The Pricing and Economic Impact of Legal Risk *

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Abstract

Legal risk is an inherent feature of markets, rooted in the institutions that enable economic activity, yet it remains difficult to measure across firms. This paper constructs a text-based measure of firm-level legal risk (**LRISK**) using earnings call transcripts. **LRISK** predicts class action lawsuits and spikes during periods of heightened legal incidents. A one standard deviation increase predicts a 3–7% decline in future investment and lowers firms' reliance on debt, consistent with precautionary motives. Legal risk is positively priced, particularly after 2010, and varies across legal origins, reflecting institutional differences.

Keywords: Legal Risk, Earnings Call Transcripts, The LAW Factor, Financing Frictions, Law and Finance

JEL Classification: G12, G14, K22, K41, C55

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1 Introduction

A well-functioning economy relies on the rule of law. Legal and regulatory institutions such as courts, enforcement agencies, and financial regulators support economic activity by enforcing contracts and protecting property rights. Yet these same institutions also introduce legal risk, arising from uncertainty in how laws and regulations are interpreted and applied. Such uncertainty may stem from litigation, regulatory actions, or enforcement proceedings, and can impose substantial financial costs on affected firms. The relevance of this risk has grown as legal frameworks have become more complex and regulatory scrutiny more stringent.[1] Legal risk, in this sense, is an inherent feature of modern financial markets.

Despite its importance, legal risk remains difficult to measure because it does not manifest explicitly on balance sheets and frequently arises through opaque and anticipatory channels influenced by evolving statutes, regulatory discretion, and strategic compliance practices. To address this challenge, this paper introduces **LRISK**, a novel text-based metric of firm-level legal risk constructed from earnings call transcripts. By quantifying the frequency of firm references to legal topics—including litigation, regulatory inquiries, and judicial proceedings—**LRISK** highlights that legal risk plays a key role in shaping both asset prices and corporate behavior (i.e., legal risk as measured by **LRISK** has both pricing impact and economic impact).

The empirical analysis yields three main results. First, **LRISK** predicts future class action lawsuits and captures firm-level attention to legal-related events—such as climate regulations and SEC enforcement actions against banking firms—in a timely manner. This evidence validates **LRISK** as a reliable measure of a firm's exposure to legal risk, in contrast to standard SEC filings (e.g., 10-Ks and 10-Qs), which typically acknowledge such risks only after a delay due to higher disclosure thresholds and more restrictive reporting practices.

Second, I examine the asset pricing implications of legal risk, showing that it carries a positive risk

[1] This trend is particularly evident in the United States. The number of securities class action lawsuits has more than doubled since the 1990s, even as the number of publicly listed firms has declined (see https://corpgov.law.harvard.edu/2021/03/11/recent-trends-in-securities-class-action-litigation/). Patent disputes have tripled since 2005 (Cohen et al. 2019), and regulatory enforcement activity has accelerated in the post-crisis period. Online Appendix Section A and Figure A.1 illustrates this trend, showing the steady expansion of litigation-prone industries over the past two decades.

premium: over the last twenty years (July 2004 – June 2024), a long–short portfolio that buys firms with high legal risk and sells firms with no legal risk (the **LAW** factor) earns an annualized return of 4.7% ($t = 3.6$). Focusing on the post-crisis period (July 2010 - June 2024) when regulatory scrutiny intensified, the legal risk premium increases to 7.1% ($t = 4.9$). The **LAW** factor captures a distinct dimension of firm-level legal uncertainty relative to existing text-based measures (such as political risk or cyber risk), remains robust to industry controls, and is orthogonal to standard asset pricing factors. To further validate the *risk-based* interpretation, I show that the premium cannot be explained by either temporary cash-flow shocks or behavioral biases. It also avoids the common "factor zoo" critique, underscoring its distinctiveness and relevance to financial markets.

The pricing effect of legal risk is interpreted as a *systematic* force that broadly influences asset prices across firms and sectors. A common misconception equates legal risk exclusively with litigation risk, which typically involves firm-versus-firm disputes that diversified investors can largely offset. In this paper, however, legal risk is defined more broadly to include both litigation-related risk and regulatory or enforcement risk, the latter capable of generating correlated shocks across industries or markets. To support this idea, I leverage the flexibility of textual analysis to construct a macro-level legal risk factor and show that it carries significant pricing implications. I also outline three possible channels through which firm-specific legal shocks can become market-relevant. Finally, I construct an *aggregate* measure of legal risk by computing the economy-wide frequency of legal terms in earnings calls. This measure captures the evolving macro-level salience of legal concerns and remains conceptually and empirically distinct from other well-known uncertainty indices such as Economic Policy Uncertainty (EPU) index (Baker et al. 2016) and the macroeconomic uncertainty measure of Jurado et al. (2015).

Third, **LRISK** has an economic impact. Faced with heightened legal uncertainty, firms behave precautionarily—postponing irreversible or hard-to-redeploy projects and shying away from fixed commitments that amplify downside risk. Quantitatively, a one standard deviation increase in **LRISK** is associated with a 3–7% reduction in investment in the following year, with the largest pullback in intangibles (R&D), where option values of waiting are greatest. On the financing margin, firms with elevated **LRISK** are significantly less likely to issue debt when they face funding deficits, consistent with tighter debt capacity, higher required yields, and concerns about legal tail events interacting with rigid repayment obligations. Local-projection estimates indicate these effects persist for multiple years, pointing to durable, rather than, transitory, distortions in capital allocation. Taken together, the evidence is consistent with legal risk operating as a financing friction that dampens investment and shapes real decisions at the firm level.

Overall, this paper highlights the role of legal risk as a first-order determinant of both asset prices and corporate decision-making. While legal and regulatory institutions underpin market stability, they also introduce frictions and uncertainty that shape corporate decisions and investor behavior. Recognizing the role of legal risk is essential to understanding capital allocation and the functioning of modern financial markets.

Literature review: This paper intersects several strands of literature on the role of legal systems in finance. A first body of work examines stock price reactions to lawsuits, generally finding negative effects at both the firm and industry level (e.g., Kamma et al. 1988; Gande and Lewis 2009; Hadlock and Sonti 2012). While these studies rely on event-based methodologies, this paper adopts a calendar-time portfolio approach to show that legal risk is systematically priced across firms. Relatedly, Cohen et al. (2013) show that political signals such as senators' voting behavior can significantly affect industry-level returns.

This paper also contributes to the literature on the economic effects of legal institutions and uncertainty. While earlier studies have focused on the role of legal origins and judicial efficiency in shaping capital markets (La Porta et al. 1998; Glaeser and Shleifer 2002), recent work has emphasized the economic costs of legal uncertainty itself. Lee et al. (2024) develop a model that distinguishes between diversifiable and non-diversifiable legal uncertainty and show empirically that systematic legal uncertainty reduces credit supply and investment in Korea's bankruptcy system. Complementing this, Ash et al. (2025) find that more detailed and contingent legislation in U.S. states spurs economic growth, particularly in sectors requiring relationship-specific investments. These findings underscore the importance of legal clarity for capital allocation—an insight this paper builds upon by introducing a firm-level measure of legal risk in the U.S. and demonstrating its real and financial consequences.

In corporate finance, legal risk is known to influence firm behavior. It can lead to IPO underpricing (Hughes and Thakor 1992; Lowry and Shu 2002), shape acquisition strategies (Gormley and Matsa 2011), alter disclosure practices (Skinner 1994), and raise audit costs (Shu 2000). Legal proceedings also impose indirect costs through reputational damage, managerial distraction, and heightened financing constraints.

Finally, this paper contributes to the growing literature on text-based methods in finance, which leverage unstructured data to measure risk and predict economic outcomes (e.g., Baker et al. 2016; Manela and Moreira 2017; Hassan et al. 2019). More recently, earnings call transcripts have been used to quantify firm-level exposures to climate risk, cyber threats, and extreme weather (Sautner et al. 2023; Jamilov et al. 2025; Kruttli et al. 2025). A growing subset of this literature focuses specifically on legal and litigation risk. Early work such as Francis et al. (1994) identifies high-litigation industries, while Hossain et al. (2023) use judicial ideology as a geographic proxy for litigation risk. Closely related are Bereskin et al. (2023), who examine patent litigation using matched samples, and Bennett et al. (2025), who extract litigious language from 10-K filings based on the Loughran and McDonald (2011) dictionary. This paper extends that framework by expanding the Loughran–McDonald dictionary to include context-specific bigrams and trigrams that more precisely identify legal terminology in practice (discussed in detail in Section 4.2), and by demonstrating that legal risk has both asset-pricing and real-economic implications.

Structure of the Paper. The remainder of the paper is organized as follows. Section 2 describes the construction of the firm-level legal risk measure **LRISK** using textual analysis of earnings call transcripts and presents validation exercises. Section 3 reports the asset pricing results, ruling out alternative cash-flow and behavioral explanations in favor of a risk-based interpretation. This section also demonstrates that the legal risk premium is systematic rather than idiosyncratic and introduces an aggregate measure of legal risk (**Aggregate LRISK**). Section 4 discusses the results in the context of the factor zoo critique, compares the **LAW** factor with other text-based measures, and examines heterogeneity across legal origins. Section 5 investigates the real effects of legal risk on corporate investment and financing decisions. Section 6 concludes.

2 LRISK: Construction and Validation

2.1 Extracting Legal Risk from Corporate Earnings Conference Calls

This paper constructs a text-based measure of ex-ante legal risk at the firm level, denoted as **LRISK**, using a simple bag-of-words approach applied to quarterly earnings conference call transcripts of U.S. public firms.[2] The measure captures how frequently firms mention legal terminology during calls with analysts and investors.

Why rely on a simple bag-of-words approach rather than large language models (LLMs) such as FinBERT (Huang et al. 2023)? The presence of legal references is inherently informative: mentions of lawsuits, regulatory scrutiny, or court proceedings are material events irrespective of tone. Because legal risk discussions are relatively sparse in earnings calls, the primary task is to detect whether firms raise these issues at all, rather than to classify nuanced sentiment. In this context, a bag-of-words method is appropriate—transparent, computationally efficient, and well-established in the literature. By emphasizing the straightforward presence of legal-related terms rather than complex embeddings or sentiment classification, **LRISK** provides a tractable and credible measure of firm-level legal risk.[3]

Why base the legal risk measure on earnings calls rather than SEC filings such as 10-Ks or 10-Qs? Earnings calls typically disclose relevant developments sooner and with greater openness than formal reports, which are highly scripted, legally vetted, and constrained by higher materiality thresholds that can delay discussion of ongoing disputes or anticipated legal challenges. The Apple–Qualcomm litigation illustrates this distinction: the case began in January 2017 and settled in April 2019, yet Apple's 10-Q and 10-K did not reference it until August and November 2018—over

[2]Typically, firms hold quarterly earnings calls aligned with their financial reporting cycle. These calls begin with a structured management presentation covering recent performance, financial metrics, and key developments, followed by a Q&A session where analysts and investors question management. The interactive nature of these calls allows real-time insights into management's concerns, strategic priorities, and potential risk exposures. In that vein, the (transcripts of) conference calls provide a natural context to learn about the risks firms face and market participants' views thereof (Hassan et al. 2019).

[3]This approach is consistent with related work in finance. For instance, Kruttli et al. (2025) identify extreme weather uncertainty by counting hurricane-related terms in transcripts, while Jamilov et al. (2025) construct a global cyber risk measure using validated keyword frequencies, demonstrating that simple, contextually grounded frequency-based methods can yield robust and informative measures of firm-level risk.

a year after filing. By contrast, Apple's January 2017 earnings call, held just a week after the lawsuit began, explicitly mentioned the dispute, highlighting the timeliness of calls. Earnings calls also benefit from scheduling advantages, as they are typically held a few days before the corresponding 10-K or 10-Q release. Moreover, formal filings have grown increasingly cumbersome: the average 10-K is now roughly six times longer than in 1995 (Cohen et al. 2020), creating processing bottlenecks for investors. They are also laden with legal jargons (Garcia et al. 2023), which, in this paper's context, risks conflating genuine legal risk with mere legalistic expression.

[INSERT FIGURE 1 HERE]

Figure 1 shows that the sample of firms analyzed in this study is highly representative of the overall U.S. stock market. The top panel tracks the number of firms publishing earnings call transcripts from 2002 to 2024. The black solid line indicates that coverage rises steadily from approximately 55% in 2002 to over 85% by the late 2010s, with a modest decline during the COVID-19 period. The same panel shows that these firms have collectively accounted for about 85% of total U.S. market capitalization since 2010 (red solid line). The bottom panel confirms that virtually all of the top 100 and 500 firms by market capitalization regularly publish earnings calls. This broad coverage underscores the representativeness of the sample and supports the generalizability of the **LRISK** measure across the market.

Using this comprehensive sample of firms, I analyze the textual content of their earnings call transcripts, focusing on the presence of legal terminology and related language to construct **LRISK**. The objective is to capture how frequently legal issues are discussed during these calls.

[INSERT TABLE 1 HERE]

Table 1 provides illustrative examples of how firms articulate legal risks during earnings calls. One additional example comes from Alphabet Inc. (Google) during a 2024 earnings call, which stated: *"But it looks like the way that the Google versus DOJ search trial is going, there's a decent likelihood that the Apple ISA contract and some of the Android pre-install contracts are going to be voided at some point in the future."* This refers to the U.S. Department of Justice's (DOJ) antitrust lawsuit, which poses a direct threat to Google's core business model. The firm's public acknowledgment of this risk highlights how legal uncertainty can materially affect investor perception and firm value.

More broadly, the fact that firms openly discuss legal risks in high-stakes earnings calls where their words are scrutinized by analysts, investors, and regulators suggests that these mentions are far from mere "cheap talk" (Crawford and Sobel 1982; Farrell and Rabin 1996). Earnings conference calls are typically broadcast live over the internet, which encourages management to avoid excessive legal language or jargon, making the information more accessible and transparent.[4] Therefore, mentions of legal risk in earnings call transcripts are meaningful, as their frequency reflects substantive concerns rather than strategic messaging or rhetorical hedging.

Central to the analysis is a curated dictionary of legal n-grams (covering unigrams, bigrams, and trigrams) that captures common patterns in legal risk language. I begin with the Loughran–McDonald (LM) Dictionary (Loughran and McDonald 2011), specifically its "litigious (Fin-Lit)" category, which contains 903 litigation-related keywords in the 2023 edition. In this paper, I argue that while the LM dictionary provides a valuable foundation, its reliance on single words can limit precision (see Section 4.2 for details). To address this, I employ a pre-training step inspired by FastText-based phrase detection on 10 years (2012–2022) of earnings call transcripts, which identifies and retains contextually meaningful multi-word expressions (e.g., *"Patent Infringement"* for bigram and *"Department of Justice"* for trigram). This procedure expands the LM terms into bigrams and trigrams frequently observed in earnings calls, ensuring that the dictionary reflects how legal risk is actually discussed in practice. The resulting dynamic set of legal n-grams captures context-specific legal expressions, reduces misclassification, and improves measurement precision. Moreover, look-ahead bias is unlikely because the legal lexicon is not time-specific: terms such as *"litigation," "settlement,"* or *"regulatory investigation"* retain consistent meanings across decades.[5]

[INSERT TABLE 2 HERE]

[4] This is in line with the 10-K sample as documented in Loughran and McDonald (2011), where the authors find that the Management's Discussion and Analysis (MD&A) section tends to contain fewer litigation-related terms compared to the full 10-K document (see Table 2 of that paper).

[5] The need for rolling estimation to avoid look-ahead bias depends on the temporal stability of the underlying language. For time-specific, event-driven discourse—such as war risk, where terminology evolves with each historical episode—a rolling approach is appropriate (Hirshleifer et al. 2025). By contrast, when language is semantically stable over time, as in the geopolitical terms of Caldara and Iacoviello (2022) or the legal risk analyzed in the present paper, a fixed dictionary applied consistently across periods provides a valid and temporally consistent measure.

With the training library of legal terms $\mathbb{L}$ established (see Table 2 and Online Appendix B), I proceed to define a simple measure of **LRISK**, representing the legal risk of firm i at quarter t as:

$$\textbf{LRISK}_{it} = \frac{\sum_{k}^{K_{it}} \left(\mathbb{1}[k \in \mathbb{L}] \right)}{\text{No. of sentences}} \tag{1}$$

where $k = 1, 2, \ldots, K_{it}$ indexes the n-grams (including unigrams, bigrams, and trigrams) contained in the call of firm i at time t, $\mathbb{1}[\cdot]$ is the indicator function, and $\mathbb{L}$ is the set of n-grams included in the legal-term dictionary. In summary, the legal risk faced by each firm at any moment is expressed as a simple sum of legal-related content, scaled by the total number of sentences in that transcript.[6] **LRISK** can be further divided into three topics: **LRISK_COURT**, which primarily captures *macro-level* legal risk, typically arising from regulatory scrutiny, court proceedings, or judicial actions; **LRISK_TRIAL**, which reflects *micro-level* legal risk associated with firm-specific litigation processes and lawsuits; and **LRISK_TERMS**, which includes broader legal terminology such as *"legal costs"* and *"regulatory compliance."*

2.2 LRISK Predicts Future Class Action Lawsuits

This section validates **LRISK** along multiple dimensions. First, I show that **LRISK** predicts future class action lawsuit filings, confirming its value as a forward-looking measure of firms' legal risk. Two case studies further illustrate how **LRISK** spikes during periods of heightened legal scrutiny affecting well-known firms and industries.

I estimate a logistic model of class action lawsuit filings.[7] If **LRISK** effectively captures firm-level legal risk, it should reflect forward-looking concerns—especially those related to potential or on-

[6]Dividing by the number of sentences follows standard practice in the textual analysis literature. When I instead focus on the absolute number of legal-risk-related sentences, the main implications of this paper remain unchanged (see Footnote 18).

[7]The data on class action lawsuits are obtained from the Stanford Law School / Cornerstone Research Securities Class Action Clearinghouse (SCAC). For firms that initiate earnings calls during the sample period, I retain all subsequent firm-quarter observations, imputing zero legal risk when an earnings call is not available. I exclude all firm-quarters prior to the first observed call and drop firms that never publish earnings calls. This design avoids excessive sample attrition while limiting extrapolation beyond observable disclosures. Compared to the more restrictive approach of dropping all observations with missing earnings calls, my strategy preserves a substantially larger sample while still maintaining a credible interpretation of silence as the absence of legal risk discussion.

going class action litigation—discussed in earnings call transcripts, as evidenced by a significant relationship with future lawsuit filings. The specification is given by:

$$\Pr(\text{Lawsuit}_{i,t+h} = 1) = \Phi(\beta_1 \cdot \textbf{LRISK}_{it} + \beta \cdot \text{Controls}_{it} + \delta_q + \varepsilon_{it}), \tag{2}$$

where $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal distribution. The dependent variable is a binary indicator equal to one if a class action lawsuit was filed against firm i in quarter $t+h$, and zero otherwise. It is constructed for three different horizons. When $h=1$, the indicator equals one if a class action lawsuit is filed in the next quarter. When $h=2$ ($h=4$), the indicator equals one if a lawsuit is filed in any of the subsequent two (four) quarters.[8] The key explanatory variable, **LRISK**, is a standardized measure of firm-level legal risk constructed in the previous section. The vector of control variables includes firm characteristics such as firm size (log of total assets), Tobin's Q, leverage, sales growth, asset tangibility, and cash flow, all measured in quarter t (see Table 8 for details on the variables). I also include a second set of variables directly related to litigation risk. These litigation-related controls include: (i) a binary indicator for litigation-prone industries—commonly referred to as FPS (Francis et al. 1994); (ii) a dummy variable for whether a firm has ever been the subject of a class action lawsuit (which switches to one at the time of the first filing and remains one thereafter); (iii) cumulative stock return; and (iv) return volatility over the previous quarter. The model further includes calendar-quarter fixed effects δ_q to account for time-varying macroeconomic influences. Standard errors are clustered at the firm level.

[INSERT TABLE 3 HERE]

The results in Table 3 provide strong evidence for the predictive validity of the **LRISK** measure. Across all specifications, the coefficient on **LRISK** is positive and highly statistically significant,

[8] That is, in quarters $t+1$ or $t+2$ for $h=2$ and in quarters $t+1$, $t+2$, $t+3$, or $t+4$ for $h=4$. In cases where earnings calls and class action lawsuit filings occurred in the same calendar quarter, I determine the correct temporal ordering based on the calendar date. If the earnings call precedes the lawsuit filing within the month, I treat the legal risk disclosure as predictive. For example, Tesla had class action lawsuits filed in November 2013, October 2017, August 2018, and February 2023. For the November 2013 case, the fourth-quarter earnings call occurred three days before the lawsuit filing, so I treat that quarter's legal risk disclosure as forward-looking. In the October 2017 case, the earnings call for the fourth quarter occurred on November 1 (i.e., after the lawsuit was filed on October 10). Accordingly, I use the previous earnings call (August 2, 2017) as the relevant predictive disclosure.

indicating that firms with greater legal risk language in earnings calls are more likely to face class action lawsuits in the near future. Given that class action lawsuits are relatively rare events in firm-quarter data, the model's performance is especially notable: the area under the ROC curve (AUC) is 0.746 (see Column (1) of the Table), indicating that the model correctly ranks a randomly selected sued firm above a non-sued firm approximately 75% of the time. Taken together, these results underscore that **LRISK** is a robust and forward-looking proxy for anticipated legal risk, consistent with both investor perception and future litigation activity.

The coefficient on the FPS variable—a binary indicator for litigation-prone industries such as pharmaceuticals, technology hardware, and electronics (see Online Appendix A)—is also positive and highly significant. This aligns with prior work by Francis et al. (1994) and Kim and Skinner (2012), who show that firms in certain sectors face heightened legal scrutiny. The past lawsuit indicator (a dummy variable that switches to one after a firm is first sued and remains one thereafter) is also strongly positive and significant, indicating that litigation risk tends to be persistent. Additionally, the coefficient on recent stock returns is negative and significant, consistent with the idea that class action lawsuits are more likely to follow steep stock price declines, which may trigger investor suspicion of managerial misconduct or disclosure failures. Related, return volatility also explains future lawsuit filings. Although not displayed in the table, firm size is consistently positive and significant across specifications, consistent with the "deep pockets" hypothesis that larger firms are more likely to be targeted given their perceived capacity to settle legal claims.

2.3 Case Study I: Brown Firms and Environmental Litigation & Regulation

A growing body of research in finance examines how climate-related risks affect financial markets, particularly those linked to carbon emissions and regulatory oversight.[9] Stroebel and Wurgler (2021) emphasize that regulatory risk is viewed as the most immediate climate-related concern for firms and investors. Within this context, legal risk represents an important dimension of climate finance. *Brown* firms—those with high carbon footprints and heavy reliance on fossil fuels—face

[9]For example, Bolton and Kacperczyk (2021) find that firms with higher carbon emissions earn higher stock returns, consistent with compensation for carbon risk, while Pastor et al. (2022) show that shifting investor preferences have boosted recent green-asset performance.

increasing scrutiny from regulators, rising exposure to environmental litigation, and reputational pressures from changing investor preferences.

[INSERT FIGURE 2 HERE]

Figure 2 plots standardized **LRISK** for major energy companies, including ConocoPhillips,[10] ExxonMobil,[11] and Halliburton.[12] Spikes in **LRISK** align closely with well-documented legal and regulatory episodes: merger approvals, environmental settlements, and major lawsuits such as the Deepwater Horizon case or California's 2024 plastics litigation. These patterns validate that **LRISK** effectively captures periods of heightened regulatory and litigation exposure among energy firms.

2.4 Case Study II: Banks and Financial Regulation

The banking sector is especially vulnerable to legal and regulatory scrutiny given its systemic importance and post-crisis oversight. Fahlenbrach et al. (2012) show that persistent risk culture and business models shape how banks respond to such shocks. Figure 3 illustrates **LRISK** for Citigroup, Bank of America, and Wells Fargo.

[INSERT FIGURE 3 HERE]

Citigroup's **LRISK** peaks in 2011 and 2014, coinciding with the SEC's $285 million fine over a mispriced CDO and a $7 billion DOJ settlement over faulty mortgage securities. Bank of America's exposure rises during the Parmalat scandal (2002–2005), the 2012 National Mortgage Settlement,

[10] ConocoPhillips (upper panel) saw increased legal risk in 2002 (FTC approval of its merger with Phillips Petroleum), 2007 (Venezuelan expropriation of the Corocoro oil field that led to arbitration proceedings), 2012 (spinoff of Phillips 66 which involved complex regulatory approvals), 2015 (the company settled $11.5 million in environmental litigation over gasoline storage violations in California), 2018 (lawsuit with Oklahoma homeowners over soil and water contamination), and 2023 (scrutiny over oil sands investments led to exclusion from sustainability-focused portfolios).

[11] ExxonMobil (middle panel) saw spikes in legal risk in 2009–2010 (shareholder litigation following its $41B acquisition of XTO Energy), 2015 (a controversial $225 million settlement with New Jersey over decades of environmental damage at two refineries), and 2024 (a lawsuit filed by the State of California accusing the company of misleading consumers about the recyclability of plastic waste).

[12] Halliburton (lower panel) experienced heightened legal risk in 2004 (a multibillion-dollar settlement to resolve extensive asbestos-related litigation stemming from its former subsidiaries' use of asbestos in construction materials), 2013 (legal proceedings related to its role in the 2010 Deepwater Horizon oil spill, culminating in a $1.1B settlement in 2014), and 2016 (failed $34.6B merger with Baker Hughes, which was blocked by regulators over antitrust concerns, resulting in a $3.5B termination fee).

and subsequent DOJ penalties. Wells Fargo shows sustained elevation following its 2016 account fraud scandal, the Federal Reserve's 2017 asset cap, and a $3.7 billion CFPB fine in 2022.

Across these institutions, **LRISK** increases precisely around major enforcement and litigation events, confirming that the measure effectively reflects evolving legal exposure within heavily regulated sectors.

3 The Pricing Impact of Legal Risk

3.1 Data and Portfolio Construction

To examine the pricing impact of legal risk, I match the firm-level legal risk exposure to stock market data from CRSP and accounting data from COMPUSTAT over the 2002–2024 period.[13] This merged panel forms the empirical backbone of the paper. I construct value-weighted, calendar-time portfolios sorted by **LRISK**. Following Florackis et al. (2023), I sort firms into terciles rather than the more common quintile or decile groupings.[14] This approach aims to mitigate noise arising from heterogeneous disclosure practices: firms with stronger compliance cultures may mention legal terms more frequently, while others with higher latent risk may disclose less. In other words, I assume that the frequency of legal-related mentions reflects the true level of legal risk, though not necessarily in a linear manner.

Portfolio 1 (L1) comprises firms with no legal risk mentions in their earnings calls, capturing the extensive margin of disclosure. Firms with nonzero legal risk mentions are then split into portfolios 2 (L2) and 3 (L3) based on the median value of the **LRISK**. Portfolios are formed annually at the end of June and are value-weighted using market capitalization as of the formation date. I adopt a

[13] While extending the analysis further back is not feasible due to the limited availability of transcripts (which begin in 2002), the 20-year sample offers a strong foundation for developing investment strategies, covering two major economic recessions (2008 and 2020). The strength of my sample lies in its coverage of the full cross-section of firms, as most publicly traded companies publish earnings calls. While Bereskin et al. (2023) focus on a carefully selected subset of firms involved in patent infringement cases using a propensity score matching algorithm, my approach complements theirs by leveraging a broader firm universe. Additionally, Figure A.1 illustrates the rising number of litigation-prone industries around the turn of the century, underscoring the growing relevance of legal risk since 2000.

[14] Strictly speaking, as outlined in the next paragraph, the portfolios are not formed using equal tercile cutoffs, but for ease of exposition I refer to them as terciles.

(12-12) strategy: portfolios are constructed using legal risk information aggregated over the past 12 months (four quarters) and held for the subsequent 12 months. This approach not only aligns with standard asset pricing methodology for forming long-short portfolios but also accommodates the delayed or strategically timed disclosure of legal risks.[15] Consistent with convention, I exclude utilities (SIC 4900–4999) and financials (SIC 6000–6411, 6500–6553, 6700–6799) due to their distinct regulatory environments and disclosure practices. Notably, utilities represent a disproportionately large share of high legal risk mentions; excluding them enhances comparability with other cross-sectional asset pricing studies (Unreported results suggest that including utilities and financial firms leaves the pricing effect unchanged or slightly stronger).

3.2 Asset Pricing Results

[INSERT TABLE 4 HERE]

Table 4 presents the results. Panel A shows that, over a given year, firms in the no (L1), middle (L2), and high (L3) legal risk groups mention on average 0, 2.5, and 10.3 sentences related to legal risk, respectively. Firms with no exposure to legal risk (L1) also tend to be smaller than those with some degree of legal risk, while the book-to-market ratio remains relatively stable across terciles. This pattern is consistent with prior evidence that firms with deeper pockets are more likely to face legal risk (DuCharme et al. 2004). Panel A further indicates that no single industry dominates any portfolio, including the so-called litigation-prone industries. In fact, the no legal risk group (L1) comprises 36.8% of firms from litigation-prone industries—a slightly higher share than that observed in the groups with positive **LRISK**.

Panel B documents the frequency of firm transitions across terciles. On average, 37.9% of firms that previously had no exposure to legal risk experience a rise in their **LRISK** in the subsequent year. Firms initially classified in the L2 group remain in the same tercile 53.6% of the time, implying that 46.2% migrate to either L1 or L3 in the following year. Meanwhile, approximately 33.7% of firms

[15] Firms may postpone bad news to low-attention periods or prioritize other topics in earnings calls (Skinner 1994; deHaan et al. 2015). Aggregating disclosures over a one-year window mitigates such timing distortions and yields a more comprehensive measure of firm-level legal risk. See Online Appendix C for results using alternative portfolio formation strategies such as (12-3).

initially in the highest legal risk group (L3) move to lower terciles. Overall, the transition matrix analysis alleviates concerns that certain firms persistently exhibit higher or lower exposure to legal risk.

In the baseline portfolio analysis presented in Panel C, the average value-weighted monthly excess returns from the tercile portfolio rise from 0.638% for no legal risk portfolio (L1) to 1.035% for high legal risk portfolio (L3) over the period from July 2004 to June 2024.[16] The corresponding zero-cost long-short portfolio (L3 - L1), which I call the **LAW** factor, generates average return difference of 40 basis points per month (0.397% per month, or 4.7% per annum), with a Newey-West adjusted t-statistic of 3.66.[17][18] This strong cross-sectional relationship between legal risk and future stock returns is notable, especially considering that existing literature has not documented such a connection. The premium associated with firms exposed to legal risk is economically significant, with the **LAW** factor exhibiting an annual Sharpe ratio of 0.713 over the sample period. Over the same period, the annual Sharpe ratios of other standard asset pricing factors, ordered by performance, are: RMW (0.672), MKT (0.621), MOM (0.077), CMA (0.007), SMB (–0.027), and HML (–0.082).[19]

Next, I examine whether existing asset pricing models account for the legal risk factor. The factor spanning tests presented in the same panel indicate that the legal risk factor remains significant across various models, including the CAPM, Fama-French three-factor model, Fama-French three-factor model with momentum, Fama-French three-factor model with liquidity, and the q-factor model. The annualized alpha results suggest that a zero-cost portfolio on legal risk earns an abnormal return of 0.439% per month (5.2% per annum) when benchmarked against the CAPM. Similar results hold when using other asset pricing models, such as the Fama-French three-factor model and the q-factor model.

[16] Although transcripts are available from 2002, widespread adoption began in 2003. Using a one-year formation period allows me to start the portfolio analysis from 2004.

[17] I use 6 lags; the results remain consistent when using 3, 9, or 12 lags, and the implications remain unchanged.

[18] When I construct the long–short portfolio based on the raw number of legal-risk-related sentences (i.e., the numerator only), rather than the ratio presented in Equation 1, the results remain consistent: the average monthly excess returns increase from 0.638% (L1) to 0.931% (L2) and 0.987% (L3), yielding a corresponding LAW factor premium of 0.349%, which translates into an annualized premium of 4.18% (Newey–West t-statistic = 3.50).

[19] I also compute the marginal contribution of each factor to the maximum squared Sharpe ratio (MSSR) following the approach of Fama and French (2018), by comparing the full model (FF5 + MOM + LAW)'s MSSR to that of the model excluding each factor in turn. Over the full sample from 2004 to 2024, the **LAW** factor delivers the third-largest contribution to MSSR, following RMW and MKT. In the subsample from 2010 to 2024, **LAW** ranks second—behind only MKT. Interestingly, during this latter period of heightened regulatory scrutiny, RMW contributes virtually nothing to the model's MSSR.

3.3 Ruling Out Non–Risk-Based Explanations

Although the preceding evidence documents a positive and robust legal risk premium, alternative non–risk-based explanations could, in principle, produce similar return patterns. Two broad mechanisms merit consideration. The first is a cash-flow–based explanation: if my result is driven by persistent in-sample cash flow shocks (Hou and Robinson 2006), then I should expect to see large positive average profitability shocks for high legal risk firms and large negative profitability shocks for no legal risk firms. The second is a behavioral explanation, whereby the premium arises from sentiment, mood, or mispricing rather than compensation for bearing systematic risk. In this section, I explicitly test and reject both alternatives. For brevity, most supporting results are omitted from the main text and reported in the Online Appendix.

To evaluate the first possibility, I follow Hou and Robinson (2006) and estimate unexpected profitability (UP_t) for each firm-year from cross-sectional Fama-MacBeth regressions of the form

$$\frac{E_t}{A_t} = \alpha_0 + \alpha_1 \frac{M_t}{B_t} + \alpha_2 \mathbb{1}_{\text{Div}} + \alpha_3 \frac{Div_t}{B_t} + \alpha_4 \frac{E_{t-1}}{A_{t-1}} + \varepsilon_t, \tag{3}$$

where E_t/A_t is earnings scaled by total assets, M_t/B_t is the market-to-book ratio, $\mathbb{1}_{\text{Div}}$ is a dummy for non-dividend-paying firms, and Div_t/B_t denotes the ratio of dividends to book equity. Following Vuolteenaho (2002), the regression includes the lagged profitability term to capture persistence in earnings. The residual ε_t from equation 3 represents UP_t, the component of profitability that is unexpected given firm fundamentals. If the legal risk premium were purely driven by in-sample cash-flow shocks, high legal risk firms would exhibit positive UP_t, while no legal risk firms would exhibit negative UP_t. In such case, the observed return differential would reflect temporary performance shocks rather than expected returns.

The data, however, reveal the opposite pattern. Firms in the highest legal risk tercile (L3) exhibit negative unexpected profitability (mean $UP_t = -0.006$), whereas firms in the lowest tercile (L1) show positive unexpected profitability (mean $UP_t = 0.020$). The difference between L3 and L1 is statistically significant ($t = -2.95$). This evidence directly contradicts the persistent in-sample cash-flow-shock hypothesis in support of the risk-based interpretation: high legal risk firms earn higher subsequent returns despite suffering negative profitability shocks, consistent with investors demanding compensation for bearing systematic downside risk associated with legal and regulatory exposure rather than responding to transitory earnings news.

A remaining concern is that the observed legal risk premium may stem from behavioral biases. However, several empirical tests contradict this view. One potential channel involves investor mood. Birru (2018) shows that speculative stocks tend to outperform on Fridays when investor sentiment peaks. If the legal risk premium were driven by mood-based mispricing, **LAW** returns should therefore be strongest at the end of the week. In contrast, as reported in Table A.2, **LAW** returns (constructed at the daily level) are significantly positive on Mondays through Thursdays, with no corresponding effect on Fridays.

Stambaugh et al. (2012) argue that anomaly returns are shaped by investor sentiment, with short-leg returns lower and long–short spreads narrower following high-sentiment periods. In contrast, I find that neither the long, short, nor long–short returns of the **LAW** factor are sensitive to market-wide sentiment, as measured by Huang et al. (2015). Furthermore, behavioral factors associated with mispricing—including PEAD and FIN from Daniel et al. (2020), and MGMT and PERF from Stambaugh (2017)—fail to subsume the **LAW** factor. Even after controlling for the aggregate disagreement index of Huang et al. (2021), which captures belief dispersion across analysts, the alpha on **LAW** remains economically large and statistically significant. These results, reported in Table A.3 of the Online Appendix, indicate that the legal risk premium is unrelated to sentiment, mispricing, or belief heterogeneity.

Finally, if the return premium on legal risk were purely behavioral, one would not expect firms to adjust their real economic decisions in response. Yet, as shown in Section 5, firms internalize legal risk as a real and costly constraint on investment and financing. Together, these findings reinforce that the legal risk premium reflects compensation for bearing systematic, non-diversifiable legal tail risk, rather than a transient behavioral anomaly.

3.4 Isn't it Idiosyncratic?

Legal risk is often viewed in asset pricing as an idiosyncratic concern: firm-specific, transitory, and diversifiable across a broad portfolio. Under this view, lawsuits or regulatory actions targeting individual firms do not warrant a risk premium. However, this paper argues that the pricing implications of legal risk reflect both idiosyncratic and systematic components. In particular, regulatory actions and legal developments may affect entire industries—or even the broader market—introducing persistent, non-diversifiable risk that is priced by investors.

[INSERT TABLE 5 HERE]

The text-based construction of the **LAW** factor allows for flexible measurement of legal risk across different dimensions. To focus on the *macro-level* legal risk, I separately construct a macro-level law factor, **LAW_COURT** based on the macro-level legal risk keywords **LRISK_COURT** defined in Table 2. The long side of **LAW_COURT** includes firms whose legal risk mentions appear exclusively within the **LRISK_COURT** category, while the short side consists of firms with no legal risk mentions in any category (L1).[20]

Panel A of Table 5 provides a diagnostic check of whether the macro- and micro-based classifications coincide. The joint distribution shows that just under half of the sample lies on the diagonal (29.4 + 8.5 + 10.5 = 48.4%), while a slight majority falls in the off-diagonal cells. These mismatches indicate that the two approaches frequently disagree: firms judged to have no macro-level legal risk are often flagged as medium or high risk by the micro measure, and vice versa. This systematic divergence underscores that the two dimensions are related but distinct—macro-level terms capture broad regulatory and institutional salience, whereas micro-level terms emphasize firm-specific litigation intensity.

Panel B then turns to the pricing evidence. Here, portfolios of firms with non-zero macro-level legal

[20]Specifically, in forming **LAW_COURT**, the long side includes firms with legal risk mentions exclusively within the **LRISK_COURT** cluster, while the short side reuses the benchmark no-risk group (L1)—firms with no legal risk mentions in any category. Holding L1 fixed across all constructions prevents contamination from unrelated exposures and ensures that return differences reflect variation only in the targeted high-risk group. For example, if portfolio groupings were redefined based solely on **LRISK_COURT**, then firms mentioning micro-level legal risk keywords from **LRISK_TRIAL** could inadvertently appear in the L1 portfolio, leading to biased results.

risk (**LAW_COURT**) earn significantly higher excess returns and positive alphas relative to the benchmark zero-risk group. Together, the results in Table 5 show that macro and micro measures are not interchangeable but complementary: Panel A demonstrates that they do not fully overlap, while Panel B confirms that at least the macro dimension is priced in asset markets.

In the rest of this section, I also outline three complementary mechanisms through which idiosyncratic legal shocks can propagate more broadly or signal systemic developments, thereby generating economy-wide pricing implications.

Economic Spillovers Firm-level legal shocks can have broader economic consequences when they affect companies embedded in interconnected production or financial networks. Through input-output relationships, long-term contracts, and shared operational dependencies, legal disruptions may alter the behavior of customers, suppliers, and competitors. These indirect effects can amplify the original shock, leading to second-order impacts that extend well beyond the initiating firm. The severity of such spillovers depends on the structure of the network and the degree of frictions—such as limited substitutability, delayed adjustment, or coordination challenges—that constrain the system's ability to absorb and reallocate risk. In this vein, legal risk serves as a transmission channel through which localized events give rise to macro-relevant outcomes.

Belief Updating About Aggregate Legal Uncertainty Firm-specific legal events may also function as informational signals about broader shifts in the legal or regulatory environment. Following the framework of Savor and Wilson (2016), investors observing such events face a signal extraction problem: they must infer whether a lawsuit, investigation, or enforcement action reflects isolated firm behavior or emerging systemic trends. For instance, the U.S. Department of Justice's 2020 antitrust lawsuit against Google heightened concerns about a broader regulatory crackdown on Big Tech. In response, peer firms such as Amazon and Meta experienced valuation declines, suggesting that market participants revised their expectations about future legal scrutiny across the sector. In this way, legal shocks at the firm level may prompt belief updating about the distribution and intensity of legal risk economy-wide.

Granularity A third channel through which legal risk may generate systematic effects is granularity. As shown in Gabaix (2011), idiosyncratic shocks to the largest firms can influence aggregate outcomes in economies with fat-tailed firm size distributions. Legal risk becomes systemically relevant when it disproportionately affects these dominant firms. A class action lawsuit, regulatory enforcement action, or major litigation involving a firm like Amazon, Meta, or JPMorgan can have macroeconomic impacts simply due to the scale of the firm involved.

3.5 Time-variation of Aggregate Legal Risk

[INSERT FIGURE 4 HERE]

This section examines fluctuations in aggregate legal risk and their broader implications. I construct an economy-wide measure, **Aggregate LRISK**, by computing the percentage of firms that mention legal risk (i.e., firm-level **LRISK**). Specifically, at each quarter, firms are classified as either non-zero (reporting at least one legal-risk reference) or zero (no mentions) in their earnings calls, and the aggregate measure is defined as the share of non-zero firms. By focusing on this 'coverage ratio,' **Aggregate LRISK** captures the extensive margin of legal uncertainty in the corporate sector—the breadth of firms for which legal and regulatory concerns are salient.

Figure 4 contains two panels. The top panel plots **Aggregate LRISK** alongside two well-known uncertainty indices (Economic Policy Uncertainty (Baker et al. 2016) and Macroeconomic Uncertainty (Jurado et al. 2015)) with all series standardized for comparability. Two patterns stand out. First, following its initial spike during the Global Financial Crisis, **Aggregate LRISK** remains elevated for several years, whereas the other uncertainty measures subside relatively quickly. Second, during the onset of the COVID-19 shock, both macro-level uncertainty indices surge sharply, while the increase in **Aggregate LRISK** is comparatively modest. The correlations between **Aggregate LRISK** and these indices range from 0.3 to 0.6, suggesting that it captures a distinct and persistent dimension of market-wide legal uncertainty.

To further highlight the distinct dynamics of **Aggregate LRISK**, the bottom panel applies the structural break procedure of Bai and Perron (2003), identifying four statistically significant break-points: 2007 Q4, 2013 Q1, 2017 Q4, and 2020 Q2. These dates closely correspond to major institutional and judicial developments that reshaped the U.S. legal landscape.

The first break in 2007 Q4 reflects the culmination of post–*Sarbanes–Oxley* enforcement and the nationwide option-backdating investigations, alongside the early tremors of the Global Financial Crisis. Together, these forces embedded compliance and disclosure uncertainty as persistent features of corporate governance. The subsequent decline around 2013 Q1 corresponds to a phase of legal normalization: most crisis-era cases had been resolved, and the Supreme Court's decision in *Gabelli v. SEC* (2013) limited retroactive enforcement, providing firms with greater temporal certainty. **Aggregate LRISK** rises again in 2017 Q4 following the Supreme Court's *Cyan v. Beaver County* (2018) ruling, which reinstated dual state–federal jurisdiction over securities class actions and reignited systemic litigation risk. The final surge in 2020 Q2 reflects pandemic-era complexity and the expansion of ESG and data-privacy enforcement, as firms faced simultaneous exposures to pandemic-related, cybersecurity, and climate-litigation risks. Overall, the structural break pattern in Figure 4 demonstrates that aggregate legal risk evolves in distinct legal regimes (See Online Appendix D for details).

[INSERT TABLE 6 HERE]

Following the Global Financial Crisis, a pronounced shift in the legal and regulatory regime occurred, as major post-crisis reforms were introduced to address systemic failures.[21] Under the risk-based interpretation, such a shift should increase the legal risk premium, which is precisely what Table 6 shows. In the 2010-2024 subsample, the pricing effect of legal risk strengthens markedly: the **LAW** factor earns an annualized return of 7.1% ($t = 4.9$), driven by a larger performance spread across legal risk portfolios. The enhanced profitability of the strategy is primarily attributable to the short leg: firms with no disclosed legal risk (L1) exhibit significantly negative alphas. This pattern suggests that as aggregate legal risk rose, investors became increasingly willing to accept lower returns from firms perceived to have minimal legal risk.

[21] Figure A.5 in the Online Appendix reports a Chow test for a structural break in **Aggregate LRISK** around 2009–2010 and confirms that a significant structural change took place.

4 Discussion

This section discusses the results in three parts. First, it addresses the "factor zoo" critique. Second, it compares the text-based legal risk exposure measure with existing firm-level text-based metrics to demonstrate its unique ability to capture legal risk–related components. Finally, it adopts a comparative economics perspective to examine how legal origins shape the pricing of legal risk, emphasizing differences between common law and civil law systems.

4.1 Addressing the Factor Zoo Critique

Although introducing a new risk factor is not the paper's main objective, it nonetheless touches upon the well-known "factor zoo" critique (Cochrane 2011). This section directly confronts those concerns by providing rigorous evidence that the legal risk factor is not a spurious result of data mining, but instead captures economically meaningful and distinct variation in asset returns. A detailed set of supporting results is provided in Online Appendix C, with key findings briefly summarized in this section.

First, the **LAW** factor is not driven by any single industry sector. While the four litigation-prone industries—Pharmaceuticals, Computer and Office Equipment, Software, and Electrical Equipment (see Online Appendix Section A for detailed descriptions)—account for a sizable share of the U.S. public market and are well represented across all portfolio groups (as shown earlier in Panel A of Table 4), a robustness check confirms that the explanatory power of the **LAW** factor is not merely attributable to them. For example, the annualized alpha of the **LAW** factor relative to the Fama–French three-factor model augmented with momentum and the four litigation-prone industry returns is 3.5% per annum, with a Newey–West adjusted t-statistic of 2.99. Moreover, these litigation-prone industries are "concentrated" industries that, on average, earn lower, rather than higher, returns (Hou and Robinson 2006).

Second, unlike standard accounting-based variables, legal risk has a clear and intuitive economic foundation, as it captures downside risk related to litigation, regulatory actions, and policy uncertainty. As such, it avoids the "Hypothesizing After Results are Known" (HARK) critique (Novy-Marx and Velikov 2025).

Third, while many accounting-based signals exhibit post-2000 decay due to declining information frictions (Chordia et al. 2014), the **LAW** factor is created from 2004 and onwards, and show robust performance during when other well-known anomalies such as SMB, HML, and MOM fail to provide robust power (see Online Appendix Figure A.3).

Fourth, the **LAW** factor is supported by strong statistical evidence, with a full-sample t-statistic of 3.66[22] over the 2004–2024 period, and rises to 4.91 in the post-2010 subsample (see Section 3.5), both comfortably exceeding the threshold of 3.0 recommended by Harvey et al. (2016) for identifying robust asset pricing anomalies. To further assess robustness, I conduct a series of spanning regressions of the **LAW** factor on the Fama–French three factors augmented with the momentum factor and one additional factor at a time from a zoo of 193 anomalies.[23] The t-statistic on the **LAW** factor exceeds 2.0 in all 193 regressions, and remains above 3.0 in 181 of them (see Online Appendix Figure A.4).

4.2 Comparison with Other Text-based Measures

How LRISK relates to the Loughran–McDonald measure: My work builds on the pioneering research of Loughran and McDonald (2011) (henceforth LM). While legal terms such as litigation and plaintiff appear in both the "Fin-Neg" and "Fin-Lit" categories proposed by LM, I adapt their approach to the spoken dynamics of earnings calls in two key ways, yielding a more precise and contextually relevant measure of legal language in financial discourse.

[22] This benchmark specification excludes firms in the utilities and financial sectors, consistent with standard asset pricing practice. When these sectors are included to maximize market coverage, the **LAW** factor delivers a slightly reduced annual premium of 4.1% over the same June 2004–July 2024 period, while maintaining strong statistical significance with a Newey-West t-statistic of 4.29.

[23] That is, I estimate the following time-series regression 193 times (with the time subscript t omitted for brevity): $\mathbf{LAW} = \alpha + \beta_{MKT}\mathbf{MKT} + \beta_{SMB}\mathbf{SMB} + \beta_{HML}\mathbf{HML} + \beta_{MOM}\mathbf{MOM} + \beta_{ZOO}\mathbf{ZOO}$ where **ZOO** refers to one of 193 benchmark anomaly factors sourced from Chen and Zimmermann (2022) (from the original set of 210+ signals, I exclude those with missing monthly return data over my sample period, resulting in 193 available risk factors). For each specification, I record the intercept term (α) and its associated Newey–West t-statistic which captures the component of the **LAW** factor that is not explained by the five-factor benchmark model augmented with the given anomaly. The collection of these alphas provides a measure of the extent to which the **LAW** factor is distinct from known pricing factors.

First, many keywords in LM's Fin-Lit dictionary are formal and specialized—terms more likely to appear in legal contracts or court rulings than in real-time corporate discussions. For example, the LM dictionary includes complex legal words such as *"appurtenance"* (a property-related right or privilege) and *"conveniens"* (from *forum non conveniens*, a doctrine on jurisdictional convenience). While useful in legal scholarship, such terms rarely arise in earnings calls, where executives communicate in more accessible language. Similarly, specialized verbs like *"exculpate," "indemnify,"* and *"usurp"* are seldom used in corporate speech and are excluded from my dictionary.

Second, my methodology emphasizes bigrams and trigrams over unigrams when analyzing legal language. Although both dictionaries include unigrams such as *"antitrust," "lawsuit," "litigation," "plaintiff,"* and *"settlement,"* many expressions referring to judicial entities, proceedings, and concepts are missed when relying solely on single words. For instance, the phrase *"Department of Justice"* may indicate regulatory scrutiny, but a unigram-based analysis would fail to capture its full legal context. Unigram approaches can also lead to misclassification, as they cannot distinguish between a benign reference to a *"patent"* and a concern involving *"patent infringement."*[24] These two refinements enhance the ability to measure legal risk more accurately and help explain its pricing relevance in this study.[25]

[INSERT FIGURE 5 HERE]

How LRISK relates to the Political Risk and Regulatory Burden Measure: In a related study, Hassan et al. (2019) construct several text-based measures of risk exposure, including political risk (**PRISK**), non-political risk (**NPRISK**), and overall risk (**RISK**), each accompanied by a corresponding sentiment measure: **PSENT** (political sentiment), **NPSENT** (non-political sentiment), and **SENT** (overall sentiment).

To assess whether **LRISK** captures a unique dimension of legal risk, I compute its correlation with these related measures, presenting the results in Figure 5. First, I find that the composite measure **LRISK** is highly correlated with its key components, **LRISK_COURT** and **LRISK_TRIAL**, with

[24] For a related discussion on the advantages of bigram and trigram approaches, see Caldara and Iacoviello (2022).

[25] On page 55 of Loughran and McDonald (2011), the authors show that portfolios based on negative litigious word counts do not yield significant abnormal returns. Similarly, Loughran and McDonald (2013) find that legal word lists are not significantly associated with first-day IPO returns.

correlations between 0.80 and 0.90 (**LRISK_TERMS**, which includes general legal phrases such as "legal costs" and "legal dimension", exhibits more modest correlations). Most importantly, **LRISK** and its components show low correlations with other text-based risk measures such as Political Risk / Sentiment (Hassan et al. 2019) and regulatory burdens (Kalmenovitz 2023), reinforcing that my legal risk metric captures a distinct legal dimension that firms face in the market.

How LRISK relates to the Cyber Risk measure: In a series of recent works, researchers have developed firm-level measures of cyber risk to assess its impact on financial markets. Florackis et al. (2023) analyze 10-K filings, Jiang et al. (2024) use machine learning techniques on firm characteristics, and Jamilov et al. (2025) apply natural language processing to earnings calls to construct firm-level cyber risk measures and assess their financial impacts.

I compare the legal risk measure with the cyber risk measure developed by Jamilov et al. (2025). Since both measures are derived from the same textual source (earnings call transcripts), their cyber risk search terms serve as a natural benchmark for my study. Specifically, I construct a cyber risk dictionary, $\mathbb{C}$, based on Table 2 of Jamilov et al. (2025), along with a law-specific cyber risk dictionary $\mathbb{C}_{\text{LAW}}$ to obtain **Cyber Risk** and **Cyber Risk Law**, respectively.

[INSERT TABLE 7 HERE]

First, I observe that **LRISK** has essentially no correlation with **Cyber Risk** but exhibits a modest correlation of 0.42 with **Cyber Risk Law**, as shown in Panel A of Table 7. This result is expected, as cyber risk and legal risk capture distinct dimensions. In the Online Appendix E, I also provide firm-level evidence using SolarWinds, which was the target of major cyberattacks, to illustrate that legal risk exposure and cyber risk exposure represent separate aspects of risk.

The legal components of cyber risk, represented by **Cyber Risk Law**, share many common keywords—such as bankruptcy court, lawsuit, legal claim, and plaintiff—which naturally explains this correlation. In Panel B of the same table, I implement a long-short portfolio strategy, as documented in Section 3, and find that both **LRISK** (replicating the results from Table 4) and **Cyber Risk** are priced, whereas **Cyber Risk Law** is not. The pricing of **Cyber Risk** independently affirms the findings of Florackis et al. (2023) and Jiang et al. (2024) that cybersecurity matter is a priced source of risk.

Importantly, Panel C presents the results of a factor spanning test, where the **LAW** factor (constructed from firms' exposure to **LRISK**) explains both factors constructed from **Cyber Risk** and **Cyber Risk Law**. Crucially, it is not subsumed by the presence of these measures under the Fama-French three-factor model augmented with momentum. Equation (1) shows that the legal risk factor loads positively on both **Cyber Risk** and **Cyber Risk Law**, yet remains distinct and not fully captured by these factors. Conversely, Equations (2) and (3) in the same panel demonstrate that the presence of the law factor (**LRISK**) not only loads positively on **Cyber Risk** and **Cyber Risk Law** as expected, but also subsumes these factors. Given that cyber risk is a type of operational risk (Kamiya et al. 2021), which in turn is a sub-component of legal risk, it follows that legal risk is a broader concept and thus encompasses the effects of cyber risk.

4.3 Legal Origins and the Cross-Country Pricing of Legal Risk

Legal systems around the world broadly fall into two traditions: common law, as seen in the United States, and civil law, as found in countries like Germany and France. Common law systems emphasize judicial precedent, decentralized adjudication, and strong private enforcement mechanisms, including class actions and broad discovery rights. In contrast, civil law systems rely heavily on codified statutes, state-controlled judges, and limited private litigation avenues, with a greater emphasis on public enforcement. As a result, firms in common law countries tend to face more frequent and visible legal disputes, while those in civil law systems often operate under stricter procedural rules and more bureaucratic forms of legal accountability.

This institutional divergence has implications for how legal risk is perceived and priced in financial markets. Drawing on Glaeser and Shleifer (2002), the civil law tradition developed as a way to protect state-controlled judges from local coercion, often at the cost of legal flexibility and transparency. Unlike the U.S., where independent juries and private lawsuits can produce large, uncertain outcomes (i.e., legal tail risk), France and Germany channel disputes through formal and predictable procedures. Furthermore, as La Porta et al. (1998) and Djankov et al. (2003) show, civil law countries generally offer weaker investor protection, making it harder for shareholders to sue or extract information about pending legal exposure. These factors—less uncertainty, reduced disclosure, and lower shareholder litigation intensity—diminish both the visibility and materiality of legal risk to outside investors, potentially muting its impact on asset prices.

Consistent with these institutional differences, my empirical results show that legal risk is priced in the United States, but not in civil law countries such as Germany or France (results are unreported but available upon request). In these civil law countries, legal risk does not appear to be a salient dimension of priced risk in cross-sectional stock returns. This finding supports the view that differences in legal origin and enforcement structures shape how legal risk enters into firm valuation, and that legal risk may simply not be priced in countries where it is procedurally muted and economically less consequential.

5 The Economic Impact of Legal Risk

Firms often respond to heightened uncertainty by deferring or reducing investment, particularly when projects are irreversible and involve long-term commitments. In such settings, the option to wait becomes valuable, as premature capital commitment entails the loss of flexibility.[26] Consistent with these insights, legal risk represents a novel and economically significant channel through which uncertainty influences firm behavior. By introducing ambiguity into the regulatory and litigation environment, legal risk increases perceived volatility, raises the cost of capital, and may lead firms to delay investment, reallocate resources, or reduce innovative activity. Online Appendix F provides simple real options frameworks to show that legal risk increases the value of waiting and thereby discouraging investment.

[INSERT TABLE 8 HERE]

[26] McDonald and Siegel (1986) show that firms optimally delay investment until expected returns substantially exceed costs, reflecting this option value. Pindyck (1988) similarly finds that uncertainty raises the opportunity cost of investment, prompting firms to scale back capacity expansion and place greater weight on growth options. Bernanke (1983) emphasizes that when information arrives gradually, uncertainty about future conditions can depress investment by increasing the value of waiting.

To empirically assess the relationship between investment and legal risk at the firm level, I estimate

$$\text{INV}_{i,t+1} = \alpha + \beta\,\text{LRISK}_{i,t} + \gamma\,\mathbf{X}_{i,t} + \theta_i + \eta_t + \varepsilon_{i,t+1} \tag{4}$$

where $\text{INV}_{i,t}$ denotes investment for firm i at year t, $\text{LRISK}_{i,t}$ represents firm-level legal risk exposure, measured as the average across all quarters within a given year. $\mathbf{X}_{i,t}$ is a vector of control variables. I add firm fixed effects (θ_i), year fixed effects (η_t). This procedure ensures that the results are not attributed to time-invariant firm characteristics, or common macroeconomic shocks. Also, independent variables are lagged one year to limit concerns of reverse causality.

For the dependent variable (INV) I use three distinct measures of investment, each scaled by beginning-of-year total assets. First, CAPX + AQC captures tangible investment, including capital expenditures and acquisitions, and reflects the firm's spending on physical assets and M&A activity. Second, R&D captures intangible investment, measuring expenditures related to innovation, product development, and technological advancement. Finally, I construct a total investment measure by summing CAPX, AQC, and R&D, thereby capturing both tangible and intangible components of investment. These broader metrics provide a more comprehensive view of firm-level investment activity (see Table 8 for details). For ease of interpretation, all investment variables are expressed in percentage terms, and legal risk is standardized.

[INSERT TABLE 9 HERE]

Table 9 presents the results. Panel A examines the benchmark specification. Across all three measures of firm-level investment—tangible (CAPX + AQC), intangible (R&D), and total investment—the regressions reveal a consistent pattern: higher legal risk significantly predicts lower future investment. For economic interpretation, consider column (1), where the dependent variable is tangible investment. A one standard deviation increase in legal risk is associated with an approximate 3.8% decline in tangible investment in the following year.[27] The effect is even more

[27] The sample mean of tangible investment (CAPX + AQC) is 8.45, implying an economic effect of $-0.277/8.45 \approx -3.79\%$.

pronounced when focusing on intangible investment. Column (2) shows that a one standard deviation increase in legal risk predicts a 6.6% decline in R&D expenditures.[28] Finally, column (3) shows that legal risk is associated with a 5.0% reduction in total investment.[29]

Panel B addresses potential endogeneity by controlling for the persistence of investment dynamics. Following Eberly et al. (2012), I include up to three lags of the dependent variable. The coefficients on legal risk remain negative and statistically significant, though slightly attenuated in magnitude, suggesting that the effect is not solely driven by past investment momentum. Panel C employs industry $\times$ year fixed effects ($\delta_{s(i),t}$), where $s(i)$ maps firm i to its two-digit SIC industry s in year t. These dummies absorb time-varying shocks that are common within an industry: for example, sector-specific regulatory changes or litigation waves. The negative relationship between legal risk and investment remains essentially the same. Finally, Panel D tests robustness to alternative proxies for financial constraints by replacing the Whited and Wu (2006) index (WW) with Ohlson's O-score. The results remain qualitatively and quantitatively similar, underscoring that the observed investment effects of legal risk are not mechanically driven by the choice of control for firm-level financial vulnerability.

[INSERT FIGURE 6 HERE]

To investigate investment dynamics, I estimate impulse response functions using a panel data adaptation of the local projection method developed by Jordà (2005), as shown in Figure 6. Specifically, for each yearly forecast horizon $h = 1, ..., 5$, I estimate the panel regression of the form: $\text{INV}_{i,t+h} = \alpha + \sum_{j=0}^{2} \beta_j \text{ LRISK}_{i,t-j} + \gamma \, \mathbf{X}_{i,t} + \sum_{j=0}^{2} \delta_j \text{ INV}_{i,t-j} + \theta_i + \eta_t + \varepsilon_{i,t+h}$, with standard errors clustered at the firm level. The impulse response of total investment shows that the negative effect of a rise in legal risk persists for up to three years, highlighting a prolonged dampening of firm-level investment activity. This pattern suggests that legal risk generates uncertainty around the future business environment, leading firms to delay or scale back capital expenditures—a response consistent with models of irreversible investment under uncertainty (Bernanke 1983).

To further examine the economic consequences of legal risk, I assess whether it also affects the

[28] The sample mean of R&D investment is 5.11, implying an economic effect of $-0.336/5.11 \approx -6.57\%$.

[29] The sample mean of total investment is 12.48, implying an economic effect of $-0.616/12.48 \approx -4.93\%$.

mode of financing. Following Malmendier et al. (2011), I estimate the following regression:

$$\text{Finance Mode}_{i,t} = \alpha + \beta_1 \, \text{FD}_{i,t} + \beta_2 \, \text{LRISK}_{i,t} + \beta_3 \, (\text{FD}_{i,t} \times \text{LRISK}_{i,t}) + \gamma \, \mathbf{X}_{i,t} + \theta_i + \eta_t + \varepsilon_{i,t} \quad (5)$$

In this specification, Finance $\text{Mode}_{i,t}$ denotes either net debt issuance (Debt) or net equity issuance (Equity) for firm i in year t, each scaled by lagged total assets. The variable $\text{FD}_{i,t}$ captures the financing deficit, defined following Frank and Goyal (2003), and measures the extent to which a firm's expenditures exceed its internal funds and thus necessitating external financing (see Table 8 for variable definitions). The coefficient of interest is β_3, which captures the interaction between the financing deficit and legal risk (FD × LRISK), and tests whether legal uncertainty moderates the firm's reliance on debt financing when internal resources are insufficient.

[INSERT TABLE 10 HERE]

Panel A in Table 10 presents strong evidence that legal risk systematically shapes corporate financing behavior, particularly when firms face a financing deficit (FD). To start with, across all model specifications, the coefficient on FD is consistently positive and highly significant, including in the baseline model in Column (1). This indicates that, in general, firms respond to funding shortfalls by raising debt, in line with traditional pecking-order theory: when internal funds are insufficient, firms first turn to debt markets before issuing equity. In contrast, LRISK is positive but statistically insignificant across all specifications. This suggests that legal risk on its own does not systematically increase or decrease a firm's propensity to issue debt when there are no pressing funding needs.

However, the interaction between FD and LRISK tells a different story. The coefficient on the interaction term LRISK × FD, β_3, is consistently negative and statistically significant at the 1% level across all models. This implies that when firms do experience a financing deficit, those with higher legal risk are significantly less likely to meet their funding needs via debt issuance. In other words, legal uncertainty introduces financing frictions that constrain debt capacity during periods of external funding demand. This effect remains robust after controlling for firm size, growth opportunities, asset structure, and (firm and year) fixed effects, with debt overhang unlikely given the inclusion of leverage and a financial constraints index.

Panel B of Table 10 examines whether firms facing legal constraints on debt issuance turn instead to equity markets. The results show that the coefficient on the interaction term LRISK $\times$ FD is small and statistically insignificant across all specifications. This suggests that firms with elevated legal risk do not offset reduced debt access by substituting into equity financing. Rather than reallocating across financing instruments, these firms appear constrained in their overall access to external capital, reinforcing the view that legal risk operates as a broad financing friction.

To summarize, the firm behavior observed in this section is consistent with a precautionary financing motive. Firms exposed to greater legal risk may deliberately avoid taking on fixed obligations such as debt, given that legal liabilities (like lawsuits or regulatory penalties) are often large, opaque, and non-diversifiable. When such firms face a financing deficit, issuing debt can be especially costly: creditors may demand higher yields due to elevated tail risk, and rigid repayment structures reduce financial flexibility. These conditions increase the likelihood of debt overhang or distress, particularly if adverse legal events materialize.

6 Conclusion

This paper develops a novel text-based measure of firm-level legal risk (**LRISK**) using earnings conference call transcripts and documents its pricing and economic impact. Legal risk is systematically priced in the cross-section: a value-weighted long–short portfolio that buys high–legal-risk firms and shorts no-risk firms (the **LAW** factor) delivers statistically robust returns over 2004–2024, with an even larger premium in the post-2010 subsample. Extensive robustness checks show that this premium cannot be explained by industry composition, common text-based factors, sentiment proxies, or a large set of known anomaly variables. Having ruled out cash-flow–based and behavioral explanations, I interpret the legal risk premium as compensation for bearing systematic legal and regulatory uncertainty.

Legal risk also has real economic consequences. Firms with higher **LRISK** invest less—particularly in intangible assets such as R&D—and are less likely to issue debt when facing financing deficits. These patterns are consistent with legal uncertainty operating as a financing friction that constrains capital allocation and shapes real corporate behavior. Overall, the evidence establishes legal risk as a key driver of both firm behavior and expected returns, emphasizing its central role in the intersection of law and finance.

The findings have implications for researchers, practitioners, and policymakers. For asset-pricing and corporate-finance scholars, this paper demonstrates how high-frequency textual disclosures can uncover economically significant sources of systematic risk that traditional data miss. For investors, **LRISK** provides a tractable signal capturing compensation for legal tail exposure beyond standard risk premia. For regulators and managers, the results underscore that legal and regulatory uncertainty carries tangible economic costs, dampening investment and risk-taking, especially in innovation-intensive firms.

Future research can extend these insights in several directions. First, applying advanced language models could refine the classification of legal topics and, more broadly, analyzing other forms of legal documents with such models—such as court opinions, regulatory filings, or enforcement releases—may yield additional insights. Second, cross-country analysis incorporating differences in enforcement intensity, discovery rules, and class-action availability could illuminate how institutional design shapes the pricing of legal risk. Finally, integrating **LRISK** into structural models of investment and credit may quantify the welfare and macroeconomic implications of legal uncertainty.

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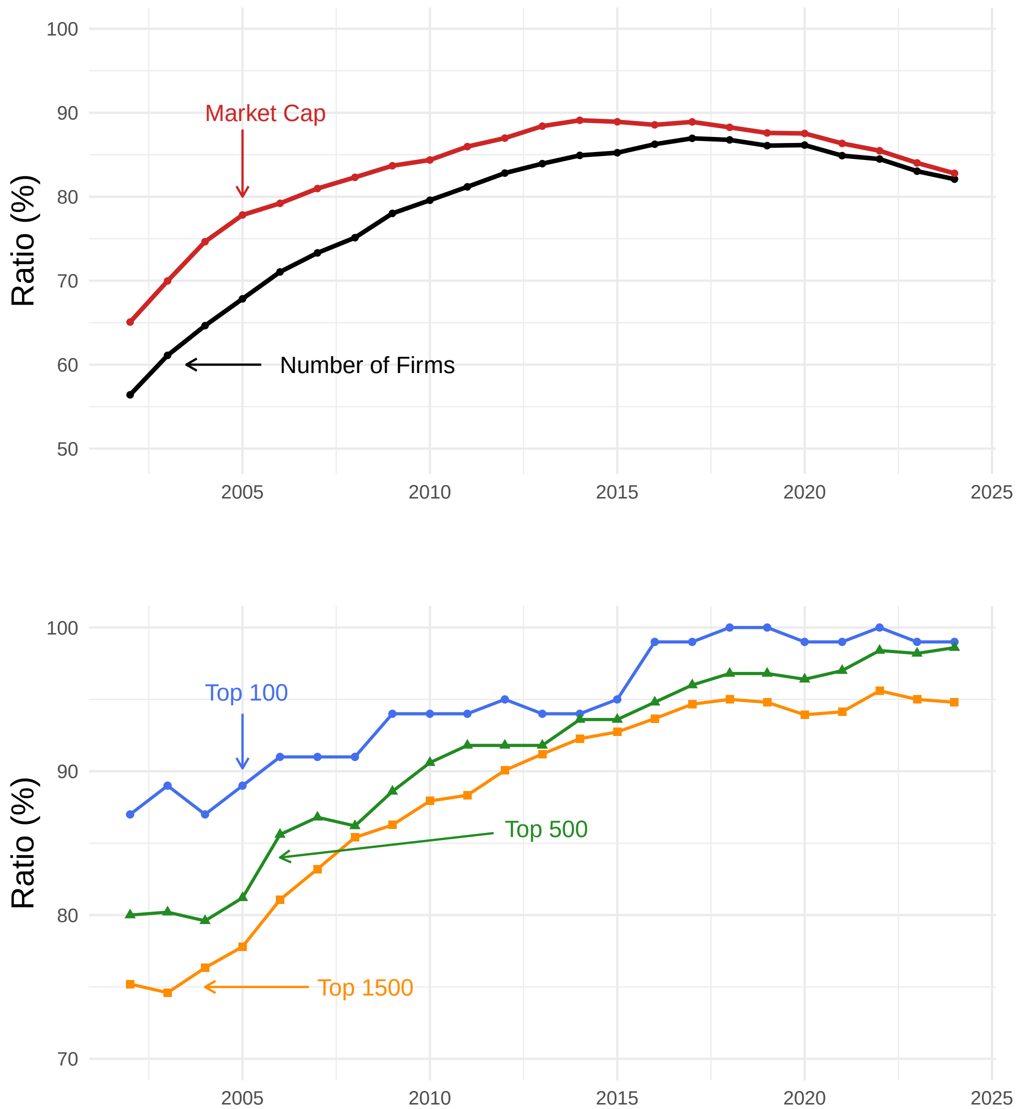
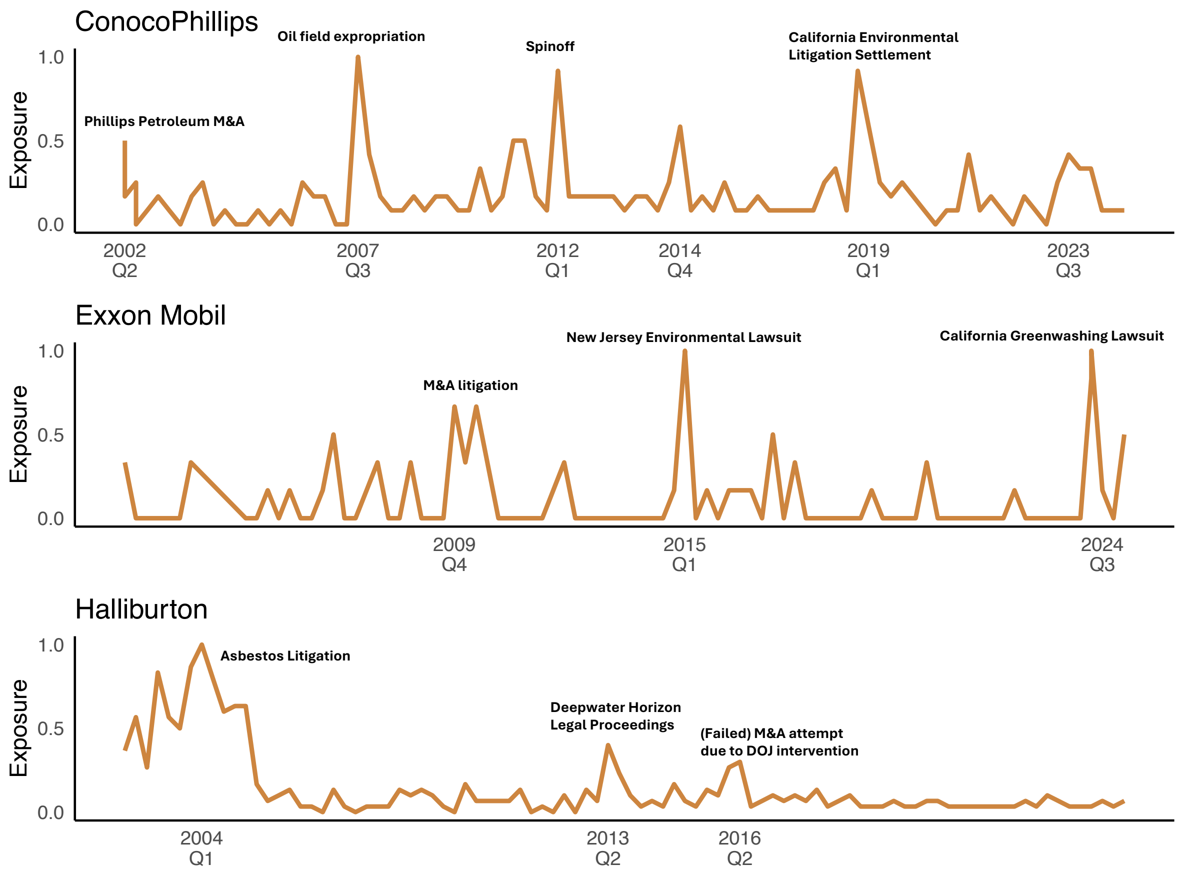
Figure 1: **Summary Statistic on U.S. Firms Publishing Earnings Calls Transcripts**



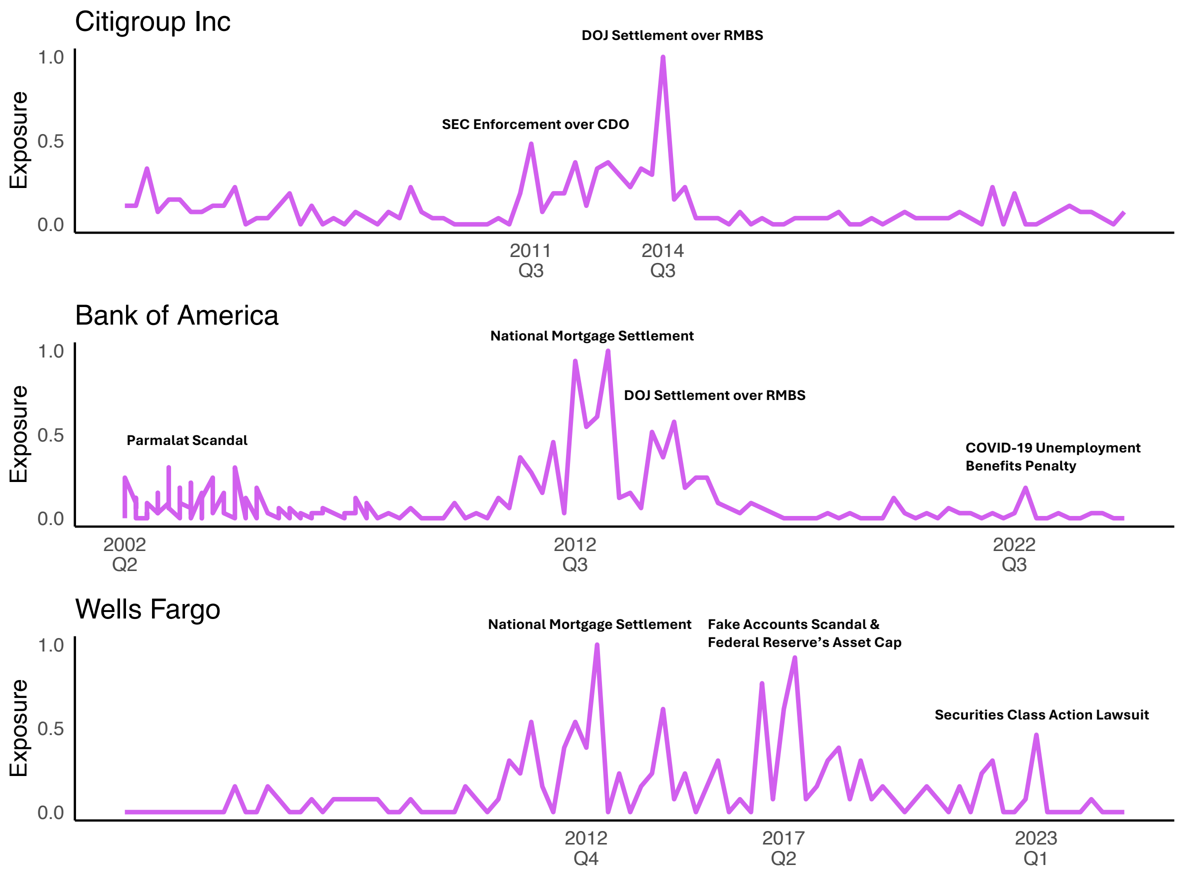
Note: The figures display the following: the proportion of firms publishing earnings call transcripts (black line in the top panel), the proportion of market capitalization of those firms that publish earnings calls (red line in the top panel), and the proportion of the top 100, top 500, and top 1500 firms by market capitalization that publish earnings call transcripts (bottom panel). The ratio is calculated by dividing the number of relevant firms by the total number of firms listed on the three major U.S. stock exchanges—NYSE, NASDAQ, and NYSE American (formerly AMEX)—with ordinary shares (CRSP share codes 10 or 11).

Figure 2: **Case Studies: Brown Firms**



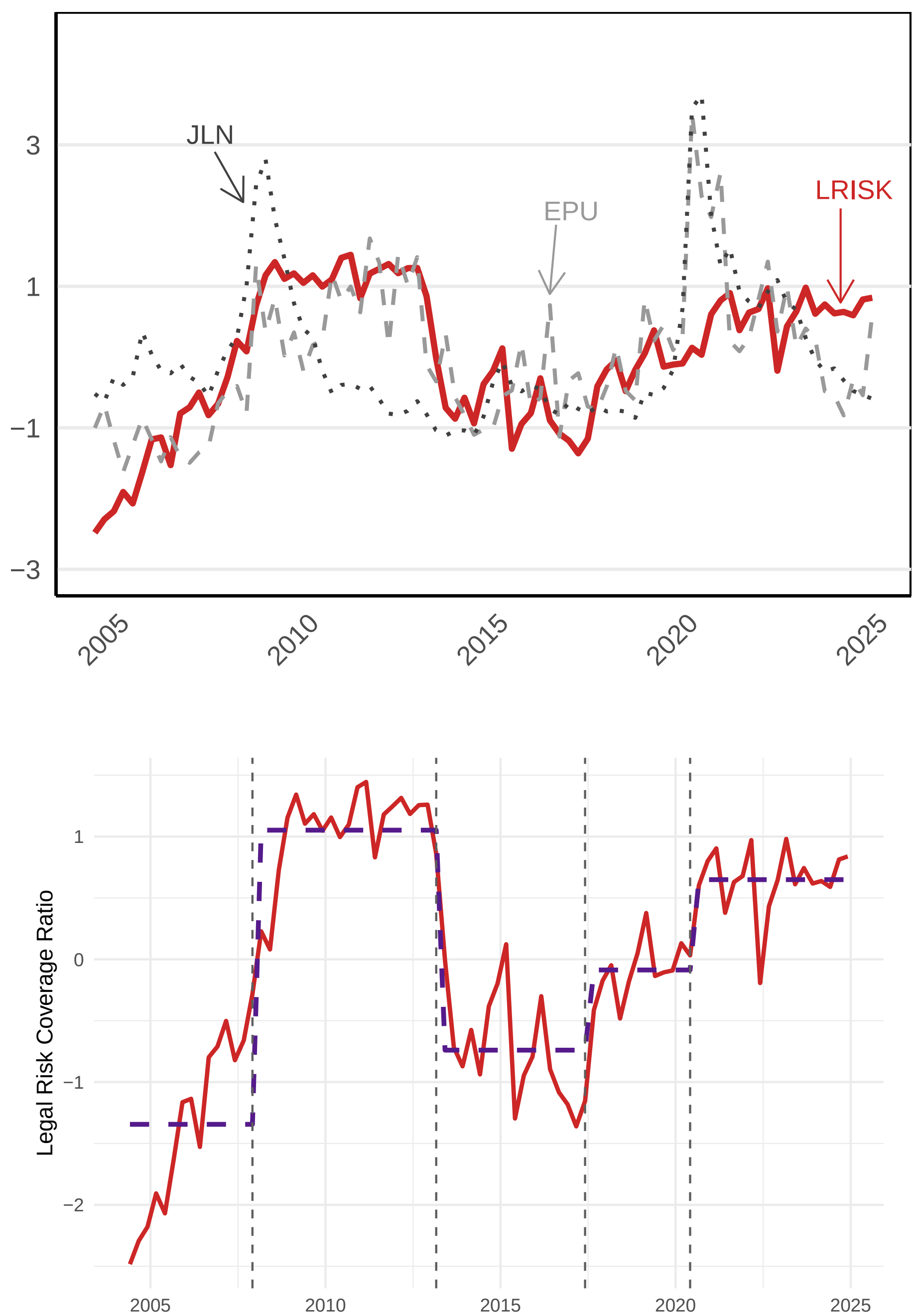
Note: This figure illustrates the firm-level legal risk exposure of three representative companies in the oil industry: ConocoPhillips, ExxonMobil, and Halliburton. All three are constituents of the S&P 500. The brown solid line in each figure represents the standardized firm-level legal risk exposure, as measured from earnings call transcripts.

Figure 3: **Case Studies: Bank Firms**



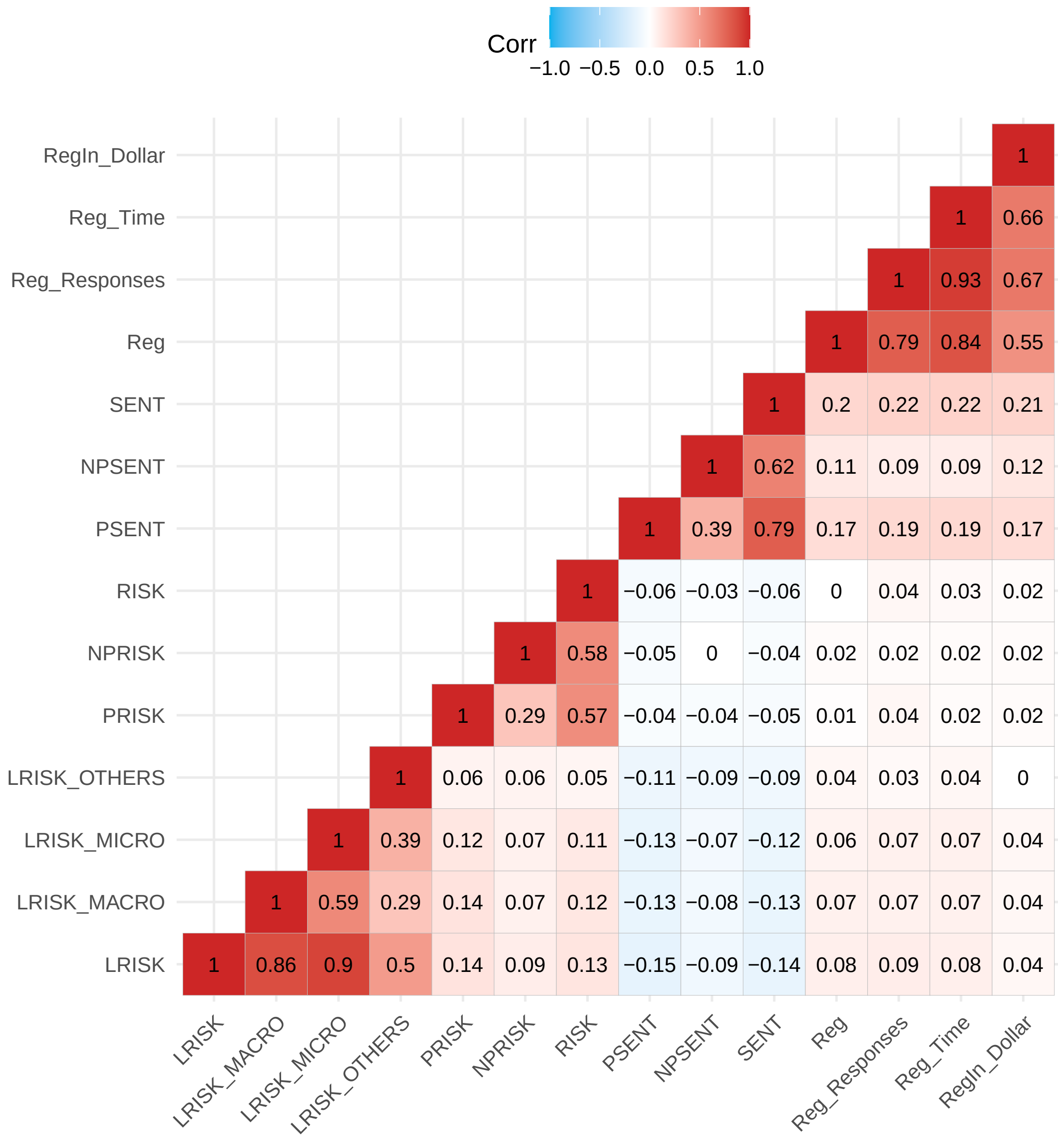
Note: This figure illustrates the firm-level legal risk exposure of three representative companies in the banking industry: Citigroup, Bank of America, and Well Fargo. All three are constituents of the S&P 500. The purple solid line in each figure represents the standardized firm-level legal risk exposure, as measured from earnings call transcripts.

Figure 4: **Aggregate LRISK**



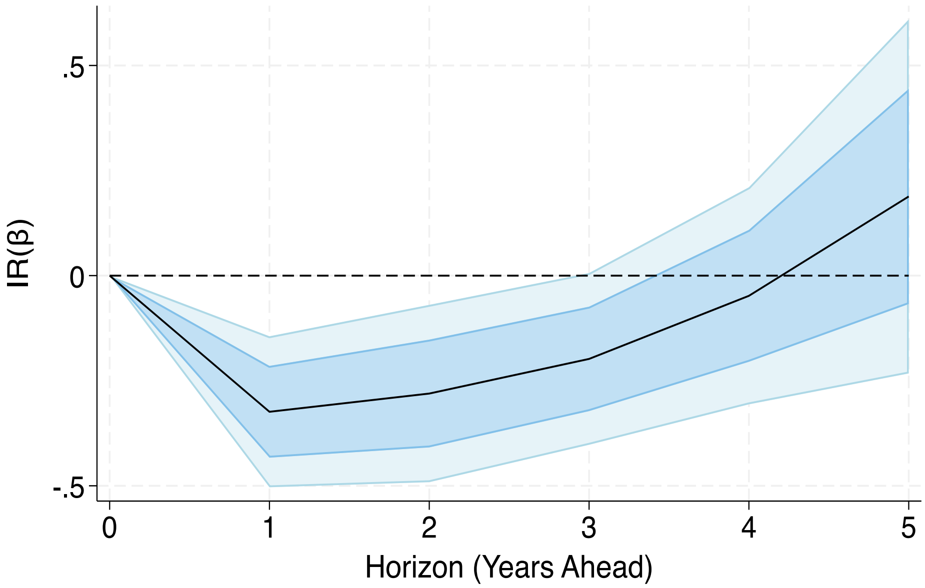
Note: The figures display an aggregate measure of legal risk, **Aggregate LRISK**, defined as the proportion of firms that reference legal risk in their earnings call transcripts in a given quarter (At each quarter, firms are classified as either non-zero (mentioning legal risk) or zero (not mentioning it), and the coverage ratio is computed). To highlight deviations from the historical norm, the series is standardized. The top panel compares **Aggregate LRISK** with well-known indicators of aggregate macroeconomic uncertainty: the Economic Policy Uncertainty (EPU) index and the Jurado, Ludvigson, and Ng (JLN) index. In the bottom panel, **Aggregate LRISK** is segmented using the Bai and Perron (2003) multiple structural break method, with segment means plotted to illustrate shifts in the underlying trend.

Figure 5: **Correlation between LRISK and other Text-based Firm-level Exposure Measures**



Note: This figure shows the Pearson correlations between **LRISK** and its three components (**LRISK_COURT**, **LRISK_TRIAL**, and **LRISK_TERMS**) alongside other relevant text-based measures. Political and non-political risk and sentiment are captured by **PRISK**, **NPRISK**, **RISK**, **PSENT**, **NPSENT**, and **SENT**, as constructed by Hassan et al. (2019). The final three measures—**Reg_Responses**, **Reg_Time**, and **RegIn_Dollar**—track firms' regulatory burden, following Kalmenovitz (2023). Correlations are computed at the aggregate level; however, grouping by firm or year prior to calculation does not materially affect the main conclusions.

Figure 6: **Investment Impulse Response Function**



Note: This figure presents impulse response functions estimated using a panel data adoption of Jordà's (2005) local projection method. For each yearly forecast horizon $h = 1, ..., 5$, I estimate the panel regression of the form: $\text{INV}_{i,t+h} = \alpha + \sum_{j=0}^{2} \beta_j \text{ LRISK}_{i,t-j} + \gamma \, \mathbf{X}_{i,t} + \sum_{j=0}^{2} \delta_j \text{ INV}_{i,t-j} + \theta_i + \eta_t + \varepsilon_{i,t+h}$, with standard errors clustered at the firm level.The y-axis shows the percentage response of investment (”total investment” as defined in Table 8) to a one-standard-deviation increase in legal risk, and the x-axis reports the horizon in years. The projections include firm and year fixed effects, and standard errors are clustered at both the firm and year levels. Shaded areas represent 68% and 90% confidence intervals, respectively.

List of Tables

Table 1: **Examples of U.S. Firms mentioning Litigation-related terms in their Transcripts**

No	Companies	Date	SIC	Texts
1	NV Energy Inc	Feb 10, 2003	4911	The **lawsuit** filed *against* us in **Federal Bankruptcy Court** by Enron is an ongoing matter.
2	Metro International SA	Feb 13, 2007	2711	However, over the years, the **case law** has developed and at the end of 2005, it became apparent that certain deductions could be challenged by the Swedish tax agency.
3	Associated Materials LLC	Nov 17, 2011	3089	But in any event, they went to the same **lawyers** that were handling the first-**class action** suit, and in order to avoid an issue in commonality they set up a second suit against us.
4	Hong Kong Technology Venture Co Ltd	Nov 21, 2012	4813	They won't be able to grant me a license of 2015 because, as I mentioned earlier, in order to protect our investor interest, if we don't get our license by end of the year we will seriously consider to raise the **judicial review** against the government and get a **court** to push the government to issue the license in a reasonable timeframe.
5	Odyssey Marin Exploration Inc	March 16, 2015	8732	The **oral argument** for this final claim is scheduled for early May, that claim was dismissed at the **trial court** level and we expect the dismissal to be upheld.
6	ParkerVision Inc	November 14, 2016	3663	It's also important to note that we filed last month an **infringement case** against Apple in Munich, citing the same patent as in the LG case, and we've just recently learned that the **hearing** for that case has been set for May 4, 2017, less than 6 months from now.
7	Digital Ally Inc	Apr 1, 2019	3663	And quite frankly, we think even the **patent infringement** that we're seeing out there is becoming more and more brazen, not only with Axon and WatchGuard, who we have active **lawsuits** with, but we believe potentially even other competitors out there.
8	Johnson & Johnson	July 20, 2023	2834	The **bankruptcy judge** is expected to rule by August 2 on the motion to dismiss hearing that took place in the last week of June.

Note: This table shows the corporate earnings calls transcripts of some U.S. companies that mention legal- or litigation-related terms. The bold red text indicates legal-related terms

Table 2: **Word Choices to Measure Legal Risk**

Categories	Key terms in this category
Judicial Entities and Key Participants (**LRISK_COURT**)	**Judicial Entities**: Bankruptcy Court, Department of Justice, Federal Circuit, Supreme Court, Trial Court, ... **Key Participants**: Administrative Law Judge, Judges, Jury, Plaintiffs, Prosecutors, ...
Legal Processes and Disputes (**LRISK_TRIAL**)	**Legal Processes**: Appeals, Arbitration, Bankruptcy Proceeding, Class Action, Oral Argument, Trial Date, ... **Legal Disputes**: Antitrust Case, Civil Litigation, Patent Infringement, ...
Legal Terms and Concepts (**LRISK_TERMS**)	Adverse Ruling, Case Law, Legal Costs, Sub Judice, ...

Note: This table shows the list of legal terms contained in the legal dictionary $\mathbb{L}$. Broadly put, there are three distinct categories, terms related to (1) Judicial Entities and Key Participants; (2) Legal Processes and Disputes; and (3) Legal Terms and Concepts. Refer to the online appendix for the full list of keywords and word choices.

Table 3: **Logistic Regression Predicting Class Action Lawsuits**

	(1) Lawsuit in $t+1$	(2) Lawsuit within $t+1$ to $t+2$	(3) Lawsuit within $t+1$ to $t+4$
LRISK	**0.104*** (5.68)**	**0.085*** (4.76)**	**0.075*** (3.92)**
FPS	0.416*** (5.68)	0.412*** (5.75)	0.415*** (5.68)
Past Lawsuit	0.189*** (2.53)	0.253*** (3.48)	0.300*** (4.02)
Return	-2.814*** (-17.43)	-1.848*** (-16.07)	-1.222*** (-13.67)
Return Vol	0.007*** (7.64)	0.006*** (7.75)	0.005*** (7.05)
Constant?	Yes	Yes	Yes
Controls?	Yes	Yes	Yes
Firm Fixed Effects?	Yes	Yes	Yes
Observations	174,563	174,563	174,563
No. of Lawsuit Filings	1,437	1,437	1,437
AUC	0.746	0.707	0.685
Pseudo R^2	0.078	0.054	0.044

Note: This table reports logistic regression results where the dependent variable is an indicator for whether a class action lawsuit is filed in quarter $t+1$ (column 1), within quarters $t+1$ to $t+2$ (column 2), or within quarters $t+1$ to $t+4$ (column 3), using a quarterly sample from 2002 to 2024. LRISK is the standardized measure of firm-level legal risk. FPS is a dummy for litigation-prone industries. Past Lawsuit is an indicator for whether the firm has previously been sued. Return is the cumulative stock return over the past quarter, and Return Vol is the return volatility over the same period. Robust z-statistics clustered at the firm level are reported in parentheses. Firm-level controls, which are suppressed for brevity, include firm size, Tobin's Q, leverage, sales growth, asset tangibility, and cash flow, all measured in quarter t. ***/**/* denote the statistical significance at 1%/5%/10% level.

Table 4: **Legal Risk Portfolio Results**

Panel A: Firm characteristics and Industry Distributions

	L1 No legal risk	L2 Middle legal risk	L3 High legal risk
Firm Characteristics			
Num. of Firms	591	846	856
LRISK (num. of sentences)	0	2.5	10.3
LRISK (ratio in %)	0%	0.61%	2.98%
Market value (log)	8.27	9.24	8.93
Book-to-market ratio	0.59	0.53	0.56
Industry distributions (% of firms in each tercile group)			
Pharmaceuticals & Biotech	18.1	8.1	10.7
Software and IT	10.5	12.9	11.5
Electronic and Elect Equip	6.7	7.8	7.6
Computer and Office Equip	1.5	2.5	1.9
Total of four litigation-prone industries	36.8	31.3	31.7

Panel B: Transition Matrix (% of firms moving from one portfolio to another)

	(to) L1	(to) L2	(to) L3	Total
(from) L1	62.1	26.9	11.0	100
(from) L2	18.2	53.6	28.2	100
(from) L3	7.6	26.1	66.3	100

Panel C: Value-weighted future excess returns (%)

	L1 No legal risk	L2 Middle legal risk	L3 High legal risk	L3 - L1 Long - Short
Excess return	0.638	0.912	1.035	**0.397*** **
	(2.02)	(3.23)	(3.37)	**(3.66)**
CAPM alpha	-0.207	0.094	0.232	**0.439*** **
	(-2.17)	(1.50)	(3.79)	**(4.15)**
FF3 alpha	-0.193	0.084	0.205	**0.398*** **
	(-1.92)	(1.39)	(4.56)	**(3.87)**
FF3 + Mom alpha	-0.157	0.095	0.215	**0.372*** **
	(-1.67)	(1.62)	(4.89)	**(3.72)**
FF3 + Liquidity alpha	-0.198	0.100	0.195	**0.392*** **
	(-1.96)	(1.65)	(4.46)	**(3.81)**
FF5 alpha	-0.193	0.028	0.178	**0.372*** **
	(-1.88)	(0.536)	(3.79)	**(3.43)**
FF5 + Mom alpha	-0.162	0.037	0.189	**0.351*** **
	(-1.65)	(0.739)	(4.01)	**(3.31)**
q-factor alpha	-0.124	0.063	0.204	**0.328*** **
	(-1.18)	(1.01)	(3.81)	**(2.96)**

Note: Panel A reports firm characteristics for the sample used in the portfolio analysis over the period July 2004 to June 2024. Panel B shows one-year transition probabilities between portfolio groups formed on **LRISK**. Each row indicates the percentage of firms initially in portfolios L1, L2, or L3 that migrate to each group in the subsequent formation period. Panel C presents average future excess returns (July 2004 – June 2024) and corresponding alphas from portfolios constructed using ex-ante legal risk measures. Firms in L1 (no legal risk) are those with no mention of legal risk in their earnings calls. Firms with positive mentions are split at the median value of **LRISK** into L2 and L3. Utility firms (SIC codes 4900–4999) and financial firms (SIC codes 6000–6411, 6500–6553, and 6700–6799) are excluded due to their highly regulated nature. Numbers in parentheses are Newey–West t-statistics with six lags. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: **Asset Pricing Effects of Macro-Level Legal Risk**

Panel A: Cross-sorting of Macro vs. Micro Legal Risk (%)

	Micro = 1 (No micro-level legal risk)	Micro = 2 (Medium micro-level legal risk)	Micro = 3 (High micro-level legal risk)
Macro = 1 (No macro-level legal risk)	29.4	15.4	11.4
Macro = 2 (Medium macro-level legal risk)	5.3	8.5	8.2
Macro = 3 (High macro-level legal risk)	5.1	6.3	10.5

Panel B: Macro-level Legal Risk (LAW_COURT) (%)

	L1 Zero legal risk	L2 Non-zero macro-level legal risk	L2 - L1 Long - Short
Excess return	0.638	0.962	**0.323*** **
	(2.01)	(3.24)	**(3.18)**
FF3 + mom alpha	-0.157	0.146	**0.303*** **
	(-1.67)	(3.12)	**(3.13)**
FF5 + mom alpha	-0.162	0.096	**0.257*** **
	(-1.65)	(2.11)	**(2.48)**

Note: Panel A reports the joint distribution of firm–date observations by macro- and micro-level legal risk sorts (in terciles). Each cell reports the percentage of total observations, with all entries summing to 100%. Diagonal cells indicate agreement across the two measures; off-diagonals capture disagreement. Panels B reports average excess returns and alphas for the macro-level legal risk factor (**LAW_COURT**). The low-risk group (L1) is held constant and consists of firms entirely free of legal content, ensuring that pricing differences reflect only variation in the high-risk group. The sample covers July 2004 to June 2024. T-statistics are Newey–West adjusted with 6 lags. Utility and financial firms are excluded due to sector-specific regulatory structures. ***/**/* indicate statistical significance at the 1%/5%/10% level, respectively.

Table 6: **Post-2010 Results**

Post-2010 Result (%)

	L1 No legal risk	L2 Middle legal risk	L3 High legal risk	L3 - L1 Long - Short
Excess return	0.841	1.173	1.434	**0.593*** **
	(2.91)	(4.47)	(5.12)	**(4.91)**
CAPM alpha	-0.371	-0.013	0.282	**0.653*** **
	(-3.64)	(-0.21)	(3.93)	**(5.58)**
FF3 alpha	-0.370	-0.027	0.0.236	**0.606*** **
	(-3.53)	(-0.432)	(4.91)	**(5.41)**
FF3 + Mom alpha	-0.319	-0.001	0.244	**0.563*** **
	(-3.28)	(-0.023)	(4.96)	**(5.18)**
FF3 + Liquidity alpha	-0.374	-0.015	0.212	**0.587*** **
	(-3.42)	(-0.24)	(4.57)	**(5.03)**
FF5 alpha	-0.339	-0.057	0.212	**0.551*** **
	(-3.26)	(-1.00)	(4.16)	**(4.93)**
FF5 + Mom alpha	-0.292	-0.034	0.223	**0.515*** **
	(-2.99)	(-0.60)	(4.30)	**(4.71)**
q-factor alpha	-0.280	-0.046	0.230	**0.509*** **
	(-2.84)	(-0.68)	(3.99)	**(4.43)**

Note: This table presents the average future excess returns alongside the alpha results derived from portfolios constructed based on **LRISK** spanning post-2010 sample (July 2010 - June 2024). Firms in L1 (no legal risk) are those with no mention of legal risk in their earnings calls. Firms with positive mentions are split at the median value of **LRISK** into L2 and L3. Utility firms (SIC codes 4900–4999) and financial firms (SIC codes 6000–6411, 6500–6553, and 6700–6799) are excluded due to their highly regulated nature. Numbers in parentheses are Newey–West *t*-statistics with six lags. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: **Comparing Legal Risk and Cyber Risk**

Panel A: Correlation

	LRISK (LAW)	**Cyber Risk**	**Cyber Risk Law**
LRISK (LAW)	1.00		
Cyber RISK	-0.05	1.00	
Cyber Risk Law	0.42	-0.01	1.00

Panel B: Risk Factor Performance

	LRISK (LAW)	**Cyber Risk**	**Cyber Risk Law**
Excess return	**0.397*** **	**0.360** **	0.142
(% per month)	**(3.66)**	**(2.05)**	(1.19)
FF5 + Mom alpha	**0.351*** **	**0.275*** **	0.070
(% per month)	**(3.31)**	**(2.25)**	(0.62)

Panel C: Factor Spanning Test

	(1)	(2)	(3)
→ Dependent variable:	**LRISK (LAW)**	**Cyber Risk**	**Cyber Risk Law**
↓ Independent variable:			
Intercept	**0.277*** **	0.164	-0.093
	(2.85)	(1.49)	(-0.96)
LRISK (LAW)		**0.244** **	**0.256** **
		(2.24)	**(2.16)**
Cyber Risk	**0.203** **		**0.361*** **
	(2.12)		**(5.24)**
Cyber Risk Law	**0.281** **	**0.475*** **	
	(2.08)	**(4.59)**	
MKT	0.004	0.005	0.007
	(0.14)	(0.21)	(0.29)
SMB	**-0.120** **	-0.029	0.061
	(-2.56)	(-0.53)	(1.37)
HML	0.06	**-0.353*** **	0.065
	(1.10)	**(-5.68)**	(1.32)
MOM	**0.05* **	-0.002	0.041
	(1.70)	(-0.04)	(1.44)

Note: This table compares Legal Risk (**LRISK** or **LAW** factor) constructed in this paper with **Cyber Risk** and its component measure, **Cyber Risk Law**. All three measures are derived from earnings call transcripts, covering the sample period from July 2004 to June 2024. Panel A reports the Pearson correlation at the firm level. Panel B presents the performance of a long-short portfolio strategy over the sample period. Panel C shows the factor spanning test, where the dependent variable is one of the three measures, and the benchmark model is the Fama-French five-factor model augmented with momentum, as well as the two remaining measures not used as the dependent variable. In Panels B and C, numbers in parentheses represent Newey-West t-statistics with six lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: **Variable Definitions and Descriptive Statistics**

Panel A: Variable Definitions

Variable	Definition
Legal Risk	
LRISK (standardized)	Standardized firm-level legal risk exposure, constructed as the annual average of quarterly textual exposure measures to legal risk from earnings calls, and standardized across all firm-year observations
Control variables	
Size	Natural logarithm of total assets: $\log(\texttt{at})$
Tobin's Q	Book value of equity plus long-term debt over total assets: $(\texttt{at} + \texttt{mve} - \texttt{ceq} - \texttt{txdb})/\texttt{at}$ where $\texttt{mve} = \texttt{csho} \times \texttt{prcc\_f}$
Leverage	Ratio of total debt (long-term + current) to total assets: $(\texttt{dltt} + \texttt{dlc})/\texttt{at}$
Sales Growth	Annual growth in sales: $(\texttt{sale} - \texttt{L1.sale})/\texttt{sale}$
Tangibility	Asset tangibility, defined as the ratio of net property, plant, and equipment to total assets: `ppent/at`
CF	Cash Flow: (`ib` + `dp`) / `at`
WW	Whited-Wu index to measure firms' financial constraints
`FD`	Financing Deficit (%): Following Frank and Goyal (2003), this variable is defined as the sum of cash dividends (`dvc`), capital expenditures (`capx`), acquisitions (`aqc`), investment in other assets (`ivch`), and the change in working capital (`act–lct`), minus operating cash flow (`oancf`); scaled by lagged total assets (`at`). All components are set to zero where missing. The variable proxies for a firm's reliance on external financing
Net Debt Issues	The net amount of long-term debt issued by the firm, defined as debt issuance (`dltis`) minus debt repayments (`dltr`), scaled by lagged total assets. Missing values are set to zero to retain sample size. This variable captures a firm's reliance on long-term debt financing relative to its size
Net Equity Issues	The net amount of equity issued by the firm, defined as sales of common stock (`sstk`) minus stock repurchases (`prstkc`), scaled by lagged total assets. Missing values are set to zero to retain sample size. This variable captures a firm's reliance on external equity financing relative to its size
Investment variables	
`CAPX + AQC`	Tangible capital investment (%): 100 × [`capx` + `aqc`] / lagged total assets. Missing values in `capx` and `aqc` are imputed with zeros
`R&D`	Intangible capital investment using R&D intensity (%): 100 × `xrd` / lagged total assets. Missing values in `xrd` are imputed with zeros
`Total Inv`	Total investment (%): 100 × [`capx` + `aqc` + `xrd`] / lagged total assets. Missing values are imputed with zeros for all components

Panel B: Descriptive Statistics

Variable	N	Mean	SD	Min	P25	P50	P75	Max
LRISK (standardized)	50,612	0.00	1.00	-0.59	-0.46	-0.26	0.05	30.28
SIZE	60,149	6.80	2.21	1.05	5.24	6.77	8.27	14.34
Tobin's Q	59,896	0.62	0.25	-1.89	0.53	0.69	0.79	0.98
Leverage	59,899	0.24	0.25	0.00	0.04	0.19	0.36	2.63
Sales Growth	53,427	-0.05	1.70	-42.76	-0.03	0.06	0.16	1.00
Tangibility	59,728	0.22	0.23	0.00	0.04	0.13	0.31	0.95
CF	58,629	-0.02	0.33	-4.12	-0.00	0.06	0.11	0.60
WW	51.980	-0.02	0.33	-4.12	-0.43	-0.34	-0.25	0.60
FD	60,149	0.15	0.51	-0.78	-0.03	0.02	0.14	7.45
Net Debt Issues	60,149	0.03	0.19	-6.74	-0.01	0.00	0.01	11.40
`CAPX + AQC`	59,935	7.24	14.48	-14.11	0.88	3.22	7.84	204.84
`R&D`	59,935	6.25	15.26	0.00	0.00	0.00	5.89	194.45
`Total Inv`	59,935	13.55	21.46	-10.64	2.32	7.22	16.34	278.00

Note: Panel A describes the variables used in this paper. Panel B provides summary statistics. **LRISK** is standardized across all firm-year observations. All other variables are winsorized at the 0.1% and 99.9% levels.

Table 9: **Legal Risk and Firm Investment**

	(1) CAPX + AQC	(2) R&D	(3) Total Inv
Panel A: Benchmark Specification			
LRISK	**-0.277********	**-0.336*****	**-0.616*****
	(-2.99)	**(-3.65)**	**(-4.53)**
Controls?	Yes	Yes	Yes
Firm Fixed Effects?	Yes	Yes	Yes
Year Fixed Effects?	Yes	Yes	Yes
Observations	43,741	43,741	43,741
R^2	0.257	0.769	0.429
Panel B: Controlling for Lagged Investment			
LRISK	**-0.230****	**-0.175****	**-0.465*****
	(-2.25)	**(-2.43)**	**(-3.43)**
Controls?	Yes	Yes	Yes
Firm Fixed Effects?	Yes	Yes	Yes
Year Fixed Effects?	Yes	Yes	Yes
Observations	36,389	36,389	36,389
R^2	0.257	0.803	0.430
Panel C: Industry × Year Fixed Effects			
LRISK	**-0.274*****	**-0.326*****	**-0.609*****
	(-2.67)	**(-3.71)**	**(-4.30)**
Controls?	Yes	Yes	Yes
Industry × Year Fixed Effects?	Yes	Yes	Yes
Observations	41,060	41,060	41,060
R^2	0.303	0.832	0.481
Panel D: Controlling for Ohlson's O-score			
LRISK	**-0.254*****	**-0.352*****	**-0.611*****
	(-2.48)	**(-3.56)**	**(-4.14)**
Controls?	Yes	Yes	Yes
Firm Fixed Effects?	Yes	Yes	Yes
Year Fixed Effects?	Yes	Yes	No
Observations	39,072	39,072	39,072
R^2	0.240	0.765	0.407

Note: This table presents yearly panel regressions of investment on lagged firm-level legal risk (LRISK), using data from 2002 to 2024. The dependent variables are: (i) capital expenditures and acquisitions (CAPX + AQC), (ii) R&D expenditures, and (iii) total investment (CAPX + AQC + R&D), all scaled by beginning-of-year total assets. **LRISK** is a text-based measure of firm-level legal risk. Controls (suppressed to save space) include firm size, Tobin's Q, leverage, sales growth, asset tangibility, cash flow, and the Whited-Wu index (a proxy for financial constraints). Standard errors are clustered at the firm level. Panel (A) shows the baseline results. Panel (B) includes up to three lags of the dependent variable to account for the strong persistence in investment dynamics, as emphasized by Eberly, Rebelo, and Vincent (2012). Panel (C) replaces firm fixed effects with two-digit SIC industry fixed effects. Panel (D) substitutes the WW index with Ohlson's O-score. t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 10: **Legal Risk and External Financing Decisions**

	Panel A: Net Debt Issues			Panel B: Net Equity Issues		
	(1)	(2)	(3)	(4)	(5)	(6)
FD	0.152***	0.156***	0.176***	0.480***	0.473***	0.462***
	(15.82)	(15.43)	(15.09)	(19.83)	(19.20)	(17.78)
LRISK	0.001	0.002	0.002	0.002	0.002	0.001
	(0.97)	(1.40)	(1.33)	(0.69)	(0.66)	(0.70)
LRISK × FD	**-0.016***	**-0.017***	**-0.019***	-0.013	-0.012	-0.013
	(-3.49)	**(-3.88)**	**(-4.08)**	(-0.80)	(-0.75)	(-0.75)
SIZE			0.027***			-0.023***
			(10.70)			(-5.91)
Tobin's Q			0.035***			-0.121***
			(3.01)			(-7.10)
Leverage			0.223***			-0.150***
			(19.18)			(-11.55)
Sales Growth			0.001			0.001
			(0.82)			(0.72)
Tangibility			-0.023			0.031
			(-1.26)			(1.13)
Intangibility			0.088***			0.052***
			(6.79)			(2.91)
Z-score			-0.002***			0.004***
			(-3.73)			(4.65)
Firm Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects?	No	Yes	Yes	No	Yes	Yes
Industry Fixed Effects?	No	Yes	Yes	No	Yes	Yes
Observations	50,308	47,665	40,728	47,083	46,446	39,727
R^2	0.280	0.293	0.361	0.702	0.700	0.698

Note: This table combines regression results for debt and equity issuance. FD denotes the financing deficit. LRISK is a standardized firm-level legal risk measure. All dependent variables are scaled by lagged assets. Fixed effects vary by specification. T-statistics (in parentheses) are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

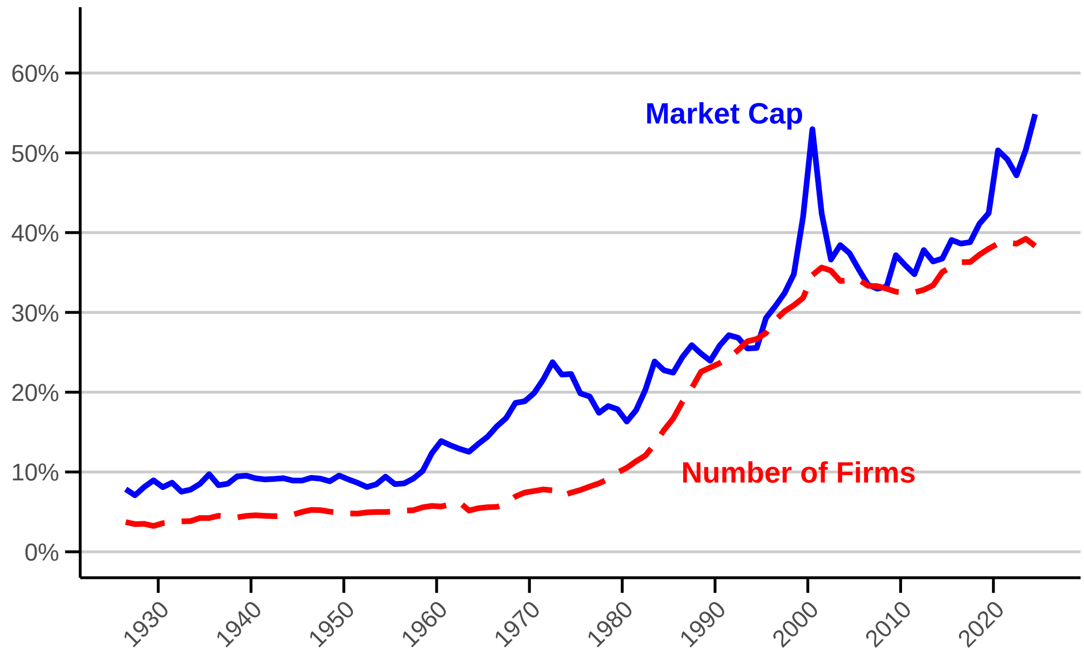
Legal Risk

Online Appendix

- **Section A**: Growth of Legal Risk through Litigation-Prone Industries
- **Section B**: The Legal Risk Dictionary
- **Section C**: Additional Asset Pricing Results and Data Mining Concerns
- **Section D**: Aggregate LRISK, Legal Shifts, and Comparison with Macroeconomic Uncertainty Measures
- **Section E**: Firm-level Evidence: Case studies using SolarWinds
- **Section F**: Modeling Legal Risk in a Real Options Framework

A Growth of Legal Risk through Litigation-Prone Industries

Figure A.1: **Growth of Litigation-Prone Industries**



Note: In this figure, the red dotted line plots the ratio of firms in high-litigation industries to all publicly traded firms on the NYSE, NASDAQ, and NYSE American (formerly AMEX) from 1926 to 2024. The blue solid line plots the corresponding ratio of market capitalization. The industries prone to litigation include pharmaceuticals and biotechnology (SIC 2833 - 2836), computer and office equipment (SIC 3570 - 3577), software and IT services (SIC 7370 - 7374), and electronic and electrical equipment (SIC 3600 - 3674). These industries are frequently involved in litigation due to intellectual property disputes, regulatory challenges, and product liability risks.

The growth of litigation-prone industries over the past two decades underscores an important structural driver of rising legal risk in the U.S. economy. Figure A.1 illustrates this pattern by tracking the number of publicly listed firms operating in high-litigation industries, such as pharmaceuticals and biotechnology (SIC 2833-2836; corresponding to Industry 13 "Drug" in the Fama-French 49 Industry classifications), computer and office equipment (SIC 3570-3577; Industry 35 "Hardware" in FF49), software and IT services (SIC 7370-7374; Industry 36 "Software" in FF49), and electronic and electrical equipment (SIC 3600-3674; Industry 22 "Electrical Equipment" in FF49).

These sectors are frequently exposed to legal disputes involving intellectual property, regulatory compliance, antitrust, and product liability, making them natural incubators of firm-level legal risk. Although the absolute number of publicly listed firms has declined since the late 1990s, the share of firms operating within these litigation-intensive sectors has increased steadily, as has their combined market capitalization relative to the overall market.

This structural reallocation of capital toward more legally exposed industries amplifies the relevance of legal risk for asset pricing and corporate decision-making. As the figure shows, firms in these sectors now account for a substantially larger fraction of public market capitalization than they did in prior decades, especially post-2000. This compositional shift implies that aggregate market exposure to legal uncertainty is not merely cyclical but reflects deeper changes in the industrial landscape. Legal risk, in this sense, is increasingly embedded in the technological and regulatory complexity of the modern economy.

These patterns, along with the evidence in Table 3 showing that firms in litigation-prone industries are significantly more likely to face class action lawsuits, reinforce the core motivation of this paper: legal risk is not an episodic concern confined to a narrow set of firms, but a pervasive and growing feature of the public firm landscape. Understanding how legal risk shapes valuation, investment, and financing decisions is therefore essential to analyzing firm behavior and return premia in modern capital markets.

B The Legal Risk Dictionary

Extracting keywords from earnings call transcripts is essential for identifying underlying signals of legal risk faced by firms. This section of the online appendix provides additional details to clarify the robustness of my analysis and ensure its accuracy.

To begin, I adopt a conservative approach and deliberately exclude the keyword *"litigation"*. This decision is guided by two key considerations. First, most firms are required to include disclaimers at the start of their earnings calls, such as:

"Before we begin, may I draw your attention to the disclaimer on our presentation and company announcement regarding forward-looking statements as defined in the U.S. Private Securities Litigation Reform Act of 1995."

This standardized disclaimer, ubiquitous across firms, could inadvertently introduce noise into the analysis by classifying firms with no genuine litigation exposure into portfolios of firms with such risks. Including the term *"litigation"* could therefore compromise the integrity of the portfolio sorting process. Second, the terms *"litigation"* and *"legal"* are often used interchangeably in earnings calls. Since *"legal"* is already incorporated into my analysis, excluding *"litigation"* does not result in any substantive loss of information or analytical rigor.

Another important aspect of keyword extraction involves handling terms with multiple meanings that vary by context. For example, the term *"judge"* can function as a verb—simply meaning to decide or form an opinion—without legal relevance, whereas *"Judge"* (capitalized) refers specifically to a legal authority. To preserve precision, I include *"Judge"* but exclude the lowercase *"judge"* to ensure that only legally relevant contexts are captured. A similar issue arises with *"court"*, which could theoretically mean to "court someone," but in corporate earnings calls it almost always refers to judicial entities. Accordingly, both *"court"* and *"Court"* are retained.

Patent-related terminology presents another challenge. Because patent litigations are common, I include only expressions with clear legal implications, such as *"patent infringement"*, while excluding broader terms like *"patent"*. Technology firms frequently mention their patents in non-legal contexts—such as innovation or intellectual property strategies—so including *"patent"* indiscriminately would introduce noise and reduce precision. Ambiguous terms such as *"complaint"*, *"claim"*, and *"settle"* also require careful treatment. For instance, *"complaint"* could denote a legal filing or simply a customer grievance, and *"claim"* might refer to insurance or warranty issues rather than legal proceedings. To address this, I exclude these words in isolation and retain only legally specific phrases such as *"amended complaint"*, *"legal claim"*, and *"counterclaim"*. By excluding ambiguous terms unless they appear in clearly legal contexts, the keyword extraction process isolates genuine legal references while minimizing noise from irrelevant mentions.

As a result, the final set of keywords used to identify firm-level legal risk is listed below. Keywords frequently appearing in corporate earnings calls are highlighted in italics.

- **Judicial Entities and Key Participants (LRISK_COURT)**
  - **Judicial Entities**: Administrative Court, Appeal Court, Apppellate Court, Arbitration Court, Arbitration Tribunal, Bankruptcy Court, ***Commission***, Constitutional Court, ***Court(s)***, ***Department of Justice (DOJ)***, District court, Eastern District, European Court, European Court of Justice (ECJ), Federal Court, Fifth Circuit, High Court, Lower Court, Northern District, Oversight Board, Patent Office, Southern District, ***Supreme Court***, Trial Court,
  - **Key Participants**: Administrative Law Judge (ALJ), Arbitrator, Attorney General, Defendants, Federal Judge, ***Judge***, Jury, Plaintiff(s), Prosecutor(s)
- **Legal Processes and Disputes (LRISK_TRIAL)**
  - **Legal Processes**: ***Appeals***, ***Arbitration***, Bankruptcy Process, Binding Arbitration, Class Action, Court Approval, Court Hearing, Court Process, Court Proceedings, Evidentiary Hearings, ***Hearing(s)***, IPR Process, Judicial Process, Judicial Review, Legal Proceeding, Legal Process, Markman, Mediation Process, Next Hearing, Oral Argument, Oral Hearing, Pending Cases, Rebuttal Testimony, Retrial, Trial Date, Full Trial, ***Petition***, Procedural Schedule, ***Settlement***, ***Settlement Agreement***
  - **Legal Disputes**: Adverse Ruling, Antitrust Case, Arbitration Case, Class Action Lawsuit, Civil Cases, Civil Litigation, Infringement, ***Injunction***, IP Litigation, ***Lawsuit(s)***, Legal Challenges, Legal Claim, Legal Disputes, Patent Case, Patent Claims, Patent Dispute, Patent Infringement, ***Ruling***, Settlement Agreement, Tentative Settlement
- **Legal Terms and Concepts (LRISK_TERMS)**
  - Amended Complaint, Case Law, Compliance Filing, Constitutionality, Counterclaims, Injunctive Relief, Legal Basis, ***Legal Costs***, ***Legal Fees***, ***Legal Expenses***, Sub Judice, Regulatory Issue

C Additional Asset Pricing Results and Data Mining Concerns

This section presents additional analyses to assess the robustness and distinctiveness of the **LAW** factor. I begin with alternative calendar-time portfolio tests including different formation windows. I then address data mining concerns to directly confront the "factor zoo" critique. I further examine whether the **LAW** factor is subsumed by broader behavioral explanations, including market sentiment, mispricing-based factors, and belief disagreement. I also test whether short-term mood fluctuations—proxied by day-of-the-week return patterns—can account for the legal risk premium. Lastly, I explore its relationship with ESG-based risk factors. Together, these exercises reinforce the robustness and economic distinctiveness of the **LAW** factor and mitigate concerns about data mining.

C.1 Robustness Checks on the Calendar-time Portfolio Analysis

This section extends the empirical analysis by introducing alternative portfolio formation strategies to test the robustness of the main findings. As a reminder, the baseline specification in the main text adopts a (12-12) strategy, where portfolios are constructed at the end of June each year using **LRISK** from the past 12 months (i.e., four quarters) of earnings call transcripts. Stocks are value-weighted using market capitalization as of that date, and the portfolio is held for 12 months (next four quarters), ending in June of the following year.

To take advantage of the quarterly frequency of earnings calls, Table A.1 presents results for four alternative strategies with more frequent rebalancing: (12-3), (12-6), (9-9), and (18-6).[1] These strategies vary in both the formation window and holding period, while maintaining a consistent tercile-sorting methodology based on ex-ante **LRISK**. In each strategy, firms with no mentions of legal risk are assigned to L1; firms with positive legal risk exposure are split at the median into L2 (medium risk) and L3 (high risk). The "L3 – L1" column reports returns from a tradable long-short portfolio that buys the high legal risk group and sells the zero-risk group. As in the main text, all

[1] In each strategy label (e.g., (12-3)), the first number denotes the formation window in months, and the second number indicates the rebalancing frequency in months. For example, the (12-3) strategy uses the past 12 months (i.e., 4 quarters) of earnings call transcripts to measure firms' legal risk exposure and rebalances the portfolio every 3 months (i.e., quarterly).

portfolios are value-weighted using market capitalization at the time of formation, and utility and financial firms are excluded. The table reports average monthly excess returns and Fama–French three-factor plus momentum alphas, along with Newey–West t-statistics computed using six lags. Across all four strategies, the long-short portfolios as presented in Table A.1 deliver statistically and economically significant returns. These results reinforce the robustness of the main findings to alternative portfolio formation schemes.

In unreported robustness checks, I confirm that the results remain qualitatively unchanged under the following variations: (1) including utility and financial firms; (2) capping the market capitalization of the earnings call sample at the 95th percentile, which roughly corresponds to the 80th percentile NYSE breakpoint used by Jensen et al. (2023); and (3) excluding the so-called "Magnificent 7" firms—Apple, Microsoft, Amazon, Alphabet (Google), Meta (Facebook), Tesla, and Nvidia—which collectively represent a substantial share of total market capitalization in recent years. Importantly, as illustrated in Figure A.2, these well-known mega-cap firms also migrate across tercile groups over time, reinforcing the notion that legal risk exposure is both dynamic and widespread.[2]

[2]Figure A.2 shows that firms frequently transition across legal risk categories. For instance, Ford Motor Company experienced an escalation from moderate to high legal risk during the mid-2000s, linked to lawsuits involving employment discrimination, loan practices, and product liability. Similarly, Coca-Cola saw increased legal risk exposure in 2020–2021, driven by lawsuits such as *Earth Island Institute v. Coca-Cola Co.* over alleged environmental greenwashing and *Swartz v. Coca-Cola Co.* regarding misleading recyclability claims.

Table A.1: **Long-Short Strategy Results using Different Formation Period**

Panel A: (12-3) strategy (%)

	L1 No legal risk	L2 Middle legal risk	L3 High legal risk	L3 - L1 long - short
Excess return	0.626	0.948	0.973	**0.347*** **
	(2.02)	(3.26)	(3.29)	**(3.34)**
FF3 + mom alpha	-0.151	0.119	0.162	**0.313*** **
	(-1.90)	(2.41)	(2.90)	**(3.08)**

Panel B: (12-6) strategy (%)

	L1 No legal risk	L2 Middle legal risk	L3 High legal risk	L3 - L1 Long - Short
Excess return	0.670	0.916	0.998	**0.328*** **
	(2.14)	(3.18)	(3.35)	**(3.66)**
FF3 + mom alpha	-0.129	0.095	0.185	**0.315*** **
	(-1.66)	(1.89)	(3.35)	**(3.35)**

Panel C: (9-9) strategy (%)

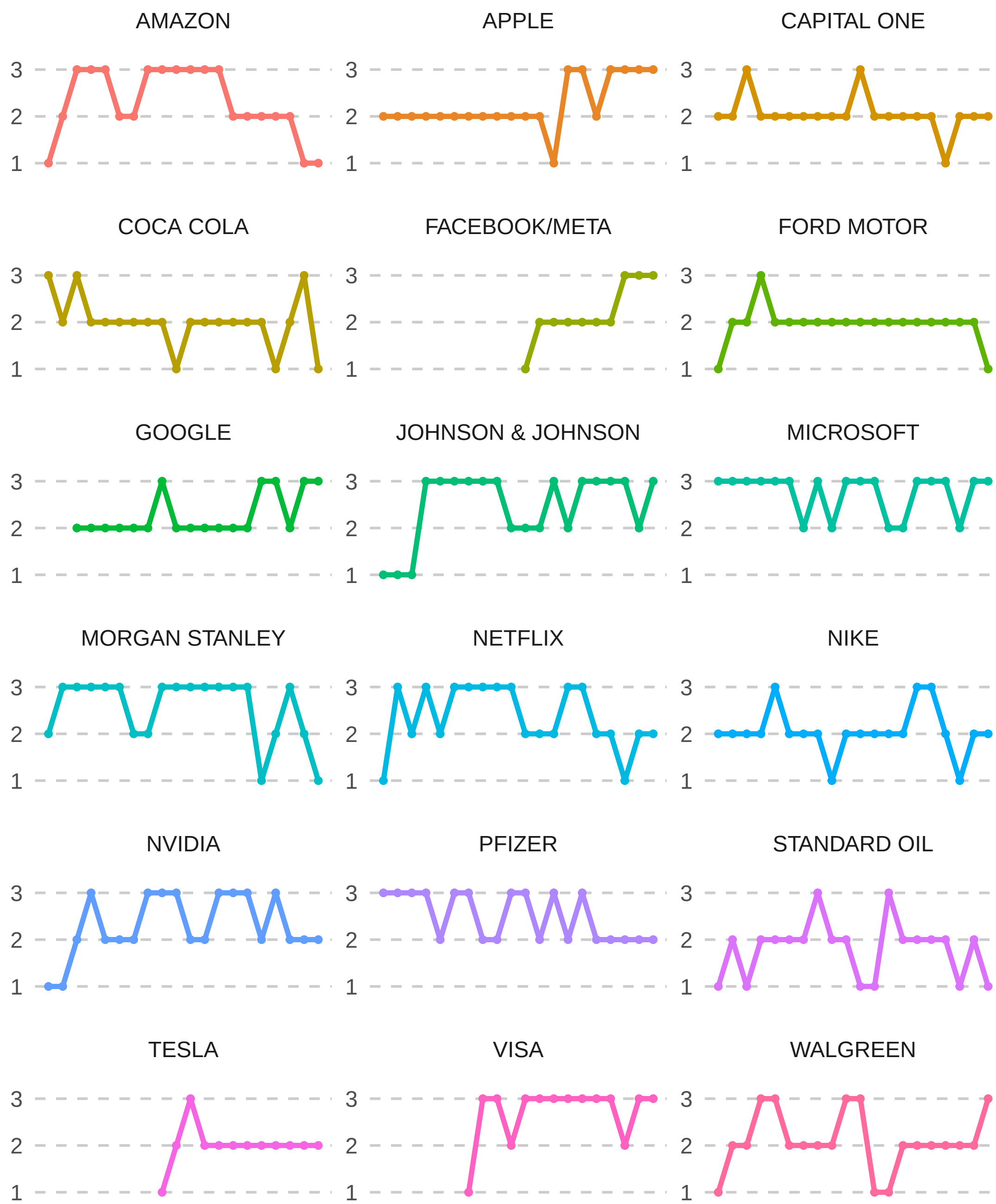
	L1 No legal risk	L2 Middle legal risk	L3 High legal risk	L3 - L1 Long - Short
Excess return	0.686	0.929	1.010	**0.325*** **
	(2.20)	(3.21)	(3.43)	**(2.94)**
FF3 + mom alpha	-0.096	0.103	0.196	**0.291*** **
	(-1.14)	(2.26)	(2.85)	**(2.68)**

Panel D: (18-6) strategy (%)

	L1 No legal risk	L2 Middle legal risk	L3 High legal risk	L3 - L1 Long - Short
Excess return	0.697	0.868	1.020	**0.324*** **
	(2.14)	(2.99)	(3.46)	**(3.17)**
FF3 + mom alpha	-0.123	0.062	0.200	**0.323*** **
	(-1.37)	(1.20)	(3.95)	**(3.13)**

Note: Each panel reports average future excess returns (July 2004 - June 2024) and FF3 + momentum alphas from portfolios formed based on **LRISK**. The strategy in each panel is defined by two parameters in parentheses: the portfolio formation window and the rebalancing frequency, both in months. For example, Panel A shows results for the (12-3) strategy, where firms are sorted based on **LRISK** observed over the past 12 months (4 quarters) and portfolios are rebalanced every 3 months (1 quarter). Panels B–D present analogous strategies: (12-6), (9-9), and (18-6), respectively. Utility firms (SIC 4900–4999) and financial firms (SIC 6000–6411, 6500–6553, and 6700–6799) are excluded due to heavy regulatory constraints. Newey-West t-statistics with 6 lags are shown in parentheses. ***/**/* indicate statistical significance at the 1%/5%/10% level, respectively.

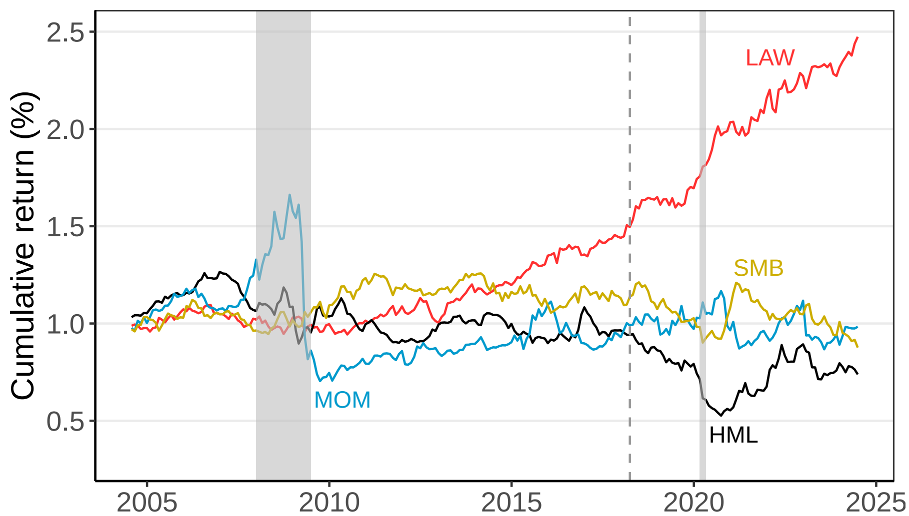
Figure A.2: **Legal Exposure of Well-known Firms**



Note: This figure illustrates the legal risk exposure of prominent corporate entities analyzed in this study. The x-axis shows the years over which portfolio sorting based on firm-level legal risk exposure was conducted, spanning from 2003 to 2023. The y-axis categorizes the legal risk into three levels: 1 indicates no legal risk, 2 represents moderate legal risk, and 3 denotes high legal risk.

C.2 Data Mining Concerns

Figure A.3: **Cumulative Return Performance of Legal Risk Factor (LAW)**



Note: This figure plots the cumulative return performance of $1 invested in each of the four risk factors (LAW, SMB, HML, and MOM) at the end of 2004:06. The shaded area are NBER economic recession periods, and the dotted vertical line represents when *Cyan, Inc. v. Beaver County Employees Retirement Fund* (*2018*) decision was released.

A recent number of articles address the potential data mining concerns. This section briefly details three reasons why I believe my **LAW** factor result is not data-mined.

First, my t-statistic result substantially exceeds the new threshold of 3.0 proposed by Harvey et al. (2016), providing strong evidence against data-mining concerns (3.66 for the full 20-year sample spanning 2004–2024, and 4.91 for the post-2010 sample). Second, unlike many anomalies that emerge from mechanical combinations of accounting variables (such as those simulated in Novy-Marx and Velikov 2025), my **LAW** factor is constructed from novel, forward-looking text-based information extracted from earnings call transcripts.

Second, while many traditional anomalies exhibit sharp decay in predictability after the early 2000s (Chordia et al. 2014), the **LAW** factor remains strong and stable throughout the post-2004 period (in fact, my sample starts in 2004). Figure A.3 plots the cumulative return to a $1 investment in the long-short **LAW** portfolio alongside standard factors. Two key inflection points stand out: the 2018 surge aligns with the Supreme Court's Cyan, Inc. v. Beaver County decision, which increased forum-shopping risk and litigation costs; the 2020 spike coincides with the onset of COVID-19, which amplified legal uncertainty across sectors. Over the full period, $1 invested in the LAW factor grows to $2.38, while SMB, HML, and MOM shrink to $0.91, $0.78, and $0.97, respectively.[3]

Importantly, the **LAW** factor demonstrates resilience during economic downturns, including the 2008 Global Financial Crisis and the 2020 COVID shock. Legal risks become particularly salient in these periods, as firms and investors are already under financial stress. Investors tend to value firms whose legal risk remains stable—or demand higher returns from those with greater exposure—driving the outperformance of the long-short strategy in downturns. By contrast, other risk factors, particularly momentum, tend to experience sharp declines during or shortly after recessions (Daniel and Moskowitz 2016).

Finally, Figure A.4 further underscores the uniqueness of the legal risk factor (**LAW**) within the broader factor zoo. Across 193 spanning regressions—each controlling for the Fama–French three factors, momentum, and one anomaly factor at a time—the **LAW** factor retains a statistically significant intercept, with Newey–West adjusted t-statistics exceeding 2.0 in all cases and remaining above 3.0 in 181 of them (93.7% of the factors zoo). These results indicate that **LAW** is not subsumed by any known return predictor and thus represents a robust, economically meaningful source of priced risk. The sample period spans July 2004 to December 2023, and the anomaly factors are obtained from Chen and Zimmermann (2022).[4]

C.3 Market Sentiment and Mispricing explanations

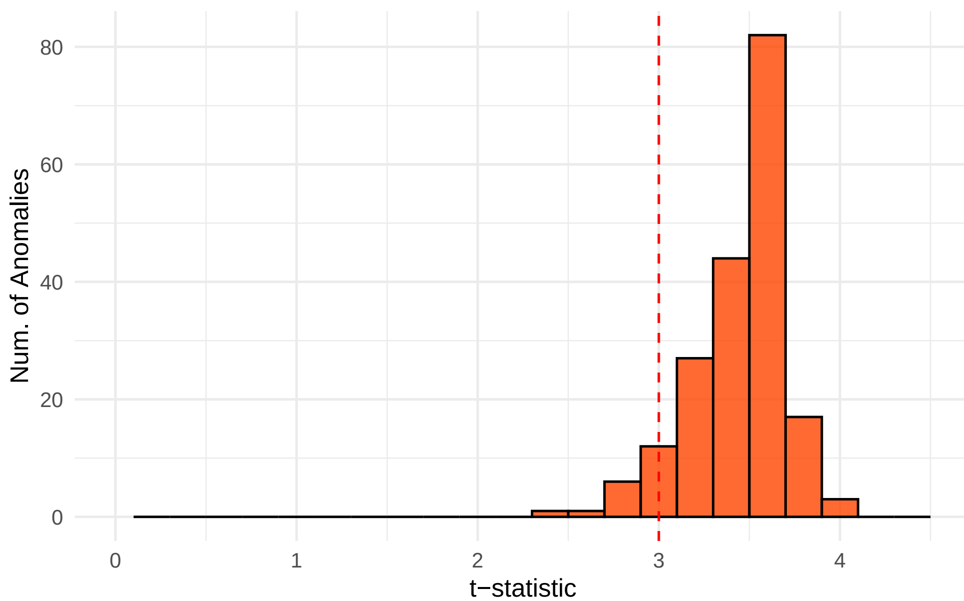
In the behavioral finance literature, there has been a sustained effort to explain return predictability and risk premia through the lens of mispricing and investor biases. Prominent examples include

[3]Individually, firms in the lowest legal risk tercile (q1) grow from $1 to $3.23, while q2 and q3 portfolios grow to $6.31 and $8.40, respectively.

[4]Additionally, I find that the Pearson correlations between the **LAW** factor and standard asset pricing factors are modest in magnitude: **MKT** (–0.14), **SMB** (–0.26), **HML** (–0.19), **MOM** (0.25), **RMW** (0.10), **CMA** (0.04), and **LIQ** (–0.02). Notably, none of the 193 anomaly factors exhibit an absolute correlation with **LAW** greater than 0.4, further reinforcing the distinctiveness of legal risk as a priced dimension in the cross-section of returns.

models that attribute anomalies to underreaction, overreaction, or limits to arbitrage, such as the PEAD and FIN factors proposed by Daniel et al. (2020), and the MGMT and PERF factors developed by Stambaugh (2017), which aggregate information across known anomalies related to managerial behavior and firm performance, respectively. A related strand of research emphasizes investor belief dispersion as a source of pricing distortions, culminating in the construction of a disagreement index by Huang et al. (2021), which combines 24 individual disagreement measures using a partial least squares (PLS) approach.

Figure A.4: **Spanning Regressions: Distinctiveness of the LAW Factor**



Note: This figure displays the distribution of Newey–West adjusted (6 lags) t-statistics for the intercept term (α) from 193 spanning regressions of the **LAW** factor on the Fama–French three factors, the momentum factor, and one of 193 additional anomaly factors from the finance literature. Each regression takes the form: $\textbf{LAW} = \alpha + \beta_{MKT}\textbf{MKT} + \beta_{SMB}\textbf{SMB} + \beta_{HML}\textbf{HML} + \beta_{MOM}\textbf{MOM} + \beta_{ZOO}\textbf{ZOO}$, where **ZOO** represents one of the benchmark anomalies. The t-statistic on α exceeds 2.0 in all cases and remains above 3.0 in 181 out of 193 specifications, indicating that the **LAW** factor remains largely unexplained by known return predictors. The sample spans July 2004 to June 2023.

Against this backdrop, I examine the **LAW** factor and find that it is not subsumed by these existing behavioral constructs. The results are presented in Table A.3. First, the returns to the **LAW** factor –

whether measured on the long leg, short leg, or as a long-short portfolio – do not exhibit sensitivity to market-wide sentiment, as proxied by the index of Huang et al. (2015), in contrast to the pattern observed for traditional anomalies (Stambaugh et al. 2012). Second, regressions controlling for PEAD, FIN, MGMT, PERF, and the aggregate disagreement index of Huang et al. (2021) all leave the alpha on LAW economically meaningful and statistically significant. These findings suggest that the premium associated with legal risk reflects a distinct pricing channel—one that is not captured by current models of mispricing, sentiment, or disagreement.

Finally, to examine the role of mood in explaining the legal risk result, following the approach of Birru (2018), I estimate separate regressions of the daily return on the legal risk factor (LAW) for each weekday. Specifically, for each day $d \in \{1, 2, 3, 4, 5\}$ corresponding to Monday through Friday, I estimate:

$$\text{LAW}_t = \alpha_d + \varepsilon_t, \quad \text{for all } t \text{ such that } \text{Day}_t = d, \tag{A.1}$$

where LAW_t denotes the daily return on the legal risk factor, α_d captures the mean return on day d, and ε_t is the residual.

Table A.2: **Day-of-the-Week Effects on LAW Returns**

	Monday	Tuesday	Wednesday	Thursday	Friday
Estimate	**0.027*****	**0.026*****	**0.021*****	**0.016*****	0.003
t-stat	**(4.67)**	**(4.50)**	**(3.56)**	**(2.82)**	(0.52)
N	939	1,032	1,034	1,018	1,010

Note: Notes: This table reports the estimated mean daily returns (%) and Newey-West t-statistics (lag = 6) from regressions of the daily LAW factor return on a constant, estimated separately for each weekday. ***/**/* denote statistical significance at the 1%, 5%, and 10% levels, respectively. The number of observations (N) varies by day.

The results, reported in Table A.2, show that the **LAW** factor earns significantly positive returns on Mondays through Thursdays. In contrast, Friday returns are smaller in magnitude and not statistically significant. This pattern is inconsistent with the mood-based mispricing hypothesis of Birru (2018), which predicts that returns for speculative long-leg factors should peak on Fridays when investor sentiment is highest. Instead, the evidence indicates that the LAW factor generates strong and persistent returns throughout the week, without a meaningful end-of-week increase. These findings suggest that legal risk exposure is unlikely to be driven by short-term mood fluctuations, and more plausibly reflects compensation for bearing systematic risk.

C.4 LAW Factor vs. ESG Factors

In Table A.4, I conduct spanning regression tests using ESG factors from Pedersen et al. (2021) and Pastor et al. (2022). The results in Panel B indicate that the LAW factor is not subsumed by any of the ESG-related factors, underscoring its distinct role in capturing priced risk. Conversely, some ESG factors—such as GMB in column (5) of Panel A—retain significance when used as dependent variables, suggesting partial overlap between ESG and legal risk. Overall, these results imply that while ESG and legal risk factors may share some common ground, the LAW factor captures a unique dimension of financial market risk premia.

Table A.3: **Sensitivity of the LAW Factor to Market-Wide Sentiment and Mispricing-Based Risk Factors**

Panel A: Predictive regression results

Regression is of the form $LAW_{t+1}^{tercile} = \alpha + \beta s_t + \varepsilon_{t+1}$, where s_t is the Huang et al. (2015) market sentiment

Dep. Variable	β	$t(\beta)$	R-squared (%)	Constant?
$\mathbf{LAW^{Long-Short}}$	0.205	(1.22)	0.3	Yes
$\mathbf{LAW^{L1}}$	-0.537	(-0.91)	0.3	Yes
$\mathbf{LAW^{L3}}$	-0.331	(-0.58)	0.1	Yes

Panel B: Mispricing Factors and Disagreement

	(1)	(2)	(3)	(4)
Dependent variable:	LAW	LAW	LAW	LAW
↓ Independent variable:				
Intercept	**0.377*** **	**0.358** **	**0.312*** **	**0.396*** **
	(3.59)	**(2.48)**	**(3.01)**	**(2.65)**
PEAD	-0.077			-0.067
	(-1.03)			(-0.75)
FIN	0.019			-0.177**
	(0.34)			(-2.44)
MGMT		0.175**		0.308***
		(2.09)		(3.49)
PERF		-0.212***		-0.139**
		(-3.91)		(-2.27)
Disagreement			-0.286*	-0.087
			(-1.83)	(-0.44)
FF3 + mom controlled?	Yes	Yes	Yes	Yes
Sample	2004:07 - 2023:12	2004:07 - 2016:12	2004:07 - 2020:12	2004:07 - 2016:12
Adj. R-squared	0.090	0.172	0.111	0.177

Note: This table examines whether the LAW factor is subsumed by market-wide investor sentiment and mispricing-based risk factors. Panel A presents predictive regressions of LAW factor returns across tercile-sorted portfolios (low, high, long-short) on lagged monthly sentiment from Huang et al. (2015). Panel B reports time-series regressions of the LAW factor on combinations of mispricing-based factors: PEAD and FIN from Daniel et al. (2020), and MGMT and PERF from Stambaugh (2017), along with a proxy for belief disagreement (Huang et al. 2021). All regressions include controls for the Fama-French three factors and the momentum factor (FF3 + MOM), but their coefficients are omitted for brevity. The sample periods vary by factor availability and are indicated in each column. T-statistics are Newey-West adjusted with 6 lags, in parentheses. ***/**/* denote the statistical significance at 1%/5%/10% level.

Table A.4: **Comparing LAW factor and ESG-relevant factors**

Panel A: ESG factors are dependent variables

	PFP factors (1 through 4)				PST factors (5 through 7)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
→ Dependent variable:	ESG	E	S	G	GMB	G	B
↓ Independent variable:							
Intercept	-0.087	0.333	-0.163	-0.119	0.289*	0.124*	-0.165
	(-0.51)	(1.61)	(-1.09)	(-0.67)	(1.69)	(1.74)	(-1.34)
LAW	0.211**	0.082	-0.050	-0.028	0.134*	0.115***	-0.019
	(2.10)	(0.86)	(-0.56)	(-0.32)	(1.86)	(2.59)	(-0.39)
Sample	2007:02 - 2019:03	2009:06 - 2019:03	2004:07 - 2019:03	2004:07 - 2019:03	2009:01 - 2023:12	2009:01 - 2023:12	2009:01 - 2023:12
FF5 + mom controlled?	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: LAW factor is dependent variable

	LAW factor						
↓ Independent variable:							
Intercept	0.330**	0.412**	0.328**	0.332**	0.391***	0.356***	0.431***
	(2.26)	(2.44)	(2.32)	(2.31)	(3.40)	(3.09)	(3.79)
(1) ESG	0.225**						
	(2.57)						
(2) E		0.055					
		(0.95)					
(3) S			-0.036				
			(-0.56)				
(4) G				-0.022			
				(-0.31)			
(5) GMB					0.131*		
					(1.77)		
(6) G						0.465**	
						(2.34)	
(7) B							-0.035
							(-0.39)
Sample	2007:02 - 2019:03	2009:06 - 2019:03	2004:07 - 2019:03	2004:07 - 2019:03	2009:01 - 2023:12	2009:01 - 2023:12	2009:01 - 2023:12
FF5 + mom controlled?	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents spanning tests using Fama-French 5 factors augmented with momentum factors. Panel A uses ESG factors from Pedersen et al. (2021) (PFP factors) and GMB factors from Pastor et al. (2022) (PST factors) as dependent variables. Panel B uses LAW factor as dependent variable. Loadings on FF5 and momentum factors are suppressed. The numbers in parentheses represent Newey-West t-statistics with six lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

D Aggregate LRISK, Legal Shifts, and Comparison with Macroeconomic Uncertainty Measures

This appendix traces the evolution of the U.S. legal landscape over the twenty-first century and links structural changes in the aggregate legal risk measure (**Aggregate LRISK**) to key institutional and judicial turning points.

To start with, a Bai–Perron multiple-break test (Bai and Perron 2003) applied to the **Aggregate LRISK** identifies four statistically significant inflection points—2007 Q4, 2013 Q1, 2017 Q4, and 2020 Q2—that delineate distinct regimes of legal intensity. These structural breaks capture how the legal environment alternated between phases of heightened enforcement and relative normalization, shaping both firm behavior and the pricing of the **LAW** factor.

Legal Episode I (2007 Q4): SOX Enforcement and the Option-Backdating Wave

The first structural break in **Aggregate LRISK** (2007 Q4) corresponds to the full institutionalization of *Sarbanes–Oxley Act* (*SOX*) enforcement and the contemporaneous wave of option-backdating litigation. Following the enactment of SOX in 2002, regulators such as the SEC, DOJ, and PCAOB shifted from rule-drafting to active enforcement between 2004 and 2006, targeting firms for false certifications, inadequate internal controls, and financial restatements. These actions marked a decisive transition from reactive crisis response to continuous legal oversight.

At the same time, the option-backdating scandal exposed widespread corporate misconduct in executive compensation. More than 130 public firms—including Apple, Brocade, and Broadcom—were investigated for falsifying stock-option grant dates to deliver in-the-money awards. The investigations triggered hundreds of SEC enforcement actions, dozens of criminal prosecutions, and a wave of shareholder class actions. This convergence of SOX enforcement and backdating litigation transformed legal risk from an episodic concern into a standing, market-wide hazard. The crisis exhibited clear litigation contagion: scrutiny spread across sectors, ensnaring firms that were not directly implicated but shared similar governance or compensation structures. Even firms with no prior legal exposure began referencing "internal reviews," "SEC inquiries," or "restatements" in earnings calls—signaling a broad elevation of perceived enforcement risk.

Simultaneously, early tremors of the GFC amplified regulatory vigilance and investor sensitivity to legal compliance. Financial restatements, credit-rating disputes, and mortgage-securitization inquiries intensified the sense of systemic fragility. As a result, the 2007 Q4 breakpoint captures the first macro-level escalation of **Aggregate LRISK**, marking the point at which overlapping regulatory, criminal, and shareholder proceedings—and emerging crisis-era scrutiny—embedded compliance and disclosure uncertainty as enduring features of the U.S. corporate landscape.

Legal Episode II (2013 Q1): Post-Crisis Legal Normalization and *Gabelli v. SEC*

The second structural break in **Aggregate LRISK** (2013 Q1) corresponds to a period of legal stabilization following the intense enforcement cycle of the Global Financial Crisis. By this point, most crisis-era cases—particularly those involving mortgage-backed securities, disclosure violations, and accounting fraud—had been settled, and the implementation of the *Dodd–Frank Act (2010)* had shifted from uncertainty to routine compliance. Regulators such as the SEC and DOJ moved from ad-hoc crisis response toward steady, institutionalized oversight, creating a more predictable enforcement environment.

A pivotal judicial development reinforced this transition. In *Gabelli v. SEC* (2013), the U.S. Supreme Court unanimously held that the five-year statute of limitations for civil penalties under 28 U.S.C. § 2462 begins when the alleged misconduct occurs—not when it is later discovered by the regulator. This ruling sharply limited retroactive liability, preventing the SEC from pursuing stale enforcement actions and providing firms with greater temporal certainty regarding potential penalties.

Together, the winding down of crisis-related litigation and the *Gabelli* decision reduced the perceived persistence of legal threats. Firms that had spent years addressing legacy investigations now faced clearer compliance horizons and less ambiguity over regulatory reach. In earnings calls, legal terminology shifted from defensive references to enforcement or litigation toward forward-looking discussions of capital allocation and growth. Consequently, the 2013 Q1 breakpoint in **Aggregate**

LRISK marks a distinct normalization phase in the U.S. legal landscape, one characterized by rule-based enforcement, diminishing retroactive exposure, and a temporary easing of aggregate legal uncertainty.

Legal Episode III (2017 Q4): *Cyan v. Beaver County* and the Return of Litigation Uncertainty

The third structural break in **Aggregate LRISK** (2017 Q4) captures a renewed escalation in litigation risk following a period of post-crisis normalization. The turning point was the Supreme Court's decision in *Cyan, Inc. v. Beaver County Employees Retirement Fund* (2018), which held that state courts retain jurisdiction over class actions brought under the Securities Act of 1933 and that such cases cannot be removed to federal court.

This ruling fundamentally reshaped the litigation landscape for public companies by reinstating dual state–federal exposure. Firms issuing securities could now face parallel class actions in multiple jurisdictions for the same alleged misconduct, increasing legal costs, procedural complexity, and settlement uncertainty. The decision also encouraged "forum shopping," as plaintiffs sought more favorable venues, particularly in states known for investor-friendly courts such as California and New York.

In practice, the *Cyan* ruling broadened the scope of securities litigation beyond traditional financial hubs, introducing venue risk and coordination challenges that had largely been dormant since the late 1990s. Even firms with strong compliance frameworks now faced unpredictable multi-jurisdictional exposure, which was quickly reflected in their earnings-call language and investor communications.

Accordingly, the 2017 Q4 breakpoint in **Aggregate LRISK** marks the reemergence of systemic litigation uncertainty—an environment in which legal risk once again became a priced source of market-wide uncertainty, extending beyond crisis-related regulation to encompass governance, disclosure, and investor-protection domains.

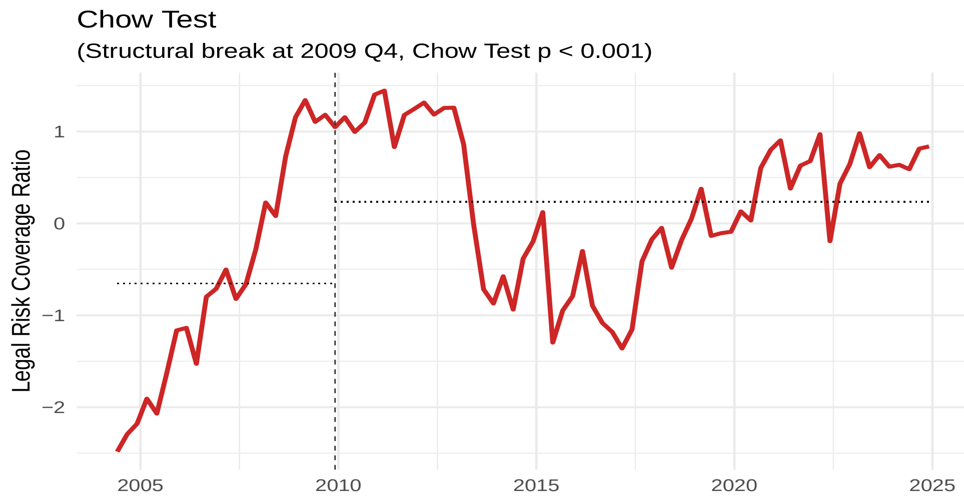
Legal Episode IV (2020 Q2): Pandemic-Era Complexity and the ESG Legal Expansion

The final structural break in **Aggregate LRISK** (2020 Q2) coincides with the onset of the COVID-19 pandemic and the subsequent broadening of corporate legal exposure across operational, technological, and environmental dimensions. The pandemic introduced abrupt uncertainty around disclosure obligations, workplace safety, and contractual performance, triggering class actions and regulatory inquiries in sectors such as travel, healthcare, and manufacturing.

At the same time, a surge in cybersecurity and data-privacy enforcement—exemplified by incidents like the SolarWinds breach—led to heightened scrutiny from the SEC, FTC, and state regulators. Firms faced expanding obligations to disclose cyber incidents promptly, reinforcing the integration of information-security oversight into mainstream compliance risk. Parallel to these developments, the rise of ESG and climate-related litigation further widened the legal perimeter. From 2020 onward, lawsuits targeting alleged "greenwashing," misleading sustainability disclosures, and environmental harm accelerated, while the SEC's creation of the ESG/Climate Task Force in 2021 (disbanded in 2024) signaled a sustained regulatory focus on environmental transparency.

Together, these forces produced a multidimensional legal environment where firms confronted simultaneous pressures across pandemic, cyber, and ESG fronts. The 2020 Q2 breakpoint thus represents a structural broadening of **Aggregate LRISK**—marking the transition of legal risk from a financial-regulatory concern to a pervasive, cross-sectoral determinant of corporate uncertainty.

Figure A.5: **Chow Test**



Note: This figure plots the Chow test around 2010 using the **Aggregate LRISK** measure introduced in Section 3.5. The measure is constructed from the coverage ratio—the proportion of firms referencing legal risk in their earnings call transcripts—computed each quarter as the share of non-zero firms relative to all firms in the sample. To facilitate interpretation over time, the series is standardized using a z-score transformation, highlighting deviations from the historical mean.

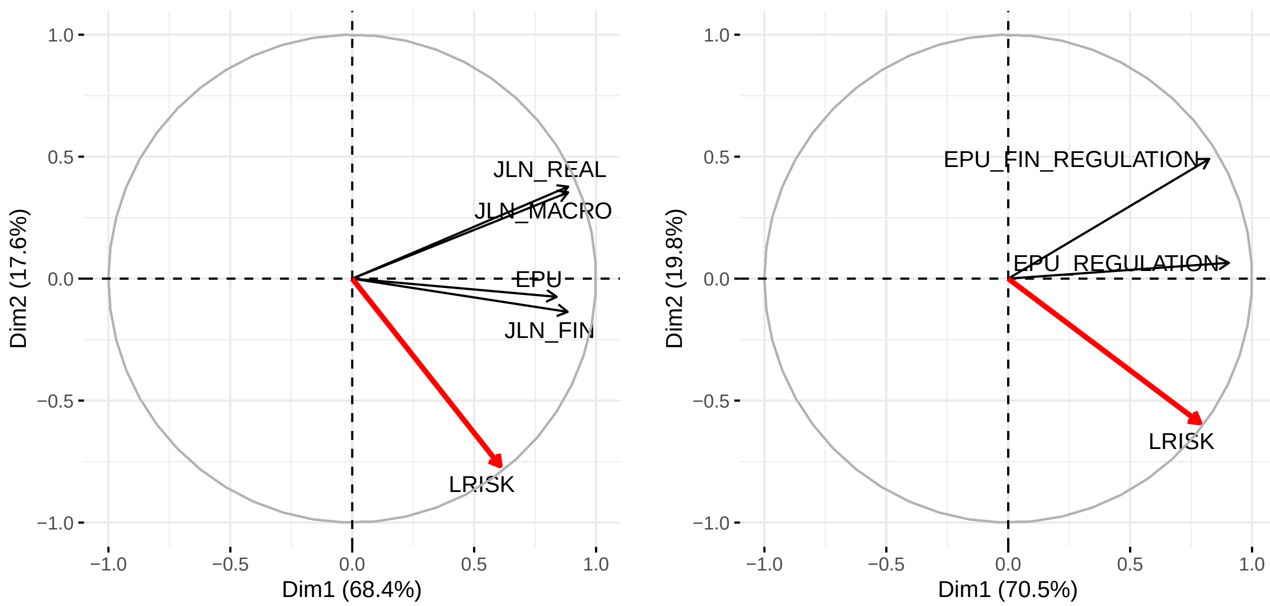
As a final remark, Figure A.5 presents the Chow test for a structural break in **Aggregate LRISK** around 2009-2010. The test reveals a pronounced regime shift at the turn of the decade, corresponding to the implementation of major post–Global Financial Crisis (GFC) reforms such as the *Dodd–Frank Act* (*2010*) and the onset of intensified regulatory enforcement. This structural change justifies the focus on post-2010 data in the main asset pricing analysis (Table 6). Together, the evidence from the Chow test and the subsequent empirical results underscore that the pricing of legal risk—and its relation to firm behavior—fundamentally changed after 2010, reflecting a new era of heightened compliance scrutiny and institutionalized legal oversight in U.S. public markets.

D.1 Aggregate LRISK vs. Macro Uncertainty Measures

This section examines how **Aggregate LRISK** compares to established measures of economic uncertainty, including the Economic Policy Uncertainty (EPU) index of Baker et al. (2016) and the

Macro Uncertainty index of Jurado et al. (2015) (JLN). To analyze the relationships among these variables, I conduct a principal component analysis (PCA) using quarterly data spanning 2004 to 2024. Since the EPU and JLN indexes are originally available at a monthly frequency, I convert them to quarterly by selecting the end-of-quarter observation. For the JLN measure, I use the $h = 3$ horizon to align with the quarterly frequency. All variables are standardized to have zero mean and unit variance prior to estimation. PCA is then applied to the correlation matrix to extract the primary dimensions of variation across the uncertainty measures.

Figure A.6: **Principal Component Loadings of Legal Risk and Other Uncertainty Measures**



(a) LRISK and JLN & EPU Index

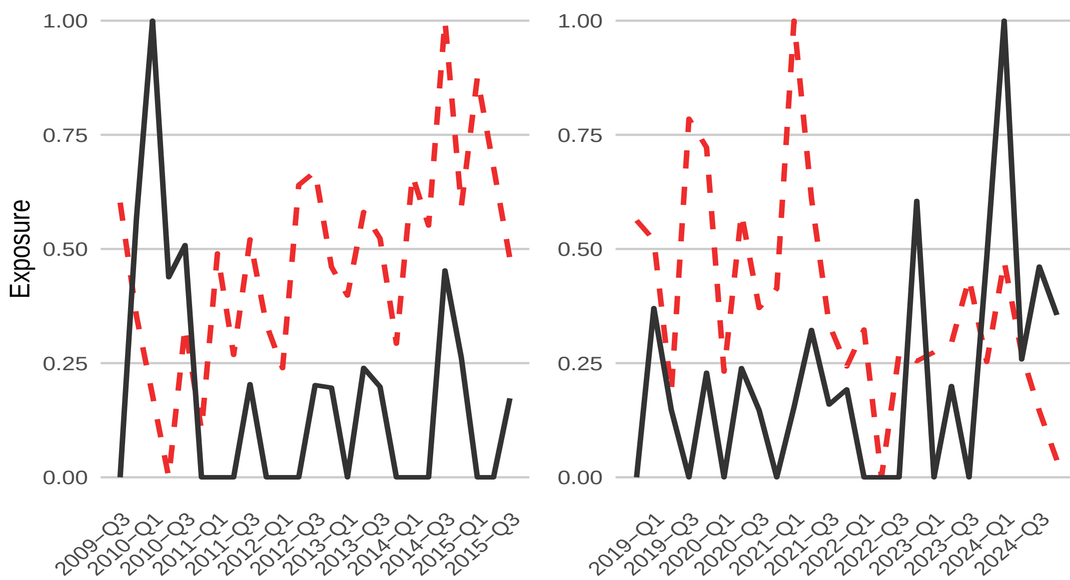
(b) LRISK and EPU Subcategories

Note: This figure presents PCA loadings for the **Aggregate LRISK** alongside other widely used measures of uncertainty. Panel (a) compares LRISK with broad indices, including the Economic Policy Uncertainty (EPU) index and three components of the Jurado-Ludvigson-Ng (JLN) framework: Macroeconomic, Financial, and Real Uncertainty. Panel (b) focuses on a narrower comparison, displaying PCA loadings for LRISK alongside two subcomponents of the EPU index—EPU Regulation and EPU Financial Regulation. In both panels, PCA is conducted using standardized variables, and the loadings are derived from the correlation matrix. The direction and length of each arrow represent the variable's contribution and alignment with the principal components. The distinct orientation of LRISK relative to the other measures indicates that it captures a unique and orthogonal dimension of uncertainty not accounted for by macroeconomic or policy-based indices.

Figure A.6 displays the resulting factor loadings. In both panels, the direction and length of each arrow represent the contribution and alignment of each variable with the principal components. Variables that point in similar directions are highly correlated, while those that are orthogonal reflect distinct sources of variation. The noticeably different orientation of **Aggregate LRISK** relative to EPU and JLN measures suggests that it loads onto a separate dimension. This visual evidence supports the interpretation that legal risk captures an independent and previously unaccounted for component of uncertainty in the cross-section of firms and over time.

E Firm-level Evidence: Case studies using SolarWinds

Figure A.7: **Case study - SolarWinds**



Note: This figure presents **LRISK** (black solid line) and **Cyber Risk** (red dotted line) for SolarWinds Inc. Both text-based exposure measures are normalized to range from 0 to 1 within each subperiod: 2009-Q3 to 2015-Q3 and 2018-Q4 to 2024-Q4. SolarWinds first went public in May 2009, was taken private in October 2015, and subsequently returned to the public market in October 2018.

SolarWinds[5] provides a compelling case study to discuss legal risk exposure of that firm. The study of SolarWinds' cyber risk exposure, pioneered in Florackis et al. (2023) and Jamilov et al. (2025)

[5] The company, a provider of IT infrastructure management software, first went public in May 2009. However, in October 2015, it was taken private in a $4.5 billion buyout by private equity firms Silver Lake Partners and Thoma Bravo. In October 2018, SolarWinds re-entered the public markets with its second initial public offering (IPO). More recently,

provide an interesting benchmark to illustrate the legal risk inherent in the cyberrisk-related issues. My analysis builds on these findings by showing that firms responding to cyber risk often face legal risk as a related but distinct mechanism. Notably, SolarWinds first encountered a securities class action lawsuit in 2010, which resulted in a Notice of Voluntary Dismissal. Despite this resolution, the textual analysis of earnings call transcripts during this period shows a noticeable increase in legal risk-related discussions (black solid line in left panel of Figure A.7). This trend reemerged in 2015 when the company was again subject to a class action lawsuit. In this instance, the case concluded with a Court's Order of Dismissal, yet the company's legal risk exposure remained heightened. These early signals suggest that, even when lawsuits do not directly impact financial outcomes, firms anticipate and communicate about potential legal risks in their disclosures, which influences investor perceptions and stock price behavior.

A defining moment for SolarWinds occurred in December 2020 when it became the target of the SolarWinds supply chain attack (SUNBURST attack) that affected thousands of government and private-sector clients. As expected, my analysis shows a sharp spike in the firm's cyber risk measure (denoted by the red dotted line on the right panel) in response to the attack. This event triggered cascading legal consequences, including a class action lawsuit from shareholders and customers who alleged that SolarWinds had failed to implement adequate cybersecurity measures. In addition to these lawsuits, regulatory scrutiny intensified. In October 2023, the U.S. Securities and Exchange Commission (SEC) filed charges against SolarWinds and its Chief Information Security Officer (CISO) for allegedly misleading investors about the company's cybersecurity practices before and during the breach. The SEC's charges significantly increased SolarWinds' legal risk exposure, as reflected in a pronounced uptick in the legal risk measure. This exposure culminated in early 2024, when SolarWinds agreed to a $26 million settlement to resolve investor claims stemming from the 2020 breach.

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the company announced its intention to delist again in 2025 following an acquisition agreement with Turn/River Capital. Because of this transition between public and private ownership, my analysis presents two separate graphs to illustrate how legal risk exposure and market perception evolved over these distinct periods.

F Modeling Legal Risk in a Real Options Framework

This section presents two complementary real options models that incorporate legal risk: a McDonald and Siegel (1986)–type model in which investment yields a one-time payoff, and a Dixit and Pindyck (1994)–type model in which investment generates an ongoing stream of cash flows. The purpose is not to provide full mathematical derivations, but rather to offer intuition for how legal risk alters investment incentives, specifically, by increasing the cost of commitment or amplifying uncertainty. In both frameworks, legal risk modifies the firm's investment behavior by raising the option value of waiting, thereby leading firms to scale back or delay irreversible investment.

F.1 McDonald–Siegel Framework with Legal Risk as an Investment Cost

Following McDonald and Siegel (1986), consider a firm that holds an irreversible option to invest in a project with stochastic value V_t. Investment requires a fixed cost F, and the firm chooses the optimal stopping time τ to maximize the expected discounted payoff:

$$\underbrace{X(V)}_{\text{Value of waiting}} = \sup_{\tau} \mathbb{E}_0 \left[e^{-r\tau}(V_\tau - F) \right], \tag{A.2}$$

where r is the discount rate.

The project value V_t evolves according to geometric Brownian motion:

$$\frac{dV_t}{V_t} = \mu\, dt + \sigma\, dZ_t, \tag{A.3}$$

with constant drift μ, volatility σ, and Z_t a standard Brownian motion.

The firm invests only when $V_t \geq V^*$, where V^* is the optimal investment threshold:

$$\beta = \frac{1}{2} - \frac{\mu}{\sigma^2} + \sqrt{\left(\frac{\mu}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2r}{\sigma^2}}, \tag{A.4}$$

$$V^* = \frac{\beta}{\beta - 1} F. \tag{A.5}$$

Equations (A.4) and (A.5) can be derived using dynamic programming and Itô's lemma.[6]

Incorporating Legal Risk Legal risk may increase the effective cost of exercising the investment option. This cost could reflect anticipated litigation, regulatory compliance expenses, or other legal frictions. Departing from the baseline assumption of a fixed investment cost F, I allow the cost to vary with a firm's legal risk exposure. Specifically, let the effective investment cost be:

$$F^*(\ell) = F + \lambda \ell, \tag{A.6}$$

where ℓ denotes firm-level legal risk and $\lambda > 0$ is the marginal legal cost per unit of exposure. For example, consider a firm planning to build a new production facility. While the construction cost is nominally fixed, high legal risk—such as exposure to environmental litigation or regulatory review—effectively inflates that cost by requiring additional legal counsel, permitting delays, insurance premiums, or contingency reserves. In this sense, legal risk operates like a surcharge: the firm must invest not only in bricks and mortar, but also in navigating the legal landscape that surrounds the project.

The new investment threshold becomes:

$$V^*(\ell) = \frac{\beta}{\beta - 1}(F + \lambda \ell), \tag{A.7}$$

[6]The value function $X(V)$ satisfies the Hamilton–Jacobi–Bellman (HJB) equation:

$$rX(V) = \mathbb{E}\left[\frac{dX(V_t)}{dt}\right].$$

Applying Itô's lemma to a twice-differentiable function $X(V_t)$, where V_t follows geometric Brownian motion:

$$dX(V_t) = X'(V_t)\,dV_t + \frac{1}{2}X''(V_t)(dV_t)^2.$$

Substituting $dV_t = \mu V_t\,dt + \sigma V_t\,dZ_t$ and noting that $(dZ_t)^2 = dt$, we obtain:

$$\mathbb{E}[dX(V_t)] = \left(\mu V X'(V) + \frac{1}{2}\sigma^2 V^2 X''(V)\right) dt.$$

Thus, the HJB equation becomes:

$$rX(V) = \mu V X'(V) + \frac{1}{2}\sigma^2 V^2 X''(V).$$

Guessing a solution of the form $X(V) = AV^\beta$ and substituting into this equation leads to the quadratic characteristic equation for β. The economically meaningful root (i.e., $\beta > 1$) yields the optimal threshold in Equation (A.5).

which increases linearly in legal risk. Thus, legal uncertainty raises the break-even point required to justify investment and makes investment less likely, even if the expected project value is unchanged.

F.2 Dixit–Pindyck Framework with Legal Risk as Uncertainty

I now consider a related model of irreversible investment under uncertainty, following Dixit and Pindyck (1994). The key difference is that investment yields a continuous stream of payoff flows rather than a one-time gain.

Assume a firm can invest at cost F to receive perpetual payoff flow $\pi(V_t) = aV_t$, where $a > 0$ and V_t evolves as in Equation (A.3). The present value of investing at time t is:

$$\Pi(V) = \frac{aV}{r - \mu}, \tag{A.8}$$

assuming $r > \mu$.[7]

Let $X(V)$ denote the value of waiting to invest. The firm invests when $V_t \geq V^*$, and otherwise waits. The option value for $V < V^*$ is:

$$X(V) = AV^{\beta}, \tag{A.9}$$

where β is given by Equation (A.4) and arises from solving the associated HJB equation.

[7]The equation (A.8) follows from taking the expected present value of the perpetual cash flow stream $\pi(V_t) = aV_t$, where V_t follows geometric Brownian motion. Since $\mathbb{E}[V_t] = Ve^{\mu t}$, we have:

$$\Pi(V) = \mathbb{E}_0\left[\int_0^\infty e^{-rt} aV_t\, dt\right] = a\int_0^\infty e^{-rt}\mathbb{E}[V_t]\, dt = aV\int_0^\infty e^{-(r-\mu)t}\, dt = \frac{aV}{r-\mu},$$

which converges only if $r > \mu$.

Using standard value matching and smooth pasting conditions,[8] the investment trigger becomes:

$$V^* = \frac{\beta}{\beta - 1} \cdot \frac{F(r-\mu)}{a}. \tag{A.10}$$

Incorporating Legal Risk Legal risk increases uncertainty about future cash flows, which I model as stochastic volatility:

$$\sigma(\ell) = \sigma_0 + \kappa\ell, \quad \kappa > 0. \tag{A.11}$$

This raises the option value of waiting and leads to a higher threshold:

$$V^*(\ell) = \frac{\beta(\ell)}{\beta(\ell) - 1} \cdot \frac{F(r-\mu)}{a}, \tag{A.12}$$

with

$$\beta(\ell) = \frac{1}{2} - \frac{\mu}{\sigma(\ell)^2} + \sqrt{\left(\frac{\mu}{\sigma(\ell)^2} - \frac{1}{2}\right)^2 + \frac{2r}{\sigma(\ell)^2}}. \tag{A.13}$$

As legal risk rises, the volatility of future payoffs increases, the firm becomes more selective, and investment is delayed despite positive expected returns. This aligns with the empirical finding that firms with greater legal exposure tend to invest less in physical and intangible assets.

[8] The value matching condition requires that the value of waiting and the value of investing coincide at the investment threshold V^*:

$$X(V^*) = \Pi(V^*) - F.$$

This ensures there is no value lost or gained from exercising the option at the optimal point. Smooth pasting requires that the derivatives also match at V^*:

$$X'(V^*) = \Pi'(V^*).$$

This condition ensures optimality by preventing kinks in the value function—i.e., if the slopes did not match, the firm could increase its value by slightly delaying or advancing the investment decision. Together, these conditions pin down the unique investment threshold V^* where the firm is indifferent between waiting and investing.

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