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Directors' and Officers' liability insurance and cross section of expected stock returns: A mispricing explanation☆

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ABSTRACT

To add to the literature on asset-pricing anomaly detection, this study tests the cross-sectional relationship between directors' and officers' liability insurance coverage (D&O insurance) and expected stock returns. A unique, near-complete sample of Taiwanese company stocks is used to document the D&O insurance anomaly that reveals stocks with high-D&O insurance significantly outperforming those with low-D&O insurance by 7% to 13% annually, after accounting for well-known risk factors. This high-minus-low D&O insurance return premium is robust to alternative weighting approaches and to the Fama–MacBeth regressions, which simultaneously control for various standard returns predictors and corporate governance measures. Furthermore, a D&O insurance-mimicking factor is used to document that the characteristic of D&O insurance can subsume the covariance of the D&O insurance-mimicking factor to predict returns, thus rejecting the rational risk explanation of the D&O insurance anomaly in favor of the behavioral mispricing explanation. Further evidence indicates that stocks of firms with high- (low-) D&O insurance tend to be undervalued (overvalued) and the high-minus-low D&O insurance return premium is concentrated among those undervalued stocks and is stronger in the presence of high limits-to-arbitrage, which are interpreted as consistent with the behavioral mispricing explanation.

1. Introduction

Literature on finance has extensively focused on whether directors' and officers' liability insurance (hereafter, D&O insurance) transfers a firm's litigation risk and, thus, creates value for insured firms' stakeholders. Researchers has increasingly investigated this issue because of the growing number of growing number of securities action lawsuits and premia of the world's top writers of D&O insurance.[1] Numerous studies on the value implication of D&O insurance have proposed that qualitative mechanisms embedded in D&O insurance coverage contribute to corporate decision-making and, consequently, performance outcomes—even if distinct value implications exist (e.g., Mayers and Smith Jr, 1990; Holderness, 1990; Core, 1997; O'Sullivan, 1997; Zou and Adams, 2008; Baker and Griffith, 2010; Lin et al., 2011; Lin et al., 2013; Li and Liao, 2014; Chen et al., 2016; Hwang and Kim, 2018; Kao et al., 2020; Donelson et al., 2021; Chiang and Chang, 2022). This study's central insight is that D&O insurance coverage policy, embodying the D&O insurers' private information about a firm's governance risk (e.g., Boyer, 2007; Boyer and Stern, 2014; Gillan and Panasian, 2015) and its

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[1] Refer to the report compiled by S&P Global Market Intelligence: https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/lawsuits-push-directors-and-officers-premiums-higher-as-esg-pandemic-risks-rise-66969716.

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internal evaluation of potential exposure to litigation risk (e.g., Lin et al., 2019), helps firms to better convert growth opportunities into higher firm value (Hwang and Kim, 2018), which, in turn, might have asset-pricing implications for predicting stock returns.

This study addresses an issue, which relates D&O insurance to the cross-sectional differences in expected stock returns, based primarily on two underlying assumptions. The first is that the disclosure of information contained in a D&O insurance contract (e.g., policy limit, deductible, and premium) is valuable to market participants (e.g., Baker and Griffith, 2007; Boyer, 2007; Boyer and Stern, 2012, 2014; Cao and Narayanamoorthy, 2014; Gillan and Panasian, 2015), thus motivating them to develop potentially profitable investment strategies. This assumption follows that by Chen et al. (2016), who documented that D&O insurance can increase the cost of equity capital and suggested that "investors factor D&O insurance information in their investment decisions." The second assumption is that firm value is endogenously driven by the D&O insurance purchase in the cross section. This assumption is common in the D&O insurance literature, which suggests cross-firm variations in D&O insurance purchase and addresses the issue of whether D&O insurance is a value add (e.g., Cross et al., 1989; Chen et al., 2016; Chang et al., 2018; Hwang and Kim, 2018; Lin et al., 2019). These two assumptions imply that, in theory, D&O insurance is important for investor's portfolio choice and asset pricing, thus explaining the cross section of expected stock returns.

For this study, stocks listed on the Taiwan Stock Exchange (TWSE) and Taipei Exchange (TPEx) were selected. Both TWSE and TPEx are the most active securities markets in the Asia-Pacific region and have a combined market capitalization of approximately $2051 billion as of September 2021 (ranked 14th globally) according to the World Federation of Exchanges. This study focuses on the Taiwan stock market for three reasons. First, most research on the role and consequences of D&O insurance has focused on developed markets, such as Canada, the US, and the UK, perhaps because of the availability of high-quality data from listed firms' common use of D&O insurance in common-law jurisdictions (Zou et al., 2008; Yuan et al., 2016). The advent of the *Taiwan Economic Journal* (*TEJ*) database allows in-depth examination of D&O insurance because, since 2008, the Taiwan Financial Supervisory Commission (FSC) has made it mandatory for TWSE/TPEx-listed companies to disclose D&O insurance information. The *TEJ* database includes companies that disclose information about D&O insurance purchases in their annual corporate filings starting in January 2008. The near-complete coverage of the *TEJ* database significantly expands the scope for researchers to test the relation between D&O insurance and a cross section of stock returns.

Second, over 10 years, studies have acknowledged that emerging markets, such as Taiwan, have benefited from the quality of corporate governance framework for corporate outcomes, as reflected in D&O insurance policies (e.g., Li and Liao, 2014; Kao et al., 2020; Huang et al., 2021).[2] Despite the advancement by firms in corporate governance, Taiwanese companies continue to face high governance risk, such as high ownership concentration and family controlled businesses, requiring special attention (e.g., Yeh, 2019). Hence, examining the effect of D&O insurance on Taiwanese equities helps investors in emerging markets better understand the governance risk they face, although global investors seeking diversification are attracted to emerging equity markets (e.g., Taiwan) that have shown higher expected returns (e.g., Harvey, 1995; Li et al., 2003; Bai and Green, 2010).

Third, like Huang et al. (2021), the data used in this study reveal that the proportion of the TWSE/TPEx-listed firms purchasing D&O insurance has grown rapidly from 44% in 2008 to 80% in 2018. Since 2019, FSC regulations stipulate that all publicly traded firms in Taiwan should purchase D&O insurance. Identification of economic implications of D&O insurance market should be studied to respond well to the rapid growth in the Taiwanese D&O insurance market. This study is the first to assess whether D&O insurance incrementally predicts the cross section of returns, particularly in the Taiwan stock market.

Using methodological approaches to identify anomalies (i.e., portfolio sorts of returns on anomaly variables and Fama and MacBeth regressions that use anomaly variables to explain the cross section of average returns) and the definition of D&O insurance coverage as the ratio of total D&O insurance limits to the market value of equity as of the fiscal year-end (denoted as *DOI*), the existence of the *DOI* anomaly in Taiwan equities from July 2009 to June 2021 is verified. This finding corroborates the new evidence that high-*DOI* firm stocks earn higher returns than low-*DOI* firm stocks for both raw and risk-adjusted returns, regardless of whether stocks are equal-, value-, price-, and share turnover-weighted in portfolios. An equal-weighted (value-weighted) hedge portfolio taking long positions in high-*DOI* decile stocks and short positions in low-*DOI* decile stocks yields significantly positive alphas of about 13.2% (7.1%) per annum, estimated based on the Fama–French five-factor model. This performance is robust and abnormal relative to other well-known benchmark risk factors, including the size/accrual mimicking factor in Hirshleifer et al. (2012), the Carhart (1997) momentum factor, the dividend yield factor, and the earnings-to-price factor. The bivariate-sorted portfolio tests that control for well-known returns characteristics individually (e.g., size, book-to-market, profitability, investment, momentum, and R&D expenditure) continue to support the existence of the *DOI* anomaly.

As literature has shown that the corporate purchase of D&O insurance promotes corporate governance mechanisms, one might argue that the new evidence on the *DOI* anomaly reflects the traditional governance premium (i.e., a hedge portfolio, long democracies, and short dictatorships generates an abnormal return) suggested by Gompers et al. (2003); Johnson et al. (2009); Giroud and Mueller (2011); and others. Thus, bivariate-sorted portfolio tests are conducted to investigate the high-minus-low *DOI* premium after controlling for various corporate governance mechanisms. There is robust evidence that there is significant spread in average returns between high and low *DOI* deciles after controlling for board structures such as ownership, size, independence, and duality, as well as other corporate governance-related measures such as the operating accruals in Sloan (1996), executives' critical control rights in Cubbin and Leech (1983), deviation of control rights to cash flow rights in La Porta et al. (1999, 2002), and block holder's ownership. This result confirms that the presence of the *DOI* anomaly in Taiwan not hitherto documented in governance-related literature.

[2] Refer to the study entitled "Corporate Governance in Emerging Markets" at a Harvard Law School Forum on Corporate Governance. https://corpgov.law.harvard.edu/2019/02/24/corporate-governance-in-emerging-markets-3/.

Furthermore, Fama and MacBeth regression results reveal that the robustness of *DOI*'s power to positively forecast the cross section of stock returns, even while controlling for other stock characteristics known to affect cross-sectional returns. According to the Fama and MacBeth regression, after controlling for various standard predictors and for the return predictors suggested to be highly correlated with *DOI*, a 2-standard-deviation increase in *DOI* predicts an increase of nearly 3.39% in the annual returns. The predictability afforded by *DOI* is highly statistically and economically significant.

Next, based on the methodological frameworks adopted by Daniel and Titman (1997), Hirshleifer et al. (2012), Li et al. (2016), Leung et al. (2020), Bongaerts et al. (2022), and Su et al. (2022), rational systematic risk and behavioral mispricing explanations are identified for *DOI* anomaly. First, this study follows the empirical asset-pricing literature is followed to create a *DOI* factor-mimicking portfolio, *DOIF*, based on the *DOI* anomaly by taking a long position on high-*DOI* stocks and a short position on low-*DOI* stocks (Section 4 describes the procedure in detail) and examines whether this *DOIF* explains the risk. From the mean-variance efficient strategy perspective, *DOIF* is an essential contributor. Specifically, during a sample period of July 2009–June 2021, when augmenting *DOIF* into the Fama–French three (five) candidate factors, the monthly Sharpe ratio of the ex-post tangency portfolio improves by 33% (19%), from 0.259 (0.418) to 0.345 (0.498), and *DOIF* constitutes a substantial weight at about 73% (33%) of the ex-post tangency portfolio. Second, analyzing the bivariate-sorted portfolios reveals that on controlling for the *DOI* characteristic, higher *DOIF* factor loadings are not associated with higher average returns. However, after controlling for the *DOIF* factor loading, the *DOI* characteristic continues to predict positive returns. The monthly Fama and MacBeth (1973) regressions at the portfolio and firm levels further show that *DOIF* factor loading does not predict returns after controlling for the *DOI* characteristic, while the *DOI* characteristic remains highly significant with or without controlling for the *DOIF* loading in cross-sectional regressions. This contradicts the argument that the *DOIF* loading proxies for the sensitivity to a fundamental risk factor and is compensated with higher expected returns. Therefore, the study findings that the *DOIF* covariation is subsumed by the *DOI* characteristic reject the covariance-based rational risk explanation of the *DOI* anomaly in favor of the characteristic-based behavioral mispricing explanation.

The limits-to-arbitrage theory claims that arbitrage is risky, costly, and limited when there are market frictions and investor mispricing is not fully eliminated (Shleifer and Vishny, 1997). As suggested by the behavioral mispricing literature, arbitrage costs directly influence sophisticated traders' ability to significantly affect corrective price, implying that costly-to-arbitrage stocks may experience greater mispricing (e.g., Lam and Wei, 2011; Cao and Han, 2016). A convincing behavioral mispricing explanation of the *DOI* anomaly requires theoretical motivations related to the limits-to-arbitrage. First, several studies have suggested that D&O insurance coverage deteriorates the quality of financial reporting and disclosure, leading to information asymmetry problem (Lin et al., 2013; Boubakri and Bouslimi, 2016; Huang et al., 2021). Accordingly, stocks of firms with more D&O insurance coverage probably exhibit “hard-to-value” characteristics, such as uncertainty, opacity, disagreement, and lack of predictive information. Hard-to-value stocks (e.g., high-*DOI* stocks) might be relatively more sensitive to speculative investment flows depending on investor behavioral biases, resulting in stock price continuation (e.g., Zhang, 2006). Second, as suggested by Barberis et al. (1998), market investors over- or underreact to information based on representativeness and conservatism heuristics. For a firm's D&O insurance policy, conservatism implies that market investors might be slow in updating their earlier beliefs in response to the corporate benefit of purchasing more D&O insurance (e.g., additional monitoring governance mechanism mentioned by Core (1997) and Jia and Tang (2018)). The corresponding stock price underreaction is subsequently corrected as market investors update. Third, an influential study by Hwang and Kim (2018) confirmed that D&O insurance acts as a value-creating mechanism to insured firms and concluded that the benefits of being insured (e.g., monitor corporate governance effect) dominate the negative effect of managerial opportunism stemming from being insured (e.g., moral hazard-driven agency problems). From the behavioral perspective, investors have limited attention and information processing power (Hirshleifer and Teoh, 2003; Barber and Odean, 2008). Therefore, inattentive investors—apart from ignoring specific features of the environment—might overestimate the negative moral hazard effect of D&O insurance and fail to incorporate its governance benefits into current financial information, thus undervaluing firms with more D&O insurance. When the governance benefits are subsequently realized, the mispricing is corrected and high-*DOI* firms earn larger positive return.

This study combines these ideas and deeply investigates the behavioral mispricing explanation of the *DOI* anomaly by assessing two testable implications. First, the cross-sectional relationship between relative valuation-based mispricing measure and *DOI* is examined. In support of behavioral mispricing, the *DOI* anomaly that high-*DOI* stocks earns higher future returns should be based on the fact that investors fail to value the benefits of D&O insurance purchase. Therefore, a positive *DOI*–return relationship might reflect investor's correction of the level of mispricing, implying that stocks of firms with high *DOI* are more likely to be undervalued, whereas those with low *DOI* may be overvalued. This study follows earlier literature to construct a relative valuation-based mispricing ratio that contradicts actual prices to imputed values derived from median industry value multiples (e.g., Doukas et al., 2005, 2010; Chen et al., 2013) and strongly supports the notion that stocks with high (low) *DOI* are generally associated with undervaluation (overvaluation). Furthermore, this study is further extended to examine whether the effect of *DOI* on expected stock returns is asymmetric, that is, the asymmetric effect of *DOI* on expected stock returns between undervalued stocks and overvalued stocks. Analyzing the bivariate-sorted portfolios, I find an asymmetric effect of *DOI*. Specifically, based on the equal-weighted (value-weighted) version of 10×3 bivariate-sorted portfolio, the high-minus-low *DOI* decile portfolio's alpha adjusted by the Fama–French five factors (FF5) is significant at 1.379% (1.194%) per month among undervalued stocks, while that is insignificant at 0.523% (−0.618%) per month among overvalued stocks, which can be interpreted as consistent with the behavioral mispricing explanation of the *DOI* anomaly.

Second, the effect of limits-to-arbitrage on the *DOI* anomaly is tested. Whether the *DOI* anomaly can be explained by behavioral mispricing hypothesis with limits-to-arbitrage proposed by literature is also examined (e.g., Shleifer and Vishny, 1997; Ali et al., 2003; Hirshleifer et al., 2012; Stambaugh et al., 2015; Li et al., 2016; Chu et al., 2020; Leung et al., 2020; Keloharju et al., 2021). The limits-to-arbitrage theory advocates that the limits of arbitrage and/or irrational pricing risk deters investors from fully correcting the mispricing, implying that stocks that are costlier or riskier to arbitrage should face greater persistent mispricing. Therefore, behavioral mispricing hypothesis predicts that the *DOI* anomaly is more pronounced for stocks with higher than with lower arbitrage costs. Following previous studies (e.g., Lam and Wei, 2011; Cao and Han, 2016), limits-to-arbitrage is considered in the form of idiosyncratic risk (proxied by idiosyncratic volatility, *IV*), transaction costs (proxied by Amihud (2002) illiquidity, *ILLIQ*), short-sale constraints (proxied by institutional ownership, *IO*), and information uncertainty (media coverage, *MEDIA*). These four common proxies for arbitrage cost levels verify that the average high-minus-low *DOI* return spread has a higher magnitude among stocks with high limits-to-arbitrage (high *IV*, high *ILLIQ*, low *IO*, and low *MEDIA*) than among stocks with low limits-to-arbitrage (low *IV*, low *ILLIQ*, high *IO*, and high *MEDIA*). For instance, testing the equal (value)-weighted version of 10×3 bivariate-sorted portfolio reveals that the high-minus-low *DOI* decile portfolio's alpha adjusted by FF5 is significant at 1.672% (1.084%) per month among high-*IV* stocks, which is higher than that among low-*IV* stocks (insignificant at 0.471% (−0.128%) per month). Consequently, certain hard-to-value and costly-to-arbitrage stocks, such as stocks with high *IV*, high *ILLIQ*, low *IO*, or low *MEDIA*, depend on greater mispricing relative to the degree of D&O insurance. To summarize, this empirical study's findings support the limits-to-arbitrage theory that the *DOI* anomaly derives mainly from investor mispricing.

It is worth mentioning that although the current paper confirms the *DOI* anomaly and attributes it to investor mispricing behavior, others may argue that there appears to be positive compensation for bearing systematic risk for the high-*DOI* firm stocks. That is, equity investors may associate higher D&O insurance coverage with greater exposure—that is imperfectly diversified—to different common risk factors (i.e., risk loadings or betas) and should receive a higher risk premium as compensation. A potential rational risk explanation for the *DOI* anomaly requires theoretical motivation that originates from the managerial risk-taking hypothesis proposed by Lin et al. (2013), Boyer and Tennyson (2015), and Chen et al. (2016).[3] With the protection offered by D&O insurance, D&Os in a firm covered heavily by D&O insurance are encouraged to invest more in risky projects that may be beneficial to shareholders (Chen et al., 2016), or even more likely to engage in more risk taking in pursuit of their own private objective (Lin et al., 2013). Regardless of whether risk-taking is beneficial or not, the behavioral phenomenon of managerial risk taking would lead entrepreneurial activity to be risky and poorly diversified (e.g., Vereshchagina and Hopenhayn, 2009; Armstrong and Vashishtha, 2012). Evidently, Chen et al. (2016) have suggested that high levels of D&O insurance coverage are associated with a firm's exposure to systematic market risk, strongly suggestive of greater risk taking as a channel by which D&O insurance coverage influences the cost of capital. Also, Lin et al. (2013) have documented that higher D&O insurance coverage is related to greater risk-taking and thus higher loan spreads as bank lenders view D&O insurance coverage as increasing default cost, which depresses asset payoffs in low states and the occurrence of low states is at least partly systematic (George and Hwang, 2010). Taken together, firm stocks with higher D&O insurance coverage, which are hypothesized to be particularly exposed to systemic shocks concerning market risk or default risk, need to offer higher equity returns to compensate their shareholders for being imperfectly diversified. If the rational risk explanation of the *DOI* anomaly was satisfied, the return spread between high- and low-*DOI* portfolios is partially or even fully subsumed by a plausible systematic risk factor driving the pricing kernel. The issues of whether *DOI* anomaly reflects a premium to compensate for systematic risk and which dimensions of systematic risk explain *DOI* anomaly should be further explored in future research.

This study makes two-fold contribution to the literature. First, this empirical study is perhaps the first to systematically provide evidence on the asset-pricing implications by relating D&O insurance to stock returns in the cross section. It is similar to but distinct from Chen et al. (2016), who documented that higher D&O insurance coverage is associated with lower earnings quality and greater risk-taking moral hazard behavior, leading to high equity cost. Despite the hypothesis proposed by Chen et al. (2016) that higher D&O insurance coverage implies higher expected returns (i.e., cost of equity), this study demonstrates that significant return differentials driven by D&O insurance address the issue of whether D&O insurance contains asset-pricing information. Alternatively, Boyer (2007) addressed this issue by showing that a profitable investment strategy, that is, long stocks with high-D&O insurance and short stocks with low D&O insurance unit prices (premium divided by coverage); however, the study did not focus on return anomaly explanations. This study adds to the literature by systematically investigating the role of D&O insurance that drives potential asset mispricing against the exposure to systematic risk implied in equity prices, which has remained understudied so far. Thus, this study explains the economic consequence of D&O insurance.

Second, this study relates to the literature focused on explaining the behavioral mispricing for asset-pricing anomalies, such as the book-to-market (Ali et al., 2003), asset growth (Lam and Wei, 2011), accrual (Hirshleifer et al., 2012), turnover premium (Chou et al., 2013), Max effect (Zhong and Gray, 2016), R&D a(Leung et al., 2020), and return seasonalities effect (Keloharju et al., 2021). This study offers new evidence that the D&O insurance characteristic can subsume the covariance of D&O insurance-based mimicking factor, and returns to *DOI* strategies are higher for undervalued stocks with higher arbitrage costs. It provides the first empirical support for the mispricing explanation of the *DOI* anomaly. Therefore, the study findings can have investment decision-making implications by better explaining how market participants respond to the private D&O insurance information possessed by insurers and insured companies on stock mispricing (Chalmers et al., 2002; Donelson et al., 2018).

This study is presented as follows. Section 2 describes the sample collection and the *DOI* characteristics in Taiwan. Section 3 presents and discusses the main empirical results of the cross-sectional relation between *DOI* and stock returns using two methodological approaches: portfolio sorts tests and Fama–MacBeth regressions analysis. Section 4 dissects the rational risk versus behavioral mispricing explanations of the *DOI* anomaly. Section 5 provides further evidence on the mispricing explanation of the *DOI* anomaly. Section 6 concludes the study.

[3] The author would like to thank the anonymous reviewer for this constructive comment.

2. Data and sample selection

2.1. Main sample: D&O insurance in Taiwan

The initial sample consists of stocks listed on the TWSE and the Taipei Exchange (TPEx) from 2008 to 2020 because the Taiwan FSC mandatorily required TWSE/TPEx-listed companies to disclose relevant information regarding D&O insurance as of 2008 (TWSE/TPEx-listed companies were not required to purchase D&O insurance until 2019). The *TEJ* database includes companies that disclose information on D&O insurance purchases in annual corporate filings starting in January 2008. According to Huang et al. (2021), during 2008–2018, several firms (an approximate average of 36% of publicly traded firms in Taiwan) failed to purchase D&O insurance and disclosed zero D&O insurance. Such a large subset of firms with zero D&O insurance is presumed to assimilate coarse and mixed information, creating difficulty in identifying firms that choose not to purchase D&O insurance for conscious strategic reasons, such as cost-cutting insurance premia, a lack of historical experience, managerial discretion, or unwilling to comply with regulations. Only firm-year observations are included in the final sample having data (nonmissing or nonzero values) on D&O insurance to mitigate the potential misinference of the results stemming from the numerous firms in the sample with zero D&O insurance.[4] Stocks in the financial services sector, such as banks, insurance companies, and financial services firms (two-digit industrial codes 28, 58, and 60), are also removed to avoid the bias that the financial services sector is tightly constrained by regulations. This filtering also helps to create a sample of firms that use homogeneous accounting principles.

Our main variable of concern is the annual D&O insurance coverage. Theoretically, the market value of equity is a proxy for the maximum liability exposure because scaling it increases the magnitude of the scaled D&O insurance measure (Lin et al., 2011). Therefore, this study follows the literature (e.g., Lin et al., 2011; Lin et al., 2013; Huang et al., 2021) and focuses on a continuous variable proxy for D&O insurance coverage as a firm's total D&O insurance coverage scaled by the firm's market value of equity at the end of the concurrent fiscal year (denoted as *DOI*).[5]

Table 1 presents the annual number of sample firms and summary statistics for D&O insurance. Here, the initial sample contains all listed firms on the TWSE/TPEx from 2008 to 2020—19,256 firm-year observations from the TEJ database. Then, 12,814 firm-years that purchased D&O insurance are identified, which represent the main sample stocks used in this study.

The D&O insurance coverage in Taiwan shows interesting patterns. First, similar to Huang et al. (2021), the proportion of the TWSE/TPEx-listed firms covered by D&O insurance gradually increased (from 44% in 2008 to 80% in 2018 and then to 100% in 2020), with an average of 64.9% for 2008–2020. The total number of D&O insurance limits among insured Taiwanese firms has increased over time (from NT$139.3 billion in 2008 to NT$323.5 billion in 2020), an average of NT$221.9 billion from 2008 to 2020.

Second, the D&O insurance coverage limits appear inadequate for insured Taiwanese firms. On average, the D&O insurance limit per covered firm is considerably low, at approximately NT$0.23 billion during 2008–2020. Furthermore, the mean rate of the D&O insurance limit to the market value (*DOI*) generally decreased, from 18.88% in 2008 to 5.61% in 2020, with an average of 8.44% during 2008–2020. These findings are consistent with Chiang and Chang (2022), who mentioned that the litigation risk protection of D&O in insured firms is relatively inadequate in Taiwan.

Third, the breadth of the D&O insurance coverage differs considerably across the insured firms, as indicated by the considerably broader inter-percentile range of 72.98% (from the 1st percentile of 0.08% to the 99th percentile of 73.06%) and the higher average standard deviation of 16.37% for 2008–2020. The year-by-year *DOI* distribution analysis reveals that the *DOI* distribution is relatively stationary over time; that is, across-firm variations induce much of the total variation in *DOI*, satisfying a sufficient condition to study whether the cross-sectional variation in asset returns can be explained by D&O insurance.

2.2. Characteristics of D&O Insurance Portfolios

Various firm characteristics (e.g., well-known return characteristics, limits-to-arbitrage measures, and the board structure and other corporate governance mechanisms) of stocks allocated into portfolios are investigated based on an annual D&O insurance coverage. On June 30 of each year t during 2009–2021, the TWSE/TPEx stocks are allocated into deciles based on *DOI*, and portfolios are formed from July of year t to June of year $t+1$. The portfolios are held for a one-year period and then rebalanced. Table 2 reports the formation-period (i.e., for the year before and including June of year t) descriptive statistics for various firm characteristics of the *DOI* decile portfolios. Consistent with Fama and French (1992), all accounting variables are considered at the end of June in year t, using accounting information from fiscal year-end $t-1$ from the *TEJ* database. For price-scaled or market value-scaled accounting ratios, such as book-to-market (*BM*), price or market value is adopted from December of year $t-1$. For firm capitalization, the market value of the firm's equity is adopted at the end of June of year t. For lagged return measures (e.g., 11-month lagged returns, used to measure momentum effect), a holding period return is estimated from July 1 of year $t-1$ to May 31 of year t. All variables are updated

[4] Slightly weaker but statistically significant results of the *DOI* return premium are obtained when firm-year observations with zero D&O insurance are included instead. For example, the untabulated results of Model (4) of the Fama−MacBeth regression in Table 5 show that the coefficient on *DOI* is significantly positive, at 0.8799 ($t = 2.19$), with the number of firm-month observations of 184,530 from July 2009 to June 2021.

[5] The overall results are quite similar when measuring the D&O insurance ratio scaled by the book value of total assets (*DOA*) and the book value of equity (*DOE*). The untabulated results of Model (4) of the Fama−MacBeth regression in Table 5 show that the coefficient on *DOA* is significantly positive, at 0.9512 ($t = 2.08$), and the coefficient on *DOE* is also significantly positive, at 0.6223 ($t = 3.37$), after controlling for the set of standard return predictors.

Table 1
Summary statistics on D&O insurance in Taiwan

Year	# Overall Firms	# Insured Firms	% Insured Firms	Summary Statistics for Insured Firms: Total Amount of Limits (NT$ in Billion)	Amount of Limits Per Covered Firm (NT$ in Billion)	Key Variable: DOI Mean (%)	SD (%)	1st (%)	Median (%)	99th (%)
2008	1206	532	44.1%	139.3	0.26	18.88	34.20	0.05	8.09	149.91
2009	1240	583	47.0%	144.5	0.25	7.43	14.96	0.09	3.65	72.59
2010	1305	634	48.6%	155.9	0.25	6.82	13.44	0.09	3.64	56.24
2011	1366	686	50.2%	166.6	0.24	10.23	18.83	0.12	5.04	84.68
2012	1418	775	54.7%	173.6	0.22	9.52	20.52	0.02	4.30	111.21
2013	1458	818	56.1%	184.4	0.23	7.22	11.97	0.04	3.57	51.99
2014	1512	885	58.5%	205.5	0.23	6.58	10.95	0.02	3.33	51.84
2015	1552	989	63.7%	242.8	0.25	8.68	16.68	0.12	3.96	80.03
2016	1595	1089	68.3%	256.6	0.24	7.64	14.23	0.10	3.71	65.59
2017	1632	1191	73.0%	261.1	0.22	6.30	12.00	0.06	3.11	54.67
2018	1657	1317	79.5%	295.2	0.22	7.74	15.75	0.09	3.68	65.40
2019	1655	1655	100.0%	335.2	0.20	7.10	18.78	0.12	3.09	57.81
2020	1660	1660	100.0%	323.5	0.19	5.61	10.44	0.09	2.72	47.79
Total/Avg	19,256	12,814	64.9%	221.9	0.23	8.44	16.37	0.08	3.99	73.06

This table presents the summary statistics on D&O insurance of TWSE/TPEx firms grouped by sample year during 2008–2020. # Overall Firms is the number of all TWSE/TPEx-listed stocks in a given year, and stocks in financial industries (two-digit industrial codes 28, 58, and 60) are removed. # Insured Firms (% Insured Firms) is the number (proportion) of sample firms that purchased D&O insurance in a given year. Total Amount of Limits is the total dollar amount of D&O insurance coverage limits for sample firms that purchased D&O insurance in a given year. Amount of Limits Per Covered Firm is calculated as Total Amount of Limits divided by # Insured Firms. *DOI* is the D&O insurance coverage limits scaled by the market value at the end of the concurrent fiscal year. All data used are collected from the *TEJ* database.

annually at the end of June each year. The definitions and exact formulas for all variables adopted in the study are also provided in Table 2.

Table 2 shows that the high-DOI decile is the portfolio with high-D&O insurance firms. The time-series average of the yearly cross-sectional mean D&O insurance (*DOI*) for these firms is substantial at 40.24%. In contrast, the low-*DOI*-decile firms are low-D&O insurance firms, with an average annual *DOI* of 0.38%. For all those with high/low-*DOI* firm characteristic comparisons, the spreads in characteristics across deciles high and low *DOI* are statistically significant.

First, for those well-known firm characteristics, I find that a generally monotonic increase in market capitalization (*ME*), operating income (*OP*), and asset growth (*INV*), but a generally monotonic decrease in *BM* equity ratios (*BM*), R&D expenditure (*RD*), and return momentum (*MOM*) from the high-DOI decile to the low *DOI* decile. For example, the high-DOI decile appears to have the smallest firms in the sample, with a time-series average of yearly cross-sectional mean capitalization (*ME*) of NT$1.21 billion, and are smaller than those firms in the low-*DOI* decile, which have capitalizations of NT$143.24 billion. The high-*DOI* firms have higher *BM* equity ratios than the low-*DOI* firms at 1.11 versus 0.56, respectively. The high-*DOI* firms tend to incur a loss and not profit (with *OP* of −14.77%) and may have low growth in asset (with *INV* of −5.78%) over a given formation-period. These patterns appear consistent with Lai and Tai (2019), who found that companies in Taiwan highly covered by D&O insurance are smaller, have lower return on assets, and lower sales growth. Moreover, such firms show greater R&D expenditure. The high-*DOI* firms have higher *RD* (6.67%) than the low *DOI* firms (1.92%), which is consistent with the finding in Hwang and Kim (2018).

Next, four proxies for the limits-to-arbitrage involving idiosyncratic risk, transaction costs, short-sale constraints, and information uncertainty are adopted to test the mispricing-linked limits-to-arbitrage explanation for *DOI*-based abnormal returns (e.g., Lam and Wei, 2011; Cao and Han, 2016). First, idiosyncratic risk is proxied by a stock's idiosyncratic return volatility (*IV*), measured as the standard deviation of weekly residuals from fitting the Fama and French (2015) five-factor model to the stock's realized returns in a given year (e.g., Pontiff, 1996; Wurgler and Zhuravskaya, 2002; Mashruwala et al., 2006). Second, transaction cost is proxied using the Amihud (2002) illiquidity measure (*ILLIQ*), calculated as the daily ratio of absolute stock returns to dollar volume averaged over a given year. Third, short-sale constraints are proxied by institutional ownership (*IOR*), measured as the ratio of the number of shares held by institutional investors to the total number of shares outstanding at the end of the most recent year (e.g., Cao and Han, 2016). Finally, this study is motivated by Veldkamp (2006) and Fang and Peress (2009), who suggested that media exposure increases asset prices by reducing the uncertainty over an asset's payoff; their study proxied for information uncertainty using a firm's media exposure (*MEDIA*), measured as the total number of newspaper articles about a stock over a given year. They focused on five influential dailies and mass media in Taiwan: *Commercial Times*, *Economic Daily News*, *DigiTimes*, *Wealth Magazine*, and *MoneyDJ*. From a limits-to-arbitrage perspective, high-DOI firms have higher degrees of limits-to-arbitrage than low-*DOI* firms. Specifically, a monotonic decrease in *IV* and *ILLIQ*, but increase in *IOR* and *MEDIA* are shown from the high- to the low-*DOI* decile. Over the sample period, the high-*DOI* (low-*DOI*) firms have *IV* at 5.54% (3.95%), *ILLIQ* at 31.43 (0.58), *IOR* at 7.04% (32.82%), and *MEDIA* at 21.10 (91.73). This

Table 2
Characteristics of D&O insurance decile portfolios.

Decile	*DOI*	Well-Known Firm Characteristics						Limits-to-Arbitrage				Board Structure and Other Governance Mechanisms							
		ME	*BM*	*OP*	*INV*	*RD*	*MOM*	*IV*	*ILLIQ*	*IOR*	*MEDIA*	*BOR*	*BSIZE*	*BIND*	*BDUAL*	*ACC*	*XCR*	*DEV*	*BLOCK*
High *DOI*	40.24	1.21	1.11	−14.77	−5.78	6.67	17.77	5.54	31.43	7.04	21.10	3.18	8.77	22.64	16.85	−6.21	2.22	2.36	20.63
9	14.55	1.59	1.06	−5.63	0.68	6.19	18.47	4.88	6.74	7.12	22.93	3.13	8.86	22.33	17.06	−3.31	2.21	2.29	19.95
8	9.28	2.51	0.97	2.16	4.66	5.34	17.43	4.54	2.41	8.53	25.26	3.08	9.00	22.73	16.85	−3.14	2.07	2.49	19.29
7	6.59	3.21	0.95	3.74	5.51	4.67	16.49	4.43	1.66	8.97	26.92	3.10	9.06	23.27	16.10	−2.99	2.24	2.94	19.16
6	4.87	4.39	0.89	5.31	5.02	4.18	14.39	4.23	2.09	10.91	31.43	3.04	9.15	22.73	16.54	−2.22	2.20	2.84	19.50
5	3.57	5.83	0.81	7.32	8.04	4.03	14.34	4.26	0.93	13.01	34.91	3.02	9.17	23.30	16.06	−2.51	2.08	3.09	19.40
4	2.60	8.72	0.81	8.64	8.78	3.63	15.66	4.17	0.56	14.61	37.07	3.00	9.31	22.57	16.53	−3.02	2.18	4.60	20.16
3	1.79	13.14	0.76	10.13	9.56	3.17	13.02	4.01	0.43	18.65	43.86	2.95	9.50	21.75	18.40	−2.31	2.28	4.00	20.82
2	1.06	23.82	0.67	11.53	11.81	2.65	13.93	4.05	0.16	23.08	53.01	2.97	9.67	21.72	18.36	−2.65	2.46	4.01	21.03
Low *DOI*	0.38	143.24	0.56	13.96	12.83	1.92	13.68	3.95	0.58	32.82	91.73	2.97	10.10	21.91	18.79	−3.03	2.49	4.80	22.36
H − L	39.86	−142.02	0.55	−28.73	−18.62	4.74	4.09	1.59	30.85	−25.78	−70.63	0.21	−1.33	0.72	−1.94	−3.17	−0.27	−2.44	−1.74
[t]	8.87	−25.79	4.09	−10.18	−11.72	6.47	2.43	5.48	4.52	−49.46	−5.16	11.86	−4.23	1.91	−6.62	−4.56	−9.75	−2.65	−5.53

This table presents the financial and return characteristics in each D&O insurance (*DOI*) decile portfolio. The sample consists of the TWSE/TPEx stocks that have purchased D&O insurance. Stocks in financial industries (two-digit industrial codes 28, 58, and 60) are removed. At the end of June of each year *t* over 2009 to 2021, sample stocks are allocated into deciles according to their *DOI* defined as the ratio of total D&O insurance limits to the market value of equity as of the fiscal year-end in calendar year *t–1*. *ME* is market equity at the end of June of year *t*. *BM* is the book-to-market ratio in year *t–1*. *OP* is the ratio of operating income (before interest, taxes, depreciation, and amortization) to net sales in year $t-1$. *INV* is the percentage change in total assets from the fiscal year ending in calendar year $t-2$ to fiscal year ending in calendar year $t-1$. *RD* is the ratio of R&D expenditure to the market value of equity as of the fiscal year-end in calendar year *t–1*. *MOM* is the 11-month buy and hold return over July($t-1$) to May(*t*). *IV* is the standard deviation of weekly residuals from fitting the Fama and French (2015) five-factor model to the stock's realized returns over January(*t–1*) to December(*t–1*). *ILLIQ* is the Amihud's (2002) daily ratio of absolute stock returns to dollar volume averaged over January(*t–1*) to December(*t–1*). *IOR* is the ratio of the number of shares held by institutional investors to the total number of shares outstanding at the end of December(*t–1*). *MEDIA* is the total number of media newspaper articles about a stock over January(*t–1*) to December(*t–1*). *BOR* is the total ownership held by all directors of the board at the end of December(*t–1*). *BSIZE* is total number of board members at the end of December(*t–1*). *BIND* is percentage of independent directors on board at the end of December(*t–1*). *BDUAL* is the board member duality defined as the percentage of directors who also occupies the top manager positions to the total number of board members at the end of December(*t–1*). *ACC* is the operating accruals, computed using Sloan (1996), in year $t-1$. *XCR* is the executives' critical control rights, computed using Cubbin and Leech (1983) at the end of December(*t–1*). *DEV* is the deviation of control rights to cash flow rights as in La Porta et al. (1999, 2002), in year $t-1$. *BLOCK* is the total ownership held by the 10 largest shareholders at the end of December(*t–1*). The numbers in each cell are time-series averages of yearly cross-sectional means. [t] presents the *t*-statistics, used to test the hypothesis that the difference in mean between High and Low *DOI* deciles is zero. All data used are collected from the TEJ database.

pattern is consistent with the ideal precondition that high-*DOI* stocks, which are hypothesized to be mispriced, are difficult to value and arbitrage.An in-depth analysis of the behavioral mispricing explanation for the *DOI* anomaly is discussed in Section 5.

Finally, when assessing the incremental return predictability of D&O insurance, traditional corporate governance structures such as board and other governance mechanisms should be considered as controls. This study focuses on four board structures, including board ownership (*BOR*), board size (*BSIZE*), board independence (*BIND*), and board duality (*BDUAL*), and four governance mechanisms, including the operating accruals (*ACC*) as in Sloan (1996) and Hirshleifer et al. (2012), the executives' critical control rights (*XCR*) as in Cubbin and Leech (1983), the deviation of control rights to cash flow rights (*DEV*) as in La Porta et al. (1999, 2002), and the 10 largest shareholders' ownership (*BLOCK*). From the board structures perspective, high-*DOI* firms in Taiwan tend to have higher board ownership, smaller board size, higher proportion of independent directors on the board, and lower likelihood that board members occupy the chair position of top managers. Additionally, from the perspectives of other governance mechanisms, the high-*DOI* firms in Taiwan also have lower operating accruals, fewer executives' critical control rights, lower deviation of control rights to cash flow rights, and lower block ownership. Firms with stronger governance may choose to purchase D&O insurance because high-DOI firms have lower *ACC*, *XCR*, *DEV*, and *BLOCK* in the year in which the *DOI* is ranked (Boyer and Tennyson, 2015). The following sections include these governance-related variables as controls to account for any direct effect of governance on equity returns.

3. Empirical results: *DOI* and stock returns in the cross section

3.1. Portfolio tests

This study conducts a univariate-sorted portfolio test to examine the relationship between D&O insurance and expected stock returns in the cross section. Every June of year *t* during 2009–2020, sample stocks are sorted into deciles on the basis of *DOI* at the end of year $t-1$. Equally weighted monthly returns on a portfolio are then calculated for the next 12 months (from July of year *t* to June of year $t+1$). Repeating this every year (annually rebalanced) yields a time-series of monthly returns for each *DOI* decile (i.e., July 2009–June 2021, 144 months). Table 3 presents the average monthly returns and risk-adjusted alphas estimated from the CAPM, the Fama and French (1993) three-factor model, and the Fama and French (2015) five-factor model for decile portfolios with high, 9, 8, …, and low *DOI*, and the difference between high and low deciles.

The results in Table 3 show that the average of the realized returns monotonically increases with D&O insurance coverage. The average monthly returns for equal-weighted portfolios with low, 2, 3, …, and high *DOI* are 0.898%, 0.872%, 1.055%, …, and 1.975%, respectively. A zero-investment portfolio that is long on high and short on low *DOI* deciles (the high-minus-low *DOI* portfolio; H − L) yields a statistically significant and economically meaningful return of 1.077% per month ($t = 3.36$) or approximately 12.9% per annum.

To evaluate whether the *DOI*-based return effect is explained by well-known factor models, the risk-adjusted alphas are observed for each *DOI* decile and H − L portfolio. For this purpose, the monthly excess returns (in excess of the one-year fixed savings deposit interest rate reported by the First Commercial Bank) is regressed for each *DOI* decile portfolio and the H–L spread against the market factor, the Fama and French (1993) three factors, and Fama and French (2015) five factors for calculating the CAPM alpha, FF3 alpha, and FF5 alpha, respectively, defined as the regression intercepts. Columns in Table 3, labeled "CAPM α," "FF3 α," and "FF5 α" show a similarly strong positive relationship between *DOI* and the abnormal future returns measured in terms of these alphas of the CAPM,

Table 3
DOI decile portfolios' returns.

Decile	Raw Ret (%)	[t]	CAPM α (%)	[t]	FF3 α (%)	[t]	FF5 α (%)	[t]	N
High *DOI*	1.975	3.83	0.863	2.38	0.657	2.56	0.776	3.08	84.8
9	1.720	3.14	0.447	1.29	0.224	1.23	0.252	1.34	85.3
8	1.324	2.42	0.004	0.01	−0.213	−1.40	−0.231	−1.45	85.1
7	1.317	2.52	0.038	0.13	−0.180	−1.38	−0.156	−1.20	85.2
6	1.144	2.22	−0.121	−0.41	−0.317	−2.41	−0.284	−2.09	85.3
5	1.183	2.38	−0.049	−0.18	−0.235	−1.76	−0.255	−1.81	85.2
4	1.056	2.15	−0.188	−0.74	−0.361	−2.99	−0.359	−2.83	85.1
3	1.055	2.33	−0.094	−0.40	−0.246	−1.74	−0.136	−0.94	85.2
2	0.872	1.99	−0.165	−0.92	−0.258	−2.03	−0.161	−1.23	85.1
Low *DOI*	0.898	2.24	−0.266	−1.26	−0.401	−3.07	−0.331	−2.42	84.7
H − L	1.077***	3.36	1.129***	3.56	1.058***	3.44	1.107***	3.59	–

This table presents average monthly returns for *DOI* decile portfolios. The sample consists of the TWSE/TPEx stocks that have purchased D&O insurance during July 2009–June 2021. Sample stocks in financial industries (two-digit industrial codes 28, 58, and 60) are removed. At the end of June of each year *t* over 2009 to 2020, sample stocks are sorted into deciles using *DOI* at the end of year $t-1$. Equally weighted monthly returns on a portfolio are then calculated from July of year *t* to June of year $t+1$. Repeating this every year (annually rebalanced) yields a time-series of monthly returns for each *DOI* decile (i.e., July 2009–June 2021, 144 months). H − L represents the monthly returns spread between high and low *DOI* deciles. The time-series average of monthly returns (Raw Ret) over July 2009–June 2021 is then computed for each *DOI* decile. CAPM α, FF3 α, and FF5 α are risk-adjusted alphas (in percentages per month) for each *DOI* decile portfolio, estimated based on the time-series regressions of the CAPM, the Fama–French three-factor model, and the Fama–French five-factor model. N is the average number of sample stocks in a given year. [t] presents the robust Newey-West (1987) *t*-statistics, used to test the hypothesis that the mean equals to zero. *** indicates statistical significance at the 1% level. All data used are collected from the *TEJ* database.

Table 4
DOI decile portfolios' returns: Robustness.

Panel A: Augmenting Additional Risk Factors

	FF5 + *ACF*		FF5 + *UMD*		FF5 + *DYF*		FF5 + *EPF*	
Decile	α (%)	[t]	α (%)	[t]	α (%)	[t]	α (%)	[t]
High *DOI*	0.671	2.65	0.888	3.40	0.787	3.10	0.777	3.07
9	0.210	1.10	0.341	1.77	0.254	1.35	0.252	1.34
8	−0.234	−1.44	−0.124	−0.76	−0.242	−1.51	−0.229	−1.44
7	−0.146	−1.10	−0.018	−0.14	−0.150	−1.14	−0.153	−1.18
6	−0.239	−1.75	−0.120	−0.91	−0.291	−2.12	−0.282	−2.08
5	−0.224	−1.57	−0.151	−1.05	−0.247	−1.74	−0.253	−1.79
4	−0.352	−2.72	−0.204	−1.65	−0.361	−2.82	−0.359	−2.82
3	−0.094	−0.64	0.016	0.11	−0.134	−0.91	−0.134	−0.92
2	−0.068	−0.54	−0.020	−0.16	−0.157	−1.20	−0.158	−1.22
Low *DOI*	−0.275	−2.01	−0.201	−1.48	−0.358	−2.64	−0.329	−2.41
H − L	0.946***	3.09	1.089***	3.39	1.145***	3.70	1.106***	3.57

Panel B: Alternative weighting approach

	Value-Weighted		Price-Weighted		Turnover-Weighted	
Decile	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]
High *DOI*	1.524	3.05	1.583	3.31	1.646	2.79
9	1.601	2.79	1.451	2.66	1.560	2.54
8	1.210	2.32	1.075	2.05	1.070	1.77
7	1.253	2.45	1.031	2.04	1.127	1.87
6	1.204	2.35	1.017	1.99	0.885	1.50
5	1.246	2.53	1.064	2.12	0.934	1.54
4	1.097	1.99	0.970	1.89	0.858	1.44
3	1.111	2.37	1.041	2.19	0.997	1.81
2	1.123	3.20	0.900	2.04	0.596	1.14
Low *DOI*	0.870	2.05	0.619	1.34	0.715	1.38
H − L	0.654**	2.61	0.964***	3.34	0.931***	2.62
CAPM α	0.588**	2.32	1.048***	3.54	0.919**	2.48
FF3 α	0.514**	2.25	0.951***	3.38	0.786**	2.26
FF5 α	0.595**	2.60	0.975***	3.45	0.923***	2.71

Panel C: Alternative characteristics-adjusted *DOI* decile portfolios

	ME-Adjusted		*BM*-Adjusted		*OP*-Adjusted		*INV*-Adjusted		*MOM*-Adjusted		*RD*-Adjusted	
Decile	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]
High *DOI*	1.777	3.40	1.844	3.63	1.892	3.82	1.936	3.81	1.838	3.74	2.100	3.88
9	1.490	3.03	1.383	2.58	1.660	3.30	1.623	3.13	1.571	3.04	1.619	3.12
8	1.333	2.55	1.291	2.40	1.354	2.68	1.309	2.41	1.498	2.68	1.320	2.51
7	1.302	2.62	1.212	2.42	1.208	2.31	1.280	2.39	1.200	2.28	1.416	2.72
6	1.246	2.49	1.255	2.44	1.131	2.28	1.331	2.67	1.168	2.32	1.169	2.34
5	1.149	2.25	1.021	2.07	1.197	2.32	1.021	2.04	1.200	2.44	1.187	2.40
4	1.077	2.21	1.307	2.74	1.222	2.47	0.979	2.04	1.061	2.17	1.172	2.47
3	1.028	2.16	1.036	2.20	1.066	2.24	0.995	2.16	1.108	2.30	1.125	2.43
2	0.951	2.13	1.038	2.34	0.795	1.76	0.939	2.14	1.015	2.29	0.906	2.04
Low *DOI*	1.101	2.61	1.070	2.66	0.974	2.34	1.033	2.53	0.892	2.12	0.888	2.20
H − L	0.676***	3.27	0.774**	2.59	0.918***	3.50	0.903***	3.29	0.946***	3.22	1.212***	3.88
CAPM α	0.486**	2.40	0.722**	2.35	0.874***	3.23	0.850***	3.00	0.978***	3.23	1.097***	3.38
FF3 α	0.418**	2.18	0.647**	2.29	0.812***	3.22	0.763***	3.02	0.906***	3.13	0.987***	3.28
FF5 α	0.485**	2.55	0.679**	2.38	0.684***	2.66	0.797***	3.12	0.913***	3.15	1.066***	3.76

This table presents average monthly returns for *DOI* decile portfolios based on a variety of robustness analyses. The sample consists of the TWSE/TPEx stocks that have purchased D&O insurance during July 2009–June 2021. Sample stocks in financial industries (two-digit industrial codes 28, 58, and 60) are removed. *DOI* decile portfolios in Panels A and B are formed as in Table 3. Panel A presents risk-adjusted alphas (in percentages per month) for each *DOI* decile portfolio, estimated based on the time-series regressions of the Fama–French five-factor model augmented by each of various risk factors, including size/accrual mimicking factor (*ACF*) in Hirshleifer et al. (2012), Carhart (1997) momentum factor (*UMD*), the dividend yield factor (*DYF*), and the earnings-to-price factor (*EPF*). Panel B presents the raw monthly returns and risk-adjusted alphas (CAPM α, FF3 α, and FF5 α) for value-, price-, and turnover-weighted portfolios. Panel C presents the raw monthly returns and risk-adjusted alphas (CAPM α, FF3 α, and FF5 α) for bivariate-sorted *DOI* decile portfolios after controlling various firm characteristics, including *ME*, *BM*, *OP*, *INV*, *MOM*, or *RD* that are defined in Table 2. At the end of June of each year *t* over 2009 to 2020, sample stocks are first sorted into terciles according to *ME*, *BM*, *OP*, *INV*, *MOM*, or *RD*. Each such tercile portfolio is further sorted into *DOI* decile portfolios. Equally weighted monthly returns on a portfolio are then calculated from July of year *t* to June of year *t + 1*. Repeating this every year (annually rebalanced) generates a time-series of monthly returns for each 3 × 10 portfolio (i.e., July 2009–June 2021, 144 months). From the 3 × 10 bivariate-sorted portfolios, the average return is calculated across characteristic terciles for a given *DOI* decile portfolio. The time-series average of monthly returns and risk factor-adjusted alphas for each *DOI* deciles and the H − L *DOI* portfolio are computed. [t] presents the robust Newey-West (1987) *t*-statistics, used to test the hypothesis that the mean equals to zero. ** and *** indicate the statistical significance at the 5% and 1% levels, respectively. All data used are collected from the TEJ database.

FF3, and FF5. For example, for the equal-weighted portfolios, the risk-adjusted FF5 alpha for the H–L portfolio equals 1.107% per month or approximately 13.3% per annum, with a *t*-statistics of 3.59. Overall, sorting stocks on *DOI* alone generates a significant return differential in the cross section, implying strong evidence for the ability of D&O insurance to predict future returns.

3.2. Robustness tests

In Table 4, several robustness analyses on the portfolio tests are presented. First, in Panel A of Table 4, risk-adjusted monthly returns are presented using the Fama and French (2015) five-factor model, which adds various risk factors, including the Hirshleifer et al. (2012) size/accrual factor-mimicking portfolio (*ACF*), the Carhart's (1997) momentum factor (*UMD*), the dividend yield factor (*DYF*), and the earnings-to-price factor (*EPF*). The results are similar to the five-factor alpha results. Specifically, a strategy that buys stocks in the high-*DOI* decile and sells in the low-*DOI* decile generates an average monthly abnormal return (alpha) of 0.946% (*t*-statistic = 3.09), 1.089% (*t*-statistic = 3.39), 1.145% (*t*-statistic = 3.70), and 1.106% (*t*-statistic = 3.57), when the risk factor model in which the *ACF*, *UMD*, *DYF*, or *EPF* is added into the Fama and French (2015) five-factor model, respectively. These results suggest that the high-*DOI* return premium cannot be fully explained by a rational asset-pricing factor model.

Second, in Table 3, equal-weighted *DOI* portfolio returns are reported to allow for comparing the results with several cross-sectional return studies that adopted equal weighting. However, to ensure that the study results are not driven primarily by the returns to small firms or other characteristics such as low price and low share turnover in the equal-weighted portfolios, Panel B of Table 4 reports the average monthly returns and risk-adjusted alphas (CAPM α, FF3 α, and FF5 α) of value-, price-, and turnover-weighted *DOI* portfolios.[6] Testing these portfolios provides qualitatively similar results. For example, the average value-, price-, and turnover-weighted monthly return spread between high- and low-*DOI* stocks (H − L) is a significant 0.654% (*t*-statistic = 2.61), 0.964% (*t*-statistic = 3.34), and 0.931% (*t*-statistic = 2.62), respectively. After adjusting for the risk factors, for example, the monthly FF5 alpha of the H − L portfolio is still significantly positive at 0.595% (*t*-statistic = 2.60), 0.975% (*t*-statistic = 3.45), and 0.923% (*t*-statistic = 2.71) for the value-, price-, and turnover-weighted portfolios, respectively.

Third, to control for the prominent firm characteristics that may predict equity returns, Panel C of Table 4 conducts the bivariate-sorted portfolio tests and reports the average monthly returns and risk-adjusted alphas (CAPM α, FF3 α, and FF5 α) of stocks bivariate-sorted by prominent return characteristic and then by *DOI*. Following the methodological approach in Zhong and Gray (2016), at the end of June of each year *t* over 2009 to 2020, sample stocks are first sorted into terciles according to each firm characteristic *ME*, *BM*, *OP*, *INV*, *MOM*, or *RD*. Each such tercile portfolio is further sorted into *DOI* decile portfolios. Equally weighted monthly returns on a portfolio are then calculated from July of year *t* to June of year $t+1$. Repeating this every year (annually rebalanced) generates a time-series of monthly returns for each 3 × 10 portfolio (i.e., July 2009–June 2021, 144 months). From the 3 × 10 bivariate-sorted portfolios, the average return is calculated across characteristic terciles for a given *DOI* decile portfolio. The time-series average of monthly returns and risk factor-adjusted alphas for each characteristic-adjusted *DOI* deciles and the H − L portfolio are computed.

Panel C of Table 4 shows that the H − L *DOI* return premium is robust to controlling for various prominent firm characteristics. For each control variable (i.e., *ME*, *BM*, *OP*, *INV*, *MOM*, or *RD*), a near-monotonic relationship exists between *DOI* and average returns, which is consistent with the findings from the univariate-sorted portfolio tests reported in Table 3. After neutralizing portfolios to the control variable, the average monthly returns of the H − L *DOI* portfolio are statistically significantly positive in all cases examined. For example, when using the *BM*-adjusted *DOI* decile portfolio test, the spread between 1.844% for the high-*DOI* decile and 1.070% for the low-*DOI* decile represents a statistically and economically significant return on the zero-cost portfolio of 0.774% per month or approximately 9.3% per annum ($t = 2.59$). After adjusting for the risk factors, the monthly CAPM, FF3, and FF5 alphas of the H − L portfolio are still significantly positive at 0.722% (*t*-statistic = 2.35), 0.647% (*t*-statistic = 2.29), and 0.679% (*t*-statistic = 2.38), respectively.

Additionally, as suggested by Chen et al. (2017), protection from D&O insurance affects managerial incentives and, thus, drives corporate R&D spending activities. Moreover, studies have well documented the R&D anomaly, i.e., higher R&D is found to earn significantly positive stock returns (e.g., Leung et al., 2020; Hou et al., 2022), thus motivating further control for the potential R&D effect and showing that after neutralizing *DOI* portfolios to the control variable R&D, the average monthly raw return, CAPM α, and FF3 α, and FF5 α of the H − L portfolio remain significantly positive at 1.212% (*t*-statistic = 3.88), 1.097% (*t*-statistic = 3.38), 0.987% (*t*-statistic = 3.28), and 1.066% (*t*-statistic = 3.76), respectively. This suggests that the evidence on the high-*DOI* return premium is not driven by the R&D effect.

To summarize, incorporating additional risk factors, considering alternative weighting approaches, and using the bivariate-sorted portfolio tests to control for the potential confounding influence of prominent return characteristics, Table 4 offers strong evidence that the return premium associated with *DOI* is robust, which supports the unconditional results in Table 3.

[6] The value- and price-weighted portfolios are formed based on the market equity and share price at the end of June in formation year, and the turnover-weighted portfolios are formed based on the total share turnover over July in pre-formation year to June in formation year.

3.3. Controlling for other corporate governance mechanisms

As documented by literature that the corporate purchase of D&O insurance promotes corporate governance mechanisms, one might argue that the new evidence on the *DOI* anomaly just reflects the traditional governance premium (i.e., a hedge portfolio, long democracies and short dictatorships, generates an abnormal return) suggested by Gompers et al. (2003), Johnson et al. (2009), Giroud and Mueller (2011), and others. To rule out this concern, bivariate-sorted portfolio tests are conducted by examining the average monthly returns for *DOI* decile portfolios, controlling for various corporate governance mechanisms.

Similar to Panel C of Table 4, at the end of June of each year *t* over 2009 to 2020, sample stocks are first sorted into terciles according to each governance mechanism, including measures of board structures (*BOR*, *BSIZE*, *BIND*, and *BDUAL*) and other governance/agency-link variables (*ACC*, *XCR*, *DEV*, and *BLOCK*). Each such tercile portfolio is further sorted into *DOI* decile portfolios. Equally weighted monthly returns on a portfolio are then calculated from July of year *t* to June of year $t + 1$.[7] Repeating this every year (annually rebalanced) generates a time-series of monthly returns for each 3×10 portfolios (i.e., July 2009–June 2021, 144 months). From the 3×10 bivariate-sorted portfolios, the average return is calculated across characteristic terciles for a given *DOI* decile portfolio. The time-series average of monthly returns and risk factor-adjusted alphas (CAPM α, FF3 α, and FF5 α) for each governance-adjusted *DOI* decile and the H − L *DOI* portfolio are computed and reported in Table 5.

Panel A of Table 5 reports the average monthly returns, CAPM α, FF3 α, and FF5 α for *DOI* decile portfolio after controlling for a set of board structures measures. As shown, the differences in the average returns on the high- and low-*DOI* decile portfolios obtained by first sorting *BOR*, *BSIZE*, *BIND*, and *BDUAL* equal 1.170% ($t = 3.56$), 0.993% ($t = 2.88$), 1.106% ($t = 3.17$), and 1.051% per month ($t = 3.05$), respectively. These *DOI* anomalies persist in the estimated alphas when adjusting for the CAPM and the FF3 and FF5. For example, the zero-cost H − L *DOI* portfolio yields a CAPM α of 1.106%, a FF3 α of 1.028%, and a FF5 α of 1.032% per month, all significant at the 1% level, after adjusting for *BIND*.

Panel B reports the average monthly returns, CAPM α, FF3 α, and FF5 α for *DOI* decile portfolio after controlling for other governance/agency-link variables (*ACC*, *XCR*, *DEV*, and *BLOCK*). Similar to patterns in Panel A, the average return, CAPM α, FF3 α, and FF5 α of the H − L portfolio double sorts based on *DOI*, in which we first sort on *ACC*, *XCR*, *DEV*, or *BLOCK*, all remain significant at the 1% level. For example, the resulting average return, CAPM α, FF3 α, and FF5 α for the H − L *DOI* portfolio obtained by first sorting on accrual (*ACC*) equal 1.169%, 1.056%, 0.939%, and, 1.040% per month, respectively. These economically large spreads also have highly significant *t*-statistics, underscoring that operating accruals (*ACC*) cannot explain the predictability of *DOI*.

Thus, Table 5 explores evidence that the future returns and *DOI* remain positively related after controlling for traditional corporate governance-related measures. This result confirms that Taiwan shows *DOI* anomaly not documented so far in governance-related literature.

3.4. Fama–MacBeth cross-sectional regressions

The portfolio tests discussed earlier ignore potentially important firm-level information by aggregating the stocks into decile portfolios. Additionally, although bivariate-sorted portfolio tests provide the advantage of controlling for any potential nonlinear impact, only one return characteristic at a time can be controlled in the test. Therefore, a regression approach that allows for multiple controls is reviewed. This section reports the results from various standard Fama and MacBeth (1973) cross-sectional type regressions that simultaneously control for multiple return predictors. The following cross-sectional regression is estimated for every month *m* during July 2009–June 2021:

$$\begin{aligned} R_{i,m,t+1} = & \gamma_{0,m} + \gamma_{1,m} DOI_{i,m,t} + \sum_{j=1}^{K} \gamma_{j,m} Z_{j,i,m,t} + \gamma_{2,m} lnME_{i,m,t+1} + \gamma_{3,m} STR_{i,m,t+1} + \gamma_{4,m} LTR_{i,m,t+1} + \gamma_{5,m} MOM_{i,m,t+1} + \sum_{b=1}^{5} \gamma_{b,m} Beta_{b,i,m,t+1} \\ & + \sum_{h=1}^{Q} \gamma_{h,m} IND_{h,m,t+1} + \epsilon_{i,m,t+1} \end{aligned} \tag{1}$$

where $R_{i,\, m,\, t+1}$ is the one-year future return for stock *i* over month *m* in year $t + 1$. Note that the one-year future returns are calculated from July$(t + 1)$ to June$(t + 2)$. $DOI_{i,\, m,\, t}$ is stock *i*'s *DOI* as of the fiscal year-end in calendar year *t*. The *K* stock-specific control variables $Z_{j,\, i,\, m,\, t}$, including *lnBM*, *OP*, *INV*, *RD*, *IV*, *ILLIQ*, *IOR*, *MEDIA*, *BOR*, *BSIZE*, *BIND*, *BDUAL*, *ACC*, *XCR*, *DEV*, and *BLOCK* as of the fiscal year-end in calendar year *t*, are defined in Table 2. $lnME_{i,\, m,\, t+1}$ is the natural logarithm of market equity at the end of June of year $t + 1$. $STR_{i,\, m,\, t+1}$ is the short-term reversal, measured as stock *i*'s past returns in month $m - 1$ beginning from July$(t + 1)$. $LTR_{i,\, m,\, t+1}$ is the long-term reversal (the 48-month buy and hold return), measured as stock *i*'s past returns during months $m - 60$ to $m - 13$ beginning from July$(t + 1)$. $MOM_{i,\, m,\, t+1}$ is the momentum effect (the 11-month buy and hold return), measured as stock *i*'s past returns during months $m - 12$ to $m - 2$ beginning from July$(t + 1)$. $Beta_{b,\, i,\, m,\, t+1}$ are the Fama and French (2015) five-factor loadings (β_{MKT}, β_{SMB}, β_{HML}, β_{RMW}, and β_{CMA}), estimated using monthly data over the previous 36 months (24 months minimum) beginning from the end of June $(t + 1)$ (annually rebalanced). $IND_{h,\, m,\, t+1}$ are industry dummies, identified by the TWSE/TPEx two-digit industrial codes as of the fiscal year-end in calendar year $t + 1$. The time-series average of the coefficient estimates from Eq. (1), along with their Newey and West (1987) robust *t*-statistics with eight lags, are reported in Table 6.

[7] The untabulated results are quite similar when the value-weighted version of *DOI* portfolios is adopted.

Table 5
DOI decile portfolios' returns: Controlling for board structure and other corporate governance mechanisms.

Panel A: *DOI*-based portfolio returns controlling for board structure

	BOR-Adjusted		*BSIZE*-Adjusted		*BIND*-Adjusted		*BDUAL*-Adjusted	
Decile	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]
High *DOI*	2.074	3.76	1.929	3.73	2.023	3.86	1.985	3.77
9	1.612	3.19	1.722	3.48	1.695	3.43	1.745	3.56
8	1.471	2.69	1.134	2.16	1.036	1.97	1.066	2.02
7	1.382	2.61	0.817	1.27	0.793	1.25	0.794	1.24
6	1.079	1.99	0.793	1.54	0.828	1.59	0.804	1.57
5	0.855	1.71	1.374	2.51	1.265	2.32	1.299	2.33
4	0.958	2.03	1.066	2.05	1.036	2.01	1.097	2.15
3	1.386	2.34	1.065	1.96	1.160	2.15	1.091	2.02
2	0.992	2.21	0.637	1.44	0.693	1.54	0.684	1.51
Low *DOI*	0.904	2.25	0.936	2.08	0.917	2.06	0.934	2.09
H − L	1.170***	3.56	0.993***	2.88	1.106***	3.17	1.051***	3.05
CAPM α	1.031***	3.02	1.027***	2.84	1.106***	3.03	1.032***	2.86
FF3 α	0.918***	2.88	0.950**	2.59	1.028***	2.87	0.952**	2.60
FF5 α	1.013***	3.37	0.972***	2.87	1.032***	3.11	0.965***	2.96

Panel B: *DOI*-based portfolio returns controlling for other governance mechanisms

	ACC-Adjusted		*XCR*-Adjusted		*DEV*-Adjusted		*BLOCK*-Adjusted	
Decile	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]
High *DOI*	2.029	3.78	2.072	3.82	2.088	3.80	2.056	3.83
9	1.664	3.36	1.519	3.13	1.637	3.21	1.618	3.21
8	1.490	2.70	1.486	2.76	1.392	2.59	1.356	2.51
7	0.945	1.41	1.439	2.67	1.435	2.72	1.400	2.62
6	1.088	2.09	1.029	1.90	1.005	1.86	1.217	2.27
5	1.235	2.54	1.002	2.01	0.946	1.89	0.670	1.35
4	0.707	1.43	1.120	2.41	1.068	2.24	1.127	2.34
3	1.335	2.36	1.353	2.22	1.337	2.25	1.418	2.36
2	1.006	2.07	0.933	1.98	0.918	2.04	0.921	2.00
Low *DOI*	0.860	2.16	0.882	2.17	0.932	2.31	0.900	2.23
H − L	1.169***	3.68	1.190***	3.75	1.156***	3.65	1.156***	3.70
CAPM α	1.056***	3.19	1.085***	3.28	1.016***	3.09	1.059***	3.24
FF3 α	0.939***	3.07	0.967***	3.17	0.905***	2.96	0.951***	3.13
FF5 α	1.040***	3.59	1.039***	3.58	0.963***	3.31	1.007***	3.50

This table presents average monthly returns and risk-adjusted alphas (CAPM α, FF3 α, and FF5 α) for *DOI* decile portfolios, after controlling for board structure (*BOR*, *BSIZE*, *BIND*, and *BDUAL*) in Panel A and other corporate governance mechanisms (*ACC*, *XCR*, *DEV*, and *BLOCK*) in Panel B. The sample consists of the TWSE/TPEx stocks that have purchased D&O insurance during July 2009–June 2021. Sample stocks in financial industries (two-digit industrial codes 28, 58, and 60) are removed. At the end of June of each year *t* over 2009 to 2020, sample stocks are first sorted into terciles according to *BOR*, *BSIZE*, *BIND*, *BDUAL*, *ACC*, *XCR*, *DEV*, and *BLOCK*. Each such tercile portfolio is further sorted into *DOI* decile portfolios. Equally weighted monthly returns on a portfolio are then calculated from July of year *t* to June of year $t + 1$. Repeating this every year (annually rebalanced) generates a time-series of monthly returns for each 3×10 portfolio (i.e., July 2009–June 2021, 144 months). From the 3×10 bivariate-sorted portfolios, the equal-weighted average is calculated across characteristic terciles for a given *DOI* decile portfolio. The time-series average of monthly returns for each *DOI* deciles is computed. [t] presents the robust Newey-West (1987) *t*-statistics, used to test the hypothesis that the mean equals to zero. ** and *** indicate the statistical significance at the 5% and 1% levels, respectively. All data used are collected from the *TEJ* database.

As shown in Models (1) and (2) in Table 6, the average *DOI* coefficients are both statistically significantly positive before and after incorporating various standard controls. When *DOI* is included as the only predictor in Model (1), the average *DOI* coefficient is 1.7107 ($t = 3.31$). In Model (2), when included jointly with various combinations of control variables such as *lnME*, *lnBM*, *OP*, *INV*, *RD*, *STR*, *LTR*, *MOM*, the five-factor loadings, and the industry dummies, the average *DOI* coefficient remains significantly positive at 0.8691 ($t = 2.93$). Note that the signs of the coefficients on those standard controls such as *BM*, *INV*, *RD*, *STR*, and *MOM* are consistent with previous literature. For example, consistent with Leung et al. (2020) and Hou et al. (2022), the longevity of the R&D anomaly in Taiwan (coefficient = 1.8140 with a $t = 2.59$), i.e., R&D expenditure, earns significant positive stock returns. The evidence in Models (1) and (2) suggests that stocks covered more by D&O insurance earn, on average, higher returns, even after controlling for the standard predictors.

Turning to Model (3) of Table 6, and the multiple regressions that simultaneously add limits-to-arbitrage-related variables (i.e., *IV*, *ILLIQ*, *IOR*, and *MEDIA*) as controls, the average *DOI* coefficient is still highly significant at 1.0024 ($t = 2.82$). Note that the signs of the coefficients on those limits-to-arbitrage-related variables are supported by previous literature. For example, a strongly negative relationship is found between *IV* and future stock return, supported by the coefficient on *IV* at −0.1614 ($t = -4.40$). This is consistent with Ang et al. (2009), who have documented that stocks with recent past high idiosyncratic volatility have low future average returns worldwide. Consistent with the study by Fang and Peress (2009) on no-media premium, the coefficient on *MEDIA* is significantly

Table 6
Fama–MacBeth cross-sectional regressions of stock returns on *DOI*.

	(1)		(2)		(3)		(4)	
Intercept	1.0751	[2.50]**	0.3236	[1.51]	0.3506	[1.12]	−0.0669	[−0.22]
DOI	**1.7107**	**[3.31]** ***	**0.8691**	**[2.93]** ***	**1.0024**	**[2.82]** ***	**0.8625**	**[2.56]** **
lnME			−0.0885	[−1.51]	−0.1649	[−2.21]**	−0.1702	[−2.03]**
lnBM			0.4010	[2.87]***	0.2521	[1.58]	0.2816	[1.83]*
OP			−0.0024	[−1.12]	−0.0031	[−1.11]	−0.0034	[−1.17]
INV			−0.0023	[−1.77]*	−0.0014	[−0.99]	−0.0011	[−0.86]
RD			1.8140	[2.59]**	1.7247	[2.40]**	1.6015	[2.33]**
STR			−0.0090	[−1.88]*	−0.0090	[−1.78]*	−0.0085	[−1.60]
LTR			−0.0003	[−1.42]	−0.0001	[−0.59]	−0.0001	[−0.56]
MOM			0.0038	[2.54]**	0.0044	[2.96]***	0.0043	[2.94]***
IV					−0.1614	[−4.40]***	−0.1567	[−4.57]***
ILLIQ					0.0090	[2.32]**	0.0085	[2.24]**
IOR					0.0062	[2.23]**	0.0063	[2.33]**
MEDIA					−0.0012	[−1.69]*	−0.0012	[−1.77]*
BOR							0.0776	[0.74]
BSIZE							0.0172	[2.21]**
BIND							0.1432	[0.35]
BDUAL							0.2034	[1.01]
ACC							−0.3390	[−2.04]**
XCR							−0.0443	[−1.78]*
DEV							0.0011	[0.45]
BLOCK							−0.0003	[−0.08]
Five-Factor Loadings	N		Y		Y		Y	
Industry Dummies	N		Y		Y		Y	
Average R^2	0.91%		11.75%		13.21%		14.55%	
Average N	851.0		838.4		835.5		833.6	

This table presents firm-level Fama–MacBeth regression results. The sample consists of the TWSE/TPEx stocks that have purchased D&O insurance during July 2009–June 2021. Sample stocks in financial industries (two-digit industrial codes 28, 58, and 60) are removed. The cross-sectional regression is estimated for every month *m*:

$$R_{i,m,t+1} = \gamma_{0,m} + \gamma_{1,m} DOI_{i,m,t} + \sum_{j=1}^{K} \gamma_{j,m} Z_{j,i,m,t} + \gamma_{2,m} lnME_{i,m,t+1} + \gamma_{3,m} STR_{i,m,t+1}$$
$$+ \gamma_{4,m} LTR_{i,m,t+} + \gamma_{5,m} MOM_{i,m,t+1} + \sum_{b=1}^{5} \gamma_{b,m} Beta_{b,i,m,t+1}$$
$$+ \sum_{h=1}^{Q} \gamma_{h,m} IND_{h,m,t+1} + \epsilon_{i,m,t+1}$$

where $R_{i,\ m,\ t+1}$ is the one-year future return for stock *i* over month *m* in year $t+1$. Note that the one-year future returns are calculated for the period July($t+1$) to June($t+2$). $DOI_{i,\ m,\ t}$ is stock *i's DOI* as of the fiscal year-end in calendar year *t*. The *K* stock-specific control variables $Z_{j,\ i,\ m,\ t}$, including *lnBM*, *OP*, *INV*, *RD*, *IV*, *ILLIQ*, *IOR*, *MEDIA*, *BOR*, *BSIZE*, *BIND*, *BDUAL*, *ACC*, *XCR*, *DEV*, and *BLOCK* as of the fiscal year-end in calendar year *t*, are defined as in Table 2. $lnME_{i,\ m,\ t+1}$ is the natural logarithm of market equity at the end of June of year $t+1$. $STR_{i,\ m,\ t+1}$ is the short-term reversal, measured as stock *i*'s past returns in month $m-1$ beginning from July($t+1$). $LTR_{i,\ m,\ t+1}$ is the long-term reversal (the 48-month buy and hold return), measured as stock *i*'s past returns during months $m-60$ to $m-13$ beginning from July($t+1$). $MOM_{i,\ m,\ t+1}$ is the momentum effect (the 11-month buy and hold return), measured as stock *i*'s past returns during months $m-12$ to $m-2$ beginning from July($t+1$). $Beta_{b,\ i,\ m,\ t+1}$ are the Fama and French (2015) five-factor loadings (β_{MKT}, β_{SMB}, β_{HML}, β_{RMW}, and β_{CMA}), estimated using monthly data over the previous 36 months (24 months minimum) beginning from the end of June ($t+1$) (annually rebalanced). $IND_{h,\ m,\ t+1}$ are industry dummies, identified by the TWSE/TPEx two-digit industrial codes as of the fiscal year-end in calendar year $t+1$. The time-series average of the coefficient estimates, Newey and West (1987) robust *t*-statistics with eight lags (in square brackets), time-series average R-squared, and time-series average number of firm-month observations are reported for each model. *, **, and *** represent the statistical significance at the 10%, 5%, and 1% levels, respectively. All data used are collected from the *TEJ* database.

negative at −0.0012 ($t = -1.69$).

Finally, Model (4) of Table 6 continues to support the incremental predictive power of *DOI* (coefficient = 0.8625 with a $t = 2.56$) when incorporating a set of corporate governance-related control variables such as *BOR*, *BSIZE*, *BIND*, *BDUAL*, *ACC*, *XCR*, *DEV*, and *BLOCK*. Considering the estimates, the average cross-sectional standard deviation of *DOI* equals 16.37% (Table 1). Hence, the average *DOI* coefficient of 0.8625 in Model (4) that controls for relevant return predictors implies that a 2-standard-deviation increases in *DOI* predicts a rise of approximately 3.39% in the annual returns (2×0.8625/100×16.37%×12).

Collectively, the Fama–MacBeth cross-sectional regression results in Table 6 conclude that *DOI* has an incremental power to positively predict returns after controlling for a set of standard characteristics-based predictors and for the return predictors suggested to be highly correlated with D&O insurance. The predictability afforded by *DOI* is not only highly statistically significant but also highly significant economically.

Table 7
Summary statistics of monthly factor returns.

Panel A: Summary statistics of portfolio returns

Portfolio	N	Mean (%)	[*t*]	SD (%)	Sharpe Ratio	Min (%)	Max (%)
DOIF	144	0.468	3.14	1.789	0.262	−3.336	6.292
MKT	144	1.064	2.93	4.349	0.245	−13.470	13.574
SMB	144	0.197	0.95	2.496	0.079	−7.060	6.005
HML	144	0.446	1.72	3.106	0.144	−8.742	20.204
RMW	144	0.187	0.71	3.177	0.059	−18.162	9.132
CMA	144	−0.072	−0.44	1.957	−0.037	−5.282	6.018
ACF	144	0.269	2.28	1.744	0.154	−3.247	9.771
UMD	144	1.011	3.59	3.381	0.299	−12.926	15.029
DYF	144	0.235	1.26	2.238	0.105	−8.471	6.624
EPF	144	0.388	2.18	2.136	0.182	−5.316	9.343

Panel B: Pairwise correlations

	DOIF	*MKT*	*SMB*	*HML*	*RMW*	*CMA*	*ACF*	*UMD*	*DYF*
MKT	0.078								
	(0.35)								
SMB	0.453	0.097							
	(<0.01)	(0.25)							
HML	0.337	0.290	0.276						
	(<0.01)	(<0.01)	(<0.01)						
RMW	−0.401	−0.273	−0.376	−0.785					
	(<0.01)	(<0.01)	(<0.01)	(<0.01)					
CMA	0.396	−0.148	0.042	0.251	−0.375				
	(<0.01)	(0.08)	(0.62)	(<0.01)	(<0.01)				
ACF	−0.107	−0.004	−0.401	−0.277	0.284	−0.056			
	(0.20)	(0.96)	(<0.01)	(<0.01)	(<0.01)	(0.50)			
UMD	−0.200	−0.047	−0.214	−0.206	0.292	−0.207	0.193		
	(0.02)	(0.58)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.02)		
DYF	0.077	−0.433	−0.068	−0.059	0.249	0.289	0.020	−0.090	
	(0.36)	(<0.01)	(0.42)	(0.49)	(<0.01)	(<0.01)	(0.81)	(0.29)	
EPF	−0.103	−0.015	−0.133	0.032	0.371	−0.172	−0.029	0.095	0.448
	(0.22)	(0.86)	(0.11)	(0.70)	(<0.01)	(0.04)	(0.73)	(0.26)	(<0.01)

Panel C: Factor spanning tests

Model	α	*MKT*	*SMB*	*HML*	*RMW*	*CMA*	*ACF*	*UMD*	*DYF*	*EPF*	N	R^2
(1)	0.434	0.032									144	0.6%
[t]	[2.83]***	[0.93]										
(2)	0.365	−0.012	0.279	0.137							144	25.4%
[t]	[2.71]***	[−0.38]	[5.13]***	[3.01]***								
(3)	0.386	0.022	0.283	0.061	−0.013	0.322					144	36.7%
[t]	[2.95]***	[0.74]	[5.36]***	[0.97]	[−0.18]	[4.58]***						
(4)	0.344	0.017	0.316	0.075	−0.017	0.317	0.137				144	38.1%
[t]	[2.60]**	[0.55]	[5.68]***	[1.18]	[−0.26]	[4.54]***	[1.78]*					
(5)	0.345	0.023	0.312	0.051	−0.049	0.298	0.142	−0.010	0.037	0.022	144	38.4%
[t]	[2.48]**	[0.67]	[5.51]***	[0.66]	[−0.55]	[3.83]***	[1.79]*	[−0.25]	[0.48]	[0.27]		

Panel D: Sharpe ratio of the Ex-post tangency portfolio

	Portfolio Weights										Ex-Post Tangency Portfolio		
	MKT	*SMB*	*HML*	*RMW*	*CMA*	*ACF*	*UMD*	*DYF*	*EPF*	*DOIF*	Mean (%)	SD (%)	Sharpe Ratio
(1a)	1.000										1.064	4.349	0.245
(1b)	0.275									0.725	0.632	1.832	0.345
(2a)	0.574	0.175	0.251								0.757	2.927	0.259
(2b)	0.275	0.000	0.000							0.725	0.632	1.831	0.345
(3a)	0.125	0.113	0.293	0.366	0.104						0.346	0.830	0.418
(3b)	0.103	0.008	0.237	0.328	0.000					0.325	0.430	0.864	0.498
(4a)	0.087	0.132	0.243	0.272	0.072	0.194					0.324	0.701	0.462
(4b)	0.079	0.049	0.212	0.265	0.000	0.150				0.245	0.393	0.751	0.523
(5a)	0.101	0.129	0.169	0.154	0.042	0.148	0.135	0.123	0.000		0.438	0.774	0.566
(5b)	0.090	0.056	0.148	0.162	0.000	0.108	0.128	0.097	0.000	0.213	0.483	0.784	0.616

This table summarizes the descriptive statistics for the *DOI* factor-mimicking portfolio, *DOIF*, and other benchmark factor portfolios. The sample consists of the TWSE/TPEx stocks that have purchased D&O insurance. Sample stocks in financial industries (two-digit industrial codes 28, 58, and 60) are removed. At the end of June of each year *t* from 2009 to 2020, all stocks on the TWSE//TPEx with size (*ME*) and nonmissing and nonzero *DOI* data are assigned into two size groups (S or B) based on their end-of-June *ME*. Stocks are also sorted independently into three *DOI* tercile portfolios (L, M, or H) based on their *DOI* for the fiscal year ending in year $t-1$. 2×3 portfolios (S/L, S/M, S/H, B/L, B/M, and B/H) are formed as the intersections of the two size (*ME*) groups and the three D&O insurance (*DOI*) groups. Value-weighted monthly returns on these 2×3 double-sorted portfolios are computed from July of year *t* to June of year $t+1$ (i.e., July 2009–June 2021, 144 months). *DOIF* is the difference between the average of the returns on the two high-*DOI* portfolios (S/H and B/H) minus the average of the returns on the two low *DOI* portfolios (S/L and B/L). That is, *DOIF* = 1/2(S/H + B/H) − 1/2(S/L + B/L). Panel A presents the summary statistics for the monthly returns of *DOIF* and well-known benchmark factors, including the Fama–French five factors (*MKT*, *SMB*, *HML*, *RMW*, and *CMA*), Hirshleifer et al.'s (2012) size/accrual factor-mimicking portfolio (*ACF*), Carhart's (1997) momentum factor (*UMD*), the dividend yield factor (*DYF*) and the earnings-to-price factor (*EPF*). Panel B presents the pairwise correlations between the factor portfolios and the corresponding *p*-values. In Panel C, *DOIF* is regressed on those benchmark risk factors, including *MKT* in Model (1), the Fama–French three factors in Model (2), the Fama–French five factors in Model (3), the Fama–French five factors augmented with *ACF* in Model (4), and the Fama–French five factors augmented with *ACF*, *UMD*, *DYF*, and *EPF* in Model (5). Panel D presents the summary statistics of the ex-post tangency portfolio (portfolio weights, average returns, and maximum monthly Sharpe ratios) from investing in subsets of benchmark factors augmented by *DOIF*. The portfolio weights are calculated as $(\delta'\Gamma^{-1}\mu)^{-1}\Gamma^{-1}\mu$, where δ is a $k \times 1$ vector of ones, Γ is the covariance matrix of the factor returns, and μ is the mean returns of the factor portfolios. All data used are collected from the TEJ database.

4. Dissecting *DOI*-based portfolio returns: Risk or mispricing?

The considerable evidence of the *DOI* anomaly earlier raises the issue of the origin of the superior performance of the *DOI*-based portfolio strategies, i.e., a reflection of compensation for higher systematic risk or investor mispricing. This section provides addresses this issue.

4.1. Constructing the DOI-mimicking Factor (DOIF)

A factor-mimicking portfolio is formed based on the *DOI* itself, which is constructed to load heavily on whatever risk factor is driving the *DOI* anomaly (if risk is indeed the driver). This procedure follows the well-known empirical asset-pricing literature that replicates a state variable highly correlated with the anomaly (e.g., Hirshleifer et al., 2012; Fama and French, 2015; Leung et al., 2020). Specifically, at the end of June of each year *t* from 2009 to 2020, all stocks on the TWSE//TPEx of size (*ME*) and nonmissing and nonzero *DOI* data are assigned into two size groups (S or B) based on their end-of-June *ME*. Stocks are also sorted independently into three *DOI* tercile portfolios (L, M, or H) based on their *DOI* for the fiscal year ending in year $t-1$. The 2×3 portfolios (S/L, S/M, S/H, B/L, B/M, and B/H) are formed as the intersections of two size (*ME*) and three *DOI* groups. Value-weighted monthly returns on these 2×3 double-sorted portfolios are computed from July of year *t* to June of year $t+1$ (i.e., July 2009–June 2021, 144 months). The *DOI*-based factor-mimicking portfolio (*DOIF*) is the difference between the average of the returns on the two high-*DOI* portfolios (S/H and B/H) minus the average of the returns on the two low-*DOI* portfolios (S/L and B/L), i.e., *DOIF* = 1/2(S/H + B/H) − 1/2(S/L + B/L).

Table 7, Panels A and B, present the summary statistics for the monthly returns of *DOIF* and well-known benchmark factors. Panel A of Table 7 shows that the average return on *DOIF* is 0.468% per month, which is considerably higher than the average return on *SMB* (0.197%), *RMW* (0.187%), *CMA* (−0.072%), *ACF* (0.269%), and *DYF* (0.235%) compared with *HML* (0.446%) and *EPF* (0.388%) and lower than that of *MKT* (1.064%) and *UMD* (1.011%). *DOIF*'s high return relative to its standard deviation of 1.789% delivers an ex-post monthly Sharpe ratio (the reward-to-risk ratio) of 0.262, which is the highest among all factor portfolios, except for *UMD* (0.299), and indicates that the payoff for bearing the *DOIF* portfolio is more attractive than suggested by its substantial returns. Panel B of Table 7 shows strong correlations among *DOIF* and *SMB* (0.453), *HML* (0.337), *RMW* (−0.401), and *CMA* (0.396), which suggests that the *DOIF* portfolio returns are related to these existing factors; thus, the impact of these correlations in the subsequent analyses is carefully considered.

Further, Panel C of Table 7 examines the covariance structure of *DOIF* and other established factors by conducting the factor spanning tests that regress *DOIF* on a set of risk factors, including *MKT* in Model (1), the Fama–French three factors in Model (2), the Fama–French five factors in Model (3), the Fama–French five factors augmented with *ACF* in Model (4), and the Fama–French five factors augmented with *ACF*, *UMD*, *DYF*, and *EPF* in Model (5). In each case, a statistically significant and economically meaningful positive risk-adjusted alpha of the *DOIF* is documented, which ranges from 0.344% to 0.434% per month on the basis of alternative model specifications. For example, as shown in Model (5), the *DOIF*'s alpha is still significantly positive, at 0.345% per month ($t =$ 2.48), in the Fama–French five-factor model augmented with *ACF*, *UMD*, *DYF*, and *EPF*. Additionally, regardless of the model specifications, the models' R-squared values are relatively low (i.e., 0.6%, 25.4%, 36.7%, 38.15, and 38.4% for Models (1), (2), (3), (4), and (5), respectively). Interestingly, the significantly positive loadings on *SMB* and *CMA* indicate that the *DOIF* portfolio exhibits positive exposure to small and conservative investment stocks. Overall, the results of Table 7, Panel C, indicates that the established risk model specifications cannot explain the return premium associated with *DOI* (shown in Section 3) and the *DOIF* portfolio yields significant abnormal returns and considerable return variation beyond those predicted by established factors.

Finally, following previous literature (e.g., MacKinlay, 1995; Gebhardt et al., 2005; Hirshleifer and Jiang, 2010; Hirshleifer et al., 2012; and Hirshleifer et al., 2013), this study examines the extent to which the *DOIF* portfolio substantially improves the Sharpe ratio of the ex-post tangency portfolio. According to mean-variance portfolio theory to study the incremental contribution of the *DOIF* portfolio in improving achievable Sharpe ratios, the maximum ex-post Sharpe ratios achievable by augmenting *DOIF* into a set of benchmark factors to form the tangency portfolio are presented in Panel D of Table 7. Model (1a) shows a monthly Sharpe ratio of

0.245 for *MKT* as a candidate portfolio. When the *MKT* is added by the *DOIF* portfolio into the tangency portfolio, the maximum Sharpe ratio improves from 0.245 to 0.345—an increase of approximately 41%—relative to Models (1a) to (1b). Markedly, as shown in Model (1b), the tangency portfolio places substantial weight (72.5%) on the *DOIF* portfolio as opposed to the *MKT* portfolio. When the Fama–French three factors are added by the *DOIF* portfolio into the tangency portfolio, similar results are generated in Model (2b). Model (3a) shows that the monthly Sharpe ratio of 0.418 for FF5 as candidate portfolios and *HML* and *RMW* receive the relatively high

Table 8
DOIF factor regressions for *DOI* decile portfolios.

Panel A: Equal-weighted *DOI* decile portfolios

	α	*MKT*	*SMB*	*HML*	*RMW*	*CMA*	*DOIF*	N	R^2
High *DOI*	0.361	0.960	0.769	−0.050	−0.148	0.163	1.074	144	86.5%
	[1.67]*	[19.64]***	[8.25]***	[−0.49]	[−1.35]	[1.35]	[7.86]***		
9	0.033	1.101	1.134	0.086	−0.019	0.091	0.566	144	91.9%
	[0.19]	[27.44]***	[14.83]***	[1.02]	[−0.21]	[0.92]	[5.04]***		
8	−0.338	1.140	1.170	0.190	0.044	0.045	0.276	144	93.4%
	[−2.11]**	[31.55]***	[16.98]***	[2.51]**	[0.54]	[0.51]	[2.73]***		
7	−0.169	1.108	1.124	0.205	−0.021	0.232	0.033	144	94.9%
	[−1.25]	[36.39]***	[19.36]***	[3.21]***	[−0.31]	[3.08]***	[0.39]		
6	−0.287	1.106	1.147	0.099	−0.043	0.146	0.008	144	94.3%
	[−2.04]**	[34.85]***	[18.96]***	[1.49]	[−0.61]	[1.86]*	[0.09]		
5	−0.247	1.062	1.057	0.212	0.032	−0.014	−0.019	144	93.4%
	[−1.70]*	[32.27]***	[16.85]***	[3.08]***	[0.43]	[−0.17]	[−0.21]		
4	−0.319	1.092	1.009	0.163	0.001	0.118	−0.105	144	94.5%
	[−2.44]**	[37.01]***	[17.93]***	[2.60]**	[0.02]	[1.61]	[−1.27]		
3	−0.100	0.993	0.803	0.046	−0.186	0.010	−0.094	144	91.6%
	[−0.67]	[29.30]***	[12.43]***	[0.65]	[−2.45]**	[0.12]	[−0.99]		
2	−0.013	0.938	0.637	−0.007	−0.182	−0.050	−0.381	144	92.6%
	[−0.11]	[33.40]***	[11.90]***	[−0.11]	[−2.89]***	[−0.72]	[−4.85]***		
Low *DOI*	−0.224	0.991	0.765	0.100	−0.127	0.011	−0.276	144	92.6%
	[−1.64]*	[32.27]***	[13.06]***	[1.56]	[−1.84]*	[0.14]	[−3.22]***		
H − L	0.585	−0.031	0.004	−0.150	−0.021	0.152	1.350	144	44.3%
	[2.24]**	[−0.53]	[0.04]	[−1.22]	[−0.16]	[1.04]	[8.18]***		

Panel B: Value-weighted *DOI* decile portfolios

	α	*MKT*	*SMB*	*HML*	*RMW*	*CMA*	*DOIF*	N	R^2
High *DOI*	0.117	0.990	0.681	0.113	−0.216	0.096	0.677	144	91.1%
	[1.10]	[25.72]***	[9.27]***	[1.40]	[−2.50]**	[1.00]	[6.29]***		
9	−0.182	1.215	1.073	0.130	0.007	0.137	0.482	144	91.4%
	[−0.95]	[27.98]***	[12.96]***	[1.43]	[0.07]	[1.27]	[3.97]***		
8	−0.141	1.092	1.014	0.136	−0.050	0.044	0.289	144	91.8%
	[−1.09]	[28.33]***	[13.80]***	[1.68]*	[−0.58]	[0.46]	[2.68]***		
7	−0.060	1.075	0.981	0.156	−0.162	0.252	−0.073	144	92.1%
	[−0.36]	[29.11]***	[13.92]***	[2.01]**	[−1.95]*	[2.76]***	[−0.71]		
6	−0.265	1.117	0.928	0.159	−0.051	0.173	0.101	144	92.0%
	[−1.60]	[29.88]***	[13.02]***	[2.03]**	[−0.61]	[1.87]*	[0.97]		
5	−0.151	1.062	0.811	0.108	−0.104	−0.139	0.152	144	89.5%
	[−0.83]	[25.81]***	[10.34]***	[1.25]	[−1.13]	[−1.36]	[1.32]		
4	−0.333	1.104	0.658	0.258	−0.063	0.199	−0.182	144	89.3%
	[−1.82]*	[26.73]***	[8.36]***	[2.98]***	[−0.69]	[1.95]*	[−1.58]		
3	−0.219	1.079	0.486	0.240	0.006	0.084	−0.038	144	86.1%
	[−1.10]	[23.97]***	[5.66]***	[2.54]**	[0.06]	[0.75]	[−0.30]		
2	0.138	0.973	−0.117	−0.038	0.104	−0.011	−0.060	144	95.9%
	[1.39]	[52.96]***	[−3.34]***	[−0.98]	[2.52]**	[−0.25]	[−1.17]		
Low *DOI*	−0.268	0.935	0.379	0.326	−0.116	−0.045	−0.119	144	91.0%
	[−1.85]*	[28.58]***	[6.08]***	[4.76]***	[−1.58]	[−0.55]	[−1.71]*		
H − L	0.385	0.055	0.301	−0.214	−0.100	0.140	0.796	144	43.9%
	[2.00]**	[1.15]	[3.32]***	[−2.14]**	[−0.93]	[1.19]	[5.98]***		

This table presents risk-adjusted alphas and factor loadings for *DOI* decile portfolios, estimated using time-series regressions of the factor model that adds *DOIF* into the Fama–French five factors during a period from July 2009 to June 2021:

$$R_{p,\,m} - R_{f,\,m} = \alpha_p + \beta_{p,\,m} MKT_m + \beta_{p,\,s} SMB_m + \beta_{p,\,h} HML_m + \beta_{p,\,r} RMW_m + \beta_{p,\,c} CMA_m$$
$$+\beta_{p,\,DOIF} DOIF_m + \varepsilon_{p,\,m}$$

where $R_{p,\,m}$ is the monthly returns of *DOI* decile portfolio (p = High, 9, 8, …, and Low), form in Table 3, on month m. $R_{f,\,m}$ is the risk-free rate on month m, measured as the one-year fixed savings deposit interest rate reported by the First Commercial Bank. MKT_m, SMB_m, HML_m, RMW_m, and CMA_m are the Fama–French five factors on month m. $DOIF_m$ is the *DOI*-based factor-mimicking portfolio, formed in Section 4.1, on month m. Panels A and B report the results for equal- and value-weighted *DOI* decile portfolios, respectively. Robust Newey-West (1987) *t*-statistics are presented in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All data used are collected from the TEJ database.

weighting at 29% and 37%, respectively. Relative to Models (3a) to (3b), adding the *DOIF* portfolio to FF5 improves the maximum Sharpe ratio from 0.418 to 0.498—an increase of approximately 19%, whereas the *DOIF* portfolio receives 32.5% weighting in the optimal portfolio. Similar results are found for the *DOIF* portfolio and the Hirshleifer et al. (2012) *ACF* portfolio added into FF5 as compared with Models (4a) with (4b). Finally, when the *DOIF* portfolio is combined with the FF5 and other benchmark factors, such as *ACF*, *UMD*, *DYF*, and *EPF* (as compared with Models (5a) with (5b)), the *DOIF* portfolio is weighted at 21.3%, which is the highest among all factors. Additionally, the *DOIF* portfolio raises the maximum monthly Sharpe ratio of the tangency portfolio from 0.566 to 0.616, an increase of approximately 9%. The overall results in Panel D of Table 7 suggest that the *DOIF* portfolio contributors to the ex-post tangency portfolio when combined with well-known candidate factor portfolios by achieving a relatively heavy weight and improving the maximum Sharpe ratios in the optimal portfolio.

4.2. How well does the DOIF explain the positive DOI return premium?

DOIF is designed to capture any factor return comovement related to D&O insurance, regardless of whether it comes from fundamentals or imperfect rationality. In this subsection, whether *DOIF* captures return comovement above and beyond other established factors and how well the loading on *DOIF* explains the positive *DOI* return premium are tested. If the *DOI* anomaly reflects rational risk premia, then the inclusion of *DOIF* in the asset-pricing tests should reduce (even eliminate) the abnormal returns associated with *DOI*.

To perform these tests, the Fama–French five-factor model that augments the *DOIF* factor is estimated by regressing the equal- and value-weighted monthly excess returns for each *DOI* decile portfolio on various factors from July 2009 to June 2021:

$$R_{p,m} - R_{f,m} = \alpha_p + \beta_{p,m}MKT_m + \beta_{p,s}SMB_m + \beta_{p,h}HML_m + \beta_{p,r}RMW_m + \beta_{p,c}CMA_m + \beta_{p,DOIF}DOIF_m + \varepsilon_{p,m} \quad (2)$$

where $R_{p,\,m}$ is the monthly returns of *DOI* decile portfolio (p = High, 9, 8, …, and Low) form in Table 3, on month m. $R_{f,\,m}$ is the risk-free rate on month m, measured as the one-year fixed savings deposit interest rate reported by the First Commercial Bank. MKT_m, SMB_m, HML_m, RMW_m, and CMA_m are the Fama–French five factors on month m. $DOIF_m$ is the *DOI*-based factor-mimicking portfolio, formed in Section 4.1, on month m. Panels A and B of Table 8 report the alphas and other coefficients of the five-factor model regressions in which the *DOIF* factor is added for the equal- and value-weighted *DOI* decile portfolios, respectively.

As shown, adding the *DOIF* factor to the Fama–French five-factor model appears to help capture the *DOI* return effect. Panel A of Table 8 shows that for the equal-weighted *DOI* decile portfolios, high- (low-)*DOI* portfolio tend to experience more positive (negative) *DOIF* loading, decreasing from 1.074 (t = 7.86) in high-DOI portfolio to −0.276 (t = −3.22) in low-*DOI* portfolio. The difference in *DOIF* loading between high-*DOI* and low-*DOI* deciles is significantly positive (1.350 with a t-statistic of 8.18). Importantly, the *DOIF*-augmented five-factor model's alpha for the H − L *DOI* portfolio, 0.585% per month (t = 2.24), is much lower than that for the *DOI* H − L portfolio, 1.107% per month (t = 3.59)—a decrease of approximately 47%, which shows that the *DOIF*-augmented five-factor model well explains the *DOI* anomaly.

Panel B of Table 8 reports the results of the *DOIF*-augmented five-factor model in fitting the value-weighted *DOI* decile portfolio returns. As shown, the *DOIF* loading of high-*DOI* stocks significantly differ from that of low-*DOI* stocks (0.796 with a t-statistic of 5.98) and the difference between the *DOIF*-augmented five-factor model's alpha of the high-*DOI* and low-*DOI* portfolios decreases from 0.595% (t = 2.60) to 0.385% (t = 2.00)—a decrease of approximately 35%, which again indicates that the *DOIF* factor plays an important role in explaining the positive *DOI*–return relationship.

Overall, Table 8 explores the evidence that the *DOIF* factor explains the cross section of average returns associated with *DOI*, which agrees with a rational factor pricing explanation as this appears to suggest a risk premium for bearing systematic factor risk in terms of *DOIF*. However, given the high correlation between the *DOIF* factor loading and the *DOI* characteristic (as the *DOIF* factor is constructed from *DOI*), the evidence may agree with the alternative characteristic-based mispricing hypothesis. The following subsection provides more direct evidence to distinguish the mispricing hypothesis from the rational risk hypothesis for the *DOI* anomaly.

4.3. Characteristics vs. Covariances tests

To distinguish between the rational risk and mispricing explanations of the *DOI* anomaly, two direct evaluations are conducted contingent to the bivariate-sorted portfolio tests from a series of such sequential sorts in which the ordering of the *DOI* and *DOIF* factor loading-based sorts are alternated, as well as the monthly Fama and MacBeth (1973) cross-sectional regression tests in a horse race between *DOI* and *DOIF* factor loading, both at the portfolio and firm levels. The methodological frameworks mentioned above are well-developed by previous literature (e.g., Daniel and Titman, 1997; Hirshleifer et al., 2012; Li et al., 2016; Leung et al., 2020; Bongaerts et al., 2022; and Su et al., 2022).[8] The rational risk explanation claims that *DOIF* factor loading continues to predict returns after controlling for the *DOI* characteristic. In contrast, the behavioral mispricing explanation claims that *DOIF* factor loading had no meaningful predictive power after controlling for variation in *DOI*.

[8] This paper follows those studies that have commonly adopted the methodological frameworks regarding the bivariate/multivariate-sorted portfolios and the Fama and MacBeth (1973) regressions to evaluate the risk (covariance-based) explanation against the mispricing (characteristic-based) explanation for specific asset pricing anomaly, including, e.g., accrual anomaly (Hirshleifer et al., 2012), idiosyncratic volatility anomaly (Li et al., 2016), R&D anomaly (Leung et al., 2020), the anomaly of intangible asset intensity (Bongaerts et al., 2022), and illiquidity anomaly (Su et al., 2022).

4.3.1. Bivariate-sorted portfolio tests via sorting on DOIF factor loading and on DOI

Empirical investigations associated with return predictability are conducted by documenting highly statistically significant positive spreads in the returns on decile portfolios comprising stocks sorted according to their pre-formation *DOIF* factor loading, denoted as β_{DOIF}.

Specifically, the sorting variable β_{DOIF}, for each stock *i*, is first estimated from a time-series regression based on the *DOIF*-augmented Fama–French five-factor model using monthly excess returns over the past 36 months (24 months minimum) as of the end of June of each year *t* beginning in 2012 (annually rebalanced)[9]:

$$R_{i,m} - R_{f,m} = \alpha_p + \beta_{i,m}MKT_m + \beta_{i,s}SMB_m + \beta_{i,h}HML_m + \beta_{i,r}RMW_m + \beta_{i,c}CMA_m + \beta_{i,DOIF}DOIF_m + \varepsilon_{i,m} \tag{3}$$

where $R_{i,\,m}$ is the monthly returns of individual stock *i* on month *m*. $R_{f,\,m}$ is the risk-free rate on month *m*, measured as the one-year fixed savings deposit interest rate reported by the First Commercial Bank. MKT_m, SMB_m, HML_m, RMW_m, and CMA_m are the Fama–French five factors on month *m*. $DOIF_m$ is the *DOI*-based factor-mimicking portfolio (Section 4.1) on month *m*. Then, at the end of June of each year *t* over 2012 to 2020, sample stocks are allocated into deciles according to their β_{DOIF} at the end of June in year *t*. Equal- and value-weighted monthly returns on a portfolio are then calculated from July of year *t* to June of year $t + 1$. Repeating this every year (annually rebalanced) yields a time-series of monthly returns for each β_{DOIF} decile (i.e., July 2012–June 2021, 108 months).

Panel A of Table 9 reports the average raw monthly returns, CAPM α, FF3 α, FF5 α, the average pre-formation β_{DOIF}, and the average *DOI* in each β_{DOIF} decile portfolio. As shown, the average equal-weighted monthly return increase generally monotonically from 1.004% ($t = 1.84$) for low β_{DOIF} decile to 1.551% ($t = 2.95$) for high β_{DOIF} decile, yielding a high–low spread of 0.547% ($t = 2.65$). The alphas from the CAPM, FF3, and FF5 models remain sizable and statistically significant, suggesting a monthly abnormal return of 0.546–0.638%. The value-weighted portfolio returns show the same increasing pattern between pre-formation β_{DOIF} and those over the next one-year period, with a high–low spread of 1.193% per month ($t = 2.20$). These results suggest a strong positive relation between the *DOIF* factor loading and next one-year stock returns.

Unsurprisingly, the pre-formation β_{DOIF} is highly correlated with the *DOI* characteristics. The average *DOI* increases generally monotonically from 7.54% for low β_{DOIF} decile to 13.65% for high β_{DOIF} decile. Unreported results also indicate that the Spearman's correlation coefficient between firm-year β_{DOIF} and *DOI* during 2012–2020 is nearly 11% (*p*-value <0.01). As the *DOIF* factor is constructed from *DOI*, there is likely to be a high correlation between the *DOIF* factor loading and the original *DOI* characteristic (which is well documented to predict returns in Section 3). Then if the original *DOI* characteristic is related to investor mispricing, the *DOIF* factor loading will be related, too. Therefore, although the findings that the *DOIF* factor loading has a predictive power for future returns agrees with the risk explanation (representing a risk premium for bearing systematic factor risk), it cannot rule out the mispricing explanation with the test in Panel A of Table 9 alone.

To compete the rational risk explanation versus the mispricing explanation for the *DOI* anomaly, the bivariate-sorted portfolio tests are conducted via sorting on *DOIF* factor loading after controlling for *DOI* and that on *DOI* after controlling for *DOIF* factor loading. First, Panel B of Table 9 presents the raw monthly returns and risk-adjusted alphas (CAPM, FF3, and FF5) for bivariate-sorted β_{DOIF} decile portfolios after controlling for *DOI*. At the end of June of each year *t* over 2012 to 2020, sample stocks are first sorted into terciles according to *DOI*. Each such tercile portfolio is further sorted into β_{DOIF} decile portfolios. Equal- and value-weighted monthly returns on a portfolio are then calculated from July of year *t* to June of year $t + 1$. Repeating this every year (annually rebalanced) generates a time-series of monthly returns for each 3×10 portfolio (i.e., July 2012–June 2021, 108 months). From the 3×10 bivariate-sorted portfolios, the average return is calculated across *DOI* terciles for a given β_{DOIF} decile portfolio. The time-series average of monthly returns for each β_{DOIF} deciles is computed. Panel B of Table 9 shows that, after controlling for the *DOI*, although the average equal-weighted monthly returns still increase monotonically from 1.080% for low β_{DOIF} decile to 1.431% for high β_{DOIF} decile, the average return spread between these high and low β_{DOIF} decile portfolios is not significant (0.351% per month with a *t*-statistic of 1.35). The risk-adjusted alphas (CAPM, FF3, and FF5) for the H − L β_{DOIF} portfolio are generally small and insignificant (e.g., the FF5 α = 0.385% per month with a *t*-statistic of 1.37). The results are qualitatively similar when value-weighted β_{DOIF} decile portfolios are tested instead. The evidence suggests that the predictive power of *DOIF* factor loading (covariance effect) reported in Panel A of Table 9 is subsumed by the *DOI* characteristic, i.e., when holding the *DOI* characteristic constant, the *DOIF* factor loading fails to deliver a premium, which rejects the rational factor pricing model.

Panel C of Table 9 further shows the equal- and value-weighted average returns from similarly constructed sequential double sorts based on *DOI*, in which we first sort on *DOIF* factor loading. Evidently, even after controlling for the *DOIF* factor loading, the difference in the average returns on the high and low *DOI* decile portfolios is still economically and statistically significant. For example, the equal-weighted average returns for the H − L *DOI* portfolio is 1.186% per month ($t = 3.92$). This return spread persists in the estimated alphas when adjusting for the CAPM (CAPM $\alpha = 1.092$% per month with $t = 3.46$) and the Fama and French three and five factors (FF3 $\alpha = 0.989$% per month with $t = 3.36$; and FF5 $\alpha = 1.128$% per month with $t = 4.01$). Although smaller than the equal-weighted H − L *DOI* portfolio, its value-weighted average return, CAPM α, FF3 α, and FF5 α all remain significant at the 5% level at 0.684%, 0.609%, 0.537%, and 0.521% per month, respectively.

Table 9 reveals that although the *DOIF* factor loading alone has a predictive power for future returns, its predictive power is

[9] It should be noted that the sample period of *DOIF* factor runs from July 2009 to June 2021 and the *DOIF* factor loadings (β_{DOIF}) are estimated using returns data over the past 36 months. Therefore, the analyses associated with the realtion between β_{DOIF} and expected stock returns in Tables 9 and 10 cover the testing period during July 2012–June 2021, which is distinct from those in Tables 3–6.

Table 9
Returns of *DOIF* loadings (β_{DOIF}) decile portfolios.

Panel A: β_{DOIF} decile portfolios' returns

	Equal-Weighted		Value-Weighted				
Decile	Ret (%)	[t]	Ret (%)	[t]	N	β_{DOIF}	*DOI* (%)
High β_{DOIF}	1.551	2.95	1.590	3.33	98.4	3.13	13.65
9	1.384	2.53	1.084	1.79	98.9	1.52	9.80
8	1.327	2.81	1.186	2.30	98.7	0.90	8.12
7	1.297	2.88	1.007	1.95	99.0	0.53	8.04
6	1.278	2.86	1.030	2.71	98.9	0.22	6.78
5	1.139	2.60	1.371	3.26	98.6	−0.07	6.80
4	1.254	2.69	1.139	2.91	98.9	−0.31	6.03
3	1.184	2.59	0.867	2.25	98.8	−0.67	6.57
2	1.284	2.92	1.005	2.68	98.8	−1.11	7.90
Low β_{DOIF}	1.004	1.84	0.397	0.64	98.3	−2.11	7.54
H − L	0.547***	2.65	1.193**	2.20			
CAPM α	0.638***	2.98	1.549***	2.79			
FF3 α	0.596***	2.88	1.642***	2.98			
FF5 α	0.546**	2.48	1.388**	2.40			

Panel B: β_{DOIF} decile portfolios' returns when holding *DOI* characteristic constant

	Equal-Weighted		Value-Weighted	
Decile	Ret (%)	[t]	Ret (%)	[t]
High β_{DOIF}	1.431	2.62	1.302	2.41
9	1.310	2.61	1.368	2.78
8	1.362	2.91	1.209	2.65
7	1.416	3.07	1.296	2.85
6	1.224	2.66	1.287	2.86
5	1.187	2.68	1.233	2.85
4	1.249	2.69	1.270	2.93
3	1.249	2.74	1.102	2.53
2	1.394	2.77	1.140	2.31
Low β_{DOIF}	1.080	1.97	0.852	1.44
H − L	0.351	1.35	0.450	1.36
CAPM α	0.419	1.62	0.435	1.59
FF3 α	0.377	1.55	0.303	1.46
FF5 α	0.385	1.37	0.267	1.19

Panel C: *DOI* decile portfolios' returns when holding β_{DOIF} characteristic constant

	Equal-Weighted		Value-Weighted	
Decile	Ret (%)	[t]	Ret (%)	[t]
High *DOI*	2.108	3.94	1.708	3.18
9	1.562	3.00	1.312	2.37
8	1.346	2.58	1.120	2.07
7	1.376	2.66	1.443	2.77
6	1.157	2.30	1.203	2.35
5	1.239	2.48	1.446	2.83
4	1.223	2.56	1.267	2.56
3	1.101	2.42	1.078	2.43
2	0.880	1.94	0.904	1.97
Low *DOI*	0.922	2.28	1.024	2.81
H − L	1.186***	3.92	0.684**	2.30
CAPM α	1.092***	3.46	0.609**	2.29
FF3 α	0.989***	3.36	0.537**	2.18
FF5 α	1.128***	4.01	0.521**	2.28

Panel A presents equal- and value-weighted average monthly percentage decile returns sorted based on pre-formation *DOIF* loadings, β_{DOIF}, from July 2012 to June 2021. The sample consists of the TWSE/TPEx stocks that have purchased D&O insurance. Sample stocks in financial industries (two-digit industrial codes 28, 58, and 60) are removed. The sorting variable β_{DOIF}, for each stock, is estimated from a time-series regression based on the *DOIF*-augmented Fama–French five-factor model using monthly excess returns over the past 36 months (24 months minimum) as of the end of June of each year *t* beginning in 2012 (annually rebalanced):

$$R_{i,\,m} - R_{f,\,m} = \alpha_p + \beta_{i,\,m} MKT_m + \beta_{i,\,s} SMB_m + \beta_{i,\,h} HML_m + \beta_{i,\,r} RMW_m + \beta_{i,\,c} CMA_m$$
$$+\beta_{i,\,DOIF} DOIF_m + \varepsilon_{i,\,m}$$

At the end of June of each year *t* over 2012 to 2020, sample stocks are allocated into deciles according to their β_{DOIF} (denoted as High, 9, 8, …, and

Low) and the equal- and value-weighted decile returns of month *m* are reported. The portfolio H − L is long on the High β_{DOIF} decile and short on the Low β_{DOIF} decile. CAPM α, FF3 α, and FF5 α are risk-adjusted alphas (in percentages per month) for each *DOI* decile portfolio, estimated based on the time-series regressions of the CAPM, the Fama–French three-factor model, and the Fama–French five-factor model. The average pre-formation β_{DOIF} and *DOI* in each of β_{DOIF} decile portfolios are also reported. Panel B presents the raw monthly returns and risk-adjusted alphas (CAPM α, FF3 α, and FF5 α) for bivariate-sorted β_{DOIF} decile portfolios when holding *DOI* characteristic constant. At the end of June of each year *t* over 2012 to 2020, sample stocks are first sorted into terciles according to *DOI*. Each such tercile portfolio is further sorted into β_{DOIF} decile portfolios. Equal- and value-weighted monthly returns on a portfolio are then calculated from July of year *t* to June of year $t + 1$. Repeating this every year (annually rebalanced) generates a time-series of monthly returns for each 3 × 10 portfolio (i.e., July 2012–June 2021, 108 months). From the 3 × 10 bivariate-sorted portfolios, the average return is calculated across *DOI* terciles for a given β_{DOIF} decile portfolio. The time-series average of monthly returns for each β_{DOIF} deciles is computed. Panel C presents the raw monthly returns and risk-adjusted alphas (CAPM α, FF3 α, and FF5 α) for bivariate-sorted *DOI* decile portfolios when holding β_{DOIF} constant, from similarly constructed sequential 3 × 10 double sorts based on *DOI*, in which we first sort on β_{DOIF}. [t] presents the robust Newey-West (1987) *t*-statistics, used to test the hypothesis that the mean equals to zero. ** and *** indicate statistical significance at the 5% and 1% levels, respectively. All data used are collected from the TEJ database.

completely subsumed by the *DOI* characteristic. In contrast, the positive relation between *DOI* characteristic and future returns is retained after controlling for the *DOIF* factor loading. Consequently, these findings reject the covariance-based risk pricing explanation for the *DOI* anomaly in favor of the behavioral mispricing explanation.

4.3.2. A horse race between DOIF factor loading and DOI in Fama−MacBeth regression tests

As a robustness check, to further test whether the *DOIF* loading predicts returns after controlling for the *DOI* characteristic, for every month from July 2012 to June 2021, the monthly portfolio and individual stock returns on *DOI* and a set of factor loadings with respect to the Fama and French five factors, *ACF*, *UMD*, *DYF*, *EPF*, and *DOIF*, are regressed.

Panel A of Table 10 presents the results of the portfolio-level regressions using the Fama–French 25 size-*BM* portfolios as base assets and regressing the value-weighted monthly returns of each portfolio on portfolio-level value-weighted *DOI* (*Avg. DOI*) and loadings on *DOIF*, together with other well-known risk factors, including the Fama–French five factors (*MKT*, *SMB*, *HML*, *RMW*, and *CMA*), the Hirshleifer et al. (2012) size/accrual factor-mimicking portfolio (*ACF*), Carhart's (1997) momentum factor (*UMD*), the DYF, and the EPF. The portfolio-level factor loadings are obtained by regressing the monthly excess returns of each size-*BM* portfolio over the past 36 months (24 months minimum) on various factors as of the end of June of each year *t* beginning in 2012 (annually rebalanced). In Panel A of Table 10, Model (1) shows that *Avg. DOI* alone explains the cross section of average returns with a positive and significant coefficient of 0.0358 ($t = 2.68$). When replacing *Avg. DOI* with β_{DOIF} in Model (2), similar qualitative results that β_{DOIF} alone is a strong positive predictor of portfolio returns (coefficient = 0.8982 with a *t*-statistic of 2.33) are found. Interestingly, a horse race between *Avg. DOI* and β_{DOIF} in Model (3) shows that *Avg. DOI* remains a highly significant predictor of average returns (0.0313, $t = 2.43$), whereas β_{DOIF} becomes insignificant (0.2131, $t = 0.55$). In the next regressions that add the loadings on the Fama–French five factors, *ACF*, *UMD*, *DYF*, and *EPF*, in Models (4), (5), and (6) as controls, the significance of *Avg. DOI* and β_{DOIF} remain unchanged. These regressions clearly demonstrate that *DOI* characteristic appears to subsume the explanatory power of the *DOIF* factor loading. Therefore, at the portfolio level, the covariance-based risk explanation is rejected in favor of the characteristic-based mispricing explanation.

Panel B of Table 10 presents the results from firm-level regressions instead, where individual stock returns are regressed on *DOI*, loadings on *DOIF*, together with other well-known risk factors, and those control predictors in Model (4) of Table 6. To mitigate the potential errors-in-variables problem from regressions of individual stock returns on measured loadings, this study follows previous literature and regresses the monthly excess returns of 100 size-*BM* value-weighted portfolios over the past 36 months (24 months minimum) on the various factors as of the end of June of each year *t* beginning in 2012 (annually rebalanced); then, assign the factor loadings (i.e., β_{DOIF}, β_{MKT}, β_{SMB}, β_{HML}, β_{RMW}, β_{CMA}, β_{ACF}, β_{UMD}, β_{DYF}, and β_{EPF}) of a size-*BM* portfolio to each stock within that portfolio. The results of firm-level regressions in Panel B largely support those from the portfolio-level regressions in Panel A. Particularly, in Model (1), the *DOI* characteristic is strongly positively related to average returns of individual stocks (1.5641, $t = 3.79$), again suggesting the existence of the high-*DOI* return premium, as documented in Section 3. Moreover, β_{DOIF} explains the cross section of average returns of individual stocks with a positive and significant price of risk (0.5419, $t = 3.44$), which is consistent with those findings in Table 9. In Model (3), where includes both *DOI* and β_{DOIF}, the *DOI* characteristic maintains its significance (1.1791, $t = 2.35$) and subsumes the *DOIF* factor loading, β_{DOIF} (0.3039, $t = 1.57$). This suggests that *DOI* characteristic, instead of *DOIF* factor loading, is more important for predicting the returns of individual stocks. The significance of *DOI* and the *DOIF* loading remains unchanged when included with various combinations of control variables in Models (4) to (7), with the average coefficient of *DOI* ranging from 0.8537 ($t = 2.00$) to 1.2178 ($t = 2.40$) and that of β_{DOIF} ranging from 0.0721 ($t = 0.37$) to 0.3325 ($t = 1.44$).

Therefore, at the portfolio- and individual-level Fama–MacBeth regression tests in Table 10, the *DOI* characteristic rather than the *DOI* factor loading predicts returns, which rejects the covariance risk hypothesis in favor of the behavioral mispricing hypothesis.

5. Further evidence on the mispricing explanation of the *DOI* anomaly

Given the strong evidence explored in Section 4 that rejects the factor risk pricing explanation for the *DOI* anomaly in favor of investor mispricing, this section provides further evidence on two testable implications of the behavioral mispricing hypothesis associated with the *DOI* anomaly. First, in support of behavioral mispricing, firms with high (low) *DOI* are expected to be more undervalued (overvalued) and, thus, the *DOI*-based abnormal profits should be concentrated among those undervalued stocks. Second, existing theories of the limits-to-arbitrage argue that arbitrage is costly in the presence of market frictions, which implies that stocks

Table 10
Fama–MacBeth cross-sectional regressions of stock returns on *DOI* and *DOIF* loadings.

Panel A: Portfolio-level Fama–MacBeth regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.9809	1.1607	0.9963	−0.8647	−0.9407	−0.7348
	[2.24]**	[2.62]**	[2.23]**	[−1.00]	[−1.08]	[−0.81]
Avg. DOI	**0.0358**		**0.0313**	**0.0567**	**0.0304**	**0.0390**
	[2.68] ***		**[2.43]** **	**[3.53]** ***	**[2.34]** **	**[2.80]** ***
$\boldsymbol{\beta_{DOIF}}$		**0.8982**	**0.2131**	**−0.0094**	**0.5549**	**0.3800**
		[2.33] **	**[0.55]**	**[−0.03]**	**[1.59]**	**[1.03]**
β_{MKT}				1.8710	2.1936	2.0493
				[1.97]*	[2.26]**	[2.06]**
β_{SMB}				−0.3663	−0.4093	−0.4267
				[−1.30]	[−1.49]	[−1.76]*
β_{HML}				0.7180	0.4816	0.4876
				[2.04]**	[1.33]	[1.32]
β_{RMW}				−0.6066	−0.3649	−0.3432
				[−1.16]	[−0.69]	[−0.63]
β_{CMA}				0.0936	0.2427	0.3584
				[0.24]	[0.60]	[0.87]
β_{ACCF}					0.8974	0.4324
					[2.93]***	[1.94]*
β_{UMD}						1.0800
						[1.76]*
β_{DYF}						−0.6964
						[−1.34]
β_{EPF}						−0.1891
						[−0.39]
R^2	13.57%	13.10%	19.63%	57.06%	62.01%	71.58%
N	108	108	108	108	108	108

Panel B: Firm-level Fama–MacBeth regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	1.1316	1.2125	1.1307	1.1035	1.1308	1.2717	0.6558
	[3.00]***	[3.12]***	[3.01]***	[2.94]***	[3.15]***	[3.23]***	[1.67]*
DOI	**1.5641**		**1.1791**	**1.2178**	**1.0068**	**1.0491**	**0.8537**
	[3.79] ***		**[2.35]** **	**[2.40]** **	**[2.07]** **	**[2.11]** **	**[2.00]** **
$\boldsymbol{\beta_{DOIF}}$		**0.5419**	**0.3039**	**0.3004**	**0.3325**	**0.3083**	**0.0721**
		[3.44] ***	**[1.57]**	**[1.53]**	**[1.44]**	**[1.48]**	**[0.37]**
β_{MKT}				−0.0116	−0.0106	−0.0060	−0.0347
				[−0.24]	[−0.22]	[−0.12]	[−1.04]
β_{SMB}				0.0395	0.0412	0.0391	0.0427
				[1.64]	[1.78]*	[1.66]*	[1.89]*
β_{HML}				0.0324	0.0308	0.0309	0.0137
				[1.15]	[1.18]	[1.11]	[0.55]
β_{RMW}				0.0052	0.0048	0.0078	0.0232
				[0.29]	[0.27]	[0.42]	[1.28]
β_{CMA}				0.0066	0.0095	0.0077	−0.0018
				[0.47]	[0.68]	[0.55]	[−0.15]
β_{ACCF}					0.3049	0.3193	0.1740
					[1.88]*	[1.71]*	[1.04]
β_{UMD}						0.3715	0.5594
						[1.57]	[1.74]*
β_{DYF}						−0.2523	−0.0265
						[−1.09]	[−0.14]
β_{EPF}						−0.1313	−0.0542
						[−0.75]	[−0.31]
Controls in Model (4) of Table 6	N	N	N	N	N	N	Y
Industry Dummies	N	N	N	N	N	N	Y
Average R^2	0.68%	0.64%	1.05%	1.63%	1.88%	2.58%	11.74%
Average N	987.6	987.6	987.6	987.6	987.6	987.6	978.4

The table presents results from portfolio-level and firm-level Fama–MacBeth cross-sectional regressions estimated every month from July 2012 to June 2021. The sample consists of the TWSE/TPEx stocks that have purchased D&O insurance. Sample stocks in financial industries (two-digit industrial codes 28, 58, and 60) are removed. Panel A uses the Fama–French 25 size-*BM* portfolios as base assets and regresses value-weighted monthly returns of each portfolio on portfolio-level value-weighted *DOI* (*Avg. DOI*) and loadings on *DOIF* together with other well-known risk factors, including the Fama–French five factors (*MKT*, *SMB*, *HML*, *RMW*, and *CMA*), *ACF*, *UMD*, *DYF*, and EPF. The portfolio-level factor loadings are obtained by regressing the monthly excess returns of each portfolio over the last 36 months (24 months minimum) on the various factors as of the end of June of each year t beginning in 2012 (annually rebalanced). In Panel B, individual stock returns are regressed on *DOI*, loadings on *DOIF* together with other well-known risk factors, as well as those control predictors in Model (4) of Table 6. To mitigate errors-in-variables problem from regressions of individual stock returns on measured loadings, we first regress the monthly excess returns of 100 size-*BM* value-weighted portfolios over the last 36 months (24 months minimum) on the various factors as of the end of June of each year t beginning in 2012 (annually rebalanced); and then assign the factor loadings of a size-*BM* portfolio to each individual stock within that portfolio. The time-series average of the coefficient estimates, Newey and West (1987) robust t-statistics with eight lags (in square brackets), time-series average R-squared, and time-series average number of firm-month observations are reported for each model. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. All data used are collected from the TEJ database.

that are more difficult to arbitrage exhibit greater mispricing. Therefore, the *DOI*-based abnormal profit is hypothesized to be stronger in the presence of high limits-to-arbitrage. I provide strong evidence to support for these hypotheses in the following sections.

5.1. D&O Insurance and undervaluation

I begin by conducting a portfolio test to compare the degree of the mispricing (undervaluation/overvaluation) between stocks with high versus low *DOI*. Specifically, at the end of June of each year t over 2009 to 2020, sample stocks are allocated into deciles according to their *DOI* as of the fiscal year-end in calendar year t–1. The average of mispricing measure (*MP*) in each of *DOI* decile portfolios are reported in Panel A of Table 11. The number in *MP* is time-series averages of yearly cross-sectional means. Following Doukas et al. (2005, 2010) and Chen et al. (2013), mispricing measure (*MP*) for stock i in year t is computed as:

$$MP_{i,t} = ln\left[Capital_{i,t}/Imputed\left(Capital_{i,t}\right)\right] \tag{4}$$

where $Capital_{i,\,t}$ is the market value of common equity plus book value of debt for stock i in year t. $Imputed(Capital_{i,\,t})$ is computed as the product of the stock i's total assets and the its primary industry-median ratio of total capital to total assets in year t. A lower (higher) *MP* represents that firms are undervalued (overvalued).

Panel A of Table 11 illustrates the mean *MP* for *DOI* decile portfolios and mean difference between high and low *DOI* deciles as well as their corresponding t-statistics for the mean difference tests. On average, *MP* is shown a generally monotonic decrease with *DOI*, from 0.351 ($t = 26.18$) in low *DOI* decile to -0.087 ($t = -14.12$) in high-DOI decile. The difference between high and low *DOI* deciles is statistically significant at -0.438 ($t = -32.82$). Consistent with the mispricing hypothesis, this finding suggests that firms with high *DOI* tend to be characterized as undervalued, compared to firms with low *DOI*.

To also provide further evidence in an asset-pricing context, I further examine how *DOI* return premium varies in low *MP* portfolio (undervalued stocks) versus in high *MP* portfolio (overvalued stocks). Given that high-*DOI* stocks are characterized as undervalued and earn higher returns when the mispricing corrects, it is expected that the return difference between high and low *DOI* stocks should be significant among those undervalued group.

For this purpose, I conduct the bivariate-sorted portfolio tests via sorting on *MP* and then on *DOI* and examine the dynamics of average returns for these *MP*-*DOI* portfolios. Specifically, at each June of year t during 2009–2020, sample stocks are first sorted into terciles according to *MP* at the end of year $t-1$ (denoted as low *MP* (Undervalued), Medium *MP*, and high *MP* (Overvalued)). Each such tercile portfolio is further sorted into decile portfolios according to *DOI* at the end of year $t-1$. Equal- and value-weighted monthly returns on a portfolio are then calculated from July of year t to June of year $t+1$. Repeating this every year (annually rebalanced) generates a time-series of monthly returns for each of 3×10 portfolio (i.e., July 2009–June 2021, 144 months). The time-series average of monthly returns and risk-adjusted alphas (CAPM α, FF3 α, and FF5 α) over July 2009–June 2021 are then computed for the 3×10 portfolios and reported in Panel B of Table 11.

As shown, consistent with the mispricing hypothesis, the return spread between high and low *DOI* decile (the H − L portfolio) in the low *MP* tercile (undervalued stocks) is particularly positive and that in the medium and high *MP* terciles is statistically indistinguishable from zero. In particular term, Among the low *MP* tercile (undervalued stocks), the H − L *DOI* portfolio achieves an economically large equal-weighted monthly average return of 1.420% ($t = 3.92$), CAPM α of 1.415% ($t = 3.78$), FF3 α of 1.366% ($t = 3.70$), and FF5 α of 1.379% ($t = 3.64$). The value-weighted portfolios show a similarly strong evidence. These results again support the behavioral mispricing as the explanation for the *DOI* anomaly.

5.2. Limits-to-arbitrage effect

Next, how limits-to-arbitrage affects the *DOI* anomaly is examined. For this purpose, the bivariate-sorted portfolio tests via sorting on each proxy of limits-to-arbitrage and then on *DOI* is conducted (e.g., Li et al., 2014; Leung et al., 2020). This test allows for the explicit analysis of the dynamics of *DOI*-based abnormal profits by comparing the H − L *DOI* return spreads between stocks with high and low limits-to-arbitrage. If the limits-to-arbitrage explains the *DOI* anomaly, then the *DOI*-based abnormal profits should be concentrated among stocks with high limits-to-arbitrage.

As studies have mentioned, the limits-to-arbitrage can be mainly considered by four dimensions: idiosyncratic risk, transaction costs, short-sale constraints, and information uncertainty (e.g., Lam and Wei, 2011; Cao and Han, 2016). Therefore, this study focuses on the proxies for the level of arbitrage costs, including idiosyncratic return volatility (*IV*) as a proxy for idiosyncratic risk, the illiquidity measure (*ILLIQ*) from Amihud (2002) as a proxy for transaction costs, institutional ownership (*IOR*) as a proxy for short-sale constraints, and media coverage (*MEDIA*) as a proxy for information uncertainty. Table 2 provides the definitions of the four variables.

Table 11
Mispricing across *DOI* decile portfolios and *DOI* decile portfolios' returns among undervalued and overvalued stocks.

Panel A: Degree of mispricing across *DOI* decile portfolios

Decile	*MP*	[t]
High *DOI*	−0.087	−14.12
9	−0.097	−10.07
8	−0.047	−3.81
7	−0.020	−3.27
6	0.026	3.56
5	0.080	6.61
4	0.128	13.26
3	0.169	13.42
2	0.262	12.23
Low *DOI*	0.351	26.81
H − L	−0.438***	−32.82

Panel B: *DOI* portfolios' returns among undervalued and overvalued stocks

	Equal-Weighted Portfolios						Value-Weighted Portfolios					
	Low *MP* (Undervalued)		Medium *MP*		High *MP* (Overvalued)		Low *MP* (Undervalued)		Medium *MP*		High *MP* (Overvalued)	
Decile	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]
High *DOI*	2.294	4.11	1.757	3.10	1.703	3.13	1.854	3.13	1.594	2.65	1.008	1.99
9	2.012	3.36	1.563	2.88	0.551	1.01	1.905	3.05	1.566	2.67	0.557	1.12
8	1.944	3.12	1.333	2.36	0.713	1.32	1.763	2.65	1.302	2.32	0.836	1.58
7	1.252	2.25	1.366	2.56	0.935	1.82	1.511	2.57	1.207	2.31	1.005	1.94
6	1.826	3.16	1.254	2.42	0.823	1.56	1.782	2.91	1.296	2.49	0.936	1.62
5	1.470	2.65	1.181	2.32	0.803	1.58	1.380	2.39	1.257	2.42	0.901	1.81
4	1.509	2.78	1.025	2.07	0.996	2.03	1.414	2.64	0.908	1.76	0.754	1.48
3	1.396	2.67	1.045	2.27	0.571	1.28	1.325	2.51	1.220	2.51	0.651	1.44
2	1.434	2.89	1.240	2.63	0.654	1.43	1.356	2.57	1.234	2.44	0.540	1.29
Low *DOI*	0.874	1.90	1.132	2.61	1.017	2.68	0.352	0.71	0.912	2.30	1.319	3.54
H − L	1.420***	3.92	0.625	1.39	0.686	1.62	1.503***	3.40	0.682	1.41	−0.312	−0.75
CAPM α	1.415***	3.78	0.631	1.35	0.623	1.51	1.253***	2.79	0.402	0.82	−0.418	−0.98
FF3 α	1.366***	3.70	0.581	1.30	0.524	1.35	1.079***	2.83	0.204	0.46	−0.641	−1.49
FF5 α	1.379***	3.64	0.607	1.30	0.523	1.33	1.194***	3.09	0.474	1.05	−0.618	−1.48

Panel A presents the mispricing characteristics (undervalued and overvalued) in each of *DOI* decile portfolios. The sample consists of the TWSE/TPEx stocks that have purchased D&O insurance. Sample stocks in financial industries (two-digit industrial codes 28, 58, and 60) are removed. At the end of June of each year *t* over 2009 to 2020, sample stocks are allocated into deciles according to their *DOI* as of the fiscal year-end in calendar year *t–1*. The average of mispricing measure (*MP*) in each of *DOI* decile portfolios are reported in Panel A. The number in *MP* is time-series averages of yearly cross-sectional means. Mispricing measure (*MP*) for stock *i* in year *t* is computed as:

$$MP_{i,\ t} = \ ln\ [Capital_{i,\ t}/Imputed(Capital_{i,\ t})]$$

where $Capital_{i,\ t}$ is the market value of common equity plus book value of debt for stock *i* in year *t*. $Imputed(Capital_{i,\ t})$ is computed as the product of the stock *i*'s total assets and the its primary industry-median ratio of total capital to total assets in year *t*. Panel B presents the equal- and value-weighted average monthly returns for 3 × 10 portfolios sorted first on *MP* and then on *DOI*. At each June of year *t* during 2009–2020, sample stocks are first sorted into terciles according to *MP* at the end of year *t* − *1* (denoted as low *MP* (Undervalued), Medium *MP*, and high *MP* (Overvalued)). Each such tercile portfolio is further sorted into decile portfolios according to *DOI* at the end of year *t* − *1*. Equal- and value-weighted monthly returns on a portfolio are then calculated from July of year *t* to June of year *t* + *1*. Repeating this every year (annually rebalanced) generates a time-series of monthly returns for each of 3 × 10 portfolio (i.e., July 2009–June 2021, 144 months). H − L represents the monthly returns spread between high and low *DOI* deciles for each of *MP* tercile portfolios. The time-series average of monthly returns over July 2009–June 2021 is then computed for the 3 × 10 portfolios. CAPM α, FF3 α, and FF5 α are risk-adjusted alphas (in percentages per month) for each *DOI* decile portfolio, estimated based on the time-series regressions of the CAPM, the Fama–French three-factor model, and the Fama–French five-factor model. [t] presents the robust Newey-West (1987) *t*-statistics, used to test the hypothesis that the mean equals to zero. *, **, and *** represent statistical significance at the 10, 5%, and 1% levels, respectively. All data used are collected from the TEJ database.

Similar to Li et al. (2014) and Leung et al. (2020), the 3 × 10 portfolios are constructed and sorted first on each limits-to-arbitrage proxy (i.e., *IV*, *ILLIQ*, *IOR*, or *MEDIA*) and then on *DOI*. For each June of year *t* during 2009–2020, the sample stocks are first sorted into terciles using *IV*, *ILLIQ*, *IO*, or *MEDIA*. Each such tercile portfolio is further sorted into decile portfolios using *DOI* at the end of year *t* − 1. Equal- and value-weighted monthly returns on a portfolio are then calculated from July of year *t* to June of year *t* + 1. Repeating this every year (annually rebalanced) generates a time-series of monthly returns for each 3 × 10 portfolio (i.e., July 2009–June 2021, 144 months). The average monthly returns for the 3 × 10 portfolios and their corresponding *t*-statistics are calculated. Table 12 presents the equal- and value-weighted average monthly returns of *DOI* decile portfolios, controlling for the limits-to-arbitrage proxies of *IV* in Panel A, *ILLIQ* in Panel B, *IOR* in Panel C, and *MEDIA* in Panel D.

Table 12 shows that under various limits-to-arbitrage proxies, the return spread between high- and low-*DOI* stocks almost monotonically increases from the portfolio with low limits-to-arbitrage (e.g., low *IV*, low *ILLIQ*, high *IOR*, and high *MEDIA*) to that with

Table 12
Limits-to-arbitrage and *DOI* decile portfolios' returns.

Panel A: Proxied by Idiosyncratic Volatility (*IV*)

	Equal-Weighted Portfolios						Value-Weighted Portfolios					
	High *IV*		Medium *IV*		Low *IV*		High *IV*		Medium *IV*		Low *IV*	
Decile	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]
High *DOI*	2.107	3.45	1.852	3.47	1.859	4.11	1.418	2.24	1.884	3.10	1.482	3.17
9	1.832	3.03	1.685	2.72	1.772	3.87	1.213	1.86	1.779	2.84	1.640	3.46
8	1.794	2.85	1.479	2.58	1.646	3.50	1.614	2.46	1.072	1.86	1.370	2.92
7	0.762	1.24	1.304	2.49	1.550	3.59	0.490	0.79	1.531	2.86	1.424	3.46
6	0.897	1.35	1.327	2.30	1.379	3.37	0.688	1.02	1.410	2.35	1.317	3.28
5	0.674	1.12	1.280	2.41	1.722	3.81	0.849	1.40	1.362	2.46	1.609	3.63
4	0.541	0.95	1.139	2.31	1.122	2.69	0.673	1.05	1.141	2.32	0.993	2.26
3	0.721	1.14	1.046	2.18	1.188	2.95	0.576	0.85	0.970	1.86	1.086	2.47
2	0.718	1.26	0.991	2.19	0.940	2.50	0.678	1.08	0.743	1.53	0.798	1.91
Low *DOI*	0.536	1.07	0.734	1.56	0.901	2.99	0.226	0.36	0.881	1.79	1.275	3.80
H − L	1.571***	4.59	1.118***	3.39	0.958***	3.31	1.192**	2.20	1.002**	2.16	0.207	0.54
CAPM α	1.756***	4.13	1.176***	3.46	0.700**	2.45	1.369**	2.46	0.960**	2.00	−0.005	−0.01
FF3 α	1.697***	4.01	1.095***	3.33	0.601**	2.52	1.157**	2.30	0.718*	1.73	−0.270	−1.12
FF5 α	1.672***	3.81	0.806**	2.32	0.471	1.27	1.084**	2.17	0.779	1.62	−0.128	−0.51

Panel B: Proxied by Amihud's Illiquidity (*ILLIQ*)

	Equal-Weighted Portfolios						Value-Weighted Portfolios					
	High *ILLIQ*		Medium *ILLIQ*		Low *ILLIQ*		High *ILLIQ*		Medium *ILLIQ*		Low *ILLIQ*	
Decile	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]
High *DOI*	2.428	4.05	1.449	2.51	1.011	1.74	2.005	3.26	1.240	2.37	1.161	2.16
9	2.073	4.01	1.163	2.00	1.029	1.86	1.859	3.36	1.582	2.76	0.979	1.92
8	1.790	3.02	1.296	2.19	1.095	1.99	1.386	2.30	1.412	2.43	1.105	2.01
7	2.030	3.60	1.167	2.26	0.936	1.79	2.135	3.47	1.293	2.56	1.029	2.01
6	1.425	2.54	1.107	2.08	1.064	2.04	1.322	2.38	1.094	2.17	1.045	2.02
5	1.363	2.53	1.315	2.53	1.020	2.19	1.194	2.25	1.517	2.94	0.964	2.03
4	1.378	2.49	1.065	2.01	0.915	1.87	1.213	2.13	1.016	2.03	0.963	1.93
3	1.230	2.48	1.256	2.59	1.000	2.67	1.166	2.35	1.236	2.76	0.675	1.68
2	1.239	2.75	1.149	2.50	0.767	1.75	1.376	2.92	1.108	2.21	0.628	1.62
Low *DOI*	1.127	2.48	0.974	2.09	0.640	1.53	1.006	1.86	0.696	1.42	1.233	3.43
H − L	1.301***	2.83	0.475*	1.71	0.372	1.25	0.999**	2.39	0.544*	1.68	−0.072	−0.18
CAPM α	1.253***	2.64	0.225	0.82	0.017	0.06	0.703**	2.00	0.392	1.17	−0.385	−0.97
FF3 α	1.224***	2.55	0.181	0.68	−0.118	−0.49	0.633*	1.88	0.309	0.95	−0.451	−1.40
FF5 α	1.433***	2.88	0.030	0.11	−0.023	−0.10	0.583*	1.73	0.188	0.57	−0.404	−1.52

Panel C: Proxied by Institutional Ownership (*IOR*)

	Equal-Weighted Portfolios						Value-Weighted Portfolios					
	High *IOR*		Medium *IOR*		Low *IOR*		High *IOR*		Medium *IOR*		Low *IOR*	
Decile	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]
High *DOI*	1.536	2.62	1.674	2.89	2.586	4.44	1.309	2.26	1.552	2.70	2.150	3.75
9	1.059	2.02	1.666	2.72	1.740	3.38	1.232	2.43	1.839	3.03	1.164	2.25
8	1.265	2.49	1.743	2.97	1.835	3.26	1.399	2.88	1.560	2.79	1.679	2.81
7	1.189	2.44	1.180	2.03	1.336	2.35	1.097	2.18	1.167	2.07	1.261	2.18
6	1.003	2.15	0.988	1.84	1.284	2.36	1.100	2.30	1.025	1.81	1.104	1.94
5	1.219	2.59	1.307	2.46	1.207	2.30	1.081	2.15	1.227	2.22	1.028	1.89
4	0.932	2.12	1.260	2.50	1.243	2.42	0.913	2.02	1.216	2.25	1.088	2.14
3	0.875	2.10	0.954	1.91	0.934	1.78	0.845	2.05	0.927	1.80	0.845	1.59
2	0.817	1.99	1.123	2.21	1.177	2.23	0.838	2.12	1.008	1.81	0.998	1.87
Low *DOI*	1.064	2.81	0.686	1.47	0.677	1.37	1.228	3.38	0.423	0.84	0.394	0.74
H − L	0.472	1.31	0.988***	2.78	1.909***	4.40	0.082	0.18	1.129**	2.75	1.756***	4.36
CAPM α	0.178	0.50	0.853**	2.34	2.004***	4.49	−0.239	−0.54	0.931**	2.23	1.763***	4.24
FF3 α	0.038	0.13	0.762**	2.14	1.968***	4.40	−0.488	−1.44	0.776**	1.99	1.691***	4.10
FF5 α	−0.065	−0.22	0.549	1.51	1.988***	4.26	−0.339	−0.96	0.652	1.59	1.393***	3.28

Panel D: Proxied by Media Coverage (*MEDIA*)

	Equal-Weighted Portfolios						Value-Weighted Portfolios					
	High *MEDIA*		Medium *MEDIA*		Low *MEDIA*		High *MEDIA*		Medium *MEDIA*		Low *MEDIA*	
Decile	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]	Ret (%)	[t]
High *DOI*	1.107	1.96	1.707	2.98	2.407	4.36	0.898	1.63	1.570	2.91	2.218	3.96
9	1.255	2.26	1.595	2.63	1.874	3.34	1.354	2.45	1.643	2.67	1.488	2.81
8	1.058	1.89	1.285	2.19	2.046	3.67	0.986	1.86	1.212	2.13	1.927	3.27
7	0.936	1.82	1.166	2.28	1.527	2.73	0.912	1.74	1.126	2.18	1.564	2.69
6	0.830	1.69	1.269	2.54	1.333	2.38	0.984	1.96	1.307	2.60	1.254	2.27
5	1.052	2.15	1.108	2.13	1.600	2.71	1.150	2.20	1.205	2.60	1.645	2.77
4	0.983	2.06	0.914	1.83	1.449	2.69	1.184	2.34	0.956	1.91	1.534	2.80
3	0.701	1.61	1.090	2.05	1.415	3.06	0.784	1.85	0.966	1.89	1.519	2.76
2	0.652	1.59	0.970	2.04	1.300	2.74	0.464	1.18	0.928	1.95	1.300	2.78
Low *DOI*	0.973	2.53	0.950	2.14	1.279	2.59	1.259	3.50	0.931	2.13	1.266	3.01
H − L	0.134	0.43	0.757*	1.92	1.128***	2.78	−0.362	−0.89	0.638*	1.67	0.952***	2.68
CAPM α	−0.169	−0.56	0.637*	1.77	1.218***	2.92	−0.400	−0.73	0.505	1.29	0.730**	1.99
FF3 α	−0.315	−1.31	0.506	1.31	1.222***	2.89	−0.579	−1.56	0.315	0.92	0.655*	1.80
FF5 α	−0.397	−1.64	0.516	1.32	1.112**	2.50	−0.626*	−1.85	0.111	0.32	0.599*	1.76

This table presents the average monthly returns for 3 × 10 portfolios sorted first on each of limits-to-arbitrage proxies (i.e., *IV*, *ILLIQ*, *IOR*, and *MEDIA*) and then on *DOI*. The sample consists of the TWSE/TPEx stocks that have purchased D&O insurance. Sample stocks in financial industries (two-digit industrial codes 28, 58, and 60) are removed. At each June of year *t* during 2009–2020, sample stocks are first sorted into terciles according to *IV*, *ILLIQ*, *IOR*, or *MEDIA* at the end of year *t − 1*. Each such tercile portfolio is further sorted into decile portfolios according to *DOI* at the end of year *t − 1*. Equal- and value-weighted monthly returns on a portfolio are then calculated from July of year *t* to June of year *t* + *1*. Repeating this every year (annually rebalanced) generates a time-series of monthly returns for each of 3 × 10 portfolio (i.e., July 2009–June 2021, 144 months). H − L represents the monthly returns spread between high and low *DOI* deciles for each of tercile portfolios grouped by *IV*, *ILLIQ*, *IOR*, or *MEDIA*. The time-series average of monthly returns over July 2009–June 2021 is then computed for the 3 × 10 portfolios. CAPM α, FF3 α, and FF5 α are risk-adjusted alphas (in percentages per month) for each *DOI* decile portfolio, estimated based on the time-series regressions of the CAPM, the Fama–French three-factor model, and the Fama–French five-factor model. [t] presents the robust Newey-West (1987) *t*-statistics, used to test the hypothesis that the mean equals to zero. *, **, and *** represent statistical significance at the 10, 5%, and 1% levels, respectively. All data used are collected from the TEJ database.

high limits-to-arbitrage (e.g., high *IV*, high *ILLIQ*, low *IO*, and low *MEDIA*). Consistent with the behavioral mispricing hypothesis, this finding indicates that the *DOI*-based abnormal return is significantly higher for stocks with high than with low limits-to-arbitrage. For example, when *IV* is the limits-to-arbitrage proxy—Panel A—the H − L *DOI* portfolio earns an equal-weighted (value-weighted) average of 0.958% per month with a *t*-statistic of 3.31 (0.207% per month with a *t*-statistic of 0.54) among low *IV* stocks. In contrast, the H − L *DOI* portfolio earns an equal-weighted (value-weighted) average of 1.571% per month with a *t*-statistic of 4.59 (1.192% per month with $t = 2.20$) among high-*IV* stocks. The results remain for the CAPM, FF3, and FF5 alphas. When *ILLIQ*, *IOR*, and *MEDIA* are considered as proxies—Panels B, C, and D—the results are similar for the *IV* proxy.

The overall evidence presented in Table 12 indicates that the profitability of a *DOI*-based trading strategy (i.e., a zero-investment portfolio that is long on high- and short on low-*DOI* stocks) is meaningfully reduced—even eliminated—in the subsample of stocks with lower arbitrage limits. In contrast, the *DOI*-based abnormal profit is stronger in the presence of highly costly arbitrage (e.g., high idiosyncratic volatility, high illiquidity, low institutional ownership, or low media exposure), allowing mispricing to persist. These findings further support behavioral mispricing as a major explanation for the *DOI* anomaly.

6. Concluding remarks

D&O insurance, one of the main triggers that help firms to better convert growth opportunities into higher firm value, is heterogeneous across firms. This study contributes to the literature on asset-pricing anomaly detection by providing evidence that D&O insurance heterogeneity at the firm level affects the cross section of expected stock returns.

Testing a near-complete unique data on D&O insurance in the Taiwan stock market from July 2009 to June 2021, the existence of the D&O insurance anomaly is documented. The portfolio of stocks with high–minus–low-D&O insurance has an average risk-adjusted return of 7–13% per year after accounting for widely accepted risk factors. This high-D&O insurance return premium persists when considering equal-, value-, price-, and turnover-weighted portfolio versions by analyzing the bivariate-sorts portfolios that controls for well-known firm characteristics such as size, value, profitability, investment, momentum, and R&D expenditure, and various governance-linked measures such as BIND, board ownership, board duality, operating accruals, the executives' critical control rights, the deviation of control rights to cash flow rights, and block holder's ownership; and estimating the Fama–MacBeth cross-sectional regressions that simultaneously controls for a set of returns predictors.

To distinguish rational risk from behavioral mispricing explanation for the D&O insurance anomaly, this study constructs a factor-mimicking portfolio, *DOIF* (i.e., long on the high-D&O insurance stocks and short on the low-D&O insurance stocks) designed to capture the D&O insurance effect. From the perspective of the mean-variance efficient strategy, the evidence suggests that *DOIF* is an essential contributor. Importantly, the D&O insurance characteristic continues to be highly significant in predicting future returns, with or without controlling for the *DOIF* factor loading in the bivariate-sorts portfolios tests and Fama–MacBeth cross-sectional regressions. In contrast, the *DOIF* factor loading becomes insignificant after controlling for the D&O insurance characteristic. Therefore, it is the characteristic of D&O insurance rather than the covariance of D&O insurance-based mimicking factor that predicts returns, which opposes the notion that the D&O insurance anomaly represents a compensation for higher systematic risk within a standard factor pricing model and supports the behavioral mispricing explanation of the anomaly.

Thus, two testable implications of the behavioral mispricing explanation for the high-D&O insurance return premium are directly assessed. First, in support of behavioral mispricing, stocks of firms with high-(low-) D&O insurance are found to be undervalued (overvalued). Second, further evidence is presented that the high-minus-low-D&O insurance return premium is concentrated among those undervalued stocks and is particularly large for stocks with high limits-to-arbitrages (i.e., high idiosyncratic volatility, high illiquidity, low institutional ownership, and low media exposure), which can be interpreted as consistent with behavioral theories that mispricing can better explain the D&O insurance anomaly.

Convincing evidence on the existence of the *DOI* anomaly in the Taiwan stock market is presented, which could assist investors in devising a potential profitable investment strategy by investing in companies that have highter D&O insurance coverage. This study has one practical implication. Consistent with Chen et al. (2016), the disclosure of D&O insurance coverage can signal to market participants that insured firms' private information and investors factor this information in their investment decisions. It is worth mentioning that while this study's overall evidence is tantalizing, the entire sampling period of 2009–2021 is relatively short (only 12 years). This data limitation brings up concerns that the predictive power of D&O insurance for stock returns may not fare well under various stock market scenarios or may be considered sensitive to the business cycles, and, therefore, this study's generalized conclusion should be drawn with caution.

CRediT authorship contribution statement

Xuan-Qi Su: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

References

Ali, A., Hwang, L.S., Trombley, M.A., 2003. Arbitrage risk and the book-to-market anomaly. J. Financ. Econ. 69 (2), 355–373.
Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Mark. 5 (1), 31–56.
Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2009. High idiosyncratic volatility and low returns: international and further US evidence. J. Financ. Econ. 91 (1), 1–23.
Armstrong, C.S., Vashishtha, R., 2012. Executive stock options, differential risk-taking incentives, and firm value. J. Financ. Econ. 104 (1), 70–88.
Bai, Y., Green, C.J., 2010. International diversification strategies: revisited from the risk perspective. J. Bank. Financ. 34 (1), 236–245.
Baker, T., Griffith, S.J., 2007. Predicting corporate governance risk: Evidence from the Directors'& (and) Officers' liability insurance market. Univ. Chic. Law Rev. 74, 487–544.
Baker, T., Griffith, S.J., 2010. Ensuring Corporate Misconduct: How Liability Insurance Undermines Shareholder Litigation? The University of Chicago Press, Chicago.
Barber, B.M., Odean, T., 2008. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. Rev. Financ. Stud. 21 (2), 785–818.
Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. J. Financ. Econ. 49 (3), 307–343.
Bongaerts, D., Kang, X., Van Dijk, M.A., 2022. The intangibles premium: risk or mispricing? Available at SSRN 3927990. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3927990.
Boubakri, N., Bouslimi, L., 2016. Directors' and officers' liability insurance and analyst forecast properties. Financ. Res. Lett. 19, 22–32.
Boyer, M.M., 2007. Three insights from the Canadian D&O Insurance Market: inertia. Inf. Insiders, Connecticut Insurance Law J. 14 (1), 75–106.
Boyer, M.M., Stern, L.H., 2012. Is corporate governance risk valued? Evidence from directors' and officers' insurance. J. Corp. Finan. 18 (2), 349–372.
Boyer, M.M., Stern, L.H., 2014. D&O insurance and IPO performance: what can we learn from insurers? J. Financ. Intermed. 23 (4), 504–540.
Boyer, M.M., Tennyson, S., 2015. Directors' and officers' liability insurance, corporate risk and risk taking: new panel data evidence on the role of directors' and officers' liability insurance. J. Risk Insurance 82 (4), 753–791.
Cao, J., Han, B., 2016. Idiosyncratic risk, costly arbitrage, and the cross-section of stock returns. J. Bank. Financ. 73, 1–15.
Cao, Z., Narayanamoorthy, G.S., 2014. Accounting and litigation risk: evidence from directors' and officers' insurance pricing. Rev. Acc. Stud. 19 (1), 1–42.
Carhart, M.M., 1997. On persistence in mutual fund performance. J. Financ. 52 (1), 57–82.
Chalmers, J.M., Dann, L.Y., Harford, J., 2002. Managerial opportunism? Evidence from directors' and officers' insurance purchases. J. Financ. 57 (2), 609–636.
Chang, S.C., Ren, Y., Yeh, J., 2018. The role of information: when is Directors' and Officers' insurance value-added? J. Bank. Financ. 97, 189–197.
Chen, C.W., Pantzalis, C., Park, J.C., 2013. Press coverage and stock price deviation from fundamental value. J. Financ. Res. 36 (2), 175–214.
Chen, L.Y., Chen, Y.F., Yang, S.Y., 2017. Managerial incentives and R&D investments: the moderating effect of the directors' and officers' liability insurance. N. Am. J. Econ. Financ. 39, 210–222.
Chen, Z., Li, O.Z., Zou, H., 2016. Directors' and officers' liability insurance and the cost of equity. J. Account. Econ. 61 (1), 100–120.
Chiang, Y.M., Chang, P.R., 2022. Overinvestment, ownership structure, and directors' and officers' liability insurance. Int. Rev. Econ. Financ. 78, 38–50.
Chou, P.H., Huang, T.Y., Yang, H.J., 2013. Arbitrage risk and the turnover anomaly. J. Bank. Financ. 37 (11), 4172–4182.
Chu, Y., Hirshleifer, D., Ma, L., 2020. The causal effect of limits to arbitrage on asset pricing anomalies. J. Financ. 75 (5), 2631–2672.
Core, J.E., 1997. On the corporate demand for directors' and officers' insurance. J. Risk Insurance 64 (1), 63–87.
Cross, M.L., Davidson, W.N., Thornton, J.H., 1989. The impact of directors' and officers' liability suits on firm value. J. Risk Insurance 56 (1), 128–136.
Cubbin, J., Leech, D., 1983. The effect of shareholding dispersion on the degree of control in British companies: theory and measurement. Econ. J. 93 (370), 351–369.
Daniel, K., Titman, S., 1997. Evidence on the characteristics of cross sectional variation in stock returns. J. Financ. 52 (1), 1–33.
Donelson, D.C., Hopkins, J.J., Yust, C.G., 2018. The cost of disclosure regulation: Evidence from D&O insurance and nonmeritorious securities litigation. Rev. Acc. Stud. 23 (2), 528–588.
Donelson, D.C., Monsen, B.R., Yust, C.G., 2021. US Evidence from D&O Insurance on accounting-related agency costs: implications for country-specific studies. Journal of Financial Reporting 6 (2), 63–87.
Doukas, J.A., Kim, C., Pantzalis, C., 2005. The two faces of analyst coverage. Financ. Manag. 34 (2), 99–125.
Doukas, J.A., Kim, C.F., Pantzalis, C., 2010. Arbitrage risk and stock mispricing. J. Financ. Quant. Anal. 45 (4), 907–934.
Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. J. Financ. 47 (2), 427–465.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33 (1), 3–56.
Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. J. Financ. Econ. 116 (1), 1–22.

Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: empirical tests. J. Polit. Econ. 81 (3), 607–636.
Fang, L., Peress, J., 2009. Media coverage and the cross-section of stock returns. J. Financ. 64 (5), 2023–2052.
Gebhardt, W.R., Hvidkjaer, S., Swaminathan, B., 2005. The cross-section of expected corporate bond returns: betas or characteristics? J. Financ. Econ. 75 (1), 85–114.
George, T.J., Hwang, C.Y., 2010. A resolution of the distress risk and leverage puzzles in the cross section of stock returns. J. Financ. Econ. 96 (1), 56–79.
Gillan, S.L., Panasian, C.A., 2015. On lawsuits, corporate governance, and directors' and officers' liability insurance. J. Risk Insurance 82 (4), 793–822.
Giroud, X., Mueller, H.M., 2011. Corporate governance, product market competition, and equity prices. J. Financ. 66 (2), 563–600.
Gompers, P., Ishii, J., Metrick, A., 2003. Corporate governance and equity prices. Q. J. Econ. 118 (1), 107–156.
Harvey, C.R., 1995. Predictable risk and returns in emerging markets. Rev. Financ. Stud. 8 (3), 773–816.
Hirshleifer, D., Jiang, D., 2010. A financing-based misvaluation factor and the cross-section of expected returns. Rev. Financ. Stud. 23 (9), 3401–3436.
Hirshleifer, D., Teoh, S.H., 2003. Limited attention, information disclosure, and financial reporting. J. Account. Econ. 36 (1–3), 337–386.
Hirshleifer, D., Hou, K., Teoh, S.H., 2012. The accrual anomaly: risk or mispricing? Manag. Sci. 58 (2), 320–335.
Hirshleifer, D., Hsu, P.H., Li, D., 2013. Innovative efficiency and stock returns. J. Financ. Econ. 107 (3), 632–654.
Holderness, C.G., 1990. Liability insurers as corporate monitors. Int. Rev. Law Econ. 10 (2), 115–129.
Hou, K., Hsu, P.H., Wang, S., Watanabe, A., Xu, Y., 2022. Corporate R&D and stock returns: international evidence. J. Financ. Quant. Anal. 57 (4), 1377–1408.
Huang, R.J., Jeng, V., Wang, C.W., Yue, J.C., 2021. Does size and book-to-market contain intangible information about managerial incentives? Learning from corporate D&O insurance purchase. Pac. Basin Financ. J. 68, 101560.
Hwang, J.H., Kim, B., 2018. Directors' and officers' liability insurance and firm value. J. Risk Insurance 85 (2), 447–482.
Jia, N., Tang, X., 2018. Directors' and officers' liability insurance, independent director behavior, and governance effect. J. Risk Insurance 85 (4), 1013–1054.
Johnson, S.A., Moorman, T.C., Sorescu, S., 2009. A reexamination of corporate governance and equity prices. Rev. Financ. Stud. 22 (11), 4753–4786.
Kao, L., Chen, A., Krishnamurti, C., 2020. Outcome model or substitute model of D&O insurance on IPO pricing without information asymmetry before issuance. Pac. Basin Financ. J. 61, 101300.
Keloharju, M., Linnainmaa, J.T., Nyberg, P., 2021. Are return seasonalities due to risk or mispricing? J. Financ. Econ. 139 (1), 138–161.
La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 1999. The quality of government. J. Law Econ. Org. 15 (1), 222–279.
La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 2002. Investor protection and corporate valuation. J. Financ. 57 (3), 1147–1170.
Lai, Y.H., Tai, V.W., 2019. Managerial overconfidence and directors' and officers' liability insurance. Pac. Basin Financ. J. 57, 101051.
Lam, F.E.C., Wei, K.J., 2011. Limits-to-arbitrage, investment frictions, and the asset growth anomaly. J. Financ. Econ. 102 (1), 127–149.
Leung, W.S., Evans, K.P., Mazouz, K., 2020. The R&D anomaly: risk or mispricing? J. Bank. Financ. 115, 105815.
Li, K., Sarkar, A., Wang, Z., 2003. Diversification benefits of emerging markets subject to portfolio constraints. J. Empir. Financ. 10 (1–2), 57–80.
Li, K.F., Liao, Y.P., 2014. Directors' and officers' liability insurance and investment efficiency: evidence from Taiwan. Pac. Basin Financ. J. 29, 18–34.
Li, X., Sullivan, R.N., Garcia-Feijóo, L., 2014. The limits to arbitrage and the low-volatility anomaly. Financ. Anal. J. 70 (1), 52–63.
Li, X., Sullivan, R.N., Garcia-Feijóo, L., 2016. The low-volatility anomaly: market evidence on systematic risk vs. mispricing. Financ. Anal. J. 72 (1), 36–47.
Lin, C., Officer, M.S., Zou, H., 2011. Directors' and officers' liability insurance and acquisition outcomes. J. Financ. Econ. 102 (3), 507–525.
Lin, C., Officer, M.S., Wang, R., Zou, H., 2013. Directors' and officers' liability insurance and loan spreads. J. Financ. Econ. 110 (1), 37–60.
Lin, C., Officer, M.S., Schmid, T., Zou, H., 2019. Is skin in the game a game changer? Evidence from mandatory changes of D&O insurance policies. J. Account. Econ. 68 (1), 101225.
MacKinlay, A.C., 1995. Multifactor models do not explain deviations from the CAPM. J. Financ. Econ. 38 (1), 3–28.
Mashruwala, C., Rajgopal, S., Shevlin, T., 2006. Why is the accrual anomaly not arbitraged away? The role of idiosyncratic risk and transaction costs. J. Account. Econ. 42 (1–2), 3–33.
Mayers, D., Smith Jr., C.W., 1990. On the corporate demand for insurance: evidence from the reinsurance market. J. Bus. 63 (1), 19–40.
Newey, W.K., West, K.D., 1987. Hypothesis testing with efficient method of moments estimation. Int. Econ. Rev. 777–787.
O'Sullivan, N., 1997. Insuring the agents: the role of directors' and officers' insurance in corporate governance. J. Risk Insurance 654 (3), 545–556.
Pontiff, J., 1996. Costly arbitrage: evidence from closed-end funds. Q. J. Econ. 111 (4), 1135–1151.
Shleifer, A., Vishny, R.W., 1997. The limits of arbitrage. J. Financ. 52 (1), 35–55.
Sloan, R.G., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? Account. Rev. 71 (3), 289–315.
Stambaugh, R.F., Yu, J., Yuan, Y., 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. J. Financ. 70 (5), 1903–1948.
Su, Z., Lyu, T., Yin, L., 2022. China's illiquidity premium: due to risk-taking or mispricing? Pac. Basin Financ. J. 76, 101861.
Veldkamp, L.L., 2006. Media frenzies in markets for financial information. Am. Econ. Rev. 96 (3), 577–601.
Vereshchagina, G., Hopenhayn, H.A., 2009. Risk taking by entrepreneurs. Am. Econ. Rev. 99 (5), 1808–1830.
Wurgler, J., Zhuravskaya, E., 2002. Does arbitrage flatten demand curves for stocks? J. Bus. 75 (4), 583–608.
Yeh, Y.H., 2019. Corporate governance and family succession: new evidence from Taiwan. Pac. Basin Financ. J. 57, 100967.
Yuan, R., Sun, J., Cao, F., 2016. Directors' and officers' liability insurance and stock price crash risk. J. Corp. Finan. 37, 173–192.
Zhang, X.F., 2006. Information uncertainty and stock returns. J. Financ. 61 (1), 105–137.
Zhong, A., Gray, P., 2016. The MAX effect: an exploration of risk and mispricing explanations. J. Bank. Financ. 65, 76–90.
Zou, H., Adams, M.B., 2008. Debt capacity, cost of debt, and corporate insurance. J. Financ. Quant. Anal. 43 (2), 433–466.
Zou, H., Wong, S., Shum, C., Xiong, J., Yan, J., 2008. Controlling-minority shareholder incentive conflicts and directors' and officers' liability insurance: evidence from China. J. Bank. Financ. 32 (12), 2636–2645.