Climate risk and executive excess perk consumption: Evidence from China

Bin Li[1], Yifan Xu[2*], Yueping Du[1], Xiangqian Lu[3]

[1] School of Business, Xi 'an International University, Xi'an 710077, China

[2] School of Economics and Finance, Xi'an Jiaotong University, Xi'an 710061, China

[3] Shanghai Quanyi Investment Co., LTD, Shanghai 200123, China

Correspondent author: Yifan Xu

E-mail address: binlixjtu922@163.com (B. Li), xuyuyuhhxx@163.com(Y. Xu), chypdu@163.com (Y. Du), 571683161@qq.com (X. Lu)

Acknowledgements

This study was supported by the Soft Science Project of Shaanxi Province (Grant No. 2023-CX-RKX-037).

Climate risk and executive excess perk consumption: Evidence from China

Abstract

We investigate the impact of climate risk on executive excess perks consumption. We construct a city-level climate risk indicator to measure the degree of damage from climate-related natural disasters and find that climate risk has a positive association with executive excess perks consumption, these patterns are not likely to be driven in different identification strategies. We further find that this positive nexus is (a) mitigated by analysts' attention and media coverage, (b) weakened in firms with high degree of digital adoption and high financing constraints, and (c) strengthened in firms with high government subsidies. Overall, our findings contribute to the existing literature of climate risk and executive excess perks consumption and provide important and timely implications for regulators and firm managers.

Keywords: Climate risk, executive excess perks consumption, agency theory, information asymmetry

1. Introduction

The heightened frequency and escalating economic repercussions of climate-related events have propelled climate risk into the spotlight, garnering heightened attention and concern. Meanwhile, with the frequent occurrence and exposure of corporate executives' allowance consumption scandals, perks have become a universal phenomenon, executives seeking private advantages like perks as that they can avoid the “anger costs” associated with large monetary salary payments (Ren et al., 2022). Since excess perks consumption is characterized by risk sensitivity and is susceptible to the environment in which the firm operates (Zhang et al., 2022), climate risk, an increasingly important determinant associated with higher environmental uncertainty, is rarely discussed. In this study, we provide a new insight into the impact of climate risk on executives' excess perks consumption.

We postulate that climate risk is positively correlated with executive excess perks consumption. Drawing from agency theory (Jensen and Meckling, 1976), climate risk introduces uncertainty and financial strain to firms (Huynh et al., 2020; Javadi and Masum, 2021; Kaviani et al., 2020), potentially prompting managers to prioritize short-term financial needs by indulging in excess perks rather than allocating funds to long-term climate adaptation efforts (Liu, 2012; Wang, 2011). Additionally, as per information asymmetry theory (Yermack, 2006), climate risk can obscure information, complicating management's ability to transparently communicate the company's status to shareholders and regulators (Luo et al., 2011). This opacity may further incentivize management to seek immediate gains through excessive perks consumption.

We leverage the Chinese context to investigate the impact of climate risk on executive excess perk consumption. China's distinctive geographical characteristics and diverse array of climate-related natural hazards offer an ideal setting to scrutinize the ramifications of climate risk within a singular country and consistent institutional framework. Moreover, the structure of China's capital market and compensation system provides an opportune environment to delve into excess perk consumption dynamics[1].

Consequently, our research makes at least three important contributions. Firstly, we adopt a novel approach by examining the influence of climate risk on a crucial aspect of firm-level dynamics—the consumption of executive excess perks. This adds depth to both climate risk and executive excess perk consumption research, enriching the emerging literature in both domains. Secondly, by utilizing the Chinese context and providing cross-city evidence, we unveil the firm-specific consequences of climate risk within a uniform institutional setting, offering valuable insights into the nuanced effects of climate risk on firms operating within a single country. Thirdly, we overcome the measurement difficulty and provide a new insight into the climate risk measurement at the city level[2].

---

[1] (i) quantifiable compensation expenditures from Chinese listed businesses are voluntarily disclosed, providing the investigation with the essential compensation information; (ii) since equity-based executive compensation packages (such as stock options) are rarely used by Chinese companies, base salary and cash bonuses are typically the only financial remuneration received by employees, which makes supplemental allowances an important part of a manager's total compensation; (iii) regulatory restrictions on cash compensation for executives in State-Owned Enterprises (SOEs) lead to additional perks comprising 15-32% of total executive compensation (Gul et al., 2011).

[2] Prior research rarely investigates the effect of climate risk at the firm level, and the limited literature prefers to use global CRI to proxy for the climate risk faced by firms (Ding et al. 2021; Huang et al. 2018). However, in view of the global CRI being calculated at the country level, using it as a proxy for climate risk faced by firms is biased. This study innovatively constructs a climate risk index at the city level within China following the compiling method of the global CRI and can provide a method reference for future related research.

2. Data and empirical design

2.1 Data sources and sample selection

We hand-collect the city-level information of the influence of climate-related natural disasters[3] (i.e., deaths and economic losses) and then construct the climate risk index (CRI) to measure climate risk by cities in China[4]. The initial sample is obtained from the China Securities Market Accounting Research Database (CSMAR) and the RESSET database over the period from 2014 to 2021[5]. After performing the data processing procedures[6], the final sample has 32,906 firm-year observations. We further winsorize observations in the 1% tails of all continuous variables.

2.2 Empirical design

We employ the following model (1) to estimate the discussed relationship:

$$Perk_{i,,t}=\alpha_0+\alpha_1 CRI_{i,t-1}+\alpha_2 SIZE_{i,t}+\alpha_3 GRO_{i,t}+\alpha_4 LEV_{i,t}+\alpha_5 ROA_{i,t}+\alpha_6 TAN_{i,t}+\alpha_7 AGE_{i,t}+\alpha_8 CAS_{i,t}+\alpha_9 SOE_{i,t}+\alpha_{10} TOP_{i,t}+\alpha_{11} IDB_{i,t}+\alpha_{12} BOA_{i,t}+\alpha_{13} DUA_{i,t}+\alpha_{14} BIG_{i,t}+\alpha_{15} OPI_{i,t}+\alpha_{16} GDPI_{i,t}+Industry_i + Year_t \quad (1)$$

[3] Direct economic losses and the number of deaths caused by extreme weather events are collected from the official website of the Ministry of Emergency Management of China, China Earthquake Administration, the China Meteorological Administration, the State Administration of Work Safety, the Ministry of Civil Affairs, the Ministry of Emergency Management on the effects of climate-related natural disasters.

[4] We identify 27 different climate-related natural disasters, including storms, floods, drought, landslide, snowstorms, etc.

[5] This time period is chosen because of the data availability on climate risk.

[6] We exclude (i) firms with negative equity or revenue due to the going-concern principle; (ii) financial and insurance companies considering different accounting methods from other industries; (iii) firms that have been listed for less than one year or have not continuously disclosed their financial data for at least two years; (iv) firms with large missing values.

The dependent variable $Perk_{i,t}$ denotes firm i's executive excess perks consumption in year t. We estimate the Eq. (2) for the firms in each industry for each year and compute the expected value of *Mpay1*and *Mpay2*[7] respectively, and then employ the residuals from the expected model to generate our proxy for excess perks consumption[8] (*Perk1* and *Perk2*).

$$Mpay_{it}/Sales_{it}=a_1LnTotalComp_{it}+a_2\,LnAsset_{it}+a_3LnTotalIncPerCap_{it} \qquad (2)$$

The independent variable $CRI_{i,t-1}$ represents the climate risk faced by firm i in year $t-1$, which is computed as the natural log of the climate risk index[9] in the sum of parent and its subsidiaries' locations plus one (*CRI1*) and the natural log of the climate risk index in parent companies' locations plus one (*CRI2*). Higher index scores indicate greater climate risk. Considering the endogeneity problems, the independent variable and all control variables are lagged by one period. In addition, we include industry- and year-fixed effects. Also, a number of variables that may affect executives excess perk consumption are added following prior research

---

[7] *Mpay1*is calculated as the sum of five different expenses: travel, business entertainment, communication, study abroad, and car (Lu, 2016); In accordance with Chen et al., (2016), the following eight categories are what we assemble as potential payment for perks consumption: (i) business hospitality, (ii) communication expenditures, (iii) study abroad, (iv) board fees, (v) office expenditures, (vi) travel expenses, (vii) car expenses, (viii) conference expenses, Mpay2 is the total of the eight types of cash payment.

[8] We estimate expected firm perk consumption based on Eq. (2), where '*LnTotalComp*' is the natural log of total compensation for all firm employees, '*LnAsset*' is the natural log of the book value of total assets, and '*LnTotalIncPerCap*' is the natural log of total income per capita of the region in which the firm is located. (Chen et al., 2016; Gul et al.,2011; Xu et al.,2014).

[9] We refer to the construction method of global CRI (Huang et al. 2018) to compute the climate risk index of Chinese companies. Specifically, we utilize the same four indicators as those used in global CRI computation: (i) the number of deaths, (ii) the number of deaths per 100,000 inhabitants, (iii) the sum of losses, and (iv) losses per unit of Gross Domestic Product (GDP). We perform sorting in each subsample of these four indicators. The lowest numbers are ranked first. The climate risk index is calculated using the weighted average ranking of the above four indicators, indicators (i) and (iii) weighting one-sixth each, and indicators (ii) and (iv) weighting one-third each.

(Andrews et al., 2017; Gul et al., 2011)[10]. The standard errors are clustered at the firm level[11].

3. Empirical findings

3.1 Descriptive statistics

Table 1 presents the descriptive statistics. The mean and variance of *CRI1* are 2.379 and 2.916 respectively, indicating that the uncertainty of climate risk faced by firms fluctuates considerably across years, which provides good conditions for this paper's test. The correlation matrix provided in the supplementary material[12] shows that the climate risk is significantly positively correlated with executive excess perk consumption.

PLESE INSERT TABLE 1 HERE

3.2 Climate risk and executive excess perk consumption

It can be seen from Table 2, the coefficients on *CRI* in all columns are positive and significant at the 1% level, showing that climate risk is positively correlated with executive excess perk consumption, which confirms our previous hypothesis analysis. With respect to the control variables, the coefficients are all in line with prior research (Chen et al. 2023).

PLESE INSERT TABLE 2 HERE

3.3 Robustness tests

[10] See online Appendix A for detailed definitions of all variables used in this model.
[11] Considering the possible heteroscedasticity in the pooled OLS regression analyses.
[12] See online Appendix B.

For robustness, we perform the following tests: (i) For climate risk, we follow Huang et al. (2018) to use the average weighted climate risk index to compute two alternative measures (*CRI3* and *CRI4*)[13]; For executive excess perk consumption, we re-estimate the perquisite consumption and generate two alternative proxy for excess perks consumption(*Perk3*and *Perk4)*[14]. (ii) According to Ding et al. (2021), we use the two-stage least square regression (2SLS) to address the endogeneity issue, the population density is chosen as the instrumental variable because it is highly associated with climate risk but not with executive excess perks consumption. (iii) In order to minimize the impact of the variations in control variables, we utilize a propensity score matching (PSM) approach. (iv) Also, identification strategies including confounding variable test, difference-in-difference approach, Fama-MacBeth approach, a series of sample selection criterion are all contribute to further examine the robustness of our results[15]. Table 3 reports the results of above tests (i)-(iii), the CRI coefficients remain significantly positive across all tests, providing reliable evidence that climate risk can positively affect executive excess perk consumption.

PLESE INSERT TABLE 3 HERE

4. Additional analyses

[13] Considering our main results may be affected by the different firm characteristics of high climate uncertainty and low climate uncertainty groups. We calculate *CRI3* using the natural logarithm of 1 plus the mean value of natural hazards at the parent and subsidiary company's location, and quantify *CRI4* as the natural logarithm of 1 plus the total number of natural hazards at the parent company’s location (county level，same weighting) (Huang et al. ,2018).
[14] See online Appendix A for detailed measurements of *Perk3* and *Perk4*.
[15] See online Appendix D.

High-quality analysts exert effective oversight on enterprises, particularly beneficial for those with lower-quality information disclosure (Guo and Jian, 2021). Additionally, scholarly studies confirm that media coverage can mitigate principal-agent problems and curb executives' opportunistic behavior (Brian, 2010; Xue et al., 2017; Zhai et al., 2015). Furthermore, digital transformation enhances management process transparency (Goldfarb and Tucker, 2019), information authenticity and security, as well as communication efficiency with external stakeholders (Ni and Liu, 2021). We hence anticipate that analyst attention, media coverage, and digital technology application can effectively mitigate the positive impact of climate risk on excess perks consumption.

In terms of financial conditions, firms facing high financial constraints tend to retain more cash flow to mitigate financing costs(Song and Lee 2012). Additionally, prior studies have indicated that government subsidies may incentivize executives to engage in opportunistic behavior by increasing firm-held cash flows (Sun, 2021). This, in turn, could potentially lead to excessive welfare consumption by business managers (Chu and Fang, 2016). We anticipate that the discussed relationship will be weakened in financially constrained firms and strengthened in firms with high government subsidies. We apply interaction term regression method to test our predictions. The results are in line with expectations[16].

5. Conclusion

[16] For brevity, please check online Appendix E for detailed results.

We posit that climate risk induces managerial uncertainty and financial strain, exacerbating information asymmetry between shareholders and managers and consequently fostering opportunistic behavior among executives. Moreover, our supplementary analyses reveal that factors such as analyst attention, media coverage, digital technology adoption levels, and financing constraints mitigate the relationship between climate risk and executive excess perk consumption, whereas government subsidies bolster it.

Our findings hold significant implications for government entities and management personnel, elucidating the mechanisms underlying the escalation of excess perk consumption due to climate risk, which can inform the development and implementation of more tailored environmental policies. Additionally, our study furnishes timely theoretical support for firms grappling with heightened climate risk, aiding them in navigating the associated challenges effectively.

References

Chen, W., X. Liu, and Y, Hong. 2023. Two heads better than one? Strategic alliance and firms excess cash holdings. Finance Research Letters 52:103575.

Chen, D., Li, O. Z., & Liang, S. (2016). Perk consumption as a suboptimal outcome under pay regulations. Asia-Pacific Journal of Accounting & Economics, 23(4), 373–399.

Ding, R., M. Z. Liu, T. T. Wang, and Z. Y. Wu. 2021. The impact of climate risk on earnings management: International evidence. Journal of Accounting and Public Policy 40 (2):106818.

Donadelli, M., Jüppner, M., Paradiso, A., & Ghisletti, M. (2020). Tornado activity, house prices, and. stock returns. The North American Journal of Economics and Finance, 52(4), 101162.

Gul, F. A., Cheng, L. T., & Leung, T. Y. (2011). Perks and the informativeness of stock prices in the Chinese market. Journal of Corporate Finance, 17(5), 1410-1429.

Huang, H. H., J. Kerstein, and C. Wang. (2018). The impact of climate risk on firm performance and financing choices: An international comparison. Journal of International Business Studies 49 (5):633-656.

Luo, W., Zhang, Y., & Zhu, N. (2011). Bank ownership and executive perquisites: New evidence from an emerging market. Journal of Corporate Finance, 17(2), 352-370

Luo, H., Fu, H., Yin, H., & Lin, Q. (2022). Carbon materials in persulfate-based advanced oxidation processes: The roles and construction of active sites. Journal of Hazardous Materials, 426, 128044.

Ren, Y., & Li, B. (2022). Digital transformation, green technology innovation and enterprise financial performance: Empirical evidence from the textual analysis of the annual reports of listed renewable energy enterprises in China. Sustainability, 15(1), 712.

Sun, Y., Yang, Y., Huang, N., & Zou, X. (2020). The impacts of climate change risks on financial performance of mining industry: Evidence from listed companies in China. Resources Policy, 69(12), 101828.

Xu, N., Li, X., Yuan, Q., & Chan, K. C. (2014). Excess perks and stock price crash risk: Evidence from China. Journal of Corporate Finance, 25(2), 419–434.

Zhang, J., Yuan, Y., Zhang, Y., & Xu, J. (2022). Public attention and executive perks: Evidence from China. Finance Research Letters, 48, 103010.

Table 1 Descriptive statistics

Variable	N	Mean	Q2	Min	Max	SD	Variance
CRI1	32906	2.379	2.860	0	4.967	1.708	2.916
CRI2	32906	1.31	0	0	5.200	1.830	3.349
Perk1	32906	-0.054	-0.065	-2.138	5.573	1.143	1.306
Perk2	32906	-0.085	-0.083	-3.279	8.350	1.693	2.866
SIZE	32906	20.904	20.774	19.040	24.616	0.966	0.934
GRO	32906	0.131	0.029	-0.667	2.473	0.393	0.155
LEV	32906	0.315	0.298	0.032	0.752	0.173	0.030
ROA	32906	0.105	0.089	-0.055	0.593	0.093	0.009

TAN	32906	0.188	0.156	0	0.681	0.146	0.021
AGE	32906	0.479	0.405	0.119	1.043	0.180	0.032
CAS	32906	0.044	0.035	-0.235	0.337	0.093	0.009
SOE	32906	0.411	0	0	1	0.492	0.242
TOP	32906	0.015	0.005	0	0.296	0.039	0.002
IDB	32906	0.281	0.333	0	0.556	0.166	0.028
BOA	32906	1.786	2.197	0	2.708	0.833	0.693
DUA	32906	0.324	0	0	1	0.468	0.219
BIG	32906	0.505	1	0	1	0.5	0.25
OPI	32906	0.795	1	0	1	0.404	0.163
GDP	32906	0.112	0.095	0.027	0.267	0.048	0.002

Table 2 Climate risk and executive excess perks consumption

Variable	(1)	(2)	(3)	(4)
	Perk1	*Perk2*	*Perk1*	*Perk2*
	CRI=CRI1		*CRI=CRI2*	
CRI	0.069***	0.109***	0.029***	0.050***
	(7.384)	(7.821)	(3.931)	(4.669)
SIZE	-0.022	-0.014	-0.026*	-0.020
	(-1.376)	(-0.570)	(-1.651)	(-0.850)
GRO	-0.248***	-0.375***	-0.244***	-0.369***
	(-12.904)	(-12.626)	(-12.733)	(-12.481)
LEV	-0.204**	-0.384***	-0.178*	-0.343**
	(-2.237)	(-2.815)	(-1.950)	(-2.514)
ROA	0.112	0.306	0.087	0.267
	(0.605)	(1.117)	(0.468)	(0.968)
TAN	-0.934***	-1.260***	-0.906***	-1.217***
	(-8.220)	(-7.676)	(-7.989)	(-7.427)
AGE	-0.064	-0.190	-0.073	-0.204
	(-0.602)	(-1.167)	(-0.686)	(-1.249)

CAS	0.259	0.301	0.236	0.267
	(1.512)	(1.171)	(1.380)	(1.041)
SOE	-0.152***	-0.207***	-0.155***	-0.212***
	(-3.879)	(-3.556)	(-3.928)	(-3.626)
TOP	0.998***	1.571***	1.009***	1.593***
	(3.397)	(3.531)	(3.418)	(3.560)
IDB	-0.095	-0.300	-0.148	-0.379
	(-0.597)	(-1.281)	(-0.932)	(-1.621)
BOA	0.027	0.025	0.033	0.034
	(1.017)	(0.610)	(1.233)	(0.828)
DUA	-0.027	-0.027	-0.032	-0.034
	(-0.806)	(-0.530)	(-0.947)	(-0.677)
BIG	0.060**	0.080*	0.071**	0.098**
	(2.017)	(1.837)	(2.416)	(2.253)
OPI	-0.232***	-0.398***	-0.119***	-0.227***
	(-5.500)	(-6.438)	(-3.340)	(-4.356)
GDP	-0.051	-0.283	0.103	-0.045
	(-0.137)	(-0.510)	(0.273)	(-0.082)
Constant	0.824**	0.978*	0.944***	1.162**
	(2.305)	(1.824)	(2.638)	(2.164)
Industry FE	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Observations	32906	32906	32906	32906
Adj. R^2	0.033	0.032	0.030	0.029

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. See online Appendix A for variable definitions. T-statistics are based on clustered (by firm) standard errors and are presented in parentheses.

Table 3: Robustness tests
Panel A: Alternative measurements for climate risk and executive excess perks consumption

Variable	(1)	(2)	(3)	(4)
	Perk3	*Perk4*	*Perk3*	*Perk4*
	CRI=CRI3		*CRI=CRI4*	
CRI	0.615***	0.036*	0.029***	0.050***
	(9.216)	(1.957)	(3.931)	(4.669)
Constant	-17.191***	6.386***	-16.141***	6.436***
	(-6.602)	(8.457)	(-6.149)	(8.537)
Industry FE	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Observations	32906	32906	32906	32906
adj. R^2	0.083	0.024	0.079	0.024

Panel B: Two stage least square method

Variables	(1)	(2)	(3)	(4)
	CRI1	*CRI2*	*CRI1*	*CRI2*
	IV=PD1	*IV=PD2*	*IV=LCR1*	*IV=LCR2*
IV	-0.000***	-0.000***	0.360***	0.387***
	(-4.752)	(-4.550)	(75.422)	(71.010)
Constant	2.038***	0.716***	1.772***	0.813***
	(11.696)	(2.877)	(10.269)	(3.199)
Industry FE	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Observations	32903	32903	28360	28360
adj. R^2	0.550	0.200	0.028	0.312
Under-identification test				
Cragg-Donald N*CDEV statistic (Chi2)	28.12***	20.83***	/	/
Kleibergen-Paap rk LM statistic	/	/	982.72***	1221.97***
Weak identification test				
Cragg-Donald F statistic (Critical value = 16.38)	28.12***	20.70***	/	/
Kleibergen–Paap Wald rk F-statistic (Critical value = 16.38)	/	/	2234.75***	2377.17***
Weak-instrument robust inference test				
Anderson–Rubin Wald test F-statistic	24.59***	8.77***	45.71***	12.30***

Second-stage regression results

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Perk1	*Perk2*	*Perk1*	*Perk2*	*Perk1*	*Perk2*	*Perk1*	*Perk2*
	$\widehat{CRI}1$ *(Estimated by PD1)*		$\widehat{CRI}2$ *(Estimated by PD2)*		$\widehat{CRI}1$ *(Estimated by LCR1)*		$\widehat{CRI}2$ *(Estimated by LCR2)*	
$\widehat{CR}_I$	1.025***	1.465***	0.422***	0.621***	0.143***	0.222***	0.063***	0.115***
	(3.260)	(3.276)	(3.129)	(3.392)	(6.805)	(6.977)	(3.514)	(4.300)
Constant	-1.104	-1.759	0.665*	0.758	0.768**	0.870	1.034***	1.275**
	(-1.389)	(-1.552)	(1.663)	(1.290)	(2.073)	(1.565)	(2.818)	(2.311)
Industry FE	Included	Included	Included	Included	Included	Included	Included	Included
Year FE	Included	Included	Included	Included	Included	Included	Included	Included
Observations	32,903	32,903	32,903	32,903	28,306	28,306	28,306	28,306
adj. R^2	\	\	\	\	0.027	0.026	0.028	0.025
Tests for relevance of instruments								
Cragg-Donald N*CDEV statistic (Chi2)	235.246	234.478	317.284	306.807	460.480	446.517	410.653	401.750

Panel C: Propensity score matching (PSM) analysis

Balancing test

Variables	(1)	(2)	(3)	(4)	(5)
	Classified by HCR1				
	Treated (N=1192)	Control (N=1192)	Difference	t-test	p>t
SIZE	20.639	20.650	-0.011	-0.670	50.1%
GRO	0.195	0.197	-0.002	-0.220	82.3%
TAN	0.259	0.260	-0.001	-0.340	73.6%

IDB	0.122	0.122	-0.000	-0.230	81.7%
BOA	1.230	1.229	0.001	0.020	98.2%
TOP	0.021	0.021	0.001	-0.520	60.0%

Regression results with matched sample

Variables	(1)	(2)
	Perk1	*Perk2*
	CRI=HCR1	
CRI	0.124**	0.207***
	(2.551)	(2.778)
Constant	0.545	0.957
	(0.845)	(0.963)
Industry FE	Included	Included
Year FE	Included	Included
Observations	2,384	2,384
adj. R^2	0.306	0.034
F-statistic	3.274	3.176

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. See online Appendix A for variable definitions. T-statistics are based on clustered (by firm) standard errors and are presented in parentheses