The More Efficient, the More Vulnerable

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Market efficiency and arbitrageurs

- Market efficiency
  - Asset prices reflect all available information
- Arbitrageurs enhance efficiency
  - If an asset is underpriced, arbitrageurs will buy the stock and the stock price will rise
  - Example of arbitrageurs: hedge funds
- Textbook argument
  - An arbitrageur buys an infinite amount of underpriced stocks
  - The stock price instantly rises to its fair value
- But, it is not so simple: Limits to arbitrage
  - An arbitrageur cannot buy an infinite amount of assets

This paper

- We build up a model in which
  - There is wealth effect: If arbitrageurs are hit by severe losses during a financial crisis, they reduce the positions and the asset price will drop more
  - Higher efficiency leads to higher tail risk
  - Higher efficiency leads to higher wealth effect
- Specifically:
  - A measure of market efficiency: how likely (or how fast) an underpriced asset recovers its fair value
    - More likely (or faster) recovery is viewed as indicating more efficient markets
  - Higher tail risk is viewed as indicating more vulnerable markets during crises
- Empirical evidence
  - Across arbitrage strategies (slope and butterfly spreads) within fixed income arbitrage
  - Across hedge fund strategies (CB arbitrage, Merger arbitrage ...)

Intuition of the results

- Wealth effect: If arbitrageurs are hit by severe losses during a financial crisis, the asset price will drop more
  - Say, a hedge fund starts with \$100M and an asset is underpriced
  - The fund takes leverage and invests \$200M in the asset by borrowing \$100M (leverage ratio = debt/capital = 100%)
  - But, suppose the asset price drops even more so that the portfolio value drops to \$150M (crisis)
  - To keep the portfolio, the hedge fund's leverage must be \$100M/\$50M = 200%
  - This raises credit risk of the hedge fund and the lender will raise the interest rate
  - Leverage is now costlier and the hedge fund wants to reduce its leverage, which reduces the asset demand and the price

Intuition of the results

- Higher efficiency leads to higher tail risk
  - Higher efficiency: an underpriced asset is more likely to recover its fair value from a shock
  - Arbitrageurs want to invest more on this underpriced asset
  - When the underpricing gets even more severe (tail event or crisis), arbitragers lose more
  - Arbitragers have to reduce their investment (wealth effect) and the price will drop even further
- Higher efficiency leads to higher wealth effect
  - Difference in prices between loss and non-loss cases becomes larger when the market is more efficient

Implication and contribution

- Trade-offs between normal-time efficiency and crisis-time stability
  - Fast recovery from a small shock means higher efficiency during normal times
  - But it leads to vulnerability during crises
- Debate on hedge funds (as arbitrageurs); do they enhance the functioning of financial markets?
  - This paper: They may make the markets vulnerable during crises

Outline

Traded Assets

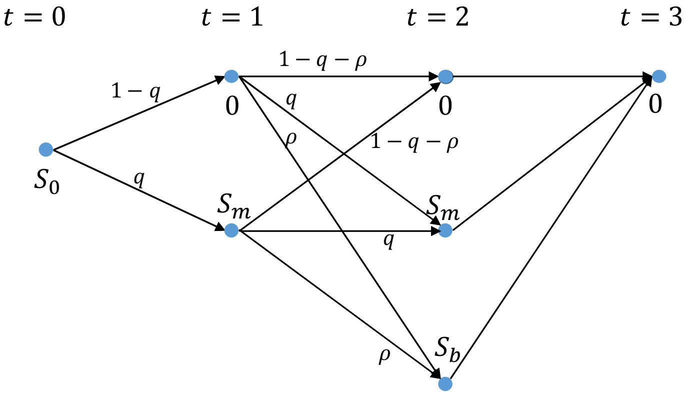
- There are one risky asset and risk-free cash in the market
  - The supply of the risky asset is normalized to 1 (referred to as the asset)
  - The one-period risk-free interest rate is normalized to 0 (viewed as cash)
- There are 4 periods, $t = 0, 1, 2, 3$
  - The risky asset pays off V (cash value) at $t = 3$
  - Only arbitrageurs know the true value V from $t = 0$
  - No interim cash flow and hence the fair value of the risky asset is V always
  - We are interested in the dynamics of the risky asset price P_t at $t = 0, 1, 2, 3$, which are determined by market participants endogenously

Market Participants

- Noise traders
  - They trade for liquidity reasons not related to the asset's fundamental value
  - Their dollar amount demand for the risky asset is assumed to be $V - S_x$
  - $S_x \geq 0$ is a random demand shock (the only source of randomness in the model)
  - Thus, their demand (in quantity) is $\frac{V - S_x}{P_x}$
  - P_x is the asset price at node x
- Arbitrageurs
  - Exploit a potential mispricing caused by noise traders
  - Future shock S_x is unknown to arbitrageurs but its distribution is known to them
  - Their demand for the risky asset is endogenous (to be discussed)

Dynamics of noise trader shock

- Add another period and a crash state: $0 < S_0 < S_m < S_b$

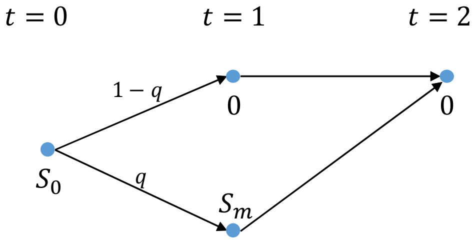


  - q is prob of moderate state and ρ prob of bad state

- Transition prob is path-independent

Dynamics of noise trader shock

- Setup by Shleifer and Vishny (1997): $0 < S_0 < S_m$



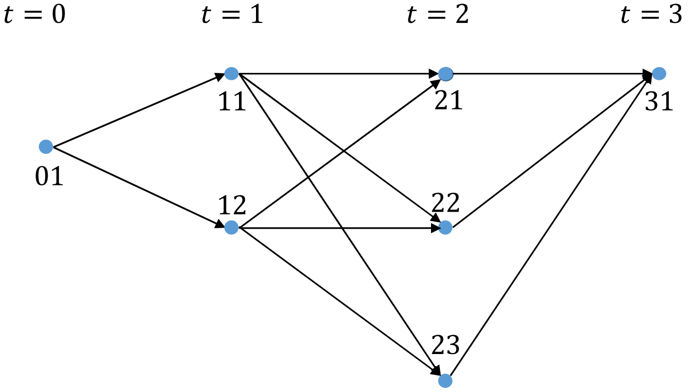
- We have one more state and one more time period

Dynamics of noise trader shock

- One more state S_b
  - Separate extremely bad state (S_b) and moderate state (S_m)
  - S_b occurs in a crisis, while 0 and S_m do in normal time. Relation between crisis and normal time
- One more time period
  - Impact of normal time on crisis may be studied
  - Crises after no shock will be different from those after a moderate shock: path-dependent
    - Path-dependency is not due to transition prob
  - Effect of normal time on crisis: the more efficient, the more vulnerable

States and nodes

- States in each time



- Nodes are history-dependent, i.e. $23|11$ and $23|12$ are two different nodes

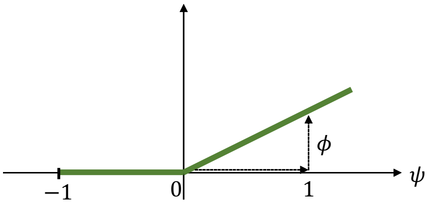
Arbitrageur

- Continuum of risk-neutral arbitragers
  - No heterogeneity across arbitragers, hence we consider a representative price-taking arbitrageur and restrict our attention to a symmetric equilibrium
- Payoff and strategy of arbitrageurs
  - Start with capital W_0 in $t = 0$
  - Their objective is to maximize the expected final capital ($t = 3$), $\mathbb{E}[W_3]$
  - At each node, they choose how much to invest in the risky asset
- Capital dynamics from node x to x':

$$W_{x'} = W_x \left(\frac{P_{x'}}{P_x} (1 + \psi_x) - \psi_x (1 + \phi \psi_x 1_{\psi_x > 0}) \right)$$

Funding cost

- Arbitrageurs may borrow money to invest in the risky asset in each period
  - The lender does not understand the arbitrageurs' strategy. Thus, short-term lending only
  - The higher level of leverage leads to the higher funding rate (credit risk)
  - $\psi_x = (borrowing\,amount\,at\,node\,x)/W_x$ is the leverage at node x
  - $c(\psi_x) = r + \phi\psi_x 1_{\psi_x>0}$ with r and ϕ constants (WLOG, let $r = 0$)



  - Total funding cost: (leverage)*(funding rate)
- Total investment (i.e. demand) is smaller for smaller capital W

Arbitrageurs' optimal leverage

- At each node x, an arbitrageur maximizes the expected value of the fund at $t = 3$,

$$E_t\left[W_3\right]$$

- When the asset is fair-valued $(P = V$; e.g., node $11)$, investment in the asset is not profitable
- When the asset is underpriced $(P < V$; e.g., possibly nodes 12 and 23|12), an arbitrageur takes positive leverage
    - Need to solve recursively from $t = 3$: trade-off between arbitrage benefit and funding cost
    - E.g., optimal leverage at $t = 2$ is given by

$$\psi_x = \begin{cases} \text{any number in } [-1, 0] & \text{if } S_x = 0 \\ \frac{1}{2\phi}\left(\frac{V}{P_x} - 1\right) & \text{otherwise} \end{cases}$$

Equilibrium

- Demand $=$ Supply
  - Supply is assumed to be 1
  - Demand of noise traders: $\frac{V - S_x}{P_x}$
  - Demand of arbitrageurs: endogenously determined
    - If arbitrageurs' demand is large enough to cover the shock S_x (i.e., S_x/P_x), the asset will be fair-valued
- Equilibrium price process P_x is determined

Assumption

Assumption 1. It holds that $W_0 < S_0 \leq S_m < S_b < V$, $\phi > \frac{1}{2}\left(\frac{S_b}{V-S_b}\right)^2$ and $W_0\left(\frac{V}{V-S_b}+\frac{1}{2}\right)^2 < S_m$.

- Assumption 1 formalizes the interpretation of:
  - limits to arbitrage ($W_0 < S_0$) at $t = 0$,
  - moderate state (S_m between S_0 and S_b) and
  - extremely bad state ($S_b > S_m$)
- The other two inequalities in Assumption 1 guarantees:

Lemma 1. Under Assumption 1, $0 < W_x < S_m < S_b$ for all x.

- This implies that, without leverage, arbitrageurs may absorb the shock only partially
- If ϕ (the funding cost ratio) were very small, arbitrageurs would take very high leverage so that $W_x = S_m$ and a crisis may be prevented. This is neither realistic nor interesting.

Existence and uniqueness of equilibrium

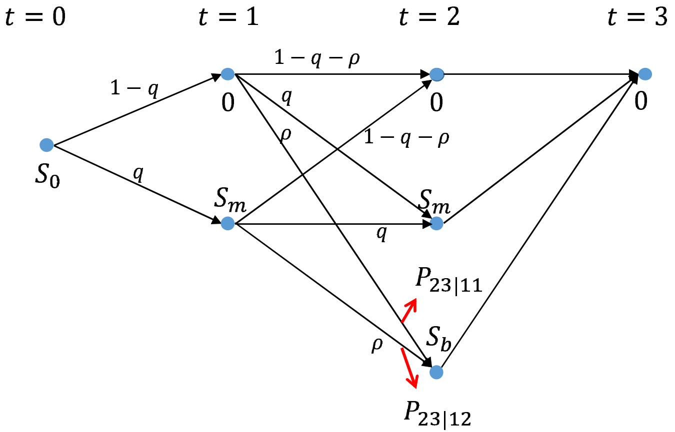
Theorem 1. Suppose Assumption 1 holds. If q and ρ are sufficiently small, there exists a unique equilibrium.

- Small q and ρ: We analyze almost efficient markets like modern financial markets
- This unique equilibrium will be considered

Outline

Notations

- More efficient: smaller q
- More vulnerable: lower $P_{23|11}$ and $P_{23|12}$



Theorems on wealth effect

Theorem 2. With Assumption 1 and sufficiently small q and ρ,

$P_{23|11} > P_{23|12}$.

- Wealth effect: if arbitrageurs are hit by a loss (state 12), they have to reduce their investment and the reduced demand lowers the price
- $P_{23|11} - P_{23|12}$ measures the wealth effect
  - $P_{23|11}$: at node 11, no mispricing and arbitrageurs do not invest. Thus no loss from node 11 to node 23|11
  - $P_{23|12}$: at node 12, underpriced asset. Arbitrageurs invest and get hit by a loss at 23|12. Thus, capital as well as demand at node 23|12 is lower than at 23|11

Theorems on tail risk

Theorem 3. With Assumption 1 and sufficiently small q, ρ and W_0, it holds that $\frac{dP_{23|11}}{dq} > 0$ and $\frac{dP_{23|12}}{dq} > 0$.

- The more (less) efficient, the more (less) vulnerable
    - If q is smaller (i.e., the asset is more likely to get recovered from a shock), arbitragers want to bet more on the mispricing
    - If the shock gets even worse, arbitrageurs are hit by larger losses and have to reduce their bets
    - Less demand and lower price

Theorem on interaction

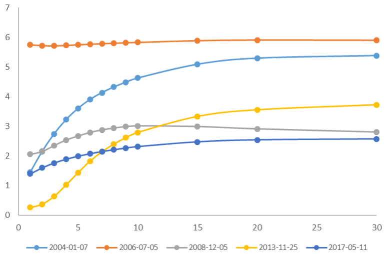
Theorem 4. With Assumption 1 and sufficiently small q, ρ and W_0, it holds that $\frac{d}{dq}\left(P_{23|11} - P_{23|12}\right) < 0$.

- The more (less) efficient, the more (less) wealth effect
  - $P_{23|11} - P_{23|12}$: wealth effect
  - $P_{23|12}$ is affected more than $P_{23|11}$ is

Outline

Fixed income arbitrage

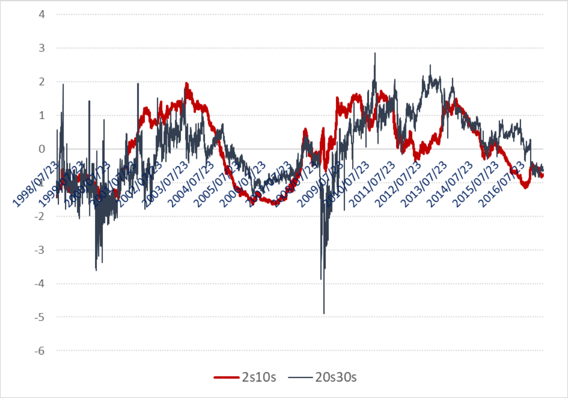
- We use the U.S. interest rate swap market as a natural candidate for testing the theoretical implications
  - Data period: 07/23/1998-05/11/2017
  - 13 tenors: 1, 2,$\cdots$, 10, 15, 20, 30 years
- Sample Yield Curve



Slope spreads strategy

- Consider a trading position with long on the long-end and short on the shorter-end (2s10s)
    - Roughly speaking, slope = (10 year yield) - (2 year yield)
    - Duration match: neutral to parallel change
    - Makes profit if the slope shrinks
    - The other directional bet is also possible (i.e., makes profit if the slope enlarges)
- Using 13 different tenors, we can construct $78\,(= 13 \cdot 12/2)$ different strategies
- We normalize the spread: mean=0 and variance=1 for each spread

Time series of normalized slope spreads



- Consider 20s30s in 2006 and 2008, respectively
- Typical leverage: 5 to 15

Heat map

Swap Slopes

3m Z-Scores 11/23/2018

	Spot	1m	3m	6m	1y	2y	3y	5y	10y	15y	20y
2s/3s	-2.2	-2.1	-1.9	-1.3	1.8	2.5	1.9	1.7	0.8	-1.1	2.6
2s/5s	-1.9	-1.7	-1.1	0.2	2.3	2.2	1.9	2.1	0.7	-0.7	1.4
2s/7s	-1.5	-1.1	-0.1	1.3	2.2	2.1	2	2	0.1	-0.5	1.3
2s/10s	-0.6	-0.2	1	1.8	2.2	2.1	2	2	-0.2	0.2	1
2s/30s	0.9	1.3	1.8	2	2.2	2.1	2	2	-0.7	-1.6	-1.9
3s/5s	-1.1	-0.7	0.6	1.6	2.3	2	1.8	2.3	0.6	-0.2	0.8
3s/7s	0	0.4	1.4	1.9	2.1	2	2	2.1	-0.1	-0.1	1
3s/10s	0.9	1.3	1.8	2	2.2	2	2	2.1	-0.4	0.5	0.7
3s/30s	1.7	1.9	2	2.1	2.2	2.1	2	2.1	-0.8	-1.6	-2
5s/7s	1.2	1.4	1.7	1.9	1.9	2	2.1	1.8	-0.7	0	0.9
5s/10s	1.6	1.7	1.9	2	2	2	2	1.9	-0.7	0.7	0.5
5s/30s	1.9	2	2	2.1	2.1	2.1	2.1	1.9	-1.1	-1.7	-2.1
7s/10s	1.8	1.9	2	2.1	2.1	2	1.9	2.1	-0.8	1.1	-0.3
7s/30s	1.9	2	2.1	2.1	2.1	2.1	2	1.9	-1.1	-1.8	-2
10s/20s	2	2	2.1	2.1	2.1	2.2	2.1	1.8	0.5	-1.8	-1.8
10s/30s	2	2	2.1	2.1	2.1	2.1	2	1.5	-1.2	-2.1	-1.9
20s/30s	1.9	2	2	2	2	1.9	1.7	0.1	-1.8	-2.2	-2

Forward horizons are on the horizontal axix, while vertical axis indicates the terms

- Many hedge funds monitor z-scores of spreads

Butterfly spread strategy

- Consider a trading position with long on the middle-leg and short on the long-end and short-end
  - E.g., 3s5s10s: long on 5 years, and short on 3 and 10 years
  - Similar to the slope spread case
- Using 13 different tenors, we can construct $286\,(= 13 \cdot 12 \cdot 11/\,(3 \cdot 2))$ different strategies

Two-step cross-sectional regressions

- Step 1: Efficiency measure from time series regression
  - Normalize the process of a spread and obtain $z_{i,t}$, and estimate the speed of mean reversion δ_i

$$\Delta z_{i,t+1} = a_i - \delta_i z_{i,t} + \epsilon_{i,t} = -\delta_i \left(z_{i,t} - (a_i/\delta_i)\right) + \epsilon_{i,t}$$

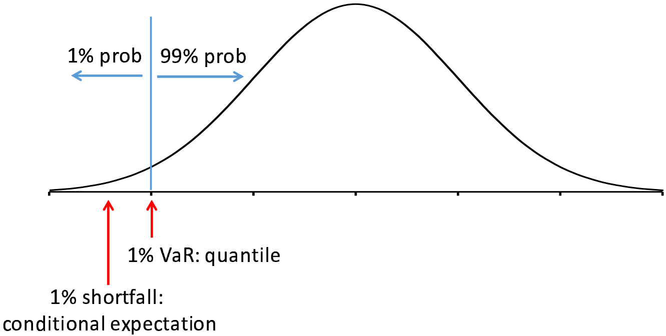
  - $z_{i,t}$ is normalized (mean 0 and std 1) so that smaller δ_i does not mechanically imply higher long-run variance of $z_{i,t}$
  - Higher δ_i: more efficient market

- Step 2: Cross-sectional regression
  - Kurtosis, VaR (Value at Risk, $p\%$ worst case), Shortfall Risk
  - Let S_i denote one of those and run regressions of

$$S_i = \beta_0 + \beta_1 \delta_i + \varepsilon_i$$

  - For left tail, our model predicts $\beta_1 < 0$

VaR and Shortfall Risk



Two-step cross-sectional regressions; daily

- 78 slope and 286 butterfly spreads

Dependent Variable		Daily					
		$p = 0.5\%$		$p = 1.0\%$		$p = 1.5\%$	
		β_1	R^2	β_1	R^2	β_1	R^2
Kurtosis		393.43	0.57	n.a.		n.a.	
		(21.82)					
VaR	Left	-2.18	0.05	-0.70	0.01	-0.10	0.00
		(-4.38)		(-2.00)		(-0.38)	
	Right	1.97	0.10	0.58	0.01	0.10	0.00
		(6.29)		(1.97)		(0.37)	
Expected Shortfall	Left	-6.62	0.26	-4.05	0.15	-2.72	0.10
		(-11.20)		(-8.08)		(-6.32)	
	Right	6.09	0.47	3.58	0.26	2.57	0.17
		(17.83)		(11.32)		(8.53)	

Two-step cross-sectional regressions; weekly

- 78 slope and 286 butterfly spreads

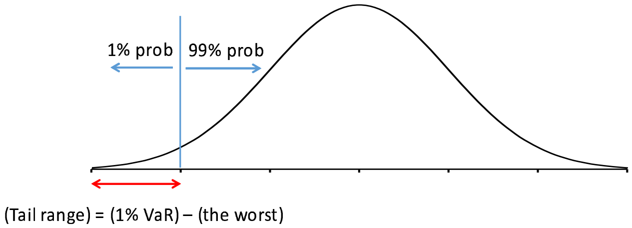
Dependent Variable		Weekly					
		$p = 0.5\%$		$p = 1.0\%$		$p = 1.5\%$	
		β_1	R^2	β_1	R^2	β_1	R^2
Kurtosis		359.67	0.68	n.a.		n.a.	
		(27.97)					
VaR	Left	-1.60	0.04	-0.46	0.01	-0.09	0.00
		(-3.98)		(-1.59)		(-0.40)	
	Right	0.98	0.04	0.16	0.00	-0.23	0.00
		(3.81)		(0.68)		(-0.97)	
Expected Shortfall	Left	-4.82	0.23	-2.63	0.11	-1.90	0.08
		(-10.31)		(-6.69)		(-5.54)	
	Right	4.76	0.45	2.80	0.26	1.87	0.14
		(17.36)		(11.16)		(7.77)	

Robustness check

Dependent Variable		Daily, $p = 1.0\%$					
		Slope		Butterfly		HP filter	
		β_1	R^2	β_1	R^2	β_1	R^2
Kurtosis		45.12	0.60	397.14	0.57	459.30	0.54
		(10.73)		(19.41)		(20.61)	
VaR	Left	-8.53	0.13	-0.39	0.00	-0.38	0.01
		(-3.35)		(-1.06)		(-1.78)	
	Right	7.45	0.07	0.50	0.01	0.08	0.00
		(2.41)		(1.55)		(0.41)	
Expected Shortfall	Left	-22.38	0.36	-3.59	0.14	-3.50	0.21
		(-6.62)		(-6.83)		(-9.87)	
	Right	9.44	0.08	3.51	0.27	2.84	0.32
		(2.53)		(10.22)		(12.93)	

- (HP: Hodrick-Prescott, time-varying average)

Wealth effect



- $P_{23|11} - P_{23|12}$ is measured by the tail range and tail volatility
  - Tail range = (1% VaR) - (the worst)
  - Tail volatility = conditional volatility on the 1% tail event

Two-step regressions; Wealth effect

- 78 slope and 286 butterfly spreads

Dependent Variable (y_i)		Daily $p = 0.5\%$ β_1	R^2	$p = 1.0\%$ β_1	R^2	$p = 1.5\%$ β_1	R^2
Tail Range	Left	34.76	0.69	36.24	0.69	36.83	0.68
		(28.30)		(28.14)		(27.69)	
	Right	40.52	0.68	41.91	0.71	42.38	0.71
		(27.97)		(29.57)		(29.81)	
Tail Volatility	Left	8.02	0.68	6.39	0.70	5.42	0.66
		(28.09)		(29.13)		(26.60)	
	Right	8.53	0.75	6.62	0.79	5.76	0.81
		(32.63)		(36.99)		(39.64)	
Non-Tail Volatility	Left	-0.01	0.00	-0.06	0.00	-0.09	0.01
		(-0.15)		(-1.02)		(-1.57)	
	Right	-0.14	0.01	-0.20	0.02	-0.22	0.02
		(-1.71)		(-2.51)		(-2.97)	

Quantile panel regressions

- Quantile panel regression

$$Q_p\left(z_{i,t}|\delta_i\right) = \gamma_0 + \gamma_1\delta_i,$$

  - Q_p: the p-th quantile of the normalized spread indexed by i ($z_{i,t}$)
  - δ_i: the mean reversion speed. The higher, the more efficient market
  - For left tail, our model predicts $\gamma_1 < 0$

Quantile panel regressions

- With wealth effect

$$Q_p\left(z_{i,t}|\mathbf{1}\left(\text{loss}\right)_{i,t}\right)=\gamma_0+\gamma_1\mathbf{1}\left(\text{loss}\right)_{i,t},$$

- $\mathbf{1}\left(\text{loss}\right)_{i,t}=\mathbf{1}\left(z_{i,t-1}<z_{i,t-1-h}<-\underline{z}\right)$
  - $\mathbf{1}\left(\text{loss}\right)_{i,t}=1$ if there was a loss in the previous day (or week), and 0 otherwise
  - For left tail, our model predicts $\gamma_1<0$
  - Wealth effect: more severely underpriced when arbitrageurs are hit by losses

- With interaction term

$$Q_p\left(z_{i,t}|\delta_i, \mathbf{1}\left(\text{loss}\right)_{i,t}\right) = \gamma_0 + \gamma_1\delta_i + \gamma_2\mathbf{1}\left(\text{loss}\right)_{i,t} + \gamma_3\delta_i\mathbf{1}\left(\text{loss}\right)_{i,t},$$

  - Consider the left tail
  - Note that $\gamma_2 + \gamma_3\delta_i$ is the effect of $\mathbf{1}\left(\text{loss}\right)_{i,t}$, and is the wealth effect
    - Our model predicts $\gamma_3 < 0$
    - The wealth effect becomes stronger when the market is more efficient

Quantile panel regressions; baseline

- $p = 1\%$ quantile, daily spreads

	Left Quantile			Right Quantile		
Panel A: Baseline						
δ	-2.61		-1.55	1.54		1.09
	(-16.14)		(-10.62)	(10.39)		(7.28)
$\mathbf{1}$ (loss)		-0.96	-0.59		0.76	0.47
		(-51.13)	(-32.15)		(43.39)	(24.62)
$\delta \times \mathbf{1}$ (loss)			-33.44			21.94
			(-64.19)			(36.46)
Pseudo R^2	0.0034	0.0652	0.0732	0.0016	0.0582	0.0631

Quantile panel regressions

	Left Quantile			Right Quantile		
Panel B: loss measure periods = 5						
δ			-1.58			1.16
			(-10.43)			(8.39)
$\mathbf{1}$ (loss)		-1.09	-0.65		0.86	0.57
		(-50.45)	(-28.61)		(48.64)	(24.46)
$\delta \times \mathbf{1}$ (loss)			-38.09			21.27
			(-86.21)			(33.41)
Pseudo R^2	0.0034	0.0817	0.0910	0.0016	0.0774	0.0826
Panel C: loss measure periods = 10						
δ			-1.52			1.19
			(-10.39)			(8.37)
$\mathbf{1}$ (loss)		-1.05	-0.72		0.90	0.60
		(-51.64)	(-30.59)		(37.72)	(25.07)
$\delta \times \mathbf{1}$ (loss)			-28.23			21.36
			(-41.17)			(32.96)
Pseudo R^2	0.0034	0.0769	0.0831	0.0016	0.0869	0.0917

Quantile panel regressions; slope and butterfly

	Left Quantile			Right Quantile		
Panel A: Using only 78 slope spreads						
δ	-10.67		-9.37	8.94		7.39
	(-13.65)		(-10.49)	(7.59)		(6.36)
$\mathbf{1}$ (loss)		-0.32	-0.25		0.37	0.22
		(-30.01)	(-14.87)		(20.63)	(11.66)
$\delta \times \mathbf{1}$ (loss)			-5.73			42.15
			(-2.76)			(15.44)
Pseudo R^2	0.0045	0.0277	0.0317	0.0052	0.0331	0.0375
Panel B: Using only 286 butterfly spreads						
δ	-1.55		-0.99	0.90		0.78
	(-8.98)		(-6.57)	(5.56)		(5.33)
$\mathbf{1}$ (loss)		-1.04	-0.71		0.81	0.55
		(-43.13)	(-26.37)		(35.26)	(21.94)
$\delta \times \mathbf{1}$ (loss)			-26.55			17.01
			(-43.94)			(29.19)
Pseudo R^2	0.0016	0.0691	0.0749	0.0006	0.0599	0.0634

Quantile panel regressions; quantile thresholds

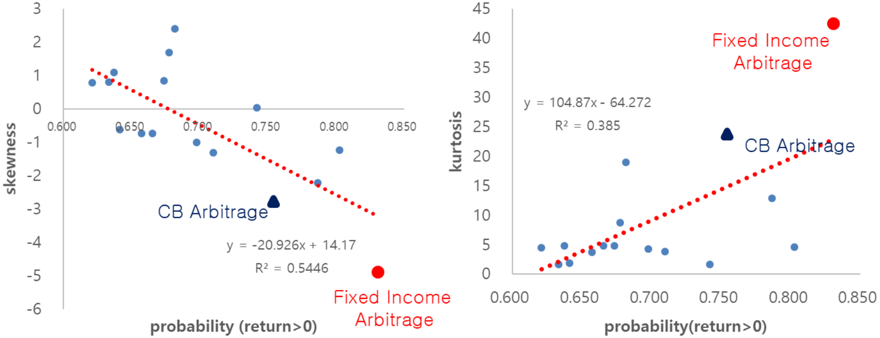
	Left Quantile			Right Quantile		
			Panel A: $p = 0.5\%$			
δ	-5.09		-3.84	4.06		2.89
	(-21.10)		(-16.25)	(20.96)		(14.66)
$\mathbf{1}$ (loss)		-1.14	-0.57		0.76	0.52
		(-33.40)	(-14.00)		(30.24)	(22.95)
$\delta \times \mathbf{1}$ (loss)			-42.77			16.69
			(-45.92)			(20.67)
Pseudo R^2	0.0086	0.0703	0.0879	0.0062	0.0540	0.0624
			Panel B: $p = 1.5\%$			
δ	-1.47		-0.63	0.88		0.41
	(-15.73)		(-6.60)	(7.19)		(3.74)
$\mathbf{1}$ (loss)		-0.86	-0.57		0.70	0.47
		(-79.97)	(-42.83)		(48.52)	(28.17)
$\delta \times \mathbf{1}$ (loss)			-26.76			19.76
			(-83.58)			(41.86)
Pseudo R^2	0.0014	0.0595	0.0639	0.0006	0.0583	0.0618

Quantile panel regressions; others

	Left Quantile			Right Quantile		
Using Hodrick-Prescott filtered spreads						
δ	-0.50		-0.40	0.86		0.64
	(-6.17)		(-4.04)	(10.64)		(6.58)
$\mathbf{1}$ (loss)		-1.06	-0.62		0.71	0.55
		(-56.12)	(-36.54)		(42.16)	(28.83)
$\delta \times \mathbf{1}$ (loss)			-23.63			7.17
			(-64.45)			(17.47)
Pseudo R^2	0.0003	0.0654	0.0717	0.0010	0.0609	0.0634
Using weekly data						
δ	-4.20		-2.11	2.56		1.01
	(-16.37)		(-8.44)	(11.11)		(4.17)
$\mathbf{1}$ (loss)		-1.04	-0.26		0.88	0.23
		(-29.85)	(-5.92)		(23.45)	(5.70)
$\delta \times \mathbf{1}$ (loss)			-30.80			24.40
			(-38.51)			(23.52)
Pseudo R^2	0.0081	0.0751	0.0888	0.0041	0.0762	0.0860

Hedge fund strategies

- Barclay Hedge Fund Index
  - Monthly Returns over Jan/1997-Aug/2017
  - 16 style indices: Convertible Bond Arbitrage, Distressed Securities, Emerging Markets, Equity Long Bias, Equity Long/ Short, Equity Market Neutral, European Equities, Event Driven, Fixed Income Arbitrage, Fund of Funds, Global Macro, Healthcare & Bio-tec, Merger Arbitrage, Multi Strategy, Pacific Rim, Equity Tech



skewness
probability (return>0)
CB Arbitrage
y = -20.926x + 14.17
R² = 0.5446
Fixed Income Arbitrage
kurtosis
probability(return>0)
y = 104.87x - 64.272
R² = 0.385
Fixed Income Arbitrage
CB Arbitrage

- The more efficient, the more vulnerable
    - Higher prob of return$>$0: it is more likely for mispriced assets to recover its fair value
    - High prob of return$>$0 is
        - negatively associated with skewness
        - positively associated with kurtosis
    - CB Arbitrage and Fixed Income Arbitrage depict the situation of "Picking up Nickels in front of a Steamroller"

Outline

Conclusion

- We build up a model in which
  - There is wealth effect
  - Higher efficiency leads to higher tail risk
  - Higher efficiency leads to higher wealth effect
- Empirical evidence
  - Across arbitrage strategies (slope and butterfly spreads) within fixed income arbitrage
  - Across hedge fund strategies
- Future research: yield spread modeling
  - Conventional affine or quadratic term structure models do not fit the distribution of spreads among yields across tenors