Does Commodity Tail Risk Exposure Affect Corporate Innovation?

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Abstract: This study examines whether commodity tail risk (CTR) exposure affects corporate innovation. Using a sample of 22,226 Chinese firm-year observations (3,112 unique firms) over the 1999–2022 period, we find a negative relationship between CTR exposure and corporate innovation. We also find that down-tail risk exposure magnifies the negative impact of CTR on innovation, while up-tail risk has no impact. Mechanism analyses show that the innovation-reduction effect operates through two channels: heightened financial constraints and forced investment cutbacks. Finally, cross-sectional analyses indicate that the innovation-reduction effect is more pronounced for firms with opaque information environments and weak corporate governance structures.

Keywords: Commodity tail risk; up tail risk; down tail risk; corporate innovation.

JEL Classification: D81; G32; O31.

1. Introduction

Corporate innovation is widely considered to be an important driver of firms' productivity, growth, and performance levels, giving it a strong competitive edge (Eberhart et al., 2004; Brown et al., 2009; Lu & Wang, 2018; Pinkus et al., 2026). In modern economies, firms are more reliant on innovation to deal with high-tech obsolescence, growth constraints, changing regulations and global competition (Autor et al., 2020; Aghion et al., 2023). Thus, exploring the determinants of corporate innovation has become an important research issue in finance, innovation, and strategy-related studies. The existing literature on corporate innovation has mostly focused on exploring internal factors such as board diversity (Bernile et al., 2018), earnings pressure (Almeida et al., 2025), CEO personal traits (Pham et al., 2014), and governance structure (Becker-Blease, 2011) as major drivers of innovation within firms. However, recent developments in the global economy suggest that external factors, especially those stemming from volatility in commodity markets, could also play a meaningful role in affecting firms' innovation activities.

Global commodity markets exhibit high volatility and occasional extreme shocks, known as commodity tail risk (CTR, hereafter). These infrequent but impactful events[1] have raised major concerns about their potential effects on firms' operations. As commodities are related to both input and output price levels (Wang et al., 2025), they play a dynamic role in the production process as either input factors or energy sources. CTR may also lead to unexpected cost hikes and operational challenges for firms (Triantafyllou et al., 2020). When firms are highly susceptible to tail risk, they can face severe financial and operational disruptions. As innovation is a resource-intensive and time-consuming process for firms (Protogerou et al., 2017), this kind of exposure might severely restrict firms' ability to spend on research and development (R&D) expenditure.

While prior studies have examined the affect of various internal factors on corporate innovation, such as CEO attributes (Sunder et al., 2017), managerial foreign experience (Yuan & Wen, 2018), manager sentiment (Xiong & Zhao, 2025), executive incentives (Li et al., 2025), management myopia (Zhang & Li, 2024), equity finance (Brown et al., 2009) and corporate culture (Fiordelisi et al., 2019), there is a lack of research on how external factors might affect corporate innovation. Some past studies have shown that external factors affect innovation, such as political uncertainty (Pertuze et al., 2019), geopolitical risk (Jia et al., 2022), policy uncertainty (Cong & Howell, 2021) and trade policy uncertainty (Zhang et al, 2025). However, little is known about how firms' CTR exposure affects innovation. Our study helps to address this gap in the literature and improve our knowledge of the relationship between CTR exposure and corporate innovation.

China provides an ideal research setting to conduct our study for several reasons. First, it is one of the world's largest commodity consumers, supported by its large economy and sustained growth (Hammoudeh et al., 2024). It has become a major force in global commodity markets, especially

[1] Some examples include the 1973 oil crisis (Yang & Fu, 2025), the global financial crisis of 2008, and the 2000s China-driven commodities boom (Berman et al., 2017).

in metals and agricultural raw materials (Roache, 2012). Wang et al. (2023) found that China accounted for 55.3% of total global refined copper consumption in 2021, revealing the scale of its infrastructure and manufacturing activities. This strong dependence on commodities makes Chinese firms sensitive to commodity price shocks and tail risk events. Second, China leads the world in patent filings, with 1.8 million applications in 2024, followed by the U.S. with 501,831, and Japan with 419,132. Despite this high volume, its total innovation capacity ranked 11th in 2024, indicating a strong ambition to enhance its innovation capabilities.

Wu and Wang (2021) have provided some evidence indicating that the negative relationship between oil prices and corporate investment is stronger amid unfavorable market conditions, suggesting that when firms are exposed to CTR, it is more likely to withdraw from its long-term investment commitments. Similarly, Jin and Jorion (2006) and Smimou et al. (2025) found that firms engaging in commodity hedging are better positioned to sustain their investment activity. These studies demonstrate that unmanaged CTR acts as a binding constraint on strategic resource allocation. Finally, Aghion et al. (2012) found that when credit constraints are tight, R&D investment declines during recession periods but does not rise during upturns. Their study suggests that firms exposed to CTR are more careful, withholding or retreating from long-term investments such as innovation towards risk containment and short-term survival.

The real options framework also suggests that, as many investments are irreversible, the costs of adjusting them tend to be nonlinear and asymmetric (Zhang et al., 2025). Due to these high adjustment costs, firms often delay investment decisions to preserve their flexibility, allowing them to wait and commit resources when business conditions improve. Huchzermeier and Loch (2001) found that managers maintain the flexibility to delay innovation projects in an unfavorable environment. When firms are exposed to CTR, this flexibility might lead to increased caution and

investment delays as CTR can significantly raise input costs, increasing the cost of failure and eroding the expected returns from innovation projects (Ammann et al., 2023). Thus, firms might decide to reduce their investment in innovation-related projects (Yuan et al., 2025).

We conjecture that firms' CTR exposure is negatively related to corporate innovation. The commodity tail risk literature suggests that where firms are exposed to CTR, which denotes sporadic but extreme movements in commodity prices, they are likely to scale back their innovation activities due to financial hardship (Brown et al., 2012). In fact, innovation-related activities, such as patent R&D investment, are linked to substantial upfront costs, have a long-term commitment (Cui et al., 2021), and depend on sustained levels of internal financing (Hall & Lerner, 2010). If firms rely on commodities, such as agriculture, precious metals, or energy products, this could lead to much higher risks from extreme price movements (Ammann et al., 2023), which not only reduce their cash flows but also cause severe earnings volatility, restricting firms' internal financial capacity. This financial hardship should foster managerial conservatism within firms, where short-term liquidity is stressed over long-term funding commitment (Jin & Jorion, 2006).

To empirically test our conjecture, we follow Wang et al. (2025) to construct a novel measure of CTR exposure. Then, we use the beta of firms' monthly stock returns to estimate CTR exposure, controlling for the five Fama-French factors and using a 36-month rolling window. We collect commodities data from the Bloomberg database, while patent and other data are taken from the China Stock Market and Accounting Research (CSMAR) database. Using a sample of 22,226 firm-year observations of 3,112 unique firms over the 1999 to 2022 period, we provide strong evidence showing that CTR exposure is negatively related to corporate innovation.

We also consider the issue of endogeneity in our study. Unobservable factors (e.g., managerial style or corporate culture) could impact innovation outcomes (Roche et al., 2022). Firms might

also self-select into higher commodity exposure based on various attributes (e.g., liquidity buffer, industry affiliation, or firm size) that might affect innovation. We employ several identification strategies to address endogeneity concerns in our study, such as difference-in-differences analysis (DID), two-stage least squares (2SLS) regression analysis, falsification and placebo tests, propensity score matching (PSM), entropy balancing (EB), and the addition of provincial fixed-effects and an expanded set of control variables in our model. Collectively, the results of these endogeneity tests show that our baseline results hold.

In additional analyses, we explore heterogeneity in the relationship between CTR exposure and corporate innovation through the potential moderating roles of up-tail risk (*UTR*) and down-tail risk (*DTR*) exposure. *DTR* exposure reflects left-tail events that erode firms' revenue streams, compress profit margins and strain the bottom line. This decline in profitability places pressure on firms' internal financial capacity and forces managers to shift resources from long-term projects to short-term obligations and liquidity protection. The ensuing operational and financial pressure leaves less capacity for firms' innovation-driven projects (Li, 2011). We find that *DTR* magnifies the negative impact of *CTR* on innovation, while *UTR* has no impact.

We also perform mechanism analyses to better understand the underlying mechanisms that explain the negative relationship between CTR exposure and innovation. In this regard, we study two plausible mechanisms, namely, financial constraints and investment cutbacks. For financial constraints, we conjecture that CTR exposure, by imposing financial constraints, reduces corporate innovation, as firms prioritize short-term operational needs over long-term R&D projects (Brown et al., 2009). For investment cutbacks, we conjecture that higher CTR exposure increases input and output costs for firms, placing pressure on their cash flows and internal resources (Tielens et al., 2025). Such firms are forced to cut discretionary investments in high-risk activities like R&D

(Kilian, 2008). These investment cutbacks restrict the ability of firms to innovate, reducing their innovation output (Fazzari et al., 1988). We provide novel evidence showing that the innovation-reduction effect operates through these two channels.

Finally, we conduct cross-sectional analyses to determine whether opaque information environments and corporate governance characteristics impact the negative relationship between CTR exposure and innovation. If CTR exposure impedes firms' innovation by boosting financial constraints and amplifying conservatism, we expect that such an effect is stronger in firms with agency frictions and weak governance. Previous studies have shown that innovation investments that are irreversible and long-term (Almeida et al., 2025) are prone to tail risk (Yuan et al., 2025). Firms with weak structure, such as fragile governance, opaque information environments, and inadequate risk-sharing mechanisms, are less able to absorb CTR exposure, leading to safe play and defensive behavior that can curb their innovation activities (Gormley & Matsa, 2016). We provide evidence showing that the negative relationship between CTR exposure and innovation is more pronounced for firms with opaque information environments and weak governance.

This study makes several contributions to the literature. First, it extends the stream of literature on tail risk by exploring its impact on corporate innovation. As far as we are aware, our study is the first to explore the impact of CTR exposure on corporate innovation. Prior literature furnishes evidence at the macroeconomic level (Massacci, 2017; Lu et al., 2024; Wang et al., 2025). For example, Massacci (2017) explored the dynamics of tail risk in the equity market and found a strong link across markets during turmoil periods. Recently, some studies have extended the microeconomics literature on tail risk (Xu et al., 2024; Yuan et al., 2025). For instance, Xu et al. (2024) examine the role of the tail risk of demand on corporate investment. They found a negative

link between tail risk and investment for Chinese manufacturing firms. Our study extends the literature by highlighting the important role of firms' CTR exposure on corporate innovation.

Second, we contribute to the literature on corporate innovation. Both practitioners and scholars have paid considerable attention to the subject of corporate innovation over the past few decades. Scholars have studied various determinants of innovation, such as CEO attributes (Sunder et al., 2017), executive incentives (Li et al., 2025), managerial foreign experience (Yuan & Wen, 2018), managerial sentiment (Xiong & Zhao, 2025), political uncertainty (Pertuze et al., 2019), geopolitical risk (Jia et al., 2022), earning pressure (Almeida et al., 2025), CEO personal traits (Pham et al., 2014), governance (Becker-Blease, 2011), and trade policy uncertainty (Zhang et al., 2025). We complement and extend this literature by exploring a key determinant of corporate innovation that has, up until recently, remained largely neglected, i.e., CTR exposure. We provide novel evidence showing that firms' CTR exposure significantly reduces corporate innovation.

Third, the results of this study offer valuable insights for investors, analysts, and policymakers. For investors, the results highlight CTR exposure as a hitherto unpriced risk factor in gauging innovation-driven growth. Investors might benefit from incorporating tail risk measures in their investment strategies, capital allocation models, and portfolio decisions. For analysts, our findings suggest that future growth could be subject to upward bias if CTR exposure is ignored. Including CTR exposure in R&D valuation frameworks, earnings forecasts, and growth estimates could improve forecast performance. From a policy perspective, our results reveal that CTR exposure impedes innovation by forcing firms to delay or abandon R&D projects with long payback horizons. Policymakers could help to support innovation-driven growth by creating R&D grants, tax credits, and subsidies. Such measures are suitable for developing economies such as China, where innovation-driven growth is critical for industrial change and long-term economic growth.

The remainder of the paper proceeds as follows. Section 2 conducts a literature review and develops our hypothesis. Section 3 describes the research design. Section 4 presents the baseline regression results. Section 5 performs robustness checks on endogeneity. Section 6 performs additional analyses. Section 7 conducts mechanism and cross-sectional analyses. Finally, Section 8 concludes the paper.

2. Literature Review and Hypothesis Development

From a real options perspective, corporate innovation requires substantial initial investment by firms that is typically long-term, irreversible, and characterized by stalled returns (Huchzermeier & Loch, 2001). Sustained innovation efforts depend on firms' financial capacity to commit resources to exploratory research, product development, and process improvement without jeopardizing ongoing operational stability (Brown et al., 2009). When firms are exposed to CTR, they experience abrupt and severe cost shocks that directly alter their financial performance. Unlike incremental cost variation, tail events in commodity markets substantially increase input costs within a very short period of time, eroding profit margins and severely disrupting firms' operations (McGee & McGroarty, 2017). When input prices escalate sharply, especially for firms that are reliant on commodities (e.g., energy, metals, or agricultural inputs), the effect leads to large increases in their operational expenses (Kilian, 2008). Since these costs are non-deferrable and essential for production continuity, firms must prioritize meeting their obligations to ensure operational sustainability (Saha et al., 2025). Such reallocation of financial resources can reduce firms' discretionary capital for high-risk and long-term innovation projects (Almeida et al., 2025).

Real-option theory suggests that under adverse cost conditions, managers may choose to delay or abandon projects with long payback horizons to preserve flexibility and avoid irreversible

commitments (Bernanke, 1983). Innovation involves sunk costs that cannot be recovered if a project is suspended or discontinued by firms (Hall & Lerner, 2010). When faced with cost shocks that strain liquidity, managers might prefer to apply the option to wait or discontinue such projects and reallocate resources to more urgent survival-oriented activities in firms (Gulen & Ion, 2016). This outcome could lead to the halting of firms' R&D projects (Bloom, 2007).

The survival-oriented behavior produced by CTR aligns with the idea of a hierarchy of corporate financing priorities, wherein firms initially allocate cash flow to operational needs, then to debt obligations, and only later to discretionary growth investments (Froot et al., 1993). During the period of CTR, the hierarchy tilts even more heavily toward liquidity preservation. So, high-risk investments, being the most deferred category of expenditures, are likely to be the first to be scaled back or discontinued (Pertuze et al., 2019). Such cost-cutting is not a sign of the short-sightedness of managers, but rather, a rational adaptation within firms to severe financial strain, which is aimed at ensuring their continuity despite a surge in operating costs (Tielens et al., 2025).

Previous research supports the idea that adverse financial shocks can have a detrimental impact on firms' innovation-related investment (Aghion et al., 2012; Almeida et al., 2021; Xu et al., 2024; Yuan et al., 2025). For instance, Aghion et al. (2012) found that R&D investment significantly falls in credit-constrained firms during a recession period and does not improve uniformly during upturns. Almeida et al. (2021) showed that financial slack reduces corporate innovation output. For tail risk, Yuan et al. (2025) investigate whether it has a real effect on corporate capital investment. They observed that tail risk significantly hampers capital investment.

CTR exposure that reflects the extreme fluctuation can trigger catastrophic losses and asset price volatility for firms (Kelly & Jiang, 2014; Yuan et al., 2025). The worsening environmental condition exerts downward pressure on firms' innovation levels. Due to its exploratory nature,

corporate innovation also requires substantial sunk costs and investment in tangible assets (Brown et al., 2009). Under unfavorable cost conditions, firms might be reluctant to wait before investing in various R&D initiatives, as such investment is linked with considerable upfront costs and is also long-term in nature (Cui et al., 2021; Almeida et al., 2025). We conjecture that firms' CTR exposure, denoting infrequent but extremely negative events, stimulates the option value to delay and lower their innovation levels. Therefore, we develop the following hypothesis:

H1: All else being equal, CTR exposure is negatively related to corporate innovation.

3. Research Design

3.1. Data and sample selection

Our sample comprises Chinese A-listed firms on the Shenzhen Stock Exchange (SZSE) and Shanghai Stock Exchange (SSE) over the 1999 to 2022 period. We source monthly commodity data from the Bloomberg database. Our commodity data covers 24 commodities,[2] which are classified into three groups: agriculture, mining, and energy. Furthermore, we collect accounting data from the CSMAR database, which has been widely used in past Chinese studies (Tian et al., 2022; Zhang & Li, 2024; Zhang et al., 2025). Consistent with previous studies by Almeida et al. (2021) and Tian et al. (2022), we drop firms from our sample if they did not have any patents in a given year,[3] they are ST firms that face financial distress, or firm-year observations with missing values for any of the regression variables. Overall, our final sample consists of 22,226 firm-year observations, covering 3,112 unique firms.

[2] Commodities cover brent oil, crude oil, gas oil, gasoline, heating oil, natural gas, live cattle, lean hog, gold, platinum, silver, aluminum, copper, nickel, zinc, wheat, corn, soybean, soymeal, soy oil, sugar, cocoa, coffee, and cotton.
[3] We also re-estimate our baseline regression model by adding these firms to the sample; the results show that they are qualitatively similar to our baseline results.

3.2. Dependent variable

The dependent variable is corporate innovation (*INNOV*). Consistent with prior studies by Cullis (2007), Lerner & Seru (2022) and He & Tian (2013), we use the total number of patents filed to firms as our main measure of *INNOV*. The China National Intellectual Property Administration (CNIPA) sorts patents into three categories: (1) invention, (2) design, and (3) utility. An invention patent denotes a new technical solution about a product, improvement, or process (Liu et al., 2021). A design patent denotes a pattern, shape, or a combination of both and a combination of the color for the entire product or part of it that experiences aesthetic appreciation and conforms to the industry application (Chen & Zhang, 2019). A utility patent denotes a technical solution for a shape or structure of the product, which satisfies a practical use (Liu et al., 2021). We weight each category based on patent applications annually and use the aggregate sum of the three categories as our measure of *INNOV* (Cullis, 2007; Lerner & Seru, 2022). We also use the natural logarithm of one plus the total number of patents granted in a year (*INNOV_PF*) as an alternative measure of corporate innovation (He & Tian, 2013) in additional tests.

3.3. Independent variable

The independent variable is commodity tail risk exposure (*CTR*). Consistent with prior research by Kelly and Jiang (2014) and Wang et al. (2025), we use cross-sectional commodity returns to compute the time-varying commodity tail risk. The tail distribution is computed as follows:

$$P\left(\left|R_{k,t+1}\right| > r \,\middle\|R_{k,t+1}|> \emptyset_t\right) = \left(\frac{r}{\emptyset_t}\right)^{\frac{\alpha_k}{\gamma_t}}, 0 < \emptyset_t < r \quad (1)$$

where $R_{k,t+1}$ represents k commodity return at time t+1, $\emptyset_t$ is a threshold to decide whether k commodity returns belong to the upper or lower tail. The sign $\frac{\alpha_k}{\gamma_t}$ indicates the tail shape, and the

high values of gamma sub t show the high possibilities of extreme returns, which is referred to as the CTR factor. CTR is calculated as follows:

$$CTR_t = \frac{1}{J_t}\sum_{J=1}^{J_t} ln\frac{R_{J,t}}{\emptyset_t} \quad (2)$$

where $R_{J,t}$ is the J[th] return lower or higher than $\emptyset_t$ and is the analogous number for the month.

We also follow Bali et al. (2017) and Cui et al (2021) and estimate firm CTR exposure by extending the Fama-French five-factor model as follows:

$$R_{i,t} - R_{f,t} = \alpha_0 + \beta_{i,t}^{CTR} CTR_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{RMW} RMW_t + \beta_{i,t}^{CMA} CMA_t + \varepsilon_{i,t} \quad (3)$$

where i and t refer to stock and month, respectively, $R_{i,t} - R_{f,t}$ (the difference between stock return and risk-free security) indicates the excess return of i stock in t month. The Fama-French five-factor model is represented by MKT_t, SMB_t, HML_t, RMW_t, CMA_t and CTR_t denotes overall commodity tail risk. We estimate Eq. (3) by using the past 36 months (t-36 and t-1) as the rolling window. The coefficient $\beta_{i,t}^{CTR}$ reflects the sensitivity of the stock return to CTR exposure. Greater values of $\beta_{i,t}^{CTR}$ indicate increased sensitivity to CTR exposure. Finally, our main variable of interest, the firm-level CTR exposure, is calculated by using the annual average of $\beta_{i,t}^{CTR}$.

3.4. Control variables

To isolate the impact of CTR exposure on corporate innovation, we follow prior studies (He & Tian, 2013; Tian et al., 2022) and include a battery of control variables in our baseline regression model. Corporate innovation is positively correlated with firm size (Acs & Audretsch, 1988), so we control for firm size (*SIZE*) in our baseline model, which is measured as the natural logarithm of the total number of employees. Debt financing hampers innovation among incumbent firms due to debt repayment (Geelen et al., 2022), so we include leverage (*LEV*) in our baseline model. We

also include several other firm attributes as control variables in our model that might affect corporate innovation, such as Tobin's Q (*TOBINQ*), cash (*CASH*) and asset tangibility (*TANG)* (He & Tian, 2013). Corporate governance characteristics might also have an impact on corporate innovation (Baysinger et al., 1991; Lu & Wang, 2018), so we include board size (*BRD_SIZE*), board independence (*BRD_IND*), and the board gender ratio (*G_RATIO*) as control variables in our baseline model. Finally, managerial stock ownership reduces agency problems and encourages managers to engage in innovation (Du & Ma, 2022), so we also control for management ownership (*MGT_OWN*) in our baseline model. We provide variable definitions in Appendix A.

3.5. Baseline regression model

This study examines whether CTR exposure is negatively related to corporate innovation, so our baseline regression model is estimated as follows:

$$INNOV_{i,t+1} = \alpha + \beta CTR_{i,t} + \gamma X_{i,t} + \varphi_i + \varphi_t + \varepsilon_{i,t+1} \quad (4)$$

where subscripts i and t represent a firm and year observation, respectively. The dependent variable is $INNOV_{i,t+1}$, which measures firms' corporate innovation at time t+1. Our main variable of interest is $CTR_{i,t}$, captures the effect of *CTR* exposure on corporate innovation. The vector $X_{i,t}$ denotes a battery of control variables. We also include industry- and year-fixed effects in our baseline model to alleviate any unobserved heterogeneity across industries and years. Additionally, all continuous variables are winsorized at the 1% level at both extremes of the distribution to remove extreme outliers that could unduly affect our empirical results (Gulen & Ion, 2016). Finally, CTR exposure might also be persistent over time, so we estimate our baseline model by clustering standard errors at the firm level (Petersen, 2009).

4. Empirical Results

4.1. Summary statistics

Table 1 reports the summary statistics. Panel A of Table 1 provides the descriptive statistics for the dependent variable (*INNOV*), independent variable (*CTR*), and the control variables (*SIZE*, *LEV*, *TOBINQ*, *CASH*, *TANG*, *BRD_SIZE*, *BRD_IND*, *G_RATIO*, and *MGT_OWN*). Finally, Panel B of Table 1 provides the Pearson correlation coefficients between the baseline variables.

Panel A of Table 1 shows that the mean value of *INNOV* is 2.747, and its 25th, 50th and 75th percentile values are 1.792, 2.639, and 3.497, respectively. *CTR* exposure has a mean value of 0.084 with a standard deviation of 0.398. On average, the *SIZE* and *TOBINQ* controls are 7.783 and 2.007, respectively. Our sample is also composed of firms that have a mean value for leverage, cash holdings, and asset tangibility of 0.405, 0.174, and 18.525, respectively. Finally, for the governance controls, *BRD_SIZE*, *BRD_IND, G_RATIO*, and *MGT_OWN* have mean values of 8.583, 37.250, 81.674, and 14.877, respectively, in line with past studies (Yousaf et al., 2022).

Panel B of Table 1 presents the Pearson pairwise correlation coefficients. We find a negative and statistically significant correlation between *CTR* exposure and innovation ($p < 0.05$ or less) that provides some initial support for our conjecture in H1 that *CTR* exposure is negatively related to corporate innovation. Finally, the low correlations between the control variables alleviate concerns about collinearity (Hair et al., 2006).[4]

[Insert Table 1 Here]

4.2. Baseline regression results

The baseline regression results based on Eq. (4) are presented in Table 2 (with coefficients and t-statistics in parentheses). We compute robust standard errors clustered at the firm level (Petersen,

[4] we also compute variance inflation factors (VIFs) to detect the presence of multicollinearity among the explanatory variables. The mean VIF value is 1.42, so multicollinearity is not a major issue in our study (Hair et al., 2006).

2009) in our study. For brevity, the coefficients for industry- and year-fixed effects are not reported. In Column (1) of Table 2, we report the regression results for the coefficient on *CTR* exposure, including industry- and year-fixed effects, while Columns (2) to (4) sequentially enter the control variables in our regression model.

The coefficient on *CTR* exposure in Column (4) is negative and significantly related to *INNOV* ($p < 0.01$). The coefficient on *CTR* exposure remains fairly stable across the specifications, with or without the control variables. These results support H1, showing a negative relationship between *CTR* exposure and corporate innovation. Our results are also economically meaningful. We find that a one standard deviation increase in *CTR* exposure is related to an average 1.246% decrease in corporate innovation.[5] For the control variables, the coefficients on *SIZE, TOBINQ, CASH, TANG, BRD_SIZE, BRD_IND* and *MGT_OWN* are significantly and positively related to *INNOV* ($p < 0.01$). Our results are similar to those of previous studies (Acs & Audretsch, 1988; Baysinger et al., 1991; Lu & Wang, 2018; Li & Lin, 2022; Du & Ma, 2022). Finally, we use *INNOV_PG* as an alternative measure of corporate innovation. Column (5) of Table 2 presents the regression results, which are similar to our baseline findings, i.e., the coefficient on *CTR* exposure is negative and significant with *INNOV_PF* ($p < 0.10$). This finding reaffirms the robustness of our baseline results to an alternative measure of corporate innovation.

[Insert Table 2 Here]

5. Endogeneity Robustness Checks

Our baseline regression results reported in Table 2 could be subject to endogeneity concerns. To address such concerns, we use the following endogeneity robustness checks: (1) DID analysis,

[5] This economic effect is calculated as: 0.398 [standard deviation of *CTR* exposure from Table 1] × -0.086 [coefficient on *CTR* exposure from Column (4) of Table 2] / 2.747 [mean value of *INNOV* from Table 1] = 0.01246 or 1.246%.

(2) 2SLS regression analysis, (3) falsification and placebo tests, (4) PSM, (5) EB, and (6) provincial fixed-effects and an expanded set of control variables.

5.1. DID analysis

Our baseline regression analysis uncovers a negative relationship between *CTR* exposure and corporate innovation. However, it is possible that this relationship can operate in both directions, which may lead to biased estimates (Roberts & Whited, 2013). To deal with this concern, we use DID analysis, using the 2014 oil crash as an exogenous shock to strengthen causal interpretation. The price of crude oil dropped by 44% between June and December 2014, one of the biggest declines in recent history (Prest, 2018). The main causes of the drop in prices were supply factors, such as the surge in U.S. oil production, weakening global economic conditions, and declining demand in European countries (Prest, 2018). As China is one of the biggest price takers in the international commodity market (Fan et al., 2020), the sharp increase in oil price volatility and downside tail risk was plausibly exogenous to firms' innovation activities. To stimulate an exogenous shock, we use the 2014 oil crash, which should have a significant detrimental impact on Chinese firms' CTR exposure.

We apply the DID analysis that compares the differences in pre- and post-shock in the *INNOV* between high *CTR* exposure (treated) and low *CTR* exposure (control) firms (Roberts & Whited, 2013). We compute the dummy variable, *TREAT*, coded 1 if *CTR* exposure is above the median, and 0 otherwise. We then compute the *POST-2014* dummy variable, coded 1 if the firm-year observation is later than 2014, and 0 otherwise. Finally, we construct the interaction term between *TREAT* and *POST-2014* (*TREAT* × *POST_2014*) that captures the difference in the *INNOV* between

treated (*HIGH_CTR*) and control (*LOW_CTR*) firms after 2014. Consistent with Gao et al. (2023) and Wang et al. (2024), we estimate the following regression model.

$$INNOV_{i,t+1} = \alpha + \beta_1 TREAT_{i,t} + \beta_2 POST_2014_{i,t} + \beta_3 TREAT_{i,t} \times POST_2014_{i,t} + \gamma X_{i,t} + \varphi_i + \varphi_t + \varepsilon_{i,t+1} \quad (5)$$

where *TREAT*, *POST_2014*, and *TREAT × POST_2014* are defined above, and other variables are the same as defined in Eq. (4).

Panel A of Table 3 presents the regression results, estimated using Eq. (5). The coefficient on the interaction term *TREAT* × *POST_2014* is negative and statistically significant ($p < 0.05$) (Column 1), corroborating the baseline results as reported in Table 2. However, a potential concern for DID analysis is the Chaori default of March 2014 (Law & Roache, 2015). As, the timing of this default coincided with our treatment period, our DID analysis could reflect risk pricing rather than the causal influence of CTR exposure on innovation. To rule out this possibility, we control for China's economic policy uncertainty (Column 2) and drop the affected industry (Column 3) as robustness tests. The coefficients on interaction term remain negative and significant ($p < 0.10$ or lower) when controlling for economic policy uncertainty and dropping the affected industry. Hence, our baseline findings are robust to reverse causality and Chaori default-related concern. We follow Bertrand and Mullainathan (2004) and perform a parallel trend test to strengthen our DID results. The parallel trend assumes that the average change in *INNOV* between *HIGH_CTR* and *LOW_CTR* firms should be the same in the absence of a shock. The estimated coefficients of the DID analysis could be biased if the parallel trend assumption does not hold (Bertrand & Mullainathan, 2004), so we re-estimate Eq. (5) by replacing the *POST-2014* and *TREAT × POST_2014* with lead, current, and lag variables.

First, we compute dummy variables: *YEAR_2012* and *YEAR_2013* coded 1 if the firm-year observation takes place before second and first year of 2014 oil crash, and 0 otherwise,

respectively, *YEAR_CURRENT* is the dummy variable coded 1 if the firm-year observation takes place in the same year of oil crash, and 0 otherwise, *YEAR_2015* and *YEAR_2016* are dummy variables coded 1 if the firm-year observation takes place in the first and second year after the 2014 oil crash, and 0 otherwise, finally *YEAR_2017* coded 1 if the firm-year observation takes place in the third and more years after the 2014 oil crash, and 0 otherwise. Second, we construct interaction terms for these six dummy variables and *TREAT* (*TREAT* × *YEAR_2012, TREAT* × *YEAR_2013, TREAT* × *YEAR_CURRENT, TREAT* × *YEAR_2015, TREAT* × *YEAR_2016,* and *TREAT* × *YEAR_2017*) and include them in Eq. (5). Our variables of interest are *TREAT* × *YEAR_2012* and *TREAT* × *YEAR_2013*. We should observe significant coefficients if there is a post-trend in *INNOV* between *HIGH_CTR* and *LOW_CTR* firms.

Panel B of Table 3 presents the regression results for the parallel trend assumption. The coefficients of the lead dummies (*TREAT* × *YEAR_2012* and *TREAT* × *YEAR_2013*) are not significant, while the coefficients of the lag dummies (*TREAT* × *YEAR_2015*, *TREAT* × *YEAR_2016*, and *TREAT* × *YEAR_2017*) are negative and significant ($p < 0.10$ or less). These results suggest that *CTR* exposure takes time to stifle corporate innovation, so our DID estimation is robust to the parallel trend assumption.

[Insert Table 3 Here]

5.2. 2SLS regression analysis

As firms with significant R&D investments might acquire advanced technologies that improve their risk management and reduce the dependence on commodities' tail risk, this also raises the issue of reverse causality (Roberts & Whited, 2013). To address this concern, we use 2SLS regression analysis. An instrumental variable (IV) must meet the requirement of not being correlated with *CTR* exposure and not affecting *INNOV* except through *CTR* to be valid (Larcker

& Rusticus, 2010). We use the infection disease equity market volatility (*ID_EMV*) as our instrument. We expect *ID_EMV* to exhibit a negative correlation with our endogenous variable, *CTR*. Likewise, *ID_EMV* is plausibly exogenous to *INNOV*, meeting the exclusion restriction and satisfying the condition for a valid instrument (Larcker & Rusticus, 2010).

Specifically, in the first stage, we regress *CTR* on the *ID_EMV* (adjusted by province-level GDP) to obtain the predicted values. The first-stage results are shown in Column 1 of Table 4, which indicates a significant and negative association between *ID_EMV* and *CTR*. In the second stage, we perform estimation on the firm level by using the predicted values and controls. The second-stage results are reported in Column (2). The coefficient value on the instrumented CTR ($\widehat{CTR}$) is negative and statistically significant ($p < 0.01$), indicating that instrumented CTR reduces corporate innovation. Accordingly, the 2SLS estimates corroborate our baseline findings reported in Table 2 of the negative impact of *CTR* on *INNOV*.

[Insert Table 4 Here]

5.3. Falsification and placebo tests

We also perform falsification and placebo tests to rule out the possibility that our baseline results are not driven by chance (Taylor et al., 2021). In this regard, we follow Roberts and Whited (2012) and re-estimate our baseline Eq. (4) by replacing the t+1 dependent variable with its lagged values at t-1, t-2, and t-3. Our underlying argument here is that if the effect of *CTR* exposure on *INNOV* in t+1 arises from tail risk exposure in year t, then this shock should not affect firms' innovation activities in the preceding one to three years (Taylor et al., 2021).

The regression results in Columns (1) to (3) of Table 5 show that the coefficients on *CTR* are not significant ($p > 0.10$), which is consistent with our conjecture. Chemmanur et al. (2019) have also shown that, on average, patents take around two years to move from the application stage to

the grant outcome. As our baseline measure uses file patents at t+1, this might introduce a timing bias into our analysis. To rule out this possibility, we re-estimate the baseline Eq. (4) using innovation measured in year t+2. The regression results in Column (4) of Table 5 show that the coefficient on *CTR* is negative and significant for *INNOV* ($p < 0.05$). Thus, our baseline findings in Table 2 are robust to timing bias and are unlikely to be driven merely by chance.

[Insert Table 5 Here]

We carry out the placebo test by randomly assigning the *CTR* exposure across firms within the same province. For each firm-year observation, we randomly select a *CTR* exposure value from a different firm within the same province to substitute the true exposure of the current firm and re-estimate the baseline regression, maintaining everything else unchanged. We repeat this process 1,000 times and plot the resulting distribution of the estimated regression coefficients.

Figure 1 illustrates the distribution of coefficients for *CTR* exposure when *INNOV* is used as the response variable. The true coefficient consistently appears at the left side of the distribution, and few of the placebo test *p*-values are significant ($p < 0.05$; 5.60% of the total). These findings suggest that our findings are unlikely to be driven by chance.

[Insert Figure 1 Here]

5.4. PSM

Our baseline regression results might also be subject to endogeneity concerns in the form of observable selection bias (Lennox et al., 2012). For instance, firms with high *CTR* exposure could systematically differ from firms with low *CTR* exposure on factors affecting corporate innovation. We address this potential endogeneity concern by using PSM.

We define the firms with *CTR* exposure in the fourth quartile as the treatment group, whereas firms in the first quartile are the control group: high CTR exposure (*HIGH_CTR*) firms and low

CTR exposure (*LOW_CTR*) firms, respectively (Zaman et al., 2021). After identifying the treatment group and its counterfactual, we construct a dummy variable, which is coded 1 for firms in the treatment group (*HIGH_CTR*) and 0 for those in the control group (*LOW_CTR*). We then follow a two-step analytical approach. First, we use the covariates (*SIZE, LEV, TOBINQ, CASH, TANG, BRD_SIZE, BRD_IND, G_RATIO* and *MGT_OWN*) and estimate a logit regression, whose results are used to predict the propensity score. This logit model is used to classify firms into *HIGH_CTR* and *LOW_CTR* groups, controlling for observable factors that may concurrently affect *CTR* and *INNOV*. Second, we match the two groups using propensity scores with a caliper of 0.05 distance (Lennox et al., 2012). The goal is to ensure better quality by pairing the *HIGH_CTR* firm with its closest *LOW_CTR* firm.[6]

Our initial sample includes 22,226 firm-year observations. After applying PSM, the matched sample consists of 10,350 observations (5,175 *HIGH_CTR* and 5,175 *LOW_CTR*), yielding a matching rate of around 46.57%. As our sample comprises firms belonging to different industries, this allows us to perform the matching procedure using the same industries. For example, we match a treated special equipment manufacturing firm (*HIGH_CTR*) to another control special equipment manufacturing firm (*LOW_CTR*). By doing this, we improve the matching quality to achieve a balance between the *HIGH_CTR* and *LOW_CTR* firms. Also, when we match the *HIGH_CTR* and *LOW_CTR* firms based on the same industry, then pairs of matched observations drop to 4,780, giving a final sample of combined 9,560 firm-year observations (*HIGH_CTR* has 4,780 firm-year observations and *LOW_CTR* has 4,780 firm-year observations), indicating a matching rate of around 43.01%, which is acceptable (Lennox et al., 2012).

[6] This approach reduces the differences in propensity scores between the treatment group and its counterfactual, allaying selection bias from firm-specific characteristics and model misspecification (Rosenbaum & Rubin, 1983).

PSM could address the sample selection bias, but the omission of unobservable factors such as managerial style or corporate culture toward risk might affect both *CTR* and *INNOV*. The link between *CTR* and *INNOV* remains weak if unobservable characteristics are not accounted for in the analysis. To address this issue, we use the Heckman (1979) method and combine it with PSM (Guenther et al., 2025). Then, we use probit regression to calculate the Inverse Mills Ratio (*IMR*) and include it in the PSM regression as another control variable (Guenther et al., 2025).

Panel A of Table 6 reports the results of a logit regression used to estimate the propensity scores. We find that *TANG* is statistically significant ($p < 0.01$), so firms with lower tangibility are more likely to exhibit higher *CTR* exposure. Governance variables, such as *BRD_SIZE, BRD_IND, G_RATIO*, and *MGT_OWN*, are also significant ($p < 0.05$ or lower). These results show that governance factors (board size, board independence, the gender ratio, and management ownership) play a vital role in determining whether firms are characterized by high *CTR* exposure.

Panel B of Table 6 provides the results of the univariate tests. The first two columns show the mean values of the covariates for both *HIGH_CTR* and *LOW_CTR* firms. The third column of Panel B presents the results of univariate tests, which show that there is no statistically significant difference between the covariates for the treated (*HIGH_CTR)* and control (*LOW_CTR*) firms. Thus, our matching process is satisfactory (Lennox et al., 2012).

Panel C of Table 6 presents the results of PSM regression using a matched sample and matching on industry, including the Inverse Mills ratio in the model. We find that *CTR* exposure is negative and statistically significant for *INNOV* ($p < 0.05$) across the regression models, aligning with the baseline evidence presented in Table 2.

[Insert Table 6 Here]

5.5. EB

We also apply EB to compute an entropy-balanced sample and mitigate the endogeneity issue (Hainmueller & Xu, 2013). This method substantially reduces model dependence in the estimation of treatment effects (Hainmueller, 2012). First, we implement the EB method to reweight the control group, ensuring that its covariate moment (mean, variance, and skewness) matches those of the treatment group (Hainmueller, 2012). Second, we use the entropy balanced sample and re-estimate our regression model in Eq. (4).

The regression results are shown in Table 7. Panels A and B show the covariate balance results before and after the reweighting, respectively. We find that covariate moments, including the mean, variance and skewness, of the control variables in Eq. (4) are balanced across the treatment and control groups. The results reported in Column (1) of Panel C show that the coefficient on *CTR* is negative and statistically significant with *INNOV* ($p < 0.01$). These regression results align with our baseline results in Table 2.

[Insert Table 7 Here]

5.6. Provincial fixed-effects and an expanded set of control variables

Finally, we estimate the baseline model using the full sample containing both patenting and non-patenting firms. We incorporate firm and year-industry fixed effects to alleviate unobserved heterogeneity across firms, industries, and time. However, our model may still be confounded by time-varying provincial characteristics, such as provincial policies, reforms and economic development that could impact *CTR* and *INNOV* (Xin et al., 2017). To better isolate the impact of *CTR* on *INNOV*, mitigate provincial or province-industry bias (Breuer & DeHaan, 2024), and deal with omitted variable bias, we follow Xin et al. (2017) and Wang et al. (2022) and extend our model to include provincial fixed-effects and an additional set of control variables.

Table 8 presents the regression results. In Columns (1) to (3) of Table 8, the coefficients on *CTR* are negative and statistically significant with *INNOV* ($p < 0.10$ or lower). Thus, our baseline results are robust to some non-time-varying macroeconomic exposure at the firm and time-varying exposure at the industry level. The Columns (4) and (5) show the results when we control for province and province-industry fixed effect. The coefficients on *CTR* remain negative and significant with *INNOV* ($p< 0.10$ or lower), indicating that our results are robust to provincial fixed effects. We also add other control variables to our regression model that could affect innovation. First, we add *SUP_SIZE, TOP3_SUM_SAL, AVG_AGE, MGT_FB, MGT_OB, MGT_SHARE* and *STAFF_INT* in Column (6) to control for the effect of management governance capacity (Zhao et al., 2021; You et al., 2020). Second, in Column (7), we control for variables that capture growth capability, such as *FA_G, OP_REV_G, NET_PROFIT_G, NCF_OA, SUS_G_RATE* and *OWN_EQUITY*. Third, in Column (8), we control for *RD_PERSON*, which is defined as a ratio of R&D employees to total employees (Gao et al., 2008), *RD_SPEND* and *RD_INVEST*. Fourth, in Column (9), we control for macro variables pertaining to *GEPU*, *WUI*, *GPR* and *LUD_MACRO_RISKS*. The regression results using the expanded set of control variables are shown in Columns (6) to (9) of Table 8. The coefficient on *CTR* again exhibits a negative and significant relationship with *INNOV* ($p < 0.01$) across the various models. We conclude that our baseline findings in Table 2 are robust to an expanded set of control variables.[7]

[Insert Table 8 Here]

[7] To provide further support for our baseline results in Table 2, we carry out several other robustness tests, such as quantile and Poisson regression analyses. Overall, the findings for these other robustness checks (untabulated) are qualitatively similar to our baseline regression results.

6. Additional Analyses

In addition to our baseline analysis, we perform two sets of additional analyses. First, sector-level regressions to examine heterogeneity across sectors, and second, tests of moderating effects.

6.1. Sector-matched analysis

Initially, we perform a sector-matched analysis to examine the heterogeneity across industries. Specifically, each commodity's tail risk exposure is estimated using both its corresponding industry subsample and the full sample. The results are reported in Table 9. Columns (1) and (2) present estimates for agricultural tail risk exposure (*CTR_AGR*) using the agricultural industry subsample as well as for the full sample, respectively. Columns (3) and (4) report the results for energy tail risk exposure (*CTR_ENR*) using the energy industry subsample and the full sample, while Columns (5) and (6) present the estimates for mining tail risk exposure (*CTR_MIN*) using the mining industry subsample and the full sample. The findings indicate that both *CTR_AGR* and *CTR_ENR* are negatively associated with *INNOV* ($p < 0.01$ or lower) across the industry-specific markets, so the heightened risk in these commodity markets discourages innovative activities. In contrast, *CTR_MIN* exhibits a positive and significant association with *INNOV* ($p < 0.01$), suggesting that firms exposed to mining-related commodities may respond to heightened risk by increasing their innovation efforts, consistent with the findings of Calzada et al. (2024). Overall, these findings highlight substantial heterogeneity in the innovation effects of CTR across sectors.

[Insert Table 9 Here]

6.2. Moderating analysis

We also conduct additional analyses on the potential moderating roles of "up-tail" and "down-tail" risk exposure on corporate innovation. *DTR* captures extreme left-tail events that erode firms'

revenue streams and weaken their financial health (Yuan et al., 2025). This deterioration in operating profitability can hinder internal financial resources and force firms to prioritize liquidity preservation for exigent survival-oriented activities over long-term strategic investments (Gulen & Ion, 2016; Cui et al., 2021). When firms are exposed to commodity tail risk, the presence of down tail risk intensifies adverse effects by magnifying cost pressures and revenue volatility, further limiting their capacity and willingness to invest in R&D projects (Yuan et al., 2025). Hence, firms with exposure to *DTR* are likely to be more vulnerable to constraints in their ability to absorb losses and may follow a conservative approach to preserve liquidity. In contrast, up-tail risk reflects right-tail events, which may not significantly moderate the relationship because firms will often maintain inventory buffers or use procurement strategies that provide a cushion against short-term cost spikes, limiting the immediate impact of up-tail events (Dodd & Liao, 2025). Based on this discussion, we conjecture that *DTR* strengthens the negative relationship between *CTR* and *INNOV*, while *UTR* has no effect.

To capture the moderating role of UTR and DTR exposure in our study, we measure the up-tail risk (*UTR*) and down-tail risk (*DTR*) as follows:

$$UTR_t = \frac{1}{J_{u,t}} \sum_{J=1}^{J_{u,t}} ln \frac{R_{u,J,t}}{\emptyset_{u,t}} \tag{6}$$

$$DTR_t = \frac{1}{J_{d,t}} \sum_{J=1}^{J_{d,t}} ln \frac{R_{d,J,t}}{\emptyset_{d,t}} \tag{7}$$

where $R_{u,J,t}$ or $R_{d,J,t}$ pertains to Jth return higher than $\emptyset_{u,t}$ or lower than $\emptyset_{d,t}$.

Then, we calculate the *UTR* and *DTR* using Eq. (3) by replacing the *CTR* with *UTR* and *DTR*, respectively. We extend the baseline regression Eq. (4) by considering the *UTR* and *DTR* and their interaction with *CTR* as follows:

$$INNOV_{i,t+1} = \alpha + \beta_1 CTR_{i,t} \times UTR_{i,t} + \beta_2 CTR_{i,t} + \beta_3 UTR_{i,t} + \gamma X_{i,t} + \varphi_i + \varphi_t + \varepsilon_{i,t+1} \quad (8)$$

$$INNOV_{i,t+1} = \alpha + \beta_1 CTR_{i,t} \times DTR_{i,t} + \beta_2 CTR_{i,t} + \beta_3 DTR_{i,t} + \gamma X_{i,t} + \varphi_i + \varphi_t + \varepsilon_{i,t+1} \quad (9)$$

where *CTR*×*UTR* and *CTR*×*DTR* represent the interaction terms of interest. We also include the firm-level controls, industry- and year-fixed effects in the regression models and cluster the robust standard errors at the firm level.

The regression results are reported in Table 10. We find that the interaction effect of *CTR*×*DTR* on *INNOV* is negative and statistically significant ($p < 0.01$), suggesting that the *CTR*-*INNOV* effect is stronger for firms under *DTR*. However, the moderation effect of *UTR* is negative but not significant. These results are consistent with our conjecture that *DTR* strengthens the negative relationship between *CTR* and *INNOV*, while *UTR* has no meaningful effect.

[Insert Table 10 Here]

7. Mechanism and Cross-sectional Analyses

Hitherto, we have provided strong evidence of a negative relationship between CTR exposure and corporate innovation. We perform mechanism analyses to gain a better understanding of the rationale underlying this relationship. We explore two plausible mechanisms through which CTR exposure might reduce corporate innovation: (1) financial constraints and (2) investment cutbacks. We also conduct cross-sectional analyses to investigate whether the information environment and corporate governance characteristics affect this relationship as well.

7.1. Mechanism analyses

7.1.1. Financial constraints

The first plausible mechanism is that CTR exposure intensifies financial constraints, leading firms to restrict their long-term investment in corporate innovation (Hyytinen & Toivanen, 2005).

Corporate innovation is a long-term and high-risk investment that consumes significant resources of firms and normally requires external financial support (Acharya & Xu, 2017). When firms are under severe financial constraints, they reduce or suspend R&D related investments and reallocate resources toward essential operational needs to ensure their long-term survival (Brown et al., 2009; Cao et al., 2023; Almeida et al., 2025). Cao et al. (2023) explore the link between financial constraints, social networks and corporate innovation in China. They argued that access to external resources (e.g., bank loans) is crucial for firms' innovation activities, especially in China, where limited collateral constrains firms' resource acquisition. Cao et al. (2023) found that financial constraints weaken innovation, so we conjecture that CTR exposure, by imposing financial constraints, reduces corporate innovation, as firms prioritize short-term operational needs over long-term R&D projects. Financial constraints are expected to be an important mechanism that magnifies the negative relationship between CTR exposure and corporate innovation.

In tandem with the studies of Kaplan and Zingales (1997) and Whited and Wu (2006), and Tsoukas & Spaliara (2014), we use three proxies to measure financial constraints: (1) KZ Index (*KZ_IND*), (2) WW Index (*WW_IND*), and (3) dividend payout (*DIV_PAYOUT*). Next, we re-estimate Eq. (4), substituting *INNOV* with *KZ_INDEX, WW_IND* and *WW_INDEX*, respectively.

The regression results are presented in Table 11. The coefficients on *CTR* are positive (negative) and significant for both *KZ_IND* and *WW_IND* (*DIV_PAYOUT,* Column 3) ($p < 0.01$ or lower) in Columns (1) and (2), supporting our conjecture that CTR exposure, by imposing financial constraints, hinders corporate innovation (Cao et al., 2023). Thus, financial constraints are an important mechanism through which CTR exposure impedes corporate innovation.

7.1.2. Investment cutbacks

The second plausible mechanism through which CTR might reduce corporate innovation is the reduction of long-term, resource-intensive investments. Elevated CTR exposure increases firms' input and output costs, placing significant pressure on cash flows and internal resources (Lin et al., 2021; Tielens et al., 2025). Nohria and Gulati (1997) found that when firms are facing a downturn in the operational environment, R&D and capital expenditures are often cut back. Thus, firms are compelled to restrict discretionary investments in high-risk activities like R&D projects (Kilian, 2008). In line with the logic for financial constraints (Fazzari et al., 1988), we conjecture that investment cutbacks limit firms' capacity to innovate, reducing their innovation output.

Following previous research by Cohen and Levinthal (1989), Xu and Li (2023), and Grieser and Liu (2019), we capture investment in our study using three measures: (1) *CAPEX*, (2) *RD_INVEST*, and (3) *INVEST_CUT*.

The regression results are reported in Panel B of Table 11. The coefficients on CTR are negative (positive) and statistically significant for both *CAPEX* and *RD_INVEST* (*INVEST_CUTS*) ($p < 0.01$ or lower), thus CTR exposure, due to investment cuts, reduces innovation activities. These results are consistent with our conjecture, so we conclude that investment cutbacks are a key mechanism through which CTR exposure reduces corporate innovation.

[Insert Table 11 Here]

7.2. Cross-sectional analyses

7.2.1. Information environment

The information environment could influence the negative relationship between CTR exposure and corporate innovation. A strong information environment reduces information asymmetries, eases access to external finance, and improves market assessment of firms' prospects (Liang et al.,

2022; Zhang & Wang, 2023). By lowering monitoring frictions and financing costs, transparency can buffer firms from the worst consequences of tail risk. However, in a weak information environment, uncertainty is compounded, which could magnify the informational frictions, worsen external financing constraints and amplify manager incentives to cut R&D when exposed to tail risk events (Xu et al., 2024). Zhang and Wang (2023) study the information environment through the lens of analyst coverage and its impact on innovation. They found a positive relationship between analyst coverage and innovation. We conjecture that *CTR* exposure more strongly affects innovation in firms with weaker information environments.

Following research by Liang et al. (2022) and Wang et al. (2024), we employ analyst coverage (*ANALYST_COV*), abnormal funds from operations (*A_FFO*), bid-ask spread (*SPREAD*), and residual of Dechow and Dichev (2002) model (*RESIDUAL*) as proxies for the information environment. We partition the full sample at the median to construct high and low *AF_COV, A_FFO*, *SPREAD* and *RESIDUAL* subsamples.

Panel A of Table 12 presents the regression results. The coefficient on CTR is statistically significant (insignificant) in the high (low) subsamples for *A_FFO*, *SPREAD* and *RESIDUAL* ($p < 0.10$). These findings support our conjecture that CTR exerts a significantly stronger effect on corporate innovation when the information environment is weak.

7.2.2. Corporate governance characteristics

We also examine how governance characteristics impact the negative relationship between CTR exposure and corporate innovation. Weak governance dents the strategic discipline and effective monitoring of firms (Jensen & Meckling, 1976), encouraging managers to adopt myopic

behaviors, especially when adverse conditions ensue (Stein, 1989).[8] Thus, the negative relationship between CTR exposure and innovation should be more pronounced for firms with weaker governance.

CEO duality is an important governance characteristic. Chen (2014) argued that CEOs exercise significant influence over the board of directors through CEO duality. This concentrated leadership allows CEOs to shape or restrict board participation in strategic decision-making by controlling the agenda (Kor, 2006) and R&D investment decisions (Yoo et al., 2025). In contrast, independent directors with overseas backgrounds and director dissent serve as governance factors that promote corporate innovation (Giannetti et al., 2015) and enhance the firm value (Lu & Wang, 2018). We conjecture that firms with weak governance encounter more difficulty in obtaining external financing to support their innovation activities.

The engagement of a Big Four auditor represents yet another important corporate governance mechanism that might influence the negative relationship between CTR exposure and corporate innovation. Big Four auditors provide superior monitoring and reduce contracting costs by improving information transparency levels of firms (Jensen & Meckling, 1976). We conjecture that the negative relationship between CTR exposure and corporate innovation is more pronounced for firms that do not engage a Big Four auditor.

Governance characteristics involve independent director (*IND_DIR*), director dissent (*DIR_DISSENT*), Big Four auditor engagement (*BIG4*) and overseas auditor (*OVERSEAS_AUDITOR*) (Lu & Wang, 2018). Next, we partition the full sample into subsamples for our governance variables. Because *DIR_DISSENT, BIG4,* and *OVERSEAS_AUDITOR* are dummy variables, subsamples are formed using the 1= yes and 0 = no dichotomy. Finally, as

[8] For example, when firms are faced with large CTR exposure, managers in poorly governed firms might reduce investment to preserve liquidity as they prioritize short-term performance over long-run value creation (Bushee, 1998).

IND_DIR is a continuous variable, we partition the full sample into subsamples based on its median value.

Panel B of Table 12 provides the regression results for the *IND_DIR*, *DIR_DISSENT*, *OVERSEAS_AUDITOR,* and *BIG4* governance characteristics. For the low *IND_ DIR* subsample, the coefficient on CTR is negative and significant *(*$p < 0.01$), and insignificant in the high *IND_ DIR* subsample. For *DIR_DISSENT*, the coefficient on *CTR* is negative and statistically significant ($p < 0.05$) in the subsample where *DIR_DISSENT* is not significant otherwise. Finally, we find that the coefficient on *CTR* is negative and statistically significant ($p < 0.05$) for firms not engaged with a BIG four auditor and overseas auditor, and not significant otherwise. Collectively, these results reveal that the effect of CTR exposure on innovation is stronger for poorly governed firms, aligning with our expectations.

[Insert Table 11 Here]

8. Conclusion

This study examines whether CTR exposure influences corporate innovation in China. We find that CTR exposure is negatively related to corporate innovation. In mechanism analyses, we find that the innovation-reduction effect operates through two channels, i.e., heightened financial constraints and forced investment cutbacks. Cross-sectional analyses also show that the negative impact of CTR exposure on corporate innovation is more pronounced for firms with an opaque information environment, non-SEO status, and weak corporate governance mechanisms.

This study makes the following contributions to the literature. First, it expands the literature stream on tail risk by examining its impact on corporate innovation. To the best of our knowledge, our study is the first to explore this issue. Prior literature mostly provides evidence at the macroeconomic level (e.g., Kelly & Jiang, 2014). Recently, some studies have extended the

literature on tail risk (e.g, Yuan et al., 2025). Our study extends this literature by highlighting the key role of CTR exposure on innovation. Second, we also contribute to the literature on corporate innovation. While past research has studied various determinants, such as CEO attributes (Sunder et al., 2017), executive incentives (Li et al., 2025), managerial foreign experience (Yuan & Wen, 2018), managerial sentiment (Xiong & Zhao, 2025), political uncertainty (Pertuze et al., 2019), geopolitical risk (Jia et al., 2022), earnings pressure (Almeida et al., 2025), CEO personal traits (Pham et al., 2014), governance (Becker-Blease, 2011), and trade policy uncertainty (Zhang et al., 2025), we extend this literature by revealing a key determinant of innovation, i.e., CTR exposure. We provide novel evidence that CTR exposure markedly reduces innovation. Third, the results of this study provide useful insights for investors, analysts, and policymakers. For investors, the results underline CTR exposure as a hitherto unpriced risk factor in assessing innovation-driven growth. Investors could benefit from including tail risk measures in their investment strategies, capital allocation models, and portfolio decisions. For analysts, our results show that future growth might be conditional on an upward bias if CTR exposure is overlooked. Including CTR exposure in R&D valuation frameworks, earnings forecasts, and growth estimates might enhance forecast performance. From a policy viewpoint, our results show that CTR exposure inhibits innovation by forcing firms to delay or abandon their R&D projects with long payback periods. Policymakers can help to support innovation-driven growth by creating R&D grants, tax credits, or subsidies.

References

Acharya, V., & Xu, Z. (2017). Financial dependence and innovation: The case of public versus private firms. *Journal of Financial Economics*, 124(2), 223-243.

Acs, Z. J., & Audretsch, D. B. (1988). Innovation in large and small firms: an empirical analysis. *The American Economic Review*, 78(4), 678-690.

Aghion, P., Askenazy, P., Berman, N., Cette, G., & Eymard, L. (2012). Credit constraints and the cyclicality of R&D investment: Evidence from France. *Journal of the European Economic Relationship*, 10(5), 1001-1024.

Aghion, P., Bergeaud, A., & Van Reenen, J. (2023). The impact of regulation on innovation. *The American Economic Review*, 113(11), 2894-2936.

Ai, H., & Bhandari, A. (2021). Asset pricing with endogenously uninsurable tail risk. *Econometrica*, 89(3), 1471-1505.
Almeida, H., Fos, V., Hsu, P.-H., Kronlund, M., & Tseng, K. (2025). Innovation under pressure. *Journal of Financial and Quantitative Analysis*, 60(5), 2088-2120.
Almeida, H., Hsu, P. H., Li, D., & Tseng, K. (2021). More cash, less innovation: The effect of the American Jobs Creation Act on patent value. *Journal of Financial and Quantitative Analysis*, 56(1), 1-28.
Ammann, M., Moerke, M., Prokopczuk, M., & Würsig, C. M. (2023). Commodity tail risks. *Journal of Futures Markets*, 43(2), 168-197.
An, H., Chen, C. R., Wu, Q., & Zhang, T. (2021). Corporate innovation: Do diverse boards help? *Journal of Financial and Quantitative Analysis*, 56(1), 155-182.
Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, 135(2), 645-709.
Bali, T. G., Brown, S. J., & Tang, Y. (2017). Is economic uncertainty priced in the cross-section of stock returns?. *Journal of Financial Economics*, 126(3), 471-489.
Baysinger, B. D., Kosnik, R. D., & Turk, T. A. (1991). Effects of Board and Ownership Structure on Corporate R&D Strategy. *The Academy of Management Journal*, 34(1), 205–214
Becker-Blease, J. R. (2011). Governance and innovation. *Journal of Corporate Finance*, 17(4), 947-958.
Berman, N., Couttenier, M., Rohner, D., & Thoenig, M. (2017). This mine is mine! How minerals fuel conflicts in Africa. *The American Economic Review*, 107(6), 1564-1610.
Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics*, 98(1), 85-106.
Bernile, G., Bhagwat, V., & Yonker, S. (2018). Board diversity, firm risk, and corporate policies. *Journal of Financial Economics*, 127(3), 588-612.
Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates?. *The Quarterly Journal of Economics*, 119(1), 249-275.
Bloom, N. (2007). Uncertainty and the Dynamics of R&D. *The American Economic Review*, 97(2), 250-255.
Bloom, N., Schankerman, M., & Van Reenen, J. (2013). Identifying technology spillovers and product market rivalry. *Econometrica*, 81(4), 1347-1393.
Breuer, M., & DeHaan, E. D. (2024). Using and interpreting fixed effects models. *Journal of Accounting Research*, 62(4), 1183-1226.
Brown, J. R., Fazzari, S. M., & Petersen, B. C. (2009). Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *The Journal of Finance*, 64(1), 151-185.
Brown, J. R., Martinsson, G., & Petersen, B. C. (2012). Do financing constraints matter for R&D? *European Economic Review*, 56(8), 1512-1529.
Bushee, B. J. (1998). The influence of institutional investors on myopic R&D investment behavior. *The Accounting Review*, 73(3), 305-333.
Calzada Olvera, B., & Iizuka, M. (2024). The mining sector: profit-seeking strategies, innovation patterns, and commodity prices. *Industrial and Corporate Change*, 33(4), 986-1010.
Cao, G., Geng, W., Zhang, J., & Li, Q. (2023). Social network, financial constraint, and corporate innovation. *Eurasian Business Review*, 13(3), 667-692.
Chemmanur, T. J., Kong, L., Krishnan, K., & Yu, Q. (2019). Top management human capital, inventor mobility, and corporate innovation. *Journal of Financial and Quantitative Analysis*, 54(6), 2383-2422.
Chen, H. L. (2014). Board capital, CEO power and R&D investment in electronics firms. *Corporate Governance: An International Review*, 22(5), 422-436.
Chen, Z., & Zhang, J. (2019). Types of patents and driving forces behind the patent growth in China. *Economic Modeling*, 80, 294-302.
Cohn, J. B., Liu, Z., & Wardlaw, M. I. (2022). Count (and count-like) data in finance. *Journal of Financial Economics*, 146(2), 529-551.
Coles, J. L., Daniel, N. D., & Naveen, L. (2008). Boards: Does one size fit all? *Journal of Financial Economics*, 87(2), 329-356.
Cong, L. W., & Howell, S. T. (2021). Policy uncertainty and innovation: evidence from initial public offering interventions in China. *Management Science*, 67(11), 7238-7261.
Cui, X., Wang, C., Liao, J., Fang, Z., & Cheng, F. (2021). Economic policy uncertainty exposure and corporate innovation investment: Evidence from China. *Pacific-Basin Finance Journal*, 67, 101533.
Cullis, R. (2007). Using patent filings to measure innovation. *Journal of Intellectual Property Law & Practice*, 2(5), 345-345.

Dai, Y., & Harris, R. D. (2023). Average tail risk and aggregate stock returns. *Journal of International Financial Markets, Institutions and Money*, 82, 101699.
Dechow, P. M., & Dichev, I. D. (2002). The quality of accruals and earnings: The role of accrual estimation errors. *The accounting review*, 77(s-1), 35-59.
Dodd, O., & Liao, S. (2025). The role of inventory in firm resilience to the COVID-19 pandemic. *European Financial Management*, 31(2), 786-818.
Du, S., & Ma, L. (2022). Non-actual controllers and corporate innovation: Evidence from China. *China Journal of Accounting Research*, 15(3), 100253.
Eberhart, A. C., Maxwell, W. F., & Siddique, A. R. (2004). An examination of long-term abnormal stock returns and operating performance following R&D increases. *The Journal of Finance*, 59(2), 623-650.
Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1-22.
Fan, J. H., Fernandez-Perez, A., Indriawan, I., & Todorova, N. (2020). Internationalization of futures markets: Lessons from China. *Pacific-Basin Finance Journal*, 63, 101429.
Fan, J., Liu, Y., Zhang, Q., & Zhao, P. (2022). Does government debt impede firm innovation? Evidence from the rise of LGFVs in China. *Journal of Banking & Finance*, 138, 106475.
Fazzari, S., Hubbard, R. G., & Petersen, B. C. (1988). Financing constraints and corporate investment. *Brookings Papers on Economic Activity*, 19(1), 141-206.
Fiordelisi, F., Renneboog, L., Ricci, O., & Lopes, S. S. (2019). Creative corporate culture and innovation. *Journal of International Financial Markets, Institutions and Money*, 63, 101137.
Froot, K. A., Scharfstein, D. S., & Stein, J. C. (1993). Risk management: Coordinating corporate investment and financing policies. *The Journal of Finance*, 48(5), 1629-1658.
Gao, L., Han, J., Pan, Z., & Zhang, H. (2023). Individualistic CEO and corporate innovation: Evidence from US frontier culture. *Research Policy*, 52(9), 104852.
Gao, S., Xu, K., & Yang, J. (2008). Managerial ties, absorptive capacity, and innovation. *Asia Pacific Journal of Management*, 25(3), 395-412.
Geelen, T., Hajda, J., & Morellec, E. (2022). Can corporate debt foster innovation and growth? *The Review of Financial Studies*, 35(9), 4152-4200.
Giannetti, M., Liao, G., & Yu, X. (2015). The brain gain of corporate boards: Evidence from China. *The Journal of Finance*, 70(4), 1629-1682.
Giglio, S., Kelly, B., & Pruitt, S. (2016). Systemic risk and the macroeconomy: An empirical evaluation. *Journal of Financial Economics*, 119(3), 457-471.
Ginglinger, E., & Moreau, Q. (2023). Climate risk and capital structure. *Management Science*, 69(12), 7492-7516.
Gormley, T. A., & Matsa, D. A. (2016). Playing it safe? Managerial preferences, risk, and agency conflicts. *Journal of Financial Economics*, 122(3), 431-455.
Grieser, W., & Liu, Z. (2019). Corporate investment and innovation in the presence of competitor constraints. *The Review of Financial Studies*, 32(11), 4271-4303.
Guenther, P., Guenther, M., Misra, S., Koval, M., & Zaefarian, G. (2025). Propensity score modeling for business marketing research. *Industrial Marketing Management*, 127, 14-28.
Gulen, H., & Ion, M. (2016). Policy uncertainty and corporate investment. *The Review of Financial Studies*, 29(3), 523-564.
Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis*, 20(1), 25-46.
Hainmueller, J., & Xu, Y. (2013). Ebalance: A Stata package for entropy balancing. *Journal of Statistical Software*, 54, 1-18.
Hair, J.F., Babin, B.J., Anderson, R.E., Tatham, R.L. (2006). *Multivariate Data Analysis*, 6th edition. Pearson Prentice-Hall, Upper Saddle River, NJ.
Hall, B. H., & Lerner, J. (2010). The financing of R&D and innovation. *In Handbook of the Economics of Innovation* (Vol. 1, pp. 609-639). Elsevier-North Holland, Amsterdam.
Hammoudeh, S., Nguyen, D. K., & Sousa, R. M. (2024). China's monetary policy framework and global commodity prices. *Energy Economics*, 138, 107767.
Hattori, M., Schrimpf, A., & Sushko, V. (2016). The response of tail risk perceptions to unconventional monetary policy. *American Economic Journal: Macroeconomics*, 8(2), 111-136.
He, J. J., & Tian, X. (2013). The dark side of analyst coverage: The case of innovation. *Journal of Financial Economics*, 109(3), 856-878.
Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, 47(1), 153–161.

Hsu, P. H., Tian, X., & Xu, Y. (2014). Financial development and innovation: Cross-country evidence. *Journal of Financial Economics*, 112(1), 116-135.
Huang, W., Goodell, J. W., Xia, Q., & Yuan, S. (2024). Trade credit provision and innovation: A strategic trade-off. *International Review of Financial Analysis*, 94, 103242.
Huchzermeier, A., & Loch, C. H. (2001). Project management under risk: Using the real options approach to evaluate flexibility in R&D. *Management Science*, 47(1), 85-101.
Hyytinen, A., & Toivanen, O. (2005). Do financial constraints hold back innovation and growth? Evidence on the role of public policy. *Research Policy*, 34(9), 1385-1403.
Jain, P., & Maitra, D. (2025). Commodity Price Crash Risk and Crash Risk Contagion. *Journal of Futures Markets*, 45(4), 343-378.
Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4), 305-360.
Jia, S., Yang, L., & Zhou, F. (2022). Geopolitical risk and corporate innovation: Evidence from China. *Journal of Multinational Financial Management*, 66, 100772.
Jin, Y., & Jorion, P. (2006). Firm value and hedging: Evidence from US oil and gas producers. *The Journal of Finance*, 61(2), 893-919.
Kaplan, S. N., and Zingales, L. (1997). Do investment-cash flow sensitivities provide useful measures of financing constraints? *The Quarterly Journal of Economics*, 112(1), 169-215.
Kelly, B., & Jiang, H. (2014). Tail risk and asset prices. *The Review of Financial Studies*, 27(10), 2841-2871.
Kilian, L. (2008). The economic effects of energy price shocks. *Journal of Economic Literature*, 46(4), 871-909.
Kor, Y. Y. (2006). Direct and interaction effects of top management team and board compositions on R&D investment strategy. *Strategic Management Journal*, 27(11), 1081-1099.
Larcker, D.F. and Rusticus, T.O. (2010). On the use of instrumental variables in accounting research. *Journal of Accounting & Economics*, 49, 186–205.
Leiponen, A., & Byma, J. (2009). If you cannot block, you better run: Small firms, cooperative innovation, and appropriation strategies. *Research Policy*, 38(9), 1478-1488.
Lennox, C.S., Francis, J.R., and Wang, Z. (2012). Selection models in accounting research. *The Accounting Review*, 87 (2), 589–616.
Tielens, J., Lenzu, S., & Rivers, D. A. (2025). Financial shocks, productivity, and prices. *Productivity and Prices* (April 20, 2023). Working Paper Research 479, National Bank of Belgium. https://ideas.repec.org/p/nbb/reswpp/202507-479.html.
Law, D., & Roache, M. S. K. (2015). Assessing Default Risks for Chinese Firms: A Lost Cause?. *International Monetary Fund*.
Lerner, J., & Seru, A. (2022). The use and misuse of patent data: Issues for finance and beyond. *The Review of Financial Studies*, 35(6), 2667-2704.
Li, D. (2011). Financial constraints, R&D investment, and stock returns. *The Review of Financial Studies*, 24(9), 2974-3007.
Li, F., & Lin, T. C. (2022). Innovative firms' cash holdings, tax policies, and institutional environments. *Financial Management*, 51(3), 869-902.
Li, H., Wang, X., Chang, Y., Zhang, N., Huang, W., & Wang, Q. (2025). Central government Ownership, geographic Distance, and firm Innovation: Evidence from Chinese State-owned enterprises. *Journal of Business Research*, 186, 115033.
Li, Y., Jin, L., & Chen, P. (2025). The role of executive incentives and corporate social responsibility in driving corporate innovation. *International Review of Financial Analysis*, 102, 104109.
Liang, S., Cui, H., & Yuan, C. (2022). Stock index adjustments and analysts' forecast optimism: a quasi-natural experiment on the CSI 300 Index. *China Journal of Accounting Research*, 15(3), 100246.
Lin, C., Schmid, T., & Weisbach, M. S. (2021). Product price risk and liquidity management: Evidence from the electricity industry. *Management Science*, 67(4), 2519-2540.
Liu, W., Song, Y., & Bi, K. (2021). Exploring the patent collaboration network of China's wind energy industry: A study based on patent data from CNIPA. *Renewable and Sustainable Energy Reviews*, 144, 110989.
Loria, F., Matthes, C., & Zhang, D. (2025). Assessing macroeconomic tail risk. *The Economic Journal*, 135(665), 264-284.
Lu, J., & Wang, W. (2018). Managerial conservatism, board independence and corporate innovation. *Journal of Corporate Finance*, 48, 1-16.
Lu, Z., Jiang, Y., & Liu, X. (2025). Commodity tail risk and equity risk premia. *Journal of Financial Research*, 48(3), 1350-1407.

Massacci, D. (2017). Tail risk dynamics in stock returns: Links to the macroeconomy and global markets connectedness. *Management Science*, 63(9), 3072-3089.
McGee, R. J., & McGroarty, F. (2017). The risk premium that never was: A fair value explanation of the volatility spread. *European Journal of Operational Research*, 262(1), 370-380.
Nguyen, L. H., Nguyen, L. X., & Tan, L. (2021). Tail risk connectedness between US industries. *International Journal of Finance & Economics*, 26(3), 3624-3650.
Nohria, N., & Gulati, R. (1997). What is the optimum amount of organizational slack? A study of the relationship between slack and innovation in multinational firms. *European Management Journal*, 15(6), 603-611.
Pertuze, J. A., Reyes, T., Vassolo, R. S., & Olivares, N. (2019). Political uncertainty and innovation: The relative effects of national leaders' education levels and regime systems on firm-level patent applications. *Research Policy*, 48(9), 103808.
Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, 22(1), 435-480.
Pham, M. H., Merkoulova, Y., & Veld, C. (2024). Award-winning CEOs and corporate innovation. *Journal of Banking & Finance*, 159, 107075.
Pinkus, D., Pozzoli, D., & Schneider, C. (2026). Pension Fund Investment and Firm Innovation. *Journal of Corporate Finance*, 97, 102918.
Prest, B. C. (2018). Explanations for the 2014 oil price decline: Supply or demand? *Energy Economics*, 74, 63-75.
Protogerou, A., Caloghirou, Y., & Vonortas, N. S. (2017). Determinants of young firms' innovative performance: Empirical evidence from Europe. *Research Policy*, 46(7), 1312-1326.
Ramzan, I., & Ali, K. (2025). Going green, growing strong: how climate policy boosts US companies' performance. *Climate Policy*, 25(4), 593-611.
Roache, M. S. K. (2012). China's Impact on World Commodity Markets. *International Monetary Fund Working Paper*. https://www.imf.org/external/pubs/ft/wp/2012/wp12115.pdf.
Roberts, M. R., & Whited, T. M. (2013). Endogeneity in empirical corporate finance. *In Handbook of the Economics of Finance* (Vol. 2, pp. 493-572). Elsevier, Amsterdam.
Roche, S., Sun, S., & Welters, R. (2022). Do financial constraints reduce process innovation? Evidence from Australian firms. *Economic Record*, 98(323), 335-353.
Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), 41-55.
Saha, A., Bose, S., & Lobo, G. J. (2025). Does Commitment to Operational Sustainability Pay Off? International Evidence. *The British Accounting Review*, in press, 101782.
Smimou, K., Abrokwah, M., & Drougas, A. (2025). Corporate investment decisions and related commodities: International evidence from energy and mining industries. *Energy Economics*, 149, 108766.
Stein, J. C. (1989). Efficient capital markets, inefficient firms: A model of myopic corporate behavior. *The Quarterly Journal of Economics*, 104(4), 655-669.
Stock, J.H. and Yogo, M. (2005). Testing for weak instruments in linear IV regression. In: D.W.K. Andrews and J.H. Stock, eds. Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg. New York, NY, *Cambridge University Press*, 80-108.
Sunder, J., Sunder, S. V., & Zhang, J. (2017). Pilot CEOs and corporate innovation. *Journal of Financial Economics*, 123(1), 209-224.
Taylor, M. P., Wang, Z., & Xu, Q. (2021). The real effects of exchange rate risk on corporate investment: International evidence. *Journal of International Money and Finance*, 117, 102432.
Tian, J., Li, H., & You, P. (2022). Economic policy uncertainty, bank loans, and corporate innovation. *Pacific-Basin Finance Journal*, 76, 101873.
Triantafyllou, A., Dotsis, G., & Sarris, A. (2020). Assessing the vulnerability to price spikes in agricultural commodity markets. *Journal of Agricultural Economics*, 71(3), 631-651.
Tsoukas, S., & Spaliara, M. E. (2014). Market implied ratings and financing constraints: Evidence from US firms. *Journal of Business Finance & Accounting*, 41(1-2), 242-269.
Wang, C., Richardson, G., & Cao, Y. (2024). Long live the walking dead? Corporate tax avoidance and zombie firms in China. *The British Accounting Review*, 56(3), 101319.
Wang, J., Liu, W., Chen, L., Li, X., & Wen, Z. (2023). Analysis of China's non-ferrous metals industry's path to peak carbon: a whole life cycle industry chain based on copper. *Science of The Total Environment*, 892, 164454.
Wang, X., Sun, K., & Xiao, Z. (2022). Industrial policy and the rise of China's strategic emerging industries. *Industrial Policy and the Rise of China's Strategic Emerging Industries*, American Economic Relationship, file:///C:/Users/mq20182373/Downloads/IndustrialPolicyAndTheRiseOfChina' _ preview.pdf.

Wang, Y., Wei, X., & Zhang, Q. (2025). Asymmetric Commodity Tails and Index Futures Returns. *Journal of Futures Markets*, 45(3), 247-265.
Whited, T. M., & Wu, G. (2006). Financial constraints risk. *The review of financial studies*, 19(2), 531-559.
Wooldridge J (2010). *Econometric Analysis of Cross-Section and Panel Data*, 2nd Edition. The MIT Press, Cambridge, MA.
Wu, X., & Wang, Y. (2021). How does corporate investment react to oil prices changes? Evidence from China. *Energy Economics*, 97, 105215.
Wunder, D., & Maula, M. (2026). Harvesting or nurturing? Corporate venture capital and startup green innovation. *Research Policy*, 55(2), 105380.
Xin, F., Zhang, J., & Zheng, W. (2017). Does the credit market impede innovation? Based on the banking structure analysis. *International Review of Economics & Finance*, 52, 268-288.
Xiong, X., & Zhao, L. (2025). Manager sentiment and its effect on corporate innovation. *Economic Modeling*, 143, 106968.
Xu, J., & Li, H. (2023). Managerial human capital and corporate R&D investment. *Journal of Economic Behavior & Organization*, 213, 151-171.
Xu, X., Li, X., Meng, J., Hu, X., & Ge, Y. (2024). The impact of the tail risk of demand on corporate investment: Evidence from Chinese manufacturing firms. *Pacific-Basin Finance Journal*, 85, 102342.
Yang, S., & Fu, Y. (2025). Interconnectedness among supply chain disruptions, energy crisis, and oil market volatility on economic resilience. *Energy Economics*, 143(C), 108290.
Yoo, S. H., Kim, D., & Jin, B. (2025). CEO turnover and innovation: Exploring the advisory role of inventor top management team members. *Technovation*, 142, 103190.
You, Y., Srinivasan, S., Pauwels, K., & Joshi, A. (2020). How CEO/CMO characteristics affect innovation and stock returns: findings and future directions. *Journal of the Academy of Marketing Science*, 48(6), 1229-1253.
Yousaf, U. B., Ullah, I., Jiang, J., & Wang, M. (2022). The role of board capital in driving green innovation: Evidence from China. *Journal of Behavioral and Experimental Finance*, 35, 100714.
Yousaf, U. B., Yousaf, I., Hussain, H., & Hussain, M. J. (2025). CEO's R&D experience and green innovation: Evidence from China. *Journal of International Money and Finance*, 157(C), 103374.
Yuan, J., Yang, L., & Xu, Q. (2025). The real side of black swans: Tail risk and corporate investment. *Journal of Banking & Finance*, 176, 107468.
Yuan, R., & Wen, W. (2018). Managerial foreign experience and corporate innovation. *Journal of Corporate Finance*, 48, 752-770.
Zaman, R., Atawnah, N., Baghdadi, G. A., & Liu, J. (2021). Fiduciary duty or loyalty? Evidence from co-opted boards and corporate misconduct. *Journal of Corporate Finance*, 70, 102066.
Zhang, J., Wu, W., Yang, J., & Xiao, Y. (2025). Trade policy uncertainty and corporate innovation: Evidence from the US-China trade war. *Pacific-Basin Finance Journal*, 89, 102590.
Zhang, P., & Wang, Y. (2023). The bright side of analyst coverage on corporate innovation: Evidence from China. *International Review of Financial Analysis*, 89, 102791.
Zhang, X. E., & Li, N. (2024). Management myopia and corporate innovation in China: Focus on the moderating role of equity incentives. *International Review of Financial Analysis*, 96, 103733.
Zhao, Q., Li, Z., & Yu, Y. (2021). Does top management quality promote innovation? Firm-level evidence from China. *China Economic Review*, 65, 101562.

Appendix A
Variable Definitions

Variable	Definition
Dependent variables	
INNOV	Natural logarithm of (1+ total patents filed in a year), where total patents represent the sum of utility, design, and invention patents, respectively.
INNOV_PG	Natural logarithm of (1+ total patents granted in a year).
Independent variable	
CTR	Firm-level commodity tail risk exposure, calculated based on the Fama-French five-factor model, $R_{i,t} - R_{f,t} = \alpha_0 + \beta_{i,t}^{CTR} CTR_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{RMW} RMW_t + \beta_{i,t}^{CMA} CMA_t + \varepsilon_{i,t}$ (Fama & French, 2015).
Control variables	
SIZE	Natural logarithm of a firm's total number of employees.
LEV	Total debt scaled by total assets.
TOBINQ	Ratio of market value to total assets, where market value is defined as: (ordinary A shares × closing price at period-end) + (B shares × closing price at period-end × exchange rate on that day) + [(total shares – ordinary A shares – B shares) × (total owners' equity at period-end / paid-in capital at period-end)] + total liabilities at period-end.
CASH	Proportion of cash holdings to total assets.
TANG	Natural logarithm of the firm's tangible assets.
BRD_SIZE	Total number of directors serving on the board of directors.
BRD_IND	Proportion of independent directors serving on the board of directors.
G_RATIO	Proportion of male directors serving on the board of directors.
MGT_OWN	The percentage of stock owned by managers.
Additional variables	
TREAT	Dummy variable, coded 1 if *CTR* exposure is above the median, and 0 otherwise.
POST-2014	Dummy variable, coded 1 if the firm-year observation is later than 2014, and 0 otherwise.
YEAR_2012	Dummy variable, coded 1 if the firm-year observation takes place before the second year of the 2014 oil crash, and 0 otherwise.
YEAR_2013	Dummy variable, coded 1 if the firm-year observation takes place before the first year of the 2014 oil crash, and 0 otherwise.
YEAR_CURRENT	Dummy variable, coded 1 if the firm-year observation takes place in the same year of the oil crash, and 0 otherwise.
YEAR_2015	Dummy variable, coded 1 if the firm-year observation takes place in the first or second year after the 2014 oil crash, and 0 otherwise.
YEAR_2016	Dummy variable, coded 1 if the firm-year observation takes place in the second year after the 2014 oil crash, and 0 otherwise.
YEAR_2017+	Dummy variable, coded 1 if the firm-year observation takes place in the third year or more years after the 2014 oil crash, and 0 otherwise.
DTR	Firm-level down tail risk exposure, calculated based on the Fama-French five-factor model (Fama & French, 2015).
UTR	Firm-level up tail risk exposure, calculated based on the Fama-French five-factor model (Fama & French, 2015).
SUP_SIZE	Size of the board of supervisors.
TOP3_SUM_SAL	Total compensation of the top three directors, supervisors and executives ranked by total compensation, excluding allowances.
AVG_AGE	Average age of all directors, supervisors and senior executives of the firm. Those whose age has not been disclosed are excluded from the calculation.

MGT_FB	Dummy variable, coded 1where the current directors, supervisors and senior executives have a financial background (including previous and current working background), and 0 otherwise. The variable is set to 0 for missing financial background data.
MGT_OB	Dummy variable, coded 1 where the current directors, supervisors and senior executives have an overseas background (including previous and current education and working background), and 0 otherwise. The variable is set to 0 for missing overseas background data.
MGT_SHARE	Proportion of shares held by directors, supervisors and senior executives to total shares of the firm.
STAFF_INT	Ratio of the number of employees at the end of the year to the operating revenue of the year.
FA_G	(Ending net fixed assets - beginning net fixed assets) / beginning net fixed assets. It will be denoted by null if the denominator is not disclosed or is equal to or below zero.
OP_REV_G	(Operating revenue in current quarter - operating revenue in previous quarter) / (operating revenue in previous quarter). It will be denoted by null if the denominator is not disclosed or is equal to or below zero.
NET_PROFIT_G	(Net profit in current quarter - net profit in previous quarter) / (net profit in previous quarter). The variable is set to 0 if the denominator is not disclosed or is equal to or below zero.
NCF_OA	(Net cash flow from operating activities in the current quarter - net cash flow from operating activities in the previous quarter) / (net cash flow from operating activities in the previous quarter. The variable is set to 0 if the denominator is not disclosed or is equal to or below zero.
SUS_G_RATE	(Net profit / ending balance of total owners' equity) * [1 - dividend per share before taxes / (net profit in current period / ending paid-in capital)] - (1 - numerator). Return on equity * earning retention ratio / (1 - return on equity x earning retention ratio) is the standard formula for this index.
OWN_EQUITY	(Ending owners' equity - beginning owners' equity) / beginning owners' equity. The variable is set to 0 if the denominator is not disclosed or is equal to or below zero.
RD_PERSON	Proportion of R&D personnel to the total number of employees.
RD_SPEND	Proportion of operating income that R&D investment accounts for.
RD_INVEST	Proportion of capitalized R&D investment expenditure in R&D investment.
ANALYST_COV	Number of analysts who have conducted tracking analysis on the company in a year.
A_FFO	Abnormal Cash Flow from Operating Activities.
SPREAD	Absolute value of (Trading price – Midpoint price between Buying and Selling price/ Midpoint price between Buying and Selling price).
RESIDUAL	Residual of accrued earnings management as per the DD model.
DIR_DISSENT	Dummy variable, coded 1 if the director dissent is present, and 0 otherwise.
IND _DIR	Natural logarithm of Independent director.
BIG4	Dummy variable, coded 1 if a firm has engaged a Big Four auditor, and 0 otherwise.
OVERSEAS_AUDITOR	Dummy variable, coded 1 if audit firm is overseas, and 0 otherwise.
KZ_IND	Financing constraints of a firm, calculated as per Kaplan & Zingales (1997).
DIV_PAYOUT	Dummy variable, coded to 1 when a dividend is paid during the year, and 0 otherwise.
WW_IND	It represents the degree of financing constraints of a firm, calculated as per Whited and Wu (2006).
RD_INVEST	Natural logarithm of Amount of R&D Investment.
CAPEX	Capital expenditure scaled by total assets.
INVEST_CUTS	The proportion of previous year investment properties to current year investment properties.
GEPU	Global economic policy uncertainty.
WUI	World Uncertainty Index.
GPR	Global political risk.
LUD_MACRO_RISKS	F1 to F8 indicate Lugdvigenson Macroeconomic Risks.

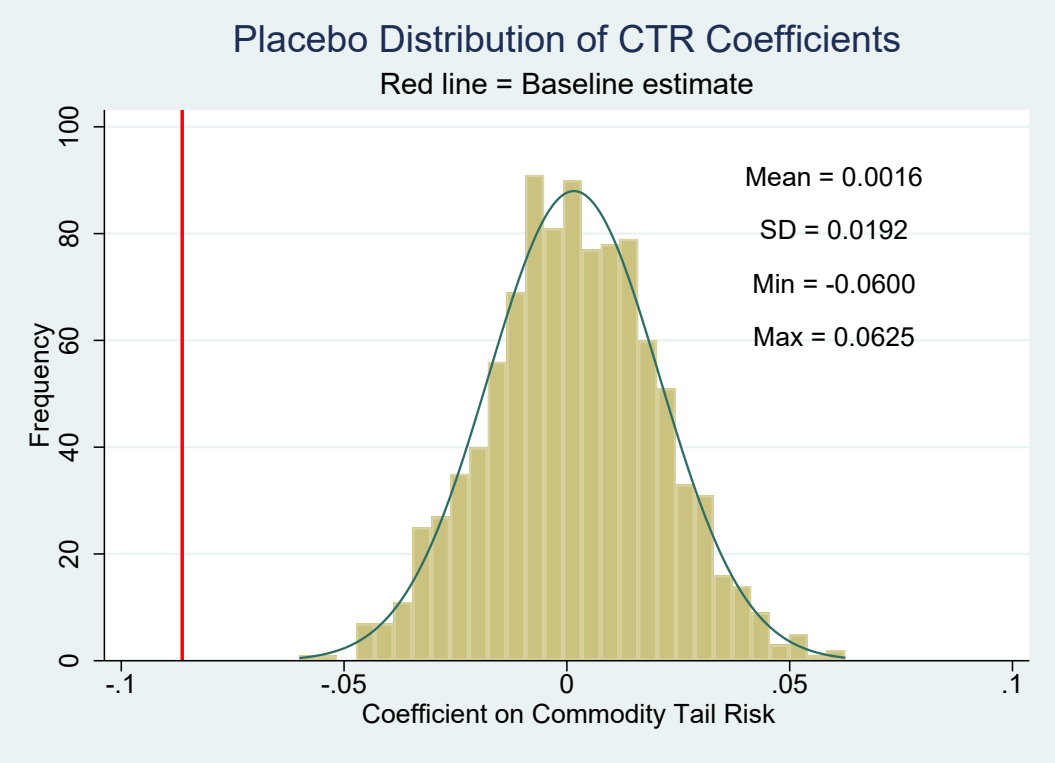


Figure 1
Histogram of the CTR Exposure Coefficient for the Placebo Test

Note(s): The figure shows the placebo test. For each firm-year, we randomly assign a CTR exposure value from other firms in the same province. We then re-estimate the baseline regressions and save the coefficients. This process is repeated 1,000 times, and the resulting coefficient distributions are shown in the figure.

Table 1
Summary Statistics

This table presents the descriptive statistics of the full sample and the Pearson pairwise correlation analysis for the dependent variable (*INNOV*), explanatory variable (*CTR*) and the control variables (*SIZE, LEV, TOBINQ, CASH, TANG, BRD_SIZE, BRD_IND, G_RATIO*, and *MGT_OWN*). Panel A shows the summary statistics. Panel B presents the correlation analysis. Bold coefficients indicate significance at the $p < 0.05$ level or lower (two-tailed). The continuous variables are winsorized at 1% at both extremes. The variable definitions are provided in Appendix A.

Panel A: descriptive statistics

Variable	Obs.	Mean	SD	p25	Median	p75
INNOV	22,226	2.747	1.313	1.792	2.639	3.497
CTR	22,226	0.084	0.398	-0.034	0.0	0.246
SIZE	22,226	7.783	1.200	6.928	7.667	8.497
LEV	22,226	0.405	0.199	0.246	0.397	0.547
TOBINQ	22,226	2.007	1.212	1.260	1.621	2.294
CASH	22,226	0.174	0.133	0.079	0.136	0.228
TANG	22,226	18.525	1.647	17.550	18.482	19.430
BRD_SIZE	22,226	8.583	1.747	7.0	9.0	9.0
BRD_IND	22,226	37.250	6.091	33.330	33.330	42.860
G_RATIO	22,226	81.674	11.144	75.0	83.330	90.0
MGT_OWN	22,226	14.877	19.700	0.006	2.185	28.323

Panel B: Pearson pairwise correlation analysis

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) *INNOV*	-										
(2) *CTR*	**-0.014**	-									
(3) *SIZE*	**0.354**	**0.018**	-								
(4) *LEV*	**0.132**	**0.049**	**0.471**	-							
(5) *TOBINQ*	**-0.019**	**0.027**	**-0.212**	**-0.262**	-						
(6) *CASH*	-0.011	**-0.045**	**-0.249**	**-0.446**	**0.148**	-					
(7) *TANG*	**0.270**	**0.013**	**0.674**	**0.393**	**-0.184**	**-0.308**	-				
(8) *BRD_SIZE*	**0.075**	**0.015**	**0.301**	**0.208**	**-0.113**	**-0.057**	**0.210**	-			
(9) *BRD_IND*	**0.061**	-0.001	-0.012	**-0.016**	**0.035**	0.007	**0.064**	**-0.442**	-		
(10) *G_RATIO*	**0.059**	**0.031**	**0.190**	**0.171**	**-0.113**	**-0.060**	**0.104**	**0.218**	**-0.104**	-	
(11) *MGT_OWN*	**-0.020**	**-0.060**	**-0.338**	**-0.349**	**0.045**	**0.198**	**-0.270**	**-0.258**	**0.114**	**-0.226**	-

Table 2
Baseline Regression Results

This table presents the baseline regression results that examine the impact of CTR on corporate innovation. The dependent variable, *INNOV*, is proxied by the number of patents filed in year t+1. The independent variable, *CTR*, and the control variables (*SIZE, LEV, TOBINQ, CASH, TANG, BRD_SIZE, BRD_IND, G_RATIO*, and *MGT_OWN*) are measured in year t. All regressions include industry- and year-fixed effects. The bracket values represent t-statistics and are based on firm-level clustering. ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.1 levels, respectively. The variable definitions are provided in Appendix A.

Variables	(1)	(2)	(3)	(4)	(5)
	INNOV	*INNOV*	*INNOV*	*INNOV*	*INNOV_PG*
CTR	-0.083**	-0.095***	-0.098***	-0.086***	-0.058*
	(-2.519)	(-3.198)	(-3.075)	(-2.923)	(-1.961)
SIZE		0.389***		0.388***	0.386***
		(15.730)		(15.570)	(15.659)
LEV		-0.002		0.062	-0.005
		(-0.023)		(0.624)	(-0.053)
TOBINQ		0.055***		0.062***	0.046***
		(4.557)		(5.133)	(3.768)
CASH		0.980***		0.928***	0.664***
		(8.204)		(7.836)	(5.617)
TANG		0.086***		0.086***	0.084***
		(5.925)		(5.986)	(5.864)
BRD_SIZE			0.122***	0.046***	0.036***
			(6.900)	(3.160)	(2.597)
BRD_IND			0.022***	0.009***	0.008**
			(5.197)	(2.635)	(2.500)
G_RATIO			0.005***	0.002	0.001
			(3.248)	(1.188)	(0.742)
MGT_OWN			-0.002**	0.004***	0.004***
			(-2.326)	(4.688)	(4.759)
Constant	2.754***	-2.154***	0.493*	-3.120***	-3.062***
	(0.022)	(0.271)	(0.288)	(0.360)	(0.412)
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Adj. R^2	0.150	0.289	0.174	0.294	0.314
Obs.	22,226	22,226	22,226	22,226	22,226

Table 3
DID Results

This table presents the DID result based on a set of firm-level characteristics. Panel A shows the regression results for the DID analysis. Panel B presents the regression results for parallel trend analysis. All regressions include industry- and year-fixed effects. The bracket values represent t-statistics and are based on firm-level clustering. ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.1 levels, respectively. The variable definitions are provided in Appendix A.

Panel A: Regression results for DID analysis

Variables	*INNOV*		
	(1)	(2)	(3)
TREAT	-0.038	-0.039	-0.042
	(-1.060)	(-1.074)	(-1.113)
POST_2014	0.041	1.111***	0.076
	(0.214)	(2.600)	(0.370)
TREAT×POST_2014	-0.103**	-0.100**	-0.079*
	(-2.365)	(-2.317)	(-1.763)
Baseline controls	YES	YES	YES
EPU Control	NO	YES	NO
Constant	-4.343***	-5.433***	-4.299***
	(-9.723)	(-8.643)	(-9.271)
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
R^2	0.299	0.300	0.296
Obs.	22,226	22,226	20,534

Panel B: Regression results for parallel trend assumption

Variables	*INNOV*
	(1)
TREAT×YEAR_2012	0.015
	(0.238)
TREAT×YEAR_2013	-0.094
	(-1.459)
TREAT×YEAR_CURRENT	-0.082
	(-1.226)
TREAT×YEAR_2015	-0.306***
	(-4.730)
TREAT×YEAR_2016	-0.218***
	(-3.581)
TREAT×YEAR_2017+	-0.113***
	(-4.010)
Baseline controls	YES
Constant	-4.342***
	(-9.690)
Industry FE	YES
Year FE	YES
R^2	0.299
Obs.	22,226

Table 4
2SLS Regression Results

This table presents the 2SLS regression results controlling for reverse causality. We use the infectious disease equity market volatility (*ID_EMV*) as an instrument. The continuous variables are winsorized at 1% on both extremes. The bracket values represent t-statistics and are based on firm-level clustering. ***, ** and * display statistical significance at the 0.01, 0.05 and 0.1 levels, respectively. The variable definitions are provided in Appendix A.

Variables	(1)	(2)
	CTR	*INNOV*
$\widehat{CTR}$		-7.103***
		(-3.789)
ID_EMV	-2.702***	
	(-2.647)	
Baseline controls	YES	YES
Constant	0.068	-4.086***
	(0.819)	(-8.960)
Industry FE	YES	YES
Year FE	YES	YES
Adj. R^2 / R^2	0.101	0.295
Obs.	22,226	22,226

Table 5
Falsification Tests Regression Results

This table presents the effects of CTR on *INNOV*, using falsification tests. All regressions include industry- and year-fixed effects. The bracket values represent t-statistics and are based on firm-level clustering. ***, ** and * display statistical significance at the 0.01, 0.05 and 0.1 levels, respectively. The variable definitions are provided in Appendix A.

Variables	(1)	(2)	(3)	(4)
	$Innov_{t-1}$	$Innov_{t-2}$	$Innov_{t-3}$	$Innov_{t+2}$
CTR	-0.048	-0.043	-0.027	-0.080**
	(-1.559)	(-1.352)	(-0.799)	(-2.271)
Baseline controls	YES	YES	YES	YES
Constant	-3.113***	-3.290***	-3.399***	-3.375***
	(-8.023)	(-7.988)	(-7.761)	(-7.981)
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Adj. R^2	0.302	0.306	0.313	0.307
Obs.	18,000	14,768	12,567	14,768

Table 6
PSM Results

This table presents the PSM results. Panel A shows the logistics regression results. Panel B indicates diagnostic statistics, with the two subsample groups whose *CTR* is in the top and bottom quartiles. It also shows the t-statistics of the univariate comparisons. Panel C reports the PSM sample regression results, which include industry- and year-fixed effects and baseline controls. The bracket values represent t-statistics and are based on firm-level clustering. ***, ** and * display statistical significance at the 0.01, 0.05 and 0.1 levels, respectively. The variable definitions are provided in Appendix A.

Panel A: Logit regression results

Variables	(1) Coefficient	(2) *z*-value
SIZE	-0.055**	-2.373
LEV	0.176	1.486
TOBINQ	-0.006	-0.363
CASH	-0.241	-1.224
TANG	-0.066***	-3.955
BRD_SIZE	0.023*	1.823
BRD_IND	0.008**	2.138
G_RATIO	0.009***	4.853
MGT_OWN	-0.004***	-3.142
Constant	0.456	1.373
Obs.	11,113	
Pseudo. R^2	0.006	

Panel B: Diagnostic statistics, differences in the means of the covariates

Variables	(1) *HIGH_CTR* (Treated)	(2) *LOW_CTR* (Control)	(3) *t*-test (*p*-value)
SIZE	7.999	7.992	0.760
LEV	0.445	0.445	0.986
TOBINQ	2.110	2.104	0.821
CASH	0.146	0.147	0.688
TANG	18.830	18.798	0.285
BRD_SIZE	8.683	8.690	0.845
BRD_IND	37.194	37.143	0.666
G_RATIO	82.580	82.630	0.812
MGT_OWN	9.858	9.883	0.936

Panel C: Regression on PSM sample

Variables	(1)	(2)
CTR	-0.075**	-0.079**
	(-2.300)	(-2.410)
IMR		-18.069
		(-0.544)
Constant	-3.533***	17.645
	(-7.668)	(0.456)
Baseline controls	YES	YES
Industry FE	YES	YES
Year FE	YES	YES
Matched on Industry	NO	YES
Adj. R^2	0.307	0.298
Obs.	10,350	9,560

Table 7
EB Regression Results

This table presents the regression results based on an entropy-balanced sample. Panels A and B show the covariate balance results before and after reweighting, respectively. Panel C shows the entropy-weighted regression results. The continuous variables are winsorized at 1% on both extremes. The bracket values represent t-statistics and are based on firm-level clustering. ***, ** and * display statistical significance at the 0.01, 0.05 and 0.1 levels, respectively. The variable definitions are provided in Appendix A.

Variables	Treatment			Control		
	Mean	Var.	Skew.	Mean	Var.	Skew.
Panel A: Covariate balance results before reweighting						
SIZE	7.998	1.372	0.481	7.597	1.424	0.693
LEV	0.443	0.038	0.222	0.373	0.039	0.419
TOBINQ	2.058	1.686	2.662	1.963	1.278	2.807
CASH	0.148	0.011	1.479	0.196	0.022	1.327
TANG	18.820	2.487	0.125	18.270	2.767	0.024
BRD_SIZE	8.691	3.185	0.752	8.489	2.917	0.645
BRD_IND	37.240	34.670	0.133	37.260	39.210	-0.631
BRD_DIV	82.270	119.10	-0.634	81.160	128.0	-0.563
MGT_OWN	10.40	269.20	1.555	18.760	458.70	0.792

Panel B: Covariate balance results after reweighting						
Variables	Treatment			Control		
	Mean	Var.	Skew.	Mean	Var.	Skew.
SIZE	7.998	1.372	0.481	7.998	1.670	0.557
LEV	0.443	0.038	0.222	0.443	0.040	0.216
TOBINQ	2.058	1.686	2.662	2.058	1.913	2.658
CASH	0.148	0.011	1.479	0.148	0.012	1.620
TANG	18.820	2.487	0.125	18.820	2.990	0.095
BRD_SIZE	8.691	3.185	0.752	8.691	3.329	0.767
BRD_IND	37.240	34.670	0.133	37.240	42.920	-0.542
BRD_DIV	82.270	119.10	-0.634	82.270	123.40	-0.652
MGT_OWN	10.40	269.20	1.555	10.400	272.60	1.643

Panel C: Entropy-weighted regression results	
Variables	(1)
CTR	-0.102***
	(-3.249)
Baseline controls	YES
Constant	-3.183***
	(-7.968)
Industry FE	YES
Year FE	YES
Adj. R^2	0.315
Obs.	22,226

Table 8
Other Fixed Effects and Additional Controls Regression Results

This table presents the regression results for other fixed effects and an extended set of control variables. The bracket values represent t-statistics and are based on firm-level clustering. ***, ** and * display statistical significance at the 0.01, 0.05 and 0.1 levels, respectively. The variable definitions are provided in Appendix A.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CTR	-0.121***	-0.053**	-0.061***	-0.086***	-0.075***	-0.079***	-0.105***	-0.107***	-0.080***
	(-5.448)	(-2.502)	(-2.771)	(-3.000)	(-2.839)	(-2.649)	(-3.022)	(-2.661)	(-2.624)
SUP_SIZE						0.025			
						(1.216)			
TOP3_SUM_SAL						0.154***			
						(5.077)			
AVG_AGE						-0.023***			
						(-4.156)			
MGT_FB						0.035			
						(1.303)			
MGT_OB						0.035			
						(1.236)			
MGT_SHARE						-0.002			
						(-1.508)			
STAFF_INT						-0.097***			
						(-5.252)			
FA_G							0.035**		
							(2.147)		
OP_REV_G							-0.012		
							(-0.371)		
NET_PROFIT_G							-0.000		
							(-0.238)		
NCF_OA							0.001		
							(1.409)		
SUS_G_RATE							1.074***		
							(4.885)		
OWN_EQUITY							0.047**		
							(2.397)		
RD_PERSON								0.016***	
								(6.735)	
RD_SPEND								0.009**	
								(1.975)	
RD_INVEST								-0.002*	
								(-1.722)	
GEPU									-0.000
									(-0.076)
WUI									0.000***
									(6.802)
GPR									-0.019***
									(-9.147)
F1									-0.195
									(-0.550)
F2									-1.629***
									(-2.715)

F3									3.640***
									(4.865)
F4									-0.367*
									(-1.918)
F5									-3.135***
									(-2.600)
F6									2.070***
									(2.848)
F7									1.196**
									(2.214)
F8									1.473***
									(4.994)
Baseline controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	-2.212***	0.262	0.470	-3.059***	-2.810***	-3.639***	-2.842***	-3.365***	-3.419***
	(-7.519)	(0.701)	(1.277)	(-8.425)	(-7.339)	(-6.435)	(-6.746)	(-7.707)	(-4.573)
Firm FE	NO	YES	YES	NO	NO	NO	NO	NO	NO
Industry FE	YES	NO	NO	YES	NO	YES	YES	YES	YES
Year FE	YES	YES	NO	YES	YES	YES	YES	YES	YES
Year-Industry FE	NO	NO	YES	NO	NO	NO	NO	NO	NO
Province FE	NO	NO	NO	YES	NO	NO	NO	NO	NO
Province-Industry FE	NO	NO	NO	NO	YES	NO	NO	NO	NO
Adj. R^2	0.325	0.679	0.695	0.303	0.386	0.315	0.316	0.310	0.298
Obs.	48,356	22,019	21,808	22,226	22,180	20,793	12,821	12,290	20,525

Table 9
Industry-Level Regression Results

This table presents the regression results for the sector-matched analysis. All regressions include industry- and year-fixed effects. The bracket values represent t-statistics and are based on firm-level clustering. ***, ** and * display statistical significance at the 0.01, 0.05 and 0.1 levels, respectively. The variable definitions are provided in Appendix A.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
CTR_AGR	-0.352***	-0.084***				
	(-2.859)	(-3.348)				
CTR_ENR			-0.781**	-0.073		
			(-2.075)	(-1.623)		
CTR_MIN					0.192***	0.117***
					(3.478)	(4.542)
Baseline controls	YES	YES	YES	YES	YES	YES
Constant	-3.536**	-2.155***	-2.075	-3.122***	-2.990***	-3.097***
	(-2.133)	(-5.271)	(-0.738)	(-8.456)	(-4.586)	(-8.418)
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adj. R^2	0.319	0.173	0.450	0.294	0.300	0.295
Obs.	460	22,226	413	22,226	5,493	22,226

Table 9
Up-tail and Down-tail Risk Exposure Regression Results

This table presents the regression results for the moderating effects of *UTR* and *DTR* on the relationship between *CTR* and corporate innovation. All regressions include industry- and year-fixed effects. The bracket values represent t-statistics and are based on firm-level clustering. ***, ** and * display statistical significance at the 0.01, 0.05 and 0.1 levels, respectively. The variable definitions are provided in Appendix A.

Variables	(1)	(2)
CTR×*UTR*	0.017	
	(0.452)	
CTR×*DTR*		-0.103***
		(-2.917)
UTR	0.176***	
	(4.287)	
DTR		-0.131***
		(-3.284)
CTR	-0.186***	0.033
	(-5.149)	(0.820)
Baseline controls	YES	YES
Constant	-2.961***	-3.125***
	(0.359)	(-8.480)
Industry FE	YES	YES
Year FE	YES	YES
Adj. R^2	0.295	0.296
Obs.	22,226	22,226

Table 10
Underlying Mechanisms Regression Results

This table presents the regression results for the underlying mechanisms of financial constraints and investment cutbacks. The bracket values represent t-statistics and are based on firm-level clustering. ***, ** and * display statistical significance at the 0.01, 0.05 and 0.1 levels, respectively. The variable definitions are provided in Appendix A.

Panel A: Regression results for financial constraints

	KZ_INDEX	*WW_INDEX*	*DIV_PAYOUT*
Variables	(1)	(2)	(3)
CTR	0.065**	0.024***	-0.041***
	(2.025)	(3.978)	(-4.223)
Baseline controls	YES	YES	YES
Constant	3.024***	0.302***	0.131*
	(9.045)	(4.903)	(1.680)
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Adj. R^2	0.694	0.238	0.147
Obs.	20,034	21,920	22,226

Panel B: Regression results for investment cutbacks

	CAPEX	*RD_INVEST*	*INV_CUT*
Variables	(1)	(2)	(3)
CTR	-0.006***	-0.070**	0.031***
	(-3.371)	(-2.544)	(2.935)
Baseline controls	YES	YES	YES
Constant	-0.010	8.180***	1.371***
	(-0.702)	(27.968)	(9.621)
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Adj. R^2	0.083	0.627	0.017
Obs.	22,226	18,527	18,000

Table 11
Cross-Sectional Analyses Regression Results

This table presents the cross-sectional regression results for the information environment and various corporate governance characteristics. Panel A reports cross-sectional regression results for the information environment. Panel B reports the cross-sectional regression results for the governance characteristics. All regressions include industry- and year-fixed effects. The bracket values represent t-statistics and are based on firm-level clustering. ***, ** and * display statistical significance at the 0.01, 0.05 and 0.1 levels, respectively. The variable definitions are provided in Appendix A.

Panel A: Cross-sectional regression results for the information environment

Variables	*ANALYT_COVERAGE*		*A_FFO*		*SPREAD*		*RESIDUAL*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low	High	Low	High	Low	High	Low	High
CTR	-0.088**	-0.055	-0.043	-0.116***	-0.046	-0.101***	-0.013	-0.127***
	(-2.262)	(-1.175)	(-1.134)	(-3.050)	(-1.106)	(-2.592)	(-0.344)	(-3.337)
Baseline controls	YES	YES	YES	YES	YES	YES	YES	YES
Constant	-1.538***	-3.656***	-3.449***	-3.150***	-3.410***	-2.750***	-3.302***	-3.277***
	(-3.536)	(-6.157)	(-7.187)	(-6.883)	(-6.983)	(-5.971)	(-8.083)	(-7.185)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.238	0.347	0.276	0.340	0.302	0.290	0.300	0.302
Obs.	8,547	7,808	9,163	9,141	10,910	10,914	9,801	9,798

Panel B: Cross-sectional regression results for corporate governance characteristics

Variables	*IND _DIR*		*DISSENT_DIR*		*BIG4*		*OVERSEAS_AUDITOR*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low	High	Yes	No	Yes	No	Yes	No
CTR	-0.106***	-0.028	0.682	-0.124**	-0.032	-0.131**	0.182	-0.090***
	(-3.280)	(-0.414)	(1.320)	(-2.339)	(-0.236)	(-2.377)	(1.234)	(-3.010)
Baseline controls	YES	YES	YES	YES	YES	YES	YES	YES
Constant	-2.006***	-3.894***	1.903	-4.345***	-9.449***	-2.927***	-7.958***	-2.949***
	(-5.384)	(-4.571)	(0.617)	(-7.749)	(-4.832)	(-5.724)	(-4.252)	(-8.216)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.256	0.425	0.212	0.347	0.570	0.288	0.535	0.280
Obs.	18,248	3,974	89	7,932	810	7,353	809	21,268