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

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Abstract

We study risk aversion (RA) spillover 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 spillover. In our lab experiment, non-US subjects when primed with a US financial bust shock exhibited asymmetrically more negative and less positive emotions, 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 spillover asymmetry in our experiment.

Keywords: risk aversion, spillover, emotions, animal spirits, 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 (2021b)). Moreover, the behavioral literature has long suggested a non-fundamental component in asset comovement (e.g., Bodurtha Jr, Kim, and Lee (1995), Baker, Wurgler, and Yuan (2012)), and comoving risk aversion could be one meaningful non-fundamental source.

In this paper, we aim to address this knowledge gap by studying how risk aversion of non-US investors respond to US risk aversion events. We first use financial market and news data (2000-2017) to identify events that lead to extreme changes in US risk aversion. 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 spillover. In the second part of the paper, we conduct two controlled experiments to examine testable mechanisms. In our main experiment, non-US subjects when primed with a US stock market bust shock exhibited asymmetrically more negative and less positive emotions, 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 spillover. This excessive emotion response to foreign negative shocks could be linked to unfamiliarity. Compared to other

[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 (2021a) explore a wide range of financial and economic data.

testable but insignificant channels such as beliefs about fundamental spillovers, such an emotion-related mechanism significantly explained 20% of the spillover 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 country risk aversion 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 (2021a)). 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. 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 obtain abnormal changes in country risk aversion (RA) by projecting country risk aversion onto a moving-average term and a collection of past fundamental variables; abnormal changes in uncertainty (UC) are obtained in a similar way. Finally, to separate RA events from UC events, we identify RA event dates as those with extreme US abnormal risk aversion changes but mild abnormal uncertainty changes. To address the country origin concern, we further link the RA event dates to the most covered news of the day according to the RavenPack database and then keep the dates with news that originated from the US. We apply similar procedures to identify US high and low UC events.

One advantage of our approach is to systematically obtain potential narratives of US risk aversion or uncertainty events, some of which have been sporadically studied in the extant literature.[2] Out of the identified 146 US risk aversion events and 77 uncertainty

[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,

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). Among the largest category – Economy news (e.g., macroeconomic and monetary policy announcements) – we find evidence that, for instance, bad Economy news that drive up risk aversion more (than future volatility expectation) tend to correspond to a period when there has already been a downward *trend* in the economy and the news articles likely contain more sentiment words such as "worried", "anxious", "less confident" and so on.

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. 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 at the 1% significance level, documenting an *asymmetric* US risk aversion spillover. Our main empirical result is robust to various news categories, country compositions, and exclusions of 2008 crisis period or stock market jump days.

Interestingly, we find that United Kingdom, France, and the Netherlands contribute more to the asymmetric responses than Switzerland, Japan and Germany. Expanding our observational event study into a panel setting, we then explore whether certain fundamental and non-fundamental country indicators explain this cross-sectional difference, using including bilateral trade, asset holdings, banking claim comovement, and Gallup's well-being survey. We find supportive evidence that country's Gallup emotional instability level significantly and positively correlates with country's asymmetric spillover response to US risk aversion events. United Kingdom, France and The Netherlands exhibit higher percentages of adults who reportedly experience emotional changes on a daily basis. This exploratory panel analysis highlights the potentially important role of non-fundamental spillover channels, which motivates the experimental design next, where we can examine mechanisms in a more controlled framework.

In the second part of the paper, we design two experiments to explore potential mechanisms for asymmetric risk aversion spillover 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 how non-US participants' risk aversion respond

and Fulghieri (2013) weather risk; Wang and Young (2020) terrorist shocks; Guiso, Sapienza, and Zingales (2018) economic crisis; and so on.

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 spillover of risk aversion.

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 the time-series cyclicality of risk aversion, we are interested in the spillover effects of risk aversion. Therefore, we design our control, 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 control for various built-in risk aversion heterogeneities (especially given that we need non-US participants), 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 the economic interpretation of our treatment shocks. In Study 2, we find that non-US participants when primed with a US bust shock exhibited asymmetrically lower risky investment level (asymmetrically 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 spillover.

To explore the underlying mechanisms for asymmetric spillover, 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 in our experimental setting.

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 and/or less positive 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)) which track both positive and negative emotions. 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. 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 whether 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)). We indeed find in our experiment that participants who are more familiar with the US and its financial markets exhibited a reduced asymmetric effect.

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 (2021b), Karolyi, Lee, and Van Dijk (2012) and so on). Our evidence shows that local shocks could transmit internationally through risk aversion spillovers.

Third, by utilizing both news and financial market data in our shock identification procedure, we are among the first to systematically suggest narratives for spikes in VIX, VRP, or stock market uncertainty in an 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 regarding risk variables; 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 spillover 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 US events that trigger US risk aversion to change, or "risk aversion" events. Section 3 conducts the event study analysis, and establishes how international risk aversion responds to US risk aversion events. 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 US events that trigger extreme responses of US market-wide risk aversion, or hereafter call them US "risk aversion events," to be used in our event studies in Section 3. There are four conceptual and empirical challenges to be addressed, as mentioned in the Introduction: measurement, comoving risk variables, country origin, and narrative validation. Section 2.1 motivates and constructs our measures of aggregate market risk aversion (RA) and its abnormal changes 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 its abnormal changes

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. For instance, habit-formation type utility as in Campbell and Cochrane (1999) hypothesizes that the time variation in risk aversion is likely driven by relative magnitudes of 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 (2021a) 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 country risk aversion. Following the literature, VRP is 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"). Take US as an example. The VIX index is the square root of variance swap with SP 500 index as the underlying asset and a maturity of one month (22 trading days), capturing the variance swap buyers' expectation of future market realized variance. As a result, the difference between variance swap buyers' and econometricians' expectations of future market variance captures precisely the compensation demanded by variance sellers in a variance swap contract for giving up their hedging position. Intuitively, when market-wide investor risk aversion is higher than normal, variance sellers would demand a higher risk compensation for giving up the hedging position, hence higher VIX and higher VRP.[4]

Notedly, we are not the first to use VRP as an empirical proxy for market-wide or country aggregate risk aversion in the recent macroeconomics and finance literature (see e.g. Bekaert, Hoerova, and Lo Duca (2013), Martin (2017), and Miranda-Agrippino and Rey (2020) among many others). Recent predictability literature has shown robust

[3] Although the National Income and Product Accounts also releases a monthly consumption series, this series is knowingly 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).

[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 that does not include 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.

empirical evidence on the 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), while 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 (2021a)).

Adding to its close economic relation with risk aversion, the second advantage of using country VRP as empirical proxy for country risk aversion in the present research 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). Given that variance swap markets are highly liquid but heavily segmented across countries (Lakonishok, Lee, Pearson, and Poteshman (2007)), one can interpret country VRP as the representative agent's risk aversion for the corresponding country. 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).[5]

Next, we obtain the abnormal changes in country VRP, relative to their recent time-series behaviors that can be explained by moving-averages and recent business cycle conditions. Our empirical design is to first identify US events that trigger abnormal US risk aversion changes using financial market and news data (hence calling them "risk aversion events"; see Section 2.2), and then examine how other countries' risk aversion behave on US event days (Section 3) that cannot be explained by predictable time-series behaviors.

2.1.2. Construction

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

$$IV_{i,t} = \underbrace{E_t\left[RV_{i,t+22}^{(22)}\right]}_{Uncertainty\ \text{``}UC\text{''}} + \underbrace{VRP_{i,t}}_{Risk\ aversion\ \text{``}RA\text{''}} . \tag{1}$$

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

[5]This non-US country list explains around 20% of the world GDP (US, 24%) and 21% of the world total market capitalization (US, 36%), according to the World Bank and the World Federation of Exchanges.

(2011), Andersen, Bollerslev, and Diebold (2010); Bekaert and Hoerova (2014), Liu, Patton, and Sheppard (2015), Bekaert, Hoerova, and Xu (2021b) among many others):[6]

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

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. Our sample is from February 15, 2000 to December 29, 2017.

We then obtain the abnormal changes in country risk aversion $\varepsilon^{RA}_{i,t}$:

$$\underbrace{VRP_{i,t}}_{Risk\ aversion\ \text{``}RA\text{''}} = \underbrace{\alpha_i + \beta_i \times MA(n)_{i,t-n,t-1} + \boldsymbol{\gamma_i} \times \boldsymbol{Z_{i,t-1}}}_{Expected} + \underbrace{\varepsilon^{RA}_{i,t}}_{Abnormal\ RA}, \tag{3}$$

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).[7] 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). Since we are interested in risk aversion responses to news, this framework allows us to obtain abnormal RA measures that tease out recent level and fluctuations driven by business cycle variables for each country.

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 "Abnormal UC." We relegate model selection details and benchmark model coefficient estimates to our 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 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; sec-

[6] There is a voluminous literature on realized variance forecasting to obtain econometricians' conditional variance measures. Although there shows different statistical power, researchers typically find that the resulting expectations are highly correlated across methods in terms of economic magnitude (e.g. Bekaert and Hoerova (2014), Liu, Patton, and Sheppard (2015)).

[7] Using first differences helps circumvent collinearity issues with the moving average term in this projection model.

ond, 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 mentioned earlier and motivates our fixes (i.e., abnormal calculation to tease out common business cycle trends, and event selection using double sorts as discussed later in Section 2.2). Indeed, Table 2 summarizes country abnormal risk aversion and uncertainty, and the correlations in Panel E are all lower, compared to those using the *raw* measures (Table 1). This observation is hence not surprising. Time series of US (international) abnormal changes in risk aversion and uncertainty 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 abnormal risk aversion. 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 RA enough." These two concerns remain to be resolved.

To address the two specific concerns, we propose a news-integrated methodology to select US high / low risk aversion events. We provide detailed step-by-step instruction in Appendix II, and below, we summarize core intuitions. The order of Step 1 and Step 2 does not matter, and the final event lists are created after Step 3:

Step 1 We use a comprehensive news database RavenPack to obtain coverage, sentiment and the country origin for each news story from 2000 to 2017. Specifically, we first consolidate news articles around the world to the "news story" level (using RavenPack's unique news story identifier); then, for each news story, we compute the total number of news articles as proxy for global coverage and the average sentiment score across news articles. We consider news stories with average sentiment scores >=50 as *positive* news stories, and those with average sentiment scores <=50 as *negative* news stories.

Step 2 We turn to the financial market data, and keep dates with extreme US abnormal RA changes $\varepsilon^{RA}_{US,t}$ but middle US abnormal UC changes $\varepsilon^{UC}_{US,t}$, as our candidates for US RA events. To be more specific, we sort dates on the US abnormal RA and UC shock series (constructed from Section 2.1) into 3 bins separately: (1) those with magnitude greater than 90th percentile of the full sample or "High", (2) between 10th and 90th or "Middle", and (3) less than 10th or "Low". We then group dates with high (low) RA shocks but middle UC shocks as the high (low) RA event candidates; high and low UC event candidates can be obtained similarly:

Event Type:	**1.High RA**	**2.Low RA**	**3.High UC**	**4.Low UC**
Abnormal RA Change	>90th	<10th	Middle	Middle
Abnormal UC Change	Middle	Middle	>90th	<10th

This step further addresses the comoving risk variable concern, and teases out the part of VRP shocks that may come from volatility-based explanations without complicating the system. The second use of this step is to ensure that we are not picking up crisis periods because they are often accompanied by both extreme RA and UC abnormal changes (as we observe in our data). By design, the four event type dates do not overlap.

Step 3 We merge RavenPack news stories (from Step 1) with RA and UC event date candidates (from Step 2) to address the US origin concern and provide potential news event narratives in a systematic way. Specifically, we assign the most covered negative (positive) news on that day to each of the High (Low) RA event dates. We do the similar steps for UC event dates. Finally, we drop events if their origin is not US.

2.3. Event Summary and Potential Narratives

Table 3 summarizes 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 throughout the paper, for comparison and benchmark purposes. Using our methodology which aims to address the four aforementioned challenges, We are able to 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 evenly distributed over time, which is expected by construction. We are interested in news-driven – rather than trend-driven – risk aversion changes.

One advantage of our integrated approach using financial market and news data is that we are able to let the data speak and obtain potential event narratives (of what may trigger US risk aversion to change) in a relatively systematic way, while the current literature typically examines the effect of one particular event type on risk aversion at one time (see e.g. Brunnermeier and Nagel (2008) studying wealth fluctuations; Bassi, Colacito, and Fulghieri (2013), weather risk; Guiso, Sapienza, and Zingales (2018), economic shocks; Wang and Young (2020), terrorist shocks; and so on). For consistency, we adopt RavenPack's five news categorizations: Business, Economy, Environment, Politics, and Society. Table 4 summarizes the distribution of event categories in each event type, given RavenPack (primary source) and Wall Street Journals (manual verification by four independent research assistants).[8]

[8]Appendix Table A6 provides more details regarding subcategories.

Through the lens of our approach, what kind of news drive risk aversion (but not uncertainty) in the US? We share two observations next. First, we focus on the comparison across news categories. Economy news share the largest fractions 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 are categorized as "Economy." Therefore, it is more meaningful to compare the presence of the same news category across different event types. 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 confirms 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 changes in emotions, fear and anxiety. This category is also what the behavioral literature typically has in mind when thinking about "risk aversion events." 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 shows that market risk appetite was high on the 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.

Second, since Economy news account for the majority of news stories in all four event types, we zoom in on this news category to gain some intuition about what economic narratives separate RA events from UC events. News articles in the Economy news category mostly land on macroeconomic and monetary policy announcement dates. Among the 46 Economy news under Event Type 1 "High RA", news about consumption, production, employment announcements share about 25% each, with the remaining 15% from interest rate news and 10% from other macro news (such as housing, public finance, balance sheet etc). This distribution of macro variable announcements looks quite similar across four event types.

While there is little literature that we can rely on to conceptualize why certain "worse-than-expected" macro numbers should affect RA more than UC, we go straight into news articles to gain insights, and Appendix III lays out a few Economy news examples for demonstration purpose. On one hand, the bad Economy news that drive up risk aversion

[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.

more ("high RA" event) tend to correspond to a period when there has already been a downward *trend* in the economy, leading up to this announcement; and this additional bad macro news makes investors "worried", "anxious", "less confident", and "skittish about job and income prospects" (see the 6/29/2010 example, following the release of the Consumer Confidence Index). On the other hand, the bad Economy news that drive up uncertainty more ("high UC" event) tend to correspond to a period when – intuitively – there has been rising fluctuations in the recent period, underscoring broad economic uncertainty. The low RA and UC narratives appear to mostly mirror the high RA and UC narratives, respectively; it is also interesting to note that a few Federal Reserve Chairman's speeches (on non-FOMC days) have also played a rule in lowering price fluctuations in the financial market (see the 4/14/2009 example).

3. Event Study

Conceptually, some US news trigger US risk aversion to change abnormally; international investors also respond to these US news, causing changes in their risk aversion. The ratio of foreign to domestic responses, or pass-through, constitutes our measure of "risk aversion spillover." To establish this story using observables, we first use an event study approach to examine domestic and international risk aversion responses in Sections 3.1 and 3.2. Then, we construct and examine the properties of the pass-through ratios, followed by a series of robustness results. We similarly obtain a measure of "uncertainty spillover" for comparison purpose. Lastly, we explore potential mechanisms using surveys and economic data in Section 3.3.

3.1. Domestic responses: Economic magnitudes of chosen events

The objection in this domestic response analysis is to obtain a baseline economic magnitude, whereas the directional effect is mechanical given the construction of US risk aversion events in Section 2.2. For each event horizon from Day -30 to Day 30 and for each event type, we construct the average US abnormal risk aversion changes across events, scaled by the sample average of US risk aversion (VRP):

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

where ε^{RA}_{US} denotes the US abnormal risk aversion (residual 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 similar effects (in terms of magnitude) 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. Some anticipatory movements in risk aversion (with a much smaller economic magnitude) show up, which is mostly from the "Economy" news category. Section 2.3 discusses that more than half of the high or low RA events are based on macro variable announcement news, which by design are mostly pre-scheduled events. To further demonstrate this point, the left panel of Appendix Table A7 shows the Economy, No-Economy, No-Economy-Business results separately, and the anticipatory movements become statistically insignificant in the two latter cases. Lastly, Column "[1, 3]" in Table 5 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).

On the other hand, 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 comprise most of the high or low UC event groups, and they are likely scheduled events.[10]

Finally, we conduct a validation analysis and examine the average abnormal risk aversion (uncertainty) changes on UC (RA) event dates, or what we call "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 significantly weaker than direct responses (see Appendix Table A8, Panel B).

3.2. Foreign responses: Asymmetric risk aversion spillover

For each event horizon from Day -30 to Day 30 and for each event type, we calculate the average country abnormal risk aversion changes across event days, scaled by the sample average of country risk aversion, and then obtain a cross-country average:

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

where ε_i^{RA} denotes the abnormal risk aversion changes 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

[10]As seen in our evidence (Table 4), more than 86% of our selected extreme UC days are explained by fundamental news categories, Business or Economy. In particular, we find that Economy news show the higher fraction in the low than the high UC event group. This result is also consistent with Baker, Bloom, Davis, and Sammon (2020) where they use a different methodology and show that "policy events (particularly monetary policy) reduce future stock-volatility."

VRP; and C indicates the total number of countries-of-interest, 6, given the data availability as explained in Section 2.1. Table 6 shows that 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. Figure 5 displays the corresponding international responses (left: US high-RA event list; right: US low-RA event list).[11] Foreign responses exhibit overall similar patterns as domestic responses.

We discuss our main Pass-Through results next. "Pass-Through" is defined 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 with the null that the international pass-through of high RA events is equal to that of low RA events. The first column uses all chosen events, as displayed in Table 4. The pass-through levels of US risk aversion events are significantly different at the 1% significance test; specifically, the high RA event type exhibits an average pass-through around 61% (Bootstrapped SE=3%), while the low RA event type 43% (Bootstrapped SE=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.

We next 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. As discussed in Section 2.2, our US risk aversion event identification strategy does not start with certain priors of what kind of news should be "risk aversion" news; instead, we let the data speak by exploiting a double-sorting strategy with asset prices and interpreting them using news data. This way, composition of news category in each event type is a result of our paper, not an assumption. As events are selected using US data, an "asymmetric" international response is not guaranteed. However, it is still worth checking 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. It is comforting to see that news categories that are normally perceived to be "risk aversion-related" in the behavioral literature – such as societal news in Wang and Young (2020) – indeed show much stronger asymmetry in the risk aversion propagation. Under the "No-Econ-Bus" group that comprises of only political, environmental and societal news, the pass-through for US high-RA events is 0.58, doubling that for US low-RA events (equality

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

test t statistics = 2.63***).[12] Similarly, set "(4)" shows robustness after dropping the events during the 2008-09 period.

Country heterogeneity "jackknife" exercise. In robustness set (3), we drop one country at a time and re-examine the pass-through (a)symmetry. The symmetry hypotheses are all rejected. Dropping United Kingdom, France or the Netherlands appears to weaken the asymmetry spillover result more than dropping Switzerland, Japan or Germany. This suggests that the underlying mechanisms of asymmetric risk aversion spillover may relate to some different features of these two groups of countries. This evidence motivates our mechanism explorations next in Section 3.3.

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 is that non-US risk aversion simply responds to US stock market jumps rather than US risk aversion events. To address this point, we exclude major US stock market jump dates as documented in Baker, Bloom, Davis, and Sammon (2020), which are downloadable at `www.stockmarketjumps.com` and indeed 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. Set "(5)" of Table 7 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 SE=6%) and 39% (Bootstrapped SE=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 A7-A9.

In summary, our observational study thus far documents the following empirical facts:

1. There are some US events that trigger extreme responses of US risk aversion as opposed to uncertainty, and international market-wide risk aversion responds more to high RA events, rendering an "asymmetric risk aversion spillover" phenomenon that we document in this paper.
2. While political, environmental and societal news are more perceived as "risk aversion events" in the behavioral literature, our methodology shows that the asymmetric spillover result holds robustly if we look within *Economy* news only.
3. The narrative discussions suggest that Economy risk aversion news typically come with an existing trend in the economy and sentiment-related words are quite visible

[12] Notice that we do not report uncertainty pass-through ratios under "No-Econ-Bus" because there are not enough data to run the test. As seen from Table 4, there are only a few non-economy-business events that trigger excessive changes in uncertainty only.

in news articles, whereas Economy uncertainty news tend to correspond to a period when there are changing fluctuations in economic conditions.

4. There is likely some degree of cross-country variation in international responses.

3.3. Potential mechanisms using observables

It is challenging to study mechanisms in a real financial market context due to the complex market and economic conditions, in the time series; therefore, we propose to exploit the *cross-country* variation.

We consider several fundamental and non-fundamental channels that may cause cross-country variation in country risk aversion responses to US risk aversion events. Take Economy news as an example. Economy news can change risk aversion (see theories in Campbell and Cochrane (1999), Brandt and Wang (2003) or empirical evidence in the present research). On one hand, countries that are more economically and fundamentally connected could make their investors think that there is a higher chance that similar (good or bad) economic news could happen in their own countries, hence revising their risk aversion more strongly. On the other hand, we consider a non-fundamental driver of risk aversion that has been examined in the behavioral literature (see e.g. Loewenstein (2000), Kuhnen and Knutson (2005), Cohn, Engelmann, Fehr, and Maréchal (2015)) – Emotions – to explain the cross-country variation. It is plausible that cultures that are more expressive / less emotionally stable could respond to foreign risk aversion events more. These are proposed channels; we test their asymmetric contribution next.

Table 8 reports the estimation results of the following framework:

$$\varepsilon_{i,t}^{RA} = a + (b_0 + b_1 \times X_i + b_2 \times I_{HighRA,t} + b_3 \times X_i \times I_{HighRA,t}) \times \varepsilon_{US,t}^{RA} + e_{i,t}, \quad (4)$$

where $\varepsilon_{i,t}^{RA}$ ($\varepsilon_{US,t}^{RA}$) is the abnormal RA changes of country i (US) on risk aversion event dates, as constructed from the Equation (3); $I_{HighRA,t}$ is 1 if this US event is a high RA event and 0 otherwise; X_i denotes the country-level variables, and in light of previous discussions, we consider the following seven variables. In Columns (1) of Table 8, we use Gallup's self-reported country emotional instability (i.e., higher=more likely to experience extreme emotions on a daily basis);[13] In the rest of the columns, we consider standard measures capturing a country's economic / trade, capital market / investment, and intermediary / banking claim comovements with US or the rest of the world, and then scaled by country GDP. The bilateral trade (exports+imports) data between two

[13]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%). In the actual regression, we consider their ranks to minimize the outlier effect from Japan.

countries are obtained from IMF's Direction of Trade Statistics; the bilateral portfolio investment (equity and debt securities) are from IMF's Coordinated Portfolio Investment Survey; the international bank claims data are from BIS; country GDP and market capitalization are from the World Bank.

Coefficient b_3 is of interest. It is interesting that Column (1) turns out significant to explain our asymmetry result in our initial mechanism exploration. Countries with higher emotional instability exhibit stronger risk aversion responses on high RA event days, given the positive coefficient estimate. The b_3 coefficient estimates with all other *fundamental* comovement measures are insignificant. Figure 6 provides graphical illustration of this exploratory result, depicting the standardized X_i on the x-axis and a country's average RA response on the y-axis, on US high (left) and low (right) RA event dates. In the first row with Gallup's emotion instability measure, the slope is significant and larger in magnitude on the high RA days than that on the low RA days, which is consistent with the positive b_3 estimate shown in Table 8, Column (1). While the trade and investment comovement measures show little power in explaining the asymmetry, banking claim comovement measures show the right directional responses but the implied asymmetry appears to be on the low-RA side (i.e., international RA decreases more on a good RA event in the US).

This exploratory analysis highlights the potentially important role of non-fundamental spillover channels, which motivates the experimental design in the next section where we can examine mechanisms in a more controlled framework.

4. Experimental Evidence and Mechanisms

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 use the priming method (commonly used in Psychology and increasingly used in Finance and Economics) to stimulate responses of non-US investors to US risk aversion events. 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 the observational part (Section 3) 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,[14] failed the attention check question, correctly guessed the purpose of the study in the existing questionnaire, 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 A10) 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 (ranging from \$0 to \$25; see more details below).

Although our participants were not recruited as financial professionals, we seemed to be able to reach a sample who were sufficiently educated in financial decisions. For example, in our screening of financial literacy, our international (non-US) participants on average answered 53% of financial literacy questions correctly (Appendix Table A10), which is comparable to the 67% accuracy rate for Swiss financial professionals surveyed in 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 in our observational study. In the exiting questionnaire about demographic information, we also asked participants questions whether they have been to the US and their international asset allocations. Among the international participants, 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 7. We choose their bust and boom scenarios in our research for the following several reasons:

First, Cohn, Engelmann, Fehr, and Maréchal (2015) have demonstrated that this pair of scenarios can stimulate statistically significant responses in participants' risk aversion.

[14] We adopted the same financial literacy questions from Cohn, Engelmann, Fehr, and Maréchal (2015), which can be found in their online appendix.

Second, different from their work (which compares bust scenario to boom scenario only), we are interested in the (a)symmetry of risk aversion shock spillover, and therefore we also need to design a control group. These fictive RA scenarios allow us to design relatively simple 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 7. Notice that these non-RA scenarios conveniently offer the "Uncertainty" analogy, while the RA scenarios keep the price fluctuations the same. Third, using 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 is quite intuitive; however, finding counterparts for low RA stimuli or control groups that may trigger *comparable* economic magnitude in an experiment has proven to be difficult. Fourth, Section 3.2 shows that Economy news in the US can trigger international investors' risk aversion to change; and those Economy news that turn out to trigger risk aversion (rather than uncertainty) typically appear around an existing trend in the economy, whereas those "Economy uncertainty" news typically appear with changing fluctuations in economic conditions. Therefore, the four experimental scenarios can be motivated from our observations in actual news articles as well.

Participants were randomly assigned into one of the four scenarios (two RA and two UC scenarios as displayed in Figure 7). 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)).[15]

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

[15]We thought about leaving our control group with a simple blank page rather than uncertainty scenarios. However, uncertainty priming is still more suitable. It is still an ongoing debate in Psychology whether a blank control is an appropriate control condition (Dien, Franklin, and May (2006), Rossell and Nobre (2004)). It is also 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. Lastly, for consistency and validation purposes, the observational part of our paper also compares risk aversion against uncertainty.

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.[16] 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 IV. Our main outcome measure is the "post-priming" risky investment level, which has a negative relationship with risk aversion.

Control variables and randomization check. Our research need both US and non-US participants, and therefore, we should be aware that participants could join the internet survey with heterogeneous risk aversion levels due to their current physical, local macro or personal environments. It would be challenging to resolve these potential heterogeneities by simply adding some fixed effects. As a result, we instructed participants to make a baseline investment decision of the same investment task before the experimental manipulation.[17]

We also confirm that participants were randomly assigned to treatment/control groups and studies. Appendix Table A10 reports the randomization check for demographic information (income, age, financial literacy, gender) about participants in our studies. On average, randomization created balance among two treatment and one control groups on participant characteristics.[18] In our main analysis, we report results with and without control variables, which include the pre-priming risky investment level, demographic information and country dummies. Appendix Table A11 verifies that the pre-priming risky investment level is not significantly different across treatment and control groups.

[16] 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).

[17] We also use this information to further identify participants who slid 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. While within-subject design can be a good way to address heterogeneity in baseline risk preferences, a potential concern is demand effect. However, this may be less of a concern in our particular setting because demand effect should still not predict "asymmetry" and one participant only saw one scenario throughout the experiment.

[18] There is one statistically significant difference in the fraction of female non-US participants between control and low RA treatment groups, but the joint equality test suggests that we cannot reject the null that the means are equal across two treatment and one control groups (p value=0.56).

4.2. Treatment Validation and Experimental Evidence of Asymmetric Spillover

In this section, we first validate our priming scenarios in Study 1 (US participants responding to US shocks, or denoted as "US/US"), and then examine our main empirical finding of asymmetric US risk aversion spillover in Study 2 (non-US participants responding to US shocks, or denoted as "US/NUS"). Participants from both studies received the same experimental manipulation, and the only difference is their current residence country.[19]

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. For illustration, we plot the average changes in risky asset investment before and after priming RA scenarios in Panel A of Figure 8. We find that US participants in Study 1 reduced their risky investment (or risk aversion ↑) when primed with the bust scenario (gray bar), while they increased their risky investment (or risk aversion ↓) when primed with the boom scenario (white bar). Both responses were statistically different from zero. In contrast, US participants' risk aversion did not respond to our non-RA or uncertainty priming. From Panel B of Figure 8, 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:

$$Y_i = \beta_0 + \beta_1 I_{HighRA,i} + \beta_2 I_{LowRA,i} + \boldsymbol{\gamma'} \boldsymbol{X_i} + \varepsilon_i, \tag{5}$$

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 as discussed above (pre-priming risky investment level, individual income, age, gender, financial literacy and country dummies). Consistent with Figure 8, Regressions (1) and (2) of Table 9 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 ($SE = 17.23$).

[19] 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.

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. From the bars on the right hand side of Figure 8, 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 spillover. 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 9 and 10 formalize this asymmetric spillover 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 asymmetric spillover, 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 10 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

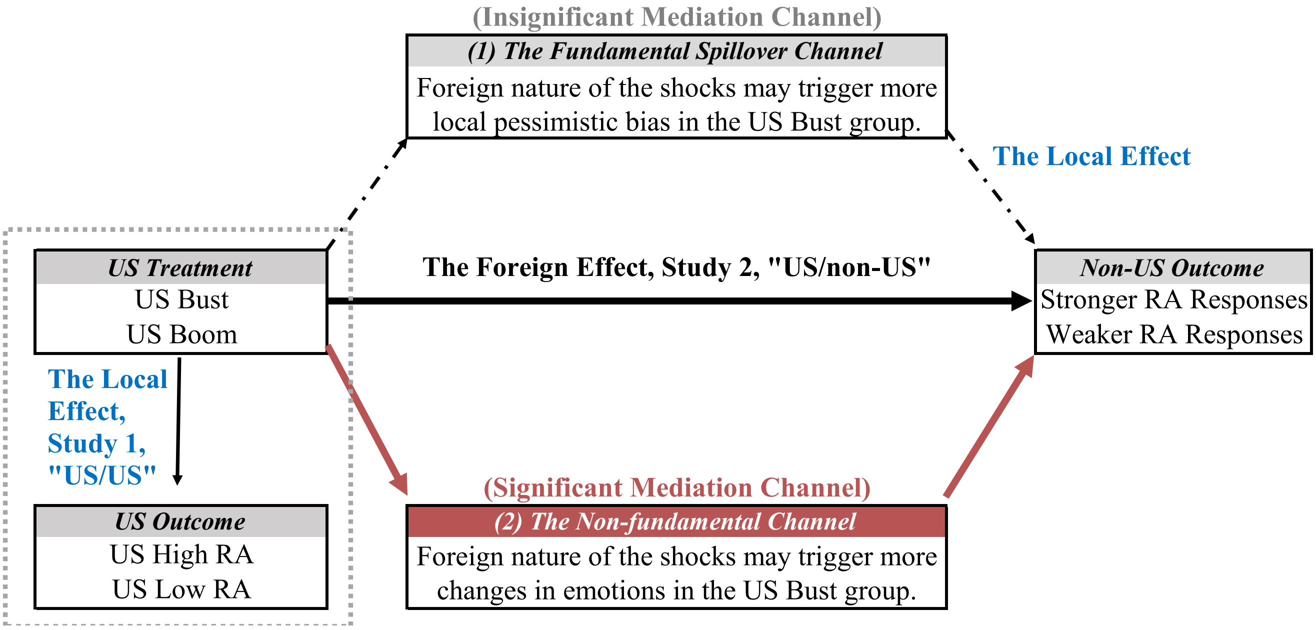
To explore the potential underlying mechanisms for the asymmetric non-US responses to the US risk aversion shocks in our study, we hypothesize and examine the following two general channels, which are also similarly discussed and explored in Section 3.3:

(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)) and our exploratory evidence in Section 3.3, 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 changes in 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*.[20] Using a similar specification as Equation (5), 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

[20] As mentioned earlier, an attention check question was inserted in this part of the survey. That is, we asked the participants to choose what pattern of US stock price they were observing in their assigned scenario (which was displayed right on top of the same page of this attention check 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).

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 accurately.

Regressions (5)–(6) of Table 11 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.[21] 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 a strong underlying mechanism that triggers an excessive non-US risk aversion response to US bust/high RA shocks.

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 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 (2021a) 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 reached 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 bust or negative shocks may change emotions more than that of boom or positive shocks, hence resulting in asymmetric risk aversion propagation.

[21] 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.

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, right after 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) of Table 11 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 spillover in our experimental setting. 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 12, we find an insignificant relationship between investment decisions and belief updating. To the contrary, in Regression (11), 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 and lower risk aversion.

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 11); 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 12, and Regression (12) simply copies over our benchmark specification from Table 9. 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 can quantify the mediation effect. 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. From Regressions (14)-(15) of Table 12, both positive and negative emotions exhibited statistically strong associations with risky investment decisions. Regressions (16)-(17) show that the mediation effects of positive and negative emotions, 12.8% and 8.3% respectively, were also comparable to each other. 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 spillover.

4.3.4. Discussion: The Role of Familiarity

Taken together, our results suggest that US events could directly affect the non-US participants' risk aversion through affecting their emotional states. The fact that US is a super power country, compared to other smaller countries as the origin of the event, can be understood as reinforcing our experimental findings. However, that is not an explanation to why emotions changed more when non-US experienced a US bust scenario. Therefore, we posit that, due to the *foreign* nature of the events, bust or negative shocks may change emotions – decreasing positive emotion and/or increasing negative emotion – *more* than that of boom or positive shocks, hence resulting in asymmetric risk aversion spillover 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 this link may behave in an international context. Therefore, regarding how and why "foreign" nature of bad RA events potentially lead to asymmetric changes in emotional states and risk aversion, one explanation we have in mind is lack of familiarity due to geographical, economic, or social distances. Psychology literature has documented that an unfamiliar (e.g., foreign) negative shock or challenge may induce more fear or reduce more positive feelings 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 relatedly 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 emotional processing) and their general risk aversion; as a result, the authors interpret the home-bias investment phenomenon with the "worse general feelings" triggered by the possibility of investing in foreign assets.

In our context, if the asymmetric spillover is (partially) driven by the lack of familiarity due to the "foreign" nature of the US shocks, we would expect that the asymmetry is stronger for non-US participants who are less familiar with the US. To test this conjecture, we separately analyze the spillover effect for two subsamples of non-US participants: those unfamiliar with the US vs. those familiar with the US. Based on the demographic information questions in the exiting questionnaire, we consider a non-US participant to be in the Unfamiliar group if she has never been to the US and her investment in the US market accounts for less than 50% of her total portfolio. In our sample, 147 (out of 243) non-US participants are classified as "Unfamiliar with US."

We modify our main analysis by interacting the two treatment indicators with a dummy variable that takes a value of one if the non-US participant is classified as unfamiliar with the US. In Table 13, we summarize the results of this single interaction regression without and with control variables. For interpretation purposes, Column (1) reports the coefficient estimates for the non-US participants who are familiar with the US, and Column (2) reports the counterpart estimates for the US-unfamiliar subsample (i.e., the familiar-group coefficient estimate plus the interaction term coefficient). We re-estimate the model with controls in Columns (3) and (4). We find that the asymmetry only appears in the subsample of non-US participants who are unfamiliar with the US, i.e., Columns (2) and (4). When the non-US participants are familiar with the US, the responses to high RA and low RA treatments are statistically symmetric. In other words, participants who are more familiar with the US and its financial markets exhibited a reduced asymmetric effect. Our evidence lends support to our conjecture that non-US participants exhibited excessively more emotional responses (hence asymmetric risk aversion responses) to a foreign bust/negative shock, partially, because they feel unfamiliar with this foreign shock.

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 asymmetric spillover we document in both observational and experimental evidence from US to other countries is likely on the larger side of the spectrum.

4.4. Link to the Observational Evidence

To study risk aversion spillover, both observational study in Section 3 and the experimental study here connect to each other in terms of establishing the pattern (domestic and foreign responses) and exploring potential mechanisms (fundamental and non-fundamental channels). Both designs trace out the risk aversion spillover of a US event. While similar results are reached, each study has its unique advantages. The observational study incorporates the news data and let the data speak; it shows that, besides the conventional "risk aversion events" (i.e., societal, war, weather events) as studied in the behavioral literature, Economy events can also significantly trigger risk aversion events as suggested in the asset pricing models. The experimental study is able to tease out the emotional channel more cleanly with directly measured emotions in a controlled setting, compared to the Gallup's proxy used in the exploratory test in Section 3.3.

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 news-integrated approach and a double-sorting strategy. 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 events (61%) is significantly higher than that of US low RA events (43%). While financial market and actual news data offer an aggregate and real-life view of this new phenomenon, we conducted two subsequent experiments to explore the underlying mechanisms of asymmetric US risk aversion spillover 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 widely-used 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 – decreasing positive emotion and/or increasing negative emotion – more than that of low RA or boom shocks, hence resulting in asymmetric risk aversion spillover. This is likely due to unfamiliarity since the asymmetric spillover mainly appears in the subsample of non-US participants who are unfamiliar with the US. Our mediation analysis shows that 19.6% of the spillover asymmetry can be explained by this general emotion channel. Hence, joining the recent growing experimental evidence of how emotions affect 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 "spillover" effect such that an emotion-related non-fundamental channel may play an important role in explaining the excessive risk aversion spillovers 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 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 abnormal risk aversion and uncertainty

This table summarizes the daily country abnormal risk aversion and uncertainty, constructed in Equation (3) where their respective expected components are discussed in Tables A4 and A5, respectively, in the Appendix. Panels A and B provide the summary statistics (unit: monthly decimal-squared). Panels C, D and E use overlapping sample 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 2.2 for the detailed event selection procedure.

Event Type:	***Total RA***	***Total UC***	***1.High RA***	***2.Low RA***	***3.High UC***	***4.Low UC***
Abnormal RA changes:			*>90th*	*<10th*	*Middle*	*MiddleNormal*
Abnormal UC changes:			*Middle*	*Middle*	*>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 2.2 for the detailed event selection procedure and Appendix II for more subcategories. The fractions of each news category in each event type are reported in parentheses so that those in each column should add up to 100%. Here are some key examples of news in each category according to RavenPack's Taxonomy and UserGuide 4.0 (see more details in Table A6):

- Business: acquisitions-mergers, credit grading, earnings, incident, market, oil, regulatory
- Economy: consumer, domestic-product, employment, interest-rate, trade balance-of-payments, production, consumer confidence
- 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). A few Economy news examples can be found in Appendix III.

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, test results 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 No-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 A7 and A9.

	(1)	***(2) News category***			***(3) Jackknife country set***						***(4) Time***	***(5) Mechanism***
	Full	Econ	No-Econ	No-Econ-Bus	No CH	No DE	No FR	No JP	No NL	No UK	No-crisis	No-jumps
News: 1. High RA	**0.6123**	**0.6213**	**0.6017**	**0.5759**	**0.6336**	**0.6192**	**0.5982**	**0.6354**	**0.6275**	**0.5521**	**0.6225**	**0.6104**
	(0.0322)	(0.0455)	(0.0467)	(0.0524)	(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**	**0.2905**	**0.3932**	**0.4156**	**0.4404**	**0.4470**	**0.4673**	**0.3919**	**0.3760**	**0.4676**
	(0.0489)	(0.0561)	(0.0856)	(0.0952)	(0.0532)	(0.0521)	(0.0521)	(0.0519)	(0.0548)	(0.0525)	(0.0558)	(0.0382)
Equality test:	3.1820	2.5899	1.9899	2.6255	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:	-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: Potential mechanisms

This table complements Figure 6 and reports panel regression results of the following equation:

$$\varepsilon^{RA}_{i,t} = a + (b_0 + b_1 \times X_i + b_2 \times I_{HighRA,t} + b_3 \times X_i \times I_{HighRA,t}) \times \varepsilon^{RA}_{US,t} + e_{i,t},$$

where $\varepsilon^{RA}_{i,t}$ ($\varepsilon^{RA}_{US,t}$) is the abnormal RA changes of country i (US) on risk aversion event dates, as constructed from the Equation (3); $I_{HighRA,t}$ is 1 if this US event is a high-RA event and 0 otherwise; X_i denotes the country-level variables. X_i **variables**: (1) "Gallup Emotion Instability" denotes the survey-reported country-level average emotional instability (i.e., higher=more likely to experience extreme emotions on a daily basis; source: Gallup); (2) "Trade-w/US-to-GDP" denotes the average total trade (exports+imports) with the United States, scaled by this country's GDP, between 2001 to 2018 (source: IMF's Direction of Trade Statistics for the bilateral trade data); (3) "AssetLib-w/US-to-GDP" denotes the average total portfolio investment (equity and debt securities) in and from the United States, scaled by this country's GDP, between 2001 to 2018 (source: IMF's Coordinated Portfolio Investment Survey for the bilateral investment data, and World Bank of GDP data); (4)-(5) are robustnesses for (2)-(3), and consider trade and total portfolio investments with respect to the rest of the world; (6) "BankingClaims-to-GDP" denotes the average international bank claims from this country to the rest of the world, scaled by this country's GDP, between 2001 to 2018 (source: BIS; no bilateral data available to the authors); (7) "MCAP-to-GDP" denotes stock market capitalization divided by GDP (source: World Bank). All X_i are standardized. The t statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

X_i:	Gallup Emotion Instability	Trade-w/US-to-GDP	AssetLib-w/US-to-GDP	Trade-w/World-to-GDP	AssetLib-w/World-to-GDP	Banking-Claims-to-GDP	MCAP-to-GDP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				$\varepsilon^{RA}_{i,t}$			
$\varepsilon^{RA}_{US,t}$	0.444***	0.443***	0.443***	0.443***	0.443***	0.443***	0.443***
	(6.578)	(6.546)	(6.528)	(6.530)	(6.525)	(6.554)	(6.537)
$X_i \times \varepsilon^{RA}_{US,t}$	0.0146	-0.00619	-0.0364	-0.0147	-0.00808	0.0825**	0.0578
	(0.390)	(-0.165)	(-0.967)	(-0.393)	(-0.216)	(2.218)	(1.557)
$I_{HighRA,t} \times \varepsilon^{RA}_{US,t}$	0.0918	0.0929	0.0931	0.0932	0.0932	0.0931	0.0930
	(0.673)	(0.680)	(0.680)	(0.681)	(0.680)	(0.682)	(0.680)
$X_i \times I_{HighRA,t} \times \varepsilon^{RA}_{US,t}$	**0.0897***	-0.0685	0.0269	-0.0262	-0.00318	-0.0449	-0.0851*
	(1.739)	(-1.323)	(0.517)	(-0.506)	(-0.061)	(-0.873)	(-1.657)
Constant	0.0233	0.0226	0.0225	0.0224	0.0224	0.0223	0.0225
	(0.513)	(0.497)	(0.495)	(0.492)	(0.492)	(0.492)	(0.496)
Observations	857	857	857	857	857	857	857
R-squared	0.30	0.29	0.29	0.29	0.29	0.29	0.29

Table 9: 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 parentheses. *, **, 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 10: Asymmetry tests

This table complements Table 9 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 9					
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 11: 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 parentheses. *, **, 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 12: 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 11. 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 9). The standard errors are in parentheses. *, **, 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%

Table 13: Asymmetric spillover and familiarity

This table presents regression coefficient estimates from two interactive regressions of post-priming investment level (dependent variable) on the treatment indicators and an interaction with a dummy variable that categorizes Non-US participants' familiarity with the US. A non-US participant is considered "Unfamiliar with US" if he/she has (self-reportedly) never been to the US and his/her investment in the US market accounts for less than 50% of their portfolio. Participants answer these two questions in the exiting page of the survey. The model of Columns (1) and (2) does not include control variables, while the model of Columns (3) and (4) does. The standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dep. Var:	***Post-priming Inv. Level***			
Exp. Sample:	***Study 2, "US/NUS"***			
Non-US participants:	***Familiar with US***	***Unfamiliar with US***	***Familiar with US***	***Unfamiliar with US***
High RA Treatment	**-57.29***	**-107.8*****	**-73.32****	**-94.46*****
	(33.703)	(27.317)	(35.030)	(30.000)
Low RA Treatment	**62.90***	**49.25***	**72.33****	**49.17***
	(34.380)	(27.777)	(35.660)	(29.235)
Pre-priming inv. Level	0.842***		0.851***	
	(0.036)		(0.038)	
Income control	N		Y	
Age control	N		Y	
Financial literacy	N		Y	
Gender	N		Y	
Country effect	N		Y	
Observations	243		243	
R-squared	0.719		0.735	
Adjusted R-squared	0.712		0.704	

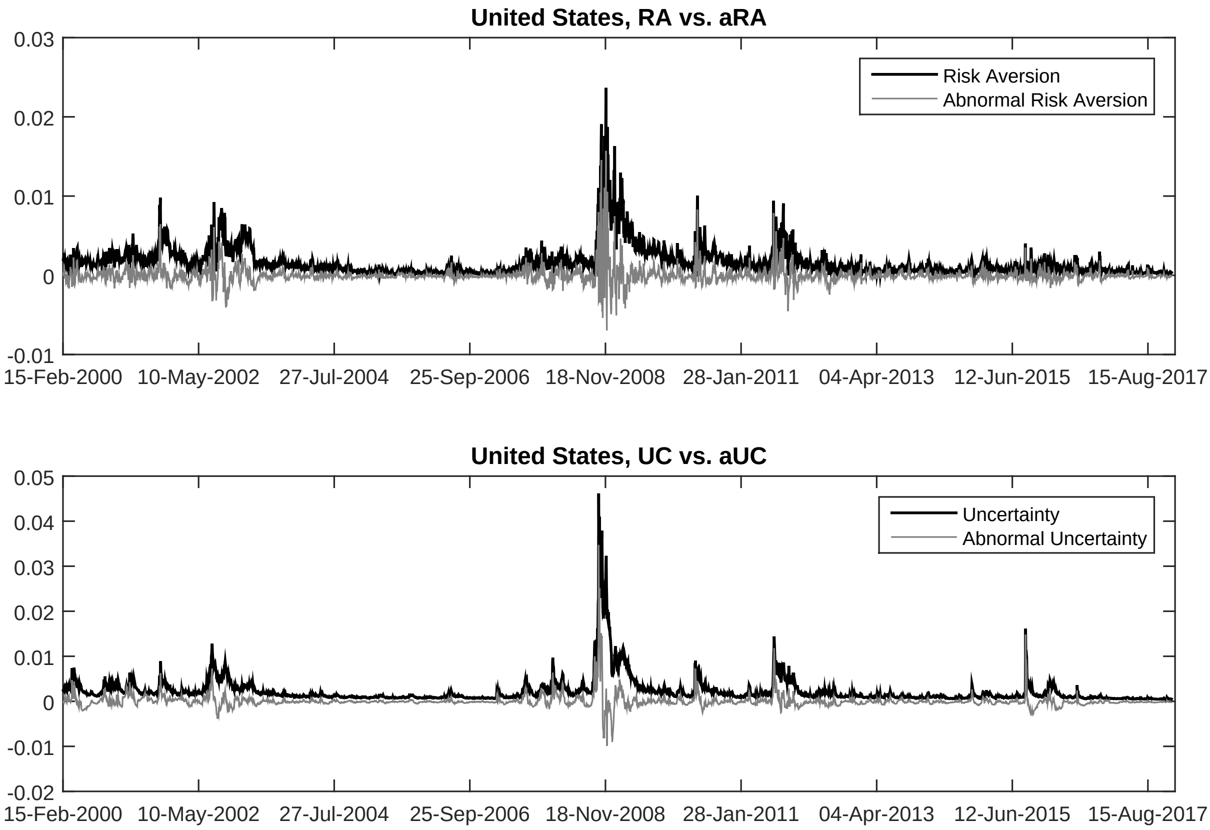


Figure 1: Time variation in US risk aversion, abnormal risk aversion (top plot), uncertainty, and abnormal uncertainty (bottom plot) in the final overlapping sample from 2000 to 2017.

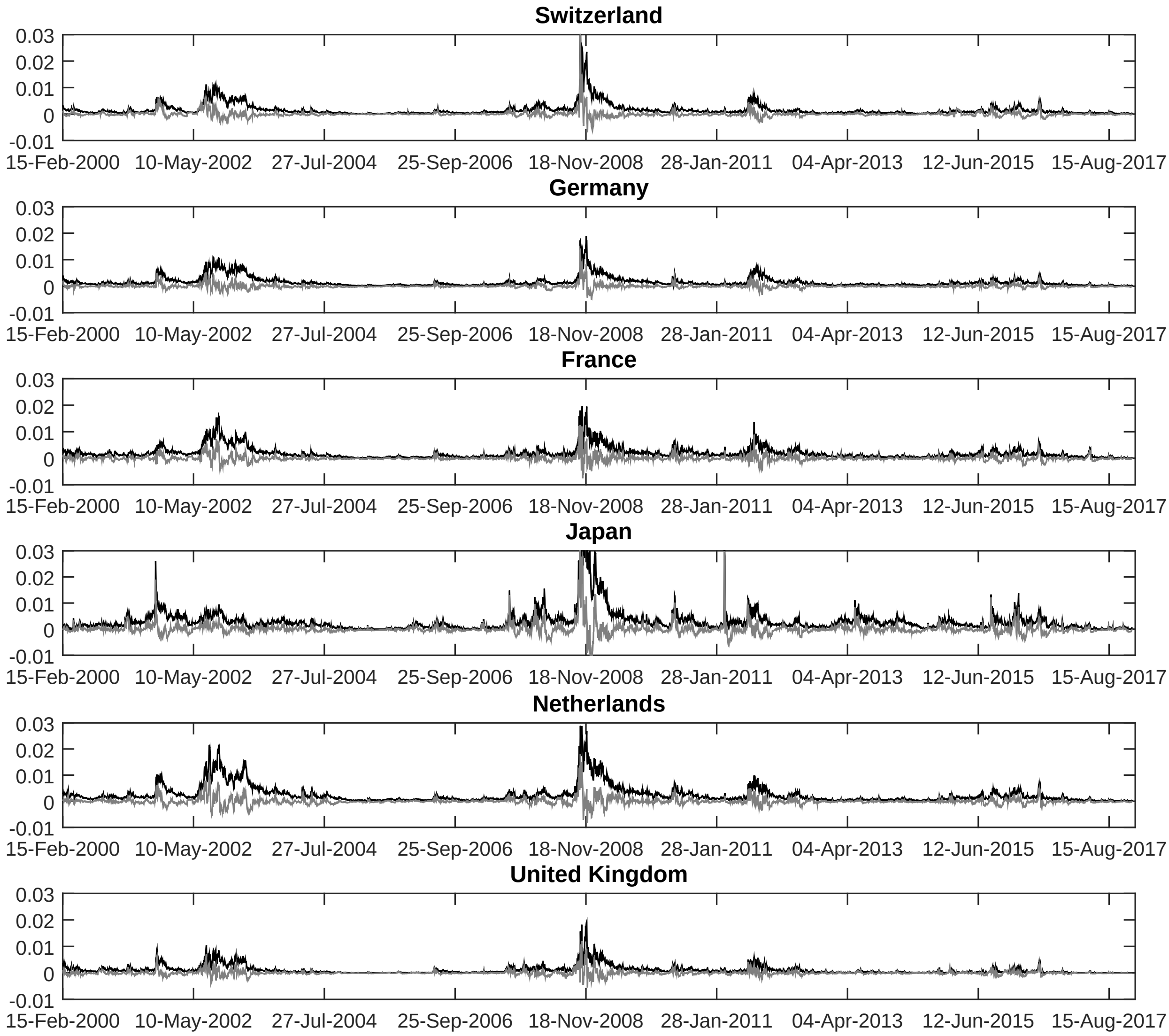


Figure 2: Time variation in international risk aversion (black) and abnormal risk aversion (gray) in the final overlapping sample from 2000 to 2017.

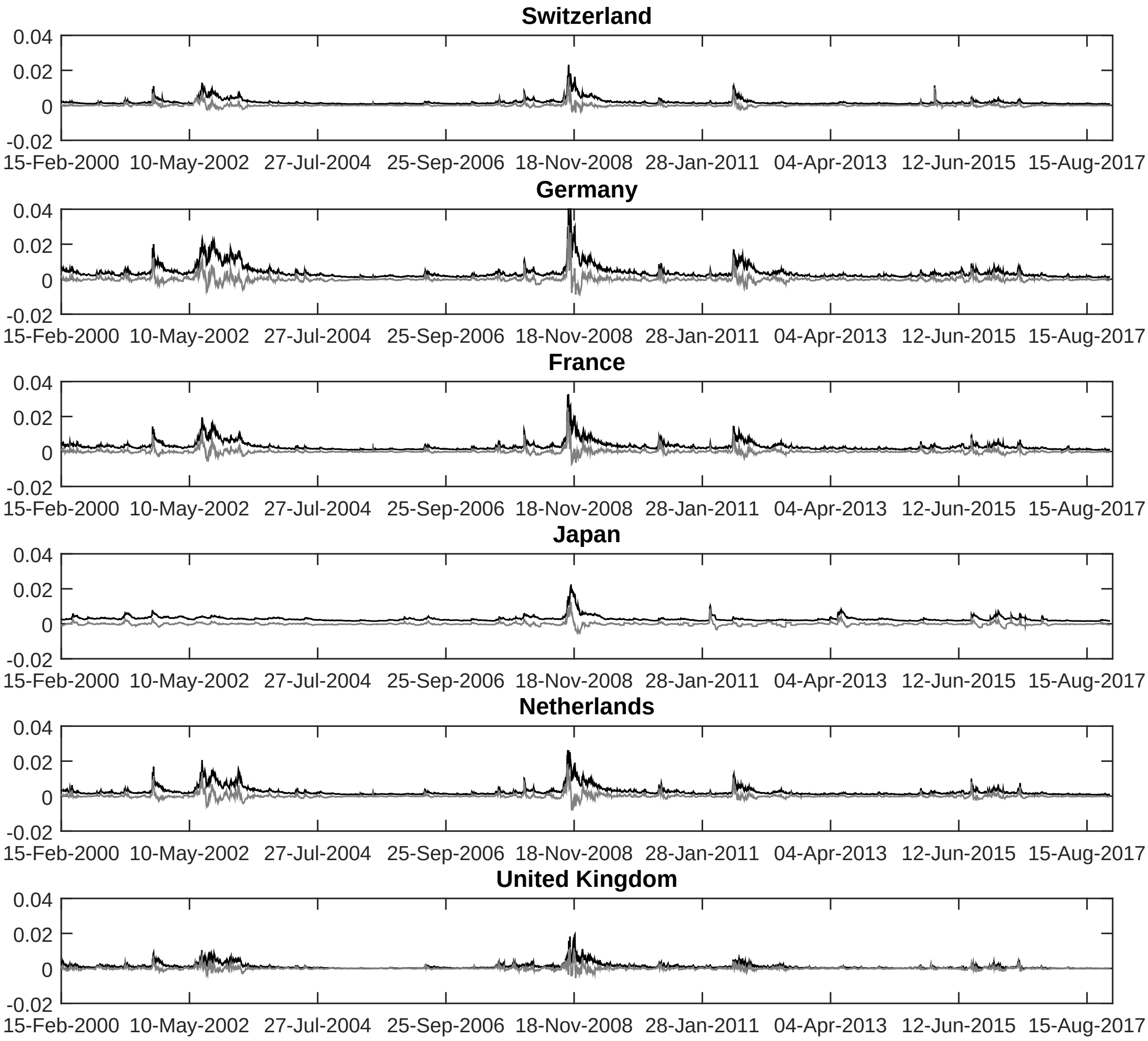


Figure 3: Time variation in international uncertainty (black) and abnormal uncertainty (gray) in the final overlapping sample from 2000 to 2017.

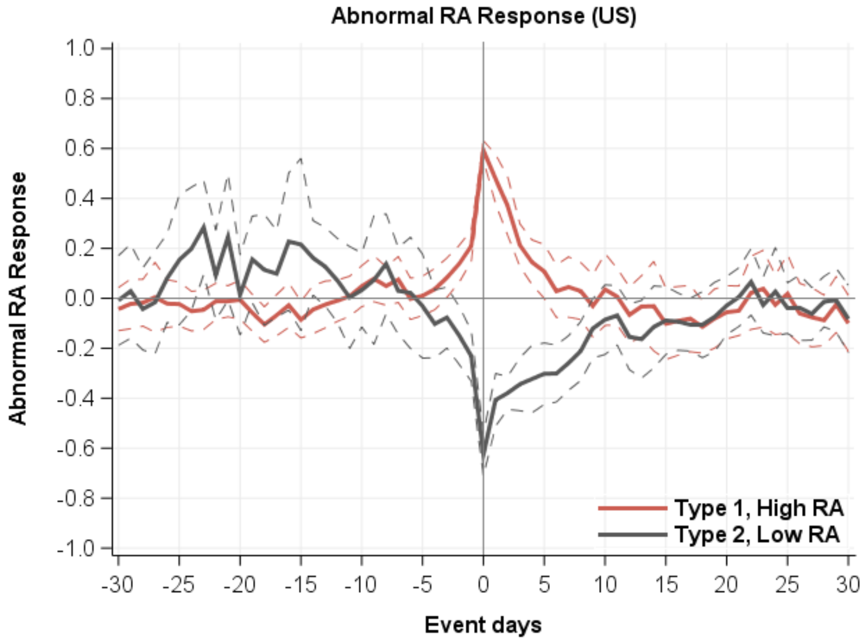


Figure 4: Event study: Abnormal US risk aversion responses to US RA shocks

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.

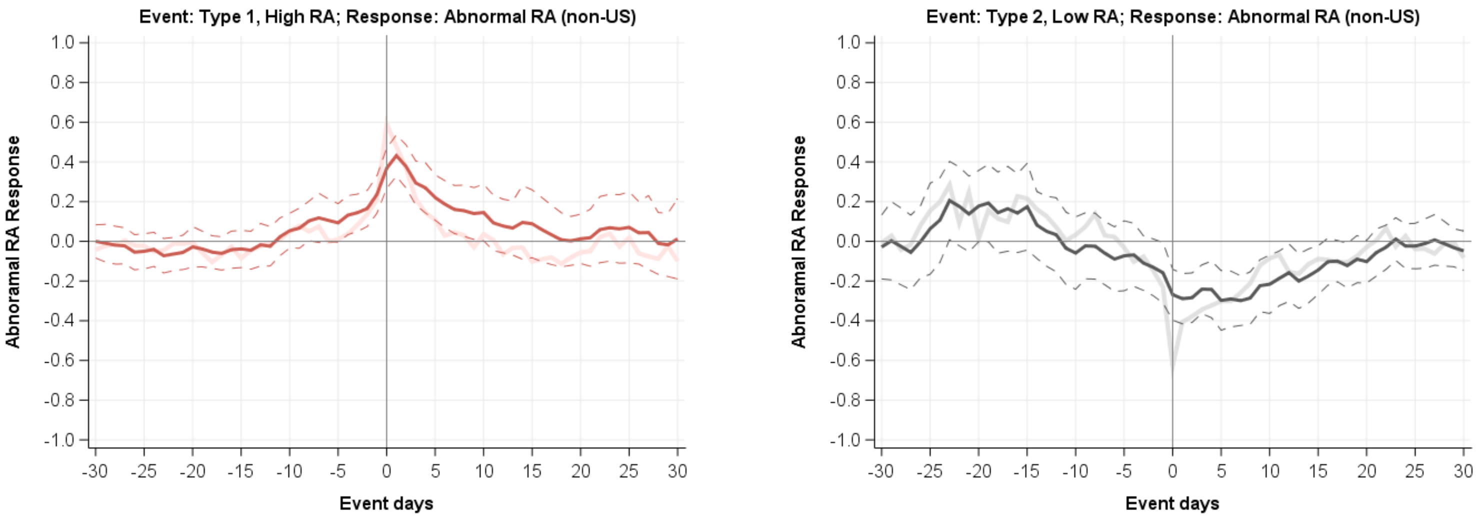


Figure 5: Event study: Average abnormal changes in international risk aversion in response to US RA events

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.

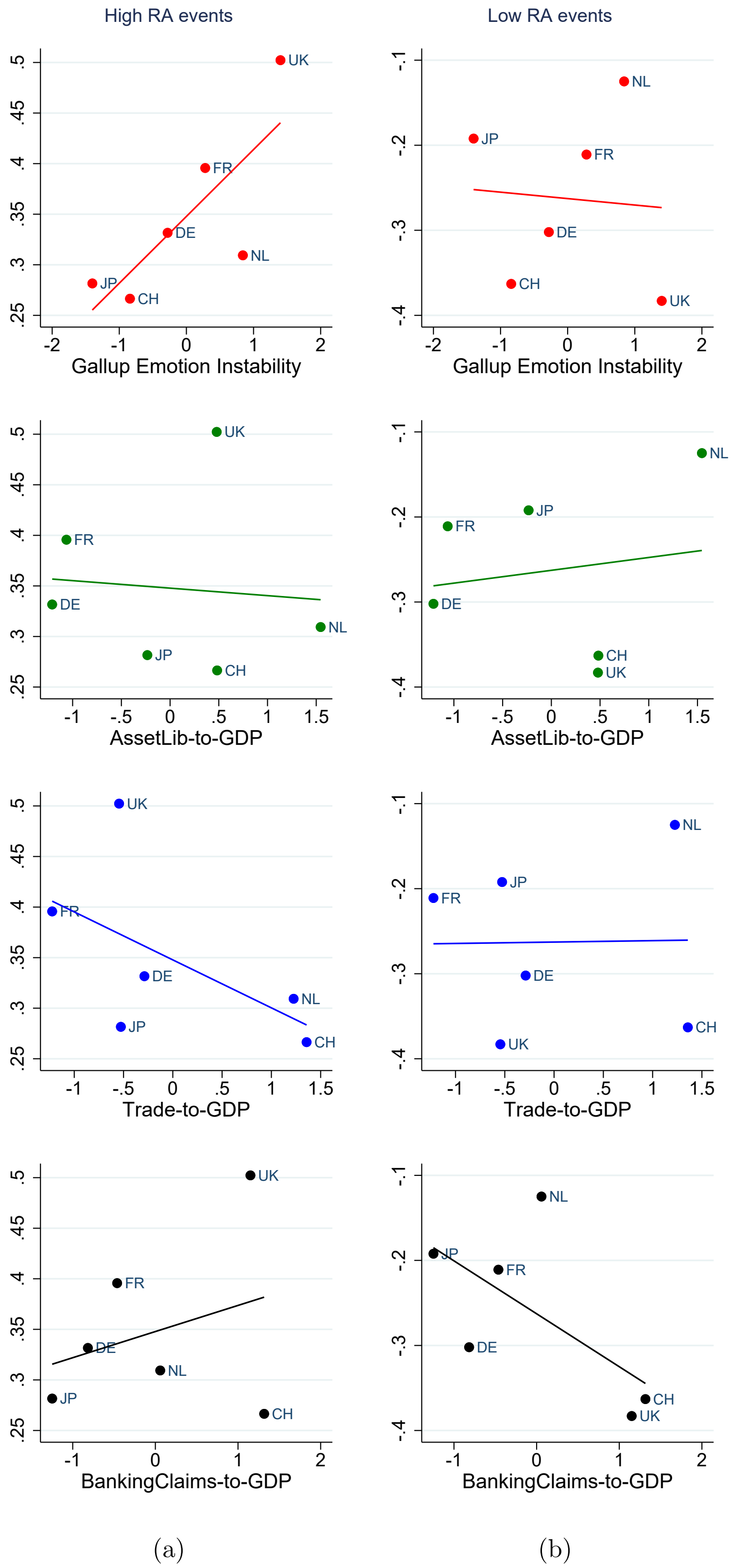


Figure 6: Potential mechanisms given the cross-country responses to US RA events

This figure plots the country-level average scaled abnormal RA responses on high or low US RA events (y-axis) against several potential mechanisms constructed at the country-level (x-axis). See details of x-axis variables in Table 8. The main relevant comparison to our paper is whether the slope of the high RA plot (left) is large than that of the low RA plot (right) in magnitude.

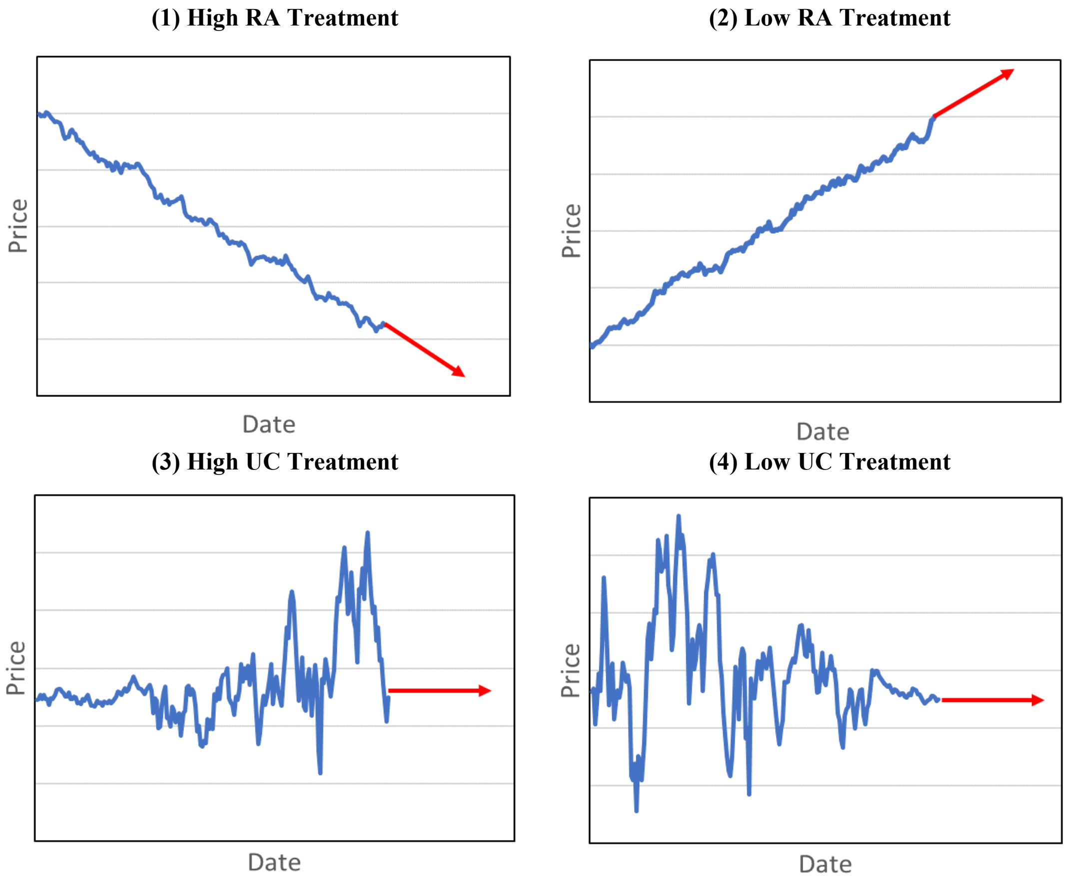
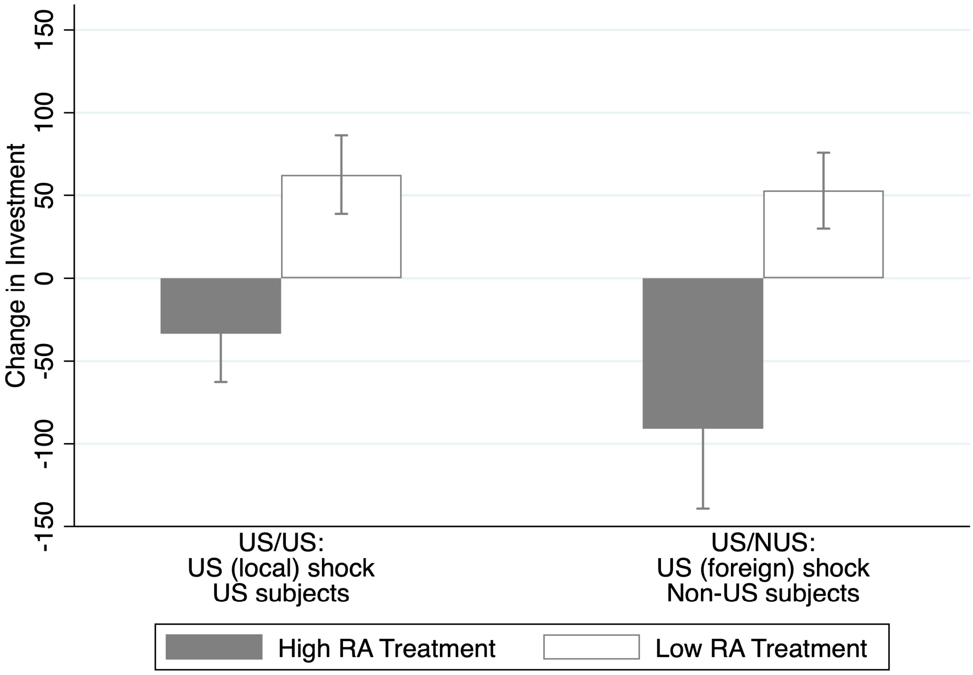


Figure 7: Treatment plots

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

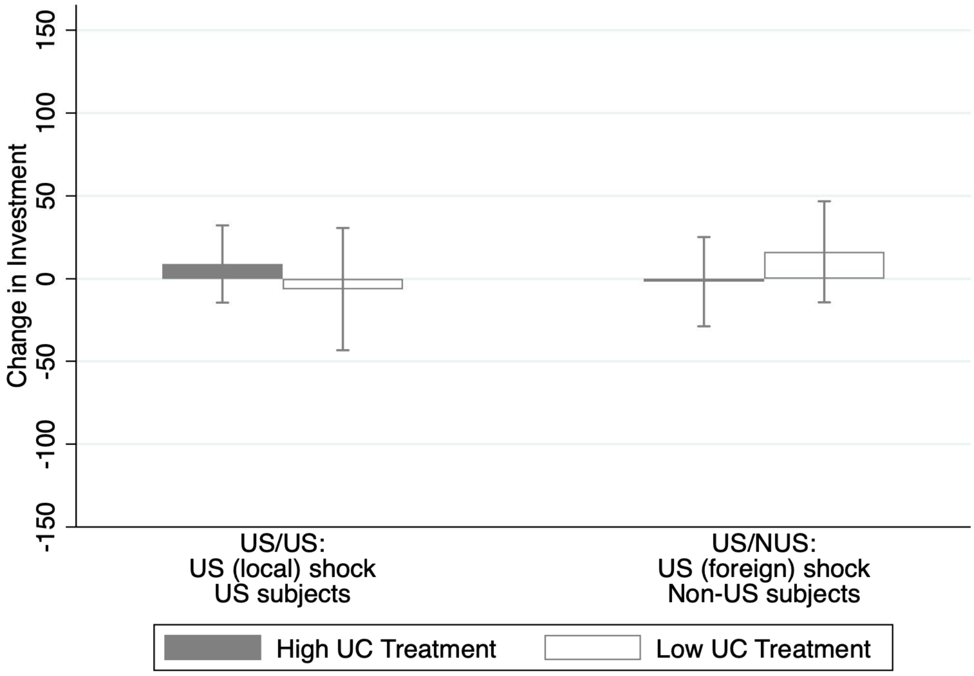


Figure 8: Preliminary demonstration of mean effects across the two studies

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 9.

INTERNET 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: 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:

$$X_{i,t} = \alpha_i + \beta_i \times MA(n)_{i,t-n,t-1} + \boldsymbol{\gamma_i} \times \boldsymbol{Z_{i,t-1}} + \varepsilon_{i,t}, \quad (6)$$

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
$\Delta DY + \Delta rf$	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
$\Delta DY + \Delta tsprd$	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
$\Delta rf + \Delta tsprd$	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
$\Delta DY + \Delta rf + \Delta tsprd$	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
$\Delta DY + \Delta rf$	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
$\Delta DY + \Delta tsprd$	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**
$\Delta rf + \Delta tsprd$	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
$\Delta DY + \Delta rf + \Delta tsprd$	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 A3: 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 A2, 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 A4: 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 A2; 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 A5: 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 A4.

	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

Table A6: 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 A7: Robustness: Domestic and foreign responses using Economy news only, No-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)
No-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)
No-Econ-Bus	*-0.0783*	0.0841	0.1107	**0.6225**	**0.4608**	-0.0141	-0.0595
	(0.0395)	(0.0501)	(0.0596)	(0.0434)	(0.0947)	(0.0456)	(0.0592)
No-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)
No-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)
No-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)
No-Econ-Bus	0.1805	0.2513	0.0196	**-0.6024**	**-0.3032**	*-0.2060*	*-0.1559*
	(0.0938)	(0.1303)	(0.0674)	(0.0578)	(0.0649)	(0.0807)	(0.0682)
No-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)
No-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)
No-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)
No-Econ-Bus				-			
No-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)
No-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)
No-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)
No-Econ-Bus				-			
No-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)
No-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)
No-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)
No-Econ-Bus	-0.1061	0.1191	0.1444	**0.3728**	**0.4690**	*0.2395*	0.0257
	(0.0919)	(0.0985)	(0.0799)	(0.0843)	(0.1021)	(0.0993)	(0.1374)
No-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)
No-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)
No-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)
No-Econ-Bus	0.1234	0.1452	-0.0155	-0.1786	-0.1794	-0.1715	-0.1519
	(0.1603)	(0.1267)	(0.1464)	(0.1326)	(0.1220)	(0.1195)	(0.0995)
No-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)
No-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)
No-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)
No-Econ-Bus				-			
No-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)
No-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)
No-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)
No-Econ-Bus				-			
No-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)
No-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 A8: 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 A9: Robustness: Non-US responses dropping one country at a time

	[-30, -11]	[-10, -4]	[-3, -1]	[0, 0]	[1, 3]	[4, 10]	[11, 30]		[-30, -11]	[-10, -4]	[-3, -1]	[0, 0]	[1, 3]	[4, 10]	[11, 30]
	News: 1. High RA; Response: Abnormal Non-US RA								News: 3. High UC; Response: Abnormal Non-US UC						
No CH	-0.0268	*0.0992*	**0.1900**	**0.3809**	**0.3785**	**0.1802**	0.0408	No CH	0.0090	0.1354	0.1365	**0.2044**	**0.2416**	*0.2081*	0.0700
	(0.0431)	(0.0475)	(0.0465)	(0.0502)	(0.0528)	(0.0641)	(0.0759)		(0.0654)	(0.0977)	(0.0784)	(0.0784)	(0.0908)	(0.0959)	(0.0945)
No DE	-0.0378	*0.1041*	**0.1939**	**0.3722**	**0.3734**	**0.1867**	0.0483	No DE	0.0175	0.1427	0.1366	*0.1925*	*0.2501*	*0.2018*	0.0608
	(0.0479)	(0.0528)	(0.0473)	(0.0528)	(0.0551)	(0.0638)	(0.0800)		(0.0703)	(0.1057)	(0.0857)	(0.0889)	(0.1049)	(0.0939)	(0.1000)
No FR	-0.0348	0.1017	**0.1730**	**0.3595**	**0.3670**	**0.1890**	0.0510	No FR	0.0234	0.1514	0.1485	*0.2156*	*0.2490*	*0.2096*	0.0717
	(0.0474)	(0.0540)	(0.0449)	(0.0510)	(0.0562)	(0.0671)	(0.0811)		(0.0656)	(0.1073)	(0.0836)	(0.0887)	(0.0989)	(0.0983)	(0.0993)
No JP	-0.0432	0.0864	**0.1814**	**0.3819**	**0.3631**	**0.1777**	0.0455	No JP	0.0319	0.1806	0.1602	**0.2438**	**0.2960**	*0.2417*	0.0912
	(0.0432)	(0.0473)	(0.0460)	(0.0502)	(0.0546)	(0.0619)	(0.0719)		(0.0784)	(0.1169)	(0.0845)	(0.0863)	(0.1074)	(0.1070)	(0.1101)
No NL	-0.0349	0.1001	**0.1859**	**0.3772**	**0.3797**	**0.1784**	0.0368	No NL	0.0236	0.1434	0.1429	**0.2061**	**0.2501**	*0.2052*	0.0621
	(0.0471)	(0.0526)	(0.0495)	(0.0517)	(0.0571)	(0.0631)	(0.0807)		(0.0679)	(0.1001)	(0.0843)	(0.0793)	(0.0944)	(0.0954)	(0.1019)
No UK	-0.0372	0.0843	**0.1625**	**0.3287**	**0.3403**	**0.1825**	0.0529	No UK	0.0461	0.1710	0.1520	*0.1925*	*0.2274*	*0.1939*	0.0605
	(0.0430)	(0.0475)	(0.0446)	(0.0492)	(0.0507)	(0.0606)	(0.0750)		(0.0765)	(0.1079)	(0.0863)	(0.0827)	(0.1000)	(0.0956)	(0.1008)
	News: 2. Low RA; Response: Abnormal Non-US RA								News: 4. Low UC; Response: Abnormal Non-US UC						
No CH	0.0960	-0.0466	-0.1102	**-0.2481**	**-0.2540**	**-0.2410**	-0.0637	No CH	0.0491	*-0.1157*	**-0.1959**	**-0.2361**	**-0.2375**	**-0.1695**	*-0.0833*
	(0.0955)	(0.0775)	(0.0725)	(0.0694)	(0.0637)	(0.0697)	(0.0605)		(0.0603)	(0.0510)	(0.0410)	(0.0392)	(0.0414)	(0.0439)	(0.0386)
No DE	0.0806	-0.0585	*-0.1435*	**-0.2622**	**-0.2717**	**-0.2699**	-0.0795	No DE	0.0300	*-0.1296*	**-0.2078**	**-0.2441**	**-0.2466**	**-0.1923**	**-0.1007**
	(0.0997)	(0.0834)	(0.0703)	(0.0663)	(0.0618)	(0.0691)	(0.0585)		(0.0633)	(0.0514)	(0.0400)	(0.0378)	(0.0407)	(0.0429)	(0.0390)
No FR	0.0822	-0.0789	*-0.1551*	**-0.2779**	**-0.2858**	**-0.2742**	-0.0872	No FR	0.0359	*-0.1231*	**-0.1929**	**-0.2322**	**-0.2379**	**-0.1772**	**-0.0948**
	(0.0971)	(0.0830)	(0.0679)	(0.0643)	(0.0609)	(0.0665)	(0.0584)		(0.0618)	(0.0505)	(0.0405)	(0.0364)	(0.0376)	(0.0420)	(0.0351)
No JP	0.0813	-0.0440	-0.1250	**-0.2820**	**-0.2532**	**-0.2467**	-0.0731	No JP	0.0313	*-0.1294*	**-0.2069**	**-0.2499**	**-0.2520**	**-0.1690**	*-0.0814*
	(0.0885)	(0.0788)	(0.0676)	(0.0595)	(0.0562)	(0.0631)	(0.0551)		(0.0631)	(0.0526)	(0.0399)	(0.0358)	(0.0421)	(0.0458)	(0.0369)
No NL	0.0895	-0.0680	*-0.1533*	**-0.2949**	**-0.3049**	**-0.2932**	-0.0874	No NL	0.0352	*-0.1252*	**-0.1998**	**-0.2369**	**-0.2437**	**-0.1854**	**-0.0976**
	(0.1049)	(0.0838)	(0.0746)	(0.0700)	(0.0631)	(0.0696)	(0.0599)		(0.0606)	(0.0512)	(0.0381)	(0.0352)	(0.0372)	(0.0404)	(0.0361)
No UK	0.0829	-0.0431	-0.1114	**-0.2473**	**-0.2588**	**-0.2638**	-0.0883	No UK	0.0368	*-0.1174*	**-0.1950**	**-0.2330**	**-0.2351**	**-0.1726**	**-0.0937**
	(0.0967)	(0.0766)	(0.0694)	(0.0686)	(0.0641)	(0.0692)	(0.0553)		(0.0604)	(0.0502)	(0.0398)	(0.0359)	(0.0368)	(0.0433)	(0.0362)

Table A10: Randomization check (1): Demographic information

This table presents the randomization balance checks for the two study samples (US/US in Panel A and US/NUS for Panel B). The four demographic 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. Columns (1)-(3) report the averages of demographic variables across treatment and control groups. Columns (4) and (5) report the statistics for the difference between treatment and control groups. Column (6) reports the p-value for the joint test whether the averages are equal across high RA treatment, low RA treatment and control groups.

	(1) Control	(2) High RA treatment	(3) Low RA treatment	(4) High RA - Control Diff	(5) Low RA - Control Diff	(6) Joint Test p-value
			Panel A: Study 1, "US/US"			
Income (in 000s, $)	63.61	61.8	72.04	-1.81	8.43	0.38
				(5.50)	(5.45)	
Age	39.35	39.52	40.22	0.16	0.87	0.44
				(1.33)	(1.32)	
Correct	0.45	0.38	0.42	-0.07	-0.03	0.62
				(0.07)	(0.067)	
Female	0.32	0.35	0.43	0.03	0.11**	0.56
				(0.06)	(0.06)	
			Panel B: Study 2, "US/NUS"			
Income (in 000s, $)	51.98	48.49	58.77	-3.49	6.79	0.15
				(6.85)	(6.96)	
Age	30.97	30.53	29.39	-0.44	-1.58	0.79
				(1.37)	(1.40)	
Correct	0.57	0.52	0.48	-0.05	-0.09	0.57
				(0.10)	(0.10)	
Female	0.34	0.32	0.26	-0.02	-0.08	0.11
				(0.07)	(0.07)	

Table A11: Randomization check (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

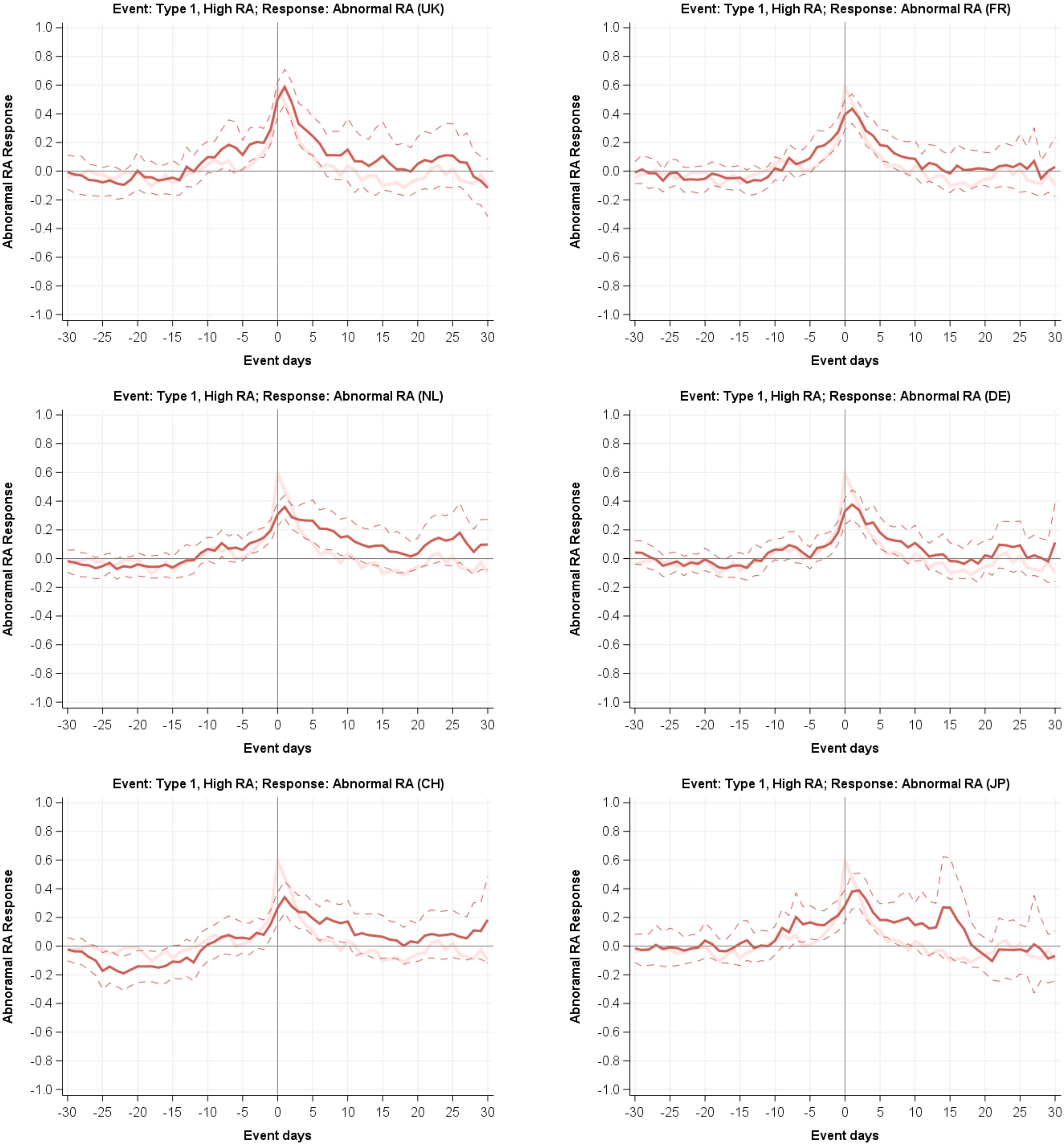


Figure A1: Event study: Abnormal country RA in response to US high-RA shocks

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).

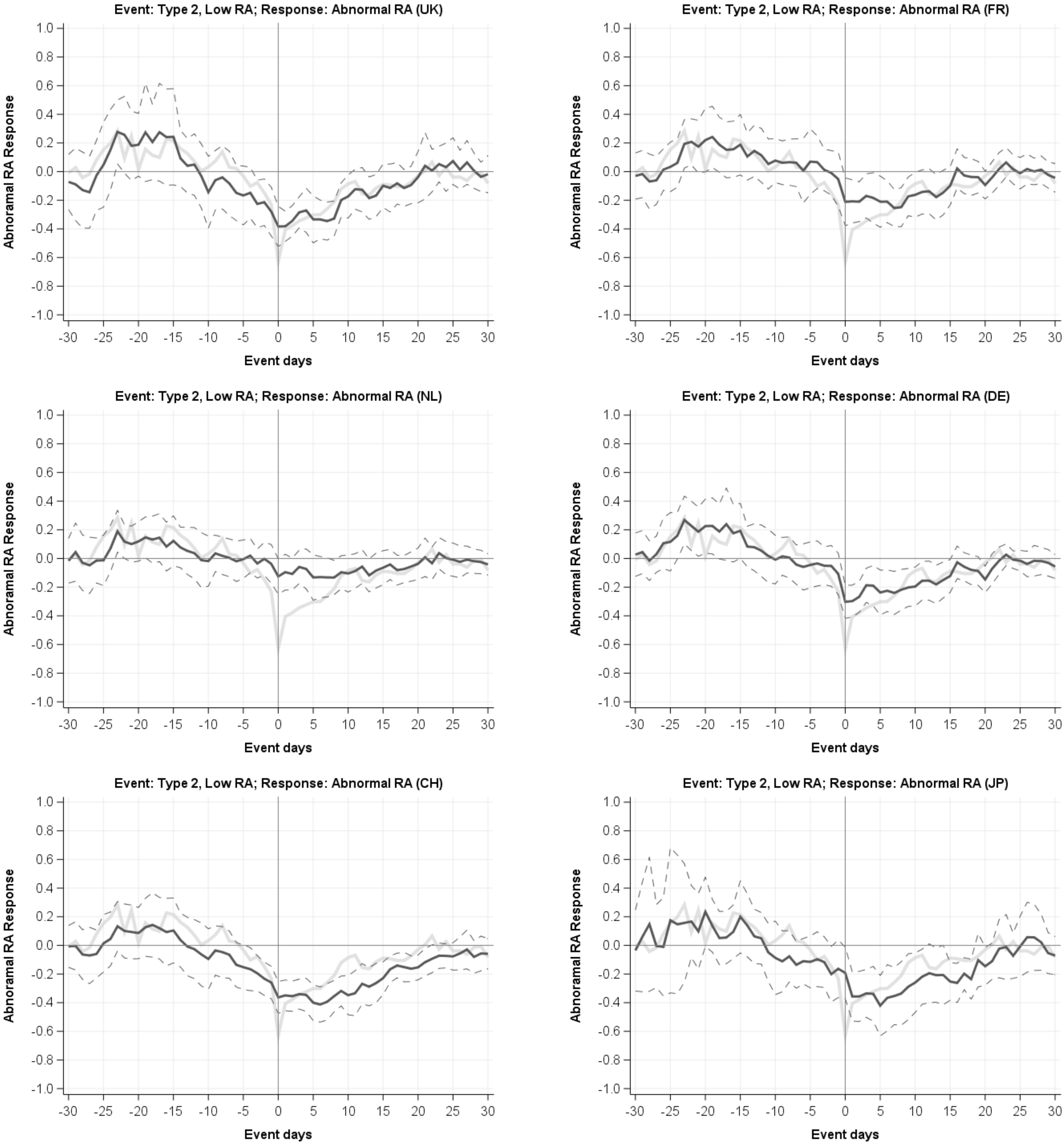


Figure A2: Event study: Abnormal country RA in response to US low-RA shocks

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).

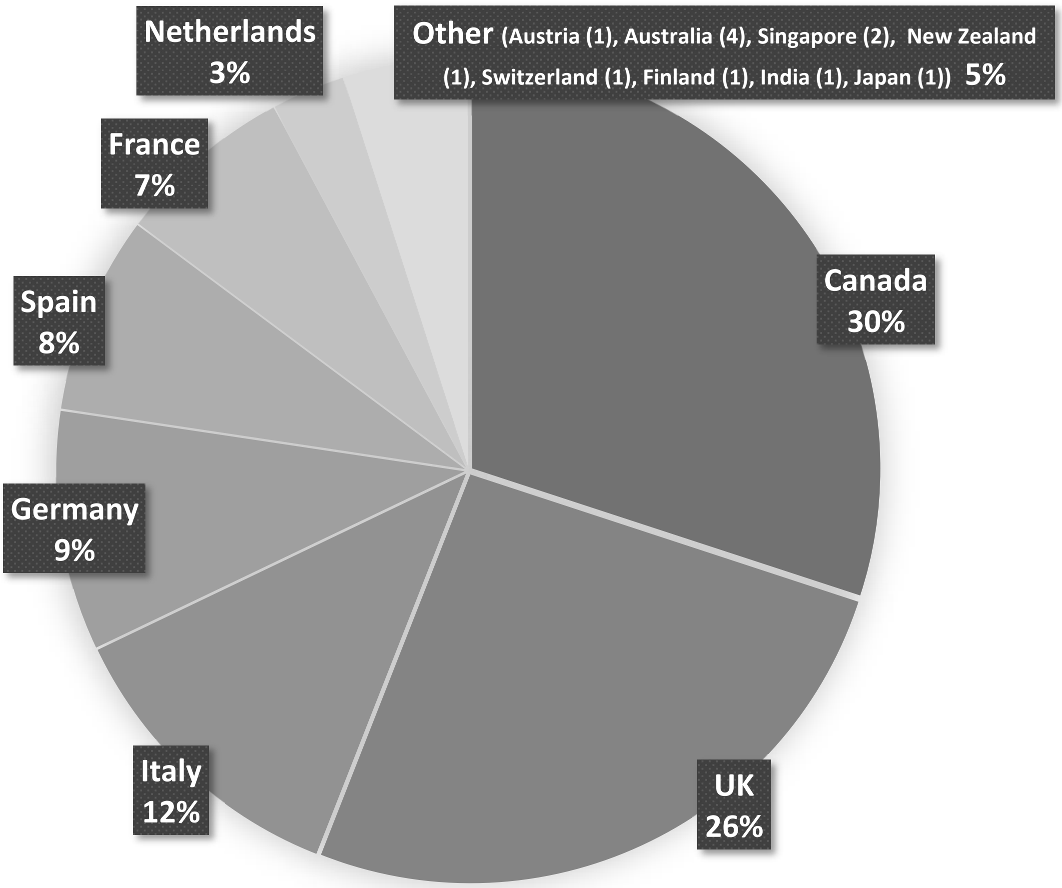


Figure A3: Residence countries of non-US participants in Study 2 (N=243)

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.

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.

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 RavenPack news stories (from Step 1) with the high (low) RA and UC event candidate dates from Step 2. 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.

One each High (Low) RA and UC date, we select the negative (positive) news story which 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* 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.

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. Examples of Economy News

This appendix section complements Section 2.3 and provides 2 examples of *economy* news in each of the four event types (High RA, Low RA, High UC, and Low UC).

1.High RA

> *[6/29/2010] U.S. stocks tumbled Tuesday as U.S. consumer confidence fell more than anticipated in June, adding to worries about a global economic slowdown. "While the recession may have technically ended last summer, consumers remain skittish about job and income prospects and are refraining from consuming in a sufficient enough manner to create substantial growth in GDP," wrote Dan Greenhaus, chief economic strategist at Miller Tabak, in a note... SP 500 Index is poised for its lowest finish this year, as U.S. consumer confidence falls more than anticipated in June, adding to worries about a global slowdown... Treasury prices climbed Tuesday morning as a slip in U.S. consumer confidence added to anxiety about the economic outlook, lifting demand for safe assets... U.S. consumers are increasingly worried about jobs and the economy, the Conference Board said Tuesday, as it reported that its consumer confidence index plummeted to 52.9 in June - the lowest level since March – from a downwardly revised 62.7 in May.*

> *[6/15/2016] Rising energy prices are starting to put upward pressure on U.S. inflation after a long stretch of broadly sluggish price growth. The producer-price index for final demand, which measures changes in the prices that U.S. firms receive for goods and services, increased a seasonally adjusted 0.4% in May from the prior month after rising 0.2% in April, the Labor Department said.*

2.Low RA

[2/3/2012] The U.S. economy gained 243,000 jobs in January and the unemployment rate slipped to 8.3%, the Labor Department said Friday. Economists surveyed by MarketWatch had forecast the U.S. would add 121,000 jobs last month, with a jobless rate of 8.5%... Average hourly earnings rose 0.2% to $23.29 and hours worked were unchanged at 34.5. Job gains for December and November were revised up by a combined 60,000. The U.S. created 1.82 million jobs in 2011, based on newly revised tax and other data, compared to an originally reported increase of 1.64 million... U.S. companies hired the most workers in nine months and the nation's unemployment rate fell to the lowest level in almost three years, according to the government's employment report for January. The U.S. gained 243,000 jobs last month and the unemployment rate dipped to 8.3% as nearly every sector of the economy added workers, the Labor Department said Friday.

[11/15/2016] Sales at U.S. retailers soared in recent months, suggesting Americans are spending briskly heading into the holidays and boosting the economy. Retail sales-measuring purchases at restaurants, clothiers, online stores and other shops- grew a seasonally adjusted 0.8% in October from a month earlier, the Commerce Department said Tuesday. Sales grew 1% in September, revised figures showed, up from a previously reported 0.6% increase.

3.High UC

[5/13/2009] U.S. retail sales fell for a second month in a row during April, as job losses and uncertainty about the economy put pressure on spending. Retail sales decreased 0.4% from the previous month, the Commerce Department said Wednesday. Economists had expected an increase of 0.1%... Sales in March were revised downward to a decline of 1.3% instead of the 1.2% previously reported. Sales rose in January and February after sliding for six straight months... Consumer spending makes up 70% of gross domestic product, the broad measure of economic activity. GDP plunged 6.1% in the first quarter. It would have fallen further if not for a 2.2% increase in consumer spending. The 2.2% increase followed a fourth-quarter spending drop of 4.3%.

[1/15/2016] US retail sales fell 0.1% in December, a downbeat finish to the weakest year for the measure of consumer spending since the country pulled out of the recession. For all of 2015, retail sales advanced only 2.1%, the slowest pace since 2009, when full-year sales tumbled 7.4%, Commerce says. By comparison, retail sales climbed 3.9% in 2014, 3.7% in 2013, 4.9% in 2012, 7.3% in 2011 and 5.5% in 2010. The latest numbers underscore broad uncertainty among consumers, falling prices for some goods and a changing retail landscape.

4.Low UC

[1/30/2001] The options market offered a relatively modest reaction to the latest action by the Federal Reserve. The Federal Open Market Committee lowered interest rates by a half- percentage point, validating the predictions of many market observers but surely disappointing a few who hoped for a steeper cut... The FOMC, as expected, cut Fed Funds rate a half point to 5.5% and warned that balance of risks favor economic weakness. Also lowered largely symbolic rate a half point to 5%.

[4/14/2009] U.S. Federal Reserve Chairman Ben Bernanke on Tuesday offered some hope that the 16-month-old recession may be losing some of its severity and he is "fundamentally optimistic" about the economy's longer term prospects. "Recently we have seen tentative signs that the sharp decline in economic activity may be slowing," Bernanke said in remarks prepared for delivery later Tuesday in Atlanta... "Today's economic conditions are difficult, but the foundations of our economy are strong, and we face no problems that cannot be overcome with insight, patience, and persistence," he said... Bernanke expressed confidence in the Fed's ability to promote economic stability through a variety of efforts including credit programs and open market securities purchases, saying "the Fed's toolkit remains potent, even though the federal funds rate is close to zero and thus cannot be reduced further."

IV. 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