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Better the devil you know than the devil you don't – financial crises between ambiguity aversion and selective perception

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Abstract:

Aim: Financial crises are dangerous and frightening events with potentially severe consequences for investors, financial systems and even whole economies. Hence, we suppose that market participants show increased proneness to emotionally biased decisions during times of market distress. We test our hypothesis by analyzing two well-known behavioral effects: ambiguity aversion and selective perception.

Design / Research methods: First, we use GARCH volatilities of major stock indices as a measure of market distress and monthly data from the Economic Policy Uncertainty Indicator (EPUI) as a proxy for the level of market uncertainty. By estimating the Granger causality, we test whether uncertainty causally influences market volatility, which could be interpreted as a sign of ambiguity aversion of market participants. Second, we use sub-indices of the EPUI regarding financial regulation, monetary policy, and economic policy as a proxy for market awareness of these topics. By regressing on GARCH volatilities, which serve again as the measure for crises, we analyze if investors' attention differs depending on market distress due to selective perception

Conclusions / findings: Overall, we find mixed results. For ambiguity aversion, we find causality for the total sample as well as for the subsamples of the first oil crisis, the Latin America crisis, the Asian crisis, and the subprime crisis. For selective perception, we find significant results for the total sample as well, as for the Dot.Com bubble and the subprime crisis.

Originality / value of the article: We add value by examining specific severe financial crises with respect to behavioral aspects of market participants. We want to learn whether the awareness of investors regarding important topics like monetary policy, financial regulation, and economic policy is stable over time and if uncertainty drives the market distress or vice versa. This knowledge is important to investors and policy makers.

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Implications of the research: Investors and decision-makers need to focus e.g. on current discussions regarding financial regulation not only in times of distress but also in normal times. Otherwise, policy makers will be forced to react in times of pressure and cannot proactively devise regulation.

Limitations of the research: First, we did not check for spill-over effects. The question if volatility creates subsequent ripple effects in our framework is left for future research.
Second, for the Japanese crisis we did not find causality in our ambiguity aversion analysis. The question whether the link between levels of uncertainty and volatility is stronger once a bubble bursts on domestic soil remains unanswered in our paper.

Key words: ambiguity aversion, economic policy, financial crisis, financial regulation, monetary policy, selective perception, uncertainty.
JEL: G01, G02, G15, N22.

1. Introduction

Financial crises are frightening events, which may have disastrous consequences for market participants and therefore are presumably linked to emotional decision making. In this paper, we examine two different behavioral effects, which are potentially related to financial crises: ambiguity aversion and selective perception. First, we focus on the relationship between uncertainty and volatility to explore if investor behavior expresses ambiguity aversion during financial crises. Investors are expected to seek "safe havens" for their investments in case of increasing degrees of uncertainty in financial markets, leading to heightened volatility. This behavior could be referred to as ambiguity aversion, a heuristic, which assumes investors to prefer quantifiable risks over non-measurable uncertainty. The distinction between risk and uncertainty has first been made by Knight (1921) and Ellsberg (1961). Ellsberg was the first one to analyze the significance of the behavioral aspect. In case of ambiguous information on an asset, investors expect higher returns and may cause excess volatility (Epstein, Schneider 2008; Daxhammer, Facsar 2012). We use monthly data from the Economic Policy Uncertainty Indicator (EPUI) to analyze its impact on the monthly GARCH volatility of the Dow Jones Industrial Average (DJIA) and Nikkei 225 during several distinctive financial crises (see table 1) to test for ambiguity aversion. Since the EPUI measures the frequency of newspaper articles covering the conjoined terms *economy*, *policy*, and *uncertainty*, it serves as a proxy for the uncertainty level in the economy. Based on Granger causality tests, we find that uncertainty indeed drives volatility in the overall sample. For individual crises, however, this is not generally the case. For the regression analysis, we use a 96-year time series of the U.S. EPUI and the DJIA; and 23 years of the Japanese EPUI and Nikkei 225.

Table 1. Analyzed crises

Uncertainty Index	**Crisis**	**Bubble Burst**	**Analyzed Period**
EPUI	Black Thursday	1929	1926 - 1932
	1st Oil Crisis	1973	1970 - 1976
	2nd Oil Crisis	1979	1976 - 1982
	Latin America Crisis	1982	1979 - 1985
	Black Monday	1987	1984 - 1990
EPUI & Sub-Indices	Japan Asset Price Bubble	1990	1987 - 1993
	Asian Financial Crisis	1997	1994 - 2000
	Dot.Com Crisis	2000	1997 - 2003
	Subprime Crisis	2008	2005 - 2011

Notes: Selection of financial crises included in the analyses.
Source: Based on Kindleberger, Aliber (2015) as well as own research interest.

Second, we use the corresponding sub-indices of the U.S. EPUI to test if market participants are fooled by selective perception with respect to *financial regulation*, *monetary policy*, and *economic policy*. To the best of our knowledge, selective perception traces back to Bruner and Postman (1949). It describes the behavior that investors subliminally neglect information, which does not fit to their investment story. Generally, market participants should be aware of financial regulation and monetary as well as economic policy at all times, but we suspect that during crises, people are seeking for a "lender of last resort" and care more about regulation and economic policy than in "good times". Against this background, we use the corresponding sub-indices of the EPUI as a proxy for media coverage and market attention with respect to the subject's financial regulation, monetary policy, and economic policy to test for selective perception. The DJIA GARCH volatility serves as a measure for the course of a crisis. Due to limited data availability for the EPUI sub-indices to 23 years and U.S. only, we regress the EPUI sub-indices on monthly

DJIA GARCH volatilities for this specific timeframe. For the Dot.Com and subprime crises, we find a statistically significant relation between stock market volatility and uncertainty sub-indices. By contrast, there is no significant relation for the Japanese and Asian crises and U.S. equity volatility.

2. Literature Review

Research into factors of uncertainty and their effects on economic and financial variables has steadily been gaining interest and relevance. Commencing with Bernanke's (1983) seminal paper on firm-level investment timing decisions under uncertainty, followed by an analysis of macro uncertainty shocks by Bloom (2009), the field has developed several statistical indicators in order to quantify uncertainty, among others the EPUI as devised by Baker et al. (2016).

This literature in general and the EPUI as a quantitative indicator in particular have frequently been employed for inquiry into the dependency between uncertainty and the economy. Several strands of research are developing, which will be reviewed hereafter in ascending order of relevance to this paper.

Studies have focused on geographical spill-over effects of uncertainty as laid out by Colombo (2013) and the IMF (2013), who show that significant spillover does occur, both between the EU and the U.S. as well as emanating from these geographies outward. The European Commission (2013) and European Central Bank (2013) shed light onto the dependency between economic policy uncertainty and economic activity, highlighting the negative correlation between uncertainty and real economic variables such as investment, employment and real GDP. An extensive body of literature has developed analyzing both correlations and causality between policy uncertainty and stock returns. Antonakakis et al. (2012) discover time-varying correlations between policy uncertainty and stock returns, Brogaard and Detzel (2015) show that economic policy uncertainty can be used as a proxy for forecasting excess market returns, while Balcilar et al. (2016) find causal relationships between economic policy uncertainty and stock returns in sub-periods of rolling-window tests.

Nodari (2013), Pastor and Veronesi (2013) show that political uncertainty commands a risk premium, leads to increased correlation between equities and most interestingly, causes heightened market volatility. Further research into the dependency between uncertainty and volatility is undertaken by Amengual and Dacheng (2013), who find evidence for significant downward volatility jumps following a reduction of policy uncertainty. Baker et al. (2016) show a significant impact of uncertainty onto future volatility by regressing the VIX, an index of the 30-day option-implied volatility of the S&P 500, against different sub-components of policy uncertainty.

We take up this general thrust of research into directional dependencies between policy uncertainty and volatility. However, where preceding analyses have utilized proxies for implied future volatility, we deviate in employing realized historical GARCH sigma time series. Furthermore, we contribute to existing literature in analyzing various financial crises sequentially over multiple decades. In regressing our volatility estimates against the EPUI and its different sub-indices, we thus close a methodological gap of immediate interest in focusing on realized volatilities in dependence on policy uncertainty levels in times of significant financial market stress. Our research aims are therefore twofold: first, realized volatility regressed against the historical EPUI in the U.S. and Japan will test for ambiguity aversion and its supposed direct consequence, a “risk-off approach” and “flight to safe havens” on the part of market participants. Second, it will be analyzed whether the prevalence of particular terms in media publications related to interventions, quantified by different U.S. EPUI sub-indices, indeed leads to heightened volatility highlighting the occurrence of selective perception in market participants.

3. Dataset

Our proxies for uncertainty are monthly data points of the Economic Policy Uncertainty Indicator and multiple sub-indicators, following Baker et al. (2016). This includes the general historical time series of policy uncertainty for the U.S. (available from 1900 onwards), which are employed in analyses regarding ambiguity aversion as well as the differentiated sub-indicators “Financial Regulation”, “Economic Policy”, and “Monetary Policy” (available starting 1985) to test for selective perception. Selection of the differentiated sub-indicators is based on our interest regarding market participants’ perception and behavioral reactions to supposed intervention around financial crises.

The EPUI calculation is based on counting the monthly publication frequency of articles containing three specific terms within ten leading American newspapers. Articles are counted when containing terms related to the three fields “economy”, “policy”, and “uncertainty”. The article count is then scaled through averaging over the number of articles per paper per month. The resulting data are standardized to unit standard deviation and averaged over all ten newspapers by month, as well as normalized to a mean of 100 regarding the timeframe 1985 to 2009. For specific sub-indicators, an additional search term relevant to the specific field (e.g. “QE” for quantitative easing) is added into the process (Baker et al. 2016).

As a measure for realized market reactions to shifts in the various measures of policy uncertainty in times of crises, we choose monthly closing prices of the Dow Jones Industrial Average (dataset: 1915 to 2017) as well as the Nikkei 225 (dataset: 1988 to 2017).

In the selection of specific time periods for further analyses, we are motivated by Kindleberger’s wave model (cf. Kindleberger, Aliber 2015) as a reference for significant financial crises. To populate our model, resulting relevant time series are chosen in a way to include the preceding and following three years with reference to the date of the outbreak of a crisis. For analyses employing the historical uncertainty indicator for the U.S., we thus study a wide range of crises comprising the Great Depression with Black Thursday (dataset: 1926 to 1932), the first oil crisis (1970 to 1976), the second oil crisis (1976 to 1982), the Latin America crisis (1979 to 1985), the turbulences around Black Monday (1984 to 1990), the Japan crisis (1987 to 1993), the Asian financial crisis (1994 to 2000), the Dot.Com bubble (1997 to 2003), and the subprime crisis (2005 to 2011). In order to analyze the intervention specific sub-indicators of policy uncertainty, i.e. financial regulation, economic policy, and monetary policy, we run additional regression analyses for the Japan crisis, the Asian financial crisis, the Dot.Com bubble and the subprime crisis, spanning the date ranges mentioned above.

4. Methods

To reach conclusions as to the explanatory power of policy uncertainty for market volatility, we use a panel regression approach. The model is estimated as follows:

$$ln\,(Sigma_{StockMarketReturns_t}) = \beta_0 + \beta_1 \cdot ln(Uncertainty\ Index_t) + {}_t \quad (1)$$

We use β_0 as a constant, β_1 as the coefficient of four different uncertainty indices we aim to estimate, with t = 1 to T for the time, and epsilon () as the error term of the model (Wooldridge 2002).

As the dependent variable, we feed monthly returns of both the DJIA as well as the Nikkei 225 into a standard GARCH(1,1) process, incorporating the most recent observations for both the continuously compounded return and the variance rate. For a technical description of GARCH models see Bollerslev (1986) and Hull (2014). From this, the natural logarithms of the GARCH(1,1) sigma values are extracted as the estimate for realized volatility. For the regression models, multiple GARCH(1,1) sigma time series are calculated to address the different time horizons of the uncertainty indices. First, a time series starting from January 1915 until January 2017 is used. Second, time series spanning from January 1985 until January 2017 (DJIA) as well as one spanning from June 1988 to January 2017 (Nikkei 225) are calculated. The GARCH calculations consider the timeframe until 2017 to incorporate the latest stock market returns, even if the regression models end with the subprime crisis in 2011. For the independent variables, the natural logarithms of the respective uncertainty indices are used.

For the first analyses, the time series GARCH(1,1) U.S. Sigma 1915 and the U.S. EPUI as well as the GARCH(1,1) Japan Sigma 1988 and the Japanese EPUI are chosen. In addition, the Granger (1969) causality, used as a robustness check for ambiguity aversion, tests if one variable can forecast another variable. The causality tests are used for each regression pair of individual time series. The estimates are sensitive to the choice of lag-length (Thornton, Batten 1985). For robustness purposes, only the tendencies of the estimates are considered and a lag-length of three is chosen. The general outcomes are similar if shorter (1) or longer (4) lag-lengths are calculated (cf. Thurman, Fisher 1988). For the second analyses, the time series GARCH(1,1) U.S. Sigma 1985 and the U.S. sub-indicators are selected.

5. Statistics and results

We aim to analyze different periods of financial distress. For that reason, regression models for the EPUI as well as regression models for sub-indices of the EPUI are calculated for up to nine different crises. The descriptive statistics for the dependent and independent variables are shown in table 2. An exemplary time series starting in 1970 with the first oil crisis for the dependent variable GARCH(1,1) Sigma 1915 and the independent variable U.S. EPUI can be seen in Appendix I.

All non-logarithmized variables can reject the null hypothesis of a Jarque-Bera test (p-value 0.000) and are therefore non-normally distributed. A Pearson's chi-squared test of independence is applied for the estimated combinations between the dependent and independent variables. All tested combinations cannot reject the null hypothesis (all p-values close to 0.240) and are therefore independent of each other. It can be doubted that a unit root for the time series exist, since the null-hypothesis of stationarity based on a KPSS test (Kwiatkowski et al., 1992) cannot be rejected for all but two subsamples. A possible explanation could be "*that most economic time series are not very informative about whether or not there is a unit root*" (Kwiatkowski et al. 1992: 160). The trend stationary results are shown in Appendix III.

Table 2. Descriptive statistics

Variable	Mean	Median	St. Dev.	Min.	Max.	1st Quant.	3rd Quant.
U.S. Sigma 1915	0.049	0.043	0.021	0.027	0.183	0.037	0.052
U.S. Sigma 1985	0.044	0.042	0.012	0.025	0.091	0.034	0.050
Japan Sigma 1988	0.060	0.0582	0.011	0.048	0.126	0.053	0.064
U.S. EPUI 1915	116.19	114.21	47.37	29.62	317.39	79.67	143.82
Japan EPUI 1988	97.54	92.31	32.11	29.92	204.73	71.59	116.44
Financial Reg.	100.60	55.85	122.72	0.000	877.55	30.56	113.24
Economic Policy	100.06	89.80	41.53	37.27	271.83	69.23	120.59
Monetary Policy	99.82	84.20	60.93	16.57	407.94	57.52	126.37

Notes: The table shows the descriptive statistics for the variables from the beginning of the time series until January 2011. The dependent variables are U.S. and Japanese Sigma calculates, which are based on a standard GARCH(1,1) process of the monthly returns for the Dow Jones Industrial Average Index and the Nikkei 225. The independent variables are the U.S. and Japanese EPUI as well as U.S. sub-indicators for financial regulation, economic policy, and monetary policy.
Source: EPUI data based on Baker et al. (2016).

6. Ambiguity Aversion

Different approaches can be used for the chosen panel regression methodology to test for ambiguity aversion. The models can be based on a random effects (RE) or a fixed effects (FE) approach. We statistically test for the appropriate model based on the total period for both time series. The FE approach, which considers unobserved effects that can be correlated with the independent variables, is chosen because both models reject the null hypotheses of a Hausman test. Furthermore, based on a F-test for individual effects, an ordinary least squares (OLS) and a FE approach are examined, which cannot reject the null hypothesis. However, it is doubted that no individual effects exist during the timeframe. Therefore, FE regressions are used.

The coefficients of the U.S. EPUI, which are presented in table 3, show positive statistically significant relationships for the Black Thursday crash, the first oil crisis, Black Monday, the Asian state crisis, the Dot.Com crash, the subprime crisis, and the total period. The U.S. EPUI seems to have an impact on the mentioned crises.

Table 3. Ambiguity aversion regressions - U.S.

Dependent: GARCH(1,1) U.S. Sigma 1915	**Black Thursday 1929**	**1st Oil Crisis 1973**	**2nd Oil Crisis 1979**	**Latin America 1982**	**Black Monday 1987**
U.S. EPUI	0.843*** (0.141)	0.354*** (0.115)	-0.237*** (0.077)	0.014 (0.082)	0.445** (0.162)
Adjusted R^2	0.323	0.114	0.115	0.000	0.165
F-Test (p-value)	0.000	0.003	0.003	0.867	0.010
Observations	73	73	73	73	37
Granger Causality	No	Yes	No	Yes	No
Dependent: GARCH(1,1) U.S. Sigma 1915	**Japan Crisis 1990**	**Asian Crisis 1997**	**Dot.Com Bubble 2000**	**Subprime Crisis 2008**	**Total Period**
U.S. EPUI	0.089 (0.121)	0.391*** (0.140)	0.204*** (0.058)	0.675*** (0.095)	0.250*** (0.021)
Adjusted R^2	0.007	0.096	0.397	0.167	0.114
F-Test (p-value)	0.464	0.007	0.000	0.000	0.000
Observations	73	73	73	73	1,153
Granger Causality	No	Yes	No	Yes	Yes

Notes: The dependent variable is the log of the GARCH(1,1) U.S. volatility 1915. The independent variable is the log U.S. EPUI. The periods for analyzing the crisis consider three years before and after the crisis started, e.g. the asset or financial bubble burst. Except for the Black Monday regression, which analyzes three years after the stock market crash. The overall period for monthly observations is January 1915 until January 2011. Standard errors in parenthesis. The Granger causality states if the uncertainty index can predict the volatility.
Level of significance: *** p<0.01, ** p<0.05, * p<0.10.
Source: EPUI data based on Baker et al. (2016).

Both, the Latin America crisis and the Japan crisis have positive albeit not significant coefficients of uncertainty. In the set of the crisis, the Black Monday crash of 1987 stands out because it has not been created by a burst of a financial bubble. Instead, computerized trading programs most probably caused the stock market crash. Therefore, only the years following the Black Monday market crash are shown in table 3. If the period for analyzing the Black Monday spans the years 1984 until 1990, the coefficient for the U.S. EPUI would account for 0.039 (standard error 0.155) with a p-value of 0.867. The second oil crisis is the only crisis that displays a negative statistically significant link. However, the second oil crisis of 1979 started shortly before the Latin America crisis of 1982. The years analyzed before 1982 overlap with the years after the 1979 crisis. If both crises are portrayed together for the years 1976 until 1985, the estimate displays a negative coefficient of 0.182 (0.062) and a p-value of 0.004. For the second oil crisis and the Latin America crisis, the uncertainty index seems to have a negative impact on the volatility of the DJIA.

The results for Granger causality estimates for the crises are indifferent. For the total period, the Asian state crisis, and the subprime crisis, the variables can forecast each other because the direction of causality between the variables is in both directions (cf. Granger 1969). That means, the uncertainty index can forecast a crisis but at the same time the crisis can predict a level of uncertainty. The Granger tests indicate a true, one-way causal relation only for the first oil crisis and the Latin American crisis, with the uncertainty index influencing the volatility. Furthermore, for Black Thursday, Black Monday, and the Dot.Com crash, we find a one-way causal link from the volatility towards the EPUI. Appendix II shows all results for Granger causalities.

The coefficient of the U.S. EPUI does not show a statistically significant link during the Japan crisis. The result indicates that the level of uncertainty in the U.S. does not seem to have influenced the Japan crisis and vise-versa. As a robustness check, the relationship between the Japanese uncertainty index, starting in June 1988 as the earliest available date, and a GARCH(1,1) sigma time series for the Nikkei 225 is tested. We find a positive, statistically significant relation of 0.339*** (standard error 0.080) from 1988 to 1993. For the total period from 1988 to 2011, a positive coefficient of 0.178*** (0.027) is found. A Granger causal link between the level of uncertainty and volatility cannot be found for the Japan crisis. However, we find that the volatility of the Nikkei can predict the Japanese EPUI for the total period. Overall, the U.S. and Japanese results during the Japan crisis indicate that a link between the level of uncertainty and volatility might be strongest if the financial bubble bursts on home soil. We leave the investigation of this assumption up for future research.

Table 4. Ambiguity aversion regressions - Japan

Dependent: GARCH(1,1) Japan Sigma 1988	**Japan Crisis 1990**	**Total Period**
Japanese EPUI	0.339*** (0.080)	0.178*** (0.027)
Adjusted R^2	0.237	0.140
F-Test (p-value)	0.000	0.000
Observations	56	272
Granger Causality	No	No

Notes: The dependent variable is the log of the GARCH(1,1) volatility for the Nikkei 225. The independent variable is the log Japanese EPUI. The Granger causality states if the EPUI can predict the volatility. Level of significance:
*** $p<0.01$, ** $p<0.05$, * $p<0.10$.
Source: EPUI data based on Baker et al. (2016).

7. Selective perception

For the test of selective perception, three indices dating back to 1985 are used as independent variables to analyze the impact on the volatility. The volatility is estimated based on the above-described GARCH(1,1) approach starting from 1985. The results for the uncertainty of financial regulation are displayed in table 5. The uncertainty of financial regulation seems to have an impact on the Dot.Com bubble and subprime crisis as well as on the total examined period since the coefficients are positive and significant. For the Japan and Asian state crises, the coefficients are positive, but not statistically significant. Especially for the subprime crisis, with the highest coefficient of 0.248*** and adjusted R-squared of 0.608 for the investigated crisis, new financial regulatory actions, such the implementation of Basel II in the

U.S. before the crisis or Basel III after the Lehman Brothers collapse, were publicly discussed and might have led to selective perception of market participants.

Table 5. Financial regulation uncertainty

Dependent: GARCH(1,1) U.S. Sigma 1985	**Japan Crisis 1990**	**Asian Crisis 1997**	**Dot.Com Bubble 2000**	**Subprime Crisis 2008**	**Total Period**
Financial Regulation	0.042 (0.037)	0.038 (0.036)	0.048*** (0.017)	0.248*** (0.022)	0.115*** (0.013)
Adjusted R^2	0.018	0.015	0.096	0.608	0.197
F-Test (p-value)	0.256	0.291	0.007	0.000	0.000
Observations	73	73	73	73	309

Notes: The dependent variable is the log of the GARCH U.S. volatility 1985. The independent variable is the log of the sub-index financial regulation. The periods for analyzing the crisis consider three years before and after the crisis started, e.g. the asset or financial bubbles burst. The overall period for monthly observations is January 1985 until January 2011. Standard errors in parenthesis.
Level of significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.
Source: EPUI data based on Baker et al. (2016).

The impact of economic policy uncertainty on crises in the U.S. is reported in table 6. It can be seen that the uncertainty of economic policy seems to have an influence on the Dot.Com bubble, the subprime crisis, and on the total timeframe. The results for the sub-index are in line with Baker et al. (2016), who find a positive impact of 0.432*** on the logarithmized 30-day implied volatility of the S&P 500 for a time horizon from 1996 to 2012. The negative coefficients for the Japan and Asian state crises are not significant. Again, the coefficient of 0.534*** and adjusted R-squared of 0.545 for the subprime crisis are highest. A possible explanation could be publicly discussed economic policy acts before and after the crisis, such as tax cuts, trade agreements, and the intended reform of the social security system during the Bush administration or the stimulus debate and the Troubled Asset Relief Program (TARP) after 2008.

Table 6. Economic policy uncertainty

Dependent: GARCH(1,1) U.S. Sigma 1985	**Japan Crisis 1990**	**Asian Crisis 1997**	**Dot.Com Bubble 2000**	**Subprime Crisis 2008**	**Total Period**
Economic Policy	-0.029 (0.084)	-0.108 (0.095)	0.133*** (0.041)	0.534*** (0.055)	0.245*** (0.035)
Adjusted R^2	0.002	0.017	0.126	0.545	0.138
F-Test (p-value)	0.728	0.261	0.002	0.000	0.000
Observations	73	73	73	73	313

Notes: The dependent variable is the log of the GARCH U.S. volatility 1985. The independent variable is the log of the sub-index economic policy. The periods for analyzing the crisis consider three years before and after the crisis started, e.g. the asset or financial bubbles burst. The overall period for monthly observations is January 1985 until January 2011. Standard errors in parenthesis.
Level of significance: *** p<0.01, ** p<0.05, * p<0.10.
Source: EPUI data based on Baker et al. (2016).

Table 7. Monetary policy uncertainty

Dependent: GARCH(1,1) U.S. Sigma 1985	**Japan Crisis 1990**	**Asian Crisis 1997**	**Dot.Com Bubble 2000**	**Subprime Crisis 2008**	**Total Period**
Monetary Policy	0.044 (0.049)	0.030 (0.047)	0.077*** (0.026)	0.151** (0.069)	0.114*** (0.025)
Adjusted R^2	0.011	0.006	0.106	0.062	0.063
F-Test (p-value)	0.375	0.526	0.004	0.031	0.000
Observations	73	73	73	73	313

Notes: The dependent variable is the log of the GARCH U.S. volatility 1985. The independent variable is the log of the sub-index monetary policy. The periods for analyzing the crisis consider three years before and after the crisis started, e.g. the asset or financial bubbles burst. The overall period for monthly observations is January 1985 until January 2011. Standard errors in parenthesis.
Level of significance: *** p<0.01, ** p<0.05, * p<0.10.
Source: EPUI data based on Baker et al. (2016).

The last reported index in table 7 is the sub-index monetary policy. The uncertainty of monetary policy actions seems to have a positive statistically significant impact on the Dot.Com crisis and the subprime crisis. Furthermore, the total period also displays a strong positive coefficient. As with the other two indices, the Japan and Asian state crises seem not to be affected by uncertainty in the U.S. Comparable to the financial regulation and economic policy sub-indices, the uncertainty of monetary policy actions of 0.151** is highest for the subprime crisis.

Surprisingly, the level of uncertainty is not as high as for the other two examined indices, which might be triggered by the overall low-interest rate level in the U.S. following the monetary policy of the Fed and Alan Greenspan after 2002. In this context, the uncertainty about the rise of the United States Fed Funds Rate in the years 2004 to 2006, which is one of the reasons for the bursting of the bubble, does not seem to have a particularly high impact on the volatility of the DJIA. Market participants might have neglected the information about the overall low-interest rate level as a future factor for the burst of the subprime bubble.

8. Conclusion

Are investors making emotionally biased decisions during financial crises? At least with respect to ambiguity aversion and selective perception, we find mixed results. For most crises, there is a significant link between uncertainty as measured by the EPUI and stock market volatility. The Granger causality test, however, only indicates for about half of the crises that uncertainty drives market volatility, which would be a sign of ambiguity aversion. During many other crises, it also seems possible that market volatility triggers uncertainty. Our findings are subject to the assumption that the EPUI really measures "Knight uncertainty". If so, considering behavioral aspects in the restoration of confidence in markets should prove to be a valuable supplementary measure alongside traditional efforts, such as the injection of liquidity into markets. Possibly, this might contribute to tackling the causes of rampant volatility in times of crisis at their root, in the behavior of market participants.

Regarding selective perception, we find a significant link between newspaper coverage of topics like financial regulation, monetary policy, and economic policy on the one hand and stock market volatility as a measure for the course of a crisis on the other hand. This link only holds true for the Dot.Com bubble and the subprime crisis, but not for the Japanese asset bubble and the Asian crisis. We suspect that from the domestic U.S. perspective, the Japanese and Asian crises did not trigger a call for a U.S. "lender of last resort" and therefore did not raise too much attention of U.S. market participants to domestic financial regulation or monetary policy. For U.S. crises, however, there seems to be selective perception with respect to terms like financial regulation, monetary policy, and economic policy. In the face of financial crises, it therefore seems advisable to act swiftly and decisively to ease media attention on issues around policy and regulation with the aim to preclude the possible impact selective perception can develop. Furthermore, in preparation to counter the behavioral routines outlined above, it should be assured that policy makers and market participants do not only react to crises in an ad-hoc manner but proactively adjust to monetary and economic policy as well as regulation.

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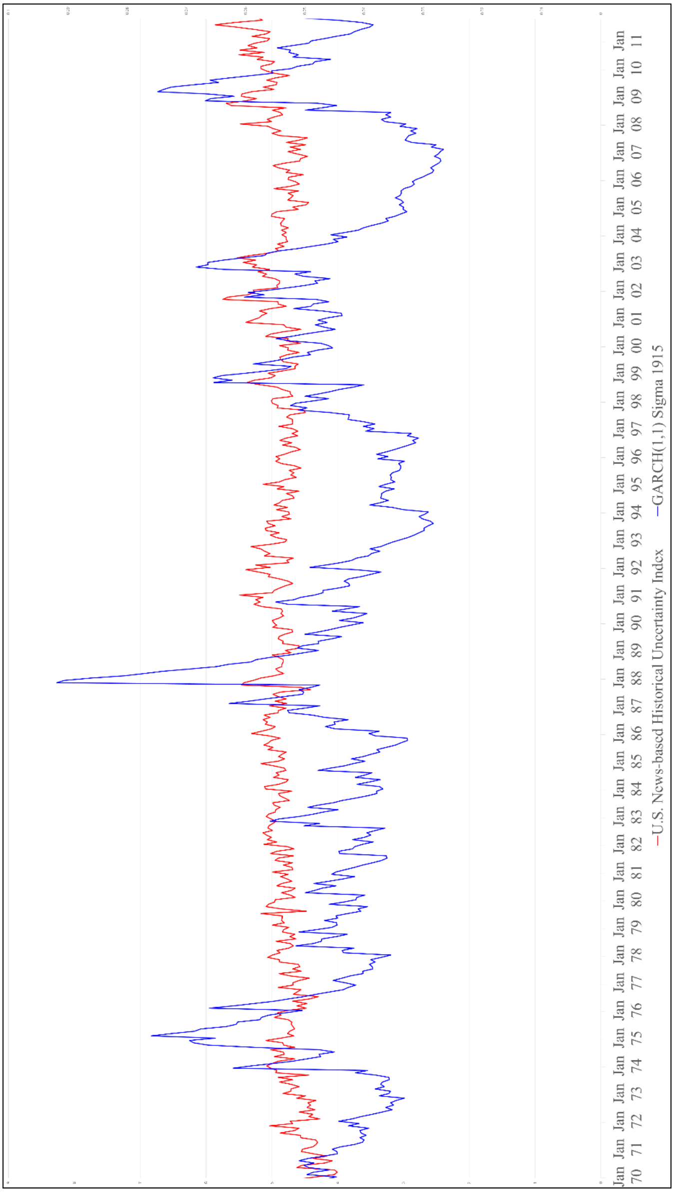
Appendix I.

Figure 1: Times series of variables.



Notes: The graph shows the time series of the monthly GARCH(1,1) volatility of the Dow Jones Industrial Average Index (blue) and the U.S. Economic Policy Uncertainty Index (red) from 1970 until 2011

Source: EPUI data based on Baker et al. (2016).

Appendix II.

Table 8 Granger causality - U.S.

Granger Causality Test			Reverse Granger Causality Test		
Variable 1	**Variable 2**	**p-value**	**Variable 1**	**Variable 2**	**p-value**
Sigma 1915 (1915-2011)	U.S. EPUI	0.013	U.S. EPUI	Sigma 1915 (1915-2011)	0.091
Sigma 1915 (1929)	U.S. EPUI	0.775	U.S. EPUI	Sigma 1915 (1929)	0.000
Sigma 1915 (1973)	U.S. EPUI	0.000	U.S. EPUI	Sigma 1915 (1973)	0.499
Sigma 1915 (1979)	U.S. EPUI	0.784	U.S. EPUI	Sigma 1915 (1979)	0.268
Sigma 1915 (1982)	U.S. EPUI	0.078	U.S. EPUI	Sigma 1915 (1982)	0.569
Sigma 1915 (1987)	U.S. EPUI	0.713	U.S. EPUI	Sigma 1915 (1987)	0.039
Sigma 1915 (1990)	U.S. EPUI	0.538	U.S. EPUI	Sigma 1915 (1990)	0.251
Sigma 1915 (1997)	U.S. EPUI	0.095	U.S. EPUI	Sigma 1915 (1997)	0.087
Sigma 1915 (2000)	U.S. EPUI	0.338	U.S. EPUI	Sigma 1915 (2000)	0.028
Sigma 1915 (2008)	U.S. EPUI	0.082	U.S. EPUI	Sigma 1915 (2008)	0.028

Notes: A Granger causality test and the reverse test to analyze if variable 1 can predict the other variable 2. The order of lags is three. If the p-value is below 0.1, the null hypotheses of "no Granger causality exists" can be rejected. Blue shading: uncertainty index can predict volatility. Green shading: both variables can predict each other. Red shading: volatility can predict uncertainty index.
Source: EPUI data based on Baker et al. (2016).

Appendix III.

Table 9 Stationarity tests

Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test										
Variable	**Total Period**	**Black Thursday**	**1st Oil Crisis**	**2nd Oil Crisis**	**Latin America**	**Black Monday**	**Japan Crisis**	**Asian Crisis**	**Dot.Com Bubble**	**Subprime Crisis**
U.S. Sigma 1915	2.630	0.270	0.173	0.055	0.052	0.179	0.135	0.255	0.131	0.181
U.S. Sigma 1985	0.304	-	-	-	-	-	0.135	0.252	0.144	0.180
U.S. EPUI	2.424	0.207	0.147	0.129	0.136	0.183	0.048	0.045	0.149	0.193
Financial Reg.	0.930	-	-	-	-	-	0.105	0.359	0.299	0.199
Economic Pol.	0.529	-	-	-	-	-	0.072	0.213	0.149	0.166
Monetary Pol.	0.666	-	-	-	-	-	0.159	0.051	0.166	0.105
Japan Sigma	-	-	-	-	-	-	0.202	-	-	-
Japan EPUI	-	-	-	-	-	-	0.235	-	-	-

Notes: The tests for stationarity are calculated for different variables and crises subsamples. The null-hypothesis of the KPSS test stands for stationarity.
Source: EPUI data based on Baker et al. (2016).