Fear and Risk: Do Visceral Factors Affect Risk Taking?

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FED/GFLEC Seminar - November 4, 2021

Outline

- Motivation/Related Literature
- Primary Research Questions
- Preview of Findings
- Identification Strategy
- Data
- Empirical Analysis
- Concluding Remarks

Motivation

- Rational agent models struggle to explain a number of empirical regularities found in asset markets
  - High volatility in asset prices (Shiller, 1981; Grossman & Shiller, 1981)
  - Large equity premium (Mehra & Prescott, 1985)
  - Countercyclical nature of expected risk premiums (Fama & French, 1989)
- Systematic time varying risk preferences may be the key
- Theoretical models that feature countercyclical risk taking can explain these patterns
  - Campbell and Cochrane (1999)
  - Barberis, Huang, and Santos (2001)
  - Ju and Miao (2012)

Related Literature

- Recent empirical work documents evidence consistent with countercyclical financial risk taking
    - Guiso, Sapienza, and Zingales (2018)
    - Dohmen, Lehmann, and Pignatti (2016)
    - Gerrans, Faff, and Hartnett (2015)
    - Necker and Ziegelmeyer (2016)
- Channel causing investors to reduce risk is difficult to identify

Related Literature

- One promising channel put forth is negative emotions or "visceral factors"
- Utility can be modeled as state dependent on negative emotions or visceral factors (Loewenstein, 2000)
- Guiso, Sapienza, and Zingales (2018) and Necker and Ziegelmeyer (2016) conjecture that negative emotions were important to decreased risk taking following the 2007-08 financial crisis - **beyond any wealth effects**

Related Literature

Are negative emotions/visceral factors important for countercyclical risk taking?

- Cohn et al. (2015)
  - In an experimental setting, prime professional investors with market booms or busts
  - Have them play real stakes risk taking games
  - Show those primed with busts take less risk
  - Report greater **fear** among those primed with busts
- Cohn et al. (2015) also show that subjects threatened with electric shocks take less risk
- Guiso et al. (2018) demonstrate that subjects shown horror film clips report higher risk aversion

Related Literature

- Negative emotions have been shown to be influential in risk taking
  - Other direct experimental evidence (Kuhnen & Knutson, 2011; Kuhnen & Knutson, 2005)
  - Indirect evidence in asset markets (Edmans et al., 2007; Hirshleifer & Shumway, 2003; Kamstra et al., 2003; Kamstra et al., 2000; Saunders, 1993)

Related Literature

- Survey-based studies have found negative exogenous shocks lead to more conservative investor risk attitudes
  - Natural disasters (Cameron & Shah, 2015, Bernile et al., 2018)
  - War (Callen, Isaqzadeh, Long, & Sprenger, 2014)
  - Violence (Moya, 2018; Brown et al., 2019)
- Many of these survey-based studies are in developing economies and use lottery type games to measure risk aversion
- Critiques argue these measures are not well-suited for developed economies and question the external validity (Chuang & Schechter, 2015; Vieider, 2018)

Primary Research Questions

Since visceral factors are fleeting, they are a potential source of volatility in risk-taking behavior

- Does fear affect financial risk taking of **actual** investors in **actual** markets?
- What are the dynamics of these effects?

Challenges

- Identify a relatively homogeneous group of investors on which to conduct analysis
- Identify a randomly assigned treatment that generates fear but is uncorrelated with personal, local, or macroeconomic factors that could affect risk taking decisions

Our Identification Strategy

We analyze the effect of **mass shootings** on the **risk-taking decisions** of U.S. domestic **equity mutual fund managers**

Preview of Findings

We document robust evidence that is consistent with fear inducing temporary reductions in financial risk taking

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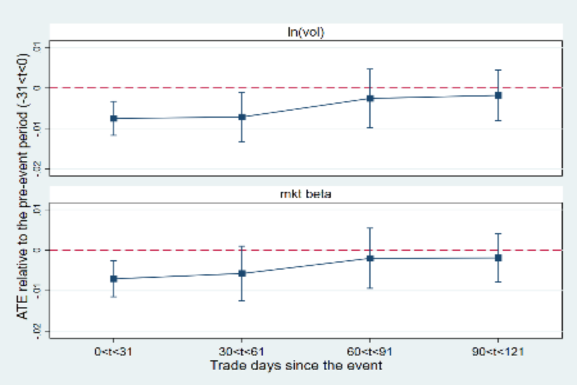
4. Results are robust to alternative:
    - risk measures
    - controls and control groups
    - event horizons
    - source of mass shooting data

Preview of Findings

- Risk reduction is temporary, lasting about one quarter following a mass shooting
- Implications different for temporary versus permanent effect. Temporary effect will induce greater volatility



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- Provide first **direct** empirical evidence that visceral factors affect financial risk taking in **actual markets**
- Provide suggestive evidence that systematic changes in investors' emotional states could exacerbate countercyclical changes in risk taking (when combine the effect we document with finding that market downturns evoke fear (Cohn et al., 2015))

Why Mass Shootings?

We utilize exposure to mass shootings as a proxy for fear

- Mass shootings induce fear in individuals and communities (Lowe & Galea, 2017; Hawdon et al., 2014; Shultz et al., 2014; Vuori et al., 2013; Kaminski et al., 2010; Addington, 2003)

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- Mass shootings are uncorrelated with macroeconomic or local economic conditions

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- Clearly stated investment objectives and styles
- Have been shown to exhibit few behavioral biases (List, 2004; List, 2003)
- Evidence that managers imprint their own preferences on portfolios, despite fiduciary duty and governance mechanisms (Chevalier & Ellison, 1997; Chevalier & Ellison, 1999; Pool et al., 2019; Shu et al., 2016; Hong & Kostovetsky, 2012; Pool et al., 2012; Hong et al., 2005; Bernile et al., 2018)

Data Sources

1. Mutual Fund Data
   - CRSP Mutual Fund Database - returns, fund characteristics, fund styles
   - Morningstar Direct - fund share class map, fund characteristics, manager information
2. Mass Shooting Data
   - Stanford Mass Shooting in America Database (SMSA) - Primary source
     - Developed by the Stanford Geospatial Center at Stanford Univ.
     - Mass shootings defined as having at least 3 victims that are unrelated to gangs, drugs, or organized crime
     - Includes dates, numbers of victims and deaths, locations, location types, etc.
   - Mother Jones Mass Shooting Database - Robustness
3. Other Data Sources - NSAR filings, NBER zip code distance files, R "gender" package, Ken French's website

Sample Construction

1. Identify sample of mass shooting events
2. Identify sample of candidate mutual funds
3. Populate events - identify treated and control groups
4. Pool events - ensure no cross contamination

1. Identify Sample Events

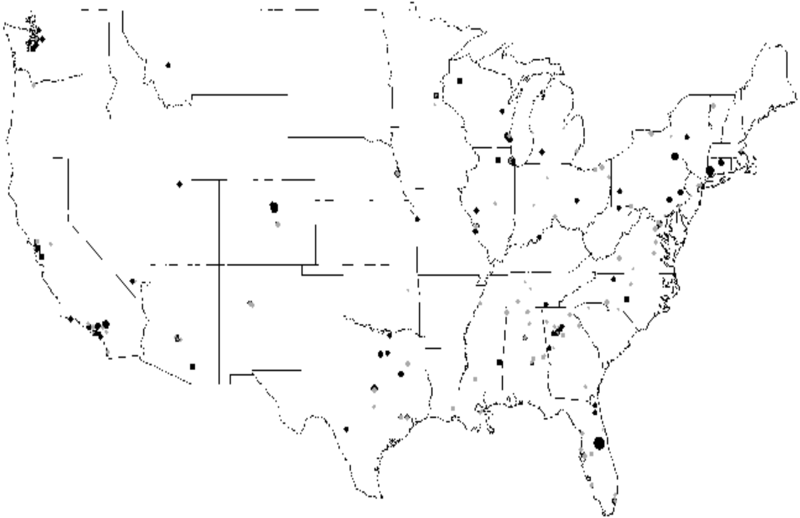
- Sample period 1Q 1999 to 2Q 2016
  - Daily return data available in CRSP as of 9-1-1998
  - SMSA database discontinued in July 2016
  - 254 total events
- Events included
  - Must have at least one fund manager within 100 miles of the event location
  - Calculate distances between event zip code and manager zip code
  - 210 sample events

Ten Deadliest Mass Shootings

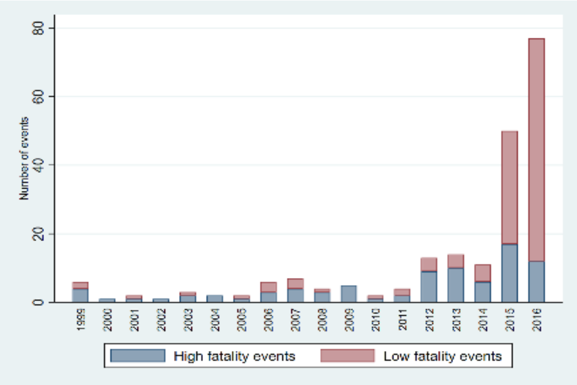
Date	Event	Location	Fatalities	Victims	Funds within 100 mi.	50 mi.
06/12/16	Orlando Nightclub Massacre	Orlando, FL	50	102	26	8
04/16/07	Virginia Tech Campus	Blacksburg, VA	33	49	0	0
12/14/12	Sandy Hook Elementary School	Newtown, CT	28	29	628	104
12/02/15	San Bernardino, California	San Bernardino, CA	16	35	112	42
04/20/99	Columbine High School	Littleton, CO	15	37	48	48
04/03/09	Immigration Services Center	Binghamton,NY	14	17	4	0
11/05/09	Fort Hood Army Base	Fort Hood, TX	13	45	22	0
09/16/13	Washington Navy Yard	Washington D.C.	13	15	168	134
07/20/12	Movie Theater in Aurora	Denver, CO	12	70	52	52
03/10/09	Geneva County, Alabama	Geneva, AL	11	16	0	0

Mass Shooting Statistics

Mass Shootings Jan 1999 - June 2016

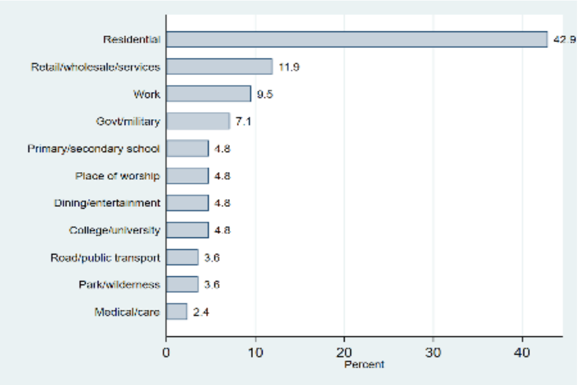


Mass Shootings by Year



Mass Shooting Statistics

Mass Shootings by Location Type



2. Identify Sample of Candidate Mutual Funds

Description	Observations	Unit of Observation
Initial CRSP share class sample 4Q1998 - 4Q2017	1,729,211	share class quarter
Drop ETFs	1,674,543	share class quarter
Drop variable annuities	1,515,912	share class quarter
Keep if CRSP objective code = "E"	853,154	share class quarter
Drop share classes not merged to MS Direct	758,857	share class quarter
Drop index funds (defined)	716,672	share class quarter
Drop "index" funds (textual)	708,602	share class quarter
Drop if US Category Group = "Allocation"	642,287	share class quarter
Drop if US Category Group = "International Equity"	471,234	share class quarter
Keep if Lipper class is in 12 box styles	374,729	share class quarter
Collapse to the fund level	131,307	fund quarter
Drop funds with missing zip codes	127,513	fund quarter
Drop funds with missing control variables	119,477	fund quarter
Drop small funds	113,604	fund quarter

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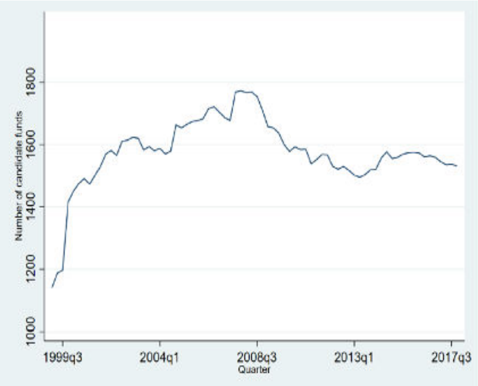
Candidate Funds



Average 1,575 funds per quarter

3. Populate Events

- From the candidate sample of funds, choose all funds during the quarter of the event
- Calculate distances between the event and fund adviser locations
- Categorize funds within 100 (or 50) miles as “treated” funds
- Categorize all other funds as “control” funds

4. Pool Events

- Pool all events
- Drop all control funds in style categories without at least one treated fund
- Drop all funds from the control group that are in the treatment group of another event during the same quarter

Pooled Event Sample
210 Mass Shooting Events
146,816 Fund-Event Observations
700 Funds Per Event
85 Funds Per Event Style

		Fund Styles		
		Value	**Growth**	**Core**
Fund Sizes	**Large-Cap**	Large-Cap Value	Large-Cap Growth	Large-Cap Core
	Mid-Cap	Mid-Cap Value	Mid-Cap Growth	Mid-Cap Core
	Small-Cap	Small-Cap Value	Small-Cap Growth	Small-Cap Core
	Multi-Cap	Multi-Cap Value	Multi-Cap Growth	Multi-Cap Core

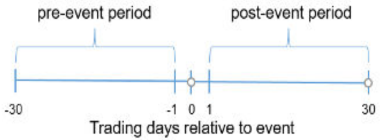
Summary Statistics

	Mean	Median	Std	5th	95th	N
MS dist	44.758	43.320	32.076	2.054	91.506	3,690
ln(1+ MS dist)	3.390	3.791	1.115	1.116	4.527	3,690
I(MS dist. $\leq$ 100)	**0.049**	0.000	0.217	0.000	0.000	74,689
I(MS dist. $\leq$ 50)	**0.026**	0.000	0.159	0.000	0.000	74,689
total volatility	1.087	0.937	0.481	0.575	2.098	74,689
market beta	**1.019**	1.007	0.188	0.726	1.349	74,689
idiosyncratic volatility	0.340	0.297	0.193	0.120	0.726	74,689
tracking error	0.378	0.318	0.233	0.127	0.864	74,689
market beta holding-based	1.065	1.044	0.178	0.807	1.384	55,851
equity weight	0.955	0.970	0.055	0.862	0.999	55,833
Δ ln(vol)	-0.021	-0.022	0.307	-0.557	0.511	74,689
Δ mkt beta	-0.008	-0.005	0.124	-0.224	0.195	74,689
Δ ln(idio vol)	-0.046	-0.051	0.255	-0.463	0.383	74,689
Δ ln(track err)	-0.045	-0.051	0.257	-0.461	0.394	74,689
Δ mkt beta hold	-0.004	-0.003	0.049	-0.086	0.077	55,851
Δ equity weight	0.000	0.000	0.024	-0.040	0.041	55,833
lag TNA	1,539.635	251.300	5,821.432	10.900	6,052.900	74,689

Methodology

$$\Delta \ln(\sigma_{i,s,k}) = \beta Exposure_{i,k} + \gamma^{\intercal}\mathbf{x}_i + \delta_{s,k} + \epsilon_{i,k}$$

- $\Delta \ln(\sigma_{i,s,k})$ is the change in risk-taking of fund i in style category s, over the event period for event k
- $Exposure_{i,k}$ is the treatment variable that is an indicator of the exposure of fund i's managers to event k
- β measures the average treatment effect of fear on fund risk-taking
- Regression includes style by event fixed effects, $\delta_{s,k}$, and a vector of lagged fund-level control variables ($\mathbf{x}_i$)
- Treatment effect is estimated relative to funds in the same style category over the same period of time
- Cluster standard errors by event and adviser zip code



Results

Fear and Risk Taking - by Severity

	All events		Low fatality		High fatality	
	(1)	(2)	(3)	(4)	(5)	(6)
I(MS dist. $\leq$ 100)	-0.003		-0.001		-0.004**	
	(-1.55)		(-0.46)		(-2.13)	
I(MS dist. $\leq$ 50)		-0.002		0.001		-0.006**
		(-1.08)		(0.36)		(-2.63)
Style-event FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R-squared	0.93	0.93	0.93	0.93	0.93	0.93
N	146,778	146,778	72,108	72,108	74,670	74,670
Num. events	210	210	126	126	84	84

Results

Fear and Risk Taking - Risk Types

	Δ mkt beta (1)	Δ ln(idio vol) (2)	Δ ln(track err) (3)
I(MS dist. $\leq$ 50)	-0.006**	0.003	0.002
	(-2.42)	(0.57)	(0.32)
Style-event FE	Yes	Yes	Yes
Adj-R-squared	0.50	0.40	0.42
N	74,670	74,670	74,670
Num. events	84	84	84

Results

Fear and Risk Taking - Distance

	Δ ln(vol)		Δ mkt beta	
	(1)	(2)	(3)	(4)
I(MS dist. quartile 1)	-0.010***		-0.009***	
	(-2.65)		(-2.75)	
I(MS dist. quartile 2)	-0.003		-0.004	
	(-1.13)		(-1.40)	
I(MS dist. quartile 3)	-0.003		-0.003	
	(-0.92)		(-0.94)	
I(MS dist. quartile 4)	0.000		0.000	
	(0.10)		(0.11)	
I(MS dist. $\leq$ 100)		-0.014***		-0.013**
		(-2.80)		(-2.60)
I(MS dist. $\leq$ 100) $\times$ ln(1+ MS dist)		0.003**		0.003**
		(2.29)		(2.09)
Style-event FE	Yes	Yes	Yes	Yes
Adj-R-squared	0.93	0.93	0.50	0.50
N	74,670	74,670	74,670	74,670
Num. events	84	84	84	84

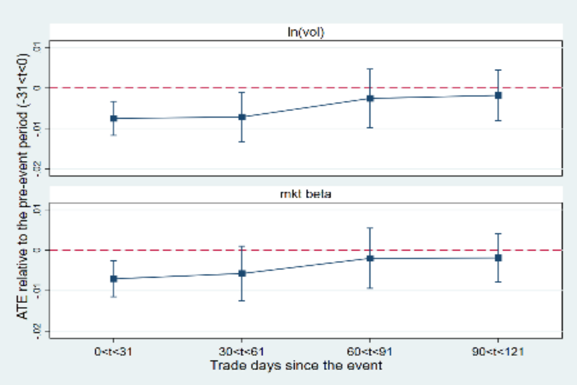
Fear and Risk Taking - Mechanism

	Δ mkt hbeta (1)	Δ equity weight (2)
I(MS dist. $\leq$ 50)	-0.003**	-0.000
	(-2.03)	(-0.14)
Style-event FE	Yes	Yes
Adj-R-squared	0.12	0.02
N	55,836	55,818
Num. events	79	79

Results

Dynamics of Fear and Risk Taking

$$\ln(\sigma_{i,s,k,t}) = \sum_{j=1}^{T} \beta_j \{I(t=j) \times Exposure_{i,k}\} + \gamma^{\intercal}\mathbf{x}_i + \delta_{s,k,t} + \psi_{i,k} + \epsilon_{i,k,t}$$



Results

Fear and Risk Taking - Manager Traits

		Δ ln(vol)			Δ mkt beta	
	(1)	(2)	(3)	(4)	(5)	(6)
I(MS dist. $\leq$ 50)	-0.004**	-0.025***	-0.150**	-0.005*	-0.022***	-0.106
	(-2.04)	(-3.13)	(-2.34)	(-1.88)	(-2.76)	(-1.47)
I(MS dist. $\leq$ 50) $\times$ Prop. female mgrs	-0.017*			-0.014		
	(-1.72)			(-1.50)		
Prop. female mgrs	0.003			0.002		
	(1.60)			(1.02)		
I(MS dist. $\leq$ 50) $\times$ ln(1+ mgr exp)		0.008**			0.007*	
		(2.33)			(1.80)	
ln(1+ mgr exp)		0.001			0.002**	
		(1.14)			(2.01)	
I(MS dist. $\leq$ 50) $\times$ ln(mgr age)			0.038**			0.026
			(2.27)			(1.41)
ln(mgr age)			0.004			0.005*
			(1.36)			(1.93)
Style-event FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R-squared	0.93	0.93	0.93	0.50	0.50	0.50
N	73,247	73,247	59,833	73,247	73,247	59,833
Num. events	84	84	84	84	84	84

Robustness Checks

- Check validity of randomness assumption ▸ Balance Test 1 ▸ Balance Test 2
- Check sensitivity of our results to choices of:
  - Risk measures
  - Controls
  - Control groups
  - Event horizons
  - Data set ▸ Alternative Data
  - Fund styles
- Placebo tests ▸ Placebo Tests
- Test of alternative mechanism for risk reduction ▸ Alternative Mechanism

Balance Test - Fund Characteristics

	ln(TNA)	ln(age)	exp ratio	turn ratio	prop fem	ln(mgr age)	ln(mgr exp)	ln(vol)	mkt beta	ln(idio vol)	ln(track err)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
I(MS dist. $\leq$ 50)	0.095	0.027	-0.000	-0.026	-0.001	-0.001	0.007	0.005	0.005	-0.003	0.002
	(1.06)	(0.82)	(-0.85)	(-0.92)	(-0.22)	(-0.16)	(0.39)	(1.21)	(0.99)	(-0.25)	(0.18)
Style-event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R-squared	0.04	0.09	0.10	0.07	0.01	0.08	0.11	0.91	0.48	0.65	0.66
N	74,670	74,670	74,670	74,670	73,247	59,833	73,247	74,670	74,670	74,670	74,670
Num. events	84	84	84	84	84	84	84	84	84	84	84

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Robustness Checks

Balance Test - Zip Code Level Demographic Characteristics

	rural% (1)	ln(pop density) (2)	female% (3)	white% (4)	married% (5)	college% (6)	ln(med income) (7)
I(MS dist. $\leq$ 50)	-0.041	0.166	-0.141	-0.265	0.522	0.106	0.031
	(-0.15)	(1.11)	(-0.22)	(-0.16)	(0.43)	(0.05)	(0.56)
Style-event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R-squared	0.01	0.01	0.01	0.02	0.02	0.00	0.01
N	62,145	63,405	62,145	62,145	61,526	61,381	61,381
Num. events	84	84	84	84	84	84	84

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Robustness Checks

Alternative Data Source

	Δ ln(vol)		Δ mkt beta		Δ ln(idio vol)		Δ ln(track err)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(MS dist. $\leq$ 50)	-0.008**		-0.008*		0.004		0.002	
	(-2.28)		(-1.96)		(0.67)		(0.22)	
I(0 $\leq$ MS alt. dist. $<$ 50)		-0.008**		-0.008**		0.005		0.003
		(-2.17)		(-2.11)		(0.75)		(0.44)
Style-event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R-squared	0.91	0.91	0.41	0.41	0.39	0.39	0.42	0.42
N	44,236	44,236	44,236	44,236	44,236	44,236	44,236	44,236
Num. Events	44	44	44	44	44	44	44	44

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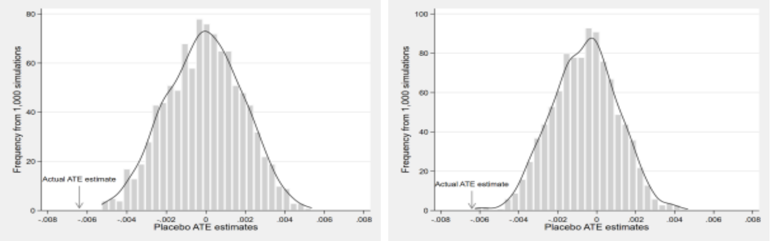
Placebo Tests

- Conduct bootstrap simulations and randomize the assignment of the treatment
  - randomly assign treatment to the same number of funds that are actually treated within that cluster in our data
  - randomly assign treatment to the same number of ZIP codes that are treated within that cluster in the actual data



- actual estimate of the average treatment effect is larger in magnitude than all coefficients generated from both bootstrap samples

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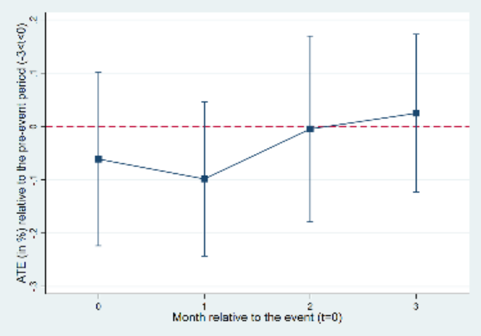
Alternative Mechanism - Could managers be responding to fund flows?

- We estimate the following equation:

$$\ln(\sigma_{i,s,k,t}) = \sum_{j=1}^{T} \beta_j \{ I(t=j) \times Exposure_{i,k} \} + \gamma^\intercal \mathbf{x}_i + \delta_{s,k,t} + \psi_{i,k} + \epsilon_{i,k,t}$$

where the dependent variable is monthly fund flows.



(Regressions include months $t = -2$ to 3)

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Concluding Remarks

- We document a *causal effect of fear on risk taking* among active mutual fund managers, consistent with the laboratory findings of Cohn et al. (2015) and Guiso et al. (2018)
- The effect is *temporary*, consistent with utility being represented as state dependent on visceral factors (Loewenstein, 2000)
- Combined with evidence that market downturns induce fear, our findings have the potential to help explain several empirical finance puzzles

Thank you for your time, attention, and feedback.