Asia-Pacific Journal of Financial Studies

Asia-Pacific Journal of Financial Studies (2025) **54**, 365–395 doi:10.1111/ajfs.70005

Directors' and Officers' Liability Insurance, Liquidity Risk, and Stock Returns: Evidence from Taiwan's Stock Market

Chih-Yuan Cheng
Department of Finance, National Kaohsiung University of Science and Technology, Taiwan

Yun-Lan Tseng*
Department of Accounting, National Pingtung University, Taiwan

Received 3 August 2024; Revised 15 March 2025; Accepted 16 April 2025

Abstract

This study reveals a notable anomaly in Taiwan's stock market, where stocks with substantial directors' and officers' (D&O) insurance coverage tend to yield higher expected returns, partly due to their exposure to liquidity risk. First, firms purchasing extensive D&O insurance coverage experience increased stock illiquidity, which is influenced by the inadequate quality of information disclosure. This observation supports the moral hazard-based information opacity hypothesis. Second, we introduce an illiquidity-based mimicking factor and show that portfolios with higher (lower) D&O insurance coverage display positive (negative) loadings on this factor, underscoring the importance of liquidity risk in asset pricing. Third, this market-wide illiquidity mimicking factor explains approximately one-third of the observed premium associated with variations in D&O insurance coverage across certain model specifications. This research challenges the behavioral mispricing hypothesis by highlighting the liquidity-driven covariance risk linked to the D&O insurance anomaly, thereby providing fresh insights into asset pricing dynamics in emerging markets.

Keywords Directors' and officers' liability insurance; Liquidity risk; Asset pricing; Moral hazard

JEL Classification: G11, G12, G34

1. Introduction

Directors' and officers' (D&O) insurance mitigates personal financial risk for executives during litigation, serving a crucial role in modern corporate risk management. While it enhances governance by reducing agency costs and improving transparency, it also introduces moral hazard by potentially weakening litigation deterrence

*Corresponding author: Yun-Lan Tseng, Department of Accounting, National Pingtung University, 51 Min Sheng E. Road, Pingtung, 90003, Taiwan. Tel: +886-8-7663800 ext. 32636, email: tyunlan@mail.nptu.edu.tw.

(Baker and Griffith 2010; Chen *et al.* 2016). Since 2008, the Financial Supervisory Commission of Taiwan has mandated public disclosure of D&O insurance, thereby promoting market transparency (Huang *et al.* 2021).

Extant research highlights D&O insurance's dual impact: strengthening governance on the one hand, while potentially exacerbating agency conflicts on the other. These effects manifest across various corporate outcomes, including IPO performance (Chalmers *et al.* 2002; Boyer and Stern 2012, 2014; Kao *et al.* 2020), reporting quality (Chung and Wynn 2008), M&A results (Lin *et al.* 2011), and innovation (Shi *et al.* 2023). Other studies explore links to cash policy (Liang *et al.* 2024), investment efficiency (Li and Liao 2014; Meng *et al.* 2023), loan terms (Lin *et al.* 2013), cost of capital (Chen *et al.* 2016), ESG (Tang *et al.* 2023; Qu 2024), and crash risk (Yuan *et al.* 2016).

Despite growing interest, the asset pricing implications of D&O insurance remain largely underexplored. Previous research indicates that insurers confidentially assess governance and litigation risks (Gillan and Panasian 2015; Lin *et al.* 2019) and suggests that D&O insurance can influence market valuations (Boyer 2007; Boyer and Stern 2014; Hwang and Kim 2018). Building on the work of Su (2023), this study investigates how liquidity risk contributes to the return premium associated with D&O insurance coverage, providing new insights into its role in asset pricing.

This study also investigates whether the return anomaly associated with D&O insurance coverage arises from rational liquidity risk driven by differences in corporate disclosure quality. We propose two competing hypotheses: the governance-based information transparency hypothesis (H1) and the moral hazard-based information opacity hypothesis (H2). H1 posits that D&O insurance enhances governance by strengthening oversight and improving disclosure quality. Insurers' underwriting assessments are external governance screens that deter managerial opportunism (Mayers and Smith 1982). Improved transparency reduces trading frictions, narrows bid–ask spreads, and boosts market participation (Welker 1995; Healy *et al.* 1999). Consequently, firms with higher D&O coverage are expected to demonstrate better governance, produce higher-quality reporting, and exhibit greater stock liquidity (Holderness 1990; Core 1997; Baker and Griffith 2010; Yuan *et al.* 2016).

In contrast, H2 posits that excessive D&O insurance coverage may result in moral hazard by shielding executives from litigation, thereby weakening their accountability in reporting (Chung and Wynn 2008; Baker and Griffith 2010; Lin *et al.* 2011). Firms with higher coverage are more likely to delay the disclosure of negative information, adopt less conservative reporting practices, and face higher restatement risk (Wynn 2008; Lin *et al.* 2013). Such behaviors can exacerbate information asymmetry, deter uninformed investors, and reduce liquidity, leading to higher equity costs (Diamond and Verrecchia 1991; Chen *et al.* 2016). These two hypotheses present competing predictions concerning the relationship between

D&O insurance, disclosure quality, and liquidity, thereby establishing the theoretical foundation for our empirical analysis.

We analyze firms listed on the Taiwan Stock Exchange (TWSE) and Taipei Exchange (TPEx) from 2008 to 2022. D&O insurance coverage (DOIC) is measured as the ratio of total D&O insurance to market capitalization, while stock illiquidity is proxied by Amihud's (2002) measure (ILL). By controlling for firm fixed effects and addressing endogeneity, our findings strongly support H2: higher DOIC is significantly associated with increased illiquidity. To assess the mediating role of disclosure quality, we employ the accrual-based proxy (DD) from Dechow and Dichev (2002), which confirms that poor financial disclosure partially explains the link between DOIC and ILL. These findings reveal a key economic mechanism through which D&O insurance influences market liquidity, providing new insights into its implications for asset pricing.

Next, expanding on Su (2023), we investigate how liquidity risk contributes to the high-minus-low D&O insurance return premium. Su (2023) identifies an anomaly where firms with higher D&O insurance coverage deliver superior abnormal returns, particularly in environments with significant arbitrage constraints. This anomaly points to potential behavioral mispricing and underscores the importance of specific features of D&O insurance contracts, such as policy limits and deductibles, in guiding investment decisions (e.g. Baker and Griffith 2007; Boyer 2007; Boyer and Stern 2012, 2014; Cao and Narayanamoorthy 2014; Gillan and Panasian 2015).

Firm-specific variables correlating with average returns often indicate sensitivity to non-diversifiable risk factors (Fama and French 1993; Cochrane 2011; Kelly *et al.* 2019). Within this framework, firms with higher D&O insurance coverage exhibit greater stock illiquidity, consistent with H2 and potential exposure to systematic liquidity risk (Amihud and Mendelson 1986; Pástor and Stambaugh 2003; Acharya and Pedersen 2005). This observation motivates a testable implication: portfolio returns sorted by D&O insurance coverage should vary with their exposure to liquidity risk factors. Specifically, firms with higher (lower) coverage are expected to exhibit higher (lower) illiquidity and correspondingly stronger (weaker) loadings on systematic liquidity factors, resulting in higher (lower) expected returns.

Adopting a methodology inspired by Fama and French (1993) and subsequent research (Hirshleifer *et al.* 2012; Leung *et al.* 2020; Su 2023), we developed an illiquidity-based factor-mimicking portfolio (ILLF). This portfolio strategy involves taking a long position on stocks characterized by high illiquidity (high-ILL) while shorting stocks with low illiquidity (low-ILL). Our findings indicate that the ILLF generates a significant alpha of 0.523% per month, even after adjusting for risk using the Fama and French five-factor model and Carhart's (1997) momentum factor (MOM).

When further analyzing portfolios sorted by DOIC, we find a consistent pattern: stocks in the high-DOIC portfolio show significantly higher loadings on the ILLF than those in the low-DOIC portfolio, irrespective of whether the portfolios are equal- or value-weighted. This implies that firms with elevated DOIC levels are more sensitive to systematic liquidity risk, which results in higher expected returns. To assess the explanatory power of the ILLF in explaining the return differential between the high- and low-DOIC portfolios, we employed a Pástor and Stambaugh (2003)-style regression framework. Our results reveal that the inclusion of the ILLF in the model specifications leads to a one-third reduction in the alpha of the high-minus-low-DOIC portfolio. For instance, when applying the Fama–French five-factor model, the alpha for the equal-weighted high-minus-low DOIC portfolio decreases from 1.154% to 0.734%, reflecting a reduction of 36.4%. Similarly, the alpha for the value-weighted counterpart falls from 0.381% to 0.247%, representing a decrease of 35.2%.

This study focuses on Taiwan's stock market for two primary reasons. First, as one of the most active markets in the Asia-Pacific region, Taiwan reported a market capitalization of approximately US$2041 billion as of December 2023 (World Federation of Exchanges). Its unique structure—characterized by daily price limits instead of trading halts—restricts trading volume when prices reach their upper or lower limits, complicating arbitrage opportunities and amplifying the role of liquidity in return formation (Lin *et al.* 2023). This regulatory feature provides a distinctive setting to examine whether a market-wide liquidity factor enhances return predictability and offers deeper insights into return anomalies in emerging markets.

Second, Taiwan presents governance characteristics typical of emerging economies, including concentrated ownership and widespread family control (Yeh 2019). In this context, D&O insurance plays a critical role in mitigating governance risks and shielding directors from personal liability (Lai and Tai 2019). Regulatory reforms—such as Article 39 of the Corporate Governance Guidelines and enhancements by the Financial Supervisory Commission in 2018–2019—Taiwan mandated in 2018 that newly listed companies must purchase D&O insurance, and in 2019, this requirement was fully expanded to include all listed companies. Consequently, coverage has significantly increased, rising from 44% in 2008 to 80% in 2018 (Huang *et al.* 2021; Su 2023). Supported by comprehensive data from the Taiwan Economic Journal (TEJ), these developments offer a robust empirical foundation for evaluating how D&O insurance affects governance quality, disclosure practices, and market outcomes in the context of an emerging market.

This study contributes to the literature on D&O insurance by introducing a liquidity-based asset pricing perspective. While previous research has focused on D&O insurance's governance and disclosure functions (Chung and Wynn 2008; Baker and Griffith 2010; Lin *et al.* 2011; Chen *et al.* 2016), its role in explaining systematic risk remains underexplored. Building on Su (2023), who identified a D&O-related return anomaly, we offer a rational explanation by linking D&O coverage to stock illiquidity—a priced risk factor in asset pricing models (Amihud and Mendelson 1986; Pástor and Stambaugh 2003; Acharya and Pedersen 2005). Empirically, firms with higher D&O coverage exhibit greater illiquidity, consistent with the moral hazard–based information opacity hypothesis (Wynn 2008; Lin *et al.* 2013), and lower disclosure quality as measured by Dechow and Dichev's (2002) accrual-based indicator. We construct an ILLF on which D&O-sorted portfolios load significantly. Adding the ILLF to extended Fama–French models improves explanatory power and captures a meaningful share of cross-sectional return variation. This research complements prior work on liquidity risk across settings such as momentum (Pástor and Stambaugh 2003), IPOs (Eckbo and Norli 2005), value-growth spreads (Akbas *et al.* 2010), and private equity (Franzoni *et al.* 2012). By integrating governance, opacity, and liquidity risk into a unified framework, this study offers novel insights into the pricing implications of corporate insurance in emerging markets.

The rest of this paper is organized as follows. Section 2 provides a literature review and proposes testable hypotheses. Section 3 outlines the dataset and describes the methods used for measuring variables. Section 4 tests the association between D&O insurance coverage and stock liquidity. Section 5 reports on the empirical findings regarding how liquidity risk contributes to the stock return premium linked to D&O insurance coverage. Finally, Section 6 provides the conclusion.

2. Literature Review and Hypothesis Development

2.1. D&O Insurance, Corporate Information Disclosure, and Stock Liquidity

The Governance-Based Information Transparency Hypothesis (H1).
A robust body of literature suggests that D&O insurance strengthens corporate governance and mitigates agency problems (Holderness 1990; Mayers and Smith 1990; Core 1997; O'Sullivan 1997; Zou and Adams 2008; Baker and Griffith 2010; Hwang and Kim 2018; Liao *et al.* 2022). By enhancing internal controls and promoting transparency, D&O insurance is associated with improved stock liquidity.

Insurers play an active role in assessing firms' governance structures during the underwriting process (Mayers and Smith 1982). Their evaluations serve as independent governance assessments, thereby improving market confidence. Bhagat *et al.* (1987) argue that such external monitoring reduces conflicts of interest between managers and shareholders. Empirical studies corroborate this view: O'Sullivan (1997) confirms that firms' high D&O insurance leads to a reduction in agency costs, while Hoyt and Khang (2000) highlight its positive effect on governance.

Beyond governance, D&O insurance is linked to enhanced disclosure quality. Yuan *et al.* (2016) show that underwriting assessments constrain managerial opportunism, thereby promoting financial transparency. These findings align with Core (2000) and Holderness (1990), who emphasize the role of external monitoring in reducing agency costs and improving reporting credibility. Improved disclosures reduce information asymmetry, increase trading activity, and tighten bid–ask spreads, ultimately boosting stock liquidity (Welker 1995; Healy *et al.* 1999). Thus, firms with higher D&O insurance coverage are expected to exhibit better governance, enhanced transparency, and superior trading performance.

Based on these observations, this study introduces the governance-based information transparency hypothesis (H1): firms that maintain substantial D&O insurance coverage tend to exhibit improved corporate governance practices and deliver higher-quality financial disclosures. This, in turn, mitigates information asymmetry and enhances stock liquidity.

The Moral Hazard-Based Information Opacity Hypothesis (H2).
D&O insurance provides crucial protection for executives against personal financial liability; however, it also presents significant concerns related to moral hazard (Lin *et al.* 2011, 2013; Li and Liao 2014; Chen *et al.* 2016; Kao *et al.* 2020; Donelson *et al.* 2021; Chiang and Chang 2022). To address these concerns, we propose the moral hazard-based information opacity hypothesis (H2): D&O insurance has the potential to weaken litigation deterrents, exacerbate agency conflicts, diminish the quality of disclosures, and impair stock liquidity due to increased information asymmetry.

Prior studies emphasize the disciplining role of litigation risk in enhancing transparency (Ball 2001; Healy and Palepu 2001). Timely disclosures help reduce executives' legal exposure (Skinner 1994, 1997), while litigation threats contribute to improved earnings quality and cash flow predictability (Khurana *et al.* 2006). However, the presence of D&O insurance diminishes these incentives by shielding executives from the financial consequences of misreporting. Such insurance not only alters executives' risk tolerance but also encourages opportunistic behavior (Kim 2015). This phenomenon of moral hazard weakens managerial accountability and undermines both internal monitoring and contractual safeguards (Warfield *et al.* 1995). Excessive coverage has been linked to lower earnings conservatism, reduced issuance of negative forecasts, and a higher likelihood of restatements (Chung and Wynn 2008; Wynn 2008; Lin *et al.* 2013). These dynamics amplify information asymmetry, discouraging participation from less-informed investors. As a result, trading volume decreases, bid–ask spreads widen, and the overall cost of capital rises (Diamond and Verrecchia 1991; Leuz and Wysocki 2008; Chen *et al.* 2016).

While D&O insurance mitigates the risk of litigation, it may inadvertently compromise the quality of financial reporting and market transparency. The moral hazard–based information opacity hypothesis captures this tradeoff by suggesting that excessive coverage can lead to reduced stock liquidity, stemming from weakened disclosure practices.

2.2. How Systematic Liquidity Risk Explains D&O Insurance Anomaly

D&O insurance may have meaningful implications for asset pricing, particularly through systematic liquidity risk, as investors often view such coverage as protection against litigation. This study examines how liquidity risk helps explain the D&O insurance anomaly, building on Su (2023), who identifies an asset pricing anomaly indicating that firms with higher D&O coverage earn greater future abnormal returns.

Our findings confirm that high-coverage firms consistently outperform their low-coverage counterparts. The characteristics of D&O insurance—such as policy limits and deductibles—seem to function as a mimicking factor that can predict returns, suggesting informational value embedded in insurance contracts (Baker and Griffith 2007; Boyer 2007; Cao and Narayanamoorthy 2014; Gillan and Panasian 2015). These patterns challenge behavioral mispricing explanations and are particularly pronounced among firms facing arbitrage constraints.

According to the moral hazard–based information opacity hypothesis (H2), elevated D&O insurance coverage can lead to moral hazard, which in turn weakens financial reporting quality and increases information asymmetry (Diamond and Verrecchia 1991; Leuz and Wysocki 2008; Chen *et al.* 2016). From an asset pricing perspective, firm-specific variables that correlate with returns often serve as proxies for non-diversifiable risk (Fama and French 1993; Cochrane 2011; Kelly *et al.* 2019). In line with this, firms with greater D&O insurance typically exhibit higher illiquidity, indicating an increased exposure to systematic liquidity risk (Amihud and Mendelson 1986; Pástor and Stambaugh 2003; Acharya and Pedersen 2005; Li *et al.* 2014). The covariance-based explanation suggests that return premia arise from distinct loadings on liquidity risk factors. Consequently, firms with higher (lower) D&O coverage should exhibit greater (lesser) sensitivity to liquidity risk and, accordingly, earn higher (lower) average returns.

Building on the work of Chen and Petkova (2012), we propose two testable implications. First, we identify a liquidity risk factor overlooked by traditional models, such as the Fama–French framework. Second, we demonstrate that high-D&O coverage stocks exhibit systematically stronger loadings on this liquidity risk factor than their low-coverage counterparts. If these implications are validated empirically, our framework offers a rational explanation for the D&O insurance anomaly by linking it to priced liquidity risk.

3. Sample Selection and Variable Description

3.1. Sample Selection

This study utilizes a dataset of firms listed on the TWSE and the TPEx from 2008 to 2022, excluding those in the financial services sector (TWSE industry codes 28, 58, and 60). Data on D&O insurance were collected from annual proxy circular filings available in the TEJ corporate governance database. Initially, around 36% of listed firms in Taiwan reported having zero D&O insurance coverage (Huang *et al.* 2021). These firms may have forgone purchasing coverage due to cost concerns, a claims-free history, managerial discretion, or regulatory noncompliance. Our analysis focuses exclusively on firm-year observations with non-missing and non-zero D&O insurance values to ensure accurate classification.

We merge D&O insurance data with the TEJ equity database to obtain daily trading volumes and stock returns, which allows us to calculate Amihud's (2002) illiquidity measures at both the firm-day and firm-year levels. Additional financial data, including monthly returns, share prices, and market capitalization, are also sourced from the same database. We retrieve accounting and financial metrics—such as market-to-book ratio, return on assets, and leverage—from the TEJ IFRS finance database. Governance-related variables, including board size, independence, ownership structure, and blockholder ownership, are derived from the TEJ corporate governance file. To estimate risk-adjusted abnormal returns, we collect the five Fama and French (2015) factors along with Carhart's (1997) MOM from the TEJ multi-factor database.

Our final dataset consists of approximately 18 000 firm-year observations used in baseline regressions to analyze the relationship between D&O insurance coverage and stock illiquidity. Additionally, for the asset pricing models, we utilized around 294 000 firm-month observations. This extensive dataset allows us to evaluate the predictive power of D&O insurance coverage and illiquidity on stock returns over the subsequent 12 months.

3.2. Measuring D&O Insurance Coverage

The primary variable in this study is D&O insurance coverage. To account for potential liability exposure, we scale the total D&O insurance coverage by the market value of equity, as suggested by Lin *et al.* (2011). This scaling results in a continuous variable referred to as DOIC. By normalizing D&O insurance coverage in relation to firm size, this metric enables consistent comparisons across companies with varying market valuations. This approach is consistent with methodologies used in previous studies, including Lin *et al.* (2011, 2013) and Huang *et al.* (2021), thereby enhancing the robustness and comparability of our evaluation of the insurance's effects.

3.3. Measuring Stock Illiquidity

To assess stock illiquidity, we utilize Amihud's (2002) illiquidity measure, which is widely recognized as a robust proxy for price impact (Goyenko *et al.* 2009; Kang and Zhang 2014). This measure is defined as the daily ratio of absolute stock returns to dollar trading volume, effectively capturing the sensitivity of price changes to variations in trading volume:

$$RV_{i,d,y} = \frac{\left|r_{i,d,y}\right|}{P_{i,d,y} \times Vol_{i,d,y}} \times 10^6 \tag{1}$$

where $r_{i,d,y}$, $P_{i,d,y}$, and $Vol_{i,d,y}$ are daily stock return, daily share price, and daily share trading volume (in one share unit) of stock i on day d in year y, respectively. The firm-year stock illiquidity measure is calculated as an equally weighted average of daily RVs in a given year for a given stock (denoted as ILL). A higher ILL value indicates a greater level of stock illiquidity, while a lower value signifies a more liquid stock.

3.4. Measuring Information Disclosure Quality

Drawing inspiration from the works of Dechow and Dichev (2002), Francis *et al.* (2005), and Rajgopal and Venkatachalam (2011), we employ an accrual-based methodology to assess the quality of information disclosure at the firm level. To accomplish this, we develop a cross-sectional regression model tailored for each industry group, as categorized by TWSE industry codes. This model is then applied to firm i in year y:

$$TCA_{i,y} = \gamma_0 + \gamma_1 CFO_{i,y-1} + \gamma_2 CFO_{i,y} + \gamma_3 CFO_{i,y+1} + \gamma_4 \Delta REV_{i,y} + \gamma_5 PPE_{i,y} + u_{i,y} \tag{2}$$

where $TCA_{i,y} = \Delta CA_{i,y} - \Delta CL_{i,y} - \Delta CASH_{i,y} + \Delta STDebt_{i,y}$, which is the total current accruals. $\Delta CA_{i,y}$, $\Delta CL_{i,y}$, $\Delta CASH_{i,y}$, and $\Delta STDebt_{i,y}$ are the year-over-year changes in current assets, current liabilities, cash, and debt in current liabilities, respectively. $CFO_{i,y-1}$, $CFO_{i,y}$, and $CFO_{i,y+1}$ are cash flow from operations in years $y-1$, y, and $y+1$, respectively. $CFO_{i,y} = IBEX_{i,y} - TCA_{i,y} + DEPN_{i,y}$, where $IBEX_{i,y}$ is the net income before extraordinary items in year y, and $DEPN_{i,y}$ is the depreciation and amortization expense in year y. $\Delta REV_{i,y}$ is changes in revenues between year $y-1$ and year y. $PPE_{i,y}$ is the gross value of property, plant, and equipment in year y. All variables are standardized by dividing by the average total assets for the year, ensuring comparability across firms. Outliers are addressed through winsorization at the 1st and 99th percentiles.

Following Rajgopal and Venkatachalam (2011), we compute the Dechow-Dichev (DD) measure as the standard deviation of residuals over a 5-year rolling window: $DD_{i,y} = \sigma(\widehat{u}_{i,y-4,y})$. A higher DD value reflects greater unpredictability in accruals relative to cash flows, signaling reduced reliability and lower quality in financial disclosures.

3.5. Other Relevant Variables

To enhance the robustness of our multiple regression analysis, we include a comprehensive set of control variables in addition to the primary variables, DOIC and ILL. These control variables are categorized into three groups: firm-level financial characteristics, market performance metrics, and corporate governance attributes.

The firm-level financial variables encompass market capitalization (ME), market-to-book equity ratio (MB), return on equity (ROE), total debt ratio (LEV), dividend yield (DIVD), and cash holdings (CASH). Market performance indicators include stock return volatility (SIGMA), skewness (SKEW), and kurtosis (KURTS).

In the context of corporate governance, the model incorporates several key variables: board size (BOSIZE), board independence (BOIND), board ownership

(BOSHR), board duality (BODUAL), the deviation of control rights from cash flow rights (BODEV), blockholder ownership (BOBLOCK), and institutional ownership (INST). To enhance the reliability and consistency of the results, the model also includes industry fixed effects, firm fixed effects, and year fixed effects. Detailed definitions and computational methodologies for all variables can be found in Appendix A.

3.6. Descriptive Statistics

Table 1 presents a summary of the descriptive statistics for the variables included in this study, along with Pearson correlation coefficients between DOIC and other variables. The average DOIC is 4.745%, suggesting that approximately 5% of these firms' market value is insured under D&O coverage. The mean value of stock illiquidity (ILL) is 3.648, accompanied by a substantial standard deviation of 27.415, indicating significant variability in stock illiquidity across the sample.

The Pearson correlation analysis indicates a significant positive correlation between DOIC and ILL, suggesting that firms with higher levels of DOIC tend to experience greater stock illiquidity. Furthermore, DOIC is also significantly and positively correlated with DD, implying that firms with higher DOIC are more likely to exhibit poorer information disclosure quality. These preliminary findings highlight a potential relationship between D&O insurance coverage, information opacity, and stock illiquidity, which merits further investigation.

4. D&O Insurance Coverage and Firm-Level Stock Illiquidity

This section explores the relationship between D&O insurance coverage (DOIC) and stock illiquidity (ILL), employing Amihud's (2002) illiquidity measure as the primary indicator. Both univariate and multivariate regression analyses are utilized to assess the potential impact of DOIC on firm-level stock liquidity.

4.1. Univariate Analysis

The univariate analysis investigates the distribution of stock illiquidity (ILL) across quintile portfolios sorted by the level of DOIC. Specifically, we rank stocks into quintiles annually based on their DOIC at the end of each year from 2008 to 2022. The average values of DOIC and ILL over the formation period are computed for each quintile portfolio (High, D4, D3, D2, and Low). To determine whether stock illiquidity significantly differs between the extreme portfolios, we perform a *t*-test to compare the ILL between the high and low DOIC quintiles.

Table 2 summarizes the ILL of the DOIC quintile portfolios during the formation period. The findings indicate that firms in the high DOIC portfolio exhibit markedly higher levels of illiquidity, with an average ILL of 17.306, compared to the low DOIC portfolio, which demonstrates an average ILL of 0.346. A clear

Table 1 Descriptive statistics of firm-year variables

This table summarizes the descriptive statistics for the firm-year variables utilized in this study. Detailed definitions of the variables can be found in Appendix A. The dataset comprises 17 926 firm-year observations of non-financial stocks listed on the TWSE and TPEx with D&O insurance coverage during the sample period from 2008 to 2022. All data are sourced from the TEJ database. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

	Mean	Median	SD	Q1	Q3	Correlation with *DOIC*
A. D&O Insurance						
DOIC (%)	4.745	0.038	28.235	0.015	0.104	1.000
B. Stock Illiquidity						
ILL	3.648	0.152	27.415	0.036	0.687	0.123***
C. Quality of Information Disclosure						
DD	3.920	3.246	3.166	2.051	4.934	0.074***
D. Firm Characteristics						
ME (in Billion)	22.344	3.073	188.144	1.127	9.234	−0.020***
MB	2.078	1.490	3.112	1.010	2.330	−0.014**
ROE (%)	5.517	7.100	22.263	0.560	14.120	−0.039***
LEV (%)	42.613	42.170	19.420	28.080	55.340	−0.002
DIVD (%)	3.583	3.420	3.108	0.000	5.640	−0.036***
CASH (%)	19.595	16.557	14.310	9.170	26.286	0.007
SIGMA (%)	3.931	3.517	2.289	2.362	4.967	0.011
SKEW (%)	0.727	0.636	0.892	0.166	1.182	0.008
KURTS (%)	2.670	1.506	3.801	0.445	3.461	0.031***
E. Corporate Governance						
BOSIZE	9.003	9.000	2.112	7.000	10.000	−0.081***
BOIND (%)	28.833	30.000	13.247	20.370	39.683	0.120***
BOSHR (%)	23.031	18.949	15.587	11.500	30.720	0.031***
BODUAL (%)	19.888	16.667	13.641	11.110	28.570	−0.042***
BODEV	4.011	1.080	44.239	1.010	1.451	−0.003
BOBLOCK (%)	22.360	19.784	12.485	13.468	28.463	0.008
INST (%)	41.706	40.310	22.888	22.980	59.470	−0.028***

decreasing trend in ILL is observed as DOIC levels decline, with the average ILL decreasing progressively from 17.306 in the high DOIC quintile to 2.105, 1.968, 0.711, and 0.346 in the D4, D3, D2, and low quintiles, respectively. The difference in ILL between the high and low DOIC quintiles is statistically significant at 16.960, supported by a *t*-statistic of 6.50.

These findings provide compelling preliminary evidence of a positive association between DOIC and ILL. Furthermore, they align with the anticipation of the moral hazard-based information opacity hypothesis, which suggests that firms obtaining higher D&O insurance coverage tend to experience greater stock illiquidity.

Table 2 The relationship between *DOIC* and *ILL*: Univariate analysis

This table presents the results of a univariate portfolio analysis examining the relationship between *DOIC* and *ILL*. The dataset comprises 17 926 firm-year observations of non-financial stocks listed on the TWSE and TPEx with D&O insurance coverage during the sample period from 2008 to 2022. Each year, stocks are grouped into quintiles based on their *DOIC* values, which are classified as high, Q4, Q3, Q2, and low. Portfolios are constructed for each quintile, and the mean values of DOIC and ILL are calculated across the entire period. *t*-tests are employed to evaluate the differences in ILL between the high and low DOIC quintiles, with *t*-statistics presented in parentheses to indicate significance. *** denotes statistical significance at the 1% level.

DOIC Quintiles	High	Q4	Q3	Q2	Low	High−Low
Mean *DOIC* (%)	6.909	1.390	0.197	0.021	0.007	6.902
Mean *ILL*	17.306	2.105	1.968	0.711	0.346	16.960
(*t*)	(5.72)***	(6.29)***	(4.27)***	(4.06)***	(3.88)***	(6.50)***

4.2. Multivariate Regression Analysis

To further evaluate whether the positive relationship between DOIC and ILL persists after controlling for firm-specific characteristics, a panel regression model is employed. The model incorporates a range of control variables that capture key determinants of stock illiquidity. The regression equation is specified as follows:

$$lnILL_{i,y} = \gamma_0 + \gamma_1 DOIC_{i,y} + \gamma_k \sum_k Control_{i,y}^k + \theta_i + \rho_j + \delta_y + \varepsilon_{i,y} \tag{3}$$

where $lnILL_{i,y}$ represents the natural logarithm of the illiquidity measure for firm i in year y, and $DOIC_{i,y}$ denotes the D&O insurance coverage for firm i in year y. $Control_{i,y}^k$ is a set of control variables for firm i in year y. θ_i, ρ_j, and δ_y are firm, industry, and year fixed effects, respectively. We select control variables based on established methodologies in the literature, particularly Chen *et al.* (2016). Detailed definitions and computation methods for these variables are provided in Appendix A. The regression results based on Equation (3) are presented in Table 3.

Model (1) in Table 3 incorporates a comprehensive set of control variables frequently linked to stock liquidity, alongside industry and year fixed effects. Even after accounting for these factors, the coefficient of DOIC remains significantly positive at 0.036, with a robust *t*-statistic of 9.70, providing strong support for H2 that D&O insurance coverage is positively correlated with stock illiquidity.

Model (2) in Table 3 further incorporates firm and year fixed effects to mitigate potential omitted variable bias arising from unobserved firm-specific or temporal factors. Although the magnitude of the DOIC coefficient is reduced to 0.011, it

Table 3 The relationship between DOIC and ILL: Regression analysis

This table presents the results of panel regressions analyzing the relationship between ILL and DOIC, while accounting for other influencing factors. The regression model is structured as follows: $lnILL_{i,y} = \gamma_0 + \gamma_1 DOIC_{i,y} + \gamma_k \sum_k Control_{i,y}^k + \theta_i + \rho_j + \delta_y + \varepsilon_{i,y}$, where $lnILL_{i,y}$ represents the natural logarithm of the illiquidity measure for firm i in year y, and $DOIC_{i,y}$ denotes the D&O insurance coverage of firm i in year y. $Control_{i,y}^k$ is a set of control variables for firm i in year y. θ_i, ρ_j, and δ_y are firm, industry, and year fixed effects, respectively. Model (1) reports the results incorporating industry fixed effects, while Model (2) includes firm fixed effects. Model (3) presents the results of the second stage of a two-stage least squares (2SLS) regression, where the industry average of *DOIC* is used as an instrument in the first-stage regression. Robust Newey-West standard errors clustered by year are applied, with t-statistics provided in parentheses. N denotes the number of firm-year observations. *, **, and ***, represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	IE (1)	FE (2)	2SLS IV (3)
Constant	7.125 (4.52)***	2.541 (2.11)**	2.014 (1.89)*
DOIC	0.036 (9.70)***	0.011 (4.52)***	0.009 (3.99)***
lnME	−0.001 (−1.70)*	0.001 (1.20)	0.001 (1.15)
MB	−0.785 (−22.26)***	−0.419 (−15.49)***	−0.434 (−16.34)***
ROE	−0.243 (−47.16)***	−0.149 (−38.10)***	−0.137 (−35.48)***
LEV	−0.004 (−0.69)	0.046 (5.89)***	0.061 (7.82)***
DIVD	−0.625 (−17.13)***	−0.505 (−16.50)***	−0.488 (−16.26)***
CASH	0.038 (4.59)***	−0.049 (−5.83)***	−0.058 (−7.04)***
SIGMA	0.099 (1.84)*	−0.580 (−14.19)***	−0.650 (−16.16)***
SKEW	−0.937 (−5.48)***	−0.054 (−0.47)	−0.008 (−0.07)
KURTS	0.325 (8.30)***	0.139 (5.27)***	0.153 (5.87)***
BOSIZE	−0.586 (−10.06)***	−0.433 (−5.57)***	−0.385 (−5.03)***
BOIND	−13.062 (−12.07)***	−1.960 (−2.03)**	−1.968 (−2.07)**
BOSHR	0.682 (82.60)***	0.418 (28.83)***	0.412 (28.95)***
BODUAL	−0.033 (−4.18)***	−0.012 (−1.26)	−0.009 (−0.98)
BODEV	−0.011 (−5.10)***	0.001 (−0.10)	0.001 (−0.22)
BOBLOCK	0.813 (82.30)***	0.454 (31.64)***	0.433 (30.74)***
INST	−0.398 (−65.69)***	−0.199 (−22.50)***	−0.186 (−21.43)***
Industry Fixed Effect	Y	N	N
Firm Fixed Effect	N	Y	Y
Year Fixed Effect	Y	Y	Y
R^2	57.7%	84.8%	85.3%
N	17 926	17 926	17 926

remains statistically significant with a t-statistic of 4.52. This suggests that the positive impact of DOIC on stock illiquidity is robust even when accounting for both firm-level heterogeneity and time-varying effects.

Next, to address potential endogeneity concerns regarding the strategic nature of firms' decisions to purchase D&O insurance, which may be influenced by stock illiquidity, we employ the Heckman (1979) two-stage approach with an exogenous instrumental variable. Following established methodologies (Lin *et al.* 2011; Han *et al.* 2024), we use the industry median D&O coverage ratio (DOICIV) as the instrumental variable. The justification for using this instrument lies in the notion that companies within the same industry often engage in competition to attract and retain skilled managerial talent. To remain competitive, these firms are likely to offer similar remuneration structures, which frequently include D&O insurance as a component of executive compensation. Furthermore, firms within the same sector are generally subject to comparable operational conditions and levels of litigation risk, as highlighted by prior studies (Han *et al.* 2024). As a result, the industry median D&O coverage ratio is presumed to be strongly correlated with an individual firm's decision to obtain D&O insurance, while its direct impact on stock illiquidity is expected to be minimal. Unreported first-stage regression results confirm the relevance of DOICIV, demonstrating a significant positive relationship with DOIC. The fitted values from this regression are then employed as explanatory variables in the second-stage regression. The second-stage results, presented in Model (3) of Table 3, validate the robustness of the findings under the instrumental variable approach. Specifically, the coefficient of the instrumented DOIC remains positive and statistically significant (0.009, with a *t*-statistic of 3.99), providing strong evidence that the observed positive relationship between DOIC and ILL is not driven by endogeneity concerns.

The findings in Table 3 corroborate those of the univariate analysis in Table 2, consistently demonstrating a significant positive relationship between DOIC and ILL. This relationship remains robust across different model specifications and controlling for endogeneity bias. These findings align with H2, suggesting that the protection afforded by D&O insurance may reduce the incentives for directors and officers to ensure high-quality financial reporting and transparency, increasing information asymmetry among market participants and thereby aggravating stock illiquidity.

4.3. Mediation Effect of Information Disclosure Quality

The findings thus far are consistent with the moral hazard-based information opacity hypothesis (H2), suggesting that D&O insurance may encourage moral hazard behavior, resulting in increased information asymmetry and reduced stock liquidity. This subsection seeks to provide direct empirical evidence that higher DOIC is associated with lower-quality information disclosure, which in turn exacerbates stock illiquidity.

To evaluate the mediating effect of information disclosure quality, we utilize established accrual-based proxies as indicators of firm-level disclosure quality. Specifically, we employ the DD metric introduced by Dechow and Dichev (2002) and refined by Rajgopal and Venkatachalam (2011). Following Wu and Lai's methodology (2020), a two-step mediation analysis is conducted using the following regression models:

Table 4 Mediation effect of information disclosure quality

This table presents the results of a two-step mediation analysis examining the role of information disclosure quality (DD) in the relationship between DOIC and ILL. The analysis is based on the following regression models: First Step (Mediation Variable): $DD_{i,y} = \beta_0 + \beta_1 DOIC_{i,y} + \beta_k \sum_k Control^k_{i,y} + \theta_i + \varepsilon_{i,y}$; Second Step (Outcome Variable): $lnILL_{i,y} = \beta_0 + \beta_1 DOIC_{i,y} + \beta_2 DD_{i,y} + \beta_k \sum_k Control^k_{i,y} + \theta_i + \varepsilon_{i,y}$, where $DD_{i,y}$ represents the proxy of information disclosure quality for firm *i* in year *y*. Other variables have been previously defined in Table 3. Constants and control coefficients are omitted for brevity. Robust Newey-West standard errors clustered by year are used, with *t*-statistics shown in parentheses. The variable N represents the number of firm-year observations. *** denotes statistical significance at the 1% level.

Dependent variable	*DD*	*lnILL*
DOIC	0.114 (3.74)***	0.105 (4.39)***
DD		0.031 (10.81)***
Controls	Y	Y
Firm Fixed Effect	Y	Y
Year Fixed Effect	Y	Y
R^2	55.0%	84.9%
N	17 926	17 926
Significance of Mediated Effect		<0.01

$$\text{First Step}: DD_{i,y} = \beta_0 + \beta_1 DOIC_{i,y} + \beta_k \sum_k Control^k_{i,y} + \theta_i + \varepsilon_{i,y}, \quad (4)$$

$$\text{Second Step}: lnILL_{i,y} = \beta_0 + \beta_1 DOIC_{i,y} + \beta_2 DD_{i,y} + \beta_k \sum_k Control^k_{i,y} + \theta_i + \varepsilon_{i,y}, \quad (5)$$

where $DD_{i,y}$ represents the measures of information disclosure quality for firm *i* in year *y*. Other variables have been previously defined in Equation (3). Table 4 reports the results of the mediation analysis.

As shown, the first step of the analysis reveals a significant positive relationship between *DOIC* and the *DD* metric, even after controlling for various determinants of information disclosure quality. Specifically, the coefficient for *DOIC* about *DD* is 0.114 (t-statistic = 3.74), providing corroborating evidence that firms with higher *DOIC* tend to exhibit lower-quality financial disclosures. This finding is indeed in favor of the moral hazard-based information opacity hypothesis (H2).

More crucially, in the second step, when regressing *lnILL* on *DOIC*, the mediating variable *DD*, and control variables, the coefficient of *DD* is positive and statistically significant at 0.031 (t-statistic = 10.81). The mediating effect of *DD* is significant at the 1% level, demonstrating that the impact of *DOIC* on stock illiquidity operates primarily through its adverse influence on the quality of information disclosure.

In sum, our findings provide compelling evidence that the association between DOIC and stock illiquidity is mediated by a decline in information disclosure quality. These findings further validate H2, highlighting the critical role of D&O insurance in potentially fostering moral hazard behaviors, which increase information asymmetry and exacerbate stock illiquidity.

5. Liquidity Risk to Explain the D&O Insurance Premium

To assess whether the anomaly in D&O insurance coverage can be attributed to rational liquidity risk, this section introduces a mimicking liquidity risk factor known as the ILLF. Following this, we conduct asset pricing tests to analyze the pattern of ILLF loadings across quintile portfolios categorized by the level of DOIC. Finally, we explore whether the liquidity risk factor can explain the risk premium observed in the high-minus-low DOIC portfolio.

5.1. Revisiting the High-Minus-Low *DOIC* Return Premium

From an asset pricing perspective, Su (2023) identifies a notable anomaly related to D&O insurance coverage, revealing that firms with higher D&O insurance consistently achieve significantly greater abnormal future returns than those with lower coverage. Su's (2023) research further demonstrates that specific features of D&O insurance, including a mimicking factor derived from coverage levels, serve as reliable predictors of future stock returns. Additionally, his findings highlight a valuation discrepancy, indicating that firms with higher D&O insurance coverage tend to be undervalued, while those with lower coverage are often overvalued. Notably, the return premium associated with the disparity between high and low D&O insurance coverage is primarily observed in companies facing significant arbitrage constraints. Based on these results, Su (2023) rejects the rational risk hypothesis and attributes this anomaly to behavioral mispricing.

To further investigate Su's (2023) findings, this subsection examines the relationship between D&O insurance coverage (DOIC) and expected stock returns by re-evaluating the high-minus-low DOIC return premium. We conduct univariate portfolio sorting tests following these steps. At the end of each June from 2009 to 2022, we sort stocks into quintiles based on their DOIC values from the prior fiscal year ($y - 1$). We then calculate equal-weighted and value-weighted monthly returns for each portfolio over the subsequent 12 months, from July of year y to June of year $y + 1$. This process is repeated annually, generating a time series of monthly returns for each DOIC quintile portfolio over 168 months (July 2009 to June 2023). To further explore the return differentials, we examine risk-adjusted alphas for each quintile portfolio and test the significance of the difference in alphas between the high- and low-DOIC portfolios. The raw portfolio returns are regressed against the Fama–French three-factor, four-factor, and five-factor models, yielding FF3 alpha, FF4 alpha, and FF5 alpha, respectively.

Table 5 Revisiting the high-minus-low *DOIC* return premium

This table presents the average monthly returns and risk-adjusted alphas for portfolios grouped into quintiles based on the level of DOIC for non-financial stocks traded on the TWSE and TPEx that had D&O insurance coverage between 2008 and 2022. Each year, specifically at the end of June (designated as year y), the stocks are ranked into quintiles based on the DOIC values from the previous year ($y-1$). These quintiles include high, Q4, Q3, Q2, and low. This process is repeated annually, producing a time series of monthly returns for each quintile. DOICHL (High − Low) represents the raw return spread between the high and low DOIC quintile portfolios. FF3 Alpha, FF4 Alpha, and FF5 Alpha denote risk-adjusted alphas estimated using the Fama–French three-factor, four-factor, and five-factor models, respectively. Panel A presents the average monthly raw returns, as well as the equal-weighted and value-weighted returns for each DOIC portfolio over the period from July of year y to June of year $y+1$. In Panel B, we compare the raw return differences and changes in alphas between the high- and low-DOIC quintile portfolios. The t-statistics are shown in parentheses to assess significance. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: The average monthly returns for *DOIC* quintile portfolios

	Average (N)	*DOIC* (%)	Equal-weighted return (%)	(t)	Value-weighted return (%)	(t)
High	200.5	23.013	2.064	(4.49)***	1.651	(3.52)***
Q4	201.0	7.482	1.390	(2.92)***	1.325	(2.89)***
Q3	201.1	3.878	1.141	(2.54)**	1.149	(2.54)**
Q2	201.0	1.961	1.008	(2.37)**	1.001	(2.36)**
Low	200.4	0.338	0.643	(1.68)*	0.748	(2.17)**

Panel B: The high-minus-low DOIC return premium

	Equal-weighted return (%)	(t)	Value-weighted return (%)	(t)
DOICHL (High – Low)	1.421	(6.37)***	0.904	(3.09)***
FF3 Alpha (High – Low)	1.234	(6.16)***	0.382	(2.75)***
FF4 Alpha (High – Low)	1.228	(5.83)***	0.438	(3.03)***
FF5 Alpha (High – Low)	1.154	(5.75)***	0.381	(2.73)***

Panel A of Table 5 displays each quintile portfolio's average monthly raw returns, including equal-weighted and value-weighted returns. Panel A reveals a clear trend: portfolios with high *DOIC* exhibit increasing monthly realized returns. The monthly raw returns consistently increase with higher levels of DOIC. For equal-weighted quintile portfolios, the average monthly returns for the high, D4, D3, D2, and low quintiles are 2.064%, 1.390%, 1.141%, 1.008%, and 0.643%, respectively. When employing value-weighted returns, the evidence also exhibits a similar pattern.

Panel B of Table 5 presents the differences in average monthly raw returns between the high- and low-DOIC portfolios and the differences in risk-adjusted alphas between the two portfolios, including equal-weighted and value-weighted returns. We also evaluate the statistical significance of these differences in monthly raw returns and alphas. Our findings indicate that the high-DOIC portfolio generates higher monthly raw returns than the low-DOIC portfolio. The monthly difference of 1.421% is statistically significant, with a *t*-statistic of 6.37. When annualized, the difference equates to approximately 17.1%. Additionally, the risk-adjusted alphas for equal-weighted portfolios show a similar upward trend across the DOIC quintiles. For example, the difference in FF4 alphas between the high- and low-DOIC portfolios is 1.228% per month, equivalent to roughly 14.7% annually, with a *t*-statistic of 5.83.

When utilizing value-weighted returns, the monthly raw returns and risk-adjusted alphas also increase as the level of DOIC rises. The difference in returns between high- and low-DOIC portfolios remains positive and statistically significant, further reinforcing this relationship. These findings indicate that firm size does not influence the relationship between DOIC and returns.

Overall, these findings indicate that sorting stocks based on the degree of DOIC results in significant return differentials across the cross-section, implying that D&O insurance coverage plays a crucial role in predicting future stock returns. These results align with the work of Su (2023) and suggest that DOIC serves as a valuable metric for understanding return dynamics in financial markets.

5.2. Constructing the Mimicking Liquidity Risk Factor

To construct the ILLF, we adopt the methodologies outlined by Francis *et al.* (2005) and Kim and Qi (2010), along with insights from the empirical asset pricing literature (e.g. Hirshleifer *et al.* 2012; Fama and French 2015; Leung *et al.* 2020; Su 2023). Our approach involves replicating a factor-mimicking portfolio utilizing ILL, a state variable closely related to the anomaly under investigation.

To implement this process, all stocks listed on the TWSE and TPEx are sorted annually into groups based on their end-June market capitalization (ME) for each year from 2008 to 2022. Stocks are categorized into two size groups: small (S) and big (B). Additionally, stocks are divided into three portfolios—high (H), medium (M), and low (L)—based on their illiquidity measure (ILL) from the previous fiscal year ($y-1$). This leads to a double sorting that results in six portfolios (2×3), representing the intersections of the two ME groups and the three ILL groups. We adopt a value-weighted method to calculate monthly returns for these six portfolios from July of year y to June of year $y+1$, covering 168 months from July 2009 to June 2023. The ILLF is then constructed as the return difference between the mean returns of the two high-ILL portfolios (S/H and B/H) and the two low-ILL portfolios (S/L and B/L), calculated as follows: (B/H + S/H)/2 − (B/L + S/L)/2.

Panel A of Table 6 presents the descriptive statistics for the ILLF and the standard Fama–French factors from July 2009 to June 2023. On average, the ILLF generates a monthly return of 0.523%, with a standard deviation (SD) of 2.005%. These figures yield an ex-post monthly Sharpe ratio of 0.261, which assesses the factor's return to its associated risk.

Table 6 Descriptive statistics for risk factor portfolios

The table presents statistics for various risk factor portfolios, specifically focusing on the ILLF, covering the period from July 2009 to June 2023. Data were sourced from TWSE/TPEx-listed firms that have purchased D&O insurance, excluding stocks from the financial sector. Panel A displays the monthly returns for the ILLF in conjunction with established risk factors, including the Fama–French five factors: MKT, SMB, HML, RMW, and CMA, as well as Carhart's (1997) MOM. Panel B presents the pairwise correlations between the ILLF and the other risk factors. Panel C conducts a time-series regression analysis, regressing the ILLF on the Fama–French five factors and MOM, with robust Newey-West (1987) t-statistics provided in parentheses to evaluate significance. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Statistics on factor returns

	MKT	*SMB*	*HML*	*RMW*	*CMA*	*MOM*	*ILLF*
Mean (%)	0.989	0.173	0.318	0.100	−0.126	0.349	0.523
(t)	(2.35)**	(0.81)	(1.15)	(0.47)	(−0.71)	(1.39)	(3.38)***
SD (%)	9.112	4.627	5.950	4.578	3.818	5.440	2.005
Min (%)	−37.242	−16.032	−18.455	−23.751	−17.766	−26.386	−5.852
Max (%)	65.862	26.848	41.052	13.810	19.358	17.141	6.149
N	168	168	168	168	168	168	168

Panel B: Pearson correlations

	MKT	*SMB*	*HML*	*RMW*	*CMA*	*MOM*
SMB	0.006					
HML	0.188***	0.050				
RMW	−0.274***	−0.344***	−0.660***			
CMA	−0.134***	0.142***	0.569***	−0.503***		
MOM	−0.154***	−0.171***	−0.277***	0.345***	−0.186***	
ILLF	−0.440***	0.447***	0.337***	−0.400***	0.433***	0.001

Panel C: Factor spanning test for *ILLF*

ILLF's alpha	*MKT*	*SMB*	*HML*	*RMW*	*CMA*	*MOM*	R^2	*N*
0.591	−0.185	0.272	0.092	−0.110	0.114	0.041	50.7%	168
(4.77)***	(−6.76)***	(5.43)***	(1.54)	(−1.61)	(1.80)*	(1.22)		

Panel B of Table 6 presents the Pearson correlation coefficients between the ILLF and the Fama–French factors. There is a significant negative correlation between the ILLF and the market factor (MKT) at −0.440, as well as with the profitability factor (RMW) at −0.400. Conversely, the ILLF shows significant positive correlations with the size factor (SMB) at 0.447, the value factor (HML) at 0.337, and the investment factor (CMA) at 0.433. These correlations indicate that the ILLF captures information related to market-wide liquidity, providing insights that intersect with, yet remain distinct from, the characteristics inherent in traditional risk factors.

Panel C of Table 6 provides a detailed analysis of the interaction of the ILLF with the established Fama–French factors through factor-spanning tests. In these tests, the ILLF is regressed against a range of risk factors, including MKT, SMB, HML, RMW, CMA, and the MOM. Our findings indicate that the ILLF yields a statistically significant alpha of 0.591% per month (t-statistic = 4.77), suggesting that the factor captures unique risk dimensions not fully explained by traditional models. Additionally, the positive loading on the SMB factor signifies a strong association between the ILLF and the returns of smaller firms, while the negative loading on the RMW factor indicates an inverse relationship with firms that exhibit high operating profitability. These loadings underscore the distinctive characteristics of the ILLF with established risk dimensions.

Overall, these findings highlight the limitations of conventional risk models in explaining the return premium associated with liquidity, as illustrated by the ILLF. The significant abnormal returns generated by the ILLF, along with its distinct variation in asset returns beyond what traditional factors predict, underscore its crucial role in understanding asset pricing dynamics. These results emphasize the necessity of integrating liquidity-based factors into asset pricing models to fully explain the diverse risks and returns in financial markets.

5.3. *ILLF* Loadings on *DOIC* Portfolios

To examine the exposure of *DOIC* quintile portfolios to the *ILLF*, we estimate factor loadings for each *DOIC* quintile portfolio using a time-series Fama–French five-factor regression model extended to include the ILLF as an additional factor. This analysis draws on data from July 2009 to June 2023 and employs the following regression model:

$$R_{p,t} = \alpha_p + \beta_{p,m}MKT_t + \beta_{p,s}SMB_t + \beta_{p,h}HML_t + \beta_{p,r}RMW_t + \beta_{p,c}CMA_t + \beta_{p,i}ILLF_t + \varepsilon_{p,t}, \tag{6}$$

where $R_{p,t}$ refers to the equal-weighted or value-weighted monthly returns for DOIC quintile portfolios—categorized as high, Q4, Q3, Q2, and low—generated in month t, as outlined in Table 5. Additionally, MKT_t, SMB_t, HML_t, RMW_t, and CMA_t represent the Fama–French five-factor model metrics for month t. Meanwhile, $ILLF_t$ denotes the firm-specific ILL factor-mimicking portfolio for the same month. Panels A and B of Table 7 present the ILLF loadings for the equal-weighted and value-weighted DOIC quintile portfolios, respectively.

Panel A of Table 7 shows that the high-DOIC portfolio reveals a significantly positive ILLF loading of 0.359 (t-statistic = 3.44), indicating a strong exposure to systematic liquidity risk. In contrast, the low-DOIC portfolio exhibits a significantly

Table 7 ILLF loadings on DOIC quintile portfolios

This table presents ILLF factor loadings for DOIC quintile portfolios, estimated using time-series regressions with the Fama–French five-factor model, augmented by the ILLF, over the period from July 2009 to June 2023: $R_{p,t} = \alpha_p + \beta_{p,m}MKT_t + \beta_{p,s}SMB_t + \beta_{p,h}HML_t + \beta_{p,r}RMW_t + \beta_{p,c}CMA_t + \beta_{p,i}ILLF_t + \varepsilon_{p,t}$, where $R_{p,t}$ denotes the equal- or value-weighted monthly returns of DOIC quintile portfolios (high, Q4, Q3, Q2, and low) in month t, as constructed in Table 5. Panels A and B report results for equal- and value-weighted portfolios, respectively. MKT_t, SMB_t, HML_t, RMW_t, and CMA_t represent the Fama–French five factors for month t. $ILLF_t$ represents the firm-specific ILL factor-mimicking portfolio for month t. Robust Newey-West (1987) t-statistics are shown in parentheses to assess significance. * and *** denote statistical significance at the 10% and 1% levels, respectively.

	High	Q4	Q3	Q2	Low	*DOICHL* (High−Low)
Panel A: Equal-weighted *DOIC* portfolios						
ILLF	0.359 (3.44)***	0.028 (0.35)	−0.031 (−0.44)	−0.029 (−0.41)	−0.070 (−1.70)	0.429 (3.36)***
FF5 Controls	Y	Y	Y	Y	Y	Y
R^2	90.1%	94.6%	95.2%	94.8%	94.0%	37.4%
N	168	168	168	168	168	168
Panel B: Value-weighted *DOIC* portfolios						
ILLF	0.134 (1.90)*	−0.024 (−0.28)	−0.046 (−0.54)	−0.110 (−1.22)	−0.214 (−6.60)***	0.348 (3.96)***
FF5 Controls	Y	Y	Y	Y	Y	Y
R^2	94.1%	93.7%	93.4%	91.2%	97.2%	82.7%
N	168	168	168	168	168	168

negative ILLF loading of −0.070 (t-statistic = −1.70). The difference in ILLF loading between the high- and low-DOIC portfolios is 0.429 (t-statistic = 3.36), providing compelling evidence that firms obtaining higher DOIC are more exposed to liquidity risk, which corresponds to higher expected returns. Conversely, firms with lower DOIC demonstrate less exposure to liquidity risk, aligning with lower expected returns.

Panel B reinforces the preceding analysis by examining value-weighted portfolios categorized by DOIC quintiles, yielding compelling results. The ILLF loading for the low-DOIC quintile portfolio is −0.214 (t-statistic = −6.60), while the high-DOIC quintile portfolio shows an ILLF loading of 0.134 (t-statistic = 1.90). The significant difference in ILLF loading between the high- and low-DOIC portfolios is 0.348 (t-statistic = 3.96). This suggests that portfolios with higher DOIC tend to have a greater exposure to systematic liquidity risk.

Overall, these results highlight a prominent relationship between DOIC levels and exposure to liquidity risk, as indicated by the ILLF loading. Firms obtaining high D&O insurance coverage exhibit positive loadings on the ILLF, suggesting they face greater liquidity risk and, consequently, higher expected returns. In contrast, firms with low D&O typically generate negative ILLF loadings, reflecting reduced exposure to liquidity risk and correspondingly lower expected returns. The following subsection will examine the extent to which the ILLF contributes to the observed return differential between high- and low-DOIC portfolios, providing additional insights into its role in driving the DOIC return anomaly.

5.4. Incremental Contribution of *ILLF* to the High-Minus-Low *DOIC* Return Premium

Given that the ILLF is a priced factor, this subsection estimates its incremental contribution to the return differential between high- and low-DOIC portfolios. Following the methodologies established by Pástor and Stambaugh (2003) and Su (2016), the intercepts in time-series regression models of asset returns are interpreted as risk-adjusted alphas, under the condition that all risk factors in the asset pricing model are tradable (i.e. returns-based factors). In this context, the ILLF is introduced as a tradable mimicking factor to capture systematic liquidity risk.

Subsequently, we estimate the risk-adjusted alphas for the high-minus-low *DOIC* portfolio (*DOICHL*) by running time-series regressions over the entire sample period. In the model specifications, the dependent variable is the return differential between the high- and low-*DOIC* portfolios. The explanatory variables include *ILLF*, along with a set of established tradable risk factors. Incorporating *ILLF* into the traditional asset pricing model enables direct estimation of alphas and deeper insights into the incremental impact of systematic liquidity risk on the return differential between high- and low-*DOIC* portfolios. The time-series asset pricing regressions to be estimated are as follows:

$$DOICHL_t = \alpha^1 + \beta_1 ILLF_t + \varepsilon_t, \tag{7}$$

$$DOICHL_t = \alpha^2 + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 ILLF_t + \varepsilon_t, \tag{8}$$

$$DOICHL_t = \alpha^3 + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 ILLF_t + \varepsilon_t, \tag{9}$$

$$\begin{aligned} DOICHL_t = {} & \alpha^4 + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \beta_6 ILLF_t \\ & + \varepsilon_t, \end{aligned} \tag{10}$$

where $DOICHL_t$ represents the difference in monthly returns between the high- and low-DOIC quintile portfolios. The variables MKT_t, SMB_t, HML_t, RMW_t, and CMA_t are the Fama–French five-factors in month t.[1] MOM_t denotes Carhart's (1997) MOM, while $ILLF_t$ signifies the ILL-based mimicking factor. Panels A and B of Table 8 display the risk-adjusted alphas and coefficient estimates for the equal-weighted and value-weighted DOICHL portfolios, respectively. These estimates are derived from various asset pricing models, both with and without the ILLF factor.

Panel A of Table 8 presents the results for the equal-weighted DOICHL portfolios. In Model (1A), the monthly raw returns of the DOICHL portfolio average 1.421%, with a *t*-statistic of 6.37, which aligns with earlier findings in Table 5. However, when *ILLF* is introduced as the sole explanatory variable in Model (1B), the average monthly return decreases to 0.953%. This decrease represents a 33.0% reduction from 1.421% in Model (1A), highlighting that *ILLF* explains a considerable portion of the DOIC return premium.

In expanding the Fama–French three-factor model presented in Model (2A), the alpha for the DOICHL portfolio is 1.234% with a *t*-statistic of 6.16. However, when *ILLF* is included in Model (2B), the alpha decreases by 34.7% to 0.805%, with a *t*-statistic of 4.62. Similarly, in the Fama–French four-factor model (Model (3A)), the initial alpha of 1.228% diminishes to 0.815% in Model (3B) upon adding *ILLF*,

[1]Building on prior research demonstrating that the inverse of the price-to-earnings ratio can serve as an alternative measure of the cost of capital (e.g., Basu 1977), which is influenced by D&O insurance (Chen *et al.* 2016; Houston *et al.* 2018), we incorporate the price-to-earnings systematic factor into the Fama–French five-factor model as an additional control variable. Our main results remain robust after accounting for the price-to-earnings systematic factor. We sincerely thank an anonymous reviewer for this constructive suggestion.

Table 8 *DOICHL* portfolio's alphas by *ILLF*-augmented factor models

This table displays the risk-adjusted alphas of the DOICHL portfolio, derived from various ILLF-augmented asset pricing models. Panels A and B present the results for equal-weighted and value-weighted portfolios, respectively. The DOICHL portfolio represents the monthly return spread between the high- and low-DOIC quintile portfolios, as defined in Table 5. Model (1A) presents the average monthly raw returns of the DOICHL portfolio from July 2009 to June 2023. Model (1B) offers risk-adjusted alphas derived from time-series regressions utilizing the ILLF as the sole factor. Models (2A) and (2B) estimate alphas using the Fama–French three-factor model and its ILLF-augmented version, respectively. Models (3A) and (3B) report alphas based on the Fama–French four-factor model and its ILLF-enhanced counterpart. Finally, Models (4A) and (4B) display alphas derived from the Fama–French five-factor model and its augmented version with the ILLF. Robust Newey-West (1987) *t*-statistics are shown in parentheses to assess significance. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1A)	(1B)	(2A)	(2B)	(3A)	(3B)	(4A)	(4B)
Panel A: Equal-weighted *DOICHL* portfolio								
Alpha (%)	1.421 (6.37)***	0.953 (5.26)***	1.234 (6.16)***	0.805 (4.62)***	1.228 (5.83)***	0.815 (4.50)***	1.154 (5.75)***	0.734 (4.20)***
ILLF		0.609 (6.00)***		0.487 (3.75)***		0.488 (3.74)***		0.429 (3.36)***
MKT			0.015 (0.36)	0.113 (2.32)**	0.016 (0.36)	0.113 (2.30)**	0.103 (2.24)**	0.183 (3.63)***
SMB			0.499 (6.27)***	0.350 (4.05)***	0.500 (6.21)***	0.347 (3.97)***	0.525 (6.27)***	0.411 (4.66)***
HML			0.179 (2.78)***	0.081 (1.20)	0.179 (2.77)***	0.080 (1.18)	0.160 (1.60)	0.119 (1.22)
MOM					0.006 (0.10)	−0.010 (−0.17)		
RMW							0.151 (1.34)	0.194 (1.77)*
CMA							0.463 (4.36)***	0.415 (3.98)***
Alpha Decline (%)		−33.0		−34.7		−33.6		−36.4
R^2	–	17.8%	25.2%	31.1%	25.2%	31.1%	33.0%	37.4%
N	168	168	168	168	168	168	168	168
Panel B: Value-weighted *DOICHL* portfolio								
Alpha (%)	0.904 (3.09)***	0.564 (2.18)**	0.382 (2.75)***	0.255 (1.70)*	0.438 (3.03)***	0.289 (2.01)**	0.381 (2.73)***	0.247 (1.78)*
ILLF		0.938 (7.35)***		0.396 (4.49)***		0.407 (4.63)***		0.348 (3.96)***
MKT			0.123 (4.16)***	0.203 (6.11)***	0.120 (4.06)***	0.201 (6.11)***	0.171 (5.35)***	0.236 (6.79)***
SMB			1.097 (19.96)***	0.975 (16.63)***	1.088 (19.68)***	0.961 (16.30)***	1.084 (18.55)***	0.991 (16.33)***
HML			0.470 (10.57)***	0.390 (8.54)***	0.466 (10.47)***	0.383 (8.39)***	0.395 (5.68)***	0.362 (5.40)***
MOM					−0.053 (−1.31)	−0.066 (−1.52)		
RMW							0.004 (0.05)	0.039 (0.52)
CMA							0.277 (3.74)***	0.238 (3.32)***
Alpha Decline (%)		−37.6		−33.3		−34.0		−35.2
R^2	–	24.6%	79.2%	81.5%	79.5%	81.9%	81.1%	82.7%
N	168	168	168	168	168	168	168	168

reflecting a 33.6% reduction. In the Fama–French five-factor model (Model (4A)), the alpha starts at 1.154% and falls to 0.734% in Model (4B) with the inclusion of *ILLF*, indicating a 36.4% decrease.

Panel B of Table 8 shows that the value-weighted DOICHL portfolios display results consistent with those observed in the equal-weighted portfolios. Notably, including the ILLF across all models leads to a significant decrease in the alpha of the DOICHL portfolio, reinforcing the consistency of these results.

Overall, the results across various model configurations consistently demonstrate that the ILLF significantly contributes to the return differential between high- and low-DOIC portfolios because the ILLF, on average, can explain approximately one-third of the observed DOIC return premium. Its inclusion enhances the explanatory power of traditional models, highlighting the importance of integrating systematic liquidity risk factors into contemporary asset-pricing frameworks.

6. Concluding Remarks

This study introduces a rational liquidity risk framework to clarify the D&O insurance coverage anomaly identified by Su (2023), who reveals that firms obtaining substantial D&O insurance coverage generate higher future abnormal returns than those with limited coverage. Building on the framework proposed by Chen *et al.* (2016), we advance the moral hazard-based information opacity hypothesis (H2), asserting that D&O insurance coverage exacerbates agency conflicts related to moral hazard, leading to diminished quality in financial reporting, increased information asymmetry, and elevated stock illiquidity.

Building on prior research indicating that firm-specific variables correlated with average returns often act as proxies for sensitivity to non-diversifiable risk factors, we propose that the elevated stock illiquidity observed in firms with significant D&O insurance coverage reflects an increased exposure to systematic liquidity risk. We hypothesize that firms opting for high D&O insurance exhibit greater sensitivity to liquidity risk, which results in higher average future returns. Conversely, firms choosing low D&O insurance demonstrate reduced sensitivity and, consequently, lower average future returns.

Analyzing firms listed on the Taiwan stock market from July 2009 to June 2023, we present compelling evidence supporting the liquidity risk explanation for the D&O insurance coverage anomaly. Consistent with the research of Chen *et al.* (2016), our key findings indicate that firms with substantial D&O insurance coverage demonstrate higher stock illiquidity. Furthermore, the mediation analysis reveals that increased D&O insurance coverage reduces firms' disclosure quality, which, in turn, deteriorates stock liquidity. Second, the D&O insurance anomaly, recognized by Su (2023), persists during our sample period. Firms holding high D&O insurance coverage generate higher abnormal returns than those with low coverage, even after adjusting for established benchmark risk factors. Additionally, by introducing an illiquidity-based factor-mimicking portfolio, we illustrate that firms with high D&O insurance coverage exhibit a positive loading on this factor. Conversely, firms with low coverage demonstrate a negative loading. This indicates that firms with high coverage are more exposed to systematic liquidity risk, whereas those with low coverage are less affected. When the mimicking factor is incorporated into a traditional asset pricing model, it explains approximately one-third of the observed D&O insurance coverage premium, with explanatory power differing across various model specifications.

Our research contributes to the D&O literature by offering a novel rational liquidity risk explanation for the D&O insurance coverage anomaly, complementing Su's (2023) behavioral mispricing hypothesis. Our findings underscore the significant economic impact of systematic liquidity risk and its crucial role in understanding the D&O insurance anomaly. Our findings have practical implications for investors, emphasizing the importance of incorporating liquidity risk into portfolio strategies, particularly when evaluating D&O insurance coverage. Moreover, investors should closely monitor D&O insurance disclosures to inform their investment decisions. Furthermore, our research offers valuable insights for management, emphasizing the need to integrate liquidity risk into risk management and governance practices to strengthen overall corporate resilience.

This study demonstrates that liquidity risk partially accounts for variations in D&O insurance premiums, highlighting an area for future research. Specifically, other rational risk factors could further clarify the determinants of D&O insurance premiums. For example, D&O insurance may influence a company's credit rating (Bradley and Chen 2011), potentially subjecting firms with higher D&O coverage to increased credit risk. This interaction could represent another important mechanism influencing D&O insurance premiums, thereby warranting further exploration in subsequent studies.

References

Acharya, V. V., and L. H. Pedersen, 2005, Asset pricing with liquidity risk, *Journal of Financial Economics* 77, pp. 375–410.

Akbas, F., E. Boehmer, E. Genc, and R. Petkova, 2010, The time-varying liquidity risk of value and growth stocks. Available at SSRN 1572763.

Amihud, Y., 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, pp. 31–56.

Amihud, Y., and H. Mendelson, 1986, Liquidity and stock returns, *Financial Analysts Journal* 42, pp. 43–48.

Baker, T., and S. J. Griffith, 2007, Predicting corporate governance risk: Evidence from the directors' & officers' liability insurance market, *The University of Chicago Law Review* 74, pp. 487–544.

Baker, T., and S. J. Griffith, 2010, Ensuring corporate misconduct: How liability insurance undermines shareholder litigation? All Faculty Scholarship 2737.

Ball, R., 2001, Infrastructure requirements for an economically efficient system of public financial reporting and disclosure, *Brookings-Wharton Papers on Financial Services* 2001, pp. 127–169.

Basu, S., 1977, Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis, *Journal of Finance* 32, pp. 663–682.

Bhagat, S., J. A. Brickley, and J. L. Coles, 1987, Managerial indemnification and liability insurance: The effect on shareholder wealth, *Journal of Risk and Insurance* 54, pp. 721–736.

Boyer, M. M., 2007, Three insights from the Canadian D&O insurance market: Inertia, information and insiders, *Connecticut Insurance Law Journal* 14, pp. 75–106.

Boyer, M. M., and L. H. Stern, 2012, Is corporate governance risk valued? Evidence from directors' and officers' insurance, *Journal of Corporate Finance* 18, pp. 349–372.

Boyer, M. M., and L. H. Stern, 2014, D&O insurance and IPO performance: What can we learn from insurers? *Journal of Financial Intermediation* 23, pp. 504–540.

Bradley, M., and D. Chen, 2011, Corporate governance and the cost of debt: Evidence from director limited liability and indemnification provisions, *Journal of Corporate Finance* 17, pp. 83–107.

Cao, Z., and G. S. Narayanamoorthy, 2014, Accounting and litigation risk: Evidence from directors' and officers' insurance pricing, *Review of Accounting Studies* 19, pp. 1–42.

Carhart, M. M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, pp. 57–82.

Chalmers, J. M., L. Y. Dann, and J. Harford, 2002, Managerial opportunism? Evidence from directors' and officers' insurance purchases, *The Journal of Finance* 57, pp. 609–636.

Chen, Z., O. Z. Li, and H. Zou, 2016, Directors' and officers' liability insurance and the cost of equity, *Journal of Accounting and Economics* 61, pp. 100–120.

Chen, Z., and R. Petkova, 2012, Does idiosyncratic volatility proxy for risk exposure? *Review of Financial Studies* 25, pp. 2745–2787.

Chiang, Y. M., and P. R. Chang, 2022, Overinvestment, ownership structure, and directors' and officers' liability insurance, *International Review of Economics and Finance* 78, pp. 38–50.

Chung, H. H., and J. P. Wynn, 2008, Managerial legal liability coverage and earnings conservatism, *Journal of Accounting and Economics* 46, pp. 135–153.

Cochrane, J. H., 2011, Presidential address: Discount rates, *The Journal of Finance* 66, pp. 1047–1108.

Core, J. E., 1997, On the corporate demand for directors' and officers' insurance, *Journal of Risk and Insurance* 64, pp. 63–87. https://doi.org/10.2307/253912

Core, J. E., 2000, The directors' and officers' insurance premium: An outside assessment of the quality of corporate governance, *Journal of Law, Economics, and Organization* 16, pp. 449–477.

Dechow, P. M., and I. D. Dichev, 2002, The quality of accruals and earnings: The role of accrual estimation errors, *The Accounting Review* 77(s-1), pp. 35–59.

Diamond, D. W., and R. E. Verrecchia, 1991, Disclosure, liquidity, and the cost of capital, *Journal of Finance* 46, pp. 1325–1359.

Donelson, D. C., B. R. Monsen, and C. G. Yust, 2021, US evidence from D&O insurance on accounting-related agency costs: Implications for country-specific studies, *Journal of Financial Reporting* 6, pp. 63–87.

Eckbo, B. E., and Ø. Norli, 2005, Liquidity risk, leverage and long-run IPO returns, *Journal of Corporate Finance* 11, pp. 1–35.

Fama, E. F., and K. R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, pp. 3–56.

Fama, E. F., and K. R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, pp. 1–22.

Francis, J., R. LaFond, P. Olsson, and K. Schipper, 2005, The market pricing of accruals quality, *Journal of Accounting and Economics* 39, pp. 295–327.

Franzoni, F., E. Nowak, and L. Phalippou, 2012, Private equity performance and liquidity risk, *Journal of Finance* 67, pp. 2341–2373.

Gillan, S. L., and C. A. Panasian, 2015, On lawsuits, corporate governance, and directors' and officers' liability insurance, *Journal of Risk and Insurance* 82, pp. 793–822.

Goyenko, R. Y., C. W. Holden, and C. A. Trzcinka, 2009, Do liquidity measures measure liquidity? *Journal of Financial Economics* 92, pp. 153–181.

Han, Y., S. Boubaker, W. Li, and Y. Wang, 2024, How does directors' and officers' liability insurance affect green innovation? Evidence from China, *International Review of Economics and Finance* 94, 103419.

Healy, P. M., A. P. Hutton, and K. G. Palepu, 1999, Stock performance and intermediation changes surrounding sustained increases in disclosure, *Contemporary Accounting Research* 16, pp. 485–520.

Healy, P. M., and K. G. Palepu, 2001, Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature, *Journal of Accounting and Economics* 31, pp. 405–440.

Heckman, J. J., 1979, Sample selection bias as a specification error, *Econometrica: Journal of the Econometric Society* 47, pp. 153–161.

Hirshleifer, D., K. Hou, and S. H. Teoh, 2012, The accrual anomaly: Risk or mispricing? *Management Science* 58, pp. 320–335.

Holderness, C. G., 1990, Liability insurers as corporate monitors, *International Review of Law and Economics* 10, pp. 115–129.

Houston, J. F., C. Lin, and W. Xie, 2018, Shareholder protection and the cost of capital, *The Journal of Law and Economics* 61, pp. 677–710.

Hoyt, R. E., and H. Khang, 2000, On the demand for corporate property insurance, *Journal of Risk and Insurance* 67, pp. 91–107. https://doi.org/10.2307/253678

Huang, R. J., V. Jeng, C. W. Wang, and J. C. Yue, 2021, Does size and book-to-market contain intangible information about managerial incentives? Learning from corporate D&O insurance purchase, *Pacific-Basin Finance Journal* 68, 101560.

Hwang, J. H., and B. Kim, 2018, Directors' and officers' liability insurance and firm value, *Journal of Risk and Insurance* 85, pp. 447–482.

Kang, W., and H. Zhang, 2014, Measuring liquidity in emerging markets, *Pacific-Basin Finance Journal* 27, pp. 49–71.

Kao, L., A. Chen, and C. Krishnamurti, 2020, Outcome model or substitute model of D&O insurance on IPO pricing without information asymmetry before issuance, *Pacific-Basin Finance Journal* 61, 101300.

Kelly, B. T., S. Pruitt, and Y. Su, 2019, Characteristics are covariances: A unified model of risk and return, *Journal of Financial Economics* 134, pp. 501–524.

Khurana, I. K., X. Martin, and R. Pereira, 2006, Financial development and the cash flow sensitivity of cash, *Journal of Financial and Quantitative Analysis* 41, pp. 787–808.

Kim, D., and Y. Qi, 2010, Accruals quality, stock returns, and macroeconomic conditions, *The Accounting Review* 85, pp. 937–978.

Kim, I., 2015, Directors' and officers' insurance and opportunism in accounting choice, *Accounting and Taxation* 7, pp. 51–65.

La Porta, R., A. Lopez-de-Silanes, A. Shleifer, and R. Vishny, 2002, Investor protection and corporate valuation, *Journal of Finance* 57, pp. 1147–1170.

La Porta, R., F. Lopez-de-Silanes, A. Shleifer, and R. Vishny, 1999, The quality of government, *Journal of Law, Economics, and Organization* 15, pp. 222–279.

Lai, Y. H., and V. W. Tai, 2019, Managerial overconfidence and directors' and officers' liability insurance, *Pacific-Basin Finance Journal* 57, 101051.

Leung, W. S., K. P. Evans, and K. Mazouz, 2020, The R&D anomaly: Risk or mispricing? *Journal of Banking and Finance* 115, 105815.

Leuz, C., and P. D. Wysocki, 2008, Economic consequences of financial reporting and disclosure regulation: A review and suggestions for future research. Available at SSRN 1105398.

Li, B., Q. Sun, and C. Wang, 2014, Liquidity, liquidity risk and stock returns: Evidence from Japan, *European Financial Management* 20, pp. 126–151.

Li, K. F., and Y. P. Liao, 2014, Directors' and officers' liability insurance and investment efficiency: Evidence from Taiwan, *Pacific-Basin Finance Journal* 29, pp. 18–34.

Liang, Q., W. Gao, and L. Yan, 2024, Directors' and officers' liability insurance and corporate cash holdings: From principal–principal perspective, *Journal of Business Finance and Accounting* 51, pp. 1432–1466.

Liao, T. L., H. L. Chuang, and J. Y. Wang, 2022, Directors' and officers' liability insurance and the pricing of seasoned equity offerings, *International Review of Economics and Finance* 80, pp. 12–26.

Lin, C., K. C. Ko, and C. L. Lu, 2023, Why is the Amihud (2002) measure priced in Taiwan: Illiquidity or mispricing? *Pacific-Basin Finance Journal* 79, 101984.

Lin, C., M. S. Officer, T. Schmid, and H. Zou, 2019, Is skin in the game a game changer? Evidence from mandatory changes of D&O insurance policies, *Journal of Accounting and Economics* 68, 101225.

Lin, C., M. S. Officer, R. Wang, and H. Zou, 2013, Directors' and officers' liability insurance and loan spreads, *Journal of Financial Economics* 110, pp. 37–60.

Lin, C., M. S. Officer, and H. Zou, 2011, Directors' and officers' liability insurance and acquisition outcomes, *Journal of Financial Economics* 102, pp. 507–525.

Mayers, D., and C. W. Smith, 1982, On the corporate demand for insurance, In: Foundations of Insurance Economics: Readings in Economics and Finance (Springer Netherlands, Dordrecht) 190–205.

Mayers, D., and C. W. Smith, 1990, On the corporate demand for insurance: Evidence from the reinsurance market, *Journal of Business* 63, pp. 19–40.

Meng, Q., Z. Zhong, X. Li, and S. Wang, 2023, What protects me also makes me behave: The role of directors' and officers' liability insurance on empire-building managers in China, *Pacific-Basin Finance Journal* 80, 102085.

O'Sullivan, N., 1997, Insuring the agents: The role of directors' and officers' insurance in corporate governance, *Journal of Risk and Insurance* 64, pp. 545–556. https://doi.org/10.2307/253764

Pástor, Ľ., and R. F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, pp. 642–685.

Qu, S., 2024, Costs may be a blessing in disguise: Litigation risk and greenwashing, *Finance Research Letters* 62, 105069.

Rajgopal, S., and M. Venkatachalam, 2011, Financial reporting quality and idiosyncratic return volatility, *Journal of Accounting and Economics* 51, pp. 1–20.

Shi, C., Y. Sun, and J. Lyu, 2023, D&O insurance, technology independent directors, and R&D investment, *International Review of Financial Analysis* 89, 102868.

Skinner, D. J., 1994, Why firms voluntarily disclose bad news, *Journal of Accounting Research* 32, pp. 38–60.

Skinner, D. J., 1997, Earnings disclosures and stockholder lawsuits, *Journal of Accounting and Economics* 23, pp. 249–282.

Su, X. Q., 2016, Does systematic distress risk drive the investment growth anomaly? *The Quarterly Review of Economics and Finance* 61, pp. 240–248.

Su, X. Q., 2023, Directors' and officers' liability insurance and cross section of expected stock returns: A mispricing explanation, *Pacific-Basin Finance Journal* 77, 101938.

Tang, Y., K. C. Ho, J. Wu, L. Zou, and S. Yao, 2023, Directors and officers liability insurance and maturity mismatch: Evidence from China, *Applied Economics* 55, pp. 3747–3765.

Warfield, T. D., J. J. Wild, and K. L. Wild, 1995, Managerial ownership, accounting choices, and informativeness of earnings, *Journal of Accounting and Economics* 20, pp. 61–91.

Welker, M., 1995, Disclosure policy, information asymmetry, and liquidity in equity markets, *Contemporary Accounting Research* 11, pp. 801–827.

Wu, K., and S. Lai, 2020, Intangible intensity and stock price crash risk, *Journal of Corporate Finance* 64, 101682.

Wynn, J. P., 2008, Legal liability coverage and voluntary disclosure, *The Accounting Review* 83, pp. 1639–1669.

Yeh, Y. H., 2019, Corporate governance and family succession: New evidence from Taiwan, *Pacific-Basin Finance Journal* 57, 100967.

Yuan, R., J. Sun, and F. Cao, 2016, Directors' and officers' liability insurance and stock price crash risk, *Journal of Corporate Finance* 37, pp. 173–192.

Zou, H., and M. B. Adams, 2008, Debt capacity, cost of debt, and corporate insurance, *Journal of Financial and Quantitative Analysis* 43, pp. 433–466.

Appendix A
Variable Definitions

This table provides the definitions of the variables utilized in this research.

A. D&O Insurance	
DOIC	Limit of D&O insurance coverage scaled by year-end market capitalization
B. Stock illiquidity	
ILL	Yearly average of Amihud's (2002) daily illiquidity
C. Quality of information disclosure	
DD	Standard deviation of firm-specific accrual residuals (calculated using Equation (2) and based on data from years $y-4$ to y)
D. Firm characteristics	
ME	Year-end market capitalization
MB	Year-end market-to-book equity ratio
ROE	Earnings after taxes divided by the book value of equity
LEV	Ratio of a firm's total debt to total assets
DIVD	Dividend yield in a given year
CASH	Cash holding divided by the book value of total assets
SIGMA	Standard deviation of weekly returns, adjusted by Fama–French five factors
SKEW	Skewness coefficients of weekly returns, adjusted by Fama–French five factors
KURTS	Kurtosis coefficients of weekly returns, adjusted by Fama–French five factors
E. Corporate Governance	
BOSIZE	Number of board members
BOIND	Fraction of independent directors
BOSHR	Fraction of shares outstanding held by the board of directors
BODUAL	Fraction of directors who also occupy top manager positions
BODEV	Deviation of control to cash flow rights, as measured by La Porta *et al.* (1999, 2002)
BOBLOCK	Fraction of shares outstanding held by the top 10 largest shareholders
INST	Ownership held by qualified foreign institutional investors (QFIIs), mutual funds, and security dealers in the TWSE/TPEx