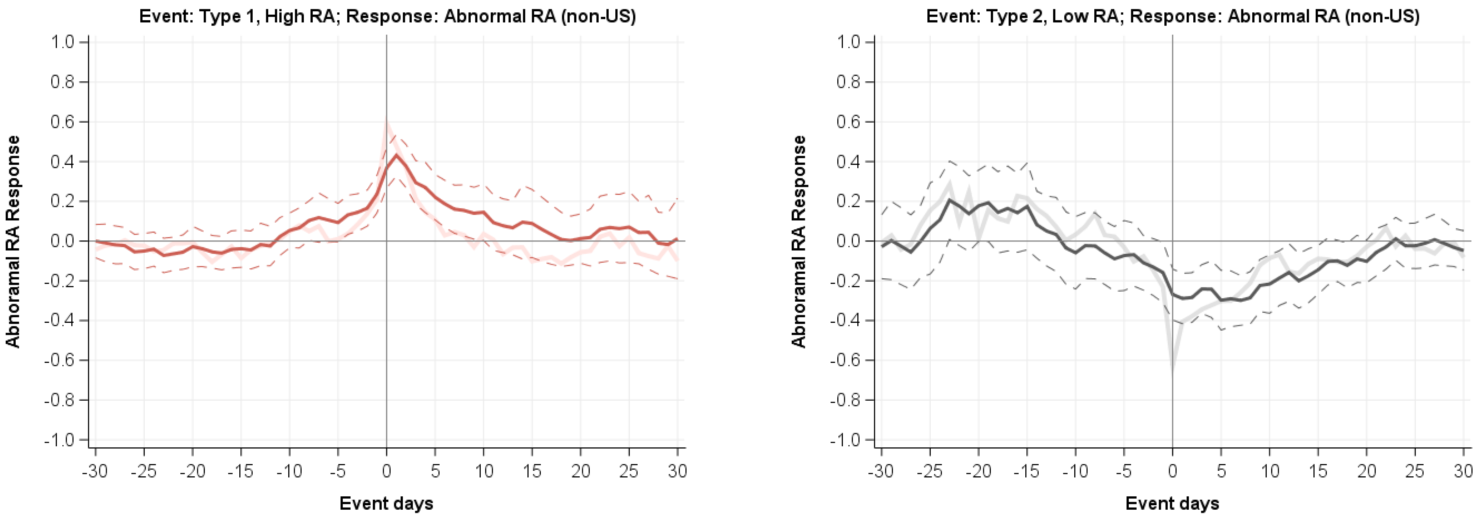


Figure 5: Event study: Abnormal international risk aversion in response to US RA shocks

The plot shows the average scaled abnormal changes in country risk aversion (RA) across the six non-US countries before, during, and after the US high (left subplot) and low (right subplot) RA events; see detailed construction in Section 3.2. The dashed lines are 95% confidence intervals; SE is obtained using bootstrapping. The lighter solid lines in the background are the US response lines (see Figure 4). Country-by-country figures are shown in the Appendix Figures A1 and A2.

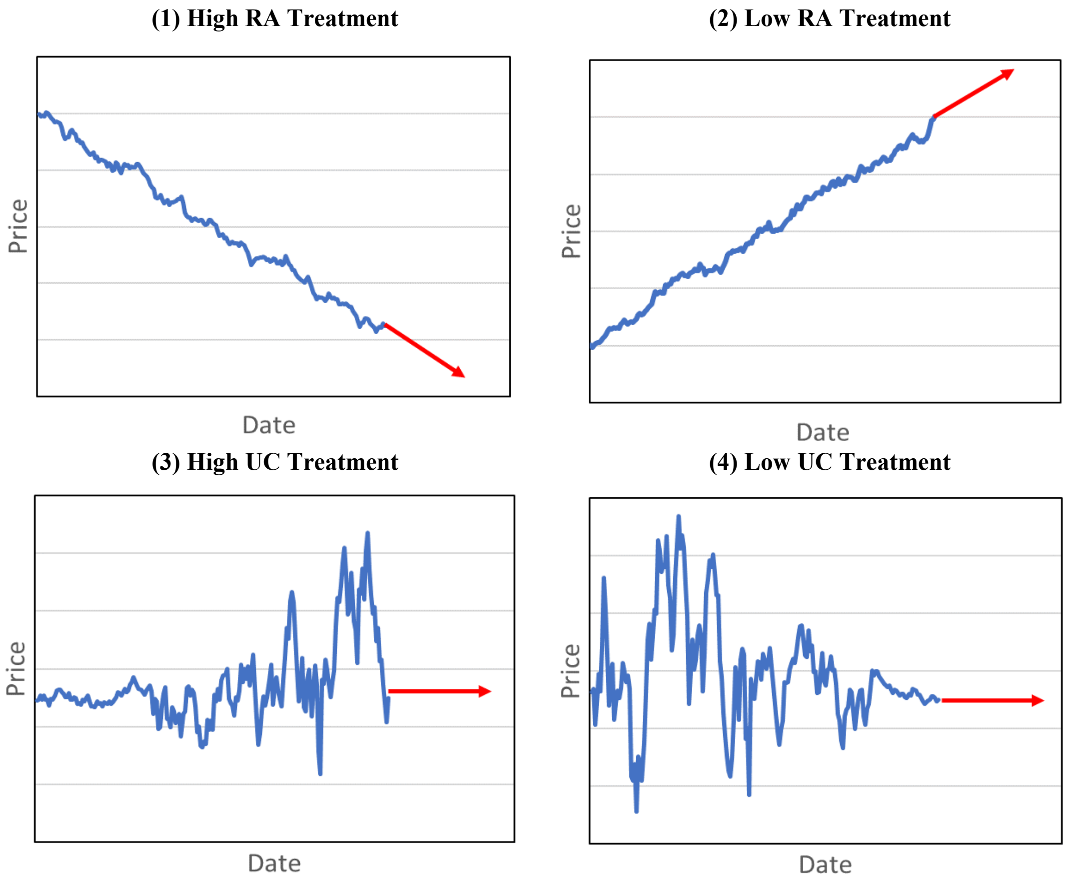
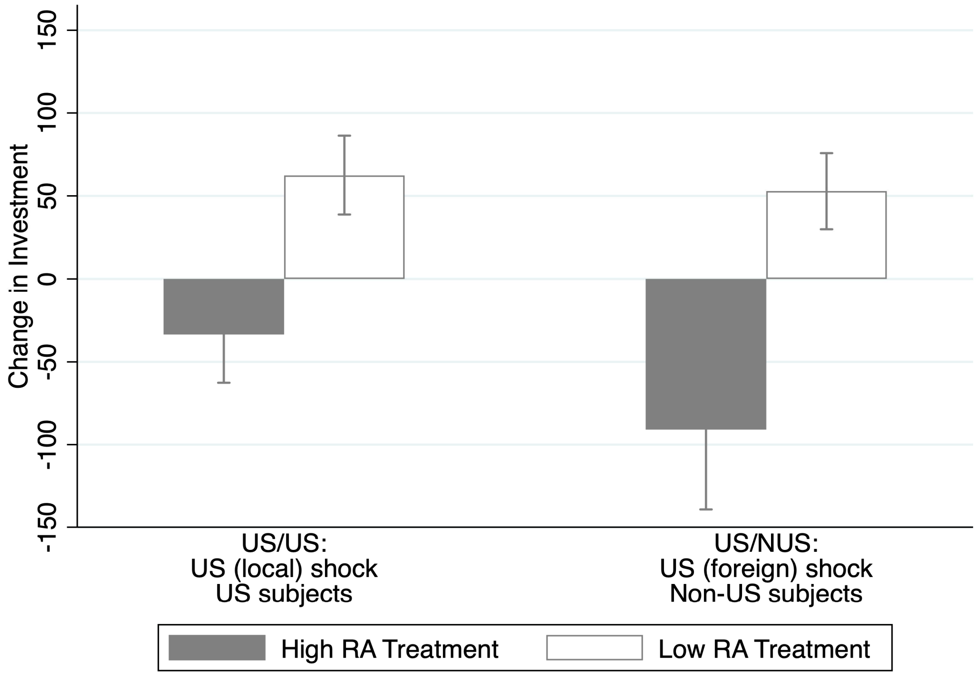


Figure 6: Treatment plots

The top two plots follow Cohn, Engelmann, Fehr, and Maréchal (2015) and depict our main risk aversion treatment scenarios; the bottom two plots depict our control scenarios, in light of the treatment designs. As in Cohn, Engelmann, Fehr, and Maréchal (2015), the arrows were used to illustrate market trends to avoid mean-reversion expectation in the near future; we also did not label the time and price axes to prevent subjects from thinking about a specific stock market event. The animated version of these charts were shown to subjects in our experiment to increase the mental salience of these fictive scenarios.

Panel A. Risk aversion priming



Panel B. Uncertainty priming

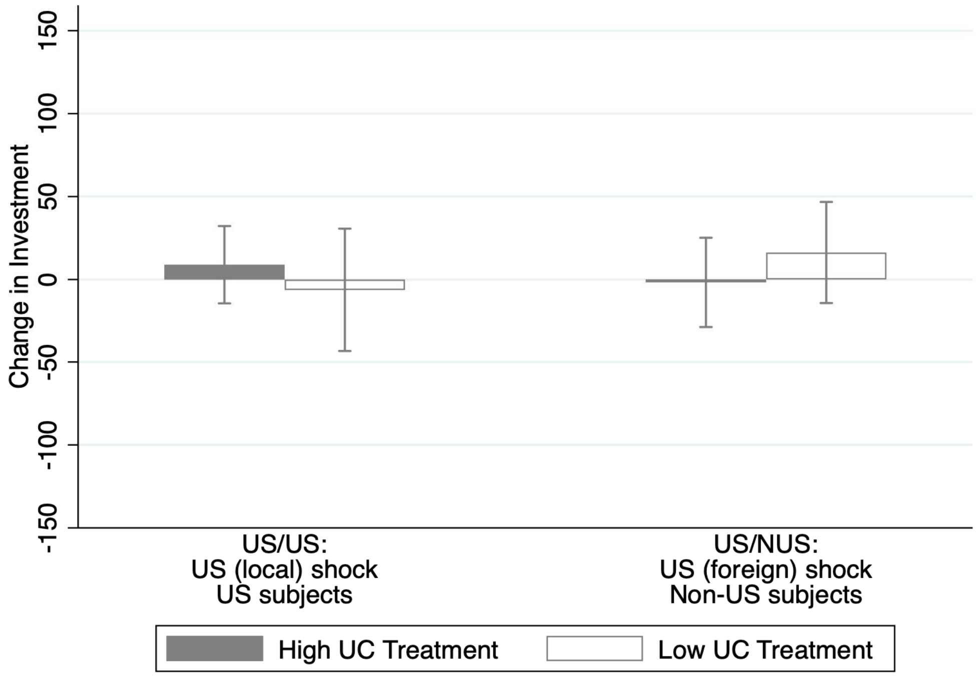


Figure 7: Preliminary demonstration of mean effects across the two studies

This figure presents the average changes in risky investment decision after treatments (more positive the bar = choosing more risky assets). Panel A (B) presents the results under the two risk aversion (uncertainty) priming groups; the left (right) set of bars presents the results for Study 1 (Study 2). Error bands indicate the 90% confidence interval. This figure serves as an illustration of the mean effects, and the formal tests are shown in Tables 8.

PAPER APPENDICES

I. Supplementary Tables and Figures

Table A1: Data availability for country implied volatility indices

This table presents the underlying asset and data availability/starting date of country-level implied volatility data (source: DataStream).

Country:	Underlying Asset:	Starting date:
Switzerland (CH)	SMI20	January 4, 1999
Germany (DE)	DAX30	January 2, 1992
France (FR)	CAC40	January 3, 2000
Japan (JP)	NIKKEI225	November 1, 1989
Netherlands (NL)	AEX	January 3, 2000
United Kingdom (UK)	FTSE100	January 4, 2000
United States (US)	S&P500	January 2, 1990

Table A2: Event summary by news subtopic

This table adds more details to Table 4, which summarizes final event list by news categories. The first four columns of Panel A are the same as presented in Table 4; we include a 5th (6th) category of RA and UC shocks being both high (low), which is not the focus of the paper.

Event Type:		***1-HighRA***	***2-LowRA***	***3-HighUC***	***4-LowUC***	***5-HH***	***6-LL***
RA shock:		*>90th*	*<10th*	*Normal*	*Normal*	*>90th*	*<10th*
UC shock:		*Normal*	*Normal*	*>90th*	*<10th*	*>90th*	*<10th*
Panel A. By Topic							
Business		13	6	8	7	6	1
		15.1%	*10.0%*	*26.7%*	*14.9%*	*27.3%*	*5.9%*
Economy		46	39	18	33	9	5
		53.5%	*65.0%*	*60.0%*	*70.2%*	*40.9%*	*29.4%*
Environment		2	0	1	0	1	0
		2.3%	*0.0%*	*3.3%*	*0.0%*	*4.5%*	*0.0%*
Politics		4	13	0	6	1	9
		4.7%	*21.7%*	*0.0%*	*12.8%*	*4.5%*	*52.9%*
Society		21	2	3	1	5	2
		24.4%	*3.3%*	*10.0%*	*2.1%*	*22.7%*	*11.8%*
Panel B. By Sub-Topic							
Business	acquisitions-mergers	0	0	0	1	0	0
Business	credit	1	2	2	1	5	0
Business	earnings	4	0	0	1	0	0
Business	incident	1	0	0	0	1	0
Business	market	1	1	0	1	0	0
Business	oil	1	1	0	1	0	0
Business	regulatory	5	2	6	2	0	1
Economy	balance-of-payments	1	0	0	2	0	0
Economy	consumer	12	4	4	8	1	1
Economy	domestic-product	6	8	4	3	0	0
Economy	employment	10	11	4	6	3	1
Economy	globalization	4	4	2	2	0	0
Economy	housing	1	3	1	3	1	1
Economy	interest-rates	6	2	2	2	1	0
Economy	manufacture	2	0	0	0	0	0
Economy	production	2	4	0	5	3	1
Economy	public-finance	2	0	1	1	0	0
Economy	treasury-bill-auction	0	3	0	1	0	1
Environment	natural-disasters	2	0	1	0	1	0
Politics	elections	1	4	0	2	0	1
Politics	foreign-relations	0	1	0	0	0	0
Politics	government	3	7	0	4	1	8
Politics	legislation	0	1	0	0	0	0
Society	accidents-with-deaths	3	0	0	0	0	0
Society	crime	2	0	0	0	1	0
Society	legal	2	1	3	1	2	2
Society	war-conflict/security	14	1	0	0	2	0
Total		86	60	30	47	22	17

Table A3: Event study: Cross responses and event type justification

This table complements Table 5, and reports and tests the cross responses. For example, in Panel A, event type 1 (high risk aversion), this row reports the average abnormal changes in the US uncertainty. The goal is to further evaluate our effort of separating RA from UC news. Block bootstrapped standard errors are reported in parentheses. Bold (italic) values indicate that a coefficient is significant at the 1% (5%) significance level. Panel B reports the absolute closeness test statistics ($|t|$) examining the equality between the abnormal direct and cross responses of the same day range; for instance, $|t| > 1.96$ rejects the null that the cross responses (Panel A of this table) are statistically close to the direct responses (as reported in Table 5) at the 5% significance level.

[-30, -11]	[-10, -4]	[-3, -1]	[0, 0]	[1, 3]	[4, 10]	[11, 30]
Panel A. Cross responses						
News: Type 1, High RA; Response: Abnormal UC						
-0.0378	0.0616	0.0434	**0.1070**	**0.1688**	**0.1771**	0.0881
(0.0379)	(0.0443)	(0.0250)	(0.0177)	(0.0305)	(0.0486)	(0.0692)
News: Type 2, Low RA; Response: Abnormal UC						
0.0295	0.0136	0.0303	-0.0321	**-0.1464**	**-0.2115**	*-0.0953*
(0.0558)	(0.0483)	(0.0394)	(0.0273)	(0.0333)	(0.0501)	(0.0453)
News: Type 3, High UC; Response: Abnormal RA						
0.0176	*0.2123*	**0.2173**	**0.0875**	0.0804	*0.1735*	0.0302
(0.0403)	(0.1036)	(0.0640)	(0.0335)	(0.0662)	(0.0848)	(0.0533)
News: Type 4, Low UC; Response: Abnormal RA						
-0.0373	**-0.1318**	**-0.1482**	**-0.1423**	**-0.2098**	**-0.1292**	-0.0130
(0.0464)	(0.0435)	(0.0530)	(0.0282)	(0.0589)	(0.0456)	(0.0338)
Panel B. Closeness test, $\|t\|$						
News: Type 1, High RA; Response: Abnormal UC						
0.1037	0.3701	2.6301	18.8763	3.7509	2.0077	1.8160
News: Type 2, Low RA; Response: Abnormal UC						
1.0956	0.1204	3.0937	11.4007	5.0083	0.2610	0.6928
News: Type 3, High UC; Response: Abnormal RA						
0.8198	0.2571	2.1202	9.6315	4.7332	2.3508	2.2047
News: Type 4, Low UC; Response: Abnormal RA						
0.4660	1.9962	4.9843	11.0173	4.3514	3.8170	1.7654

Table A4: Robustness: Domestic and foreign responses using Economy news only, non-econ news only, years except for 2008-2009, and non-jump event days only. See summary in Table 7.

	[-30, -11]	[-10, -4]	[-3, -1]	[0, 0]	[1, 3]	[4, 10]	[11, 30]
News: 1. High RA; Response: Abnormal US RA							
Econ	-0.0071	0.0397	**0.1653**	**0.5831**	**0.2588**	0.1134	-0.0491
	(0.0334)	(0.0317)	(0.0360)	(0.0228)	(0.0394)	(0.0604)	(0.0439)
Non-Econ	*-0.0629*	0.0458	*0.1183*	**0.6023**	**0.4619**	-0.0195	-0.0501
	(0.0306)	(0.0427)	(0.0461)	(0.0324)	(0.0721)	(0.0436)	(0.0460)
Non-Crisis	-0.0332	0.0471	**0.1555**	**0.5886**	**0.3805**	0.0320	**-0.0848**
	(0.0266)	(0.0295)	(0.0299)	(0.0202)	(0.0405)	(0.0325)	(0.0311)
Non-Jumps	*-0.0516*	*0.0581*	**0.1758**	**0.5859**	**0.3533**	*0.0928*	-0.0558
	(0.0205)	(0.0278)	(0.0243)	(0.0199)	(0.0302)	(0.0386)	(0.0306)
News: 2. Low RA; Response: Abnormal US RA							
Econ	0.0850	-0.0602	**-0.2213**	**-0.6601**	**-0.4042**	**-0.2470**	-0.0183
	(0.0634)	(0.0855)	(0.0623)	(0.0603)	(0.0374)	(0.0577)	(0.0336)
Non-Econ	*0.1575*	0.1785	-0.0226	**-0.5636**	**-0.3241**	**-0.1945**	**-0.1327**
	(0.0724)	(0.1023)	(0.0575)	(0.0426)	(0.0501)	(0.0599)	(0.0500)
Non-Crisis	0.0780	-0.0010	**-0.1807**	**-0.6277**	**-0.3994**	**-0.2135**	*-0.0626*
	(0.0437)	(0.0666)	(0.0544)	(0.0494)	(0.0324)	(0.0438)	(0.0308)
Non-Jumps	0.0729	-0.0647	**-0.2349**	**-0.5743**	**-0.3463**	**-0.1995**	*-0.0617*
	(0.0520)	(0.0675)	(0.0420)	(0.0226)	(0.0282)	(0.0443)	(0.0246)
News: 3. High UC; Response: Abnormal US UC							
Econ	-0.0050	0.1444	**0.3790**	**0.7109**	**0.6661**	**0.4832**	*0.3066*
	(0.0912)	(0.1527)	(0.1066)	(0.0768)	(0.1298)	(0.0691)	(0.1213)
Non-Econ	0.2802	**0.4126**	**0.4761**	**0.6694**	**0.4990**	*0.3920*	0.2297
	(0.1845)	(0.1600)	(0.0895)	(0.0749)	(0.0631)	(0.1558)	(0.1245)
Non-Crisis	0.1629	0.1096	**0.3237**	**0.6580**	**0.4815**	**0.2902**	0.2033
	(0.1405)	(0.1207)	(0.0706)	(0.0451)	(0.0418)	(0.0695)	(0.1266)
Non-Jumps	0.0374	0.1011	**0.4119**	**0.6458**	**0.6030**	**0.5010**	**0.3582**
	(0.0664)	(0.0915)	(0.0776)	(0.0484)	(0.0944)	(0.0908)	(0.1195)
News: 4. Low UC; Response: Abnormal US UC							
Econ	0.0206	**-0.2871**	**-0.5218**	**-0.6450**	**-0.5973**	**-0.4664**	*-0.2010*
	(0.0972)	(0.0930)	(0.0630)	(0.0421)	(0.0553)	(0.0658)	(0.0833)
Non-Econ	-0.0190	*-0.4621*	**-0.4873**	**-0.5581**	**-0.4009**	*-0.2313*	-0.0267
	(0.1637)	(0.2215)	(0.0926)	(0.0423)	(0.0869)	(0.0908)	(0.0971)
Non-Crisis	-0.0032	**-0.2941**	**-0.5087**	**-0.6351**	**-0.5730**	**-0.4362**	**-0.2346**
	(0.0860)	(0.0822)	(0.0520)	(0.0345)	(0.0466)	(0.0573)	(0.0573)
Non-Jumps	0.0088	**-0.3392**	**-0.5115**	**-0.6191**	**-0.5388**	**-0.3964**	*-0.1491*
	(0.0865)	(0.0960)	(0.0515)	(0.0322)	(0.0463)	(0.0579)	(0.0690)

	[-30, -11]	[-10, -4]	[-3, -1]	[0, 0]	[1, 3]	[4, 10]	[11, 30]
News: 1. High RA; Response: Abnormal Non-US RA							
Econ	-0.0326	0.0863	**0.2097**	**0.3635**	**0.3277**	*0.1701*	0.0319
	(0.0494)	(0.0610)	(0.0699)	(0.0739)	(0.0709)	(0.0848)	(0.0937)
Non-Econ	-0.0397	0.1083	**0.1476**	**0.3738**	**0.4183**	*0.1980*	0.0599
	(0.0721)	(0.0736)	(0.0510)	(0.0677)	(0.0806)	(0.0893)	(0.1153)
Non-Crisis	-0.0396	0.0950	**0.1771**	**0.3726**	**0.3863**	**0.1763**	-0.0162
	(0.0491)	(0.0537)	(0.0502)	(0.0555)	(0.0607)	(0.0625)	(0.0709)
Non-Jumps	-0.0542	*0.0887*	**0.1926**	**0.3635**	**0.3535**	**0.1650**	0.0188
	(0.0417)	(0.0438)	(0.0482)	(0.0548)	(0.0546)	(0.0608)	(0.0772)
News: 2. Low RA; Response: Abnormal Non-US RA							
Econ	0.0581	-0.1539	*-0.1781*	**-0.2881**	**-0.2913**	**-0.3000**	-0.0426
	(0.1188)	(0.1077)	(0.0889)	(0.0774)	(0.0689)	(0.0854)	(0.0707)
Non-Econ	0.1373	0.1280	-0.0478	*-0.2319*	*-0.2337*	*-0.1982*	-0.1505
	(0.1254)	(0.1044)	(0.0958)	(0.1083)	(0.0998)	(0.0943)	(0.0848)
Non-Crisis	0.0451	-0.0153	-0.0733	**-0.2382**	**-0.2448**	**-0.1985**	-0.0854
	(0.0818)	(0.0787)	(0.0656)	(0.0693)	(0.0595)	(0.0624)	(0.0564)
Non-Jumps	0.0873	-0.0985	*-0.1578*	**-0.2686**	**-0.2552**	**-0.2542**	-0.0624
	(0.1028)	(0.0877)	(0.0676)	(0.0560)	(0.0566)	(0.0714)	(0.0567)
News: 3. High UC; Response: Abnormal Non-US UC							
Econ	0.0036	0.1470	0.1153	*0.1780*	0.2200	0.1291	0.0220
	(0.0767)	(0.1420)	(0.0962)	(0.0897)	(0.1232)	(0.0945)	(0.0938)
Non-Econ	0.0539	0.1537	0.1996	*0.2750*	**0.3263**	0.3699	0.1658
	(0.0915)	(0.0951)	(0.1177)	(0.1350)	(0.1266)	(0.1894)	(0.1857)
Non-Crisis	0.0101	0.0216	0.1197	*0.2457*	**0.2177**	*0.1710*	0.1150
	(0.0709)	(0.0750)	(0.0801)	(0.1004)	(0.0744)	(0.0758)	(0.1340)
Non-Jumps	-0.0163	0.0696	0.1917	*0.2611*	*0.2850*	*0.2547*	0.1288
	(0.0685)	(0.1040)	(0.1011)	(0.1063)	(0.1289)	(0.1209)	(0.1217)
News: 4. Low UC; Response: Abnormal Non-US UC							
Econ	0.0580	-0.0800	**-0.1976**	**-0.2388**	**-0.2486**	**-0.1911**	*-0.1112*
	(0.0667)	(0.0587)	(0.0464)	(0.0380)	(0.0391)	(0.0473)	(0.0465)
Non-Econ	-0.0130	*-0.2237*	**-0.2060**	**-0.2395**	**-0.2281**	*-0.1468*	-0.0471
	(0.1192)	(0.0905)	(0.0677)	(0.0689)	(0.0861)	(0.0747)	(0.0542)
Non-Crisis	0.0308	-0.0896	**-0.2070**	**-0.2478**	**-0.2580**	**-0.2009**	**-0.1113**
	(0.0558)	(0.0510)	(0.0408)	(0.0347)	(0.0362)	(0.0392)	(0.0372)
Non-Jumps	0.0364	*-0.1238*	**-0.2001**	**-0.2390**	**-0.2423**	**-0.1776**	*-0.0917*
	(0.0620)	(0.0499)	(0.0407)	(0.0361)	(0.0399)	(0.0434)	(0.0383)

Table A5: Robustness: Non-US responses dropping one country at a time

	[-30, -11]	[-10, -4]	[-3, -1]	[0, 0]	[1, 3]	[4, 10]	[11, 30]
	News: 1. High RA; Response: Abnormal Non-US RA						
No CH	-0.0268	*0.0992*	**0.1900**	**0.3809**	**0.3785**	**0.1802**	0.0408
	(0.0431)	(0.0475)	(0.0465)	(0.0502)	(0.0528)	(0.0641)	(0.0759)
No DE	-0.0378	*0.1041*	**0.1939**	**0.3722**	**0.3734**	**0.1867**	0.0483
	(0.0479)	(0.0528)	(0.0473)	(0.0528)	(0.0551)	(0.0638)	(0.0800)
No FR	-0.0348	0.1017	**0.1730**	**0.3595**	**0.3670**	**0.1890**	0.0510
	(0.0474)	(0.0540)	(0.0449)	(0.0510)	(0.0562)	(0.0671)	(0.0811)
No JP	-0.0432	0.0864	**0.1814**	**0.3819**	**0.3631**	**0.1777**	0.0455
	(0.0432)	(0.0473)	(0.0460)	(0.0502)	(0.0546)	(0.0619)	(0.0719)
No NL	-0.0349	0.1001	**0.1859**	**0.3772**	**0.3797**	**0.1784**	0.0368
	(0.0471)	(0.0526)	(0.0495)	(0.0517)	(0.0571)	(0.0631)	(0.0807)
No UK	-0.0372	0.0843	**0.1625**	**0.3287**	**0.3403**	**0.1825**	0.0529
	(0.0430)	(0.0475)	(0.0446)	(0.0492)	(0.0507)	(0.0606)	(0.0750)
	News: 2. Low RA; Response: Abnormal Non-US RA						
No CH	0.0960	-0.0466	-0.1102	**-0.2481**	**-0.2540**	**-0.2410**	-0.0637
	(0.0955)	(0.0775)	(0.0725)	(0.0694)	(0.0637)	(0.0697)	(0.0605)
No DE	0.0806	-0.0585	*-0.1435*	**-0.2622**	**-0.2717**	**-0.2699**	-0.0795
	(0.0997)	(0.0834)	(0.0703)	(0.0663)	(0.0618)	(0.0691)	(0.0585)
No FR	0.0822	-0.0789	*-0.1551*	**-0.2779**	**-0.2858**	**-0.2742**	-0.0872
	(0.0971)	(0.0830)	(0.0679)	(0.0643)	(0.0609)	(0.0665)	(0.0584)
No JP	0.0813	-0.0440	-0.1250	**-0.2820**	**-0.2532**	**-0.2467**	-0.0731
	(0.0885)	(0.0788)	(0.0676)	(0.0595)	(0.0562)	(0.0631)	(0.0551)
No NL	0.0895	-0.0680	*-0.1533*	**-0.2949**	**-0.3049**	**-0.2932**	-0.0874
	(0.1049)	(0.0838)	(0.0746)	(0.0700)	(0.0631)	(0.0696)	(0.0599)
No UK	0.0829	-0.0431	-0.1114	**-0.2473**	**-0.2588**	**-0.2638**	-0.0883
	(0.0967)	(0.0766)	(0.0694)	(0.0686)	(0.0641)	(0.0692)	(0.0553)

	[-30, -11]	[-10, -4]	[-3, -1]	[0, 0]	[1, 3]	[4, 10]	[11, 30]
	News: 3. High UC; Response: Abnormal Non-US UC						
No CH	0.0090	0.1354	0.1365	**0.2044**	**0.2416**	*0.2081*	0.0700
	(0.0654)	(0.0977)	(0.0784)	(0.0784)	(0.0908)	(0.0959)	(0.0945)
No DE	0.0175	0.1427	0.1366	*0.1925*	*0.2501*	*0.2018*	0.0608
	(0.0703)	(0.1057)	(0.0857)	(0.0889)	(0.1049)	(0.0939)	(0.1000)
No FR	0.0234	0.1514	0.1485	*0.2156*	*0.2490*	*0.2096*	0.0717
	(0.0656)	(0.1073)	(0.0836)	(0.0887)	(0.0989)	(0.0983)	(0.0993)
No JP	0.0319	0.1806	0.1602	**0.2438**	**0.2960**	*0.2417*	0.0912
	(0.0784)	(0.1169)	(0.0845)	(0.0863)	(0.1074)	(0.1070)	(0.1101)
No NL	0.0236	0.1434	0.1429	**0.2061**	**0.2501**	*0.2052*	0.0621
	(0.0679)	(0.1001)	(0.0843)	(0.0793)	(0.0944)	(0.0954)	(0.1019)
No UK	0.0461	0.1710	0.1520	*0.1925*	*0.2274*	*0.1939*	0.0605
	(0.0765)	(0.1079)	(0.0863)	(0.0827)	(0.1000)	(0.0956)	(0.1008)
	News: 4. Low UC; Response: Abnormal Non-US UC						
No CH	0.0491	*-0.1157*	**-0.1959**	**-0.2361**	**-0.2375**	**-0.1695**	*-0.0833*
	(0.0603)	(0.0510)	(0.0410)	(0.0392)	(0.0414)	(0.0439)	(0.0386)
No DE	0.0300	*-0.1296*	**-0.2078**	**-0.2441**	**-0.2466**	**-0.1923**	**-0.1007**
	(0.0633)	(0.0514)	(0.0400)	(0.0378)	(0.0407)	(0.0429)	(0.0390)
No FR	0.0359	*-0.1231*	**-0.1929**	**-0.2322**	**-0.2379**	**-0.1772**	**-0.0948**
	(0.0618)	(0.0505)	(0.0405)	(0.0364)	(0.0376)	(0.0420)	(0.0351)
No JP	0.0313	*-0.1294*	**-0.2069**	**-0.2499**	**-0.2520**	**-0.1690**	*-0.0814*
	(0.0631)	(0.0526)	(0.0399)	(0.0358)	(0.0421)	(0.0458)	(0.0369)
No NL	0.0352	*-0.1252*	**-0.1998**	**-0.2369**	**-0.2437**	**-0.1854**	**-0.0976**
	(0.0606)	(0.0512)	(0.0381)	(0.0352)	(0.0372)	(0.0404)	(0.0361)
No UK	0.0368	*-0.1174*	**-0.1950**	**-0.2330**	**-0.2351**	**-0.1726**	**-0.0937**
	(0.0604)	(0.0502)	(0.0398)	(0.0359)	(0.0368)	(0.0433)	(0.0362)

Table A6: Randomization test (1): Demographic information about the experiment samples

This table presents the averages of demographic variables, across the two study samples (US and non-US) and across treatment and control groups. The four variables are also our main control variables in the regression analysis: income (in 000s, $), age, financial literacy (proxied by the fraction of correct answers in the financial literacy test), and gender indicator.

	Income (in 000s)	Age	Correct%	Female%
	Study 1, "US/US"			
High RA treatment	61.80	39.52	38%	35%
Low RA treatment	72.04	40.22	42%	43%
Control Group	63.61	39.35	45%	32%
All	65.83	39.70	42%	36%
	Study 2, "US/NUS"			
High RA treatment	48.49	30.53	52%	32%
Low RA treatment	58.77	29.39	48%	26%
Control Group	51.98	30.97	57%	34%
All	52.86	30.39	53%	31%

Table A7: Randomization test (2): pre-priming investment level

Dep. Var:	***Pre-priming Investment Level***	
Exp. Sample:	***Study 1***	***Study 2***
Shock:	***US***	***US***
Participants:	***US***	***Non-US***
High RA treatment	-32.18	44.43
	(28.883)	(40.385)
Low RA treatment	-36.34	43.96
	(28.760)	(40.413)
Observations	457	243
R-squared	0.088	0.090
Adjusted R-squared	0.074	0.003

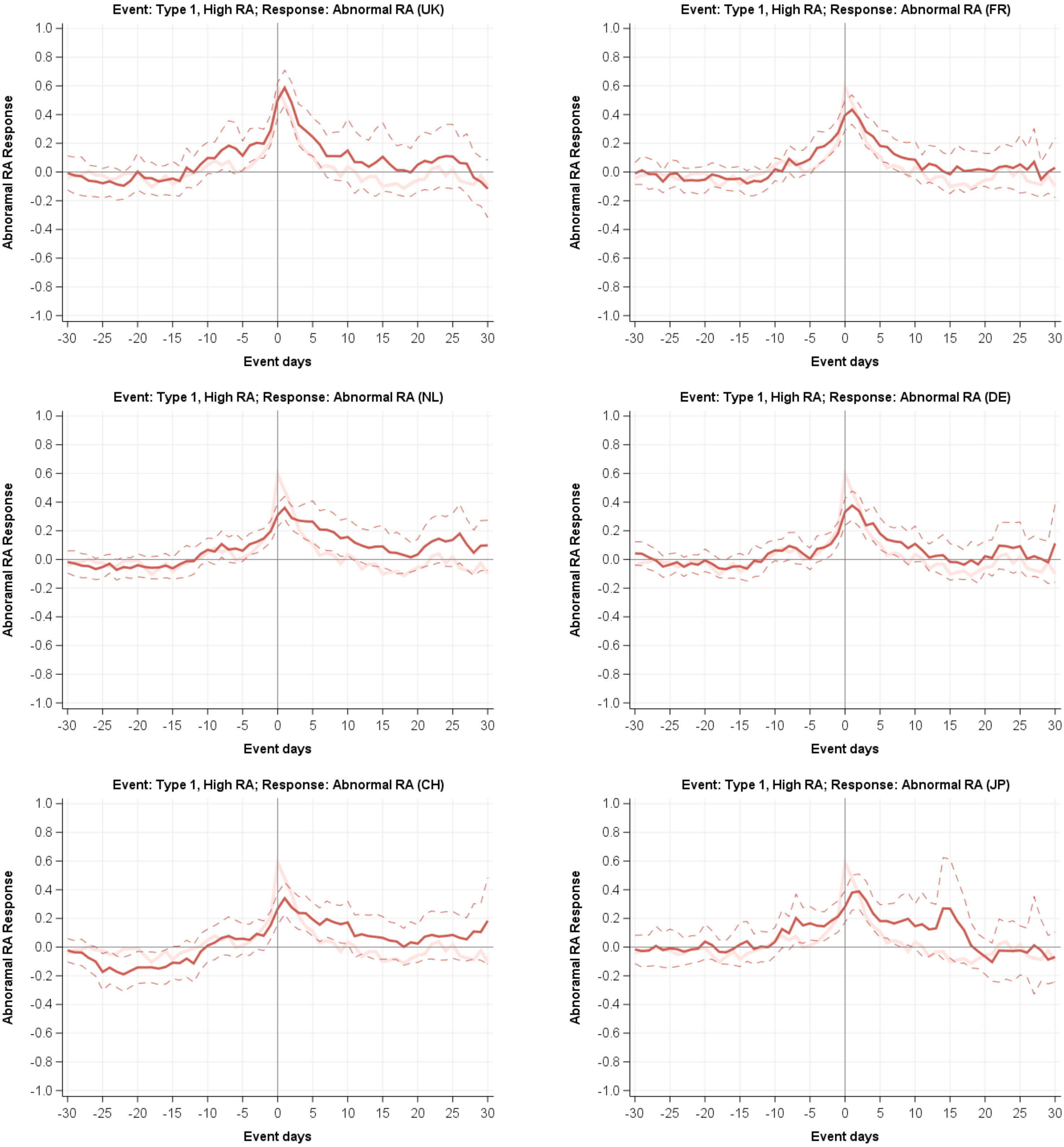


Figure A1: Event study: Abnormal country RA in response to US high-RA shocks

This figure provides the country-level evidence of the left plot of Figure 5. That is, average abnormal changes in country risk aversion on **high** US RA days, scaled by the average level of country risk aversion during the sample period. The dashed lines are 95% confidence interval. The light solid lines in the background are the US response lines (see Figure 4).

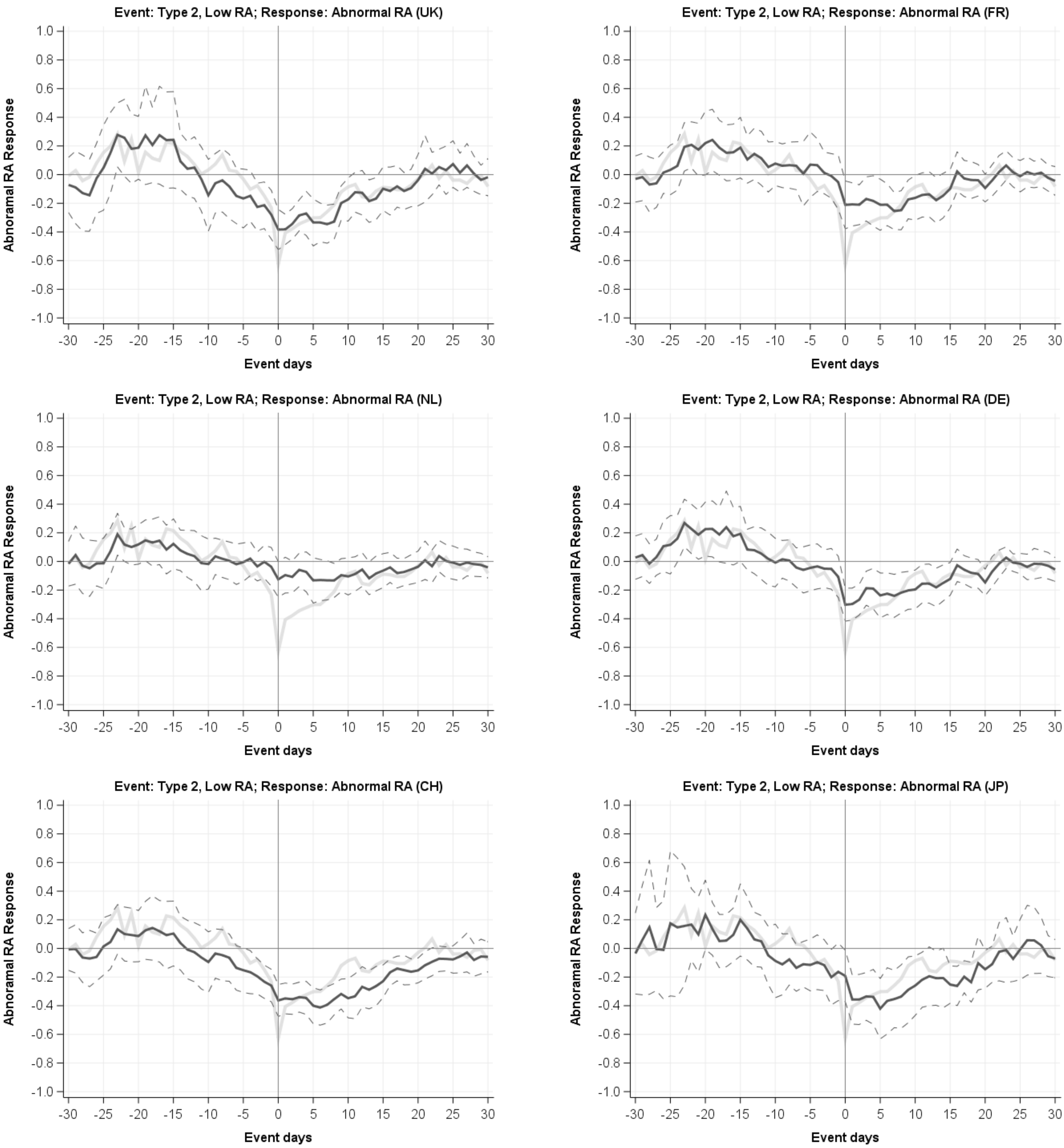


Figure A2: Event study: Abnormal country RA in response to US low-RA shocks

This figure provides the country-level evidence of the right plot of Figure 5. That is, average abnormal changes in country risk aversion on **low** US RA days, scaled by the average level of country risk aversion during the sample period. The dashed lines are 95% confidence interval. The light solid lines in the background are the US response lines (see Figure 4).

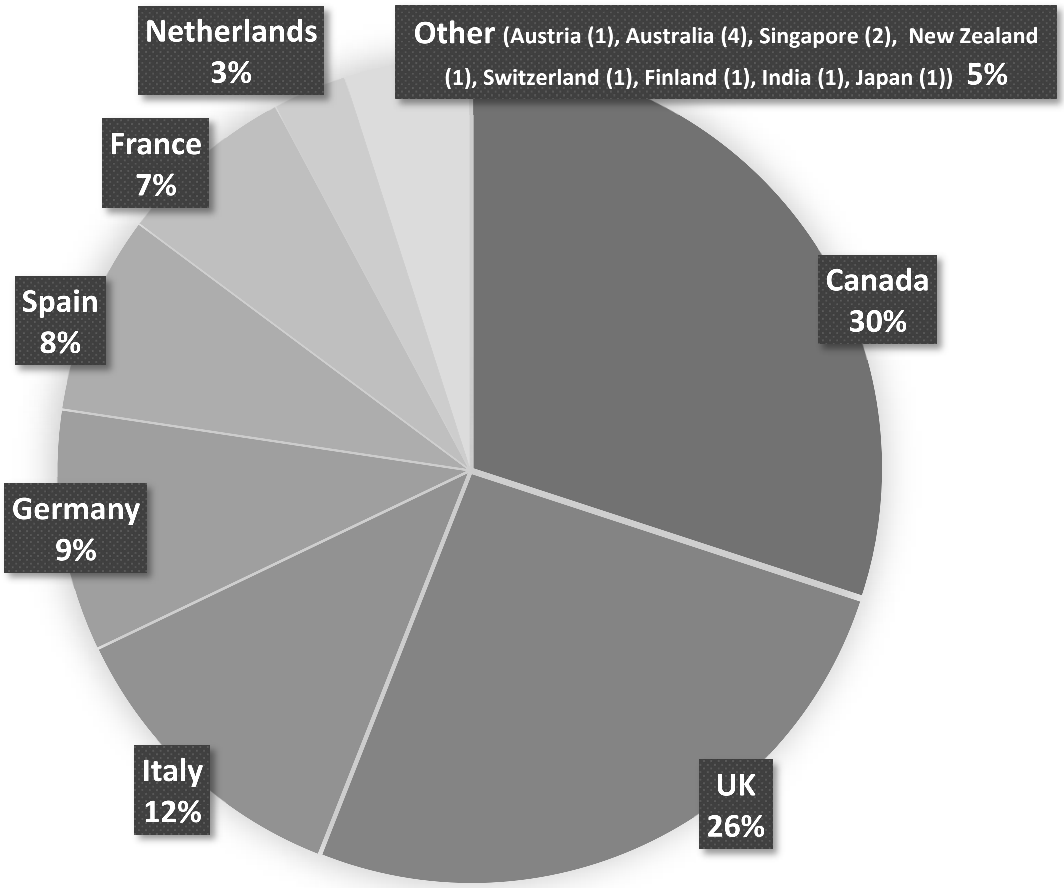


Figure A3: Residence countries of non-US participants in Study 2 (N=243)

II. Detailed event selection procedures for Section 2.2

Our event selection procedure has three steps, where the order of Step 1 and Step 2 does not matter, and the final event lists are created after Step 3. In short, we aim to assign news narratives to extreme abnormal RA or UC shocks (see Section 2.1), which helps with filtering out large shocks that are likely driven by other country news (rather than US) and identifying large shocks that are simply post-event responses. Here are more details.

Step 1. Select one positive and one negative global news of the day.

We use the full data set of the "Global Macro - Dow Jones" edition of RavenPack News Analytics from 2000/1/1 to 2017/12/30. In RavenPack, news articles around the world corresponding to the same news story are already linked by RavenPack's "g_ens_key" variable; each news article is assigned a sentiment score (ESS) (higher=more positive; lower=more negative); each news story is assigned a country code to indicate the news origin. Note that we remove news articles that are weakly related to the underlying news story (given variable "Relevance" constructed by RavenPack), and remove news stories that describe financial market prices (labeled as "foreign-exchange", "technical-analysis", or "commodity-prices" by RavenPack). Then, according to RavenPack's UserGuide 4.0, the ESS score is derived from a collection of surveys where financial experts (major brokerage firms, investment banks, and credit rating agencies) rated entity-specific events as conveying positive or negative sentiment and to what degree (e.g., having short-term positive or negative financial or economic impact). The algorithms then can dynamically assign an ESS score based on score ranges assigned by the experts and by performing analysis and computation when factors such as magnitudes, comparative values or ratings are disclosed in the story.

First, we consolidate news articles around the world to the "news story" level, and compute an average ESS and total global coverage (total number of news articles) for each news story. We consider news stories with average ESS scores >=50 as positive news stories and those with average ESS scores <=50 as negative news stories. RavenPack marks certain authority news stories as exactly neutral (ESS=50); for instance, one major category is election.

Next, on each day, we select one negative (positive) news story if it has the highest global coverage among all negative (positive) news stories on that day when its global coverage is $\geq$ 90th percentile among all news stories during the sample period (2000-2017), *or* if it has the lowest (highest) average ESS when global coverage of all negative (positive) news stories on that day is all < 90th percentile. The idea is that we mostly rely on global coverage to tell us about the news impact; but if coverage is all weak on that day, we then resort to the ranking of sentiment scores. Notice that all news, regardless of their country origins, are recorded at the UTC time, which allows us to conveniently compare news impact within the same 24 hours. At the end of this step, we obtain one positive and one negative global news of the day, with the corresponding country origin, global coverage and average ESS.

Step 2. Disentangle US risk aversion and uncertainty event candidates

We sort the US RA and UC *shock* series (constructed from Section 2.1) into 3 bins each: (1) those with magnitude greater than 90th percentile of the full sample or "High", (2) between 10th and 90th or "Normal", and (3) less than 10th or "Low". We then group dates with high (low) RA shocks but normal UC shocks as the high (low) RA event type; high and low UC event types can be obtained similarly:

Event Type:	**1.High RA**	**2.Low RA**	**3.High UC**	**4.Low UC**
RA Shock:	>90th	<10th	Normal	Normal
UC Shock:	Normal	Normal	>90th	<10th

This step potentially addresses the comoving risk variable concern. Moreover, because some stylized models would also interpret VRP as "volatility of volatility" (as discussed in Section 2.1) and empirical evidence typically finds that "vol of vol" likely strongly comoves positively with volatility itself (e.g., Segal, Shaliastovich, and Yaron (2015)), this step further controls for the changes in VRP driven by volatility-related higher moments as well without complicating the system. The third use of this step is to ensure that we are not picking up crisis period because these are almost surely accompanied by extreme RA and UC shocks (as we see in our data).

Step 3. Merge the two steps and address post events and the US origin

We merge the high (low) RA and UC event candidate dates from Step 2 with the negative (positive) news list from Step 1. Given that asset prices are only available on trading days but events can occur on any calendar day, we select the most covered news story from Saturday∼Monday as the corresponding event for Monday. Similarly, some extreme events have caused stock markets to completely shut down, such as 9/11, and the next trading day was 9/17, 2001; for 9/17, we pick the news story with the highest coverage from 9/11 to 9/17.

The news coverage metrics further helps identify post-event dates among consecutive extreme risk reaction dates (Step 2), given that we are interested in independent events. We always consider the first date of consecutive extreme risk reaction dates (from the same event group) as one event; the following days are not considered a new event unless the news story coverage is >90th percentile again. Finally, we keep the event dates in each type if the corresponding country origin is identified as "US" by RavenPack.

III. Measuring risk aversion in experiments

The Investment Task

You are managing a project with initial funding of **$1000**. You will receive **1%** of the final value of the project.

You need to decide how much to invest in a risky asset (abbreviated as **$Investment**). You keep the remaining amount (**$1000-$Investment**) as cash.

The risky asset has a **50% success rate**:

- If the investment is a success: You **earn 2.5 times** of the investment amount
- If the investment is not a success: You **lose** the investment amount

As a result, the final value of the project (including the remaining cash) can be calculated as follows:

- If the investment is a success: **$1000 - $Investment** + (**2.5 x $Investment**)
- If the investment is not a success: **$1000 - $Investment**

Please decide the investment amount (\$Investment) using the slide bar below. There are no right or wrong answers.

How many dollars would you like to invest in this risky asset ($0 - $1000)?

0 100 200 300 400 500 600 700 800 900 1000

In case it is helpful, here is a table of potential total earnings **depending on the risky investment outcome** and **your investment amount**. At the end of the task, a random number from 1 to 100 will be shown. If the number is greater than 50, then your investment turns out to be a success.

A Success (50% chance)			NOT A Success (50% chance)		
$Investment	**$Final Value**	**$Your Payment**	**$Investment**	**$Final Value**	**$Your Payment**
0	1000	10	0	1000	10
100	1150	12	100	900	9
200	1300	13	200	800	8
300	1450	15	300	700	7
400	1600	16	400	600	6
500	1750	18	500	500	5
600	1900	19	600	400	4
700	2050	21	700	300	3
800	2200	22	800	200	2
900	2350	24	900	100	1
1000	2500	25	1000	0	0

NOT FOR PUBLICATION:

Online Appendices for

"Risk Aversion Propagation: Evidence from Financial Markets and Controlled Experiments"

Table OA.1: Model selection of linear coefficient benchmark models for US and international risk aversion (proxied by VRP).

This table presents model selection results of the "expected" component of risk aversion:

$$X_{i,t} = \alpha_i + \beta_i \times MA(n)_{i,t-n,t-1} + \boldsymbol{\gamma_i} \times \boldsymbol{Z_{i,t-1}} + \varepsilon_{i,t}, \tag{.5}$$

where $X_{i,t}$ denotes variance risk premium of country i on day t; $MA(n)_{i,t-n,t-1} = \frac{1}{n}\sum_{\nu=1}^{n} VRP_{i,t-\nu}$ is a n-day moving average; $Z_{i,t-1}$ is the last available monthly or quarterly macro variable shock (first-differenced macro variable). Model 1 restricts $\beta = 1$ and $\gamma = 0$. Model 2 frees up β but sets $\gamma = 0$. Model 3 uses the best moving average model (30-day) with $\beta = 1$ and frees up γs. Model 4 is Model 3 with β as a free parameter. All models are estimated using the longest sample period of each country; sample across models is the same for each country for a fair comparison. Source: international financial market data including dividend yield are downloaded from DataStream; international macro data are downloaded from FRED; benchmark models are estimated at the daily frequency; AIC and BIC are divided by 10000 for reporting purpose. Bold indicates the best linear model.

	Switzerland, CH			Germany, DE			France, FR			Japan, JP			Netherlands, NL			United Kingdom, UK			United States, US		
	R2	AIC	BIC	R2	AIC	BIC	R2	AIC	BIC	R2	AIC	BIC	R2	AIC	BIC	R2	AIC	BIC	R2	AIC	BIC
Model 1: Restrictive																					
BM1(30)	0.846	-4.785	-4.784	0.875	-7.203	-7.203	0.822	-4.613	-4.613	0.823	-6.385	-6.384	0.893	-4.388	-4.388	0.814	-4.762	-4.761	0.758	-7.528	-7.527
BM1(60)	0.747	-4.557	-4.556	0.799	-6.891	-6.890	0.751	-4.460	-4.459	0.741	-6.108	-6.108	0.818	-4.160	-4.160	0.742	-4.600	-4.600	0.687	-7.320	-7.320
BM1(90)	0.667	-4.459	-4.458	0.737	-6.750	-6.749	0.692	-4.365	-4.365	0.667	-5.990	-5.989	0.755	-4.048	-4.048	0.678	-4.518	-4.517	0.637	-7.218	-7.217
BM1(120)	0.602	-4.397	-4.397	0.685	-6.648	-6.647	0.639	-4.301	-4.300	0.608	-5.894	-5.893	0.701	-3.972	-3.972	0.625	-4.459	-4.459	0.596	-7.144	-7.143
BM1(360)	0.336	-4.243	-4.242	0.434	-6.364	-6.363	0.376	-4.111	-4.111	0.350	-5.704	-5.704	0.431	-3.759	-3.759	0.377	-4.315	-4.315	0.424	-6.956	-6.955
Model 2: Nonrestrictive																					
BM1(30)	0.736	-4.791	-4.790	0.787	-7.210	-7.209	0.735	-4.617	-4.616	0.700	-6.395	-6.394	0.811	-4.393	-4.391	0.720	-4.766	-4.765	0.682	-7.532	-7.531
BM1(60)	0.568	-4.569	-4.568	0.654	-6.904	-6.902	0.624	-4.466	-4.465	0.551	-6.128	-6.127	0.682	-4.169	-4.167	0.595	-4.608	-4.607	0.571	-7.329	-7.327
BM1(90)	0.465	-4.474	-4.472	0.569	-6.766	-6.764	0.534	-4.374	-4.373	0.465	-6.012	-6.010	0.590	-4.059	-4.058	0.511	-4.528	-4.526	0.503	-7.228	-7.227
BM1(120)	0.389	-4.414	-4.413	0.496	-6.667	-6.665	0.462	-4.312	-4.311	0.386	-5.920	-5.919	0.514	-3.985	-3.984	0.441	-4.471	-4.470	0.447	-7.157	-7.155
BM1(360)	0.144	-4.263	-4.262	0.220	-6.392	-6.391	0.179	-4.130	-4.128	0.178	-5.727	-5.726	0.216	-3.779	-3.778	0.216	-4.327	-4.326	0.273	-6.971	-6.970
Model 3: Restrictive BM1(30) + country macro shocks																					
ΔDY	0.858	-4.786	-4.785	0.912	-7.220	-7.219	0.858	-4.621	-4.620	0.844	-6.388	-6.387	0.967	-4.425	-4.423	0.874	-4.792	-4.790	0.779	-7.538	-7.536
Δrf	0.735	-4.816	-4.814	0.841	-7.215	-7.214	0.770	-4.619	-4.618	0.825	-6.387	-6.385	0.827	-4.399	-4.398	0.763	-4.765	-4.764	0.733	-7.531	-7.530
$\Delta tsprd$	0.823	-4.806	-4.805	0.871	-7.214	-7.212	0.804	-4.618	-4.617	0.823	-6.385	-6.383	0.868	-4.397	-4.396	0.796	-4.763	-4.762	0.747	-7.532	-7.530
ΔDY+Δrf	0.749	-4.819	-4.817	0.878	-7.232	-7.230	0.804	-4.628	-4.626	0.845	-6.390	-6.388	0.897	-4.438	-4.436	0.828	-4.794	-4.792	0.756	-7.540	-7.538
ΔDY+$\Delta tsprd$	0.834	-4.807	-4.805	0.906	-7.229	-7.227	0.840	-4.625	-4.623	0.845	-6.389	-6.387	0.943	-4.432	-4.430	0.861	-4.792	-4.790	0.768	-7.540	-7.538
Δrf+$\Delta tsprd$	0.749	-4.819	-4.817	0.850	-7.217	-7.215	0.774	-4.620	-4.618	0.825	-6.387	-6.385	0.833	-4.401	-4.399	0.764	-4.765	-4.763	0.736	-7.532	-7.530
ΔDY+Δrf+$\Delta tsprd$	0.761	-4.822	**-4.819**	0.883	-7.233	-7.231	0.807	-4.628	-4.626	0.846	-6.391	-6.388	0.898	-4.438	-4.436	0.828	-4.794	-4.791	0.758	-7.541	-7.538
Model 4: Nonrestrictive BM1(30) +country macro shocks																					
ΔDY	0.738	-4.794	-4.792	0.795	-7.234	-7.232	0.742	-4.629	-4.627	0.704	-6.403	-6.401	0.831	-4.439	-4.437	0.743	-4.801	**-4.799**	0.688	-7.544	-7.542
Δrf	0.750	-4.816	-4.814	0.790	-7.217	-7.215	0.736	-4.620	-4.618	0.701	-6.398	-6.395	0.814	-4.399	-4.397	0.721	-4.766	-4.764	0.683	-7.533	-7.531
$\Delta tsprd$	0.747	-4.809	-4.808	0.790	-7.219	-7.217	0.737	-4.620	-4.618	0.700	-6.395	-6.393	0.814	-4.399	-4.397	0.721	-4.766	-4.764	0.684	-7.534	-7.532
ΔDY+Δrf	0.752	-4.819	-4.816	0.797	-7.239	-7.237	0.743	-4.631	-4.628	0.705	-6.406	**-6.403**	0.832	-4.443	**-4.440**	0.743	-4.801	-4.799	0.688	-7.544	-7.541
ΔDY+$\Delta tsprd$	0.748	-4.812	-4.809	0.797	-7.240	-7.238	0.743	-4.631	**-4.628**	0.704	-6.404	-6.401	0.832	-4.442	-4.440	0.743	-4.801	-4.799	0.689	-7.545	**-7.542**
Δrf+$\Delta tsprd$	0.752	-4.819	-4.816	0.791	-7.220	-7.218	0.737	-4.621	-4.618	0.701	-6.397	-6.395	0.815	-4.401	-4.398	0.721	-4.766	-4.764	0.684	-7.534	-7.532
ΔDY+Δrf+$\Delta tsprd$	0.754	-4.821	-4.818	0.798	-7.241	**-7.238**	0.744	-4.631	-4.628	0.705	-6.406	-6.403	0.832	-4.443	-4.440	0.743	-4.801	-4.798	0.689	-7.545	-7.541

Table OA.2: Model selection of linear coefficient benchmark models for US and international stock market uncertainty (proxied by physical variance).

This table presents model selection results of the “expected” component of uncertainty. See detailed table notes in Table OA.1, with $X_{i,t}$ being the country i's physical expected stock market uncertainty as estimated in Equation (2).

	Switzerland, CH			Germany, DE			France, FR			Japan, JP			Netherlands, NL			United Kingdom, UK			United States, US		
	R2	AIC	BIC	R2	AIC	BIC	R2	AIC	BIC	R2	AIC	BIC	R2	AIC	BIC	R2	AIC	BIC	R2	AIC	BIC
Model 1: Restrictive																					
BM1(30)	0.826	-4.924	-4.923	0.854	-6.206	-6.205	0.826	-4.382	-4.381	0.794	-7.013	-7.013	0.835	-4.422	-4.421	0.824	-4.327	-4.326	0.840	-6.918	-6.917
BM1(60)	0.714	-4.720	-4.719	0.764	-5.926	-5.925	0.723	-4.207	-4.207	0.633	-6.734	-6.733	0.737	-4.255	-4.254	0.712	-4.138	-4.137	0.717	-6.556	-6.555
BM1(90)	0.630	-4.637	-4.636	0.696	-5.799	-5.798	0.646	-4.124	-4.124	0.531	-6.652	-6.651	0.666	-4.174	-4.174	0.631	-4.068	-4.067	0.626	-6.446	-6.445
BM1(120)	0.567	-4.589	-4.589	0.641	-5.712	-5.711	0.585	-4.070	-4.070	0.465	-6.607	-6.607	0.610	-4.123	-4.123	0.571	-4.023	-4.022	0.561	-6.376	-6.376
BM1(360)	0.318	-4.448	-4.448	0.399	-5.473	-5.472	0.331	-3.931	-3.930	0.285	-6.482	-6.482	0.365	-3.962	-3.961	0.332	-3.897	-3.897	0.318	-6.203	-6.202
Model 2: Nonrestrictive																					
BM1(30)	0.694	-4.932	-4.931	0.745	-6.215	-6.214	0.698	-4.389	-4.388	0.598	-7.036	-7.034	0.710	-4.429	-4.428	0.692	-4.335	-4.333	0.704	-6.931	-6.930
BM1(60)	0.523	-4.734	-4.732	0.605	-5.940	-5.939	0.551	-4.218	-4.217	0.393	-6.764	-6.762	0.576	-4.265	-4.263	0.525	-4.150	-4.149	0.503	-6.581	-6.579
BM1(90)	0.427	-4.652	-4.650	0.519	-5.816	-5.814	0.458	-4.137	-4.135	0.311	-6.679	-6.678	0.491	-4.186	-4.184	0.441	-4.081	-4.079	0.415	-6.470	-6.469
BM1(120)	0.364	-4.605	-4.603	0.450	-5.731	-5.730	0.388	-4.084	-4.083	0.261	-6.633	-6.632	0.427	-4.135	-4.134	0.379	-4.036	-4.035	0.352	-6.401	-6.400
BM1(360)	0.136	-4.467	-4.466	0.203	-5.498	-5.496	0.158	-3.947	-3.945	0.112	-6.511	-6.510	0.178	-3.979	-3.978	0.168	-3.911	-3.910	0.158	-6.224	-6.223
Model 3: Restrictive BM1(30) + country macro shocks																					
ΔDY	0.834	-4.924	-4.923	0.873	-6.209	-6.208	0.858	-4.385	-4.384	0.833	-7.027	-7.026	0.897	-4.433	-4.432	0.892	-4.347	-4.346	0.881	-6.926	-6.925
Δrf	0.683	-4.973	-4.972	0.822	-6.217	-6.216	0.751	-4.396	-4.394	0.807	-7.015	-7.014	0.760	-4.434	-4.432	0.716	-4.339	-4.337	0.798	-6.987	-6.985
$\Delta tsprd$	0.804	-4.952	-4.951	0.854	-6.215	-6.213	0.812	-4.387	-4.386	0.796	-7.019	-7.017	0.817	-4.428	-4.427	0.782	-4.334	-4.332	0.847	-6.953	-6.952
$\Delta DY+\Delta rf$	0.699	-4.976	-4.974	0.842	-6.220	-6.218	0.785	-4.400	-4.399	0.847	-7.030	-7.028	0.821	-4.447	-4.445	0.788	-4.358	-4.356	0.831	-6.992	-6.990
$\Delta DY+\Delta tsprd$	0.811	-4.952	-4.950	0.871	-6.217	-6.215	0.843	-4.390	-4.388	0.833	-7.031	-7.029	0.877	-4.438	-4.437	0.853	-4.353	-4.351	0.879	-6.959	-6.957
$\Delta rf+\Delta tsprd$	0.698	-4.976	-4.974	0.831	-6.218	-6.216	0.753	-4.396	-4.394	0.807	-7.020	-7.018	0.765	-4.434	-4.432	0.719	-4.339	-4.337	0.804	-6.988	-6.986
$\Delta DY+\Delta rf+\Delta tsprd$	0.711	-4.978	**-4.975**	0.848	-6.221	-6.218	0.785	-4.400	-4.398	0.845	-7.033	-7.030	0.822	-4.447	-4.444	0.789	-4.358	-4.356	0.836	-6.994	-6.991
Model 4: Nonrestrictive BM1(30) +country macro shocks																					
ΔDY	0.695	-4.934	-4.932	0.748	-6.222	-6.220	0.704	-4.398	-4.396	0.611	-7.059	-7.057	0.724	-4.450	-4.448	0.713	-4.364	**-4.362**	0.712	-6.951	-6.949
Δrf	0.721	-4.974	-4.972	0.748	-6.221	-6.219	0.704	-4.397	-4.395	0.601	-7.041	-7.039	0.714	-4.435	-4.433	0.695	-4.339	-4.337	0.729	-6.990	-6.988
$\Delta tsprd$	0.710	-4.956	-4.954	0.748	-6.223	-6.221	0.701	-4.393	-4.391	0.601	-7.041	-7.039	0.713	-4.433	-4.431	0.694	-4.337	-4.336	0.719	-6.966	-6.964
$\Delta DY+\Delta rf$	0.722	-4.976	-4.973	0.750	-6.228	-6.225	0.709	-4.404	**-4.402**	0.616	-7.065	-7.063	0.727	-4.454	**-4.451**	0.713	-4.364	-4.362	0.733	-7.002	-6.999
$\Delta DY+\Delta tsprd$	0.711	-4.957	-4.955	0.751	-6.229	-6.226	0.706	-4.400	-4.398	0.614	-7.062	-7.059	0.726	-4.452	-4.450	0.713	-4.365	-4.362	0.725	-6.980	-6.977
$\Delta rf+\Delta tsprd$	0.722	-4.976	-4.974	0.749	-6.224	-6.221	0.704	-4.397	-4.394	0.604	-7.046	-7.043	0.715	-4.435	-4.433	0.696	-4.339	-4.337	0.730	-6.993	-6.990
$\Delta DY+\Delta rf+\Delta tsprd$	0.723	-4.978	-4.975	0.751	-6.230	**-6.227**	0.709	-4.404	-4.401	0.617	-7.068	**-7.065**	0.727	-4.454	-4.450	0.713	-4.365	-4.361	0.734	-7.004	**-7.000**

Table OA.3: Empirical measures of risk aversion shocks: Benchmark model estimation results

This table presents the estimation results of statistical models for country risk aversion of each country. Model 1 (Model 2) is the chosen model assuming constant (time-varying) predictive coefficient according to the BIC criteria; model selection are reported in Table OA.1; macro shocks are standardized first; their coefficients are multiplied by 10000 for reporting purpose. The time variation in the predictive coefficient is spanned by the country-specific OECD recession indicator (1=recession; 0=non-recession) to capture the potential cyclical forecast model instability. Bold (italic) values indicate that the coefficient is significant at the 1% (5%) significance level.

	CH	DE	FR	JP	NL	UK	US
				Model 1: Constant loadings			
Constant	-0.1411	**0.8593**	**1.3235**	**2.3716**	**1.5143**	**0.9619**	**0.9830**
	(0.1606)	(0.1287)	(0.2342)	(0.2976)	(0.2814)	(0.1586)	(0.1714)
BM1(30)	1	**0.9398**	**0.9293**	**0.8996**	**0.9379**	**0.9103**	**0.9386**
		(0.0063)	(0.0087)	(0.0077)	(0.0078)	(0.0085)	(0.0078)
ΔDY	**0.7188**	**1.4395**	**1.8462**	**2.4613**	**4.6808**	**2.5525**	**1.2724**
	(0.1621)	(0.0953)	(0.1664)	(0.2445)	(0.2069)	(0.1259)	(0.1117)
Δrf	**1.8283**	**0.4019**		**1.3373**	**1.2757**		
	(0.2009)	(0.1215)		(0.2375)	(0.2362)		
$\Delta tsprd$	**-1.1226**	**-0.5507**	**-0.7241**				**-0.4913**
	(0.2000)	(0.1168)	(0.1645)				(0.1122)
R2	0.793	0.801	0.741	0.686	0.831	0.739	0.687
AIC	-51829.0	-76517.7	-50116.9	-66876.5	-48114.2	-51960.7	-79032.3
BIC	-51803.1	-76483.7	-50091.2	-66849.1	-48088.4	-51941.4	-79004.8
				Model 2: Time-varying loadings			
Constant	**0.4904**	**1.3684**	**1.9110**	**3.2111**	**2.4691**	**0.7571**	**1.1542**
	(0.1663)	(0.1420)	(0.2726)	(0.3106)	(0.3079)	(0.1601)	(0.1753)
BM1(30)	1.0000	**0.8689**	**0.8478**	**0.7998**	**0.8617**	**0.9228**	**0.9119**
		(0.0138)	(0.0225)	(0.0157)	(0.0206)	(0.0118)	(0.0107)
BM1(30)$\times I_{rece.}$		**0.0770**	**0.0755**	**0.0906**	**0.0814**	-0.0161	**0.0364**
		(0.0129)	(0.0200)	(0.0158)	(0.0193)	(0.0134)	(0.0106)
ΔDY	0.3069	**0.5166**	0.3502	0.1983	**1.3795**	**1.0196**	*0.4169*
	(0.2696)	(0.1548)	(0.2390)	(0.3293)	(0.3431)	(0.1712)	(0.1787)
$\Delta DY \times I_{rece.}$	**0.9405**	**1.2658**	**2.6943**	**4.5558**	**4.7430**	**3.2114**	**1.3602**
	(0.3352)	(0.1952)	(0.3271)	(0.4941)	(0.4227)	(0.2479)	(0.2293)
Δrf	*-0.7357*	-0.1237		0.0749	**-1.7221**		
	(0.3290)	(0.1838)		(0.4025)	(0.3997)		
$\Delta rf \times I_{rece.}$	**3.2756**	**0.9660**		**2.0296**	**4.4545**		
	(0.4360)	(0.2463)		(0.5010)	(0.4830)		
$\Delta tsprd$	0.2822	0.1950	0.4488				-0.1038
	(0.2598)	(0.1583)	(0.2505)				(0.1770)
$\Delta tsprd \times I_{rece.}$	**-2.8484**	**-1.3693**	**-2.1593**				**-0.8341**
	(0.3950)	(0.2335)	(0.3305)				(0.2300)
R2	0.796	0.808	0.748	0.693	0.839	0.749	0.689
AIC	-52074.2	-76719.4	-50246.9	-67014.2	-48340.5	-52122.2	-79094.0
BIC	-52028.9	-76658.2	-50201.8	-66966.3	-48295.4	-52090.0	-79045.9
N	4817	6630	4642	6956	4644	4589	7098

Table OA.4: Empirical measures of uncertainty shocks: Benchmark model estimation results

This table presents the estimation results of empirical, reduced form benchmark models for country uncertainty of each country. Other table details are discussed in Table OA.3.

	CH	DE	FR	JP	NL	UK	US
Model 1: Constant loadings							
Constant	-0.0887	**2.5659**	**2.2728**	**5.2519**	**2.4509**	**3.1828**	**1.4864**
	(0.1345)	(0.3304)	(0.3749)	(0.3290)	(0.3314)	(0.3151)	(0.2156)
BM1(30)	1.0000	**0.9293**	**0.9226**	**0.8423**	**0.9036**	**0.8762**	**0.9242**
		(0.0071)	(0.0103)	(0.0087)	(0.0102)	(0.0090)	(0.0074)
ΔDY	**0.4747**	**1.7599**	**2.1007**	**2.8974**	**3.0932**	**3.8993**	**1.6387**
	(0.1358)	(0.2152)	(0.2209)	(0.1634)	(0.2104)	(0.2124)	(0.1708)
Δrf	**2.2958**	**0.9073**	**1.7656**	-0.1960	**1.1984**		**3.0981**
	(0.1682)	(0.2698)	(0.2321)	(0.1629)	(0.2264)		(0.2104)
$\Delta tsprd$	**-0.8349**	**-1.2427**		**0.9368**			**-1.0714**
	(0.1674)	(0.2611)		(0.1620)			(0.2032)
R2	0.741	0.755	0.706	0.610	0.725	0.711	0.731
AIC	-53539.0	-65882.8	-47690.8	-72343.7	-48220.7	-47303.5	-73695.5
BIC	-53513.1	-65848.8	-47665.0	-72309.4	-48194.9	-47284.2	-73661.1
Model 2: Time-varying loadings							
Constant	**0.4971**	**3.8668**	**4.0323**	**5.6260**	**3.8965**	**3.1189**	**2.7039**
	(0.1386)	(0.3709)	(0.4472)	(0.3625)	(0.3857)	(0.3383)	(0.2387)
BM1(30)	1.0000	**0.8671**	**0.8197**	**0.8071**	**0.7903**	**0.8713**	**0.8549**
		(0.0140)	(0.0231)	(0.0138)	(0.0226)	(0.0133)	(0.0145)
BM1(30)$\times I_{rece.}$		**0.0528**	**0.0922**	*0.0230*	**0.1059**	0.0010	**0.0721**
		(0.0120)	(0.0192)	(0.0103)	(0.0193)	(0.0128)	(0.0140)
ΔDY	-0.0066	-0.3137	*0.6357*	**0.9745**	**0.9719**	**1.8790**	**0.9922**
	(0.2247)	(0.3468)	(0.3155)	(0.2223)	(0.3441)	(0.2872)	(0.2579)
$\Delta DY \times I_{rece.}$	**1.0418**	**2.8265**	**2.9866**	**4.0536**	**3.1435**	**4.2988**	**1.4485**
	(0.2794)	(0.4369)	(0.4310)	(0.3244)	(0.4252)	(0.4167)	(0.3355)
Δrf	-0.1322		-0.0800	*0.6174*	-0.3879		-0.2653
	(0.2742)		(0.4748)	(0.2732)	(0.4027)		(0.3369)
$\Delta rf \times I_{rece.}$	**3.2096**		**3.1705**	**-1.1966**	**2.4525**		**3.8839**
	(0.3634)		(0.5470)	(0.3409)	(0.4805)		(0.4423)
$\Delta tsprd$	0.3275	0.5255		**1.7209**			0.4909
	(0.2166)	(0.2947)		(0.2658)			(0.2681)
$\Delta tsprd \times I_{rece.}$	**-2.3099**	**-4.3677**		**-1.3519**			**-3.0978**
	(0.3292)	(0.4158)		(0.3338)			(0.4075)
R2	0.761	0.762	0.714	0.621	0.732	0.718	0.731
AIC	-53829.1	-66052.4	-47813.3	-72532.6	-48334.4	-47408.5	-74058.4
BIC	-53783.7	-66004.8	-47768.2	-72471.0	-48289.3	-47376.3	-73996.6
N	4817	6630	4642	6956	4644	4589	7098