# DOES THE OPTIONS MARKET UNDERREACT TO FIRMS' LEFT TAIL RISK?

Based on Chen, Gan & Vasquez (2024) | Journal of Financial & Quantitative Analysis

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# SCOPE

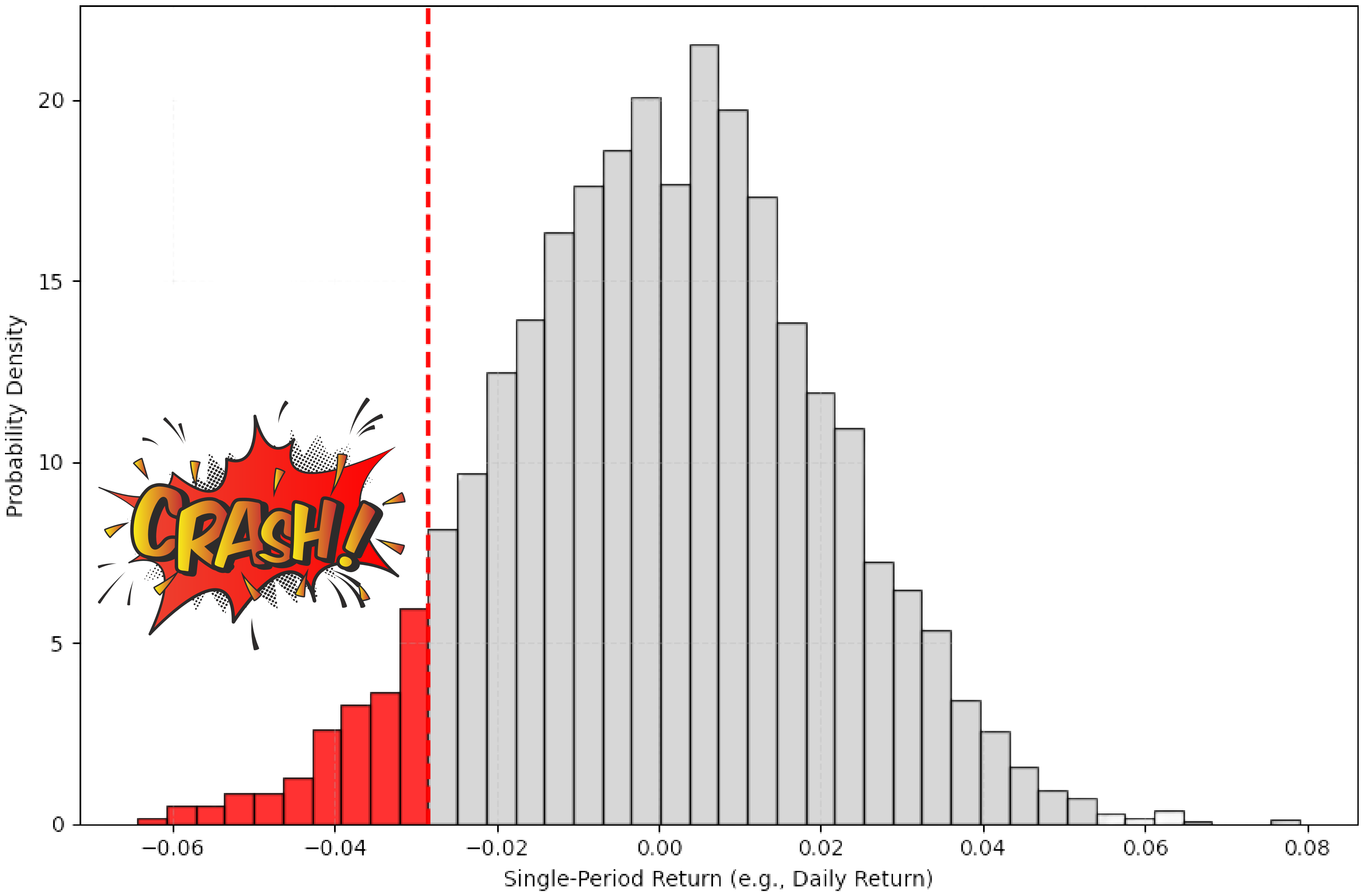
Olivia Tang Shu Hui

# PART 1: OVERVIEW OF KEY FINDINGS

Olivia Tang Shu Hui

# What Is Left-Tail Risk?

**Left-tail risk is the probability that an asset experiences extreme negative returns over a single time period (i.e. a crash).**

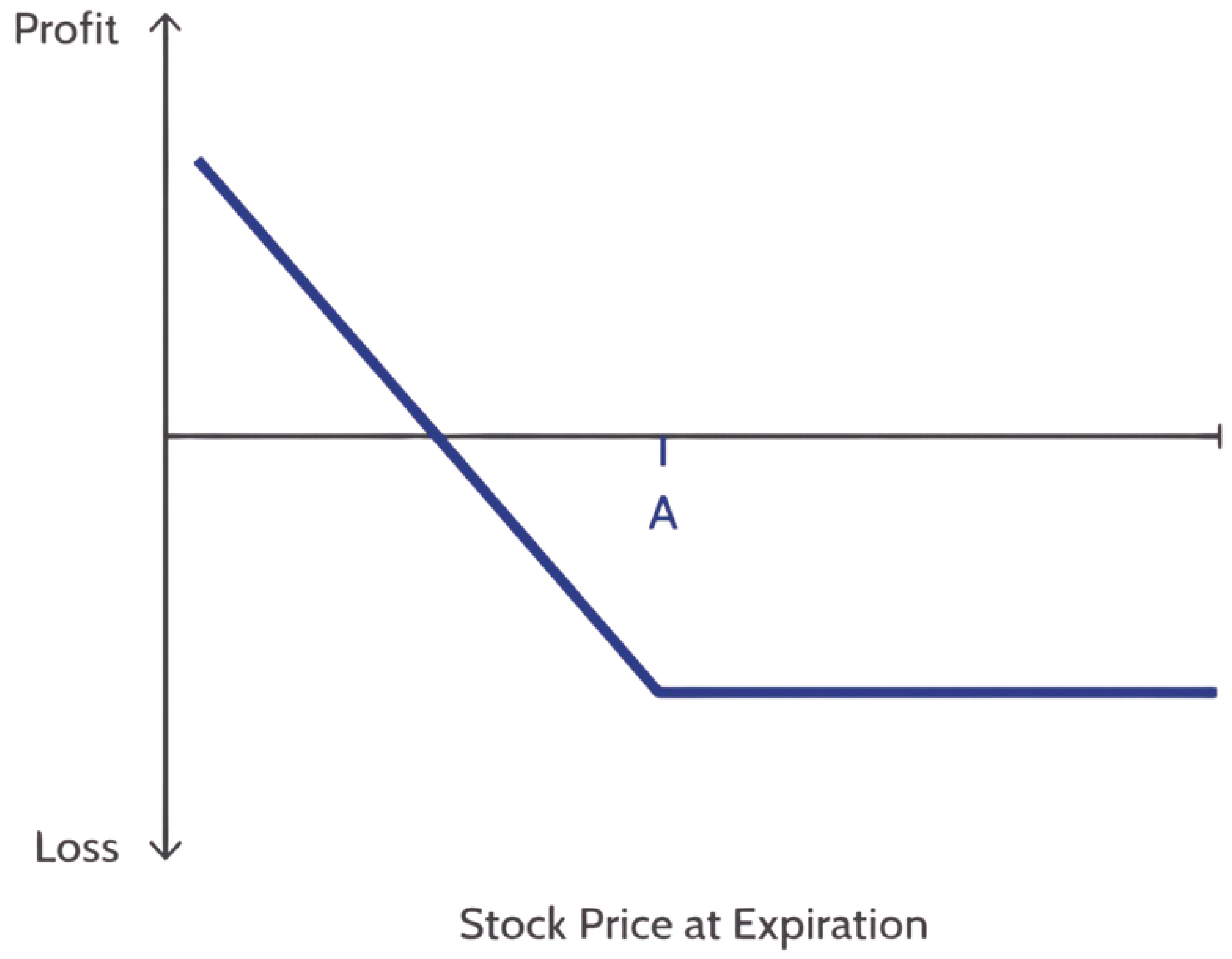


Olivia Tang Shu Hui

# What Is Crash Insurance?

**Crash insurance is insurance against crashes. It involves purchasing assets that safeguards against crashes.**

**Crash insurance can come in many forms...**
**For example, buying a put option**



Olivia Tang Shu Hui

# THE VALUE OF CRASH INSURANCE FOR ASSETS WITH HIGHER LEFT TAIL RISK SHOULD BE HIGHER

## Just like car and health insurance...

### Car Insurance

Drivers who have a **higher risk of getting into an accident should pay a higher premium**.

As such, on balance, they will **have similar returns on insurance** vis-a-vis safer drivers who pay a lower premium due to a smaller probability of getting into similar accident.

### Health Insurance

Individuals with a **higher risk of developing severe illnesses should pay a higher premium**.

As such, on balance, they will **have similar returns on insurance** vis-a-vis healthier individuals who pay a lower premium due to a smaller probability of experiencing similar medical condition.

# THIS SHOULD ALSO BE THE CASE FOR THE OPTIONS MARKET FOR CRASH INSURANCE ON ASSETS

*"If options markets efficiently incorporate downside risks, firms with higher left-tail risk should have more expensive crash insurance."*

*"Correspondingly, given that they are more expensive, the returns on crash insurance should <u>on balance</u> be similar for firms with different left-tail risks."*

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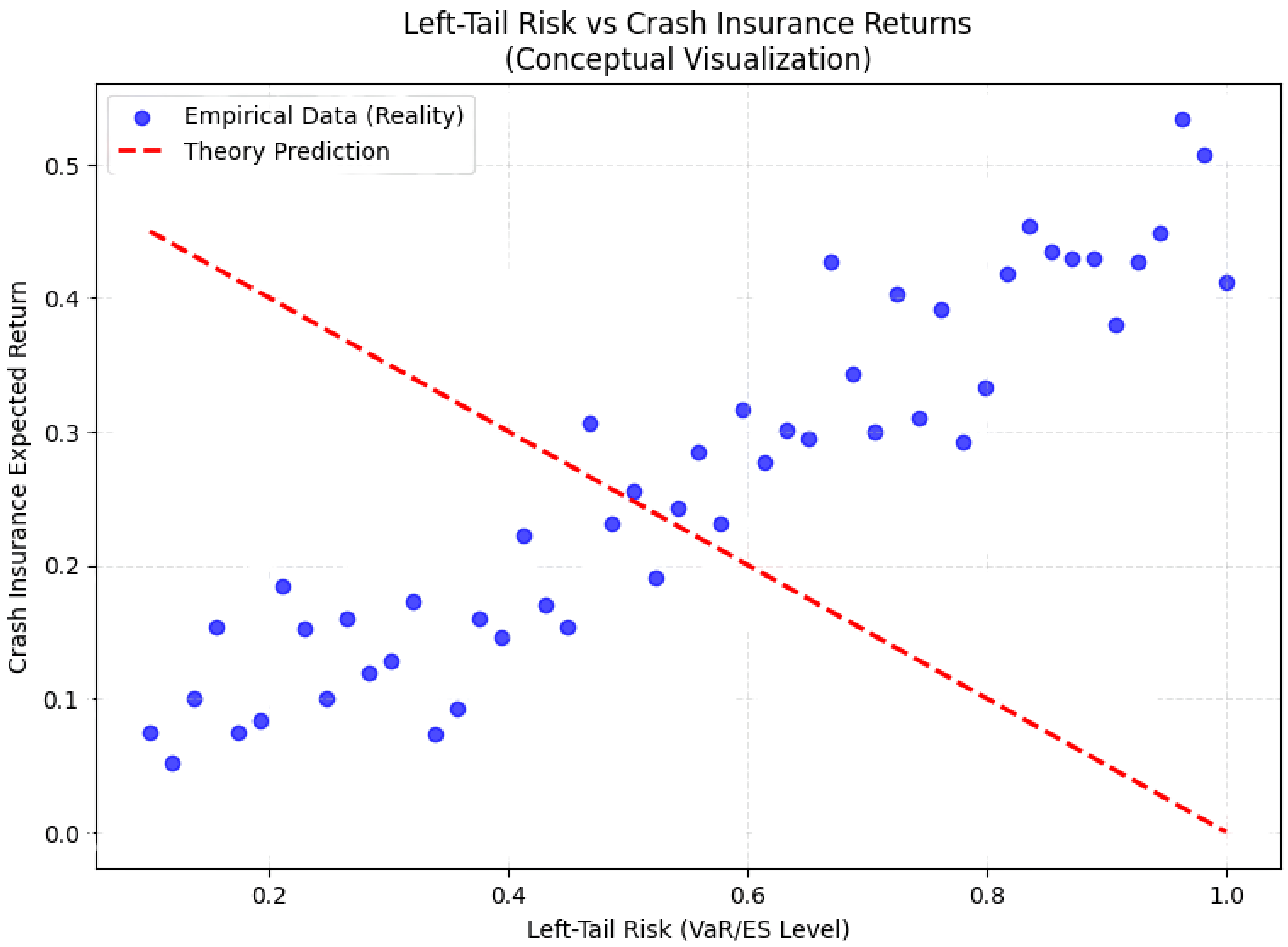
# HOWEVER, THE AUTHORS FOUND THAT THIS IS NOT THE CASE IN REALITY




**"We find a significantly positive relation between firms' left-tail risk and returns on crash insurance."**

Olivia Tang Shu Hui

# IN SIMPLER TERMS, THIS MEANS THAT THE RETURNS ON CRASH INSURANCE WAS HIGHER FOR HIGH RISK ASSETS

This means that...

Reckless drivers were paying underpriced car insurance!

AND

Unhealthy individuals were paying underpriced health insurance!

# HOW DID THE AUTHORS DETERMINE THIS?

Koh Thoong Yip

# PART 2:
# DATA AND RESEARCH METHODOLOGY

Koh Thoong Yip

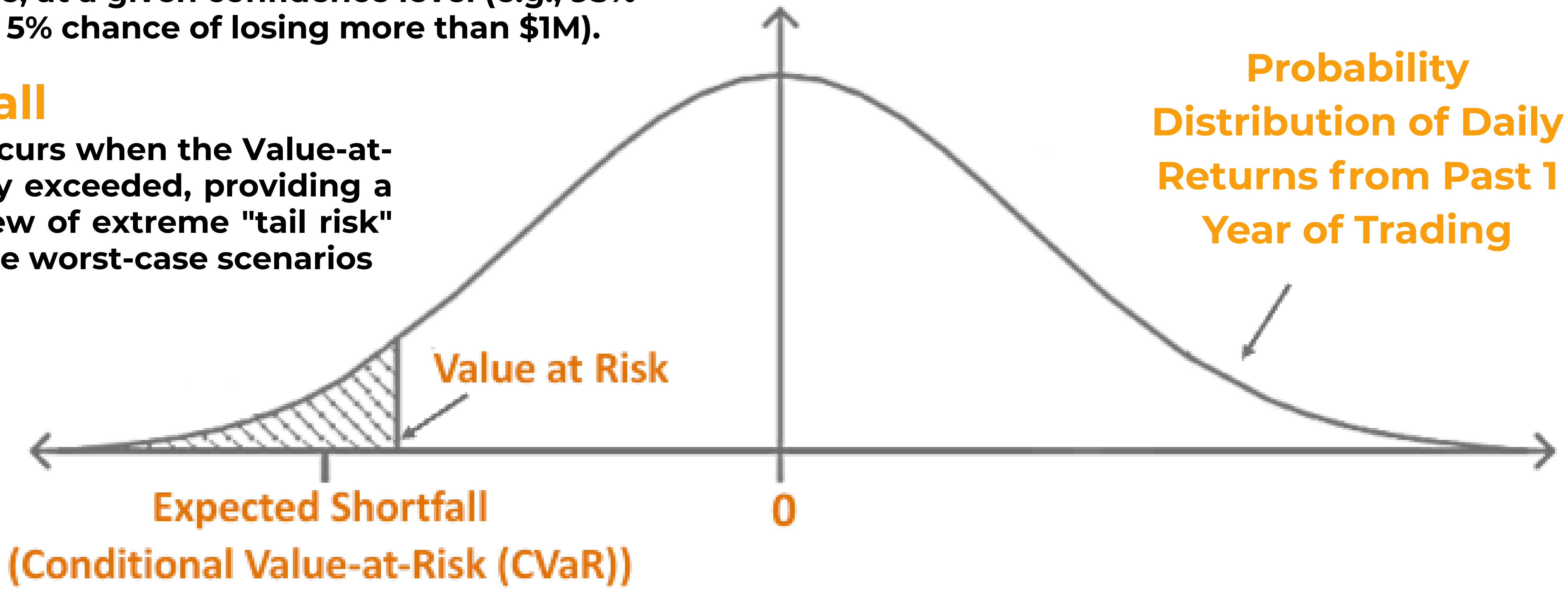
# THE AUTHORS USED VALUE-AT-RISK AND EXPECTED SHORTFALL TO MEASURE THE ASSETS' LEFT-TAIL RISK

## Value-at-Risk

**A measure of the maximum potential loss on an investment over a specific time frame, at a given confidence level (e.g., 95% VaR of $1M means only a 5% chance of losing more than $1M).**

## Expected Shortfall

**The average loss that occurs when the Value-at-Risk threshold is actually exceeded, providing a more comprehensive view of extreme "tail risk" by averaging losses in the worst-case scenarios**



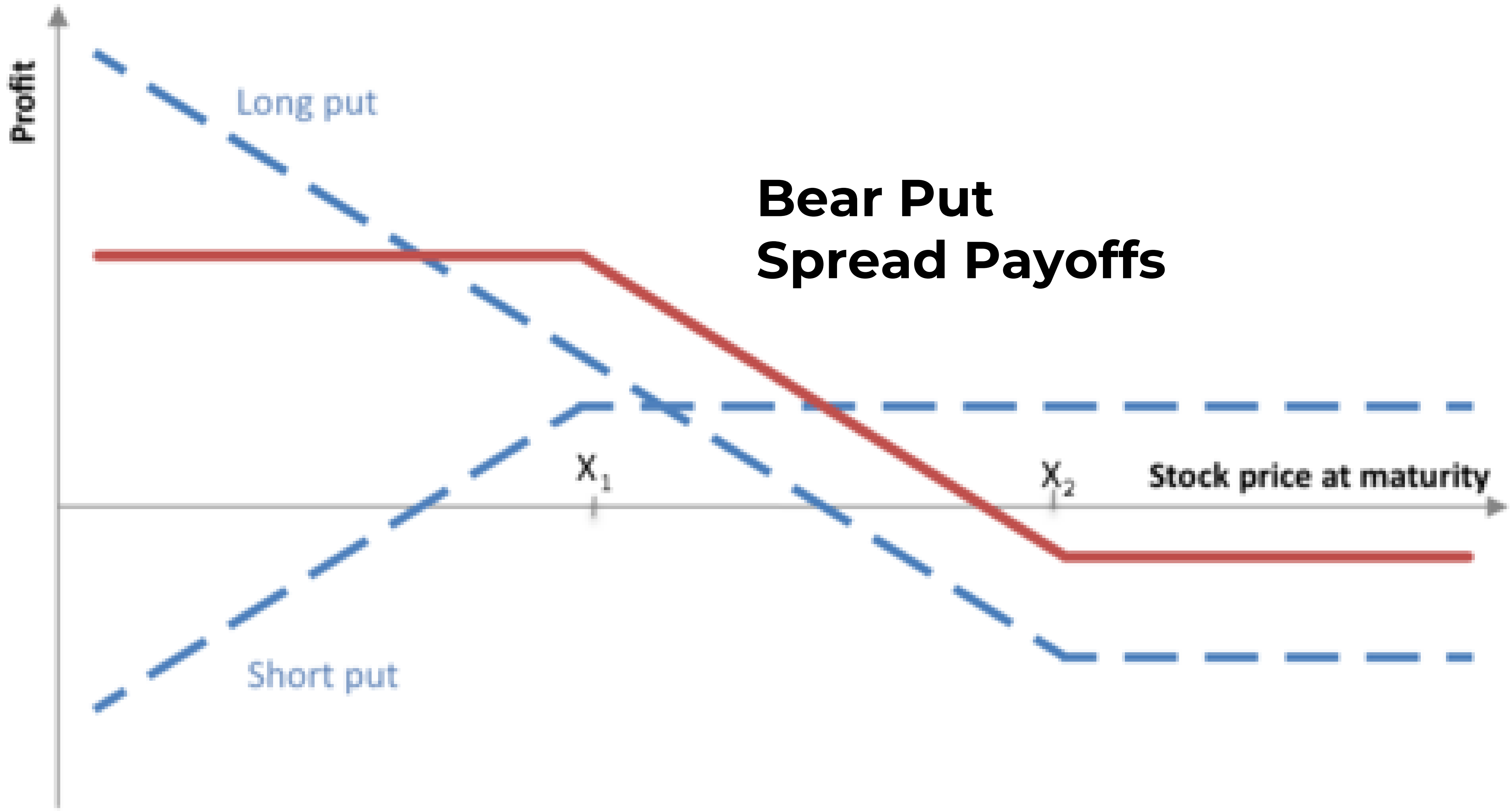
# THEY ALSO USED A BEAR PUT SPREAD TO MEASURE THE CRASH INSURANCE RETURNS

Bear Put Spread = Long Put + Short Put

Koh Thoong Yip

# THIS GAVE A FIXED INSURANCE PREMIUM IN GOOD TIMES AND FIXED INSURANCE PAYOUT IN BAD TIMES

FIXED INSURANCE PAYOUT




FIXED INSURANCE PREMIUM

# THE AUTHORS ALSO CONSTRUCTED 19 CONTROL VARIABLES FOR THE STUDY

| Firm characteristics | Trading Characteristics | Option-Based Controls | Systematic Factor Exposures |
|---|---|---|---|
| • Size<br>• Book-to-market<br>• Leverage | • Momentum<br>• Short-term reversal<br>• Illiquidity<br>• Idiosyncratic volatility<br>• Skewness<br>• Kurtosis | • Variance risk premium<br>• Volatility-of-volatility<br>• Risk-neutral skewness<br>• Option demand | • β BEAR<br>• β STRAD<br>• β JUMP<br>• β VOL<br>• β TAIL<br>• β DOWN |

Koh Thoong Yip

# THE AUTHORS USED ASSET LEVEL DATA FROM JAN 1996 TO DEC 2017 WITH 155,003 DATA POINTS

### Used CRSP data for Stock Prices

Used in Calculation of Value-at-Risk and Expected Shortfall Variables and Trading Controls

### Used OptionMetrics Data for Options Prices

Used in Calculation of Bear Put Spread Returns and Option-Based Controls

### Used Compustat Data for Control Variables

Including information on Firm-Related Characteristics which Served as Controls

Caveat: Only Stocks with Exchange-Listed Options were Used

# THE STUDY USED FOUR DIFFERENT METHODS TO DETERMINE THE RELATIONSHIP BETWEEN LEFT-TAIL RISK AND CRASH INSURANCE RETURNS

| | | |
|---|---|---|
| 1 | **Univariate Analysis** | Sort firms into deciles based on left-tail risk and compare bear spread returns between highest versus lowest groups |
| 2 | **Bivariate Analysis** | Same as univariate analysis, but sorting firms into deciles within each control group |
| 3 | **Fama-Macbeth Regression** | Multivariate regression of bear spread returns on assets' left-tail risks |
| 4 | **Systematic Risk Tests** | Multivariate regression of bear put spread returns on systematic risk control variables |

Randolph Lee Zhen Yang

# PART 3:
# KEY FINDINGS AND MECHANISMS

# THE STUDY FOUND THAT ASSETS WITH HIGHER LEFT TAIL RISK HAD HIGHER BEAR PUT SPREAD RETURNS

| Methodology | Findings |
|---|---|
| Univariate Analysis | Assets in the top decile of left-tail risk had ~0.2% higher bear put spread returns than assets in the lowest decile of left-tail risk |
| Bivariate Analysis | Assets in the top decile of left-tail risk had significantly higher bear put spread returns than assets in the lowest decile of left-tail risk |
| Fama-Macbeth Regression | Assets with an additional 1% of left-tail risk had ~16-20% higher bear put spread returns |
| Systematic Risk Tests | Differences in bear put spread returns across assets with different levels of left-tail risk could not be explained by systematic market risk factors |

Randolph Lee Zhen Yang

# The Puzzle:

## Why are Crash Insurance Returns Higher for Assets with Higher Left-Tail-Risk?

Randolph Lee Zhen Yang

# MECHANISM #1: THE MARKET UNDERREACTS TO PRICE VOLATILITY

**When volatility begins to increase,**

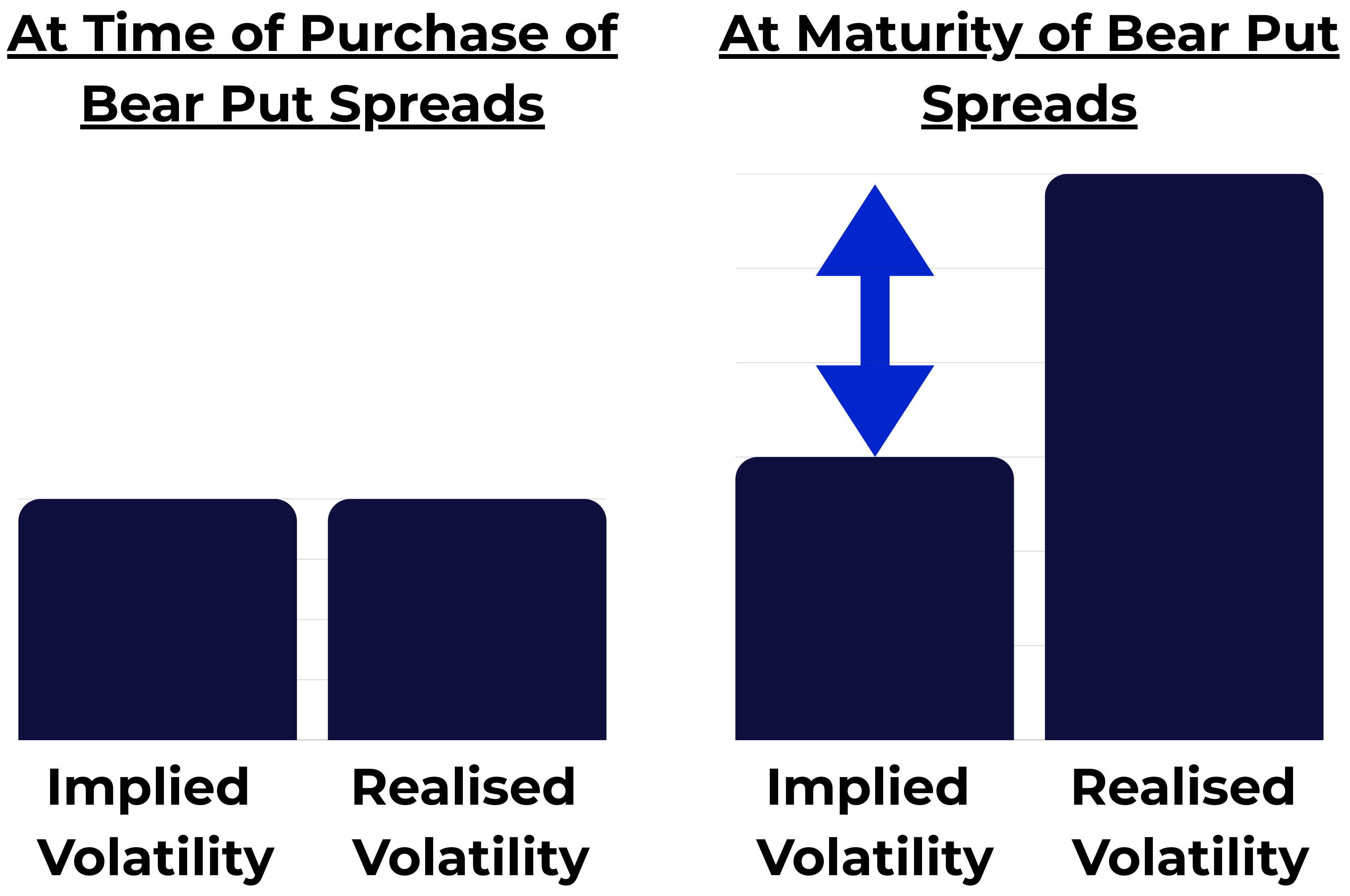
**The market underestimates future increases in volatility...**

**As such, crash insurance is not valued sufficiently by the market to hedge against future volatility increases.**

**When volatility spikes later, the value of the crash insurance appreciates disproportionately.**

Randolph Lee Zhen Yang

# THE AUTHORS DETERMINED THIS BY COMPARING THE IMPLIED VOLATILITY OF THE BEAR PUT SPREAD RETURNS AT PURCHASE WITH THE REALISED VOLATILITY




- Firms with higher left-tail risk faced higher realised volatility at maturity
- However, the implied volatility at the time of purchase of the bear put spreads did not reflect the likelihood of volatility increasing more for firms with higher left-tail risk
- As such, the authors' hypothesised that part of the reason for undervaluation of bear spreads was underexpectation of volatility spiking

Randolph Lee Zhen Yang

# MECHANISM #2: THE MARKET UNDERESTIMATES THE PERSISTENCE OF LEFT-TAIL RISK

**in other words, investors are buying the dip TOO SOON**


Randolph Lee Zhen Yang

# FIRMS WITH HIGH LEFT-TAIL RISK OFTEN SEE “BAD DAYS” CLUSTERING TOGETHER

- Firms with high left-tail risk often see days with falling asset prices clustering together
- Explained simply, when the stock price crashes, they often continue to crash
- If the aset price falls significantly today, it is likely to continue over the next few days

# THIS SHOULD RESULT IN THE VALUE OF CRASH INSURANCE INCREASING AFTER A "BIG DIP"

**in other words…**

**"When the asset price dips, don't buy the dip straightaway! Buy crash insurance first because the asset is going to dip further!!"**

# HOWEVER, RETURNS ON CRASH INSURANCE IN FACT INCREASED AFTER THE ASSET PRICE FELL

**This means investors were "undervaluing" their crash insurance for future crashes.**

**Implies that investors were underreacting to the persistence of left-tail risk.**

Randolph Lee Zhen Yang

# PART 4: REPLICATING THE DATA PART 1

Randolph Lee Zhen Yang

# WHILE THE PAPER IS GENERALLY ROBUST, IT IS IMPORTANT TO UNDERSTAND ITS ASSUMPTIONS

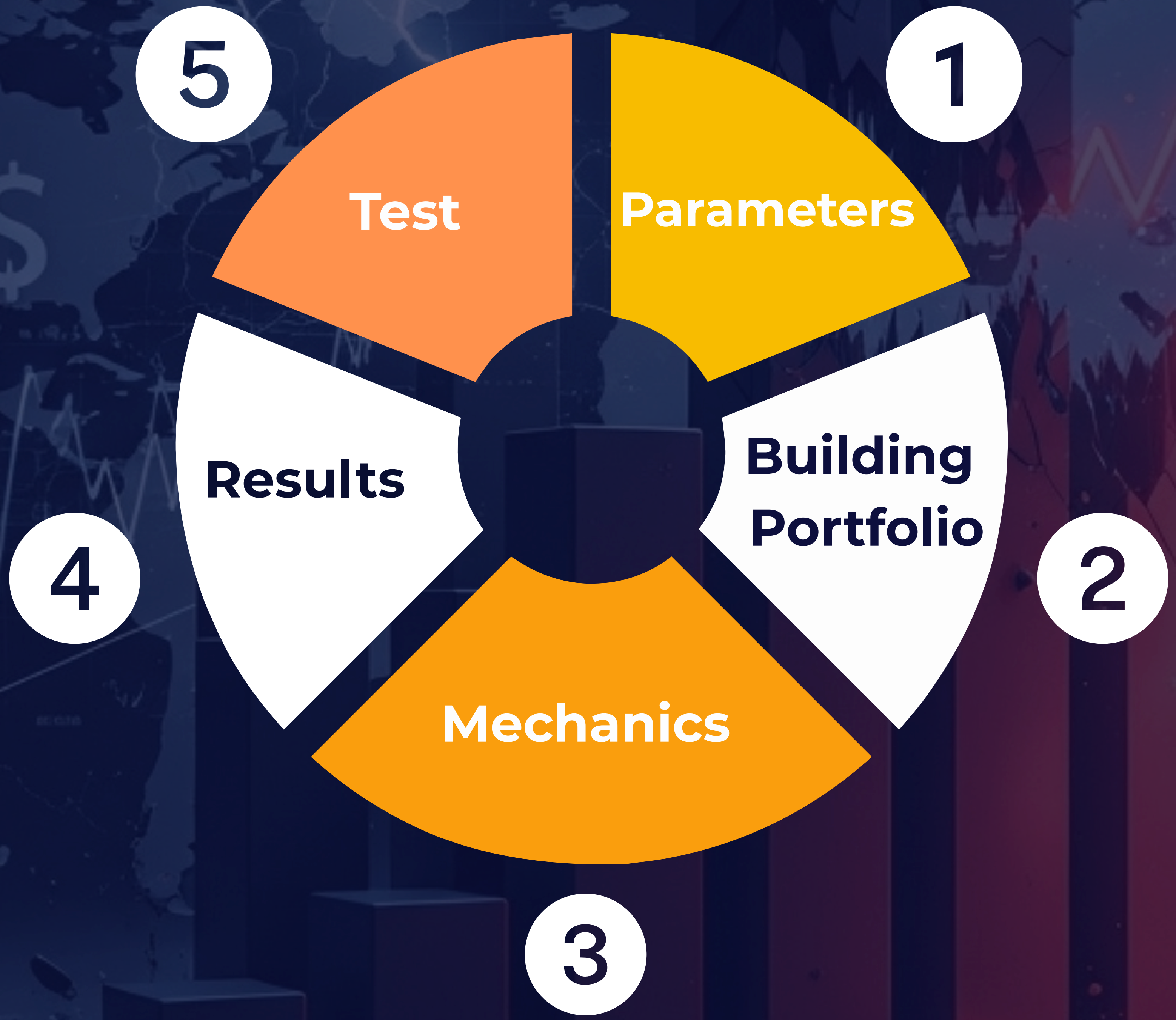
| Factor | Assumption | Potential Limitations |
|---|---|---|
| **Overall Dataset** | • Usage of US Data from 1996 to 2017 is a good reflection of reality<br>• Usage of Asset-Level Analysis is a good reflection of portfolios | • Unclear whether results are generalisable to other regions, timeframes and portfolios |
| **Measure of Left-Tail Risk** | • Value-at-Risk and Expected Shortfall are good measures of left-tail risk<br>• Usage of Past 1 Year of Daily Returns is a good measure of left-tail risk | • Unclear whether results are generalisable to other forms of construction of left-tail risk |
| **Measure of Crash Insurance** | • Bear Put Spreads are a good measure of crash insurance<br>• Usage of Options with 1 Month to Maturity are a good measure of crash insurance returns<br>• Usage of Midpoint of Bid-Ask spread provides a sufficient counterfactual<br>• Usage of Delta-Hedged Strike Prices reflect appropriate crash insurance prices | • Unclear whether results are generalisable to other forms of crash insurance |
| **Measure of Control Variables** | • Firm Characteristics, Firms Characteristics, Option Based Controls and Systematic Market Risk Exposure Factors are sufficient controls | • Unclear whether there are other potential confounding factors which were not accounted for |

Randolph Lee Zhen Yang

# WE FOCUSED ON DIVING INTO TWO LIMITATIONS WHEN SEEKING TO REPLICATE THE STUDY

| | Limitation | Approach |
|---|---|---|
| 1 | The study analysed crash insurance at the asset level | #1: To study crash insurance at the portfolio level |
| 2 | The study analysed crash insurance using bear put spreads | #2: To study crash insurance using simple long put options |

# OVERVIEW OF OUR SIMPLE CRASH INSURANCE PORTFOLIO METHODOLOGY



# 1 PARAMETERS

**Simulation Timeline:** 2 Jan 2015 - 19 Nov 2025

**Crash Risk:** 10%

**Rebalancing Frequency:** Quarterly

**Hedge Ratio:** 30%

**Target Strike Price:** 85% of current SPY (For Deep OTM put options)

**Option Maturity:** 1 Month

**Rolling Schedule:** New OTM puts are long monthly and held to expiry

**Data Used:** S&P 500 Historical Data, SPX options features data public and Volatility Risk Premium Data

# 2 BUILDING PORTFOLIO

**Crash insurance = Long S&P 500 stock + Systematic option hedge that pays off during crashes**

| Equal-Weighted Hedge Portfolio | Volatility-Weighted Hedge Portfolio |
| --- | --- |
| Constant 30% Hedge Ratio regardless of VIX | Dynamic Hedge Ratio based on VIX: 50% if VIX is above median, otherwise 30% |
| Quarterly Rebalancing | Quarterly Rebalancing |
| Insurance cost is incurred monthly for options purchased, and payoff from expiring options is added. | Insurance cost is incurred monthly for options purchased, and payoff from expiring options is added. |

# 3 MECHANICS

Every month long new OTM puts with target strike price 85% of current SPY with 1 month expiry is bought to ensure continuity.

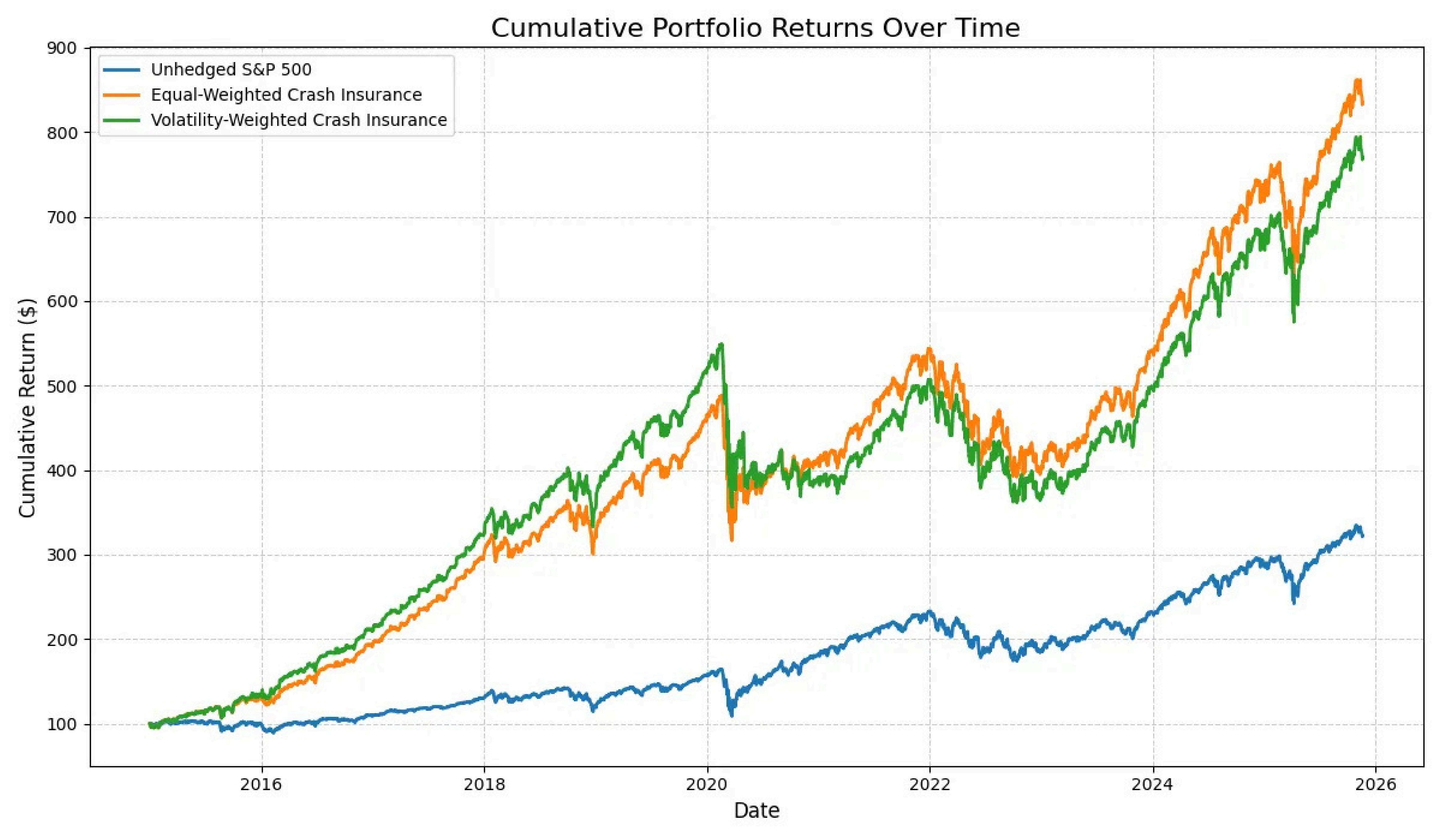
At expiry:

**If SPY > Strike,** options expire worth lesser. This would be deemed as insurance cost

**If SPY < Strike,** options pay intrinsic value. This would be gained as crash protection
* Payoff = Max(0, K-ST) X 100 X Contracts (Where K = Put Strike, ST = SPY price at expiry)

Final Portfolio Return = Portfolio Return - Option Cost + Crash Payoff

# 4 RESULTS


Cumulative Portfolio Returns Over Time
Unhedged S&P 500
Equal-Weighted Crash Insurance
Volatility-Weighted Crash Insurance
Cumulative Return ($)
Date
900
800
700
600
500
400
300
200
100
2016
2018
2020
2022
2024
2026

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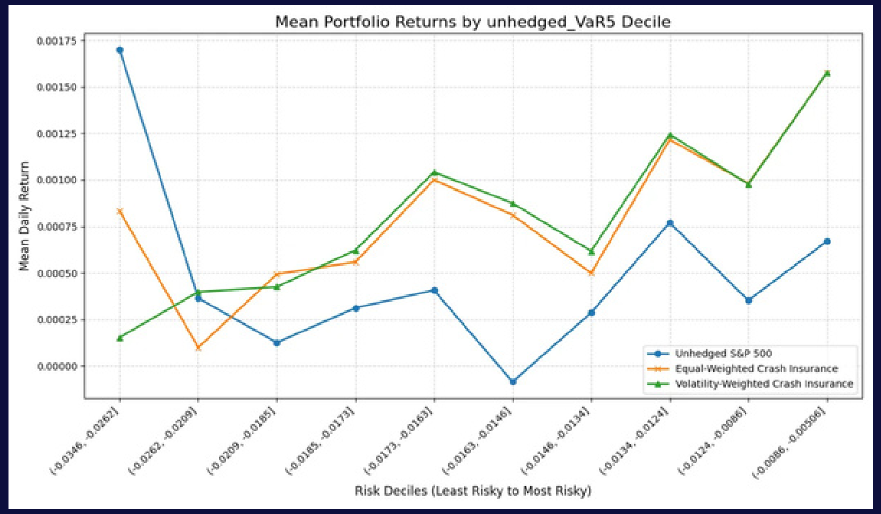
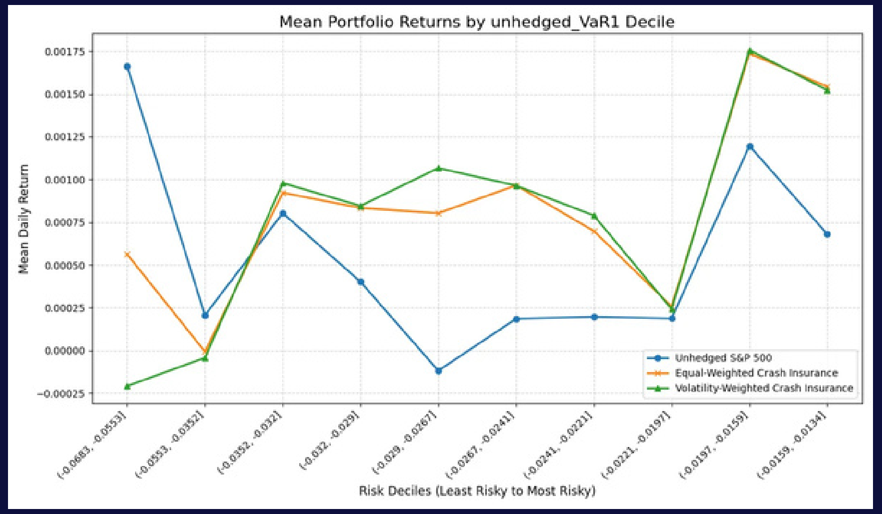
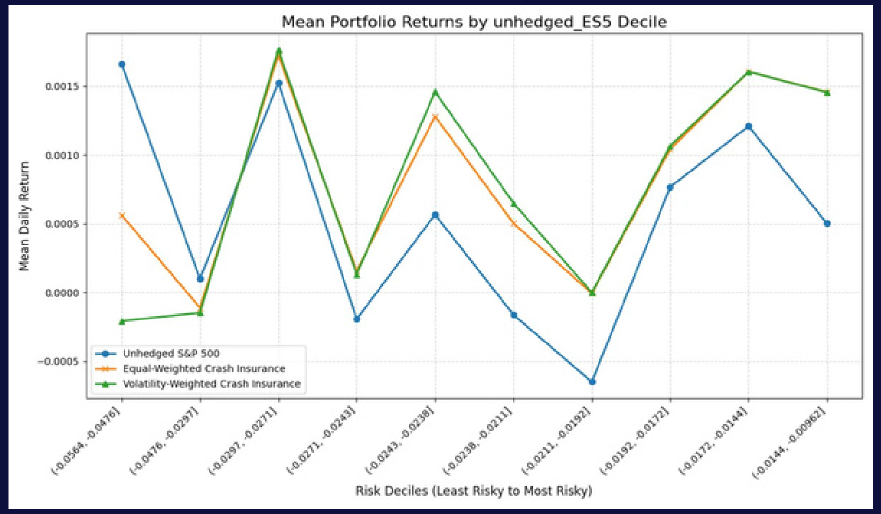
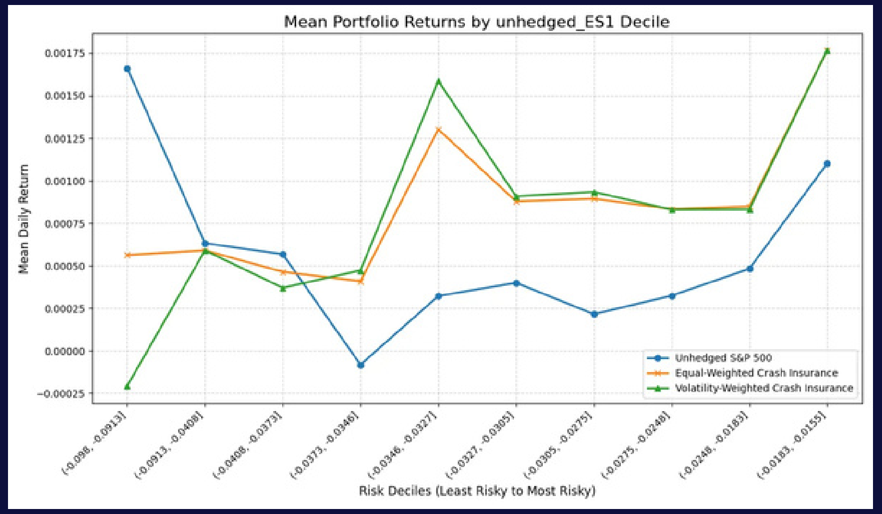
# 5 TEST

- As risk level increases, in general there is an increase in retrurns due to returns becoming relatively more stable or show a less severe decline, demonstrating the protective benefit of the crash insurance.



Tang En Ci Nathan

# PART 5: REPLICATING THE DATA PART 2

# OUR SECOND APPROACH FOCUSES ON REPLICATING THE STUDY WITH ANOTHER CRASH INSURANCE MEASURE

| | Limitation | Approach |
|---|---|---|
| 1 | The study analysed crash insurance at the asset level | #1: To study crash insurance at the portfolio level |
| 2 | **The study analysed crash insurance using bear put spreads** | **#2: To study crash insurance using simple long put options** |

# FOR THIS, WE USED US OPTION LEVEL AND DAILY STOCK SECURITY DATA

**US Option Level Output Data**

By Wharton Research Data Services

**Daily Stock Security Data**

By **Centre for Research in Security Prices**

# THE KEY CHALLENGE HERE WAS THE OVERWHELMING AMOUNT OF DATA VIZ. TIME FOR ANALYSIS

1

## Too Much Data

Over 12 million data points from 1 year worth of data

2

## Too Little Time

Challenging to calculate bear put spread returns

# HENCE, WE FOCUSED ON A SMALL TIME FRAME AND USED ONLY LONG PUT OPTIONS

| | Approach #1 | Approach #2 |
|---|---|---|
| Description | Focused only on options expiring on 20 Nov 2020 | Focused only on Long Put Options as Crash Insurance |
| Rationale | • Crash insurance would be highly valued given that it was at the height of the COVID-19 pandemic - most likely to “disprove” study<br>• Left tail risk could be best estimated given that it was one year into pandemic | • Most obvious and accessible form of crash insurance, particularly among retail investors<br>• Hence, least likely to be “undervalued”, as opposed to bear put spreads, where “undervaluation” could be due to accessibility |

# FROM THERE, WE CONSTRUCTED OUR INDEPENDENT AND DEPENDENT VARIABLES

1

## Dependent Variable

Return on long put option that expires on 20 Nov 2020, from 12 Oct 2020 to 30 Oct 2020

2

## Independent Variables

95% Value-at-Risk and Expected Shortfall based on stock price from 14 Oct 2019 to 14 Oct 2020

Tang En Ci Nathan

# THIS GAVE US 2,421 DATA POINTS BASED ON THE SAME NUMBER OF ASSETS

**US Option Level Output Data in 2020 - 12.9 Million Data Points**

**US Option Level Output Data Expiring on 20 Nov 2020 - 599 Thousand Data Points**

**US Option Level Output Data with Available Security Data - 8,405 Data Points**

**US Option Level Output Data with Available Security Data on 12 Oct 2020 and 30 Oct 2020 - 2,421 Data Points**

**Notes:**

- **We did not use the delta hedge methodology to compute the appropriate strike price, but used all the strike prices available**

# FROM THERE, WE RAN TWO SIMILAR TESTS AS PER THE STUDY

1

## Univariate Analysis

Comparison of top decile with bottom decile

2

## Fama-Macbeth Regression

Regression of returns on left-tail-risk measures

# FINDING #1: RETURNS ON LONG PUT OPTIONS WERE WORSE FOR FIRMS WITH HIGHER LEFT TAIL RISK

- To be precise, returns on long put options for firms in the top decile of left tail risk were about 200% lower than returns for firms in the bottom decile of left tail risk
- This runs contrary from the study

```
=== Test 1: Sorted by VaR_0.05 (descending) ===
Average return (top decile):     -2.475267
Average return (bottom decile): -0.274783
Difference (top - bottom):       -2.200485

=== Test 2: Sorted by ES_0.05 (descending) ===
Average return (top decile):     -2.982624
Average return (bottom decile): -0.494484
Difference (top - bottom):       -2.488140
```

Tang En Ci Nathan

# FINDING #2A: FIRMS WITH HIGHER VALUE AT RISK HAD LOWER RETURNS ON LONG PUT OPTIONS

- Value-at-risk and returns on long put options were found to be negatively correlated
- In particular, 1% higher value-at-risk found to be correlated with 74% lower returns on long put options
- While not statistically significant, this also contradicts the study

```
=== Regression 1: Returns on VaR_0.05 ===
                            OLS Regression Results
==============================================================================
Dep. Variable:                returns   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.000
Method:                 Least Squares   F-statistic:                    0.8226
Date:                Mon, 01 Dec 2025   Prob (F-statistic):              0.365
Time:                        21:36:57   Log-Likelihood:                -14239.
No. Observations:                2416   AIC:                         2.848e+04
Df Residuals:                    2414   BIC:                         2.849e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -1.5590      5.269     -0.296      0.767     -11.891       8.773
VaR_0.05     -74.8289     82.506     -0.907      0.365    -236.618      86.960
==============================================================================
Omnibus:                     3847.223   Durbin-Watson:                   1.950
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          2654927.514
Skew:                          10.022   Prob(JB):                         0.00
Kurtosis:                     164.157   Cond. No.                         46.4
==============================================================================
```

Tang En Ci Nathan

# FINDING #2B: FIRMS WITH HIGHER EXPECTED SHORTFALL HAD LOWER RETURNS ON LONG PUT OPTIONS

- Expected shortfall and returns on long put options were found to be negatively correlated
- In particular, 1% higher expected shortfall found to be correlated with 51% lower returns on long put options
- While not statistically significant, this also contradicts the study

```
=== Regression 2: Returns on ES_0.05 ===
                            OLS Regression Results
==============================================================================
Dep. Variable:                returns   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                  0.000
Method:                 Least Squares   F-statistic:                     1.012
Date:                Mon, 01 Dec 2025   Prob (F-statistic):              0.314
Time:                        21:36:57   Log-Likelihood:                -14239.
No. Observations:                2416   AIC:                         2.848e+04
Df Residuals:                    2414   BIC:                         2.849e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -2.1583      5.370     -0.402      0.688     -12.688       8.371
ES_0.05      -51.8665     51.548     -1.006      0.314    -152.949      49.216
==============================================================================
Omnibus:                     3845.909   Durbin-Watson:                   1.950
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          2651471.525
Skew:                          10.015   Prob(JB):                         0.00
Kurtosis:                     164.053   Cond. No.                         29.1
==============================================================================
```

Tang En Ci Nathan

# WHILE NOT STATISTICALLY SIGNIFICANT, THIS RAISES QUESTIONS ON THE STUDY'S FINDINGS

## Conclusions

The paper's findings, while robust, may not hold in all situations

This may especially be when crash insurance is more easily valued

## Limitations

Results are not statistically significant, and did not include controls

Dataset is small and limited to a single period only

## Areas to Study

Alternative forms of crash insurance - such as long put options

Differences in crash insurance value across different market contexts

Kenneth Chan Jian Da


# PART 6: IMPLICATIONS OF THE STUDY

# DRAWING THINGS TOGETHER: USING CAR INSURANCE AS AN ANALOGY

- Left-Tail Risk = Accident/Catastrophic Risk
- Crash Insurance = Catastrophic Accident Policy
- Crash Insurance Returns = Profitability of the Policy

# EXPECTATION VS ANOMALY

| | Expected Scenario (Fair Pricing) | Anomaly (Underreaction) |
|---|---|---|
| **Car Insurance Analogy** | Drivers with the highest accident risk should pay the highest premiums and they should expect negative returns (i.e., it costs money to maintain the protection). | Drivers with the highest accident risk can buy underpriced policies such that, over time, they earn positive returns. |
| **Supporting Basis** | Our findings using real data from 2020. | Our findings using simulated data. |

# IMPLICATIONS OF THE PAPER’S FINDINGS FOR BUSINESS OWNERS

Owners should not trust calm markets and must proactively act before market realizes the risk

Persistence of left-tail risk requires proactive risk management

Use crash insurance proactively as it is most valuable before market realizes the risk

## Implication #1: Owners should not trust calm markets and must act proactively

As options markets underreact to rising crash risk, businesses' true exposure to left-tail risk is higher than it seems.

For firms with high left-tail risks, any failure to obtain crash insurance is costly as protection is underpriced.

## Implication #2: Persistence of Left-Tail Risk requires proactive management

77% of the firms in the highest left-tail risk portfolio (Decile 10) remain in Deciles 9 and 10 a year later

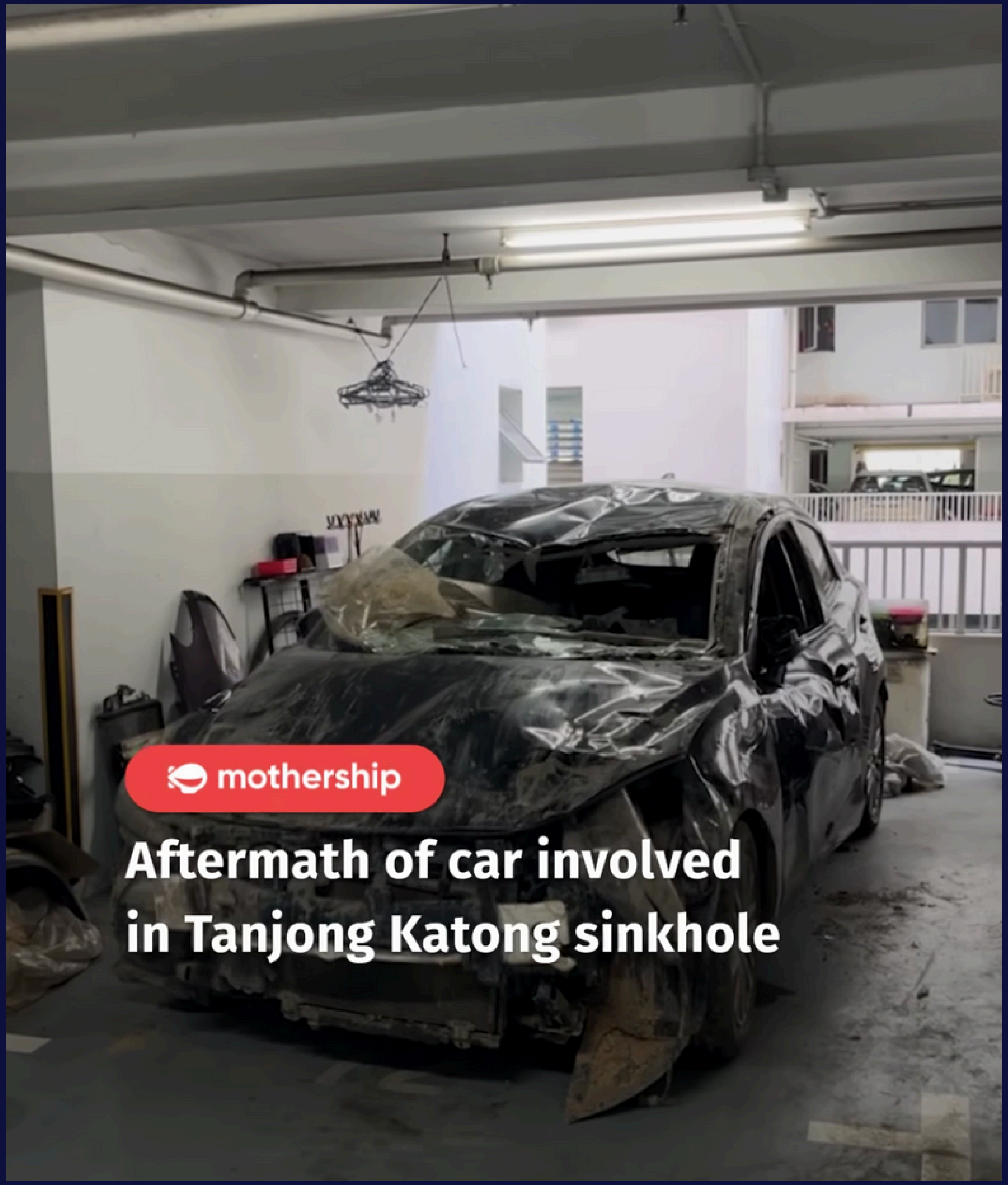
Owners must treat small signs as early warnings; e.g. Stock price near 52-week low, rising volatility, declining margins

## Implication #3: Use crash insurance proactively when it is most valuable before markets realize the risk

Crash insurance is most profitable when when investor sentiment suggests markets are overlooking future risk

Crash insurance can be an offensive strategic tool instead of a defensive tactic

# HOW CAN WE GUARD AGAINST "SINK-HOLE" EVENTS?

# LEFT-TAIL RISK ASSESSMENT FRAMEWORK

## PHASE 1

Perform Left-Tail Risk Stress Testing

## PHASE 2

Identify Signs of Market Underreaction

## PHASE 3

Choose Mitigation/ Hedge/ Transfer Strategies

## PHASE 4

Monitoring "Tail Persistence"

# PHASE 1
# PERFORM LEFT-TAIL RISK STRESS TESTING

**Operational Tail Risk**
E.g., Supply chain volatility, regulatory exposure

**Financial Tail Risk**
E.g., Leverage ratios, liquidity buffers

**Market-Based Signals**
E.g., Industry stock volatility, competitor tail events

**Actions Include:**

- Running worst-case cash-flow scenarios
- Stress-test liquidity, supply chain, and debt structure
- Evaluate customer concentration and operational single points of failure
- Model substantial revenue drop (e.g., 20%-50%) to assess the business's resilience

# PHASE 2
# IDENTIFY SIGNS OF MARKET UNDERREACTION

Is the business in a state where negative info is slow to be priced in?

Has the business's risk increased without external visibility?

Are external conditions masking the business's internal fragility?

# PHASE 3
# CHOOSE STRATEGIES

## MITIGATE
internally if the left-tail risk arises from the business model

## HEDGE
using underpriced crash insurance to protect against left-tail risk

## TRANSFER
externally to shift the left-tail risk to another party

Kenneth Chan Jian Da

# PHASE 4
# MONITOR “TAIL PERSISTENCE

## Use dashboards to monitor metrics monthly

- **Internal indicators:** Cash burn rates, customer concentration, short-term debt proportion?
- **External indicators:** Industry volatility, credit spreads, commodity/FX swings?

## Establish a crash severity index and automatic response triggers when tail scores moves up index

| Score | Meaning |
|---|---|
| 1 | Mild downside risk |
| 2 | Manageable but noticeable downside risk |
| 3 | Elevated asymmetric downside |
| 4 | High chance of extreme outcomes |
| 5 | High left-tail risk with systemic amplification |

# THANK YOU!

Crash Insurance Returns

# BEAR PUT SPREAD RETURNS WERE BASED ON PUT OPTIONS WITH ONE MONTH TO MATURITY

- **Bear put spreads were constructed based on put options with a one month maturity**

- **Returns were calculated based on the value of the bear put spread at maturity**

$$\text{RETURN} = \frac{(\Delta_{2,t} - \Delta_{1,t})S_{t+1} + \max(K_1 - S_{t+1}, 0) - \max(K_2 - S_{t+1}, 0)}{(\Delta_{2,t} - \Delta_{1,t})S_t + P_1 - P_2} - 1$$

Koh Thoong Yip

# <u>BONUS</u>: ADDITIONAL TECHNICAL DETAILS IN CALCULATION OF BEAR PUT SPREADS

**Issue #1: What is the appropriate strike price for the long and short puts?**

**Solution:** Use delta hedging - based on 30% and 10% chance of finishing in the money respectively

**Issue #2: How do we know what the options could be sold for in reality?**

**Solution:** Use the midpoint of the bid and ask prices to determine the prices which the options could be bought or sold