The Probability of Rare Disasters: Estimation and Implications

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Introduction
Rare Disasters

- Recent growth in “rare disasters” (RD) paradigm
  - e.g. Rietz (1988), Barro (2006)

- Main Idea: rare macroeconomic disasters can explain asset prices
  - Equity premium puzzle
  - Can also account for business cycles in production economies

- Why should we care?
  - Unified framework between macroeconomics and asset pricing
  - Capital costs: do some firms do worse in disasters? Is it priced?
  - Welfare: benefits of financial asset trade in the presence of disasters
Empirical Work on Rare Disasters

- International macro data paints a positive picture

- With reasonable risk-aversion, the average frequency and severity of disasters matches unconditional stock market returns

- This is true even if:
  - Disasters unfold over a number of years
  - The economy recovers after disasters

- Most empirical work has assumed a constant probability of a disaster
Time-Varying vs. Constant Disaster Probability

- **Time-series variation in the probability of a disaster is critical**

- **Theoretically:**
  - Explains many asset pricing patterns (excess vol, term structure, FX rates, etc.)
  - Necessary to generate realistic business cycles

- **Empirically:**
  - With constant probability, S&P 500 options imply a disaster probability that disagrees with macro data...
  - But with time-varying disasters, macro data implies realistic option prices
Is there evidence that the probability of a disaster is time-varying?

Can we estimate this variation?

How do asset markets and the macroeconomy respond to changes in the probability of a disaster? Is it consistent with theory?

This paper sheds light on these questions
The Probability of a Disaster

Model-Implied Probability of Disaster (%)

Russian/LTCM Default
Dot Com Bubbles Bursts
U.S. Plans to Invade Iraq
U.S. Financial Crisis
Euro Crisis,
Gaza Strip
Euro Crisis
(Greece/Spain)
High Level Logic of My Approach

- Start in the options markets. Why?
  - RD hypothesis has unique predictions for options

- Core assumption of all rare disaster models:
  - Disasters happen at same time for every firm in the economy
  - Firms just differ in how exposed they are to the event

- Using options, I form a non-parametric estimate of jump-risk:

\[
D_{it} \equiv \left( p_{it}^* \right) \times \Psi_i
\]

  prob. of firm \( i \) jumping determined by jump size of firm \( i \)

- RD hypothesis says that \( p_{it}^* = p_t^* \) should be same across firms
Summary of Findings

Three core facts...

1. Time series variation in firm-level jump risk is driven by single factor.
   • \( \hat{\rho}^*_t \) = Extracted factor. Clearly not constant

2. An increase in \( \hat{\rho}^*_t \) forecasts declines in short-run economic activity:
   • Unemployment rises
   • Industrial production, manufacturing, and total capacity utilization fall

3. Disaster risk is priced in cross-section of U.S. equities
   • Disaster risky stocks earn 7.6% in risk-adjusted returns

Plus a calibration to sharpen the mapping between the model and the data...

1. S&P 500 falls when \( \hat{\rho}^*_t \) increases - matches calibrated model

2. Reasonable cross-sectional loss rates of stocks in a disaster
   • Model: disaster risky stocks must lose 57%. Data: 51%

Findings are consistent with a standard time-varying rare disasters model
A Model of Rare Disasters: Quick Overview
Outline

- Out-of-the-box endowment economy with variable disasters:
  - Continuous time version of Barro (2006); Gabaix (2012)

- Purpose of going through the model:
  - Overview of RD hypothesis
  - Intuition for how option prices comove under null of the model

- Roadmap:
  1. Economy primitives
  2. Equilibrium P-D ratios
  3. “Risk-neutral” returns
  4. Option prices + disaster likelihood
Consumption and Dividend Dynamics

Aggregate Consumption

\[ \frac{dC_t}{C_t} = g_C dt + \sigma_C dW_{C,t} + (B_t - 1) dJ_t \]

- \( J_t \) is macroeconomic jump process
- Disaster occurs over next \( dt \) with probability \( p_t dt \)
- \( B_t > 0 \) is a stochastic disaster recovery rate

Dividend Growth

\[ \frac{dD_{it}}{D_{it}} = g_{iD} dt + dN^D_{it} + (F_{it} - 1) dJ_t \]

- \( dN^D_{it} \) is a mean-zero martingale and is independent of disasters
- Stocks with higher \( F_{it} \) do better in disasters
Preferences and State Variable Dynamics

- Preferences = Epstein-Zin-Weil
  - risk-aversion $\equiv \gamma$. IES $= \psi$
  - $\chi \equiv (1 - 1/\psi)/(1 - \gamma)$

- State variable dynamics:
  - One route is to model $p_t$, $B_t$, $F_{it}$ separately
  - Instead, I model them jointly...

- Define resilience: $H_{it} \approx p_t E_t \left[ B_t^{-\gamma} (F_{it} + (\chi - 1) B_t) - \chi \right]
  - Stocks with high resilience do better in crises
  - Resilience is a linearity-generating (LG) process $\approx AR(1)$
  - Mean-reverts to $\bar{H}_i$ at speed $\phi_{H,i}$

- Gabaix (2012) or Farhi and Gabaix (2015) for other examples
Price-dividend ratios are given by:

\[
\frac{P_{it}}{D_{it}} = \frac{1}{\delta_i} \left( 1 + \frac{\tilde{H}_{it}}{\delta_i + \phi_{H,i}} \right)
\]

- \(\delta = \rho + g_C / \psi\)
- \(\delta_i = \delta - g_{ID} - \bar{H}_i\)

\(\tilde{H}_{it} = H_{it} - \bar{H}_i\), so measures deviations from mean
  - Stocks with high resilience have high valuation ratios
  - Mean-reversion in resilience generates mean-reversion in P-D ratio

A useful quantity for empirical work = so-called “risk-neutral” returns
Risk-Neutral Probability Measure
A Primer

- Risk-neutral probability is proportional to Arrow-Debreu state price

- Discrete time analogue:
  - Suppose there are $s = 1, \ldots, S$ possible states of the world
  - Each state has a probability $\pi(s)$
  - Marginal utility in each state is $m(s)$

- State prices ($AD$) and risk-neutral probabilities ($\pi^*$)
  - $AD(s) = \pi(s) \times m(s)$
  - $\pi^*(s) = AD(s) / \sum_s AD(s) = (1 + r_f) \times AD(s)$

- I’m interested in how $\pi^*(s = \text{disaster})$ moves around
Equilibrium Returns Under the Risk-Neutral Measure

In the model

\[
\frac{dP^*_it}{P^*_it} = r_ft dt + \sigma_it dW^*_it - p_tE_t \left[ B_t^{-\gamma} (F_it - 1) \right] dt + (F_it - 1) dJ^*_t
\]

- \(J^*_t\) is the RN macroeconomic jump (disaster) process
- Under the RN-measure, disasters no longer occur with a probability \(p_t\)
- \(p^*_t \equiv p_tE_t [B_t^{-\gamma}]\) is the RN probability of a disaster:
  - When \(E_t [B_t] < 1\) and \(\gamma > 0\), then \(p^*_t > p_t\)
- Intuition: risk-averse agent prices assets as if disaster is more likely
I. Intuition: Using Options to Learn About Jumps

- For simplicity, shut off time-varying disasters and assume $F_i \ll 1$

- RN returns take a simple form:

$$\frac{dP_{it}^*}{P_{it}^*} = (r_f - B^{-\gamma} (F_i - 1)) dt + \sigma_i dW_{it}^* + (F_i - 1) dJ_t^*$$

- In this case, the value of a short-dated put option is given by:

$$Put(P_{it}, K_P) \approx p^* \times Put^{BS}(F_i P_{it}, K_P) + (1 - p^*) \times Put^{BS}(P_{it}, K_P)$$

  - value if there is a disaster
  - value if there is no disaster

- $Put^{BS}(X, K)$ is a Black-Scholes put with initial price $X$, strike $K$, and volatility $\sigma_i$
II. Intuition: Using Options to Learn About Jumps

\[
\text{Put}(P_{it}, K_P) \approx p^* \times \text{Put}^{BS}(F_i P_{it}, K_P) + (1 - p^*) \times \text{Put}^{BS}(P_{it}, K_P)
\]

\[
\text{value if there is a disaster} \quad \text{value if there is no disaster}
\]

- Since \( F_i \ll 1 \), a call option with strike \( K_C > P_{it} \) has no value in disaster:

\[
\text{Call}(P_{it}, K_C) \approx (1 - p^*) \times \text{Call}^{BS}(P_{it}, K_C)
\]

- Next, form an option portfolio called a risk-reversal:

\[
RR = \text{Put}(P_{it}, K_P) - m \times \text{Call}(P_{it}, K_C)
\]

\[
\text{• } m \text{ and } K_C \text{ chosen to exactly offset the non-disaster portion of the put}
\]

\[
\text{• } \text{Thus, } RR = p^* \times \text{Put}^{BS}(F_i P_{it}, K_P)
\]

- Takeaway: every firm’s risk-reversal contains information on \( p^* \)
A More General Way to Estimate Jumps

- Can estimate jumps for broader class of risk-neutral return processes

- Carr and Wu (2009) and Du and Kapadia (2013):
  - Use a portfolio of options (across strikes) to isolate the jump
  - Resembles the construction of the VIX.
  - Basically, a more general version of a risk-reversal

- For a given date and firm, I call this measure $\mathbb{D}_{it}$:
  
  $$ \mathbb{D}_{it} = \Psi_i p_t^* $$

- $\Psi_i$ a simple function of the recovery, $F_{it}$:
  
  $$ \Psi_i = 2 \times \mathbb{E} \left[ (1 + \ln(F_i) + \ln(F_i)^2 / 2 - F_i) \right] $$
A Comment on this Jump Risk Estimator

\[ \mathbb{D}_{it} = \Psi_i p_t^* \]

- **Testable hypothesis:** the model suggests that a panel of \( \mathbb{D}_{it} \) should obey a single factor structure

- The single factor should capture time-series variation in \( p_t^* \)

- The option pricing theory behind \( \mathbb{D}_{it} \) is actually non-parametric:
  - Doesn’t impose that \( p_t^* \) is the same across firms
  - i.e. if each firm just has an idiosyncratic jump process, then \( \mathbb{D}_{it} = \Psi_i p_{it}^* \)

- Useful because we can check whether option-implied tails are consistent with the model, without imposing anything on the data
The Factor Structure of Option-Implied Tails
I form a jump risk measure, $D_{it}$, for each firm and each date

- Includes the entire universe of U.S. traded options in OptionMetrics
- January 1996-April 2015

$D_{it}$ is a 30-day measure of expected jumps for a given firm.

- 6,762,860 firm-day pairs

Keep in mind that this measure does not depend on the RD model!

- No prior structure is assumed on the panel of $D_{it}$
Factor Structure of Jumps (Principal Component Analysis)

The bar chart shows the percent of variation captured by each factor. Factor 1 captures a significantly higher percentage of variation compared to the other factors. Factors 2 and 3 also show notable captures, with factors 4 through 10 capturing much less variation.
A Single Factor Drives Variation in Option-Implied Jumps

- Panel of $D_{it}$ has clear one-factor structure
  - Very robust to subsamples, inclusion of firms, etc.

- Implies that jump intensities are indeed the same across firms,
  - i.e. $p_t^*$ is common across firms

- This is the core of the rare disasters paradigm

- Can also map the extracted factor, $\hat{p}_t^*$, to the model:

\[
\hat{p}_t^* = \bar{\Psi} p_t^*
\]
\[
= \bar{\Psi} \times E_t \left[ B_t^{-\gamma} \right] \times p_t
\]

**Bottom Line: Time-series variation in factor = time-series variation in $p_t^*$**
The Probability of a Disaster

Assume constant disaster severity + use Barro (2006) calibration to recover $p_t$

Data: $\overline{p} = 3.1\%$... Barro and Ursua (2008)/Nakamura et al. (2013): $\overline{p} \approx 3.2\%$
Supporting Evidence: $p_t^*$ and Future Economic Activity
Motivation: The Probability of Disaster in GE


- Example of intuition:
  1. Capital stock is reduced by disasters (think wars)
  2. Capital is riskier when disasters are imminent
  3. So firms invest less when disasters become more likely

- Motivated by these models, I use forecasting regressions as a way to validate the interpretation of $p_t^*$:
Forecasting Regressions

- Basic setup:

\[ Y_{t+1} = c + \sum_{i=1}^{4} \gamma_i Y_{t+1-i} + \phi' X_t + \kappa \hat{p}_t^* + u_{t+1} \]

- \( Y_t \) is one of a few macro-variables

- \( X_t \) are competing forecasting variables:
  - Real federal funds rate
  - Term structure of Treasury yields (10Y-3M)
  - Aggregate stock market returns

- Monthly horizon from April 1996-2015. \( \hat{p}_t \) is standardized.
When the Probability of Disaster ↑, Economic Activity ↓

Unemployment and TCU in % points.

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Y_{t+1} = c + \sum_{i=1}^{4} \gamma_i Y_{t+1-i} + \phi' X_t + \kappa \hat{p}_t^* + u_{t+1}
\]

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<tr>
<th>Dependent Variable at ( t + 1 )</th>
<th>Coefficient on ( \hat{p}_t^* )</th>
<th>( t )-stat</th>
<th>Adj. ( R^2 )</th>
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- Increases in \( \hat{p}_t^* \) lead to:
  - 6.4bp rise in unemployment, ≈ 100K people (Kilic and Wachter (2015))
When the Probability of Disaster ↑, Economic Activity ↓

Unemployment and TCU in % points.

\[ Y_{t+1} = c + \sum_{i=1}^{4} \gamma_i Y_{t+1-i} + \phi' X_t + \kappa \hat{\rho}_t^* + u_{t+1} \]

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- Increases in \( \rho_t^* \) lead to:
  - 6.4bp rise in unemployment, ≈ 100K (Kilic and Wachter (2015))
  - Decreased production and investment (Gourio (2012))
Discussion and Robustness

- Macroeconomy almost always responds more to $\hat{\rho}_t^*$ than:
  - Aggregate stock market returns
  - Real federal funds rate
  - Slope of the term structure

- Unemployment most sensitive to changes in $\hat{\rho}_t^*$

- Results not driven entirely by the crisis:
  - Most go through if I exclude Dec 2007-June 2009

- For forecasting, $\hat{\rho}_t^*$ generally outperforms the VIX
  - $\hat{\rho}_t^*$ has unique information on the macroeconomy

Results in line with $\hat{\rho}_t^*$ measuring variation in disaster probability
Supporting Evidence: Disaster Risk and Cross-Section of Equity Returns
The Cross-Section of Equity Returns

- In the model, expected excess returns given by:

\[ \mu_{it} - r_{ft} = \rho_t \mathbb{E}_t [B_t^{-\gamma} (1 - F_{it})] \]

- Firms that recover a lot in disasters (high $F_{it}$) have low premiums

- $\hat{\rho}_t^*$ also useful for determining which stocks are disaster risky:

\[ r_{it} = a_i + \beta_{i}^{\text{Disaster}} \times \Delta \hat{\rho}_t^* + \text{error}_{it} \]

  - Disaster-$\beta$’s are increasing in $\mathbb{E}_t [F_{it}]$.

- Punchline: stocks with high disaster-$\beta$’s should earn low returns
  - Disaster-$\beta > 0$, means stock rises when $\hat{\rho}_t^*$ rises. Hedges disaster.
A Simple Test

- Sort stocks into portfolios based on disaster-$\beta$’s
- Trading strategy done in real time, so fully implementable
- Includes entire universe of CRSP stocks
- Monthly frequency
Disaster Risk is Priced in Cross-Section of U.S. Equities

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For $\alpha$’s, ** = 5% significance and * = 10% significance. All CAPM-$\beta$’s significant.

Excess returns monotonically increase from low to high disaster risk
Disaster Risk is Priced in Cross-Section of U.S. Equities

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Same pattern after adjusting for exposure to Fama-French factors
Disaster Risk is Priced in Cross-Section of U.S. Equities


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Reject joint hypothesis that all $\alpha$’s = 0. $p$-value = 1.28%
Disaster Risk is Priced in Cross-Section of U.S. Equities


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CAPM- $\beta$ doesn’t really capture disaster risk (Gabaix (2012))
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**Takeaway:** Disaster risk is priced. Premium for bearing disaster risk $\approx 7.6\%$
Two Calibration Exercises
What is the Disaster-\(\beta\) of the Aggregate Stock Market?

Calibration: Disaster severity, \(B = \overline{F} = 0.6\). Risk-aversion, \(\gamma = 4\). \(IES = 2\)

- Simple regression of S&P 500 returns on \(\Delta\hat{\rho}_t^*\):
  - Disaster-\(\beta = -6.4\)
  - \(t\)-stat = -7.9

- The fact that disaster-\(\beta < 0\) implies an IES > 1
  - Barro (2009)
  - Nakamura, Steinsson, Barro, and Ursua (2013)

- In calibrated model, disaster-\(\beta \approx -11\). So in the same ballpark.
  - Can also roughly match range of observed disaster-\(\beta\)’s in cross-section
How Much Should Disaster Risky Stocks Fall in the Crisis?

Calibration: Disaster Likelihood and Severity, $p = 0.028$ and $B = 0.6$. Preferences unchanged

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<td>0.58</td>
<td>0.46</td>
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<tr>
<td>5</td>
<td>0.49</td>
<td>0.43</td>
</tr>
</tbody>
</table>

Model suggests disaster risky stocks should fall slightly more during crisis. They also fall less than low disaster risk stocks. Government distortions?
How Much Should Disaster Risky Stocks Fall in the Crisis?

**Calibration:** Disaster Likelihood and Severity, $p = 0.028$ and $B = 0.6$. Preferences unchanged

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Realized Recovery ($\hat{F}_i$)</th>
<th>Model-Implied Recovery ($F_i$)</th>
</tr>
</thead>
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<tr>
<td>1</td>
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<td>0.76</td>
</tr>
<tr>
<td>2</td>
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<td>0.51</td>
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</tbody>
</table>

Model overshoots low disaster risk stocks. Additional factors needed?
Conclusion
In Summary

- This paper contains a set of facts about options/equities.
  1. A panel of option-implied jump measures is driven by single factor, $\hat{\rho}_t^*$
  2. $\hat{\rho}_t^*$ forecasts declines in future economic activity
  3. Stocks that fall when $\hat{\rho}_t^*$ rises are risky, so require a premium
     - Price of disaster risk is about 7.6% annually

- These facts are consistent with the rare disasters model:
  • Two calibration exercises to sharpen the mapping

- Interpret $\hat{\rho}_t^*$ as the (risk-neutral) probability of a disaster
Next Steps

- What are disaster risky stocks?
- What drives movements in $\hat{p}^*_t$?
  - Good place to start: who is pricing the risk?
  - Link to intermediary-based asset pricing?
- Estimate a structural model
  - Non-parametric analysis suggests this is a good idea
  - Identification via entire cross-section of options (firms + strikes)
Thank You!


