The Effect of Sunk Costs on High-Risk Decision Making

Evidence from Mount Everest

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Introduction

- How do increases in mountaineering permit royalties affect risk and decision-making on Mount Everest?
- Previous studies have investigated decision making where there exist sunk costs, mostly using experimental data gathered in lab
- Mountaineers make decisions facing high-risk, life threatening situations many times throughout their careers
- This context allows us to analyze the decisions of professional high-risk decision makers facing uncertainty and sunk costs

Background

- Both Nepal and Tibet introduced large-scale permit systems as commercial expeditions begin in 1990s as a way of regulating market and extracting rents
- Paying permit royalty mandatory for climbing, and account for a sizable portion of expenses paid to undertake the climb
- New permit system in Nepal 2015, amounted to a $1000 increase

Data and Summary Statistics

- The Himalayan Database ©:
  - Eight 8000m peaks in the Nepal Himalaya
  - 2000-2019
  - Representative dataset
- Permits are measured in USD, found from various sources

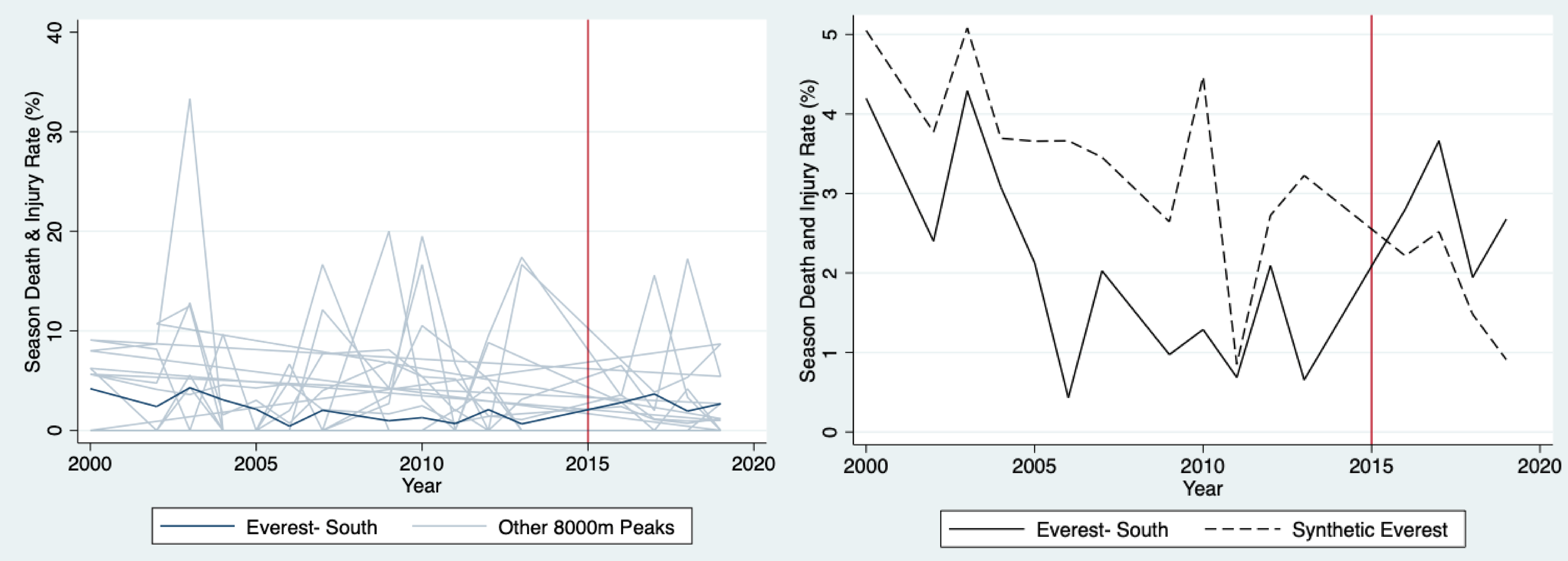
Table 1: Summary Statistics of Key Variables

	Obs.	Mean	Std. Dev.	Min.	Max.
Deaths & Injuries in 24h	3,381	1.7610	4.8446	0	8
Permit Royalty (1000's USD)	3,802	10.0952	1.4792	0.757	15
Individual Controls					
Age	3,802	40.1394	10.4088	14	81
Oxygen Used	3,802	0.8611	0.3459	0	1
Previous 8000m Experience	3,802	1.7636	3.4913	0	40
Expedition Composition Controls					
Climbers: Hired Climbers	3,562	1.3011	0.7211	0.2	6
Team Size	3,802	11.4761	8.5762	1	42
Crowding	3,154	0.1237	0.3292	0	1
Bad Weather	3,802	0.3254	0.4686	0	1
Bad Conditions	3,802	0.0513	0.2206	0	1
Same Day Climbers	3,154	84.9214	61.2123	0	240

Table 2: Summary Statistics for Synthetic Control

	Treated		Control	
	Mean	Std. Dev.	Mean	Std. Dev.
Season Death & Injury Rate (%)	8	5.8652	2.9770	3.4658
Number of Climbers	406.5	194.6864	95	104.4323
Average Hired Ratio	1.2350	0.2265	2.1461	1.1929

Synthetic Control



Negative Binomial Regression Results

Table 3: Regression Results

Dependent Variable: Everest South Number of Deaths & Injuries in 24h	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Negative Binomial Regression						
Permit Royalty	0.00793	−0.00637	−0.00747	−0.00599	−0.00595	−0.00313
	(0.0131)	(0.00864)	(0.00849)	(0.00741)	(0.00751)	(0.00756)
Crowding				1.057***	1.062***	1.046***
				(0.0642)	(0.0640)	(0.0639)
$\ln \alpha$	0.256***	−0.785***	−1.117***	−19.28***	−15.29***	−16.39***
	(0.0418)	(0.0780)	(0.111)	(0.134)	(0.885)	(0.269)
Pseudo R-Squared	0.0000345	0.110	0.128	0.175	0.176	0.179
Panel B: Zero-inflated model						
Permit Royalty	−0.00122	−0.00776	−0.00780	−0.0109**	−0.0113**	−0.00882*
	(0.0111)	(0.00612)	(0.00609)	(0.00533)	(0.00533)	(0.00522)
Crowding				0.529***	0.533***	0.526***
				(0.0426)	(0.0426)	(0.0424)
Zero Prediction						
Same Day Climbers	−0.0339***	−0.0420***	−0.0540***	−0.0542***	−0.0542***	−0.0605***
	(0.00338)	(0.00235)	(0.00271)	(0.00272)	(0.00272)	(0.00312)
$\ln \alpha$	−1.111***	−16.65***	−17.41***	−17.53***	−17.98***	−17.06***
	(0.0894)	(0.0553)	(0.0491)	(0.0238)	(0.164)	(0.0230)
Year FE	*No*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Conditions FE	*No*	*No*	*Yes*	*Yes*	*Yes*	*Yes*
Individual Controls	*No*	*No*	*No*	*No*	*Yes*	*Yes*
Expedition Controls	*No*	*No*	*No*	*No*	*No*	*Yes*
N	3126	3126	3126	3126	3126	3010

Robust standard errors in parentheses. α is the dispersion parameter of the count model. The inflated model is a logit model.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Estimation Strategy

Synthetic Control model using weighted outcomes from other 8000m peaks to create counterfactual Everest

$$Y'_{EV,t} = \Sigma_{m \in M}\left(W_m Y_{EV,t}\right)$$

- M – set of peaks m
- $Y_{m,t}$ – observed rate of death & injury(%) on peak m in year t
- W – $1 \times m$ vector $\Sigma_{m \in M} W_m = 1$, $W_m \geq 0$, weights of each peak

Estimate the effect of a $1000 increase in permit prices on the incidence of death and injury in 24 hours. Using the negative binomial distribution, as described in Hilbe (2014):

$$p(y) = P(Y = y|\mu_i, \alpha) = \frac{\Gamma(y + \alpha^{-1})}{\Gamma(y+1)\Gamma(\alpha^{-1})}\left(\frac{1}{1+\alpha\mu}\right)^{\alpha^{-1}}\left(\frac{\alpha\mu}{1+\alpha\mu}\right)^{y}$$

Negative Binomial Regression Model:

$$\ln(\mu) = \beta_0 + \beta_1 R_{m,t} + \delta X_{m,t} + \psi_{m,t} + \rho_{m,t} + \ln(t_i)$$

- R – Permit Royalty, measured in 1000's of USD
- X– individual, expedition, and weather controls
- ψ, ρ– Year, peak fixed effects
- y -- Injury and Death count in 24 hours
- μ– mean of Y
- α – heterogeneity parameter
- t – time

Probability distribution of zeros:

$$P(y = j) = \begin{cases} \pi + (1-\pi)P(Y = y) & if\ j = 0 \\ (1-\pi)P(Y = y) & if\ j > 0 \end{cases}$$

Where π is the logistic link function defined as:

$$\pi = \frac{\lambda}{1+\lambda}$$

And $\ln(\lambda) = \gamma_0 + \gamma_1 D + \ln(t_I)$

- D –Number of other climbers reaching a high point in the same period

Synthetic Control Composition

- The composition of the synthetic control was generated using a combination of season and expedition predictors
- The peaks used to construct the Synthetic Everest are Everest –North, Cho Oyu, and Dhaulagiri I

Table 4: Peak Weights in Synthetic Everest

Peak	Weight
Everest-North	0.764
Annapurna I	0
Cho Oyu	0.129
Dhaulagiri I	0.107
Kangchenjunga	0
Lhotse	0
Makalu	0
Manaslu	0

Table 5: Predictor Balance

Predictor	Year	Treated	Synthetic
Average Hired Ratio	2009	1.267295	1.556037
Average Hired Ratio	2013	1.072262	1.446104
Number of Climbers	2005	235	241.261
Number of Climbers	2009	462	155.953
Number of Climbers	2013	626	139.941
Death & Injury Rate	2000	4.195804	5.050046
Death & Injury Rate	2006	0.4310345	3.662985
Death & Injury Rate	2007	2.027027	3.455463
Death & Injury Rate	2010	1.28866	4.471751
Death & Injury Rate	2011	0.6864989	0.8502481
Death & Injury Rate	2012	2.09205	2.724465
Death & Injury Rate	2013	0.6557377	3.225901
Root Mean Squared Prediction Error		1.787304	

Interpretation

- The Synthetic Control Model demonstrates a reversal of trends wherein the season death and injury rate on Everest begins trending higher than than the Synthetic Everest after treatment
- Negative Binomial Regressions allow us to examine the effects at a much finer level and include more precise controls with which to analyze results
- Using the full specification, and the zero-inflated model:
  - A $1000 increase in permit royalties on Everest is associated with 0.1 fewer deaths or injuries within a 24-hour window during a climber's summit push
  - More than 150 climbers on a single route during a 24 hour window is associated with 0.5 more deaths or injuries in that same period

Discussion

- The results of the negative binomial and zero-inflated negative binomial regressions suggest:
  - Permit royalty increases associated with lower risk
  - Mechanism: higher-risk seekers, i.e. those undertaking No oxygen, solo, speed ascents, dispersing to other, relatively cheaper, 8000m peaks
- Higher death and injury rate on Everest following permit royalty increase in 2015 appears be associated with crowding from the higher numbers of climbers on Everest

- Potential endogeneity: permit increases occurred concurrent with exogeneous events including 2014 Khumbu Avalanche and 2015 Nepal Earthquake.

Robustness

These results are robust to:

- Different specifications of risk (climbing above high camps, pre-summit bid climbing)
- Inclusion of fall and winter climbing seasons
- Inclusion of seasons with high numbers of deaths and injuries from Acts of God
- Inclusion of a wide range of varying controls for individual, expedition, season, and summit date characteristics
- Using alternative zero-predictors in the zero-inflated model

Future Paths

- Perform nuanced behavioural analysis to determine specific decisions whilst facing uncertainty
- Determine whether permits affect conformation bias and updating in this context
  - Potential for asymmetric processing of new information
- Examine these effects in commercial teams versus professional climbing teams

Works Cited

J. Hilbe, *Negative Binomial Regression*, 2nd ed., New York: Cambridge University Press, 2011.