Three Essays on Financial Economics: Legal, Political, and Behavioral Forces in Asset Pricing

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Introduction

This dissertation, titled *"Three Essays on Financial Economics: Legal, Political, and Behavioral Forces in Asset Pricing,"* investigates how traditionally neglected sources of risk (particularly institutional and political uncertainty) shape the behavior of firms, investors, and asset prices. While modern asset pricing theory has long focused on economic fundamentals and aggregate risk factors, financial markets are embedded in institutional and political environments that are neither static nor frictionless. Legal enforcement, political control, and investor sentiment collectively influence how risks are perceived, priced, and transmitted across firms and sectors. Yet, despite their salience, these dimensions of risk remain underexplored in mainstream empirical asset pricing. This dissertation addresses this gap by demonstrating that legal, political, and behavioral forces constitute first-order determinants of risk premia and capital allocation in modern financial markets.

The first essay, *"The Pricing and Economic Impact of Legal Risk,"* examines law and finance from an asset pricing perspective. It begins from the observation that legal risk (defined as uncertainty surrounding litigation, regulatory enforcement, and the application of legal rules) has become an increasingly salient but poorly measured dimension of firm risk. Using a novel text-based measure (LRISK) derived from earnings call transcripts, the essay quantifies firm-level exposure to legal uncertainty in real time. LRISK predicts future class action lawsuits and identifies periods of heightened legal scrutiny. Beyond its predictive power, the paper demonstrates that legal risk carries a significant risk premium in the cross-section of returns: firms with greater legal exposure earn higher expected returns, especially after the post-2010 tightening of regulatory oversight. It also shows that legal risk materially affects firm behavior—discouraging investment and reducing reliance on debt finance. These results reveal that the legal system, while providing the foundation for market exchange, simultaneously generates a priced source of uncertainty that distorts financing and investment decisions. The essay thus bridges the gap between institutional finance and asset pricing, showing that the "rule of law" is not merely a background condition but a priced determinant of capital costs.

The second essay, *"Divided Government and the Stock Market,"* coauthored with Theofanis Papamichalis and Mungo Wilson, turns to political economy and examines how the composition of political power in Washington affects financial markets. Building on the long-standing “Presidential Puzzle,” the paper documents a new and robust Government Cycle: stock returns and economic growth are substantially higher during unified (single-party) governments than during divided ones. Over nearly a century of data, U.S. equities earned an annualized excess return of 10.3% under unified governments but only 1.6% under divided governments. The essay attributes this difference to political gridlock—legislative stalemates, vetoes, and policy inertia that raise uncertainty and dampen economic activity. The effect is particularly pronounced among small firms, offering a novel political explanation for the long-run decline of the size premium. By isolating this “government premium,” the paper extends the literature on political cycles in asset pricing and demonstrates how institutional arrangements of power—not merely ideology—shape macroeconomic and financial outcomes.

The third essay, *"From Anomalies to Norms: A Unified Framework for Sentiment, Risk, and Mispricing,"* coauthored with Theofanis Papamichalis, explores the behavioral dimension of asset pricing. It develops a theoretical and empirical framework that integrates cross-sectional anomalies with aggregate market dynamics through the lens of investor sentiment. Departing from the conventional “positive” approach of cataloging anomalies, the paper adopts a “normative” perspective—proposing how investors should structure long–short portfolios that go long on safer (less mispriced) and short on riskier (more mispriced) stocks. The model, grounded in limits-to-arbitrage theory, predicts a negative contemporaneous link between aggregate market returns and anomaly performance: when sentiment is high, aggregate returns fall while mispricing-based anomalies widen. Testing over one hundred U.S. anomalies, the paper provides strong empirical support for these predictions, offering a unified behavioral explanation for both the low-volatility and distress risk puzzles. This essay situates investor sentiment as the key behavioral force connecting cross-sectional and time-series asset pricing phenomena.

Collectively, the three essays advance a broader agenda: integrating institutional, political, and behavioral perspectives into the study of asset prices. The first essay demonstrates how legal institutions shape firm risk and pricing; the second shows how political structures condition aggregate returns and the business cycle; and the third elucidates how collective sentiment drives deviations from fundamental value. Together, they underscore that understanding modern financial markets requires looking beyond traditional risk factors to the institutional and behavioral context in which markets operate. In doing so, this dissertation contributes to a more comprehensive vision of financial economics—one that recognizes that prices in capital markets ultimately reflect the complex interplay between law, politics, and human behavior.

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Chapter 1

The Pricing and Economic Impact of Legal Risk

Abstract: Legal risk is an inherent feature of the market, arising from the institutional foundations that enable economic activity, yet it remains difficult to observe systematically across firms. To address this gap, this paper constructs a text-based measure of firm-level legal risk (**LRISK**) using earnings call transcripts. **LRISK** predicts class action lawsuits and exhibits sharp spikes during periods of heightened legal exposure. Legal risk has real and financial consequences: a one standard deviation increase predicts a 3–7% decline in future investment and reduces firms' reliance on debt when facing financing needs, consistent with a precautionary motive. Legal risk is positively priced, particularly after 2010 when regulatory oversight intensified. The pricing of legal risk varies across legal origins, reflecting its institutional foundations.

1.1 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. At the same time, these institutions introduce legal risk — stemming from uncertainty in how rules are applied and the financial burdens that follow. The salience of this risk has increased in tandem with the rising complexity of legal systems and the tightening of regulatory scrutiny.[1] Legal risk, in this sense, is an inherent feature of modern financial markets.

[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. The Appendix Section 1.7.1 and Figure 1.7 illustrates this trend, showing the steady expansion of litigation-prone industries over the past two decades.

Despite its importance, legal risk remains difficult to measure systematically, as it often materializes through opaque and anticipatory channels shaped by evolving statutes, regulatory discretion, and strategic compliance behavior. To address this challenge, I develop a simple text-based measure of firm-level legal risk, **LRISK**, derived from earnings call transcripts. This measure, which captures how frequently firms reference legal-related terms such as litigation, regulatory investigations, or court proceedings, is used to advance the view that legal risk is a first-order determinant of both asset prices and corporate behavior.

Specifically, using **LRISK**, the paper presents three main findings. First, **LRISK** effectively predicts future class action lawsuits and captures firm-level attention to litigation, regulatory enforcement, climate regulations, and cybersecurity threats in a timely manner. This validates **LRISK** as a reliable measure of a firm's exposure to legal risk—contrasting with standard SEC filings such as 10-Ks or 10-Qs, which often mention such risks only with 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 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-stat: 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-stat: 4.9). The **LAW** factor captures a unique dimension of firm-level legal uncertainty than existing text-based measures, subsumes the effect of cyber risk, and remains largely orthogonal to standard asset pricing factors. It also avoids the common "factor zoo" critique, underscoring its distinctiveness and relevance to the financial market.

The pricing effect of legal risk appears to be driven by both systematic and idiosyncratic components. Leveraging the flexibility of textual analysis, I separately construct a macro-legal risk factor and show that it carries significant pricing implications. I also outline three possible channels through which ostensibly firm-specific legal shocks can become market-relevant. Moreover, I rule out behavioral explanations for the **LAW** factor—such as mispricing, or investor mood—as primary drivers of the observed premium. I also construct an aggregate measure of legal risk by calculating the economy-wide coverage ratio of legal terms in earnings calls. This measure captures the evolving macro-level salience of legal concerns. Importantly, it is conceptually and empirically distinct from well-known uncertainty indices such as the 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 or regulatory 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 5–7% reduction in investment, 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. Together, the patterns are consistent with legal risk operating as a financing friction that depresses investment.

Taken together, 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 adds to the growing literature on text-based methods in finance, which use unstructured data to measure risk and predict 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 on legal and litigation risk. However, many existing measures lack firm-level precision, relying instead on industry or regional proxies. For example, Francis et al. (1994) identify high-litigation sectors, while Hossain et al. (2023) use judge ideology as a geographic proxy for litigation risk. Among studies that do construct firm-level measures, Bereskin et al. (2023) focus on patent litigation using matched samples, and Bennett et al. (2025) extract litigious language from 10-K filings based on the Loughran and McDonald (2011) dictionary. In contrast, this study develops a more comprehensive and forward-looking firm-level measure, capturing a broad range of legal risks—including class action lawsuits, regulatory investigations, and Supreme Court cases—based on bigram and trigram expressions in earnings calls. As discussed in Section 1.4.1, this conversational-text approach provides a unique and real-time perspective on firm-specific legal risk.

Structure of the Paper: The remainder of the paper is organized as follows. Section 1.2 details the construction of the firm-level legal risk measure using textual analysis of earnings call transcripts and validates the measure by showing that **LRISK** predicts class action lawsuits, supplemented with case studies that illustrate how it captures meaningful firm-level variation in legal exposure. Section 1.3 presents the asset pricing results, demonstrating that legal risk is a priced factor in the cross-section of stock returns and addressing concerns related to data mining and the broader "factor zoo" critique. This section also discusses potential mechanisms underlying the pricing of legal risk. Section 2.3 evaluates the robustness and distinctiveness of the **LRISK** factor relative to other text-based measures, rules out behavioral explanations, and considers heterogeneity across legal origins. Section 1.5 explores the real effects of legal risk on corporate investment and financing decisions. Section 1.6 concludes.

1.2 LRISK: Construction and Validation

1.2.1 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 le-

[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).

gal terminology—such as litigation, regulatory investigations, or court proceedings—during calls with analysts and investors. By relying on the straightforward presence of legal-related terms rather than sentiment classification or complex embeddings, **LRISK** provides a transparent and tractable way to quantify firm-level legal exposure.

Why rely on a simple bag-of-words approach rather than large language models (LLMs) such as FinBERT (Huang et al., 2023)? First, legal risk mentions are sparse in earnings calls, so the central task is detecting whether firms raise these issues at all, rather than classifying subtle sentiment. Second, the presence of legal references is inherently meaningful—mentions of lawsuits, regulatory scrutiny, or court proceedings are material events regardless of tone. Third, bag-of-words methods are transparent, computationally efficient, and widely used in related literatures. For example, 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 based on validated keyword frequencies. These examples demonstrate that simple, contextually grounded frequency-based approaches can yield credible and informative measures of firm-level risk.

Why base the legal risk measure on earnings calls rather than SEC filings such as 10-Ks or 10-Qs? Calls typically disclose relevant developments sooner and with greater openness than formal reports, which are highly scripted, subject to legal review, and bound by higher materiality thresholds, which can delay disclosure of ongoing disputes or anticipated legal challenges. The Apple–Qualcomm litigation offers a clear example: 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 a year after it started. By contrast, Apple's earnings call at the end of January 2017—held just a week after the lawsuit was filed—explicitly mentioned the dispute, illustrating the timeliness with which earnings calls can address such matters. Calls also enjoy a scheduling advantage, as they are generally held a few days before the corresponding 10-K or 10-Q is released, allowing key developments to reach the market earlier. Moreover, formal filings have become increasingly unwieldy: the average 10-K is now roughly six times longer than in 1995 (Cohen et al., 2020), creating a processing bottleneck for investors, and they are often laden with dense legal jargon (Garcia et al., 2023).

Figure 1.1 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—for example, references to regulatory investigations, litigation threats, or changes in legal exposure.

Table 1.1 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 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—reflected in earnings call discourse—can materially affect investor perception and firm value.

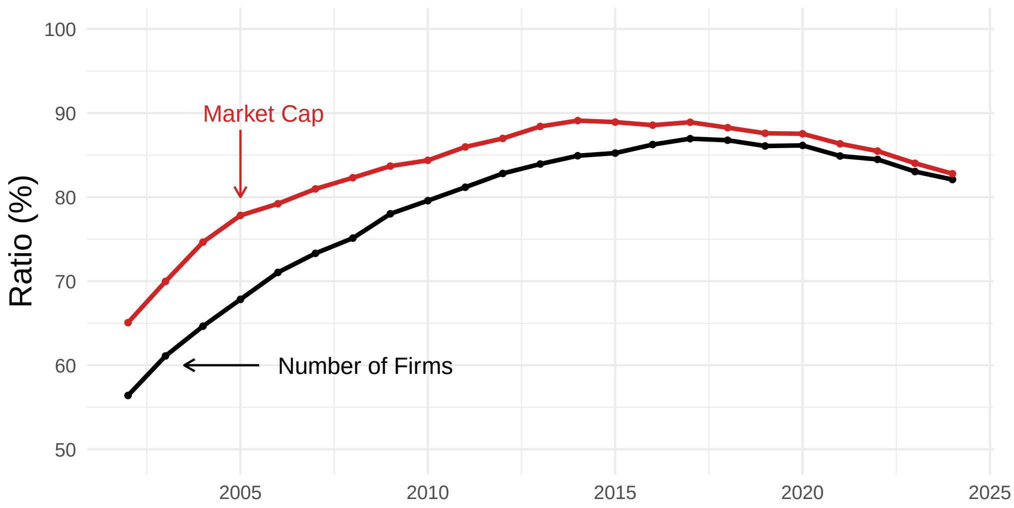
More broadly, the fact that firms openly discuss legal risks in high-stakes earnings calls where their words are scrutinized by analysts, investors, and regulators suggests that these mentions are far from mere "cheap talk" (Crawford and Sobel, 1982; Farrell and Rabin, 1996). Earnings conference calls are typically broadcast live over the internet, which encourages management to avoid excessive legal language or jargon, making the information more accessible and transparent.[3] Therefore, mentions of legal risk in earnings call transcripts are particularly meaningful, as their frequency reflects substantive concerns rather than strategic messaging or rhetorical hedging.

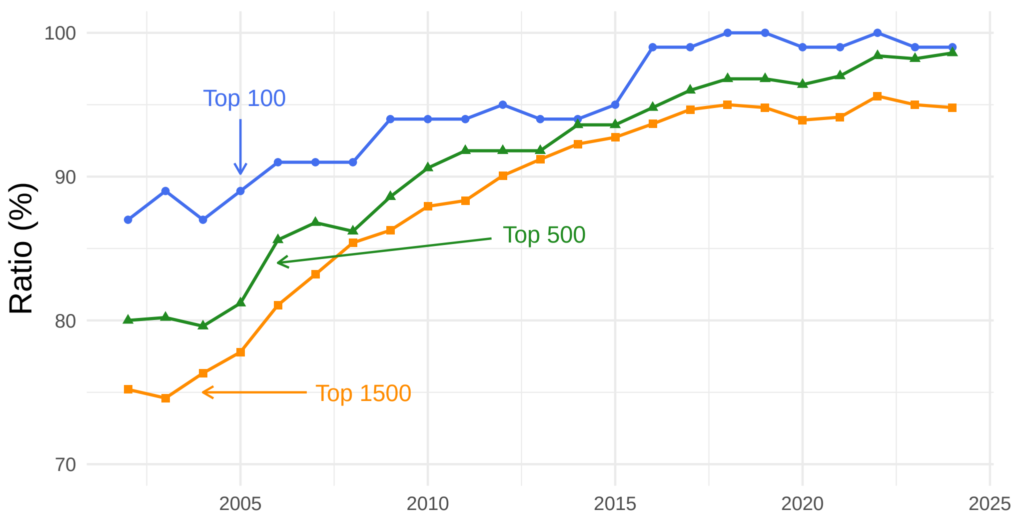
Central to the analysis is a curated dictionary of legal n-grams (covering unigram, bigrams, and trigrams) that captures common patterns in legal risk language. I initiate this process using the Loughran–McDonald (LM) Dictionary (Loughran and McDonald, 2011), specifically its "litigious (Fin-Lit)" category, which includes legal terminology and litigation-related terms. The 2023 edition of the LM Dictionary contains 86,553 keywords, 903 of which are classified as litigious. While the LM dictionary provides a valuable foundation, this paper refines and extends it by constructing a dynamic set of legal n-grams tailored to the context in which legal risk is discussed. In contrast to the traditional reliance on unigrams, my approach systematically incorporates bigrams and trigrams to better capture context-specific legal expressions, thereby reducing misclassification and improving measurement precision.[4]

[3]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).

[4]Refer to Section 1.4.1 for a comparison highlighting how my approach differs from that of Loughran and McDonald (2011).

Figure 1.1: **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).

Table 1.1: **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

With the training library of legal terms $\mathbb{L}$ established (see Table 1.2 and Appendix 1.7.2), I proceed to define a simple measure of **LRISK**, representing the legal or litigation risk of firm i at quarter t as:

$$\textbf{LRISK}_{it} = \frac{\sum_{b}^{B_{it}} \left(\mathbb{1}[b \in \mathbb{L}] \right)}{\text{No. of sentences}} \tag{1.1}$$

where $b = 0, 1, ...B_{it}$ are the bigrams contained in the call of firm i at time t, $\mathbb{1}[\cdot]$ is the indicator function, $\mathbb{L}$ is the set of bigrams contained in $\mathbb{L}$. 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. **LRISK** can be further divided into three categories: **LRISK_COURT**, which captures references to court proceedings and judicial actions; **LRISK_TRIAL**, which focuses on mentions of trials and litigation processes; and **LRISK_TERMS**, which includes broader legal terminology such as "legal costs" and "regulatory compliance."

Table 1.2: **Word Choices to Measure Litigation 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 Appendix for the full list of keywords and word choices.

1.2.2 LRISK Predicts Future Class Action Lawsuits

This section validates **LRISK** along multiple dimensions. First, I demonstrate that **LRISK** predicts future class action lawsuit filings, confirming its value as a forward-looking measure of firms' exposure to legal risk. In addition, detailed case studies illustrate how well-known firms and industries respond to emerging legal threats, with **LRISK** exhibiting sharp spikes during periods of heightened legal concern related to their business environment. Taken in conjunction with the evidence of non-overlap with other textual constructs described in Section 1.4.1, these findings substantiate that **LRISK** measures legal risk with precision, avoiding conflation with broader narrative or risk-related language.

To validate my measure of legal risk, I estimate a logistic model of class action lawsuit filings.[5] If **LRISK** effectively captures firm-level legal risk, it should reflect forward-looking

[5]The data on class action lawsuits are obtained from the Stanford Law School / Cornerstone Research

concerns—especially those related to potential or ongoing class action litigation—discussed in earnings call transcripts, as evidenced by a significant relationship with future lawsuit filings. The specification is given by:

$$\Pr(\text{Lawsuit}_{i,t+h} = 1) = \Phi(\beta_1 \cdot \mathbf{LRISK}_{it} + \beta \cdot \text{Controls}_{it} + \delta_q + \varepsilon_{it}), \tag{1.2}$$

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.[6] 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 1.8 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.

The logistic regression results in Table 1.3 provide strong evidence for the predictive validity of the **LRISK** measure. Across all specifications, the coefficient on **LRISK** is positive and highly statistically significant, 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

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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.

[6] 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.

Table 1.3: **Logistic Regression Predicting Class Action Lawsuits**

	(1)	(2)	(3)
	Lawsuit in $t+1$	Lawsuit within $t+1$ to $t+2$	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.

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 Appendix 1.7.1)—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 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.

1.2.3 Case Study I: Brown firms and Environmental Litigation & Regulation

A growing body of research in finance examines the implications of climate change for financial markets, with particular attention to the risks associated with carbon emissions and regulatory oversight.[7] Stroebel and Wurgler (2021), in particular, emphasize that regulatory risk is perceived as the most immediate climate-related concern for businesses and investors. Given these insights, legal risk presents a crucial dimension of climate finance. *Brown* firms (those with high carbon footprints and heavy reliance on fossil fuels) face increasing scrutiny from regulators, litigation risks from environmental lawsuits, and reputational damage due to changing investor and consumer preferences.

Figure 1.2 illustrates standardized **LRISK** of major energy companies (*Brown* firms), including ConocoPhillips, ExxonMobil, and Halliburton, highlighting periods of heightened legal concerns related to climate regulations, relevant litigations, and firm-specific legal events such as M&A transactions. ConocoPhillips (upper panel) saw increased legal risk

[7] Studies such as Bolton and Kacperczyk (2021) find that firms with higher carbon emissions tend to earn higher stock returns, suggesting that investors demand compensation for exposure to carbon risk. Similarly, Pastor et al. (2022) highlight how green assets have delivered strong returns in recent years due to shifting investor preferences and regulatory developments, though their expected future returns may be lower.

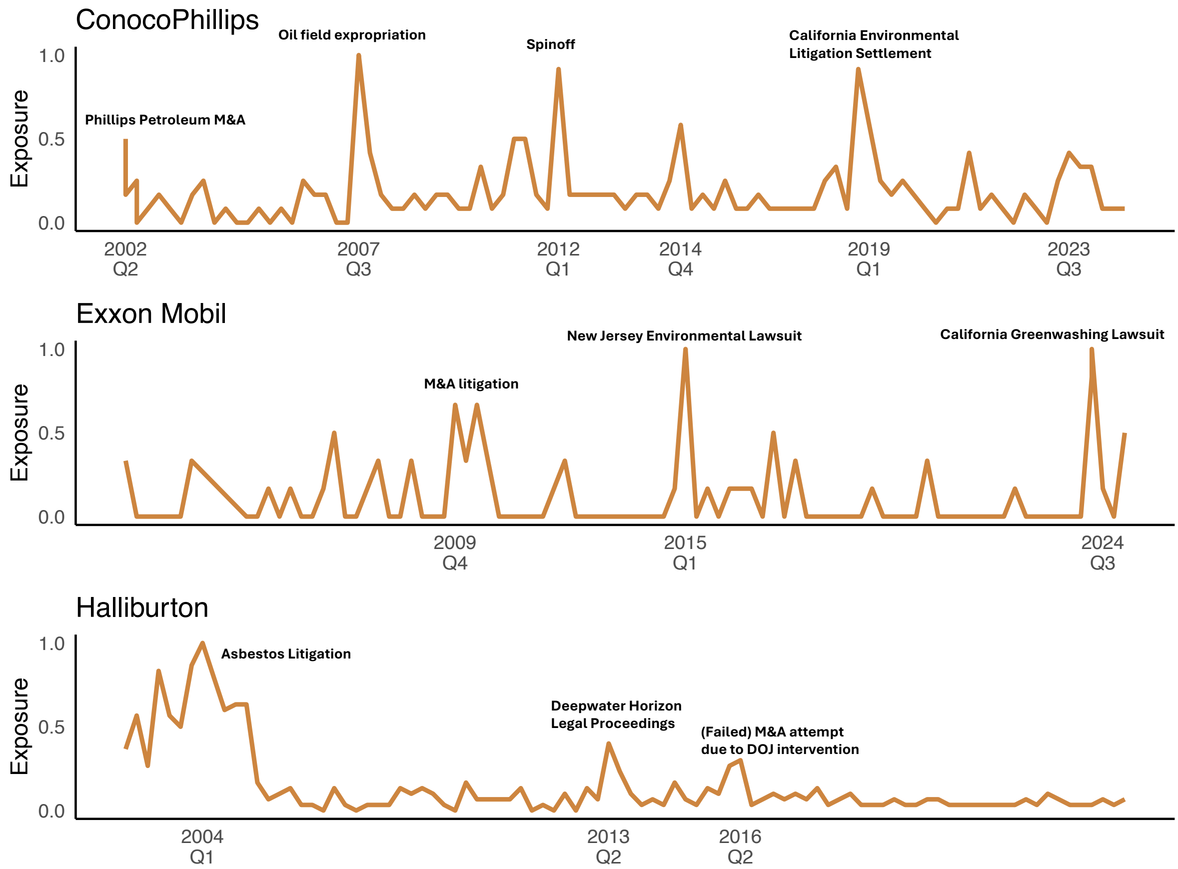
in 2002 (FTC approval of its merger with Phillips Petroleum), 2007 (Venezuelan expropriation of the Corocoro oil field that led to arbitration proceedings), 2012 (spinoff of Phillips 66 which involved complex regulatory approvals), 2015 (the company settled \$11.5 million in environmental litigation 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). 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). Finally, 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).

Overall, the spikes in legal risk exposure in Figure 1.2 align with major legal disputes, validating the effectiveness of the firm-level legal risk measure in capturing periods of heightened regulatory and litigation risk.

1.2.4 Case Study II: Bank firms and Financial Regulation

The banking sector has long been a focal point for legal and regulatory risk, owing to its systemic importance and tight supervision. Legal exposure has intensified following the 2008 financial crisis, with post-crisis reforms and heightened enforcement actions increasing banks' vulnerability to litigation and reputational damage. Case studies of Citigroup, Bank of America, and Wells Fargo illustrate how legal risk has shaped firm strategy and investor perceptions over time. Notably, recent research in Fahlenbrach et al. (2012) finds that bank performance in past crises strongly predicts outcomes in future crises—suggesting that persistent risk culture and business models play a significant role in how banks navigate legal and systemic shocks.

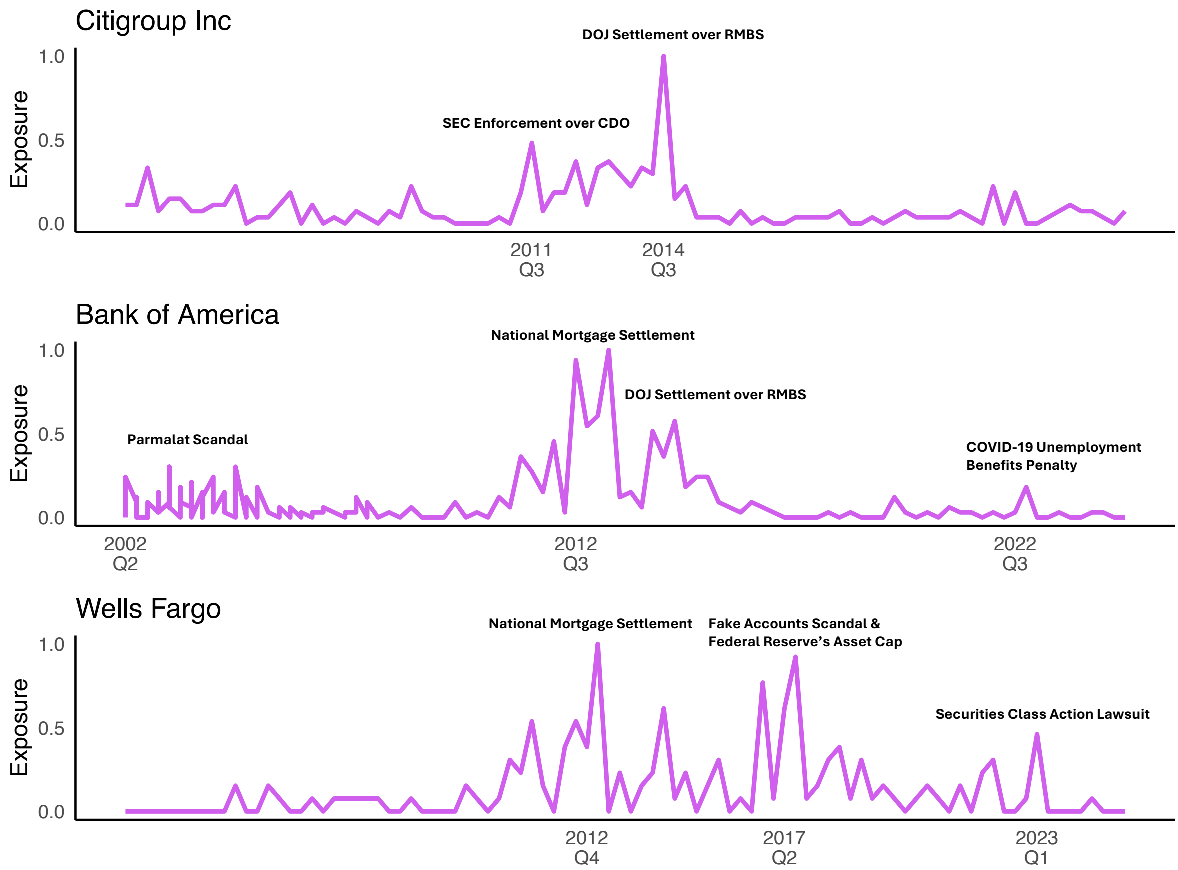
Figure 1.2: **Case Studies: Brown Firms**



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.

This section examines Citigroup, Bank of America, and Wells Fargo to assess how legal risk has shaped their operations and investor perceptions over time. Citigroup faced major legal challenges in 2011 and 2014. In 2011, the SEC fined Citigroup $285M for misleading investors about a $1B collateralized debt obligation (CDO), concealing its role in asset selection while betting against it. In 2014, the DOJ imposed a $7B settlement for its role in selling faulty residential mortgage-backed securities (RMBS) pre-2009, including a record $4B civil penalty under FIRREA. These legal risks were reflected in earnings call transcripts, as shown in Figure 1.3 (Panel A). In Panel B, Bank of America's legal risk spiked during 2002–2005, 2012, and 2022. During this period, it was implicated in the Parmalat scandal, resulting in a $98.5M settlement, joined the $26B National Mortgage Settlement in 2012 over foreclosure abuses, and was fined $16.65B by the DOJ in 2014 for mortgage fraud. In Q4 2022, regulators imposed a $225M penalty for mishandling unemployment benefits during COVID-19.

Figure 1.3: **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.

Lastly, Wells Fargo has faced major legal challenges over the past decade. In 2012, as part of the National Mortgage Settlement, the bank agreed to a $5.4B settlement to address allegations of improper foreclosure practices. In 2016, its fraudulent account scandal led to a $185M CFPB fine, followed by the Federal Reserve's 2017 asset cap. In December 2022, the CFPB imposed a $3.7B fine for consumer protection violations. In mid to late 2022, Wells Fargo faced a securities class action lawsuit (*SEB Investment Management AB v. Wells Fargo*) over allegations that it misled investors about its diversity hiring practices. These key legal events, captured in the lower panel of the Figure, corroborate that legal risk is effectively reflected in earnings conference calls.

1.3 The Pricing Impact of Legal Risk

1.3.1 Data

To examine the financial and real effects 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.[8] The CRSP dataset provides information on stock returns, market capitalization, and share characteristics, allowing for the construction of asset pricing tests such as portfolio returns and factor loadings. COMPUSTAT offers detailed firm-level fundamentals, including balance sheet and income statement items, which are essential for analyzing investment behavior, capital structure decisions, and control variables in regression analyses. This merged panel forms the empirical backbone of the paper.

1.3.2 Portfolio Construction and Asset Pricing Results

I assess the pricing impact of legal risk by constructing value-weighted, calendar-time portfolios sorted by firms' ex-ante legal risk exposure. To reduce noise from heterogeneous disclosure practices—where firms with stronger compliance may mention legal terms more often, while others with high latent risk may disclose less—I sort firms into terciles rather than standard sortings like quintiles or deciles. This grouping helps smooth out reporting extremes and provides a more reliable categorization of legal risk.

Following Florackis et al. (2023), portfolio 1 (L1) includes firms with no legal risk mentions in their earnings calls, capturing the extensive margin. Firms with non-zero legal risk are split into portfolios 2 (L2) and 3 (L3) based on the median value of the exposure metric. Portfolios are formed annually at the end of June and weighted by market capitalization as of the formation date. The sample begins in July 2004, using transcripts from the prior year to construct the signal.[9]

I adopt a (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. Firms may postpone bad news to low-attention periods or prioritize other topics in earnings

[8] 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 1.7 illustrates the rising number of litigation-prone industries around the turn of the century, underscoring the growing relevance of legal risk since 2000.

[9] While transcripts are available from 2002, their widespread adoption began in 2003. Using a one-year lookback aligns with standard practices and ensures adequate data coverage.

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 Appendix 1.7.3 for results using alternative portfolio formation strategies such as (12-3)). 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 (however, unreported results show that the pricing effect becomes stronger when utilities and financial firms are included).

Table 1.4 presents the results. In the baseline analysis, average monthly excess returns rise from 0.638% for low legal risk stocks to 1.035% for high legal risk stocks in value-weighted portfolios over the period from July 2004 to June 2024. The corresponding zero-cost long-short portfolio (L3 - L1) 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.[10] 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).[11]

Next, I examine whether existing asset pricing models account for the legal risk factor. The factor spanning tests presented in the same table 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. To summarize, legal risk remains unexplained by standard asset pricing models, representing a distinct and priced source of systematic risk.

In Panel B of the same table, I demonstrate that firms generally exhibit balanced charac-

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

[11] 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.

teristics across portfolios. Firms with no exposure to legal risk tend to be smaller compared to those with some degree of legal risk. This is consistent with the previous literature that deep pockets are associated with legal risk (DuCharme et al., 2004). Finally, Panel C documents the frequency of firms positioned in each tercile. On average, 38% of companies that had no previous experience with legal risk saw a rise in their exposure within the subsequent year. Interestingly, around 33% of companies previously at the highest levels of legal risk also transitioned to other terciles. Overall, the transition matrix exercise helps alleviate concerns about certain firms consistently having higher or lower exposure to legal risk.

1.3.3 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 Appendix 1.7.3, with key findings briefly summarized in this section.

First, 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).

Second, the **LAW** factor is supported by strong statistical evidence, with a full-sample t-statistic of 3.66[12] over the 2004–2024 period, and rises to 4.91 in the post-2010 subsample (see Section 1.3.5), 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.[13] The t-statistic on the **LAW** factor exceeds 2.0 in all 193 regressions, and remains above 3.0 in 181 of them (see Appendix Figure 1.10).

[12]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.

[13]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.

Table 1.4: **Legal Risk Portfolio Results**

Panel A: 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)**

Panel B: Firm characteristics

	L1 No legal risk	L2 Middle legal risk	L3 High legal risk
Num. of Firms	701	895	895
Market value (log)	5.5	7.16	6.69
Book-to-market ratio	0.72	0.60	0.64
Gross Profit	0.23	0.32	0.31
Investment	0.33	0.26	0.29
Momentum	0.13	0.12	0.11
Asset Tangibility	0.20	0.22	0.19
Long-term Debt / Total Liabilities	0.27	0.33	0.30

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

	(to) L1	(to) L2	(to) L3	Total
(from) L1	62.0	26.6	11.3	100
(from) L2	17.8	53.8	28.4	100
(from) L3	7.5	26.3	66.2	100

Note: Panel A presents the average future excess returns (2004:07 - 2024:06) alongside the alpha results derived from portfolios constructed based on ex-ante legal risk measures. Firms in L1 (No legal risk) are those with no exposure to legal risk. Firms with non-zero exposure to legal risk are split into two groups, placed in L2 or L3 according to their level of exposure. Utility firms (SIC codes 4900–4999) and financial firms (SIC codes 6000 - 6411, 6500 - 6553, and 6700 - 6799) are excluded due to the highly restrictive nature of government regulation. The numbers in parenthesis are Newey-West t-statistics with 6 lags. Panel B records the firm characteristics of companies analyzed in the portfolio analysis. Panel C reports the one-year transition probabilities between portfolio groups based on legal risk. Each row shows the percentage of firms originally in portfolio L1, L2, or L3 that migrate to each group in the subsequent portfolio formation period. ***/**/* denote the statistical significance at 1%/5%/10% level.

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 Appendix Figure 1.9).

1.3.4 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.

Table 1.5: **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.

The text-based construction of the **LAW** factor enables flexible measurement of legal risk at both the macro and micro levels. To operationalize this, I decompose the long-side portfolio exposures using the legal content taxonomy in Table 1.2, which classifies legal language into three subcomponents: **LRISK_COURT** (references to courts and regulators), **LRISK_TRIAL** (litigation-specific terminology), and **LRISK_TERMS** (broader legal language). Separate long–short portfolios are then formed for each subcomponent to assess their distinct pricing implications.[14]

Panel A of Table 1.5 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 risk (**LAW_COURT**) earn significantly higher excess returns and positive alphas relative to the benchmark zero-risk group. Together, the results in Table 1.5 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.

[14] In forming subcomponent factors, the long side includes firms with any legal risk mentions exclusively in the relevant cluster (e.g., **LRISK_COURT**), while the short side recycles the benchmark no-risk group (L1)—firms with no legal risk mentions in any category. Holding L1 fixed across all constructions avoids contamination from unrelated exposure and ensures that return differences reflect only variation in the high-risk group. The resulting long–short portfolio on macro-level legal risk is labeled **LAW_COURT**.

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.

This granular mechanism also aligns with the observed return asymmetries in the data. Firms with high legal exposure exhibit more negatively skewed return distributions,[15] indicating a higher likelihood of extreme negative outcomes. Rational investors, anticipating this asymmetry, demand compensation for holding such firms. Legal risk thus operates as a granular shock—idiosyncratic in origin but macro-relevant in consequence—particularly when concentrated among the largest firms in the economy.

1.3.5 Time-variation of Aggregate Legal Risk

This section examines fluctuations in aggregate legal risk and their broader implications. To do so, I construct an *aggregate* measure of legal risk by classifying firms each quarter as either non-zero (mentioning legal risk in at least one of the past four earnings calls) or zero

[15] I test this by comparing the ex-ante return skewness of portfolios L1 (no legal risk) and L3 (high legal risk). Following Jondeau et al. (2019), I compute monthly skewness for each stock i as

$$Sk_{i,t} = \sum_{d=1}^{D_t} \left(\frac{r_{i,d} - \overline{r}_{i,t}}{\sigma_{i,t}} \right)^3,$$

where $r_{i,d}$ is the daily excess return, $\overline{r}_{i,t}$ is the monthly mean, and $\sigma_{i,t}$ is the standard deviation over D_t trading days. The results, suppressed for brevity, show that firms in L3 consistently exhibit lower skewness than those in L1, indicating greater downside risk. Importantly, legal risk is not merely a proxy for skewness: co-skewness-based models (Harvey and Siddique, 2000) do not explain the pricing of the LAW factor, suggesting that legal risk captures distinct, priced information.

(no mentions). The coverage ratio—defined as the share of non-zero firms—captures the extensive margin of legal risk in the corporate sector.

Figure 1.4 presents two panels. The top panel applies the structural break procedure of Bai and Perron (2003) to the standardized coverage ratio (Aggregate LRISK), identifying four statistically significant breakpoints: December 2007, March 2013, June 2017, and June 2020. These align closely with key regulatory and macroeconomic events. From 2003 to 2007, aggregate legal risk trended upward amid both regulatory tightening (e.g., post-SOX compliance requirements) and deregulatory shifts (e.g., GLBA and Universal Demand laws).[16] Following the Global Financial Crisis, reforms such as Dodd-Frank's whistleblower provisions and heightened SEC enforcement sustained elevated legal risk.

A brief dip around 2012–2013 may reflect regulatory adjustment, but legal risk rose again from 2018 onward. Key developments include the Supreme Court's *Cyan (2018) ruling*, which enabled forum shopping in securities class actions, and the growing legal salience of cybersecurity—driven by evolving SEC rules and major data breaches. The COVID-19 shock further intensified legal exposure.

The bottom panel compares this legal risk measure (LRISK) with two established uncertainty indices: Economic Policy Uncertainty (Baker et al., 2016) and Macroeconomic Uncertainty (Jurado et al., 2015). LRISK shows only moderate correlation with these indices (0.3–0.6), indicating that it captures a distinct dimension of firm-level risk.

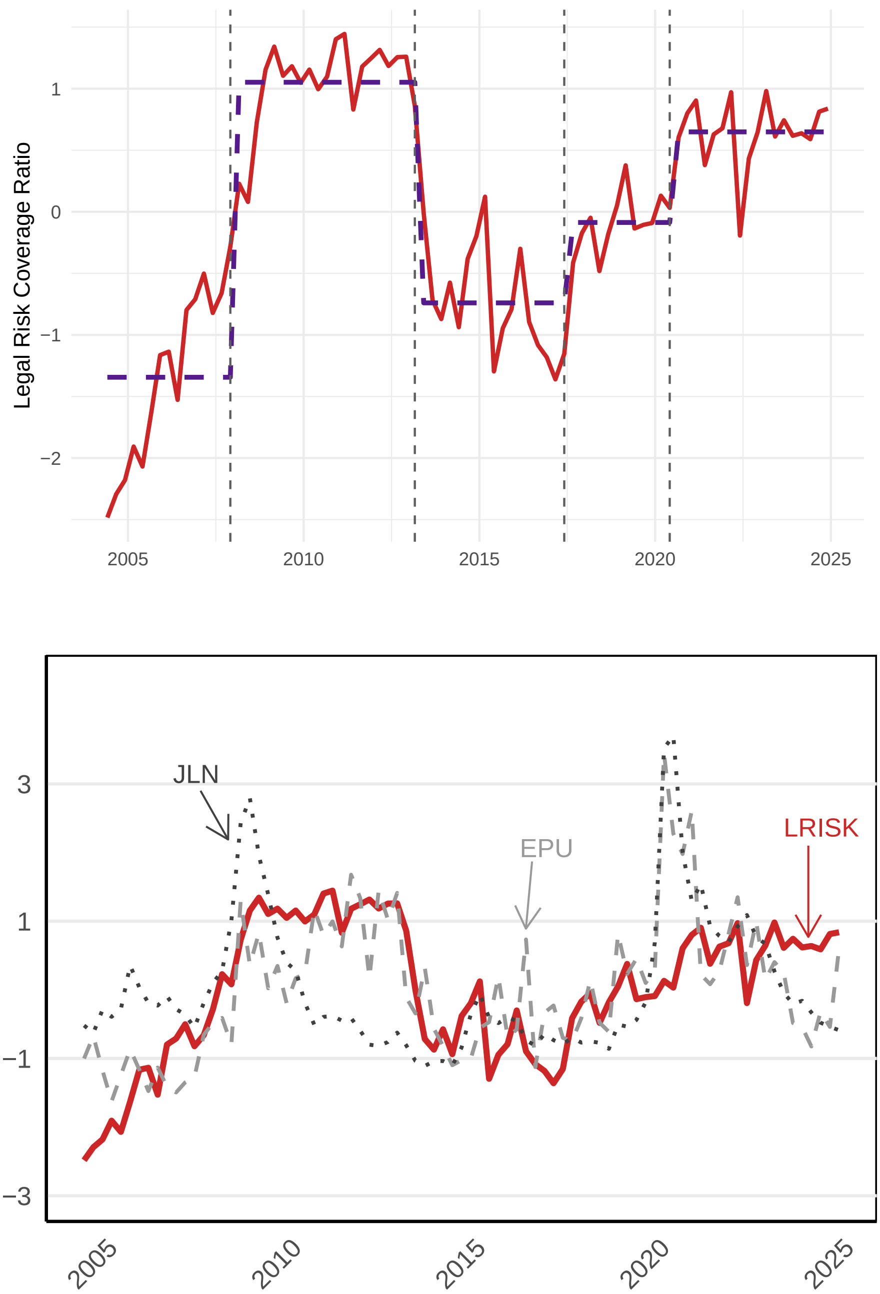
Consistent with an increase in aggregate legal risk following the Global Financial Crisis (GFC), Table 1.6 reports a stronger pricing effect of legal risk in the 2010–2024 subsample. The **LAW** factor now earns an annualized return of 7.1% (t-stat: 4.91), driven by the strong performance differential across legal risk portfolios. Notably, the enhanced performance of the strategy is largely attributable to the short leg of the portfolio: firms with no disclosed legal risk (L1) exhibit significantly negative alphas. This suggests that as aggregate legal risk increased, investors became more willing to accept lower returns from firms perceived to have minimal legal exposure. This pricing dynamic reinforces the notion that legal risk has become a salient dimension of cross-sectional return variation in the post-GFC era.

1.4 Discussion

This section compares the text-based legal risk exposure measure with existing firm-level text-based metrics to establish its distinct role in capturing legal risk-related components. It also rules out potential behavioral explanations. Finally, the section adopts a comparative economics perspective to examine how legal origins shape the pricing of legal risk, highlighting differences between common law and civil law systems.

[16]While SOX increased disclosure obligations and board accountability, deregulatory reforms reduced litigation exposure. On balance, the compliance effects of SOX appear to have prevailed.

Figure 1.4: **Aggregate Measure of Legal Risk**



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

Table 1.6: **Post-2010 Results**

Post-2010 Result (%)

	P1 No legal risk	P2 Middle legal risk	P3 High legal risk	P3 - P1 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 ex-ante legal risk measures, spanning post-2010 sample (2010:07 - 2024:06). Firms in P1 (No litigation risk) are those with no exposure to legal risk. Firms with non-zero exposure to legal risk are split into two groups, placed in P2 or P3 according to their level of exposure. The portfolio return data spans from July 2003 to December 2023. Utility firms (SIC codes 4900–4999) and financial firms (SIC codes 6000 - 6411, 6500 - 6553, and 6700 - 6799) are excluded due to the highly restrictive nature of government regulation. The numbers in parenthesis are Newey-West t-statistics with 6 lags. ***/**/* denote the statistical significance at 1%/5%/10% level.

1.4.1 Comparison with Other Text-based Measures

How the legal risk measure relates to the Loughran-McDonald measure: My work builds on the pioneering work of Loughran and McDonald (2011) (henceforth LM). While legal terms such as litigation and plaintiff appear in "Fin-Lit" categories proposed by LM, I tailor the approach to the spoken dynamics of earnings calls in two major ways, and these refinements provide a more precise and contextually relevant measure of legal language.

Many keywords in LM's Fin-Lit dictionary are formal and specialized: they are terms that are more likely to be found in legal contracts or court rulings rather than in real-time corporate discussions. To illustrate this distinction, consider a few examples. The LM dictionary includes complex legal terms such as *"appurtenance"* (referring to a right, privilege, or improvement associated with a piece of property) and *"conveniens"* (derived from *forum non conveniens,* a legal doctrine that determines the most appropriate or convenient forum for a case). While these terms may be useful in legal scholarship, they are unlikely to appear in earnings calls, where executives communicate in a more accessible and practical manner. Similarly, complex legal verbs such as *"exculpate"*, *"indemnify"*, and *"usurp"* are rarely used in corporate discussions and thus are excluded from the legal dictionary.

Furthermore, my methodology highlights the importance of bigrams (or trigrams) over unigrams in analyzing legal language. While both the LM dictionary and my legal dictionary include unigrams such as antitrust, lawsuit, litigation, plaintiff, prosecutor, and settlement (all of which clearly signal legal risks associated with a firm), many legal terms related to judicial entities, legal proceedings, and legal concepts (the three broad categories in the keyword library) are often overlooked when relying solely on unigrams. For instance, mentioning the term *"Department of Justice"* during earnings calls may suggest potential regulatory scrutiny or legal challenges related to a firm's future operations. However, a unigram-based analysis would fail to capture the phrase in its entirety, missing the broader legal context it conveys. Additionally, relying solely on unigrams can lead to misinterpretation, as they may fail to distinguish between a positive statement about a valuable *"patent"* and a legal concern involving *"patent infringement,"* thereby distorting the assessment of legal risk.[17] To conclude, these two key refinements enhance the ability to measure legal risk more effectively, contributing to the pricing of legal risk in this work, in contrast to prior studies.[18]

How the legal risk measure 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 1.5. First, I find that the composite measure **LRISK** is highly correlated with its key components, **LRISK_COURT** and **LRISK_TRIAL**, with 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 the legal risk measure 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

[17] For a related discussion on the advantages of using bigram or trigram approaches over unigrams, see Caldara and Iacoviello (2022).

[18] On page 55 of Loughran and McDonald (2011), the authors document that a calendar-time portfolio strategy based on negative words ("Fin-Neg") does not generate significant abnormal returns: *"We calculate the Fama and French (1993) four-factor portfolio returns generated by taking a long position in stocks with a low negative word count and a short position in stocks with a high negative count. [...] [N]one of the [alpha] values are statistically significant. Hence, after controlling for various factors, the relation between 1-year returns and negative word counts is not enough to warrant active trading by investors."* Similarly, Loughran and McDonald (2013) find that legal word lists are not significantly associated with first-day IPO returns.

language processing to earnings calls to construct firm-level cyber risk measures and assess their financial impacts.

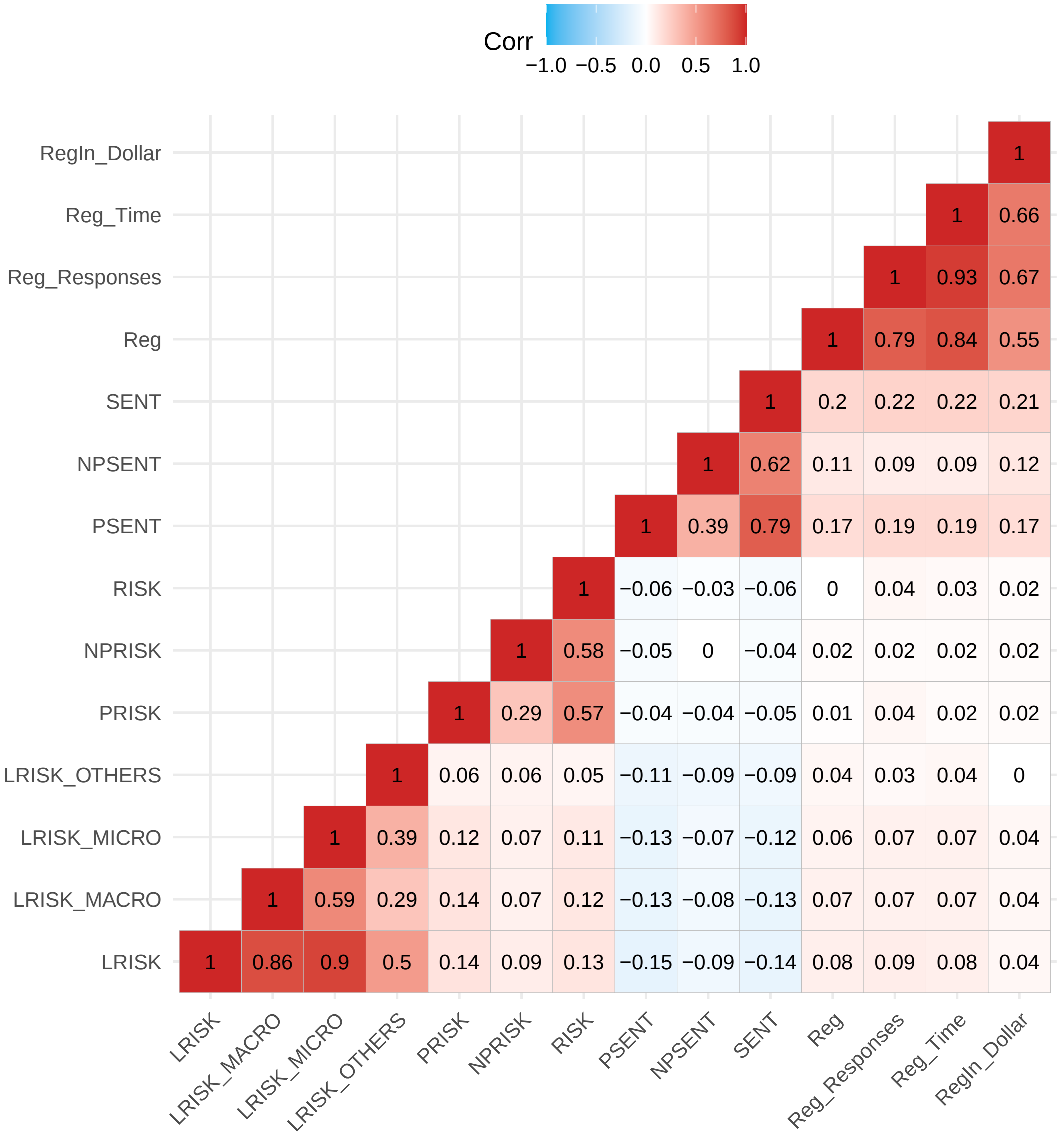
I compare the legal risk measure with the cyber risk measure developed by Jamilov et al. (2025). Since both measures are derived from the same textual source (earnings call transcripts), their cyber risk search terms serve as a natural benchmark for my study. Specifically, I construct a cyber risk dictionary, $\mathbb{C}$, 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.

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 1.7. This result is expected, as cyber risk and legal risk capture distinct dimensions. In the Appendix 1.7.5, 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 1.3, and find that both **LRISK** (replicating the results from Table 1.4) 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 subcomponent of legal risk, it follows that legal risk is a broader concept and thus encompasses the effects of cyber risk.

Figure 1.5: **Correlation between LRISK and other Text-based Firm-level Exposure Measures**



	LRISK	LRISK_MACRO	LRISK_MICRO	LRISK_OTHERS	PRISK	NPRISK	RISK	PSENT	NPSENT	SENT	Reg	Reg_Responses	Reg_Time	RegIn_Dollar
RegIn_Dollar														1
Reg_Time													1	0.66
Reg_Responses												1	0.93	0.67
Reg											1	0.79	0.84	0.55
SENT										1	0.2	0.22	0.22	0.21
NPSENT									1	0.62	0.11	0.09	0.09	0.12
PSENT								1	0.39	0.79	0.17	0.19	0.19	0.17
RISK							1	−0.06	−0.03	−0.06	0	0.04	0.03	0.02
NPRISK						1	0.58	−0.05	0	−0.04	0.02	0.02	0.02	0.02
PRISK					1	0.29	0.57	−0.04	−0.04	−0.05	0.01	0.04	0.02	0.02
LRISK_OTHERS				1	0.06	0.06	0.05	−0.11	−0.09	−0.09	0.04	0.03	0.04	0
LRISK_MICRO			1	0.39	0.12	0.07	0.11	−0.13	−0.07	−0.12	0.06	0.07	0.07	0.04
LRISK_MACRO		1	0.59	0.29	0.14	0.07	0.12	−0.13	−0.08	−0.13	0.07	0.07	0.07	0.04
LRISK	1	0.86	0.9	0.5	0.14	0.09	0.13	−0.15	−0.09	−0.14	0.08	0.09	0.08	0.04

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.

Table 1.7: **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 2004:07 to 2024:06. 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.

1.4.2 Behavioral Explanations?

One potential concern is that the observed legal risk premium may reflect behavioral biases rather than compensation for systematic risk. However, my empirical analyses point against this interpretation.

Stambaugh et al. (2012) argue that anomaly returns are significantly influenced by investor sentiment—particularly that short-leg returns are lower and long-short spreads narrower following high-sentiment periods, consistent with mispricing and limits to arbitrage. In contrast, I find that neither the long-leg, short-leg, nor long-short portfolio returns of the LAW factor exhibit sensitivity to market-wide sentiment, as measured by Huang et al. (2015). This suggests that the LAW premium is unlikely to be driven by sentiment-induced mispricing. Moreover, I show that existing behavioral and mispricing-based factors—such as PEAD and FIN from Daniel et al. (2020), and MGMT and PERF from Stambaugh (2017)—are unable to subsume the LAW factor. Even after controlling for the aggregate disagreement index proposed by Huang et al. (2021), which captures belief dispersion by aggregating 24 individual disagreement measures using a partial least squares (PLS) method, the alpha on LAW remains economically large and statistically significant. These findings, presented in Table 1.15 in the Appendix, suggest that legal risk, as captured by the LAW factor, is unrelated to sentiment, mispricing, or belief heterogeneity as proxied by analyst disagreement.

Furthermore, if the returns to the LAW factor are primarily driven by mispricing linked to investor mood, as suggested by Birru (2018), then the LAW factor should exhibit stronger returns on Fridays.[19] However, my empirical results in Table 1.14 in the Appendix indicate the opposite pattern: LAW returns are significantly positive on Mondays, with no statistically significant improvement on Fridays. Limited attention also plays a limited role here. According to

Finally, if the return premium on legal risk were purely driven by mispricing or behavioral biases, one would not expect firms to alter their real economic decisions in response. However, the evidence to be presented in the next Section shows that firms internalize legal risk as real and costly. These real effects reinforce the interpretation that legal risk is a priced source of systematic risk, rather than a behavioral anomaly.

1.4.3 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

[19] Birru (2018) documents that investor mood improves throughout the week, leading speculative stocks to outperform on Fridays when mood is highest. Applying this framework, if high legal risk firms represent the speculative leg—given that lawsuits, regulatory actions, and litigation outcomes introduce significant uncertainty into their future cash flows and valuations, making them more difficult to price and more sensitive to shifts in investor sentiment—then LAW returns should be elevated at the end of the week.

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.

1.5 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.[20] 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. Appendix 1.7.7 provides simple real options frameworks to show that legal risk increases the value of waiting and thereby discouraging investment.

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

[20] 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.

I estimate

$$\text{INV}_{i,t+1} = \alpha + \beta\,\text{LRISK}_{i,t} + \gamma\,\mathbf{X}_{i,t} + \theta_i + \eta_t + \varepsilon_{i,t+1} \tag{1.3}$$

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 1.8 for details). For ease of interpretation, all investment variables are expressed in percentage terms, and legal risk is standardized.

Table 1.11 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.[21] The effect is even more 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.[22] Finally, column (3) shows that legal risk is associated with a 5.0% reduction in total investment.[23]

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

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

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

Table 1.8: **Variable Definitions and Descriptive Statistics**

Panel A: Variable Definitions

Legal Risk
Control Variables
Investment variables

Panel B: Descriptive Statistics

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.

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 at-

Table 1.11: **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 Fixed Effects			
LRISK	**-0.480*** **	**-0.366*** **	**-0.853*** **
	(-6.53)	**(-4.18)**	**(-7.29)**
Controls?	Yes	Yes	Yes
Industry Fixed Effects?	Yes	Yes	Yes
Year Fixed Effects?	Yes	Yes	Yes
Observations	41,681	41,681	41,681
R^2	0.101	0.546	0.247
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 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.

tenuated in magnitude, suggesting that the effect is not solely driven by past investment momentum. Panel C replaces firm fixed effects with two-digit SIC industry fixed effects ($\delta_{s(i)}$), where $s(i)$ maps firm i to its industry. The negative relationship between legal risk and investment becomes even stronger in magnitude across all specifications. However, the R^2 values decline, reflecting the loss of within-firm variation captured by the more granular firm fixed effects. 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.

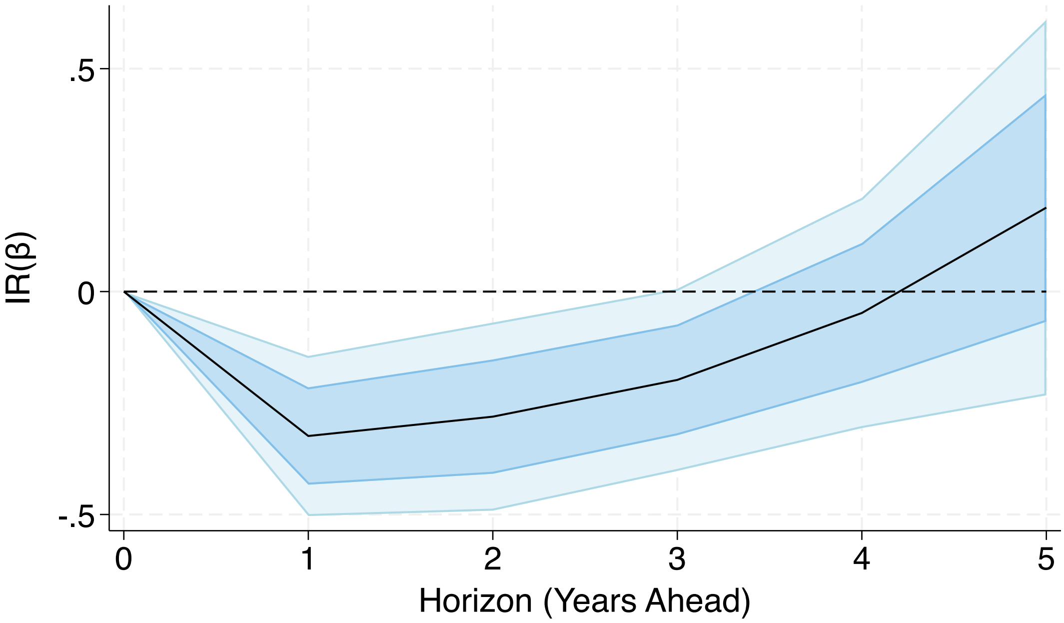
To investigate investment dynamics, I estimate impulse response functions using a panel data adaptation of the local projection method developed by Jordà (2005), as shown in Figure 1.6. Specifically, for each yearly forecast horizon $h = 1, ..., 5$, I estimate the panel regression of the form: $\text{INV}_{i,t+h} = \alpha + \sum_{j=0}^{2} \beta_j \text{ LRISK}_{i,t-j} + \gamma \mathbf{X}_{i,t} + \sum_{j=0}^{2} \delta_j \text{ INV}_{i,t-j} + \theta_i + \eta_t + \varepsilon_{i,t+h}$, 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 mode of financing. Following Malmendier et al. (2011), I estimate the following regression:

$$\text{Finance Mode}_{i,t} = \alpha + \beta_1 \text{ FD}_{i,t} + \beta_2 \text{ LRISK}_{i,t} + \beta_3 \left(\text{FD}_{i,t} \times \text{LRISK}_{i,t}\right) + \gamma \mathbf{X}_{i,t} + \theta_i + \eta_t + \varepsilon_{i,t} \tag{1.4}$$

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 1.8 for variable definitions). The coefficient of interest is β_3, which captures the interaction between the financing deficit and legal risk (FD $\times$ LRISK), and tests whether legal uncertainty moderates the firm's reliance on debt financing when internal resources are insufficient.

Figure 1.6: **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.

Panel A in Table 1.12 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 is robust to the

Table 1.12: **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.

inclusion of controls for firm size, leverage, growth opportunities, and asset structure, as well as to firm, year, and industry fixed effects.

Panel B of Table 1.12 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.

1.6 Conclusion

This paper identifies legal risk as a distinct, priced, and economically meaningful dimension of firm-level uncertainty. Using textual analysis of earnings call transcripts, I construct a firm-level measure of legal risk (**LRISK**) that captures forward-looking concerns related to litigation, regulatory scrutiny, and legal exposure. This measure offers a scalable and dynamic proxy that reflects how both firms and investors perceive legal uncertainty in real time.

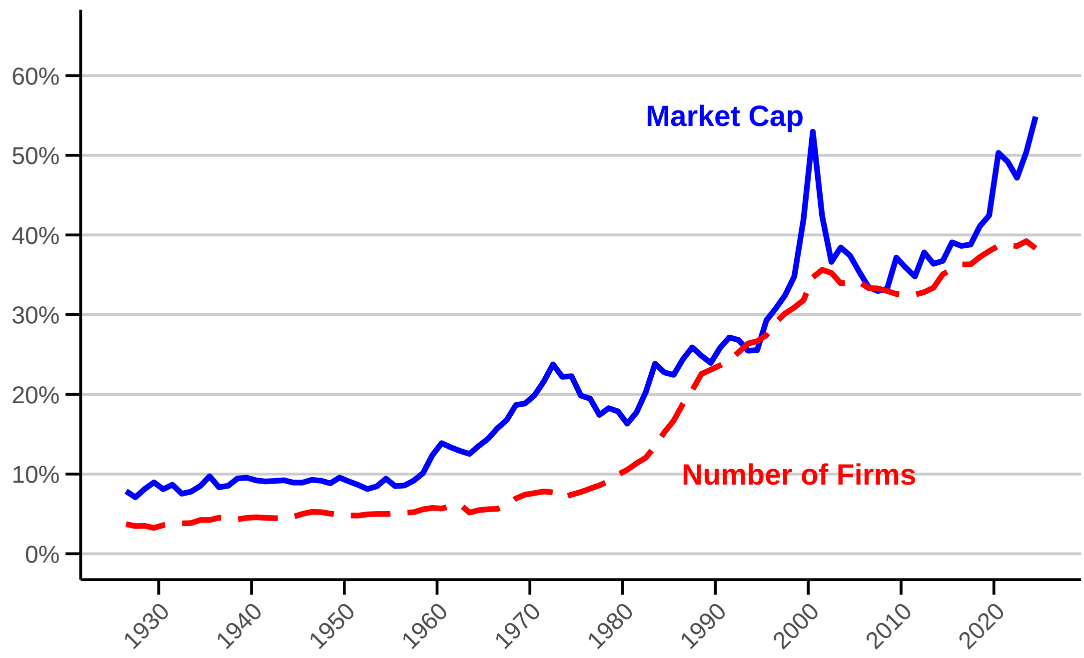
At the firm-level, I show that higher legal risk is associated with significantly lower future investment (particularly in intangible assets) and reduced reliance on debt financing during periods of funding need. These findings suggest that legal risk acts as a friction in both capital allocation and financing decisions, consistent with a precautionary motive. At the aggregate-level, legal risk is robustly priced in the cross-section of stock returns. A long-short portfolio that buys high-legal-risk firms and sells no-risk firms earns an annualized return of 4.7% over the full sample (2004–2024), rising to 7.1% post-2010—a period characterized by intensified regulatory enforcement. The return premium is not explained by standard factor models, ESG proxies, sentiment measures, or existing anomaly variables. Further, the legal risk premium survives the factor zoo critique, and is closely tied to legal tail events, suggesting that investors demand compensation for downside risk uniquely associated with legal exposure. In comparative perspective, I show that legal risk is priced in common law countries—like the United States—but not in civil law systems such as France or Germany, where legal procedures are more codified and litigation risk less salient. This cross-country variation reinforces the idea that institutional foundations shape how markets perceive and price legal uncertainty.

Together, these findings establish legal risk as a first-order determinant of both firm behavior and expected returns. Understanding how legal systems contribute to firm-level risk, investor behavior, and capital market outcomes is central to the broader agenda of law and finance.

1.7 Appendix

1.7.1 Growth of Legal Risk through Litigation-Prone Industries

Figure 1.7: **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 highlights an important structural source of rising legal risk in the U.S. economy. Figure 1.7 illustrates this trend by tracking the number of publicly listed firms operating in high-litigation industries—such as 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)—as well as their aggregate market capitalization relative to the overall market. These sectors are frequently exposed to legal disputes involving intellectual property, regulatory compliance, antitrust, and product liability, making them natural incubators for firm-level legal risk. While the absolute number of public firms has declined since the late 1990s, the share of firms operating in these litigation-intensive sectors has grown steadily, as has their combined market value.

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 1.3 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.

1.7.2 Earnings Call Signals of Legal Exposure

Extracting keywords from earnings call transcripts is essential for identifying underlying signals of litigation risk faced by firms. This section of the 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” and closely related terms. 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 is dealing with terms that have multiple meanings, which can vary significantly based on context. Take, for example, the term “judge.” As a verb, it could simply mean making a decision or forming an opinion, which may have no legal relevance. However, the term “Judge” (i.e., used with a capital letter) specifically refers to a legal authority figure. To maintain the precision of the dataset, I include “Judge” but exclude the lowercase ”judge” to ensure that I capture relevant legal contexts. While a similar approach could be applied to the term “court” (which could imply an attempt to entice someone), I include both “court” and “Court” because it is unlikely that “court” would refer to social enticement given the corporate context of earnings calls.

Litigations related to patents are quite common, making patent-related terms an important consideration in this analysis. However, to maintain precision, I include only terms with clear legal implications, such as ”patent infringement,” while excluding broader terms like ”patent.” The rationale for this distinction is that technology firms often reference their patents in contexts unrelated to legal issues, such as discussing innovation or intellectual property strategies. Including the term ”patent” indiscriminately could introduce noise, as it might capture mentions that have no legal significance, thereby diluting the accuracy of the analysis. By focusing on terms with explicit legal linkage, I ensure the analysis remains targeted and relevant. Ambiguity in language poses a significant challenge in text analysis, particularly when extracting legal nuances from corporate communications. For example, the term ”complaint” could refer to a legal filing but may also be used in non-legal contexts, such as describing a customer’s dissatisfaction with a product. Such ambiguity can obscure the legal relevance of the term if not carefully managed.

To address this, terms like ”complaint” when used in isolation are excluded so that I focus on more legally specific phrases, such as ”amended complaint,” which refers to a formal revision of a plaintiff’s original filing. Similarly, ambiguous terms such as ”claim”—which could refer to insurance claims or warranty claims in non-legal contexts—are excluded unless they appear in explicitly legal contexts, such as ”legal claim,” ”counterclaim,” or terms associated with clear legal proceedings. Additionally, terms like ”settle” are carefully evaluated, as they may relate to financial contexts rather than legal settlements. By excluding these ambiguous or context-dependent terms unless they are part of a legally meaningful phrase, the keyword extraction process is refined to more accurately identify instances of litigation risk 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

1.7.3 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.

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. The baseline specification in the main text adopts a (12-12) strategy, where portfolios are constructed at the end of June each year using legal risk exposures measured 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, ending in June of the following year. This approach follows standard conventions in the asset pricing literature for constructing long-short anomaly portfolios.

To take advantage of the quarterly frequency of earnings calls, Table 1.13 presents results for four alternative strategies with more frequent rebalancing: (12-3), (12-6), (9-9), and (18-6).[24] These strategies vary in both the formation window and holding period, while maintaining a consistent tercile-sorting methodology based on ex-ante legal risk. 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.

All portfolios are value-weighted using market capitalization at the time of formation. To isolate the effect of formation and rebalancing frequencies, the original sample restrictions are preserved: utility and financial firms are excluded due to regulatory constraints. 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 1.13 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 1.8, 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.[25]

[24] 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).

[25] Figure 1.8 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 1.13: **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 (%)

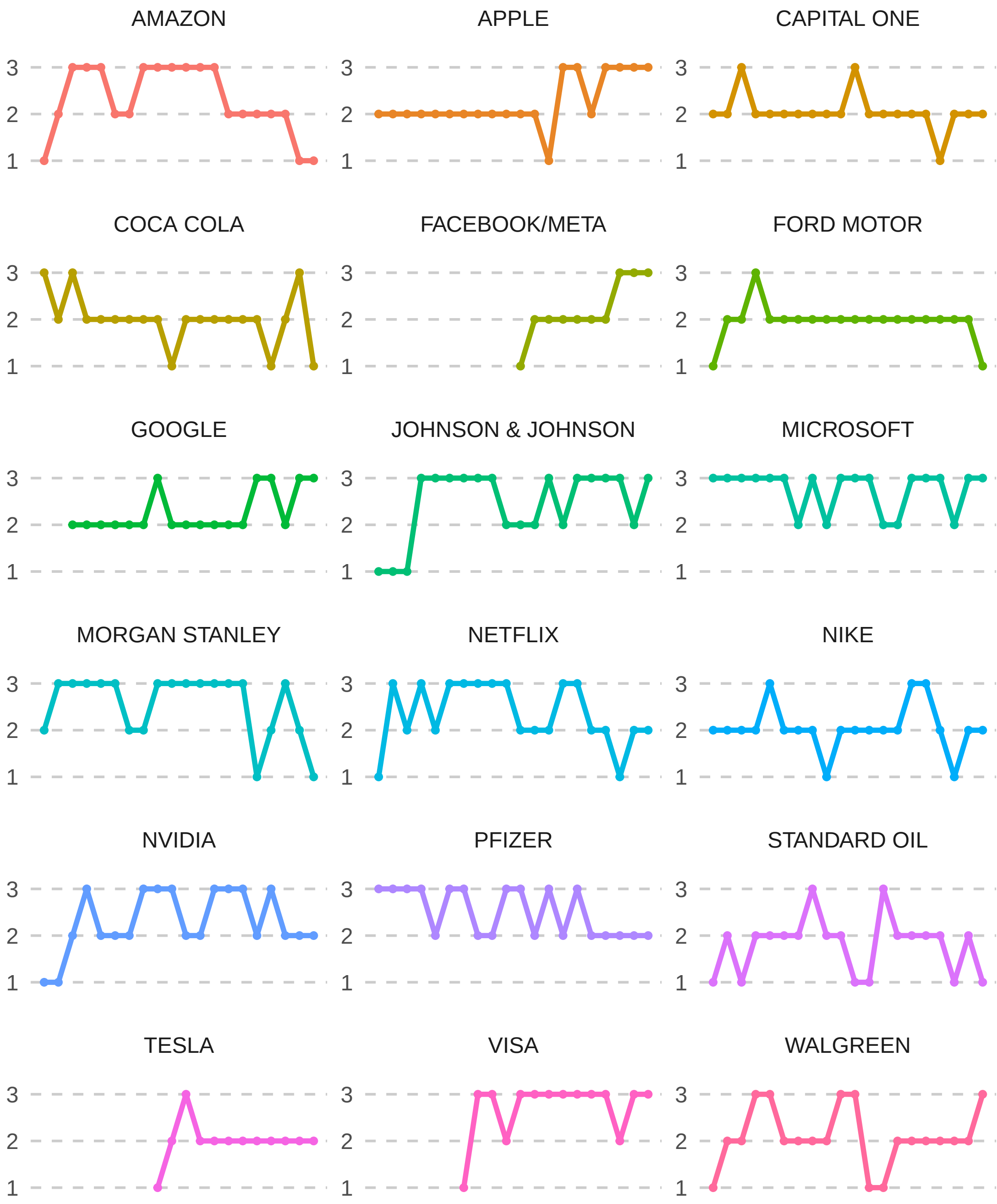
	L1 No legal risk	L2 Middle legal risk	L3 High legal risk	L3 - L1 Long - Short
Excess return	0.686	0.929	1.010	**0.325*******
	(2.20)	(3.21)	(3.43)	**(2.94)**
FF3 + mom alpha	-0.096	0.103	0.196	**0.291*******
	(-1.14)	(2.26)	(2.85)	**(2.68)**

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 (2004:07 - 2024:06) and FF3 + momentum alphas from portfolios formed based on ex-ante legal risk measures. 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 legal risk 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. In each formation period, firms are sorted into terciles based on their legal risk exposure. L1 includes firms with no legal risk mentions. Firms with nonzero legal risk are split at the median into L2 (medium risk) and L3 (high risk). The “L3 – L1” column shows long-short portfolio results (high minus no legal risk). 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.

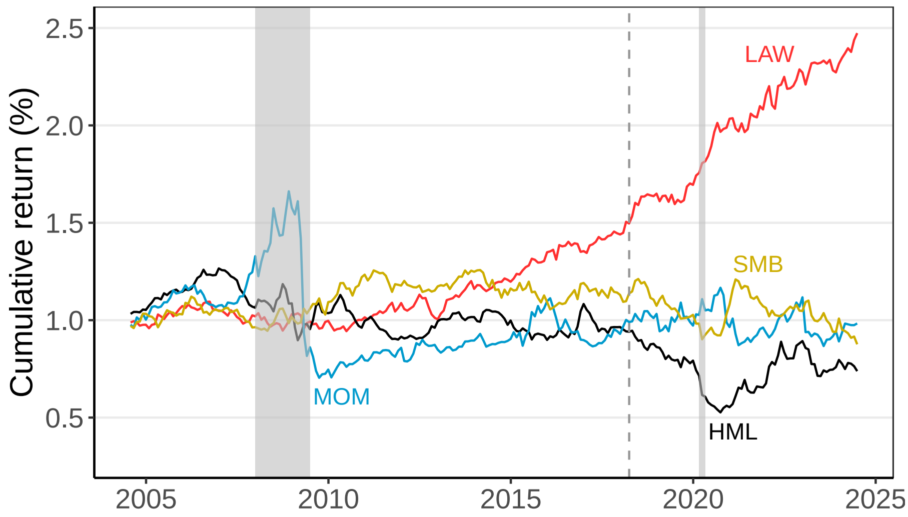
Figure 1.8: **Legal Exposure of Well-known Firms**



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.

Data Mining Concerns

Figure 1.9: **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 Chen and Dim, 2024 and 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 1.9 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.[26]

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 1.10 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).[27]

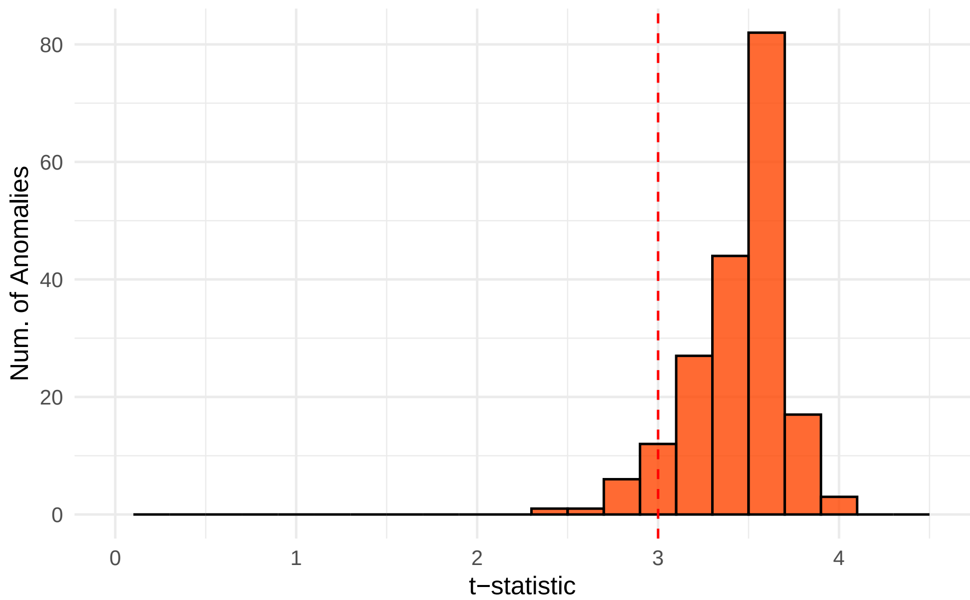
Market Sentiment and Mispricing explanations

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 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.

[26]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.

[27]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.

Figure 1.10: **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 1.15. 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:

$$\text{LAW}_t = \alpha_d + \varepsilon_t, \quad \text{for all } t \text{ such that } \text{Day}_t = d, \tag{1.5}$$

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. Additionally, I estimate a pooled regression for midweek days by restricting the sample to $d \in \{2, 3, 4\}$ (Tuesday through Thursday).

The results, reported in Table 1.14, 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.

LAW Factor vs. ESG Factors

In Table 1.16, 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 1.14: **Day-of-the-Week Effects on LAW Returns**

	Monday	Tuesday	Wednesday	Thursday	Friday
Estimate	**0.027*** **	**0.016*** **	**0.017*** **	**0.017*** **	0.009
t-stat	**(5.07)**	**(2.89)**	**(3.17)**	**(3.07)**	(1.57)
N	939	1,032	1,034	1,018	1,010

Note: Notes: This table reports the estimated mean 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.

Table 1.15: **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

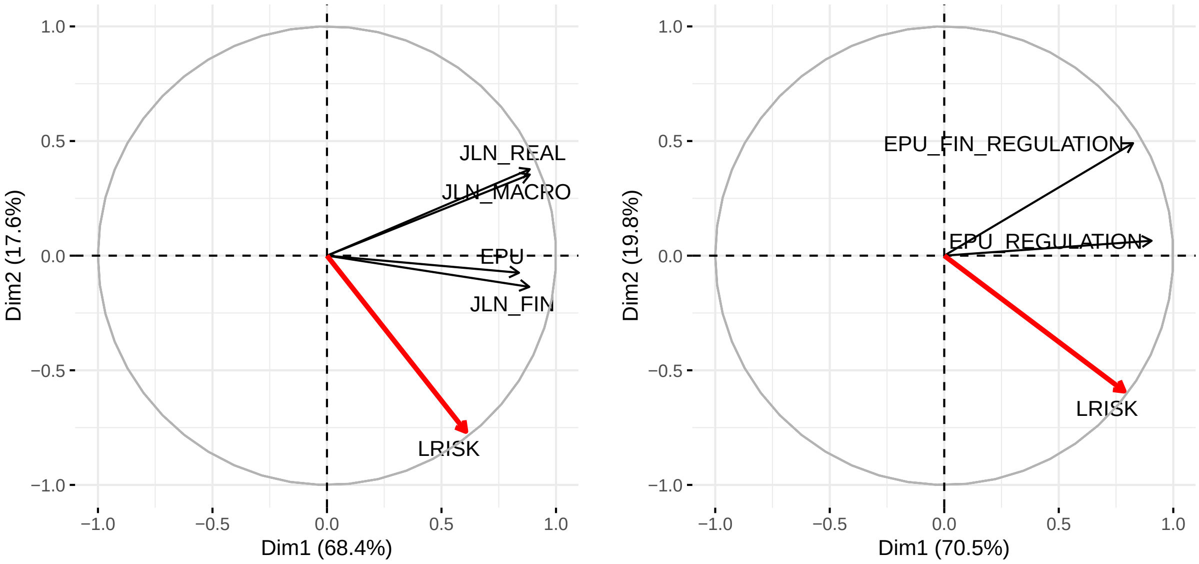
Panel B: Mispricing Factors and Disagreement

	(1)	(2)	(3)	(4)
Dependent variable:	LAW	LAW	LAW	LAW
↓ Independent variable:				
Intercept	**0.377***** **(3.59)**	**0.358**** **(2.48)**	**0.312***** **(3.01)**	**0.396***** **(2.65)**
PEAD	-0.077 (-1.03)			-0.067 (-0.75)
FIN	0.019 (0.34)			-0.177** (-2.44)
MGMT		0.175** (2.09)		0.308*** (3.49)
PERF		-0.212*** (-3.91)		-0.139** (-2.27)
Disagreement			-0.286* (-1.83)	-0.087 (-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.

1.7.4 Aggregate LRISK vs. Uncertainty Measures

Figure 1.11: **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 legal risk measure (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.

This section examines how my measure of aggregate legal risk—constructed as a coverage ratio, as described in Section 1.3.5—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 1.11 displays the resulting factor loadings for LRISK and the alternative indices. 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 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.

1.7.5 Firm-level Evidence: Case studies using SolarWinds

SolarWinds[28] 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) 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 1.12). 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

[28]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, 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.

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.

1.7.6 Legal Shifts: Implications for Firms and Markets

This section examines the evolution of the U.S. legal landscape throughout the 21st century and its implications for firms and markets. Specifically, I explore how the early 2000s were characterized by a mix of deregulatory measures and heightened regulatory oversight, while the post-Global Financial Crisis (GFC) era introduced a wave of stringent reforms that reshaped the regulatory framework.

The Rise of Aggregate Legal Risk in the Early 2000s

Background: The early 2000s were characterized by a series of mixed legal developments that, in aggregate, contributed to an increase in firm-level legal risk and shaped the regulatory climate leading up to the Global Financial Crisis (GFC). On one hand, deregulatory measures such as the repeal of key provisions of the Glass-Steagall Act via the Gramm-Leach-Bliley Act (GLBA) in November 1999 facilitated financial consolidation. Originally enacted in 1933 to separate commercial and investment banking, the Glass-Steagall Act aimed to limit conflicts of interest and systemic risk. Its repeal under the GLBA allowed financial institutions to operate across banking, securities, and insurance sectors, accelerating the formation of financial conglomerates such as Citigroup. This deregulatory shift expanded the operational scope of financial firms, but also exposed them to more complex and potentially risk-laden legal environments.

Simultaneously, legal reforms at the state level contributed to a more insulated corporate governance regime. In particular, the widespread adoption of Universal Demand (UD) laws during the 1980s and 1990s, and their ongoing effects into the 2000s, substantially weakened shareholder litigation as a mechanism for corporate accountability. These laws required shareholders to make a formal demand to the board before initiating derivative lawsuits, thereby granting directors increased discretion to block litigation. The long-lasting effect of UD laws was a decline in shareholder lawsuits and reduced external monitoring of managerial behavior. Firms incorporated in UD states, as shown by Houston et al. (2018), experienced significantly fewer lawsuits, even in instances of governance failures—effectively lowering litigation risk for managers while raising latent risks for investors and stakeholders.

Table 1.16: **Comparing LAW factor and ESG-relevant factors**

Panel A: ESG factors are dependent variables

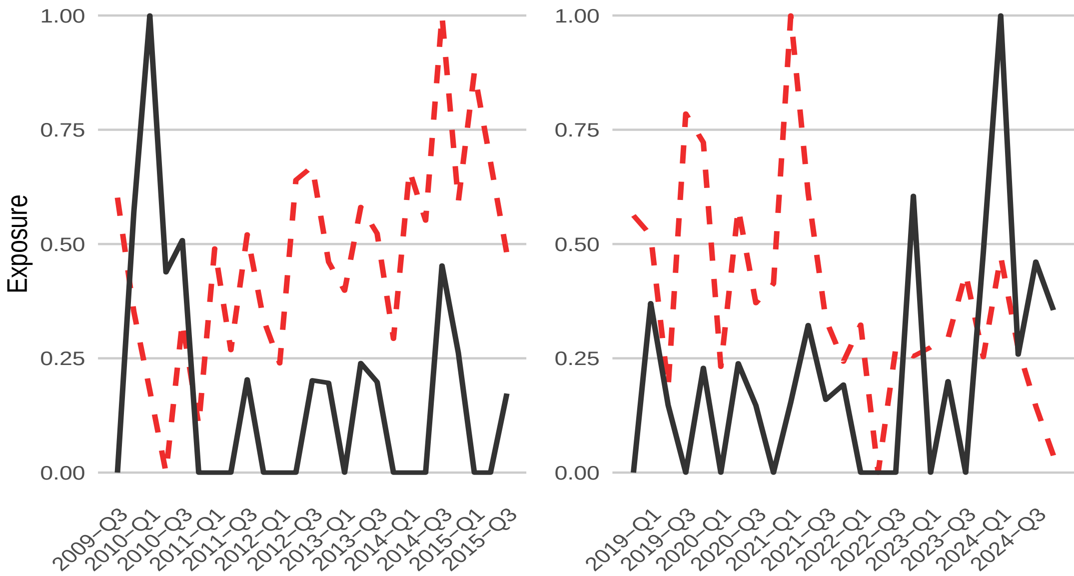
	PFP factors (1 through 4)				PST factors (5 through 7)		
→ Dependent variable:	(1) **ESG**	(2) **E**	(3) **S**	(4) **G**	(5) **GMB**	(6) **G**	(7) **B**
↓ Independent variable:							
Intercept	-0.087 (-0.51)	0.333 (1.61)	-0.163 (-1.09)	-0.119 (-0.67)	**0.289*** **(1.69)**	**0.124*** **(1.74)**	-0.165 (-1.34)
LAW	**0.211**** **(2.10)**	0.082 (0.86)	-0.050 (-0.56)	-0.028 (-0.32)	**0.134*** **(1.86)**	**0.115***** **(2.59)**	-0.019 (-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**** **(2.26)**	**0.412**** **(2.44)**	**0.328**** **(2.32)**	**0.332**** **(2.31)**	**0.391***** **(3.40)**	**0.356***** **(3.09)**	**0.431***** **(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.

Figure 1.12: **Case study - SolarWinds**



Note: This figure presents the legal risk exposure (black solid line) and cyber risk exposure (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.

In contrast to these deregulatory trends, the Sarbanes-Oxley Act (SOX) of 2002 marked a sharp shift toward regulatory tightening in response to high-profile accounting scandals such as Enron and WorldCom. SOX introduced stringent rules on internal controls, mandated executive certification of financial reports, and imposed heavier disclosure burdens on public firms. While SOX sought to restore investor confidence and strengthen oversight, its implementation introduced considerable legal and compliance risk, particularly for firms with opaque reporting practices or weak governance structures.

Taken together, these concurrent shifts created a complex legal landscape. On one side, deregulatory measures such as the GLBA and the enduring impact of UD laws reduced the external constraints on managerial behavior, encouraging risk-taking and innovation. On the other, SOX raised the cost of non-compliance and increased the legal consequences of disclosure failures. The aggregate effect was an elevation in firm-level legal risk, as companies navigated a regulatory environment that was both permissive and punitive. This asymmetry—lax enforcement in some domains and heightened scrutiny in others—contributed to mounting systemic fragilities that were ultimately exposed during the GFC.

Stringent Legal Shifts After the Global Financial Crisis

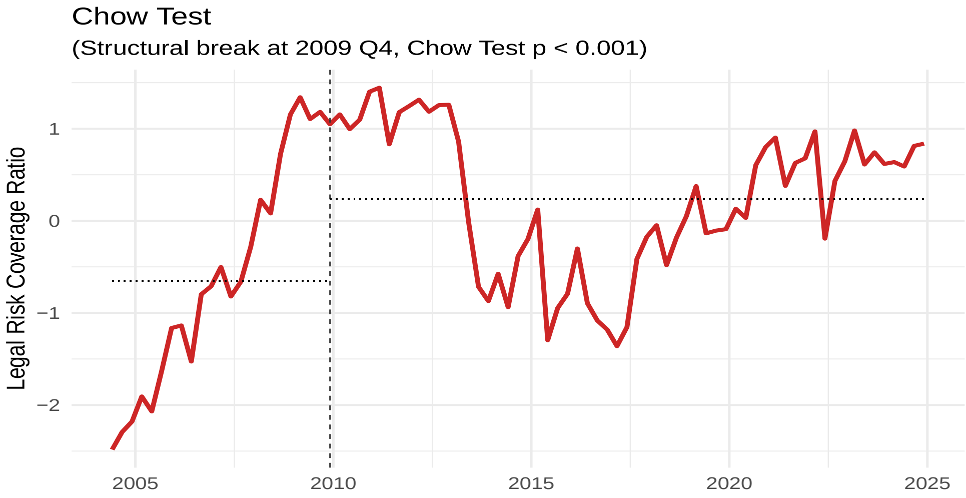
Background: The 2008 GFC exposed systemic weaknesses in the U.S. financial system, including excessive risk-taking, regulatory gaps, and corporate misconduct. The resulting economic downturn and public outrage over corporate malfeasance prompted a wave of legislative and regulatory reforms designed to prevent similar crises in the future. The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 was a cornerstone of these reforms, introducing comprehensive measures to enhance market oversight, improve transparency, and promote corporate accountability.

The Securities and Exchange Commission (SEC) played a pivotal role in these reforms by implementing stricter enforcement measures. In 2010, the SEC established specialized units within its Enforcement Division, such as the Market Abuse Unit and the Asset Management Unit, to address complex financial misconduct more effectively. Additionally, the SEC's cooperation program encouraged firms and individuals to assist in investigations through tools like cooperation agreements, deferred prosecution agreements, and non-prosecution agreements. According to Leone et al. (2021), the program's early years were marked by higher enforcement probabilities and increased penalties. However, from 2011 to 2014, enhanced cooperation led to reduced enforcement probabilities and lower penalties, reflecting the program's evolving effectiveness.

A landmark provision in securities law enforcement came with the whistleblower program established under Section 922 of the Dodd-Frank Act. This program offered monetary rewards ranging from 10% to 30% of sanctions collected from SEC enforcement actions exceeding $1 million, alongside robust anti-retaliation protections for whistleblowers. These incentives encouraged individuals to report misconduct early, thereby strengthening the SEC's ability to detect and deter securities violations. Heese and Perez-Vacazos (2021) examine how the costs of retaliation influence employees' decisions to whistleblow, underscoring the program's effectiveness. Beyond the SEC's whistleblower program, the *Cyan, Inc. v. Beaver County Employees Retirement Fund (2018)* decision further heightened legal risk in the U.S. by allowing class-action lawsuits under the Securities Act of 1933 to proceed in state courts, increasing the risk of forum shopping. This exposed public companies, particularly those undergoing IPOs or secondary offerings, to costly and unpredictable litigation across multiple venues. Beyond direct legal costs, Cyan raised uncertainty around liability, complicated securities defense strategies, and increased the legal risk premium investors demanded. The prospect of parallel lawsuits in different states strained corporate legal teams, drove up settlement costs, and deterred some firms from capital-raising activities. The ruling also impacted D&O insurance markets, as insurers adjusted premiums to reflect heightened litigation exposure. Alongside other post-GFC regulatory shifts, Cyan played a key role in shaping the modern U.S. legal risk landscape and its asset pricing implications.

Impact on Firms Listed on U.S. Public Markets: The post-GFC reforms significantly elevated the legal risk exposure for publicly listed firms. Companies faced greater regulatory scrutiny and higher compliance costs as they bolstered internal controls and governance frameworks to mitigate legal risks. Financial institutions like JPMorgan Chase and Goldman Sachs incurred substantial penalties for past misconduct and adopted stringent compliance measures in response. The whistleblower provisions of the Dodd-Frank Act further amplified firms' legal risk, evidenced by high-profile cases like the $104 million reward to UBS whistleblower Bradley Birkenfeld, whose disclosures led to significant penalties for the firm. These reforms marked a transformative shift in the U.S. legal landscape, with firms now encountering intensified accountability for both historical and ongoing practices.

Figure 1.13: **Chow Test**



Note: This figure plots the Chow test around 2010 using the aggregate legal risk measure introduced in Section 1.3.5. The measure is based on the coverage ratio—the proportion of firms referencing legal risk in their earnings call transcripts. Each quarter, firms are classified into two groups: zero firms, which made no mention of legal risk in the past four quarters, and non-zero firms, which did. The coverage ratio is computed as the share of non-zero firms relative to the total number of firms. To facilitate interpretation over time, the series is standardized using a z-score transformation, highlighting deviations from the historical average.

The findings in this paper, based on post-2010 data, are consistent with the results in Figure 1.13, where the Chow test clearly indicates a structural break around 2010. This break marks a significant shift in the legal environment, corresponding to the implementation of major post-GFC reforms. Together, these results underscore the substantial impact of legal regime changes on U.S. public markets.

1.7.7 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.

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:

$$\underbrace{X(V)}_{\text{Value of waiting}} = \sup_{\tau} \mathbb{E}_0 \left[e^{-r\tau}(V_\tau - F) \right], \tag{1.6}$$

where r is the discount rate.

The project value V_t evolves according to geometric Brownian motion:

$$\frac{dV_t}{V_t} = \mu\, dt + \sigma\, dZ_t, \tag{1.7}$$

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:

$$\beta = \frac{1}{2} - \frac{\mu}{\sigma^2} + \sqrt{\left(\frac{\mu}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2r}{\sigma^2}}, \tag{1.8}$$

$$V^* = \frac{\beta}{\beta - 1} F. \tag{1.9}$$

Equations (1.8) and (1.9) can be derived using dynamic programming and Itô's lemma.[29]

[29] 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:

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

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:

$$F^*(\ell) = F + \lambda \ell, \tag{1.10}$$

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:

$$V^*(\ell) = \frac{\beta}{\beta - 1}(F + \lambda \ell), \tag{1.11}$$

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.

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

---

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 (1.9).

$a > 0$ and V_t evolves as in Equation (1.7). The present value of investing at time t is:

$$\Pi(V) = \frac{aV}{r-\mu}, \tag{1.12}$$

assuming $r > \mu$.[30]

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:

$$X(V) = AV^{\beta}, \tag{1.13}$$

where β is given by Equation (1.8) and arises from solving the associated HJB equation.

Using standard value matching and smooth pasting conditions,[31] the investment trigger becomes:

$$V^* = \frac{\beta}{\beta-1} \cdot \frac{F(r-\mu)}{a}. \tag{1.14}$$

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

$$\sigma(\ell) = \sigma_0 + \kappa\ell, \quad \kappa > 0. \tag{1.15}$$

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

$$V^*(\ell) = \frac{\beta(\ell)}{\beta(\ell)-1} \cdot \frac{F(r-\mu)}{a}, \tag{1.16}$$

[30] The equation (1.12) 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 $r > \mu$.

[31] 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.

with

$$\beta(\ell) = \frac{1}{2} - \frac{\mu}{\sigma(\ell)^2} + \sqrt{\left(\frac{\mu}{\sigma(\ell)^2} - \frac{1}{2}\right)^2 + \frac{2r}{\sigma(\ell)^2}}. \tag{1.17}$$

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.

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Chapter 2

Divided Government and the Stock Market

Abstract: We show that during United governments, where the same political party controls the White House, the Senate, and the House of Representatives, the U.S. stock market earns substantially higher average excess returns and the U.S. economy experiences higher economic growth than during Divided governments. Consistent with a political gridlock mechanism, the government cycle has a more pronounced impact on small firms, accounting for the recent vanishing of the firm size effect. We examine causal mechanisms through closely contested elections, and show that the government cycle is consistent with theoretical models that link under-performance during Divided-Republican governments to increasing political uncertainty.

2.1 Introduction

The *Presidential Puzzle*, named and first described in the academic literature by Santa-Clara and Valkanov (2003), is the phenomenon that U.S. stock market excess returns are on average higher during Democrat presidencies than Republican ones. Together with stock market excess returns, the literature indicates that the U.S. economy performs much better when the president is from the Democratic party (see, among others, Alesina et al., 1997; Faust and Irons, 1999; Comiskey and Marsh, 2012; and Blinder and Watson, 2016).

In this paper, we document a related but separate phenomenon, the *Government Puzzle*. We define a U.S. government as *United* if the same party controls the White House and holds a majority in both houses of Congress: the Senate and the House of Representatives. A non-united government is *Divided*.[1] [2] The central result of this paper is that, in our sample of 94 years, we find a significant difference in stock market performance between United and Divided governments. The value-weighted excess monthly stock market return under United governments is 10.3% per annum versus 1.6% under Divided governments (8.7% per annum difference with statistical significance). We obtain more striking results for equal-weighted returns: under United (Divided) governments the average equal-weighted annual excess return over the same period is 16.8% (0.0%). These key findings from the stock market are resilient against outliers and remain valid even after accounting for the persistence issues caused by the sporadic changes in government (Stambaugh, 1999). We also demonstrate that the government cycle exists not only at the state level but also internationally, as seen in the United Kingdom, suggesting that it is a widespread phenomenon.

We argue that the government cycle is driven by political gridlock, which is inherent in Divided governments and largely absent under United governments. Divided governments are more prone to legislative stalemates, increased veto activity, and heightened partisan conflict—all of which contribute to elevated policy uncertainty and institutional inertia. Political gridlock has a greater impact on small firms compared to large firms, consequently leading to a more pronounced influence on the stock returns of small firms during the government cycle. We show this through the lens of size risk factor (SMB or Small Minus Big, Fama and French, 1993): across the government cycle, a surprising 7% per annum difference in the SMB strategy return arises. The resurgence of SMB under United Governments is robust, evident from its outstanding performance even without accounting for the quality factor QMJ (Asness et al., 2018). The government cycle also helps to explain the recent decline of the size effect post-1980s, as during this period, the U.S. government was characterized by a prevalence of Divided rather than United governments. The well-established evidence of the size effect in financial markets naturally connects to the similar size effect observed in the macroeconomics literature (see Gertler and Gilchrist, 1994; Crouzet and Mehrotra, 2020). Our findings suggest a political explanation, where the greater cyclicality of small firms is driven largely by political gridlock, which disproportionately hampers their growth during economic cycles.

The government cycle we identify is new, and it stands out as distinct from other related political cycles that have been studied in the economics and finance literature. The

[1] In our definition, denoting D as Democrats and R as Republicans for brevity, {Incumbent President's party, Majority of the Senate, Majority of the House} $\in$ {R, R, R} or {D, D, D} are United governments, and the remaining 6 combinations ({R, D, R}; {R, R, D}; {R, D, D}; {D, D, R}; {D, R, D}; and {D, R, R}) are Divided governments. The United government is also called 'unified government' or 'government trifecta.' In a similar vein, Divided government is often called 'hung government' in a Westminster system. In this paper, we use these terms interchangably.

[2] The concept of United and Divided government is rooted in the separation of powers model in the U.S. political system. In the United States, there are three branches of government. The executive branch, which includes the White House and the president, enforces laws. The legislative branch, made up of the Senate and the House of Representatives, creates laws. The judicial branch interprets laws.

first one is the presidential cycle (Pastor and Veronesi, 2020, henceforth PV), where Democratic presidents tend to earn higher equity premia than Republican presidents. The presidential and government cycles are closely connected since the government status depends on the political affiliation of the sitting presidents. In what follows, we show that the government layer uncovers many new empirical findings that the presidential cycle alone does not explain, thereby emphasizing the distinct influence of government status. First, we show that subpar performance during Republican presidents is specific to Divided governments. Indeed, equity returns under unified Republican presidencies are comparable to those observed under Democratic presidents, regardless of the broader government composition. In this vein, the government cycle allows us to refine the widely known presidential puzzle into a *Divided-Republican government puzzle*. When we examine the interaction of political variables within the regression framework, we demonstrate that the impact of the government cycle on explaining stock market movements outweighs that of the presidential cycle, often completely subsuming it. We next show that the U.S. economy experiences recessionary periods during Divided governments, leading to a noticeable increase in the treasury premium[3] in comparison to united governments. Meanwhile, we do not find a difference in treasury premium across the presidential cycle. Specifically, our analysis reveals that Divided-Republican governments coincide with the majority of NBER recessionary periods, which also happen to be the periods when September crashes occur.

Another related political cycle is the post-midterm election premium documented in Chan and Marsh (2021) (CM), where strikingly high returns are documented after each midterm election, irrespective of who runs the White House. Both midterm and presidential elections result in a change in government status, making it essential to draw a clear distinction between these two political cycles (PV and CM). Our analysis reveals that the election premium documented in CM does not account for the government cycle. Excluding the post-election months does not impact the government gap; in fact, it strengthens it. When we put it all together, we can observe that after an election resulting in divided governments, the stock market typically experiences an initial uptick (as found by CM), followed by a subsequent downturn (the main point of this paper). These two distinct patterns help to address the long-standing debate on whether 'gridlock is good or not'.[4]

As we detail in the paper, real economic growth also varies significantly across government regimes. Throughout 121 years of U.S. history, the average GDP growth gap is more salient under the government cycle (4.51% for United vs. 2.01% for Divided; 2.5% government gap) than under the presidential cycle (4.49% for Democratic presidents vs. 2.54% for

[3]The treasury premium is a long term government bond return less a three month T-bill return. See Table 2.12.

[4]On Wall Street, there is a famous saying that "gridlock is good," because a divided government with checks and balances makes it unlikely for politicians to enact drastic legislative changes (Persson et al., 1997). However, dissenters argue that a lack of control over Congress could lead to political conflicts that may have repercussions in the financial market.

Republican presidents; 1.95% presidential gap).

Finally, we attempt to infer the causality of our observed government premium. In our sample of 47 midterm and presidential elections, we identify several instances where voters were nearly evenly split in their decision. These cases serve as a quasi-natural experiment, allowing us to observe significant disparities in stock returns. We find significant differences in stock market reactions immediately following election results and in the longer-term performance of the market under 'barely unified' versus 'barely divided' governments, suggesting that government composition has a direct impact on market outcomes. We also rule out alternative explanations that could undermine our causal interpretation.

Related Literature The current paper contributes to a growing literature that describes the political cycle of asset prices. Along with two seminal papers discussing the presidential puzzle (Santa-Clara and Valkanov, 2003 and Pastor and Veronesi, 2020), the president's political affiliation predicts a number of patterns such as stock market performance of politically sensitive industries (Addoum and Kumar, 2016) and cash flow of firms with government exposures (Belo et al., 2013). Political relationships of key individuals as well as investors are of importance, as CEO political access to key government officials is associated with positive abnormal stock returns (Brown and Huang, 2020), and senior leaderships' political affiliation affects Corporate Social Responsibility (CSR) ratings as well as the profits of the firm they manage (Di Giuli and Kostovetsky, 2014). Kim et al. (2012) shows that local firms' proximity to political power, measured by Political Alignment Index (PAI), predicts stock returns. The present paper is unique in that it does not focus on the bipartisan implications, as the status of the government can come from either political party in the United States.

There is also a dense empirical and theoretical research literature on the effects of political cycles on the macroeconomy. For surveys in this area, see Alesina et al. (1997) and Harms (2001). These books offer convincing evidence that political variables have an impact on the state of the macroeconomy. The political angle has received fair attention from the economic growth literature. Hibbs (1987), Alesina and Sachs (1986), and Blinder and Watson (2016) constitute the core papers that discuss the partisan growth gap. Finally, both Poterba (1994) and Alt and Lowry (1994) show, at the state level, that unified control of state government assigns flexibility to adjust to unexpected revenue shocks.

Outline The rest of this paper is organized as follows. Section 2.2 establishes a government premium where there is a substantial gap in stock market performance and economic growth between United and Divided governments. Section 2.3 presents our novel findings and highlights how the government cycle stands out as distinct from other related political cycles. Section 2.4 explores possible mechanisms that generate our results. Finally, Section

2.5 concludes.

2.2 The Government premium

2.2.1 Data

The main sample we consider uses monthly stock returns provided by the Center for Research in Security Prices (CRSP) spanning 1927:01 - 2020:12. This entire sample period contains 1128 monthly observations during which 47 different Congresses were in place. We refer to each two-year combined regime of a Congress and President as a Government. Of these 47 Governments, 23 were united (556 monthly observations) and 24 divided (572 observations). There were 16 presidents in total, nine of them Republicans and seven Democrats. The Democratic Party (Republican Party) obtained the majority of the Senate 30 (17) times. At the same time, the House of Representatives was dominated 33 (14) times by Democrats (Republicans). For the stock market data, we consider the logarithm of monthly returns of the value-weighted as well as equal-weighted portfolios. From these log returns we subtract the log monthly return on a three-month Treasury bill to obtain excess returns. Real U.S. GDP growth data since 1900[5] is used to examine the difference in economic growth conditional on the government cycle.

We construct two main political dummy variables: the first is a government dummy, **GOV**, defined as $\mathbf{GOV} = 1$ when a unified government is in place and $\mathbf{GOV} = 0$ otherwise (Divided). We follow United States House of Representatives Archives[6] in defining which months belong to the United or Divided governments. Following past literature, we also construct a president dummy **PRESID** assigning unity when a Democratic president is controlling the White House.[7] While a detailed overview of U.S. political regimes is available in the Appendix,[8] a brief summary is insightful. During the first two years of Donald Trump's first presidency (115th Congress), he worked with a unified Republican government, followed by a divided government in his final two years (116th Congress). Similarly, Joe Biden's first two years as president (117th Congress) were marked by a unified Democratic government, transitioning to a divided government in the subsequent two years (118th

[5]We thank Professor Valerie A. Ramey for sharing her real GDP data from 1900 to 2016, used in her paper Owyang et al. (2013). We extend up to 2020 using BEA economic growth whose correlation with Ramey's data during 1947 - 2016 is above 99%.

[6]See https://history.house.gov/Institution/Presidents-Coinciding/Party-Government.

[7]In doing so, we assume that each month belongs to the latest scheme assuming office on that particular month. For instance, if a Congress assumes office on January 3 and the president assumes office on January 20 (which is the case for all presidents since 1950 unless in special circumstances), we then assign the month of January to the new president and to the new combination of the legislative and executive branch. Assigning the latest scheme to the next month does not change our results.

[8]The Appendix provides a comprehensive list of U.S. presidents, their affiliated political parties, and the party control of the Senate and the House of Representatives during their terms.

Congress). This pattern suggests that political control of the government is not a bipartisan issue. In our main CRSP sample, we find Democratic presidents (**PRESID** $= 1$) 50.9% of the time, while United governments were in place (**GOV** $= 1$) 49.3% of the time.

2.2.2 Stock market performance over types of government

The descriptive statistics in Panel A of Table 2.1 show that the market portfolio earned significantly higher returns under United regimes than under Divided ones. The average monthly excess stock return of 0.86% under United regimes is equivalent to an annual excess return of 10.3%. Under Divided government, on the other hand, the stock market averaged a meager 0.13% per month (1.6% per annum). The difference in average realized excess returns was 0.73% (8.7% annualized) with a t-statistic of 2.3.

United government does not appear to be associated with riskier stock return distributions: The percentile distribution is not materially different and somewhat more benign under United governments, notably with a much higher median as well as mean return of 1.3% versus 0.7%. The standard deviation of monthly stock returns is slightly lower under United governments, and stock returns are less negatively skewed. We also check whether this difference is driven by either extremely good (bad) returns in the United (Divided) government. In Panel B of the table, we present the descriptive statistics trimming the top and bottom 1% of the sample. The average monthly stock return of the Divided regime increases to 0.25% per month. This shrinks the monthly difference from 0.73% to 0.59% (7.1% annualized) with a t-statistic of 2.2. Finally, Panel C reports in-sample Sharpe Ratios for the full, untrimmed sample: 0.57 under United governments, 0.08 under Divided. Overall, although average excess returns were significantly higher under United regimes, and in particular returns under Divided regimes not significantly different from zero, United regime returns do not appear to be drawn from an obvious riskier distribution. If anything the opposite it true, and the distribution of United government returns appears slightly less risky.

Table 2.2 shows that the government gap exists across various measures of stock performance. The first column in Panel A, which uses value-weighted excess stock returns (VWR-TBL), reaffirms that the findings of Table 2.1 with a Newey-West adjusted t-statistic of 2.08.[9] Equal-weighted log excess stock returns (EWR-TBL, the second column) averaged 16.78% per annum during United governments, but exactly zero under Divided governments (t-statistic for the difference of 3.07).

[9] We set Newey-West lags to 24, given that the government status lasts for 2 years. Our results are robust to setting lags to 6, 12, or 48.

Table 2.1: **Distributions of Monthly Excess Returns**

Panel A: Entire sample

	United	Divided	Difference
Mean (%)	**0.86*****	0.13	**0.73****
	(3.90)	(0.58)	**(2.28)**
1% percentile (%)	-13.8	-16.9	3.1
25% percentile (%)	-1.65	-2.40	0.75
Median (%)	1.30	0.71	0.59
75% percentile (%)	3.68	3.42	0.26
99% percentile (%)	12.1	11.8	0.3
Std. Dev (%)	5.19	5.51	
Skewness	-0.43	-0.62	
Kurtosis	9.16	10.1	
No. of Obs.	556	572	

Panel B: Excluding 1% - 99%

	United	Divided	Difference
Mean (%)	**0.83*****	0.25	**0.59****
	(4.47)	(1.33)	**(2.23)**
1% Percentile (%)	-12.0	-11.8	0.2
25% Percentile (%)	-1.64	-2.3	0.66
Median (%)	1.29	0.726	0.56
75% Percentile (%)	3.60	3.40	0.20
99% Percentile (%)	10.0	9.83	0.17
Std. Dev (%)	4.35	4.38	
Skewness	-0.64	-0.51	
Kurtosis	3.90	3.47	
No. of Obs.	556	572	

Panel C: Sharpe Ratios

	United	Divided
Annual	**0.57*****	0.08
Sharpe Ratios	**(3.90)**	(0.58)

Note: Monthly excess log returns (log value-weighted returns less log T-bill, VWR-TBL, in monthly percentage), 1927:01 - 2020:12. Panel A uses the entire sample, while Panel B uses the same dataset with the top and bottom 1% trimmed to ensure that the united versus divided results are not driven by extreme outliers. Panel C reports annual in-sample Sharpe ratios (with test statistics in parentheses assessing whether they differ from zero). In Panels A and B, the parentheses under the top row indicate OLS t-statistics, with corresponding ***/**/* denote the statistical significance at 1%/5%/10% level.

Table 2.2: **Average Stock Market Returns Under Political Regimes**

Panel A: Full sample (1927:01 - 2020:12)

		(1) VWR-TBL	(2) EWR-TBL
Governments	United	10.30	16.78
	($N = 556$)	(3.66)	(4.07)
	Divided	1.60	-0.00
	($N = 572$)	(0.56)	(-0.01)
	Difference	**8.7****	**16.78*****
		(2.08)	**(3.07)**
Presidents	Democrat	10.72	15.70
	($N = 574$)	(4.22)	(4.11)
	Republican	0.88	0.57
	($N = 554$)	(0.28)	(0.15)
	Difference	**9.85****	**15.13*****
		(2.20)	**(2.59)**

Panel B: Post-World War II (1947:01 - 2020:12)

		(1) VWR-TBL	(2) EWR-TBL
Governments	United	10.11	16.84
	($N = 340$)	(4.20)	(5.16)
	Divided	3.87	2.00
	($N = 548$)	(1.54)	(0.61)
	Difference	**6.23***	**14.84*****
		(1.76)	**(3.16)**
Presidents	Democrat	9.84	12.92
	($N = 408$)	(4.61)	(4.36)
	Republican	3.21	3.23
	($N = 480$)	(1.16)	(0.88)
	Difference	**6.63***	**9.69****
		(1.92)	**(2.00)**

Note: This table reports average returns across political regimes. Panel A uses data spanning from 1927 to 2020, while Panel B restricts the analysis to the post-war period beginning in 1947. VWR–TBL represents excess stock returns, calculated as value-weighted market returns minus the three-month Treasury bill rate; EWR–TBL is computed using equal-weighted portfolio returns. Numbers in parentheses are t-statistics, adjusted using the Newey–West procedure with 24 lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The lower part of Panel A reports estimates for the Presidential puzzle of Santa-Clara and Valkanov (2003) for the updated sample ending in 2020. Average value-weighted excess returns were 10.72% annualized under Democrat presidents versus 0.88% under Republicans, with a t-statistic for the difference of 2.2. For equal-weighted returns, the averages were respectively 15.7% and 0.57% with a t-statistic for the difference of 2.59. We find that these outcomes closely parallel those for united versus divided governments, and we show in the next section that the two relationships are independent.

In Panel B of the same table, we report post-war results from 1947. We focus on this sample for three reasons. First, we want to make sure our results do not entirely depend on the Great Depression and the Second World War. Second, the 20$^{\text{th}}$ amendment to the

Constitution of the United States was adopted on January 23, 1933 in order to decrease the so called "lame duck" period, the period served by the president and the Congress after an election but before the end of the terms of those that were not re-elected.[10] Finally, Hibbs (1987) argues that the macroeconomic structure of the economy has changed substantially since World War II.

As Panel B demonstrates, average value-weighted excess returns under United versus Divided governments differ by 6.23% per annum (Newey–West adjusted t-statistic of 1.8), comparable to the presidential gap of 6.63% (t = 1.9). For equal-weighted excess returns, the government gap is even more pronounced at 14.84% (t = 3.2), whereas the presidential premium is considerably weaker, amounting to 9.69% with a t-statistic of 2.0. Taken together, the government gap is comparable to the previously documented presidential gap for value-weighted stock return results, and shows a larger difference for equal-weighted returns. We demonstrate in Section 2.3.1 that the slightly weaker post-war outcomes in the value-weighted excess returns are primarily caused by the election premium (CM). By eliminating these small samples of months, the magnitude of the government gap in stock returns becomes more evident.

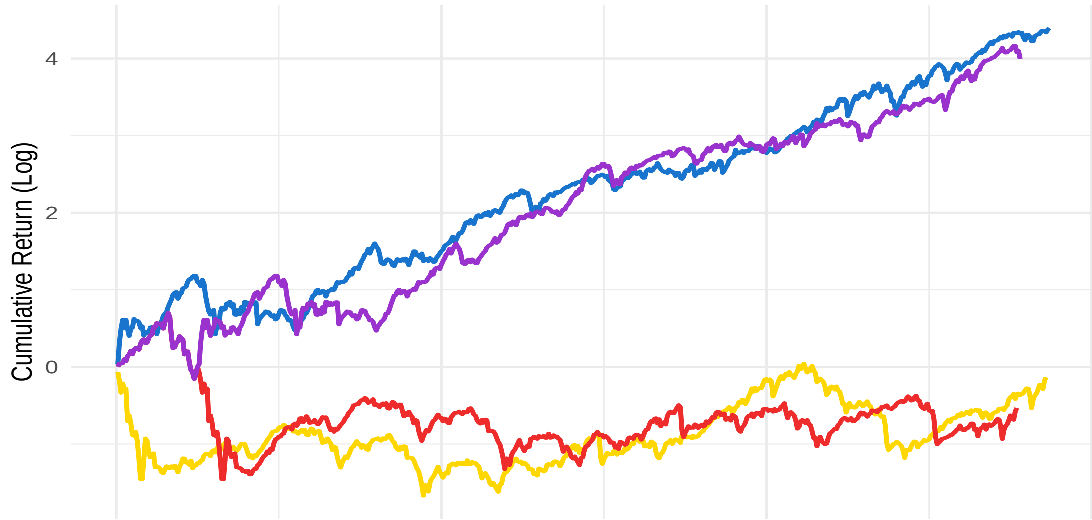
2.2.3 How does government cycle interact with presidential cycle?

Two political dummies we defined earlier (**GOV** and **PRESID**) coincide 72% during 1927-2020, with much higher rate of coincidence in the first half.[11] Since the government's status is inherently linked to the political affiliation of the presidents, it is crucial to carefully distinguish between the two. In particular, is the government premium simply a repackage of the presidential premium? Our findings demonstrate that the government cycle is a distinct and independent phenomenon.

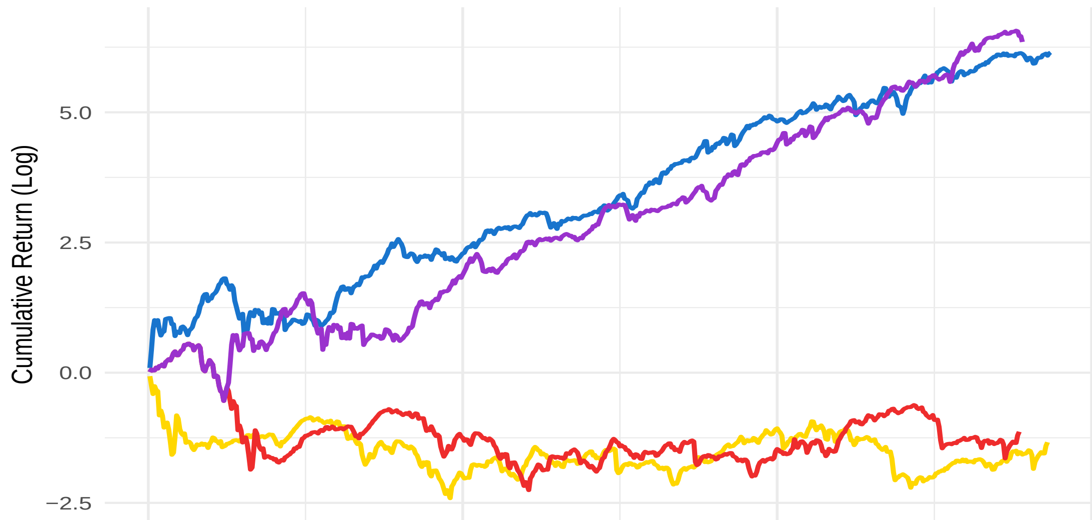
[10] Under section 1 of the amendment, it reads *"The terms of the President and Vice President shall end at noon on the 20th day of January, and the terms of Senators and Representatives at noon on the 3rd day of January, of the years in which such terms would have ended if this article had not been ratified; and the terms of their successors shall then begin."* So, since after the amendment, congressional terms start before presidential ones, it becomes clear that the new incoming Congress would hold a possible election in case that no presidential candidate gets the majority of the electoral vote. Before the amendment, new members of Congress and the new president had to wait until March 4 of the upcoming year to give them sufficient time to settle their affairs in their home states as well as to travel to Washington D.C. The problem of distance was no longer a problem by the first quarter of the 20th century. Furthermore, six months of waiting were considered a very long period. For example, examining the 72nd Congress (March 1931 - March 1933), we see that almost a quarter of its members were not re-elected due to the Great Depression. Nevertheless, both the newly elected members of Congress and President Roosevelt faced an extensive delay before they could finally commence their governance duties. See https://constitution.congress.gov/browse/amendment-20/ for more details.

[11] Splitting the CRSP sample into two equal parts, we find that Democratic presidents and United governments coincide 83% (61%) of the time during the first (second) half of the sample. The high correlation in the first half is due to two Democratic presidents, Franklin D. Roosevelt and Harry S. Truman. During this time, the government was mostly unified.

Figure 2.1: **Cumulative Stock Market Returns Across Political Regimes (1927–2020)**



(a) Value-weighted excess returns (VWR–TBL)



(b) Equal-weighted excess returns (EWR–TBL)

Note: These figures illustrate the cumulative return performance of value-weighted average excess returns (Panel A) and equal-weighted average excess returns (Panel B) across four distinct political regimes over time. The political regimes considered are: United Governments (purple), Divided Governments (yellow), Democratic Presidents (blue), and Republican Presidents (red). The cumulative return is calculated using monthly stock return samples from 1927 to 2020. Returns are tracked separately for each political regime, pausing at the end of a regime and resuming at the start of the next.

Figure 2.1 highlights one of the central findings of this paper. Panel A plots the monthly cumulative excess value-weighted returns over time across four distinct political regimes:

United government (purple), Divided government (yellow), Democratic president (blue), and Republican president (red). The purpose is to illustrate long-term trends and assess which political regime best explains stock market performance. As the figure shows, both the Democratic president and United government regimes are associated with consistently strong cumulative returns. Notably, the United government regime independently delivers the high cumulative log returns, suggesting that alignment between the executive and legislative branches plays a key role in driving market performance. In contrast, Republican president and Divided government regimes exhibit much weaker results. Panel B, which presents cumulative excess returns based on equal-weighted portfolios, provides further support, showing that United governments not only outperform Divided governments, but also exceed the performance of Democratic presidencies alone.

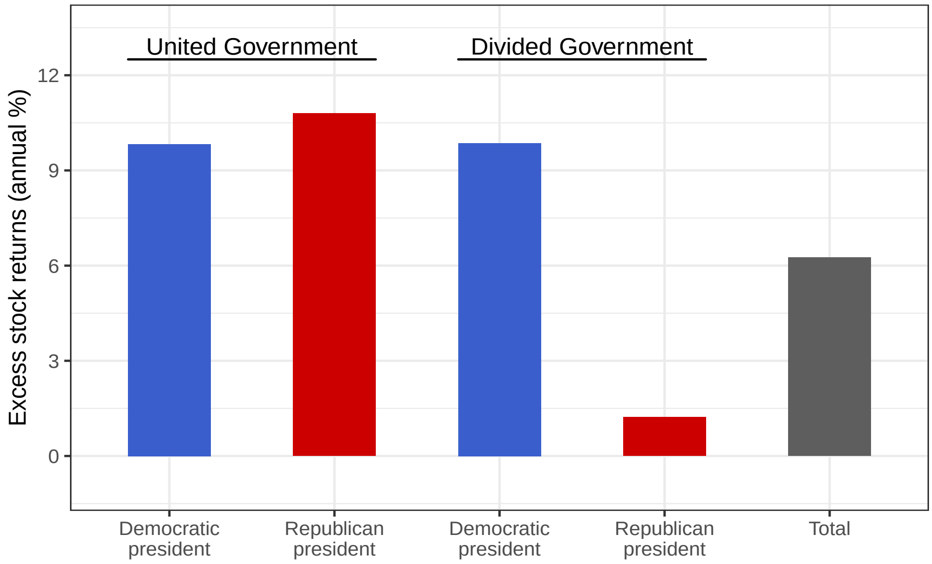
In Figure 2.2, we conduct two-way sorts based on the presidential and government cycles, recording the average value-weighted and equal-weighted stock returns during the post-war period (1947–2020). Each bar represents mean excess stock returns, with blue bars indicating Democratic presidents and red bars indicating Republican presidents. The first two bars correspond to United governments, while the following two represent Divided governments. The black bar labeled "Total" on the right represents the average excess stock returns for the entire sample considered.

A key observation is that Republican presidents delivered significantly higher stock market returns when they held unified control of government, with average excess returns of 10.8% for value-weighted portfolios and 14.4% for equal-weighted portfolios. This strong performance rivals that of Democratic presidents under any government configuration and often exceeds both their outcomes and the overall market average (black bar). In other words, contrary to conventional wisdom in the economics and finance literature, the so-called presidential gap in stock market performance is not driven by a general underperformance of Republican presidents. Instead, it is specifically Republican presidents governing under a divided government who are associated with weak market returns.

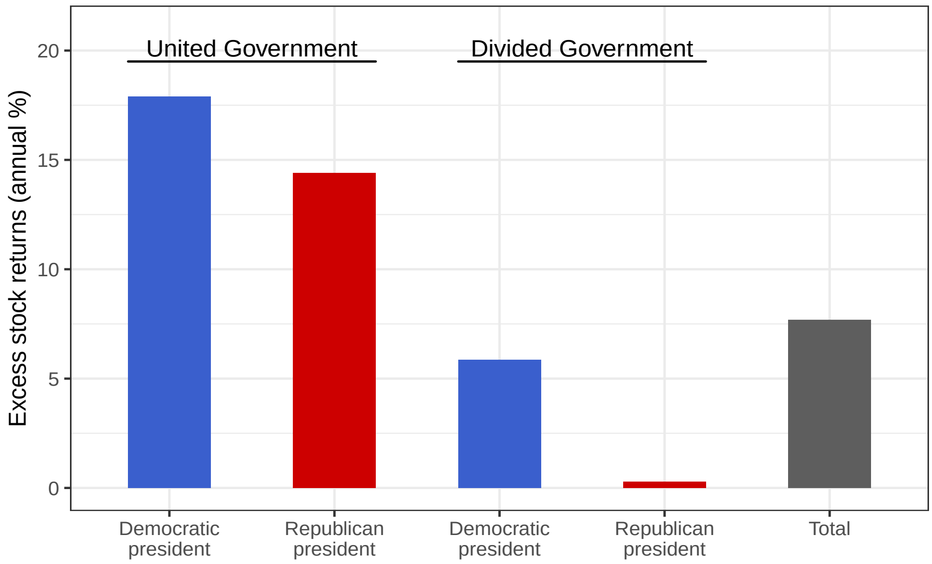
To further validate our findings, we implement a regression framework to examine the government cycle's role in explaining stock returns. We run the following regression:

$$
\begin{aligned}
r^e_{t+1} &= \alpha + \beta'\mathbf{X}_t^{\text{political}} + \gamma'\mathbf{X}_t^{\text{macro}} + \varepsilon_t \\
&= \alpha + \underbrace{\beta_1\mathbf{GOV}_t + \beta_2\mathbf{PRESID}_t + \beta_3\mathbf{ELECTION}_t^{mid} + \beta_4\mathbf{ELECTION}_t^{pres}}_{\mathbf{X}_t^{\text{political}}} \\
&\quad + \gamma'\mathbf{X}_t^{\text{macro}} + \varepsilon_t
\end{aligned} \tag{2.1}
$$

Figure 2.2: **President-Government Two-way Sorts**



(a) Value-weighted excess returns (VWR–TBL)



(b) Equal-weighted excess returns (EWR–TBL)

Note: These figures show average excess stock returns (per annum) using two-way sorts: presidents' political party and the government status. Panel A (B) uses value-weighted (equal-weighted) excess returns VWR-TBL (EWR-TBL) during the post-war periods 1947:01 - 2020:12. The labels on X-axis are the political party of the presidents. The last column (Total) shows the average excess stock returns during the relevant periods.

where r^e_{t+1} is the monthly excess stock returns (either excess value-weighted stock returns or excess equally-weighted stock returns), **GOV** is the government dummy that equals one (zero) when the government is unified (divided), **PRESID** is the presidential dummy that equals one (zero) when the incumbent president is from the Democratic party (Republican party), **ELECTION** is the post-midterm or post-presidential election dummies, which will be further detailed in Section 2.3.1. We control for a comprehensive set of macroeconomic variables,[12] as stock returns are influenced by business cycles, which are in turn linked to political variables. It is crucial to determine whether the observed political effects genuinely impact stock returns or merely reflect macroeconomic fluctuations. For this reason, we include well-established financial predictors of market returns, such as the dividend-price ratio. If political variables simply act as proxies for business cycles, they should not provide additional predictive value once these financial controls are included.

Table 2.3 presents the results. We first observe that each of **GOV**, **PRESID**, and **ELECTION**^{mid} individually explain aggregate stock market returns (columns (1), (2), and (3), respectively). Next, we examine the interplay of political variables in columns (4) through (7) and uncover two findings. Adding the post-midterm (and post-presidential) election months to either the presidential dummy or government dummy does not alter the impact of these two variables. This is expected as post-election months take up small percentages of the entire samples. Secondly, and most importantly, we find that the presidential dummy variable loses its explanatory power in explaining aggregate stock markets once we control for the status of government. In panel A, the coefficient for **PRESID** displays a striking 40% reduction, dropping from 0.898 in column (2) to 0.543 in column (6) when the government dummy **GOV** is added. It also loses its statistical significance in explaining the value-weighted stock returns. Furthermore, when we examine equal-weighted stock returns in Panel B, the presidential dummy experiences a comparable loss in explanatory power (though it still retains statistical significance at the 10% level).

Overall, our findings emphasize the importance of the government cycle in explaining stock market behavior. Once government status is accounted for, the president's political affiliation no longer plays a significant role in value-weighted excess returns and, while it retains some explanatory power in equal-weighted returns, its statistical significance is notably reduced. This highlights that it is the alignment or division of government—rather than presidential party alone—that better captures variation in market performance.

[12]Following earlier literature, we make use of many available macroeconomic factors: log of dividend-price ratio (dp), default yield (dfy), term spread (ts), long-term yield (lty), relative interest rate (rrel), aggregate book-to-market ratio (bm), equity issuing and repurchasing relative to the price level (ntis), inflation (infl), and stock market variance (svar). While including all available information reduces concerns related to omitted variables, our results remain unchanged when we use partial lists of these macroeconomic variables.

Table 2.3: **Regressions on Political Dummies and Macroeconomic Variables**

Panel A: Dependent variable is VWR_TBL (%)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GOV	**1.120****			**1.145****		**0.886****	**0.918****
	(2.47)			**(2.54)**		**(2.06)**	**(2.14)**
PRESID		**0.898****			**0.892****	0.543	0.523
		(2.29)			**(2.25)**	(1.55)	(1.46)
Election^{mid}			**1.280*****	**1.334*****	**1.264*****		**1.313*****
			(3.18)	**(3.32)**	**(3.08)**		**(3.24)**
Election^{pres}			0.333	0.272	0.367		0.304
			(0.67)	(0.55)	(0.74)		(0.61)
No. of Obs.	1128	1128	1128	1128	1128	1128	1128
Constant?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{X}_t^{macro}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2 (%)	2.5	2.3	2.1	3.0	2.6	2.7	3.0

Panel B: Dependent variable is EWR_TBL (%)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GOV	**2.092*****			**2.115*****		**1.730*****	**1.757*****
	(3.37)			**(3.45)**		**(3.12)**	**(3.21)**
PRESID		**1.530*****			**1.532*****	**0.837***	**0.826***
		(2.71)			**(2.69)**	**(1.85)**	**(1.80)**
Election^{mid}			**2.193*****	**2.292*****	**2.165*****		**2.260*****
			(3.29)	**(3.47)**	**(3.20)**		**(3.40)**
Election^{pres}			**1.319***	1.21	**1.376***		1.256
			(1.66)	(1.58)	**(1.75)**		(1.63)
No. of Obs.	1128	1128	1128	1128	1128	1128	1128
Constant?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{X}_t^{macro}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2 (%)	4.4	3.6	3.6	5.4	4.6	4.6	5.6

Note: This table presents regressions of monthly excess value-weighted stock returns (Panel A) and excess equal-weighted stock returns (Panel B) on political variable dummies and macroeconomic variables. The data spans from 1927 to 2020. Macroeconomic variables include log of dividend-price ratio (dp), default yield (dfy), term spread (ts), long-term yield (lty), relative interest rate (rrel), aggregate book-to-market ratio (bm), equity issuing and repurchasing relative to the price level (ntis), inflation (infl), and stock market variance (svar). They are scaled before we conduct the regression, and results are suppressed for brevity. Numbers in parenthesis are t-statistics, adjusted using 24 lags Newey-West standard errors. ***/**/* denote the statistical significance at 1%/5%/10% level.

2.2.4 Economic growth

The partisan theory argues that, in capitalist democracies, Republicans (or right-wing parties) are more concerned about inflation while Democrats (or left-wing parties) opt for low unemployment at the cost of inflation (Hibbs, 1977). The Phillips curve argument of Nordhaus (1975) combined with the empirical regularity of Okun's law suggests a simple intuition on how Democratic presidents earn higher economic growth, which is supported in the U.S. data (Blinder and Watson, 2016).

Economic growth depends also on the government cycle, and is in fact stronger than the presidential growth gap. The government story is markedly different from earlier work. The decision to prioritize unemployment or inflation is not determined by the government's status, as both Republican and Democratic presidents can face united or divided governments. Indeed, our estimates suggest that the inflation difference between United versus Divided governments is virtually none (about 0.05% across 121 years), while Democratic presidencies experienced 1.2% higher inflation compared to Republican presidencies during the same period. Rather, it appears that the political conflict or sabotage that comes from the absence of unified control over the government. A simple analog can be found in the division of labor between the policymakers and the professional staff à la Romer and Romer (2008). Just as monetary policy is influenced both by the FOMC and the supporting members (i.e. staff who prepare a comprehensive forecast ahead of each FOMC gathering), it is possible that leaders should not bear the sole responsibility for growth, as the supporting entities (Congress) must also collaborate to foster favorable economic outcomes.

Table 2.4: **Average Economic Growth, 1900 to 2020**

Presidents / Governments	Democratic presidents	Republican presidents	Average growth
United	5.40% (4.01) (40 years)	3.31% (2.39) (29 years)	4.51% (4.76) (69 years)
Divided	2.28% (2.91) (16 years)	1.94% (2.70) (36 years)	2.05% (3.15) (52 years)
Average growth	4.51% (4.53) (56 years)	2.56% (3.32) (65 years)	121 years

Note: This table records average real GDP growth in percentage term. The sample period is between 1900 and 2020. Numbers in parentheses are t-statistics, adjusted using Newey-West procedure with 24 lags. Number of years in each category is also presented. They are calculated to the nearest integer, so sum up may not be exact.

Table 2.4 categorizes real economic growth into presidential and government cycles, and shows that the government gap (2.5%) is higher than the presidential gap (2.0%) across 121 years. The economic growth advantage is salient during Democratic-United governments. The low t-statistics during Republican-United governments come mainly from the 1930s where the economy is commonly described as extremely volatile: for instance, the standard deviation of the quarterly growth rate is 12.4% pre-World War II. We see that, despite the high pre-WWII volatility, the difference of real growth rates between unified and Divided governments remains economically and statistically significant.

To partially alleviate concerns that economic growth is endogenous with respect to political variables, we conducted the same analysis without including NBER recession periods (this result is undocumented but available upon request). We observe that NBER recession months are concentrated during Republican presidencies,[13] so that pulling these months out shrinks the presidential growth gap to 0.9%. On the other hand, NBER recessions were fairly shared between United and Divided governments, and we see that removing these months widens the government growth gap to 3.6%. Hence, the government gap in economic growth is salient regardless of the business cycles. In sum, the results presented in this section confirm that Divided government is associated with lower economic growth, and the magnitude of the government effect is stronger than the president effect on growth (Jones and Olken, 2005).

2.3 Discussion

2.3.1 The Divided discount

In a related work, Chan and Marsh (2021) (CM) document election cycles where post-midterm election months exhibit higher asset prices due to lower future discount rates as the embedded political risk decreases. There is a natural link between this paper and ours, as we examine government status that results from midterm elections.

To ensure that our government premium result is not the same as the election premium, we repeat the Table 2.2 exercise without post-election months.[14] Table 2.5 shows that the government gap strengthens and becomes more pronounced relative to the presidential premium. Specifically, compared to Table 2.2, the government premium in value-weighted excess stock returns (Panel A, column (1) VWR–TBL) increases from 8.70% to 11.64%. A similar rise is observed in the post-war sample, where the premium grows from 6.23% to 10.74%.

The key insight from the previous table is that the strengthened government gap is largely driven by the post-election premium when the resulting government is divided. As shown in the right side of Panel A in Figure 2.3, during 1927–2020, the 1.6% annualized average excess returns under Divided governments (labeled ‘C’) can be decomposed into two distinct periods: post-election months (labeled ‘A’ or “Post-Election (PE)”), where stock returns are high due to the resolution of uncertainty, and non-post-election months (labeled ‘B’ or “Non-PE”), where returns are negative.

[13]Throughout the CRSP sample 1927 - 2020, Republican presidents are over-represented in NBER recessions (4 years for Democratic presidents vs. 14 years for Republican presidents). See also Figure 2.6 and related discussion.

[14]We drop both the post-midterm election months (December of the midterm election year up to April of the subsequent year) and the post-presidential election months (December of the presidential election year up to April of the subsequent year) as government status meets a possible change every two years. This also levels the playing field in comparing the government premium with the presidential premium as post-presidential election is an amalgam of both the change of presidents and government status.

Table 2.5: **Average Stock Market Returns Under Political Regimes, Post-Election Months Removed**

Panel A: Full sample (1927:01 - 2020:12), Excluding Post-Election Months

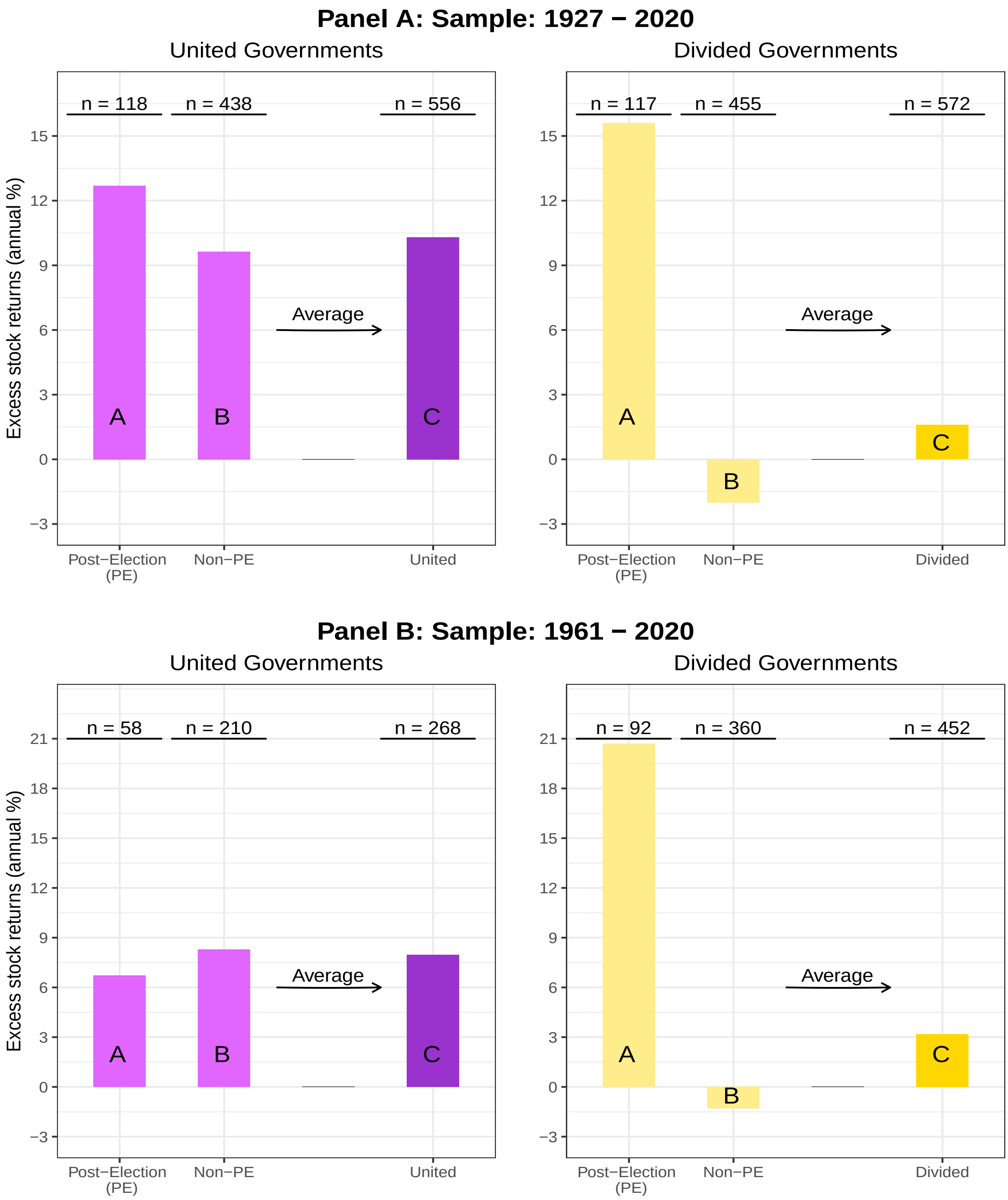
		(1) VWR-TBL	(2) EWR-TBL
Governments	United	9.64	14.90
	($N = 438$)	(3.32)	(3.68)
	Divided	-2.00	-5.30
	($N = 455$)	(-0.60)	(-1.28)
	Difference	**11.64*****	**20.20*****
		(2.73)	**(3.82)**
Presidents	Democrat	9.17	13.2
	($N = 456$)	(3.42)	(3.38)
	Republican	-1.98	-4.36
	($N = 437$)	(-0.54)	(-0.94)
	Difference	**11.15****	**17.56*****
		(2.38)	**(2.99)**

Panel B: Post–World War II (1947:01–2020:12), Excluding Post-Election Months

		(1) VWR-TBL	(2) EWR-TBL
Governments	United	10.63	15.81
	($N = 267$)	(4.15)	(4.49)
	Divided	-0.10	-4.11
	($N = 436$)	(-0.04)	(-1.15)
	Difference	**10.74****	**19.92*****
		(2.40)	**(3.94)**
Presidents	Democrat	8.46	10.45
	($N = 323$)	(3.49)	(3.16)
	Republican	0.16	-2.50
	($N = 380$)	(0.05)	(-0.62)
	Difference	**8.29****	**12.95*****
		(2.25)	**(2.65)**

Note: This table reports average returns across political regimes. Unlike Table 2.2, we exclude post-election months defined by Chan and Marsh (2021) as these periods may distort comparisons of long-term performance between united and divided governments. Panel A uses data spanning from 1927 to 2020, while Panel B restricts the analysis to the post-war period beginning in 1947. VWR–TBL represents excess stock returns, calculated as value-weighted market returns minus the three-month Treasury bill rate; EWR–TBL is computed using equal-weighted portfolio returns. Numbers in parentheses are t-statistics, adjusted using the Newey–West procedure with 24 lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 2.3: **Government Cycle: Post-Election vs. Non Post-Election months**



Note: These figures show average excess stock returns (per annum) during two groups of periods: 'Post-Election (PE)' indicates five months after midterm election and presidential election periods. Non-PE are all other months. The above panel uses the full sample (1927:01 - 2020:12), and the below panel uses the latter half sample (1961:01 - 2020:12) during when political polarization has been known to rise. n is the number of months that fall into each category.

This decomposition yields two key findings. First, the post-election premium is especially pronounced when the election results in a Divided government. Competitive elections that lead to such outcomes heighten pre-election uncertainty and risk aversion. Once resolved, this uncertainty—especially prominent under Divided outcomes—reduces future discount rates, boosting asset prices. This is exactly what Chan and Marsh (2021) finds in their paper and is clearly visible when we compare 'A' across the upper panels. The lower panels, which focus on the 1961–2020 sample (a period marked by rising political polarization (Baker et al., 2014)) further reinforce this dynamic. When the resulting government is united, the post-election premium is much smaller (Panel B, left).

Second, examining non-post-election months ('B') reveals a stark contrast between government types. United governments are associated with strong positive returns, while Divided governments exhibit negative returns. To contextualize these results, the average returns reported in Table 2.2 correspond to the comparison of the 'C' bars across each panel, while the adjusted results in Table 2.5 reflect the comparison of the 'B' segments. The key takeaway is that rising political polarization in recent decades has led to sharply higher stock prices in the brief window following elections that result in divided control, temporarily inflating the average performance of Divided governments. This post-election bump obscures the underlying long-term underperformance of Divided regimes—precisely why we exclude these short-lived episodes and reexamine the government gap in Table 2.5. While post-election months benefit from a temporary drop in discount rates, broader Divided government periods are likely marked by persistently higher discount rates, leading to weaker market performance.[15] Removing post-election months therefore reveals the true magnitude of the underperformance associated with Divided government regimes.

2.3.2 Only 47 Governments

Although our study covers 94 years of stock return data, government changes occurred only 46 times or fewer within this timeframe. The infrequency of these transitions raises potential concerns about statistical artifacts, including spurious correlations.

To tackle this issue, we provide five additional results. First, we find that our main finding remains when we consider pre-CRSP stock return results from 1871 to 1925. As the results in Table 2.6 suggest, the government cycle emerges as a robust fact across 149 years of U.S. history. Second, the dominance of a political party in either the Senate or the House alone does not explain the variation in excess stock returns. This placebo test reinforces our argument that it is the government trifecta (or the lack of it) that makes a difference (result is available in the Appendix).

[15]In the Appendix, we show that the government premium remains robust when dividends are not reinvested.

Table 2.6: **149 Years of Political Cycles**

Panel A: 149 years of data (1871:03 - 2020:12)

Governments	United ($N = 761$)	Divided ($N = 664$)	Difference
	4.87%	-2.35%	**7.21%****
	(2.48)	(-0.89)	**(2.18)**
Presidents	Democrats ($N = 608$)	Republicans ($N = 817$)	Difference
	5.62%	-1.56%	**7.18%****
	(2.90)	(-0.64)	**(2.11)**

Panel B: First half (1871:03 - 1946:01)

Governments	United ($N = 484$)	Divided ($N = 228$)	Difference
	2.21%	-6.64%	**8.85%***
	(0.83)	(-1.31)	**(1.70)**
Presidents	Democrats ($N = 275$)	Republicans ($N = 437$)	Difference
	3.25%	-3.05%	6.30%
	(0.91)	(-0.83)	(1.15)

Panel C: Second half (1946:02 - 2020:12)

Governments	United ($N = 277$)	Divided ($N = 436$)	Difference
	9.47%	-0.10%	**9.57%****
	(4.30)	(-0.03)	**(2.13)**
Presidents	Democrats ($N = 333$)	Republicans ($N = 380$)	Difference
	7.55%	0.16%	**7.39%***
	(3.99)	(0.06)	**(1.78)**

Note: This table presents average returns (% per annum) across different political regimes. We obtain pre-CRSP stock return data (1871:03 - 1925:12) from the Yale website and match it with the CRSP sample. Panel A displays the full 149 years of data, categorized by government type and presidential cycle. Panels B and C report the results for the first and second halves of the period, respectively. To analyze average stock return performance during specific stages of government or presidential regimes, we exclude post-election months defined by Chan and Marsh (2021) as these periods may distort comparisons of long-term performance between united and divided governments. Numbers in parenthesis are t-statistics, adjusted using Newey-West procedure with 24 lags. ***/**/* denote the statistical significance at 1%/5%/10% level.

Third, we address the persistence issue using a randomization-bootstrap procedure following Santa-Clara and Valkanov (2003) and Cheng (2022). The analysis is done in the following way. (1) First, we produce 10,000 time series of $\mathbf{r}^e_{t+1}$ where each time-series is drawn randomly from the 94 years of monthly stock returns ($T = 1128$) with replacement. $\mathbf{r}^e_{t+1}$ is the value-weighted excess stock returns (VWR_TBL) or equal-weighted excess stock returns (EWR_TBL). (2) Next, we independently and randomly select the government dummy $\mathbf{GOV}_t$, ensuring that the government structure remains consistent for two years. In other words, regardless of the randomly chosen government status, it will last for a duration of 24 months. We then do a coin toss to determine the next government, which also would last for 24 months.[16] (3) For each of $j = 1, 2, \ldots, 10000$ simulation, we run a predictive regression $\{\mathbf{r}^e_{t+1} = \alpha + \beta\mathbf{GOV}_t + \varepsilon_{t+1}\}_j$ and obtain t_j, t-statistics for $\widehat{\beta}$ using standard errors adjusted for heteroskedasticity. (4) Letting t_0 the t-statistics obtained using the original U.S. sample of 94 years (we find that $t_0 = 2.42$ when r^e_{t+1} is VWR_TBL, and $t_0 = 3.29$ when r^e_{t+1} is EWR_TBL), compute the bootstrapped p-value for the coefficient $\widehat{\beta}$ as sum of the number of t_js that are greater than or equal to t_0 and the number of t_js that are less than or equal to t_0, divided by the number of simulation. As a result, the bootstrapped p-values that we obtain are 0.016 when the dependent variable r^e_{t+1} is VWR_TBL (0.001 when EWR_TBL), corroborating the significance of the government cycle we establish in the previous section.

Table 2.7: **Government Cycle exists in the United Kingdom**

Countries	Sample	United Government	Divided Government	Difference
United Kingdom	1922 - 2022	5.04	-9.06	**14.10****
		(2.47)	(-1.08)	**(2.11)**

Note: This table reports average returns across government cycles in the United Kingdom, using monthly data from 1922 to 2022. Excess stock returns—calculated as value-weighted returns minus the three-month Treasury bill rate—are obtained from the Global Financial Database. Numbers in parentheses are t-statistics, adjusted using the Newey–West procedure with 6 lags. Although results using 24 lags also show statistical significance at the 10% level (unreported), we rely on the standard 6 lag specification since changes in government status in the UK occur at irregular intervals, unlike the fixed 24-month election cycle in the United States.
***/**/* denote the statistical significance at 1%/5%/10% level.

Fourth, we increase the power of our test by examining whether countries outside the U.S. demonstrate a similar governmental cycle. For this purpose, we use stock market data from the United Kingdom.[17] In the United Kingdom, a 'hung' parliament takes place when no single party holds a majority of seats (usually 326 out of 650 seats) in the House of Commons. We make use of this fact to define a government as Unified (Divided) when a single party holds (does not hold) a majority of seats. As presented in Table 2.7, we observe that a large government gap (14% per annum) exists in the UK as well.

Finally, we present evidence that the government cycle also exists at the U.S. state level. We run the following monthly panel regression with state- and time-fixed effects:

$$\mathbf{r}^e_{i,s,t+1} = \alpha + \beta\ \textbf{State-GOV}_{s,t} + \gamma\ \textbf{State-PRESID}_{s,t} + \delta\ \textbf{State-EPU}_{s,t} + \theta_s + \eta_t + \varepsilon_{s,t+1} \quad (2.2)$$

where $\mathbf{r}^e_{i,s,t}$ is the excess return on firm i headquartered in state s at month t; $\textbf{State-GOV}_{s,t}$ is the state level government dummy that equals 1 when one party controls all of the gov-

[16]Given that our sample includes 47 governments, resulting in 46 changes of government, the probability of the government maintaining a unified (or divided) status throughout the entire sample is an unlikely 1.4e-12%.

[17]The data is obtained from Global Financial Database, where we use FTSE All-Share Index as the main stock market measure. Similar to our main empirical work, we subtract 3-month UK Treasury bills to construct excess stock returns.

ernor, state Senate, and state House (i.e., the state government is united) and 0 otherwise; **State-PRESID**$_{s,t}$ is the state level president (i.e., the governor) dummy that equals 1 when the incumbent governor is from the Democratic party (0 when the governor is from the Republican party); **State-EPU**$_{s,t}$ is the state level Economic Policy Uncertainty measure of Elkamhi et al. (ming) as a control variable; θ_s and η_t are state- and time-fixed effects, respectively. The data we use for this analysis is from 1992 to 2020.

Table 2.8: **State Level Government Cycle of Stock Returns**

	(1) Full-sample	(2) Sub-sample (No NY firms)	(3) Sub-sample (No TX firms)	(4) Sub-sample (No CA firms)	(5) Sub-sample (No S&P 500 firms)
State-GOV$_{s,t}$	**0.118*****	**0.122*****	**0.101*****	**0.062***	**0.120*****
	(3.78)	**(3.75)**	**(3.07)**	**(1.90)**	**(3.49)**
State-PRESID$_{s,t}$	**0.060***	0.044	**0.067****	-0.028	**0.067***
	(1.88)	(1.30)	**(2.08)**	(-0.86)	**(1.93)**
State-EPU$_{s,t}$	**-0.047***	**-0.049***	-0.023	-0.013	-0.044
	(-1.68)	**(-1.72)**	(-0.82)	(-0.45)	(-1.48)
No. of firm-month obs.	1,621,260	1,417,926	1,451,481	1,387,559	1,474,330
Adj. R squared (%)	8.7	8.7	8.9	8.5	8.5
Time FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports the monthly panel regression of the excess one-month-ahead firm stock returns that are headquartered in each U.S. state on state level government dummy (1 when the state level government is united; 0 divided), state level presidential dummy (1 when the state governor is from the Democratic party; 0 Republican party), and the state-EPU (Elkamhi et al., ming). The data spans from 1992 to 2020. Sub-sample results in columns (2) - (4) address the concern about some states having more firms than others. Sub-sample result in column (5) exclude firms when they are listed as part of S&P 500 index. They are moved back to this analysis once they disband from the index. The t-statistics are based on standard errors clustered at the firm-level. ***/**/* denote the statistical significance at 1%/5%/10% level.

Table 2.8 reports the panel regression results, and show that the government cycle also exists at the state-level. In column (1) of the table, we run the panel regression with all available samples (a total of 16,351 firms with 1,621,260 firm-month observations) and observe that the state-level government dummy (**State-GOV**) positively predicts the one-month ahead excess stock returns. In column (2) to (4) of the same table, we make our results more reliable by re-running the panel regression using sub-samples.[18] Each of the regression in column (2) to (4) pulls out the entire sample in each state and reaffirms that the government cycle result is not dependent on a single state. For example, column (2) shows that the panel regression that excludes all firms headquartered in New York (firm-month observations

[18]The data used in this panel regression is an unbalanced panel where firms are disproportionately headquartered in some states. Indeed, listed firms in three major states, New York (NY), Texas (TX), and California (CA), account for 38% of all firms and hold a significantly higher share of market capitalization. If the government cycle does exist at the state level, then the main specification laid out in column (1) should not be influenced by an omission of a single state.

headquartered in NY take up 12.5% of the total sample) still exhibits the government cycle of stock returns. Finally, in column (5), we exclude firm-month samples when stocks are part of S&P 500 because they attract national or global attention from investors, rather than the state level focus relevant to this analysis. The result is very similar to previous findings. The state level governor dummy (**State-PRESID**), on the other hand, is only weakly significant in the full-sample panel regression in column (1), and sometimes not significant.

2.3.3 United to Divided, Divided to United

What makes a change of government status, i.e., from united to divided and the other way around? We conclude this section by establishing a series of stylized facts on the political cycle.

Stylized fact 1. (United to Divided): It's not easy to retain the control of Congress. During almost every presidential term, the party in control of the White House typically experiences a decline in congressional seats during the midterm election. It seems that voters gain a deeper understanding of the president's competence, personality, and policies in the two years following the presidential election.[19] This is especially true in the post-1960s where the level of political polarization increased significantly. Prior to this period, both Republicans and Democrats were able to control Congress for quite a time. For instance, Democrats in the 1960s (both John F. Kennedy and Lyndon B. Johnson) were able to control Congress until the end of the presidency, and Republicans also survived midterm elections quite a few times. All in all, voters' expectations turn into disappointment, leading to cold showers. The sitting presidents tend to lose grip, never to regain complete control of Congress.

Stylized fact 2. (Divided to United): You (re-)gain control of Congress only through presidential elections. Throughout the 20th and 21st U.S. election history in our sample, government status changed from Divided to United only through presidential elections. We also observe a bipartisan difference on this matter. When Democrats won presidential elections, they always did so with control of Congress. Half of Republican presidents, on the other hand, won the presidential election but not control of Congress. Consistent with the first stylized fact, presidents who started their term without control of Congress never gained full control until their presidency ended.

Stylized fact 3. (Exceptions): Exceptions come from unexpected circumstances. We note two exceptions to the above rules. First, George W. Bush at the end of 2002 was able to regain control of Congress. As a matter of fact, George W. Bush started his first term with the support of Congress, but lost control in June 2001 as Vermont Republican senator James Jeffords unexpectedly left the Republican party (Jayachandran, 2006). Also, the 9/11 attack in 2001 resulted in a 'rally around the flag' effect that had led to strong support toward the

[19] See, for instance, Knight (2017) for a simple model that jointly describes midterm penalty, decreased voter turnout during midterm elections, and mean reversion to the voter partisanship.

incumbent political party. Democratic president Harry S. Truman is another exception. He was able to revert to united status from his second to third term, but this was his de-facto first presidential election: Truman took over the presidency after the unanticipated death of the former president Roosevelt (Jones and Olken, 2005). Hence, Truman's case aligns more closely with the second stylized fact.

2.3.4 Causality

To examine the causal mechanism, we focus on elections decided by a narrow margin to generate quasi-natural experimental estimates of the impact of a randomized change in the government status.

Table 2.9: **Close-tie Elections in the U.S., 1927 - 2020**

Election Date	The White House	Senate	House of Rep.	Election Results (Subsequent government)
Nov 1930	N/A	R: 48 - D: 47 (1.04%)	R: 218 - D: 216 (0.46%)	Divided (1931-1932)
Nov 1942	N/A	-	R: 209 - D: 222 (2.99%)	United (1943-1944)
Nov 1950	N/A	R: 47 - D: 49 (2.08%)	-	United (1951-1952)
Nov 1952	-	R: 49 - D: 47 (2.08%)	R: 221 - D: 213 (1.84%)	United (1953-1954)
Nov 1954	N/A	R: 47 - D: 48 (1.04%)	-	Divided (1955-1956)
Nov 1956	-	R: 47 - D: 49 (2.04%)	-	Divided (1957-1958)
Nov 1994	N/A	R: 52 - D: 48 (4%)		Divided (1995-1996)
Nov 1996	N/A	-	R: 226 - D: 207 (4.37%)	Divided (1997-1998)
Nov 1998	N/A	-	R: 223 - D: 211 (2.76%)	Divided (1999-2000)
Nov 2000	R: 271 - D: 266 (0.93%)	R: 50 - D: 50 (0%)	R: 221 - D: 212 (2.07%)	Divided* (2001-2002)
Nov 2002	N/A	R: 51 - D: 48 (3%)	-	United (2003-2004)
Nov 2006	N/A	R: 49 - D: 49 (0%)	-	Divided (2007-2008)
Nov 2010	N/A	R: 47 - D: 51 (4%)	-	Divided (2007-2008)
Nov 2016	-	R: 52 - D: 48 (4%)	-	United (2017-2018)

Note: This table records the history of close-tie U.S. elections. The percentages in each of the column 2, 3, and 4 represent the following: (Column 2): percentage difference between electoral votes to Republican vs. Democratic; (Column 3): percentage difference of Senate seats; and (Column 4): percentage difference of the House of Representatives seats. N/A in the second column indicates that the presidential election was not held on that date. The control of Senate as a result of presidential election in 2000 changed hands several times. The inauguration of George W. Bush met government trifecta, blurring the interpretation. so we treat them as unified.

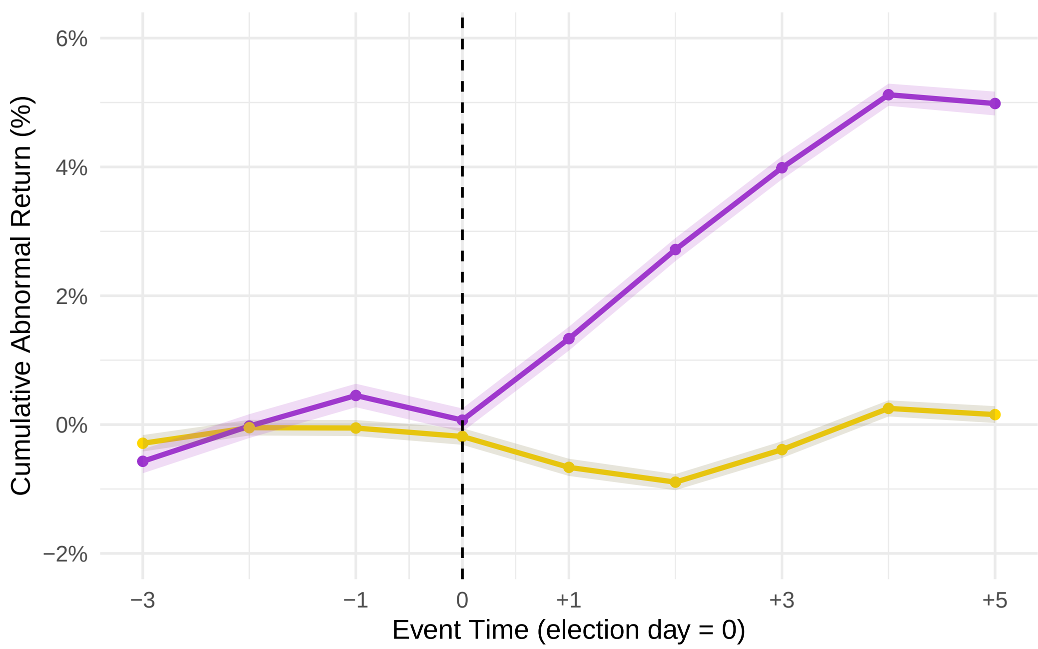
We start by defining a 'close-tie' political election. After a close election, the government's status can be seen as randomly assigned due to the fact that the voters were almost evenly divided in their choice. The split nature of this situation serves as a platform to assess how the shift in government status will influence investors' expectations once voting results are revealed. To determine which events fall into such category, we analyze the results of each election[20] and define close elections as those with vote margins less than 3%. Out of

[20] We choose to analyze every possible election in our sample, as a change in government status can arise from any one of the presidential, Senate, or House of Representatives elections. See Eggers et al. (2015) for a comprehensive work on this issue.

47 elections in our main sample, we found nine that fit into this category, as shown in Table 2.9. Each column represents the difference in electoral votes or Congress/House seats in percentage terms. For instance, the midterm election in November 1930 resulted in a difference of one Senate seat (48 seats for Republicans and 47 seats for Democrats, a difference of 1.04% out of the 96 seats) and two House seats (218 seats for Republicans and 216 seats for Democrats, 0.46% of the 435 seats). The resulting government was a barely divided one. The November 2006 midterm election resulted in a 49-49 Senate tie.[21]

Following Lee et al. (2004), our key identifying assumption is that governments that narrowly won the past election and are unified can be meaningfully compared to those that narrowly won but are divided, allowing us to establish causality. We classify governments emerging from close elections as either 'barely unified' or 'barely divided' and examine the resulting gap in stock returns between these randomly assigned regimes.

Figure 2.4: **Event Study: Cumulative Abnormal Return around Close-Tie Elections**



Note: This figure presents the cumulative abnormal return (CAR) following close-tie election results that resulted in either a barely unified (purple line) or barely divided government (yellow line). Abnormal returns are computed using the market-adjusted model, where each stock's return is adjusted for the CRSP value-weighted market return, assuming a market beta of 1. The election day for these close-tie elections (defined in Table 2.9 as those with a voting margin of less than 5%) is set to event time = 0. The shaded areas indicate bootstrapped 95% confidence intervals.

[21] The majority of seats went to Democrats as two independents caucused with the Democrats. Since we are interested in differences in votes, we also consider this election event as part of our sample.

Figure 2.4 presents the cumulative abnormal returns (CAR), averaged across all firms available during close-tie elections where the voting margin was less than 5%.[22] The results reveal a significant difference of stock market reaction up to 3–5% over the following five days, indicating that the stock market reacts positively to elections leading to a unified government and somewhat negatively to those resulting in a divided government.

Table 2.10: **Close-tie Election Results**

Panel A. Close-tie election is defined as vote margins less than 3% (9 elections)

Governments	Barely Unified	Barely Divided	Gap
VWR-TBL (per annum %)	14.10	-8.05	**22.15****
	(2.84)	(-0.93)	**(2.32)**
EWR-TBL (per annum %)	22.26	-5.61	**27.87****
	(2.92)	(-0.54)	**(2.29)**

Panel B. Close-tie election is defined as vote margins less than 5% (14 elections)

Governments	Barely Unified	Barely Divided	Gap
VWR-TBL (per annum %)	13.12	-0.78	**13.91****
	(3.45)	(-0.13)	**(2.04)**
EWR-TBL (per annum %)	20.26	-1.65	**21.91****
	(3.38)	(-0.24)	**(2.55)**

Note: This table records the close-tie U.S. elections and stock market outcomes, following the close-election definition in Table 2.9. Both value-weighted excess returns (VWR-TBL) and equally-weighted excess returns (EWR-TBL) for the government regimes as a result of close elections. ***/**/* denote the statistical significance at 1%/5%/10% level.

Table 2.10 reinforces the causal interpretation by examining long-term stock market performance under barely unified versus barely divided governments. Markets under barely unified governments exhibit strong performance over time, whereas barely divided governments are associated with persistent underperformance. The resulting gap is both economically meaningful and statistically robust, suggesting that shifts in political regime can have a direct impact on equity returns.[23]

We conclude this section by addressing two plausible challenges to our causal interpretations. The first is the reverse-causality argument that stock markets affect the change of

[22] We use a market-adjusted model that subtracts market returns from firm returns. Abnormal returns for each firm are then averaged separately for elections resulting in barely unified and barely divided governments. To be included in the sample, a firm must be present for at least six months before and after the close-tie election period.

[23] Using the same close-tie election sample, we also compare outcomes under "barely Democrat" versus "barely Republican" governments and find only weakly positive effects (unreported but available upon request). This classification, however, is not always meaningful. For example, the 3% Senate tie in November 2002 resulted in a unified Republican government in 2003–2004, yet would still be labeled "barely Republican," despite the continuity of Republican control. Accordingly, we treat this comparison as a placebo test, reinforcing the notion that the effects of close-tie elections on government status are not spurious.

government. We believe it is unlikely that stock market performance is the dominant determinant of voting decisions and hence the change in government.[24] Also, this concern is not supported by the data. Suppose, contrary to our argument, that divided government is the result of low asset prices. The stock market should experience a significant decrease prior to the midterm or presidential election, as this would allow investors to witness the abysmal performance of the stock market during election years and encourage them to vote in favor of divided governments. We test this hypothesis by calculating average returns on election year (from January up to October) and examine whether mean yearly returns that result in divided government is lower than the mean yearly returns where voters choose united government. We do not find results that support this claim (results are unreported). Second, given that we consider an entire set of firms traded on the major U.S. stock markets, selection issue on specific types of stocks does not apply.

2.4 Mechanisms

We now turn to the mechanism behind our government cycle results, focusing on the political gridlock or sabotage that tends to occur during periods of divided government. Our argument explores whether, and how, this gridlock translates into negative outcomes in financial markets.

2.4.1 Political gridlock channel

When political parties with divergent ideologies assume control of separate branches of government, it frequently results in a legislative stalemate, hindering the effective resolution of urgent matters (see, among others, Coleman, 1999). Partisan conflict and disagreements hinder quick and effective responses to negative shocks, worsening the situation (Alt and Lowry, 1994). Moreover, a filibuster is more likely to occur when the government is Divided,[25] and this period also coincides with fewer significant pieces of legislation being passed (Edwards III et al., 1997, Ansolabehere et al., 2018).

To put this into perspective, in 2011, President Obama and Democratic lawmakers made efforts to advance a budget proposal, but negotiations with Republicans in the House of Representatives ultimately faltered. As a result of this political gridlock, Congress passed a

[24] In a recent article by Pew Research (https://www.pewresearch.org/short-reads/2022/11/03/key-facts-about-u-s-voter-priorities-ahead-of-the-2022-midterm-elections/), voters answered that while economic concerns remain the top issue, other issues such as education, healthcare, and crime concerns are also very important. In other words, voters are multi-dimensional in their decision regarding election, and stock markets would play only a limited role.

[25] See https://www.senate.gov/legislative/cloture/clotureCounts.htm for details. Cloture has become increasingly common starting in 92nd Congress (starting in 1971), and we observe that Divided government face more frequent cloture motions during 1971 - 2020.

series of short-term funding measures known as continuing resolutions to keep the government funded temporarily, rather than passing a full budget. These stopgap measures led to uncertainty and disruptions in government operations and programs. In another example, negotiations between President Obama and Republican congressional leaders over raising the debt ceiling became highly contentious, with Republicans demanding significant spending cuts in exchange for their support. The standoff led to a prolonged and acrimonious debate, with fears of a potential default looming over the economy. Eventually, a last-minute agreement was reached to raise the debt ceiling, but not without significant political uncertainty. On the opposite end, the Economic Growth and Tax Relief Reconciliation Act of 2001 and the Jobs and Growth Tax Relief Reconciliation Act of 2003 (commonly known as the "Bush tax cuts") were smoothly approved with the backing of Congress members from the same party.

Indeed, divided governments, also known as gridlock periods, are associated with mounting political tensions, heightened economic policy uncertainty, increased stock market volatility, and a rise in the treasury premium.[26] Figure 2.5 presents two figures that showcase how political gridlock is severe during Divided regimes. The above plots the yearly Partisan Conflict Index (PCI) of Azzimonti (2018) that uses a semantic search method to measure the frequency of newspaper articles recording lawmakers' disagreement about policy, and shows that political conflict is indeed higher during Divided governments (shaded areas). A notable exception is during Trump's era, where his first term (the government was unified at that time) scored the highest value of PCI. This seems to come from the U.S. - China trade dispute in 2018. Regardless, the average PCI remains statistically lower during United government: 86.8 (Divided) vs. 60.8 (United government) with a t-statistic of 4.5.[27]

In the below panel, we use all congressional bills proposed from 80th Congress to 114th Congress from Congressional Bills Project Database. The database, at the time of writing, enumerates all congressional bills proposed from 1947 to May 2020. We are interested in how many proposed bills are eventually vetoed by the sitting president, as this indicates a form of political conflict. [28] It shows that Divided governments tend to meet higher ratio of vetoes. The large number of bills introduced in Congress means that even a small percentage difference makes a significant impact. In fact, a 0.04% (0.127% - 0.083%) difference

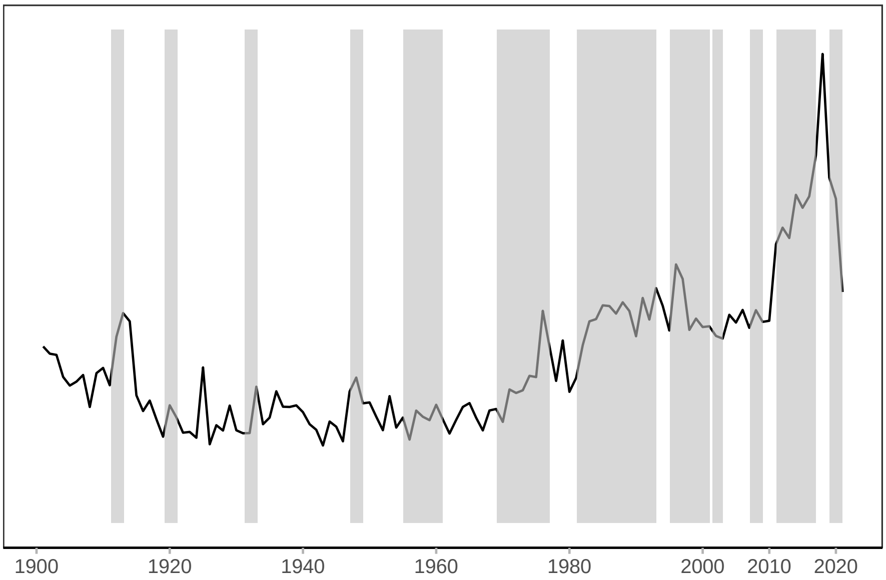
[26] The government spending channel is another potential avenue to explain the government gap in stock returns and economic growth. Higher government deficits, whether caused by Unified-Republicans' tax cuts or Unified-Democrats' spending increases, can reduce private investment by competing for funds in financial markets (Cohen et al., 2011). This can lead to lower investment levels by businesses, which can ultimately impact economic growth and corporate profitability, potentially affecting stock returns and economic growth.

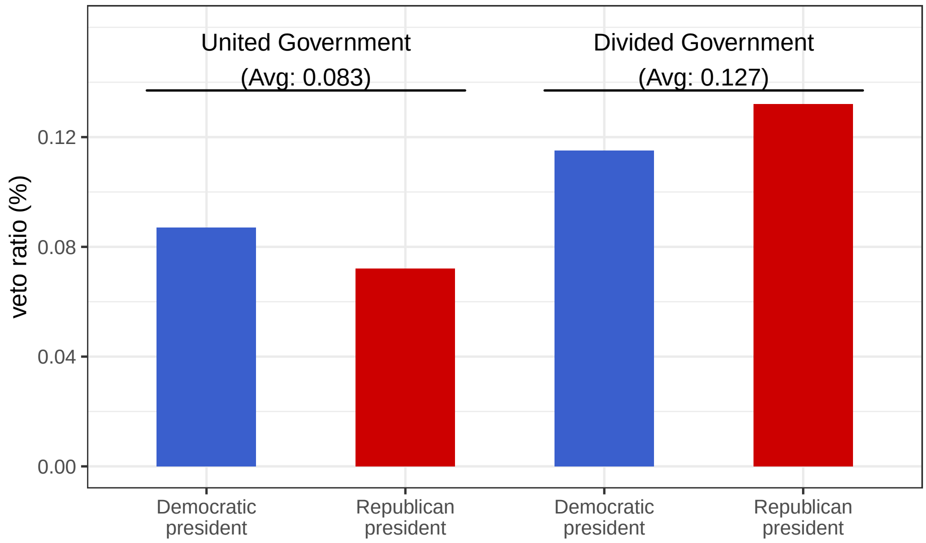
[27] The elevated measure after 2010 seems to reflect more polarized nature of U.S. politics. Excluding post-2010 yearly index does not change the significance of PCI gap across governments. Repeating the same exercise conditional on the party of the sitting president does not show significant difference in PCI index: 74 (Republican) vs. 70 (Democratic president) with a t-statistic of 0.74.

[28] We don't consider bills that aim to help specific individuals because they're not related to the current economic situation. Quite a few bills have the title "For the relief of PERSON A". We remove those observations.

translates to 2.5 more bills being vetoed during divided governments compared to united governments.

Figure 2.5: **Political Gridlock**





Note: The above figure plots Political Conflict Index (PCI, Azzimonti, 2018) at a yearly frequency, where higher value indicates higher level of lawmakers' disagreement about policy captured in a semantic search method (the measure is set to have a value of 100 in 1990 by Azzimonti, 2018). The shaded areas are times when the government is divided. The below figure shows veto ratio of the incumbent president using bills data from 1947 (80th) to May 2020 (114th) Congress. The labels on X-axis are the political party of the presidents. The first two bar plots correspond to United governments, and the last two correspond to Divided governments.

Table 2.11: **Regressions of EPU Index and Monthly Stock Market Volatility on Political Dummies**

Panel A: Dependent variable is log EPU index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
United	**-0.036***		**-0.079*****	**-0.036***		**-0.084*****	**-0.055****
Government	**(-1.65)**		**(-4.01)**	**(-1.70)**		**(-4.20)**	**(-2.36)**
Democratic		**0.145*****	**0.166*****		**0.158*****	**0.181*****	-0.003
President		**(6.88)**	**(8.50)**		**(7.33)**	**(8.97)**	(-0.15)
NBER				0.024	**0.065*****	**0.072*****	
				(0.97)	**(2.61)**	**(2.88)**	
CFNAI							**-0.049****
							(-2.51)
Observations	1451	1451	1451	1451	1451	1451	645
Constant?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2 (%)	2.0	3.2	4.1	3.0	3.6	4.6	4.0

Panel B: Dependent variable is stock market volatility (%)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
United	**-0.393****		**-0.309***	-0.276		**-0.456*****	**-0.838*****
Government	**(-2.18)**		**(-1.71)**	(-1.64)		**(-2.64)**	**(-5.01)**
Democratic		**-0.330***	-0.201		0.246	**0.444*****	-0.171
President		**(-1.83)**	(-1.11)		(1.57)	**(2.79)**	(-0.99)
NBER				**2.721*****	**2.822*****	**2.855*****	
				(8.36)	**(8.70)**	**(8.84)**	
CFNAI							-0.404
							(-1.25)
Observations	1140	1140	1140	1140	1140	1140	645
Constant?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2 (%)	0.4	0.3	0.5	12.7	12.6	13.1	6.6

Note: This table presents regressions of monthly EPU index and stock market volatility on political variable dummies. In both panels, independent variables are political dummies (united government dummy and democratic president dummy) and NBER recession dummy. We also include CFNAI in place of NBER dummy. Dependent variable in Panel A (Panel B) is log of EPU index (monthly stock market volatility of French et al. (1987)) Except for regression (7) where CFNAI has limited coverage, all other regressions in Panel A span 1900:01 - 2020:12 and Panel B 1927:01 - 2020:12. Numbers in parenthesis are t-statistics, adjusted using robust standard errors. ***/**/* denote the statistical significance at 1%/5%/10% level.

Economic policy uncertainty (EPU index, Baker et al., 2016) is influenced in a negative way by the status of United governments. In Table 2.11, we observe that the change of government status from Divided to United predicts, at one month horizon, negative 8% change in EPU index ($100 \times (\exp\{-0.084\} - 1) = -8.06$, equation (6)), even after controlling for the presidents' political party as well as macroeconomic indicators. Similarly, United government negatively predicts stock market volatility as measured by French et al. (1987). Given the extant literature that political uncertainty has a negative impact on the economy via depressing investment (Azzimonti, 2018 and Jens, 2017), the analysis in this section gives us assurance that periods of Divided government are detrimental to the financial market and the economy. The presidential cycle, on the other hand, shows the opposite pattern in that both the EPU index and stock volatility tends to be positive when the Democratic president is occupying the White House.

Table 2.12: **Average Treasury Premium under Political Regimes**

		(1) B30_TBL	(2) B20_TBL	(3) B10_TBL
Governments	United	-2.71 (-1.87)	-2.05 (-1.60)	-1.52 (-1.69)
	Divided	3.88 (2.21)	3.75 (2.60)	2.73 (2.51)
	Difference	**-6.60***** **(-2.76)**	**-5.76***** **(-3.04)**	**-4.20***** **(-3.10)**
Presidents	Democrat	-0.77 (-0.48)	-0.21 (-0.15)	-0.19 (-0.19)
	Republican	3.16 (1.95)	3.01 (2.22)	2.20 (2.11)
	Difference	-3.96 (-1.62)	-3.24 (-1.53)	-2.40 (-1.54)

Note: This table reports the average annual Treasury term premium across different political regimes. B30_TBL represents the return on 30-year U.S. Treasuries minus the return on the three-month Treasury bill; B20_TBL and B10_TBL are defined analogously using 20-year and 10-year Treasuries, respectively. Due to data availability, the Treasury data span the period from 1947 to 2020. Numbers in parentheses are Newey-West adjusted t-statistics, using 24 lags. ***/**/* denote the statistical significance at 1%/5%/10% level.

We also present evidence of a robust treasury premium gap across the government cycle in Table 2.12. The analysis of treasury premiums reveals that divided (united) governments correspond to periods of higher (lower) excess bond returns, suggesting that these are indeed unfavorable (favorable) times where investors seek assets that are deemed safe to invest.[29]

Times when Republican presidents operate under a Divided Congress deserve special attention. To start with, we find that 70% of post-war NBER recession periods occured under Republican presidents who failed to control the Congress. This is illustrated in Figure 2.6.[30] To the best of our knowledge, this paper is the first to identify that most of the macroeconomic downturns happened during certain political regimes.

Moving further, we observe that the "September effect"[31] [32] (Kamstra et al., 2003) is concentrated exclusively in the Divided-Republican regimes, which partially explains the low stock market performance during this period. As the upper panel in Figure 2.7 shows,

[29] In contrast, repeating the same analysis based on the presidential cycle yields no significant results, consistent with the findings of Pastor and Veronesi (2020), as reported in Tables A11–A16 of their Online Appendix.

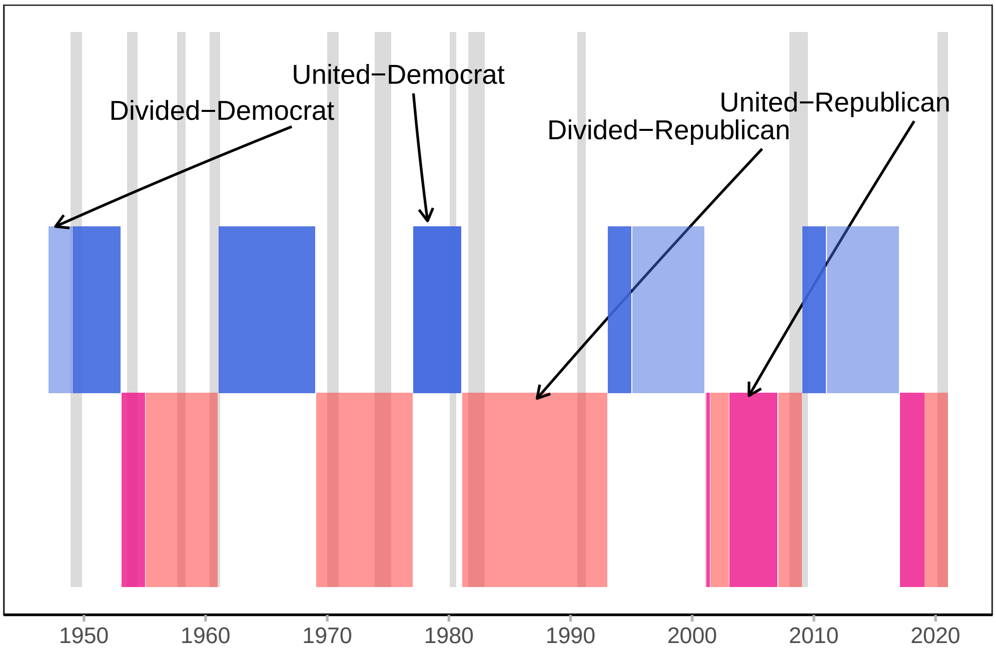
[30] During the pre-1947 period, the Unified-Republican times experienced frequent NBER recessions as well. Republicans held power during two-thirds or more of the NBER recessions, regardless of whether they controlled Congress.

[31] More generally, month-of-the-year effect refers to the empirical findings that aggregate stock markets perform significantly better or worse in certain calendar months. January is known to produce abnormally high small firm returns (Keim, 1983; Reinganum, 1983), while May (Bouman and Jacobsen, 2002) and September, October (Hirshleifer et al., 2020) produce low returns.

[32] Media has been reporting this effect quite often: see, among others, https://www.bbc.co.uk/news/business-30793329

September predicts the lowest stock market performance throughout U.S. history. What we show in the below panel is that this dismally low performance occurs exclusively under Divided-Republican administrations. The red solid line is the calendar stock returns during Divided-Republican era, and the black dotted line is all other times (i.e., United-Republican, United-Democrats, and Divided-Democrats' calendar months all combined). As we clearly see, only Divided-Republican administrations are associated with low September returns.[33]

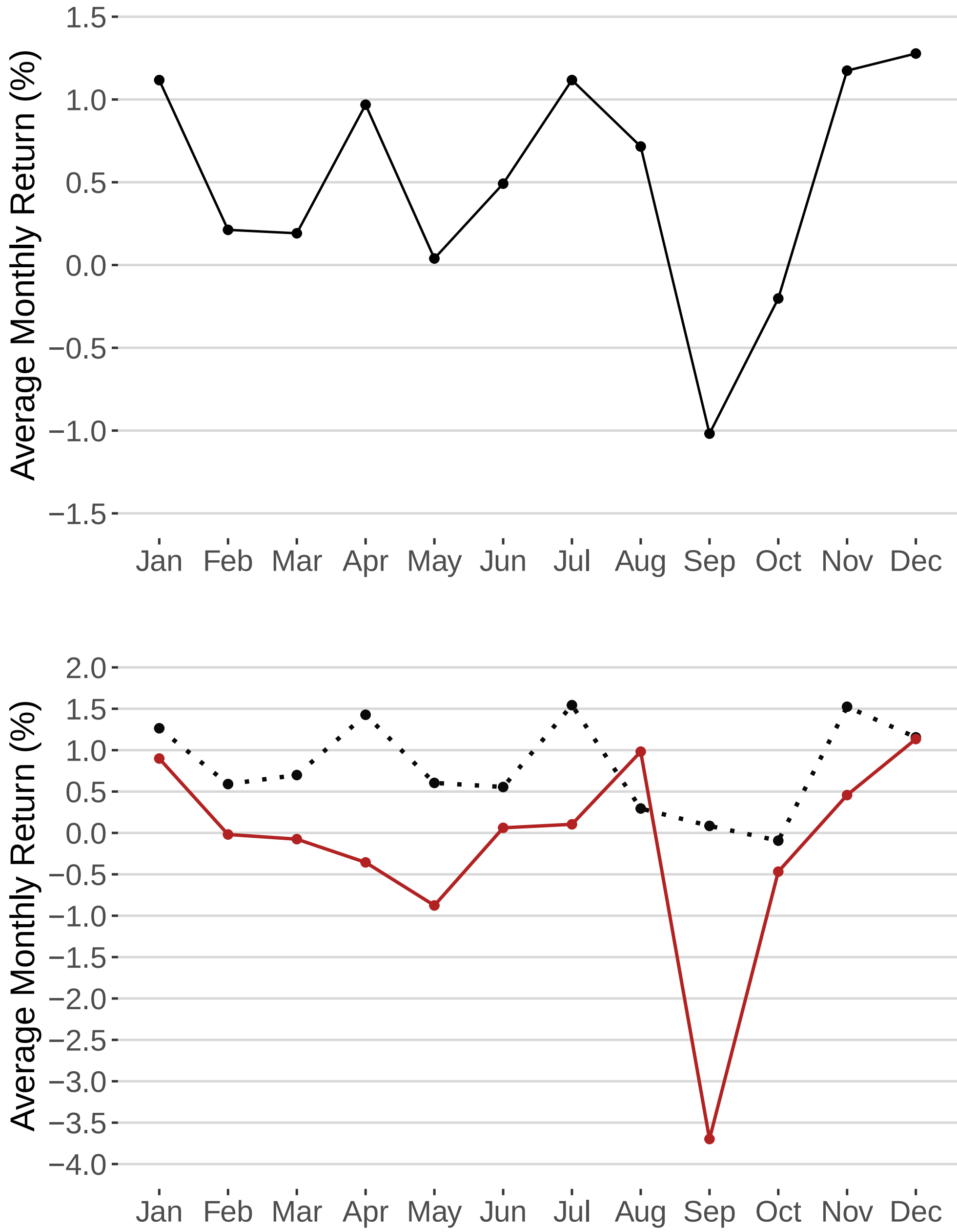
Figure 2.6: **NBER recessions and Political Regimes**



Note: This figure plots NBER recession periods and the political regimes. Grey shaded areas are NBER recession months. The red-colored areas in the bottom are times when Republican presidents rule the White House. Darker red indicates United governments and shallow red indicates Divided governments. Similarly, the blue-coloured areas in the middle are times when the sitting president is from the Democratic Party. Darker blue indicates United governments and shallow blue indicates Divided governments.

[33] Although the September return is affected by two exogenous shocks (the 9/11 attack in 2001 and the Global Financial Crisis in 2008, both occurring during the Divided-Republican era), there is evidence that even when excluding these two events and analyzing subsamples and equally-weighted returns, the same negative pattern emerges. We also individually record the results for September of other political regimes (United-Republican regime, United-Democrats regime, and Divided-Democrats regime) in the same table. All these results are demonstrated in the Appendix.

Figure 2.7: **September Effect and Divided-Republican Regimes**



Note: This figure plots value-weighted excess stock returns by each month. The upper panel shows average of 94 calendar returns by month (1927 - 2020). The lower panel shows calendar month returns specific to Divided-Republican times (solid red line) and all other regimes (United-Republican, United-Democrats, and Divided-Democrats all combined; dotted black line).

Why is this September crash specific to Divided-Republican times? We suggest this empirical regularity can be attributed to the "August recess" and a subsequent "Back to School" Effect. Congress takes a break in July and August, known as the August recess. During this time, pro-business Republicans, including the president and Congress members, discuss their plans for the legislative agenda. After reconvening in September (back to school), they face bitter disappointment due to lack of control of Congress. Investors, absent political risk during the Summer break, build positive expectations but are dismayed by incumbent Republicans that translates into negative market reaction in September. Consistent with this hypothesis, we find that average asset prices during the Divided-Republican era rise from July to August, and then sharply drop in September.[34] Since the U.S. federal government's fiscal year starts on October 1st, September is a crucial month for Congress to finalize the federal budget and appropriations for the upcoming year, as well as address other urgent fiscal issues facing the government. Under the weak leadership of the Republican president, important activities are frequently disrupted, causing negative effects on the stock market.

This political-risk-based explanation on the calendar effects is markedly different from existing hypotheses. For instance, Hirshleifer et al. (2020) argue that low mood around Autumn (September and October) explains low stock returns. We confirm that the September effect we document does not continue into October, providing further support that it is unrelated to weather conditions. In fact, October isn't necessarily associated with low returns, as value-weighted excess returns are mildly positive. Moreover, negative equally-weighted excess returns are concentrated in two extreme Octobers.[35] In a similar vein, both mutual fund tax harvesting and school holidays (Fang et al., 2018) explanations do not fit into this political cycle of September returns.

2.4.2 Political gridlock and small firms

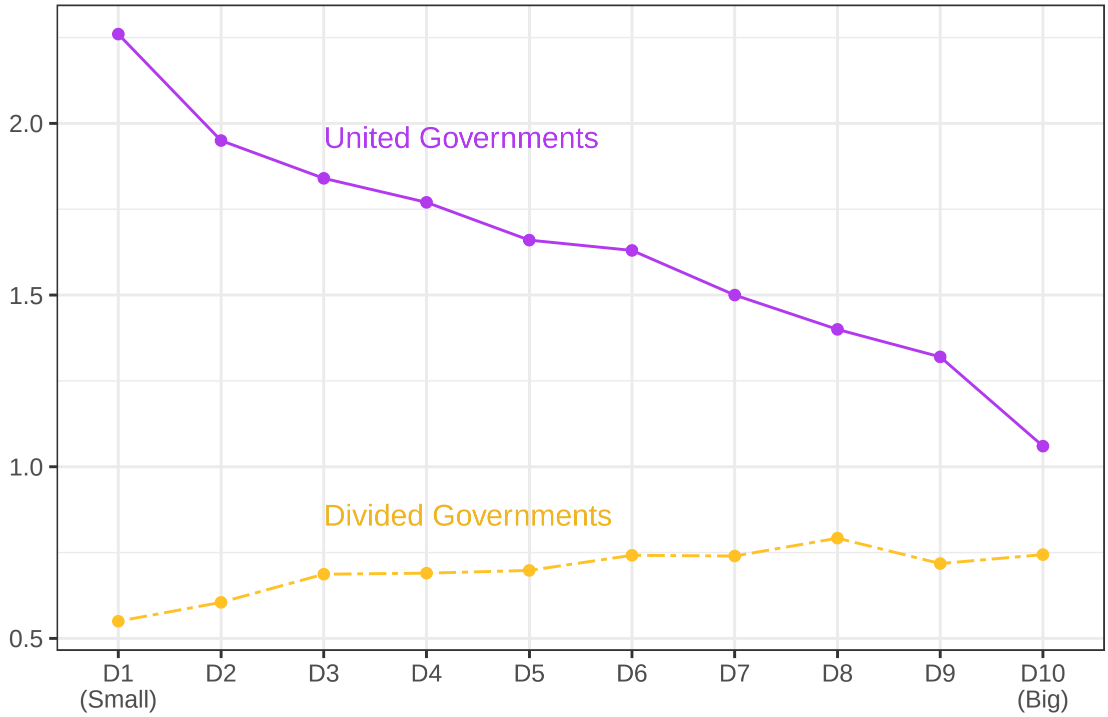
In Section 2.2.2, we showed that the stock market difference conditional on government cycle is much higher in equally-weighted stock returns, suggesting that small firms are severely affected by this cycle. This also aligns with our proposed economic mechanism of political gridlock, as these adverse effects would impact small firms more than large firms. Undoubtedly, small firms tend to struggle more during difficult times as they exhibit greater bank dependence, cannot issue debt publicly, and face greater idiosyncratic risk (Gertler and Gilchrist, 1994). Large firms, on the other hand, have considerable power in influencing the rules of the game (Zingales, 2017), and can borrow to smooth the impact of a downturn (Gertler and Gilchrist, 1994). Small business also lack the resources to actively form political connections through political donations or lobbying efforts (Faccio, 2006, Hassan et al., 2023). In a similar vein, Liu et al. (2017) use Chinese examples to show that small firms (as well as firms with high leverage and high idiosyncratic risk) earn lower returns in the face of

[34] This pattern is already shown in Figure 2.7 (see below panel, solid red line). We also observe similar patterns across subsamples except Eisenhower's presidency (1955-1960). Since August recess started from late 1960s, Eisenhower's Divided-Republican times do not count toward our hypothesis.

[35] Stock markets crashed heavily in October 1987 and October 2008. Without them, October EW returns are only mildly negative or sometimes positive across subsamples.

exogenous political shocks.

Figure 2.8: **Decile portfolio returns formed on firm size**



Note: This figure plots decile portfolio returns formed on firm size, obtained from Professor French's website. The data spans 1927 - 2020 monthly. Purple line is the average decile returns formed on firm size under the United governments, and yellow line is the average decile size returns under the Divided governments.

Inspired by this, we investigate the small firm issues through the lens of well-known size anomalies (Small Minus Big or SMB; Fama and French, 1993). We start by documenting that the size premium is concentrated almost entirely during unified governments, shown by the surprising SMB gap of 7% per annum (6% during United vs. -0.9% during Divided). Excluding January from the sample diminishes the SMB premium in both types of governments, but the SMB gap remains essentially the same at 6.6%. This outperformance of SMB under United governments come mostly from the long-side of the portfolio returns (small firms or 'S'), which we further show in Figure 2.8. In this figure, the decile portfolio returns formed on firm size are plotted to show that a monotonic decrease in the stock returns across firm size takes place only under United governments, consistent with our political gridlock explanation that small firms perform well when there is no or less political sabotage.[36] This

[36]We provide two additional checks on this result. First, we check that the business cycle explanation of Ahn et al. (2019) does not fit into our framework since about half of the 'troughs' as defined in that paper falls into the Divided governments. Next, while the Figure 2.8 result holds when we restrict our sample to post-1980s, the same exercise under the Presidential cycle does not work (see Appendix Figure **??**).

result aligns with the earlier findings of Chan and Chen (1991), which suggest that small firms tend to be "marginal" in the sense that their prices are more sensitive to changes in the economy and they are less likely to withstand adverse economic conditions.

Table 2.13: **Size Matters Under United Governments**

Panel A: Fama-Macbeth regression

	Full sample (1927:01 - 2020:12)			Post-1980s (1983:01 - 2020:12)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All samples	United only	Divided only	All samples	United only	Divided only
log (ME)	**-0.13*****	**-0.23*****	-0.03	**-0.09***	**-0.20*****	-0.05
	(-3.70)	**(-4.42)**	(-0.71)	**(-1.91)**	**(-2.84)**	(-0.81)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
B/M included?	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	2,474,568	876,294	1,598,274	1,604,919	408,711	1,196,208

Panel B: SMB subsample

Sample period	Regime	Mean (monthly %)	SD (%)	n
Golden age (1957:07 - 1979:12)	Entire period	0.35	2.88	270
	United Government only	**0.91**	2.61	132
	Divided Government only	-0.19	3.04	138
Embarrassment (1980:01 - 1999:12)	Entire period	-0.06	2.69	240
	United Government only	**0.31**	2.26	36
	Divided Government only	-0.12	2.76	204
	Democratic Presidents only	-0.13	3.07	96
	Republican Presidents only	-0.00	2.42	144
Resurrection (2000:01 - 2020:12)	Entire period	0.25	3.25	252
	United Government only	**0.41**	2.43	100
	Divided Government only	0.15	3.69	152
	Democratic Presidents only	0.15	3.88	108
	Republican Presidents only	0.33	2.70	144

Panel C: SMB interaction with QMJ (1957:01 - 2020:12)

$SMB_t = \alpha + \beta RMRF_t + \beta_{-1} RMRF_{t-1} + h \times HML_t + m \times MOM_t + q \times QMJ_t + \varepsilon_t$

Regime	α	$t(\alpha)$	R-squared	QMJ included?
United Government	**0.38*****	**2.63**	0.19	No
	0.45***	**3.30**	0.28	Yes

Note: This table records the size effect conditional on the government cycle. Panel A performs month-by-month Fama-MacBeth regressions of stock returns on size and book-to-market equity (B/M). Panel B provides descriptive statistics in subsamples. In the golden age, united (divided) governments perfectly coincide with Democratic (Republican) presidents. Panel C presents the SMB (Fama-French size factor) performance across the regimes. QMJ is the Quality-Minus-Junk factor in Asness et al. (2018). In both panels, the parentheses indicate t-statistics, with corresponding ***/**/* denoting the statistical significance at 1%/5%/10% level.

We also run a monthly Fama-MacBeth regression that starts from 1927, and from 1983. The latter sample is to examine a recent debate on the disappearance of the size premium (see, among others, Hou and van Dijk, 2019). In Panel A of Table 2.13, the coefficients as well as strong t-statistics say that a reliable negative relation between firm size and stock returns is established only when the United government is in place (columns (2) and (5)). Divided government regimes fail to show this pattern.[37] The SMB descriptive statistics shown in panel B indicate that the outperformance of SMB during United governments are not specific to sample periods.[38] By combining the results presented here with the fact that the United States has experienced more divided governments than united governments since the 1980s, we can conclude that the recent disappearance of size effect is entirely attributable to the government cycle.

In Panel C, we run the factor redundancy test in the spirit of Asness et al. (2018) to assess whether SMB adds explanatory power to the asset pricing model. The regression model is specified as

$$SMB_t = \alpha + \beta RMRF_t + \beta_{-1} RMRF_{t-1} + h \times HML_t + m \times MOM_t + q \times QMJ_t + \varepsilon_t \quad (2.3)$$

where $RMRF$ is the market, HML the value factor, MOM the momentum factor, and QMJ the quality-minus-junk factor proposed in Asness et al. (2019). Aligning the sample period to match the QMJ sample, we see that the alpha is already 38 bps per month (t-statistics: 2.63) absent quality control. With a helping hand from QMJ, the size premium strengthens to 45 bps with a stronger t-statistics. All the other political regimes (Divided government and two presidential dummies), on the other hand, show poor SMB alpha but revives after QMJ enters the regression. This result is presented in the Appendix.

2.5 Conclusion

This paper introduces the concept of a government cycle—the impact of unified versus divided political control—on stock market performance and economic growth. We find that unified governments are associated with significantly higher excess stock returns and stronger economic outcomes, particularly for small firms. These effects are economically substantial, statistically robust, and analytically distinct from the well-documented presidential cycle. Once government status is accounted for, the explanatory power of presidential party affiliation largely disappears.

To support a causal interpretation, we leverage close-tie elections as quasi-natural experiments. The patterns we uncover persist across time periods, asset classes, and geogra-

[37]We observe a robust pattern when running FMB regressions on earlier samples (1927:01 - 1982:12), or excluding B/M as a covariate.

[38]The subsample period definitions come from Asness et al. (2018). The Golden age period has diminished slots as the United (Divided) governments perfectly coincide with the time when Democratic (Republican) presidents were ruling the White House. Quite interestingly, 85% of the 'embarrassment period' (1980:01 - 1999:12) met Divided governments, whereas half of 'golden age' (1957:07 - 1979:12) is dominated by United governments.

phies—including U.S. states and the United Kingdom. The government cycle also provides a novel explanation for the post-1980s disappearance of the size premium, which we find persists only under unified governments.

A central mechanism driving these results is political gridlock. Divided governments are more prone to legislative stalemates, heightened veto activity, and intensified partisan conflict—all of which contribute to greater policy uncertainty and institutional inertia. These effects are particularly pronounced for small firms, which are more reliant on external financing and less able to navigate complex political environments. In contrast, unified governments reduce uncertainty and enable more coordinated policy action, fostering conditions that support both economic growth and market performance. Together, these findings establish the government cycle as a new stylized fact in political economy.

2.6 Appendix

This Appendix is organized as follows: Section 2.6.1 details the political affiliations of U.S. presidents, along with the Senate and House majorities, from 1871 to 2020. Section 2.6.2 presents additional stock market results, demonstrating the robustness of the established government cycle. Section 2.6.3 provides a more detailed analysis of the small firm issue. Section 2.6.4 offers further explanation of the September effect, and Section 2.6.5 addresses media mentions on this topic.

2.6.1 The U.S. Political Regimes

The below list reports the political affiliation of the incumbent president, along with the majority party in both the Senate and the House of Representatives, for each congressional term from 1871 to 2020. R indicates Republican party, and D indicates Democratic party. The definition of government status, whether it is united or divided, follows United States House of Representatives Archives. The asterisk in Bush's term (2001 - 2002) is an exception as the early four months (2001:02 - 2001:05) saw united regime. Until 72nd Congress, the term lasted from March 4 of the starting year to March 4 two years later. For instance, 70th Congress met from March 4, 1927 to March 4, 1929. 73rd Congress met from March 4, 1933 to January 3, 1935. 74th Congress met from January 3, 1935 to January 3, 1937. From 74th Congress, the meeting was held from January 3 of the starting year to January 3 two years later. For ease of exposition, the first column contains two years where Congress was held mostly throughout those periods.

- 1871–72 (42nd): Grant (R); Senate R; House R; **United**
- 1873–74 (43rd): Grant (R); Senate R; House R; **United**
- 1875–76 (44th): Grant (R); Senate R; House D; **Divided**
- 1877–78 (45th): Hayes (R); Senate R; House D; **Divided**
- 1879–80 (46th): Hayes (R); Senate D; House D; **Divided**
- 1881–82 (47th): Garfield/Arthur* (R); Senate D*; House R; **Divided**
- 1883–84 (48th): Arthur (R); Senate R; House D; **Divided**
- 1885–86 (49th): Cleveland (D); Senate R; House D; **Divided**
- 1887–88 (50th): Cleveland (D); Senate R; House D; **Divided**
- 1889–90 (51st): Harrison (R); Senate R; House R; **United**

- 1891–92 (52nd): Harrison (R); Senate R; House D; **Divided**
- 1893–94 (53rd): Cleveland (D); Senate D; House D; **United**
- 1895–96 (54th): Cleveland (D); Senate R; House R; **Divided**
- 1897–98 (55th): McKinley (R); Senate R; House R; **United**
- 1899–00 (56th): McKinley (R); Senate R; House R; **United**
- 1901–02 (57th): McKinley / T. Roosevelt (R); Senate R; House R; **United**
- 1903–04 (58th): T. Roosevelt (R); Senate R; House R; **United**
- 1905–06 (59th): T. Roosevelt (R); Senate R; House R; **United**
- 1907–08 (60th): T. Roosevelt (R); Senate R; House R; **United**
- 1909–10 (61st): Taft (R); Senate R; House R; **United**
- 1911–12 (62nd): Taft (R); Senate R; House D; **Divided**
- 1913–14 (63rd): Wilson (D); Senate D; House D; **United**
- 1915–16 (64th): Wilson (D); Senate D; House D; **United**
- 1917–18 (65th): Wilson (D); Senate D; House D; **United**
- 1919–20 (66th): Wilson (D); Senate R; House R; **Divided**
- 1921–22 (67th): Harding (R); Senate R; House R; **United**
- 1923–24 (68th): Harding / Coolidge (R); Senate R; House R; **United**
- 1925–26 (69th): Coolidge (R); Senate R; House R; **United**
- 1927–28 (70th): Coolidge (R); Senate R; House R; **United**
- 1929–30 (71st): Hoover (R); Senate R; House R; **United**
- 1931–32 (72nd): Hoover (R); Senate R; House D; **Divided**
- 1933–34 (73rd): Roosevelt (D); Senate D; House D; **United**
- 1935–36 (74th): Roosevelt (D); Senate D; House D; **United**
- 1937–38 (75th): Roosevelt (D); Senate D; House D; **United**
- 1939–40 (76th): Roosevelt (D); Senate D; House D; **United**

- 1941–42 (77th): Roosevelt (D); Senate D; House D; **United**
- 1943–44 (78th): Roosevelt (D); Senate D; House D; **United**
- 1945–46 (79th): Roosevelt / Truman (D); Senate D; House D; **United**
- 1947–48 (80th): Truman (D); Senate R; House R; **Divided**
- 1949–50 (81st): Truman (D); Senate D; House D; **United**
- 1951–52 (82nd): Truman (D); Senate D; House D; **United**
- 1953–54 (83rd): Eisenhower (R); Senate R; House R; **United**
- 1955–56 (84th): Eisenhower (R); Senate D; House D; **Divided**
- 1957–58 (85th): Eisenhower (R); Senate D; House D; **Divided**
- 1959–60 (86th): Eisenhower (R); Senate D; House D; **Divided**
- 1961–62 (87th): Kennedy (D); Senate D; House D; **United**
- 1963–64 (88th): Kennedy / Johnson (D); Senate D; House D; **United**
- 1965–66 (89th): Johnson (D); Senate D; House D; **United**
- 1967–68 (90th): Johnson (D); Senate D; House D; **United**
- 1969–70 (91st): Nixon (R); Senate D; House D; **Divided**
- 1971–72 (92nd): Nixon (R); Senate D; House D; **Divided**
- 1973–74 (93rd): Nixon / Ford (R); Senate D; House D; **Divided**
- 1975–76 (94th): Ford (R); Senate D; House D; **Divided**
- 1977–78 (95th): Carter (D); Senate D; House D; **United**
- 1979–80 (96th): Carter (D); Senate D; House D; **United**
- 1981–82 (97th): Reagan (R); Senate R; House D; **Divided**
- 1983–84 (98th): Reagan (R); Senate R; House D; **Divided**
- 1985–86 (99th): Reagan (R); Senate R; House D; **Divided**
- 1987–88 (100th): Reagan (R); Senate R; House D; **Divided**
- 1989–90 (101st): Bush (R); Senate D; House D; **Divided**

- 1991–92 (102nd): Bush (R); Senate D; House D; **Divided**
- 1993–94 (103rd): Clinton (D); Senate D; House D; **United**
- 1995–96 (104th): Clinton (D); Senate R; House R; **Divided**
- 1997–98 (105th): Clinton (D); Senate R; House R; **Divided**
- 1999–00 (106th): Clinton (D); Senate R; House R; **Divided**
- 2001–02 (107th): W. Bush* (R); Senate D; House R; **Divided**
- 2003–04 (108th): W. Bush (R); Senate R; House R; **United**
- 2005–06 (109th): W. Bush (R); Senate R; House R; **United**
- 2007–08 (110th): W. Bush (R); Senate D; House D; **Divided**
- 2009–10 (111st): Obama (D); Senate D; House D; **United**
- 2011–12 (112nd): Obama (D); Senate D; House R; **Divided**
- 2013–14 (113rd): Obama (D); Senate D; House R; **Divided**
- 2015–16 (114th): Obama (D); Senate R; House R; **Divided**
- 2017–18 (115th): Trump (R); Senate R; House R; **United**
- 2019–20 (116th): Trump (R); Senate R; House D; **Divided**

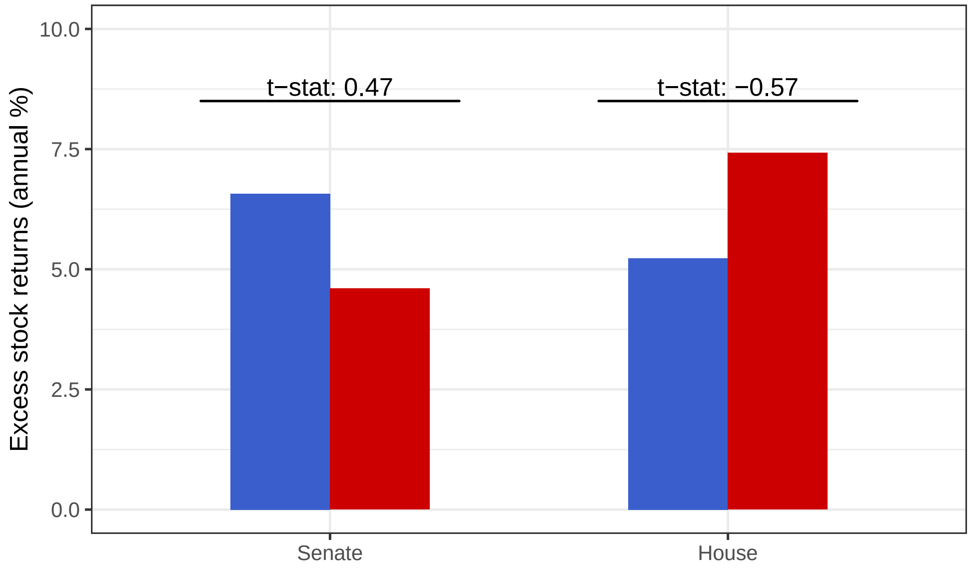
2.6.2 Additional stock market results

This section records additional stock market results.

Figure 2.9 demonstrates that political party dominance in either the Senate or the House alone does not lead to higher stock market returns. This supports our view that it is the government trifecta that matters for the stock market.

In Table 2.14, we present results for VWRETX, where dividends are not reinvested. If the cash flow channel were the primary driver of the government cycle, we would expect the government gap to narrow significantly. However, we still observe a strong gap in excess VWRETX returns, suggesting that the discount rate channel may play a key role in explaining the government cycle of stock returns.

Figure 2.9: **No Evidence of a Congressional Cycle in Stock Returns**



Note: This graph presents the average annualized excess value-weighted returns for each partisan majority in the Senate (on the left) and in the House of Representatives (on the right). The sample period is 1927 to 2020. In both, the left blue bar indicates the excess stock returns when the Democratic party ruled the Senate (the House), and the right red bar when the Republican party ruled the Senate (the House). The t-statistics of return difference between Democrat- and Republican-majority in each of the Senate and the House is indicated above.

Table 2.15 extends the factor redundancy tests conducted in the main body of the paper (Panel C in Table 2.13). While full sample analysis shows that SMB alpha is weak at 12 bps per month (t-statistics: 1.17), controlling for QMJ factor resurrects SMB to 43 bps (t-statistics: 4.37), consistent with Asness et al. (2019). When we divide the sample into political regimes, the similar implications are derived. However, as documented in the main body of the paper, size premium is already strong at 38 bps (t-statistics: 2.63) when the status of government is unified. When we consider all the elements, we can confirm that the outstanding performance of SMB, subject to the political cycle, is exclusive to the United States government.

Panel A: Full sample (1927:01 - 2020:12), Excluding Post-Election Months

Excess VWRETD	United ($N = 438$)	Divided ($N = 455$)	Difference
	9.64%	-2.00%	**11.64%*** **
	(3.32)	(-0.60)	**(2.73)**
Excess VWRETX	United ($N = 438$)	Divided ($N = 455$)	Difference
	5.48%	-5.33%	**10.80%** **
	(1.87)	(-1.58)	(2.46)

Panel B: Post-World War II (1947:01 - 2020:12), Excluding Post-Election Months

Excess VWRETD	United ($N = 267$)	Divided ($N = 436$)	Difference
	10.63%	-0.10%	**10.74%** **
	(4.15)	(-0.04)	**(2.40)**
Excess VWRETX	United ($N = 267$)	Divided ($N = 436$)	Difference
	6.92%	-3.29%	**10.20%** **
	(2.71)	(-1.11)	(2.33)

Table 2.14: Government Cycle without Cash Flows

Note: This table presents average returns (% per annum) across government cycles. We report both excess value-weighted return (Excess VWRETD), which includes reinvested dividends, and excess value-weighted return (Excess VWRETX), which excludes dividends to isolate the impact of discount rate variations across government cycle. The Excess VWRETD results are identical to those in Table 2.5 and are included here as a benchmark. To focus on the long-term effects of government structure rather than temporary resolution of uncertainty, we exclude post-election months following midterm and presidential elections, as these periods typically exhibit higher returns due to a short-term decline in uncertainty rather than reflecting the persistent effects of government status (Chan and Marsh, 2021). Numbers in parenthesis are t-statistics, adjusted using Newey-West procedure with 24 lags. ***/**/* denote the statistical significance at 1%/5%/10% level.

2.6.3 SMB and United Governments

Sample period: 1957:01 - 2020:12

$$SMB_t = \alpha + \beta RMRF_t + \beta_{-1} RMRF_{t-1} + h \times HML_t + m \times MOM_t + q \times QMJ_t + \varepsilon_t$$

Regime	α	$t(\alpha)$	R-squared	QMJ included?
Full sample	0.12	1.17	0.10	No
	0.43	4.37	0.27	Yes
United Government	**0.38**	**2.63**	0.19	No
	0.45	3.30	0.28	Yes
Divided Government	0.01	0.05	0.11	No
	0.44	3.32	0.28	Yes
Democratic presidents	0.15	0.88	0.17	No
	0.46	2.97	0.34	Yes
Republican presidents	0.11	0.88	0.16	No
	0.35	2.86	0.25	Yes

Table 2.15: Additional results on SMB interaction with QMJ

Note: All political regimes (United / Divided governments; Democratic / Republican presidents) as well as full-sample analysis are recorded. Coefficients and corresponding t-statistics for other variables are suppressed for brevity.

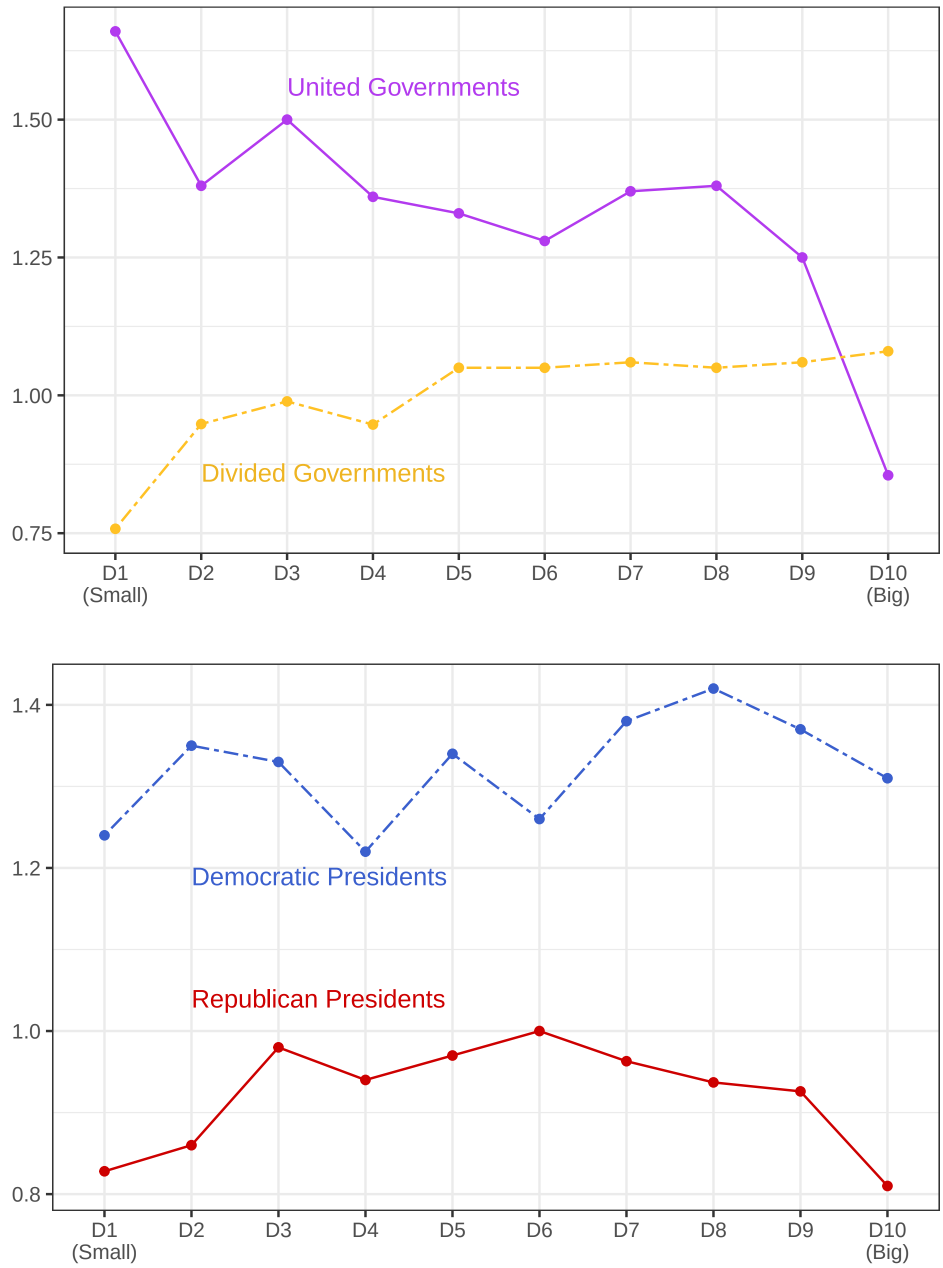
Figure 2.10 extends the results of Figure 2.8 by focusing on the post-1980s period (1983–2020), during which the size effect is known to have largely disappeared in the U.S. market. Consistent with the political gridlock hypothesis, a conditional size effect persists under United governments, whereas Divided governments fail to exhibit the expected negative relationship between firm size and portfolio returns. The lower panel replicates this analysis conditioned on the presidential cycle, serving as a placebo test. As shown, neither Democratic nor Republican presidential regimes produce a significant size effect. These findings highlight the unique role of government status—rather than presidential affiliation—in shaping stock market behavior through the lens of the size premium, a phenomenon of ongoing interest to both investors and academics.

2.6.4 Additional results on September Effect

Table 2.16 provides additional explanations on the September effect. For each subsample periods, we calculate September monthly returns (log value-weighted stock returns less log 3-month T-bill; log equal-weighted stock returns less log 3-month T-bill) and record them. Computing with raw returns less raw 1-month T-bill show very similar results (undocumented). We observe that negative stock market responses in September is concentrated almost entirely when Republican presidents are ruling with divided Congress. Since Unified-Republican and Divided-Democratic regimes are small in some subsamples, we also tried Divided-Republican versus other-three-regimes-combined approaches where relevant, and find that only Divided-Republican regimes stand out.

Figure 2.11 presents two examples of media coverage—Reuters and CNN—that suggest political gridlock may benefit financial markets. In contrast, our findings challenge this narrative by showing that Divided governments are associated with weaker stock market performance.

Figure 2.10: **Post-1980s Size Premium across Government and Presidential Cycles**



Note: This figure extends the Figure 2.8 results by focusing on the post-1980s sample (1983 - 2020) where size effect is known to disappear in the United States. The above panel plots monthly decile portfolio returns sorted on firm size conditional on the status of governments. The below panel plots the same portfolio returns (also post-1980s sample) conditional on the sitting presidents.

Table 2.16: **September Effect and Political Cycles**

Panel A. Subsample Analysis on September Effects

Sample period	President-Government	September returns Value-weighted (monthly %)	September returns Equal-weighted (monthly %)	n
Full sample (1927 - 2020) 94 Septembers	**Rep. - Div.**	**-3.7**	**-3.86**	34
	Rep. - Uni.	-0.01	-0.01	12
	Dem. - Div.	-0.13	-0.37	14
	Dem. - Uni.	0.39	1.07	34
First half (1927 - 1973) 47 Septembers	**Rep. - Div.**	**-4.03**	**-3.89**	13
	Rep. - Uni.	-0.9	-1.83	6
	Dem. - Div.	-1.8	-1.95	2
	Dem. - Uni.	0.1	0.51	26
Second half (1974 - 2020) 47 Septembers	**Rep. - Div.**	**-3.49**	**-3.84**	21
	Rep. - Uni.	0.88	1.8	6
	Dem. - Div.	0.15	-0.11	12
	Dem. - Uni.	1.36	2.89	8
Post-war (1947 - 2020) 74 Septembers	**Rep. - Div.**	**-2.76**	**-2.74**	32
	Rep. - Uni.	1.44	1.71	8
	Dem. - Div.	-0.13	-0.37	14
	Dem. - Uni.	0.98	1.86	20
Middle sample (1940 - 1999) 60 Septembers	**Rep. - Div.**	**-2.25**	**-2.01**	26
	Rep. - Uni.	3.11	1.44	2
	Dem. - Div.	1.76	1.41	7
	Dem. - Uni.	0.27	0.89	25
Recent era (1991 - 2020) 30 Septembers	**Rep. - Div.**	**-3.82**	**-4.27**	8
	Rep. - Uni.	0.88	1.8	6
	Dem. - Div.	0.15	-0.11	12
	Dem. - Uni.	2.68	4.6	4

Panel B. Excluding two outliers (2001:09 and 2008:09)

Full sample	**Rep. - Div.**	**-3.29**	**-3.25**	32
Second half	**Rep. - Div.**	**-2.78**	**-2.81**	19
Post-war	**Rep. - Div.**	**-2.26**	**-2.02**	30
Recent era	**Rep. - Div.**	**-1.66**	**-1.17**	6

Note: This table records the September monthly stock returns (excess value-weighted and excess equal-weighted returns) conditional on political cycles. n is the number of Septembers in the relevant samples. Panel A includes all relevant September data, while Panel B specifically focuses on Republican-Divided September returns, excluding two outliers (September 2001 and September 2008). Both 2001 and 2008 Septembers suffer from exogenous shocks and happen to fall into Republican-Divided times.

2.6.5 Political Gridlock and Stock Market - Media

Figure 2.11: **Screenshots show Reuters (above) and CNN (below) article**

GRIDLOCK IS GOOD?

Election concerns have not made much of a ripple in markets so far this year, with investors consumed by the Federal Reserve's jumbo-sized rate hikes to tame surging inflation. read more

Worries over the vote could become more prominent as November approaches. Many investors believe divided government makes sweeping reforms less likely to pass, keeping the investment backdrop more stable.

"The market tends to like gridlock," said Nadia Lovell, senior U.S. equity strategist at UBS Global Wealth Management. "I think it's fair to say a split government is what investors right now expect and are positioned for."

Historical data showed that stocks tend to do better in periods of divided government, although investors cautioned that data is limited and markets have generally risen over time regardless of the governmental make-up.

Average annual S&P 500 returns have been 14% in a split Congress and 13% in a Republican-held Congress when a Democrat is in the White House, according to data since 1932 analyzed by RBC Capital Markets. That compares to 10% when Democrats controlled the presidency and Congress.

(CNN) — Now that CNN has projected Republicans will win the House of Representatives, it's time to consider a Washington where both parties have some control.

Despite underperforming on Election Day, the GOP gains will have a major impact on what's accomplished in the coming two years.

Additional climate change policy? Don't count on it. National abortion legislation? Not a chance. Voting rights? Not likely.

Plus, Republicans have indicated they will use any leverage they can find – including the debt ceiling – to force spending cuts.

While you might immediately think this is all a recipe for a stalemate in Washington, I was surprised to read the argument, backed up by research, that the US government actually overperforms during periods of divided government.

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Chapter 3

From Anomalies to Norms: A Unified Framework for Sentiment, Risk, and Mispricing

Abstract: This paper introduces a novel portfolio construction framework that goes long on safer stocks (less risky or mispriced) and short on unsafe ones. Rooted in limits-to-arbitrage theory with transaction costs, our *normative* approach provides a strong rationale for cross-sectional anomalies driven by mispricing and helps address well-known asset pricing challenges, such as the low-volatility puzzle and the distress risk puzzle. In addition, our theoretical framework predicts: i) a negative *contemporaneous* link between aggregate stock market returns and cross-sectional signals, ii) a short-term sentiment-driven effect on expected returns versus a long-term fundamental risk effect, and iii) a decline in returns on both portfolio sides as sentiment rises, with the latter being an unexplored aspect in prior research. Testing 100 U.S. cross-sectional anomalies, we find robust empirical support, highlighting sentiment's role in linking cross-sectional and time-series stock return dynamics.

3.1 Introduction

In this paper, we develop a framework for constructing portfolios where relatively safer stocks (defined as less risky or less mispriced) are placed on the long side, while less safe stocks are allocated to the short side.[1] This approach, which is novel to the finance literature, is able to explain four insights into both the cross-section of stock returns and the time-series variation of aggregate stock market returns.

First, our model explains why anomalies driven by mispricing (rather than risk) emerge,

[1]The classification of whether maximum or minimum exposure to a given firm characteristic is considered "safe" is open to interpretation. In the Appendix, we include a full list of the anomalies analyzed, along with our interpretations of the associated firm characteristics, grounded as closely as possible in the original literature.

offering a *normative* perspective on the anomalies literature. Traditionally, the factors zoo literature has taken a *positive economics* approach, focusing on empirically identifying and validating anomalies—whether by testing their out-of-sample performance (McLean and Pontiff, 2016) or using dimension-reduction techniques to isolate key factors (Feng et al., 2020; Bryzgalova et al., 2023). In contrast, our paper adopts a *normative* view, providing one such guidance on how investors *should* construct long-short portfolios. Our model builds upon the theoretical foundation of noise trader risk (De Long et al., 1990) and limits to arbitrage (Shleifer and Vishny, 1997). The presence of noise traders lead to systematic pricing errors, particularly in riskier assets typically found in the short-leg of portfolio strategies. This mispricing is amplified during high sentiment periods as unsophisticated investors flood the market, pushing prices further away from their fundamental values. Our empirical findings confirm this, showing that stocks more susceptible to sentiment changes exhibit greater deviations from expected returns. By aligning the long and short sides of portfolios with safer and riskier characteristics, respectively, we offer an economically grounded explanation for the emergence and persistence of well-known cross-sectional puzzles where firm characteristics associated with lower levels of risk yield higher returns, such as the low-volatility puzzle Ang et al. (2006b), the distress risk puzzle Campbell et al. (2008), and the quality anomaly Asness et al. (2019).

This economic interpretation is important and is best illustrated by comparing two prominent factors: the size factor (SMB, Fama and French, 1992) and the quality factor (QMJ, Asness et al., 2019). Both factors are priced in the stock market, yet SMB places riskier firms (small-cap stocks) in the long leg, whereas QMJ assigns similarly risky firms (low-quality or junk" stocks) to the short leg.[2] How should we reconcile this inconsistency? While the risk-based explanation that forward-looking investors demand compensation for bearing higher levels of risk associated with certain firm characteristics are well-established, the mispricing argument lacks a comparable framework to justify its role in explaining cross-sectional anomalies. Our first contribution is to provide a framework showing that sentiment-driven stocks—those that are riskier or more prone to mispricing—tend to deliver higher returns than sentiment-immune stocks following periods of low (high) sentiment.

Our second contribution is to leverage the sentiment model to provide a unified explanation for both time-series variations in aggregate stock returns and cross-sectional anomalies. As Fama (1991) aptly noted,[3] achieving this coherence is a crucial objective in asset pricing. Our framework reveals that periods of strong market performance often coincide with weaker cross-sectional anomaly returns, and vice versa, prompting the key question: *"Is there a common force driving these patterns simultaneously?"* We identify this common

[2]Figure 4 in Asness et al. (2018) shows that many small firms are ranked as low-quality ("junk").

[3]*"In the end, I think we can hope for a coherent story that [...] relates the cross-section properties of expected returns to the variation of expected returns through time[.]"*

force as market sentiment.[4]

The key insight in our framework stems from the simple intuition that both time-series and cross-sectional patterns emerge from the same set of equity prices: the long and short legs of equity portfolios. Unlike the single risky asset assumed in De Long et al. (1990), we incorporate two risky assets. We interpret one as the long side of portfolio returns and the other as the short side. In this setup, aggregate stock market returns are the average of the two risky assets, while cross-sectional anomaly returns are the return difference between the long and short sides of the portfolio. When sentiment is low, diminished demand for risky assets elevates aggregate returns but weakens long-short strategies. Conversely, high sentiment inflates prices, reducing aggregate returns while amplifying the profitability of anomalies, particularly for sentiment-sensitive short-leg stocks. These dynamics create a *negative contemporaneous relationship* between aggregate market returns and the average performance of long-short portfolios based on firm characteristics. This unified explanation of time-series and cross-sectional patterns constitutes a key contribution of our paper.

Our empirical analysis classifies a broad set of cross-sectional anomalies into three categories. First, anomalies that are fully accounted for[5] by the market factor are grouped under "Market Risk." Second, consistent with Amihud and Mendelson (1986a), anomalies explained entirely by the "Illiquidity" factor are assigned to the "Illiquidity" category. Finally, following Barberis et al. (1998), anomalies that can be attributed to the "Number of Earnings Streaks" factor are categorized under "Mispricing.". Then, following our normative approach, we flip the legs of Market Risk and Illiquidity anomalies so that the long leg becomes safe and the short unsafe. Our methodology provides two additional contributions regarding the performance of portfolio strategies conditioned on sentiment. First, contrary to the existing literature, we find that during high-sentiment periods, even a broad range of long-leg strategies become unprofitable.[6] Additionally, the negative relationship between market sentiment and short-leg returns, as shown in Stambaugh et al. (2012), is pervasive across many well-established risk anomalies. Taken together, our findings reveal that both long- and short-leg returns, on average, decline as sentiment rises.

Literature review: Our paper relates to a large literature on theoretical and empirical asset pricing. Sentiment is a powerful empirical predictor of difficult-to-arbitrage stocks, as demonstrated by Baker and Wurgler (2006), and also of the aggregate stock market, as shown by the time-series result of Huang et al. (2015). In the cross-section, numerous works have attempted to link the role of sentiment to individual or a small number of anomalies.[7]

[4] One of the early attempts to provide a unified explanation is Yogo (2006), which attributes cross-sectional variation to differences in portfolio consumption betas and time-series variation in the equity premium to the countercyclicality of risk premia.

[5] That is, we regress each anomaly on the market factor, requiring an alpha statistically indistinguishable from zero and a significantly positive beta.

[6] See Section 3.3.4 for more details.

[7] Antoniou et al. (2013) relate momentum with sentiment, and Stambaugh et al. (2012) uses 11 number of

Instead, we document the role of sentiment across the 100 number of anomalies. Other related papers in the cross section include Hong et al. (2000) and Avramov et al. (2013).

Dong et al. (2022) investigate links between long-short anomaly portfolio returns from the cross-sectional literature and the U.S. market excess returns (See, however, Engelberg et al. (2023) and Cakici et al. (2024) for some conflicting pieces of evidence). Specifically, they show that a group of 100 long-short anomaly portfolio returns is indeed useful for forecasting the future monthly market excess return on an out-of-sample basis. We differentiate in two ways. First, Dong et al. (2022) focus on forecasting relationship between time-series of stock market and cross-sectional signals. Our work focuses on documenting *contemporaneous* relationship of the two. Second, through our model, we provide a sentiment-based explanation which drives the underlying dynamics. Yu and Yuan (2011) show that a positive mean-variance relation holds only during periods of low sentiment, indicating that beta works when market sentiment is low. Building on this, our work demonstrates that alpha works when market sentiment is high. In a related work to ours, Bordalo et al. (2024) construct a sentiment index based on analyst expectations of long-term expected earnings growth for S&P 500 firms. We share a similar mechanism where return predictability in the time-series stock market as well as cross-section anomalies arises from the non-rational beliefs that lead to systematic pricing errors that are eventually corrected. We believe that our paper is an important complement to their work, as we provide a theoretical underpinning and consider a wide range of anomalies.

Finally, this paper relates to Pukthuanthong et al. (2019), which establishes a normative framework for factor identification from the rational framework. Our work takes a complementary perspective by incorporating behavioral insights, offering an alternative yet aligned viewpoint.

Outline: The remainder of the paper is organised as follows: Section 3.2 introduces our model. Section 3.3 provides empirical results that support the model. Section 3.4 examines how our model addresses well-known asset pricing challenges, including the low-volatility and distress risk puzzles. It also categorizes certain anomaly groups and discusses exceptions to our reformulation, which allocates safer (riskier) firm characteristics to the long (short) leg of portfolios. Section 3.5 concludes.

3.2 Model

3.2.1 The toy model

We begin by introducing a simple toy model that captures the essence of our main framework. The economy consists of two agents—rational (sophisticated) traders and irrational (noise)

anomalies.

traders—and two risky assets, Q and J. Here, Q represents a stock of decent quality, while J is more "junky." We assume an economy composed solely of these two assets,[8] making the market return the average of their returns:

$$R^{mkt} = \frac{Q + J}{2}.$$

Additionally, a representative cross-sectional strategy can be formed as their return differential:

$$R^{cs} = Q - J.$$

When sentiment is high at time t, demand for both stocks (Q and J) increases, inflating prices. This deviation from fundamental value corrects at $t + 1$, causing R^{mkt}_{t+1} to decline. Since noise traders tend to favor riskier assets, J is more sentiment-sensitive, making its price drop larger than Q's. This results in a positive QMJ (Quality Minus Junk) effect (Asness et al., 2019).

To quantify, assume a one-unit increase in sentiment (s_t) raises the price of Q by 3% and J by 5%. Noise traders disproportionately gravitate toward harder-to-arbitrage stocks (J, in this case), and the correlated trading behavior (i.e., co-movement) of retail investors amplifies this effect (Kumar and Lee, 2006), driving its price higher relative to Q. When prices correct in the following month, the market return declines by 4%:

$$R^{mkt}_{t+1} = \frac{Q_{t+1} + J_{t+1}}{2} = \frac{-3\% - 5\%}{2} = -4\%.$$

Moreover, since J declines more than Q, cross-sectional strategy returns increase by 2%:

$$R^{cs}_{t+1} = Q_{t+1} - J_{t+1} = (-3\%) - (-5\%) = +2\%.$$

This example illustrates how sentiment fluctuations create predictable patterns in both market and cross-sectional returns, reinforcing their contemporaneous negative relationship. It also demonstrates that a strategy allocating safer (riskier) firm characteristics to the long (short) side of the portfolio can yield positive returns.

3.2.2 The baseline model

We now formally describe our theoretical framework, which is based on the noise trader model of De Long et al. (1990) (henceforth DSSW). This original paper draws on a simple overlapping generation (OLG) framework with one risky and one risk-free asset and two types of agents, sophisticated investors and irrational noise traders. Both agents live for two

[8]This assumption is reasonable; in the empirical section, we show that the correlation between the average returns of all anomalies and aggregate market returns exceeds 0.9.

periods and then they die. Rational investors can not take full advantage of arbitrage opportunities because of *noise trader risk* created by the uncertainty of noise traders' stochastic misperception. In particular, sophisticated investors (denoted as "si") are fully rational, in contrast to noise traders (denoted as "nt") whose beliefs are biased and, thus, their trades are polluted with noise. There is a continuum of agents on the interval $[0, 1]$, and the ratio of noise traders is defined as μ. All agents maximize a constant absolute risk aversion (CARA) utility function of wealth, given by

$$U = -\exp^{-(2\gamma)\omega} \tag{3.1}$$

where γ is the coefficient of absolute risk aversion and ω is wealth. With normally distributed returns of holding a unit of the risky asset, the maximization of equation 3.1 is equivalent to the maximization of :

$$\overline{\omega} - \gamma\sigma_{\omega}^2 \tag{3.2}$$

where $\overline{\omega}$ is the expected final wealth, and σ_{ω}^2 is the one period ahead variance of wealth.

Our extension is to include two risky assets instead of one as in the original model of DSSW. When a single risky asset explains the entire market, we are not able to form a portfolio strategy. The innovation of our model is to have two risky assets to concurrently explain the general stock market as well as portfolio strategy. We denote them as u_1 and u_2, which are in fixed supply of one unit and bear the price $p_{t,i}$ where $i \in \{1, 2\}$. As we later show, each risky asset represents long- and short-leg of stock returns, respectively. While this setting comes from a simple observation that both time-series and cross-sectional market pattern come from the same set of stock prices, it not only simplifies the notations required to derive the results, but also is highly intuitive.

For instance, assume that operating profitability is the only firm characteristics that matter for investors in this economy. Denoting u_1 as less profitable firm and u_2 as more profitable firm, the aggregate market performance is simply the average of returns of u_1 and u_2, while the cross-sectional signal based on operating profitability is return of u_2 less that of u_1. The risk-free asset is assumed to be in perfectly elastic supply, rendering its priced as fixed. Furthermore, we assume that all assets pay identical dividends at the fixed rate r.

For each period, sophisticated investors maximize their expected utility by optimally choosing to hold $\alpha_{t,1}^{si}$ of the risky asset u_1 and $\alpha_{t,2}^{si}$ of the risky asset u_2. On the other hand, noise traders maximize their expected utility, given their misperception, by choosing to hold $\alpha_{t,1}^{nt}$ of risky asset u_1 and holding $\alpha_{t,2}^{nt}$ of risky asset u_2. We further assume that both agents cannot make unlimited bidding against each other, due to limits of arbitrage (see Shleifer and Vishny, 1997).

We also assume that the aggregate market sentiment s_t is a martingale with drift $s_t^{\star}$ and volatility σ_s^2.[9] Finally, we assume that the misperception of noise traders for risky assets u_1 and u_2 is different and is given by:

$$\begin{gathered} s_{t,i} = \beta_i^m s_t + \epsilon_{t,i} \quad \text{for} \quad i \in \{1, 2\} \\ \epsilon_{t,i} \sim \mathcal{N}(0,\, \sigma_{\epsilon_i}^2) \quad \text{with} \quad cov(\epsilon_{t,i}, s_t) = 0 \quad \text{and} \quad cov(\epsilon_{t,i}, \epsilon_{t,j}) = 0 \quad \forall\, i \neq j \end{gathered} \tag{3.3}$$

The idea behind equation 3.3 is that the misperception of the risky asset includes a systematic as well as an idiosyncratic component $\epsilon_{t,i}$. Intuitively, β^m captures the elasticity of misperception to the systematic sentiment component. What we are interested in is to assess the pricing role of market sentiment, s_t.

3.2.3 Expected returns conditional on sentiment

The equation 3.3 above directly imply that $\sigma_{s_i}^2 = (\beta_i^m)^2\sigma_s^2 + \sigma_{\epsilon_i}^2$ where $i \in \{1, 2\}$. Since we do not focus on the idiosyncratic component, we simplify the matter by assuming $\sigma_{\epsilon_1}^2 = \sigma_{\epsilon_2}^2$. Without loss of generality, assume $\beta_1^m > \beta_2^m > 0$: u_1 has larger exposure to market sentiment than asset u_2 and implies higher noise trader risk $\sigma_{s_1}^2 > \sigma_{s_2}^2$. This is exactly the risk that sets limits to arbitrage for rational investors to trade against irrational investors.

Due to equation 3.2, sophisticated investors maximize the following expected utility:

$$\begin{aligned} \overline{\omega}^{si} - \gamma\sigma_{w^{si}}^2 = c_0 &+ \alpha_{t,1}^{si}(r + tp_{t+1,1} - p_{t,1}(1 + r)) + \alpha_{t,2}^{si}(r + tp_{t+1,2} - p_{t,2}(1 + r)) \\ &- \gamma[(\alpha_{t,1}^{si})^2 t\sigma_{p_{t+1,1}}^2 + (\alpha_{t,2}^{si})^2 t\sigma_{p_{t+1,2}}^2 + 2\alpha_{t,1}^{si}\alpha_{t,2}^{si}\, tcov(p_{t+1,1}, p_{t+1,2})] \end{aligned} \tag{3.4}$$

c_0 is a function of first-period labor income, and the anterior subscript denotes the time at which an expectation is taken (e.g., $tp_{t+1,1} \equiv E_t[p_{t+1,1}]$) for ease of exposition. Similarly, $t\sigma_{p_{t+1,i}}^2$ denotes the conditional expectation of one-step-ahead variance of $p_{t+1,i}$ and $tcov(p_{t+1,1}, p_{t+1,2})$ is the conditional expectation of the covariance of the one-step-ahead risky assets' prices $p_{t+1,i}$ $\forall i \in \{1, 2\}$.

Noise traders likely maximize the following expected utility:

$$\begin{aligned} \overline{\omega}^{nt} - \gamma\sigma_{w^{nt}}^2 = c_0 &+ \alpha_{t,1}^{nt}(r + tp_{t+1,1} - p_{t,1}(1 + r)) + \alpha_{t,2}^{nt}(r + tp_{t+1,2} - p_{t,2}(1 + r)) \\ &- \gamma[(\alpha_{t,1}^{nt})^2 t\sigma_{p_{t+1,1}}^2 + (\alpha_{t,2}^{nt})^2 t\sigma_{p_{t+1,2}}^2 + 2\alpha_{t,1}^{nt}\alpha_{t,2}^{nt}\, tcov(p_{t+1,1}, p_{t+1,2})] \\ &+ \underbrace{\alpha_{t,1}^{nt}(\beta_1^m s_t + \epsilon_{t,1}) + \alpha_{t,2}^{nt}(\beta_2^m s_t + \epsilon_{t,2})}_{\text{misperception of noise traders}} \end{aligned} \tag{3.5}$$

[9] This assumption is crucial for the basic result of the paper and differentiates us with Ding et al. (2019). We empirically validate this assumption in Section 3.2.4.

Note that noise traders maximization equation 3.5 has sentiment components, $\alpha_{t,1}^{nt}(\beta_1^m s_t + \epsilon_{t,1}) + \alpha_{t,2}^{nt}(\beta_2^m s_t + \epsilon_{t,2})$. Absence of such sentiment concerns ($\beta_1^m = \beta_2^m = 0$) reduces down to the same trade-off equation in 3.4. Taking the first order conditions with respect to risky asset holdings yields:

$$\alpha_{t,1}^{si} = \frac{tcov(p_{t+1,1}, p_{t+1,2})R_{t+1,2} - \sigma_2^2 R_{t+1,1}}{2\gamma(tcov(p_{t+1,1}, p_{t+1,2})^2 - \sigma_1^2\sigma_2^2)} \tag{3.6}$$

$$\alpha_{t,2}^{si} = \frac{tcov(p_{t+1,1}, p_{t+1,2})R_{t+1,1} - \sigma_1^2 R_{t+1,2}}{2\gamma(tcov(p_{t+1,1}, p_{t+1,2})^2 - \sigma_1^2\sigma_2^2)} \tag{3.7}$$

where, for ease of notation, we define the excess return from date t to date $t+1$ as $R_{t+1,i} \equiv r + tp_{t+1,i} - p_{t,i}(1+r)$, and the conditional volatility as $\sigma_i^2 \equiv t\sigma_{p_{t+1,i}}^2$ for $i \in \{1,2\}$. For noise traders,

$$\alpha_{t,1}^{nt} = \frac{tcov(p_{t+1,1}, p_{t+1,2})(R_{t+1,2} + \beta_2^m s_t + \epsilon_{t,2}) - \sigma_2^2(R_{t+1,1} + \beta_1^m s_t + \epsilon_{t,1})}{2\gamma(tcov(p_{t+1,1}, p_{t+1,2})^2 - \sigma_1^2\sigma_2^2)} \tag{3.8}$$

$$\alpha_{t,2}^{nt} = \frac{tcov(p_{t+1,1}, p_{t+1,2})(R_{t+1,1} + \beta_1^m s_t + \epsilon_{t,1}) - \sigma_1^2(R_{t+1,2} + \beta_2^m s_t + \epsilon_{t,2})}{2\gamma(tcov(p_{t+1,1}, p_{t+1,2})^2 - \sigma_1^2\sigma_2^2)} \tag{3.9}$$

Prices are obtained by the following market clearing conditions:

$$(1-\mu)\alpha_{t,j}^{si} + \mu\alpha_{t,j}^{nt} = 1 \quad \forall j \in \{1,2\} \tag{3.10}$$

where the left hand side follows from the assumption that the supply of risky assets is fixed and equal to 1. Thus current prices are given by:

$$p_{t,1} = \frac{1}{1+r}[r + tp_{t+1,1} - 2\gamma(tcov(p_{t+1,1}, p_{t+1,2}) + \sigma_1^2) + \mu(\beta_1^m s_t + \epsilon_{t,1})] \tag{3.11}$$

$$p_{t,2} = \frac{1}{1+r}[r + tp_{t+1,2} - 2\gamma(tcov(p_{t+1,1}, p_{t+1,2}) + \sigma_2^2) + \mu(\beta_2^m s_t + \epsilon_{t,2})] \tag{3.12}$$

From equation 3.8 - 3.9 it is easy to see that the β_1^m and β_2^m have a positive effect on portfolio allocations of $u_1(u_2)$. Since we have assumed that $\beta_1^m > \beta_2^m$, the current market sentiment will affect investors holding u_1 more. As a result, we get:

$$R_{t+1,i} = \frac{\mu\beta_i^m}{1+r}\big[s_{t+1} - (1+r)s_t - s^*\big] + 2\gamma(k + \sigma_i^2) + \theta_i \tag{3.13}$$

where θ_i is given by:

$$\theta_i = \frac{\mu\epsilon_{t+1,i}}{1+r} + \mu\epsilon_{t,i} \tag{3.14}$$

Equation 3.13 clearly illustrates that the presence of noise traders ($\mu \neq 0$) affects returns. While we remain agnostic about the size of noise traders in the market, their mere presence is sufficient to cause stock prices to deviate significantly from their fundamental values, even in markets with relatively few noise traders (Mendel and Shleifer, 2012).

We now present two main theorems using equation 3.13 for two risky assets ($i = 1, 2$).

There is a negative relationship between sentiment and future aggregate stock market returns.

Using equation 3.13, the average of aggregate stock market returns are given by:

$$\begin{aligned} R_{t+1}^{mkt} &= \frac{R_{t+1,1} + R_{t+1,2}}{2} \\ &= \frac{\mu(\beta_1^m + \beta_2^m)}{1+r}\Big[s_{t+1} - (1+r)s_t - s^*\Big] + 2\gamma(\sigma_1^2 + \sigma_2^2) + (\theta_1 + \theta_2) \end{aligned} \tag{3.15}$$

The expected returns conditional on low or high sentiment period is given by:

$$\begin{aligned} E(R_{t+1}^{mkt} \mid s_t) &= E\Big(\frac{R_{t+1,1} + R_{t+1,2}}{2}\Big| s_t\Big) \\ &= \frac{\mu(\beta_1^m + \beta_2^m)}{1+r}\Big[E([s_{t+1} - (1+r)s_t \mid s_t)] - s^*\Big] + 2\gamma(\sigma_1^2 + \sigma_2^2) + (\theta_1 + \theta_2) \\ &= \frac{-\mu(\beta_1^m + \beta_2^m)}{1+r}\Big[rs_t + s^\star\Big] + 2\gamma(\sigma_1^2 + \sigma_2^2) + (\theta_1 + \theta_2) \end{aligned} \tag{3.16}$$

The last equation follows from the fact that sentiment is assumed to be a martingale.[10] Thus, the higher the sentiment s_t, the lower the aggregate stock market returns in the next period (or β_{mkt}).

There is a positive relationship between sentiment and future strategy returns.

Consider forming a portfolio strategy where investors long the second risky asset u_2 and short the first risky asset u_1. Taking conditional expectations with respect to the current sentiment s_t, we obtain:

[10] The same results are obtained when sentiment is assumed to be a supermartingale.

$$
\begin{aligned}
E(R^{cs}_{t+1} \mid s_t) &= E(R_{t+1,2} - R_{t+1,1} \mid s_t) \\
&= \frac{\mu(\beta^m_2 - \beta^m_1)}{1+r}\Big[E([s_{t+1} - (1+r)s_t \mid s_t)] - s^*\Big] + 2\gamma(\sigma^2_2 - \sigma^2_1) + (\theta_2 - \theta_1) \\
&= \frac{-\mu(\beta^m_2 - \beta^m_1)}{1+r}\Big[rs_t + s^*\Big] + 2\gamma(\sigma^2_2 - \sigma^2_1) + (\theta_2 - \theta_1)
\end{aligned}
\tag{3.17}
$$

Again, the last equation follows from the fact that sentiment is assumed to be a martingale. Since $\beta^m_2 - \beta^m_1 < 0$, it follows that higher level of sentiment s_t is followed by higher strategy returns in the next period (or α).

From Theorems 3.2.3 and 3.2.3, the inverse relationship between market anomalies and aggregate stock returns naturally arises.

There is an inverse relationship between aggregate stock market returns (β_{mkt}) and market anomalies (α).

Omitted for brevity.

Following the sentiment beta assumption $\beta^m_1 > \beta^m_2 > 0$, one can interpret risky asset u_1 as short legs of characteristics-based portfolios, and u_2 as long legs. This is in line with existing literature that short legs are in general more responsive to changes in sentiment (Stambaugh et al., 2012). But the second part of our sentiment beta assumption, $\beta^m_2 > 0$, differs from Stambaugh et al. (2012) and Stambaugh et al. (2014) who argue β^m_2 is indistinguishable from 0. While our theorems still hold when $\beta^m_1 > \beta^m_2 = 0$, we show that $\beta^m_2 \neq 0$ in the empirical section.

3.2.4 Is sentiment index a martingale?

A basic assumption driving the main results in Theorems 3.2.3 and 3.2.3 is that the sentiment index is a martingale. A sequence of random variables X_t is a martingale process if, for any time t, the following two conditions hold:

(i) $E(\mid X_t \mid) < \infty$

(ii) $E(X_{t+1} \mid \mathcal{F}_t) = X_t$

where $\mathcal{F}_t$ is the information set available up to time t. In this section we use the market sentiment index of Huang et al. (2015) (henceforth HJTZ) to show that this sentiment index empirically qualifies to be martingale. We employ three tests. The first one is to consider the increments and assess whether they have zero mean. We find that the average of the increments is 0.002 which is indistinguishable from 0 (t-stat: 0.24). Secondly we run the Ljung-Box test to check whether the index is independently distributed.

In particular, we test the following hypothesis:

- H_0: The data are independently distributed, i.e. the correlations in the population from which the sample is taken are 0, so that any observed correlations in the data result from randomness of the sampling process.

- H_a: The data are not independently distributed; they exhibit serial correlation.

Table 3.1: **HJTZ Sentiment index is a martingale**

Panel A: Test Statistics

Test	Value	t-stat	Result
Average of Increments	0.002	0.24	Fail to Reject
Ljung-Box	2.52	0.11	Fail to Reject
Durbin-Watson	1.88	0.055	Fail to Reject

Panel B: AR(1) test

The equation is $s_t = \alpha + \beta s_{t-1} + \epsilon_t$

	$\hat{\alpha}$	$t(\hat{\alpha})$	$\hat{\beta}$	$t(\hat{\beta})$	$t(\hat{\beta}-1)$
Results	0.0009	0.1018	0.9886	77.39	-0.8935

Note: This table records test results to check whether HJTZ sentiment index is a Martingale.

Panel A in Table 3.1 presents the results. For $lag = 1$, we find that the χ^2 is equal to 2.52 (p-value: 0.11). Thus, we fail to reject H_0. With $lag = 2$, we find that the χ^2 is equal to 2.54 and the p-value is 0.028. Again, we fail to reject H_0. We also run the Durbin-Watson test, an alternative test statistic used to detect the presence of autocorrelation at lag 1 in the residuals (prediction errors) from a regression analysis. If e_t is the residual given by $e_t = \rho e_{t-1} + \nu_t$ the Durbin-Watson test statistic is

$$d = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2} \tag{3.18}$$

where T is the number of observations. For large T, d is approximately equal to $2(1-\hat{\rho})$, where $\hat{\rho}$ is the sample autocorrelation of the residuals. $d = 2$, therefore, indicates no autocorrelation. The value of d always lies between 0 and 4. If the Durbin–Watson statistic is substantially less than 2, there is evidence of positive serial correlation. If $d > 2$, successive error terms are negatively correlated. We find that $DW = 1.88$ with a p-value 0.055 and, therefore, we fail to reject the null hypothesis. From all the above, we can conclude that the assumption that HJTZ sentiment index is a martingale is supported empirically.

Finally, we follow Hall (1978) to estimate the following AR(1) process:

$$s_t = \alpha + \beta s_{t-1} + \epsilon_t \tag{3.19}$$

Martingales should have $\alpha = 0$ and $\beta = 1$, which leads to $E(s_{t+1} \mid s_t) = s_t$. Panel B in Table 3.1 presents the results of the regression where the t-statistics are adjusted using Newey-West procedure with 6 lags.

The AR(1) process, reveals that the coefficient of the lagged variable is statistically insignificant different from 1, thus we can infer that s_t is a martingale process.[11]

3.3 Empirical results

3.3.1 Data

We use monthly market-based sentiment series constructed by Huang et al. (2015) (henceforth HJTZ). The HJTZ sentiment index data that we use spans over 55 years, from January 1966 to December 2020 and uses the same six variables[12] as in Baker and Wurgler (2006) (henceforth BW). HJTZ index refines the original sentiment index of BW by extracting information via Principal Least Squares (PLS) regression. We opt for this measure over the widely known BW version of sentiment as it shows to have greater predictive power for the aggregate stock market.[13] Figure 3.1 examines the time-series behavior of this sentiment index over time. The figure contains two measures, the HJTZ sentiment index (solid red) and the Baker-Wurgler (BW) sentiment index (dotted blue). Both measures are orthogonalized to macroeconomic conditions. The correlation between the two measures is about 70%, and they tend to show a similar trajectory. Closely examining the graph, we find that sentiment tends to spike on a number of occasions. In the late 1960s, investor sentiment rose to a peak around the electronic bubble. During the 1970s, it faced a period of decline, only to witness a remarkable resurgence, reaching its peak once again in the early 1980s amidst the biotech bubble. During the internet bubble in the late 1990s, sentiment met another pinnacle.

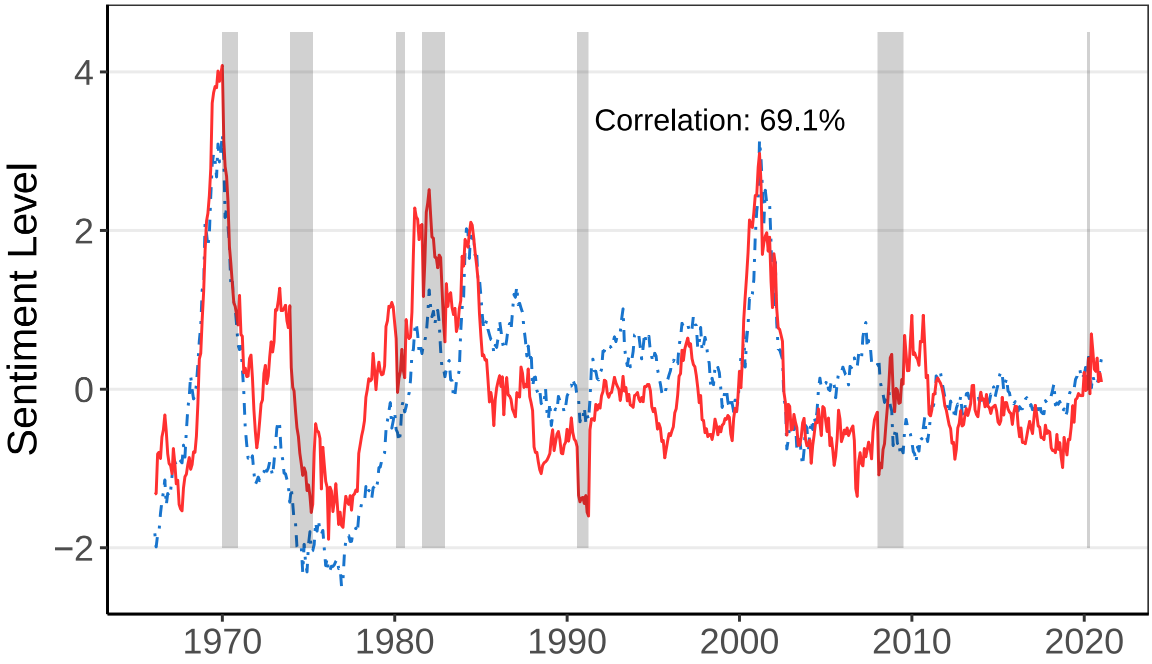
For stock market returns, we use log monthly returns of the value-weighted and equal weighted stock market portfolios from the Center for Research in Security Prices (CRSP). We compute excess value weighted (VWR_TBL) and equal weighted stock returns (EWR_TBL) using log of the three-month Treasury bill, also from CRSP.

[11] If we do not adjust standard errors using the Newey-West procedure with 6 lags, $t(\hat{\beta} - 1)$ becomes -1.996 which makes s_t statistically less than 1. In that case, our results still hold since the process is a supermartingale.

[12] The six measures are the closed-end fund discount, the number and the first-day returns of IPOs, NYSE turnover, the equity share in total new issues, and the dividend premium.

[13] Recall that this paper aims to explain the driving factor that explains both the aggregate stock markets and cross-sectional signals. Main empirical results remain unchanged when we use BW sentiment rather than HJTZ sentiment, as shown in the Appendix.

Figure 3.1: **The Sentiment Measure**



Note: This figure illustrates sentiment index over time. Red solid line is the HJTZ sentiment index that we use in the main analysis. We also plot Baker-Wurgler index in dotted blue line. Both sentiment measures are macroeconomics variables-orthogonalized version. Shaded areas are NBER recessions.

We use risk anomalies (long-leg, short-leg, and long-short portfolio returns) from the public data repository by Chen and Zimmermann (2022).[14] From the April 2023 release that we use, there are 212 anomalies published in the economics/finance/accounting literature. We trim down this list of anomalies to 100 for a number of reasons. First, we require the anomalies data to match the availability of sentiment data that spans from January 1966 to December 2020. For instance, we do not use a risk factor formed on consensus recommendation (Barber et al., 2001) that is available from 1993 due to analyst recommendation database. Since sentiment reached its highest and lowest level in 1960s and 1970s, missing the first half of our analysis time frame is undesirable. This procedure leaves 147 anomalies. Next, many anomalies contain essentially the same information and are thus duplicates of each other. Moreover, some cross-sectional signals are purely based on performance (for instance, all of momentum-based strategies simply bet on winning stocks, regardless of the underlying fundamentals of firms) or have ambiguous interpretation regarding whether safe firm characteristics are placed on the long-legs or short-legs. For instance, risk factors based

[14]We thank Andrew Chen and Tom Zimmermann for making this data public. This data is available at https://www.openassetpricing.com/.

on leverage could have different interpretations based on the underlying economy. A firm with strong fundamentals can have high leverage because they perceive the current economic condition as good. A company with poor fundamentals may still maintain high leverage due to its low revenue, which inherently raises the leverage ratio. We therefore pull out these anomalies. This leaves us with 100 anomalies that we use to establish main empirical findings.

Our sentiment framework establishes that long-legs contain stocks with (relatively) safe characteristics whereas short-legs include stocks with (relatively) risky characteristics (recall that $\beta_1^m > \beta_2^m > 0$, where β_1^m represents the misperception of noise traders regarding risky asset 1, which we interpret as the short side of portfolio returns, while β_2^m represents the misperception for the long side of portfolio returns). In about 30+ anomalies, we follow this intuition and switch the long-leg returns with short-leg returns. In other words, we reformulate the existing cross-sectional signals to have safe firm characteristics assigned to the long-leg returns and risky characteristics to the short-leg returns.

For example, we switch the legs for the following risk factors: (1) bid-ask spread, (2) investment, and (3) firm age, for the following reasons. For the bid-ask spread measure (Amihud and Mendelson, 1986b), liquid stocks have lower bid-ask spreads (as liquid stocks tend to have spreads close to zero). For the investment factor (Titman et al., 2004), higher levels of investment expenditures, which are generally viewed favorably due to greater investment opportunities, are originally assigned to the short leg of portfolio returns. For firm age (Barry and Brown, 1984), younger firms, which are assigned to the long side of portfolio returns, tend to be riskier due to less public information and smaller size. For other risk factors, such as gross profitability (Novy-Marx, 2013), which assigns relatively safer characteristics (higher profitability) to the long side of portfolio returns, we maintain the original assignment. The final set of 100 cross-sectional signals aligns with the relevant literature, including McLean and Pontiff (2016) and Dong et al. (2022). The full list of anomalies considered in our main empirical exercise, along with our decision on whether to flip the long and short sides of returns, is provided in Appendix Section 3.6.1.

3.3.2 Sentiment and aggregate stock returns

As in Section 3.2, consider an economy with two risky assets, u_1 and u_2 with returns $R_{t,1}$ and $R_{t,2}$, respectively. Consistent with earlier literature that sentiment has an asymmetric effect on stocks with certain characteristics, we interpret u_2 as the long leg of portfolio strategy, and u_1 as the short leg of portfolio strategy. The representative long-short strategy return would be $R_t^{cs} = R_{t,2} - R_{t,1}$, and aggregate market returns $R_t^{mkt} = (R_{t,2} + R_{t,1})/2$.

We start our analysis by examining the relationship between market sentiment and aggregate stock market returns. We regress the aggregate stock market returns on one month lagged HJTZ sentiment index, following earlier papers such as Baker and Wurgler (2006) and Huang et al. (2015).

$$R_{t+1}^{mkt} = \alpha + \beta s_t + \varepsilon_{t+1} \tag{3.20}$$

where mkt = {VWR_TBL, EWR_TBL} is the aggregate market returns, and s_t is the macro-economics-orthogonalized version of HJTZ market sentiment index. We are interested in whether we can reject the null hypothesis of $\beta = 0$, that investor sentiment has no predictive ability.

The result, depicted in Table 3.2, demonstrates a strong negative relationship between market sentiment and aggregate stock returns. A simple forecasting regression model suggests that sentiment negatively predicts market returns (both value-weighted and equal-weighted returns). This holds robust when we divide the available sample into two equal parts (second and third part of Panel A). The low aggregate stock market return following high investor sentiment seems to represent investors' overly optimistic belief about future cash flows that cannot be justified by subsequent economic fundamentals, and aligns well with the prediction stated in Theorem 3.2.3.

3.3.3 Sentiment and cross-sectional risk anomalies

We now turn to portfolios formed on firm characteristics that are known to earn strategic profits in the stock market. Because the model framework developed in Section 3.2 explicitly assumes the presence of long- and short-legs (and henceforth long-minus-short strategy) returns, we separately analyze all of long-leg returns, short-leg returns, and long-short strategy returns.

Figure 3.2 plots this result. In this graph, we first categorize months into quintile buckets based on their one-month lagged sentiment level. We calculate the average returns for the 100 long-short strategy returns over a 55-year time frame, conditioned on the sentiment quintile buckets. As the graph suggests, the average returns of the long-short strategy increase as sentiment moves from lower to higher quintile, lending support to Theorem 3.2.3. Importantly, the average of long-short strategy returns is statistically not different from zero when the sentiment is at its lowest quintile, while that under high sentiment period is positive and statistically significant. This suggests that alpha, or cross-sectional anomalies, is effective when market sentiment is high and ineffective when sentiment is low, complementing earlier findings that market beta works when sentiment is low (Antoniou et al., 2016; Yu and Yuan, 2011).

Table 3.2: **Forecasting aggregate market returns with sentiment**

Panel A: Predictive regression results

Regression is of the form $R^{mkt}_{t+1} = \alpha + \beta s_t + \varepsilon_{t+1}$

1. Full Sample (1966:01 - 2020:12)

Dep. Variable (R^{mkt}_{t+1})	β	$t(\beta)$	R-squared	Constant?
VWR_TBL	**-0.61*** **	**-4.07**	0.02	Yes
EWR_TBL	**-0.84*** **	**-4.45**	0.02	Yes

2. First-half (1966:01 - 1993:06)

Dep. Variable (R^{mkt}_{t+1})	β	$t(\beta)$	R-squared	Constant?
VWR_TBL	**-0.48*** **	**-2.69**	0.01	Yes
EWR_TBL	**-0.93*** **	**-3.82**	0.03	Yes

3. Second-half (1993:07 - 2020:12)

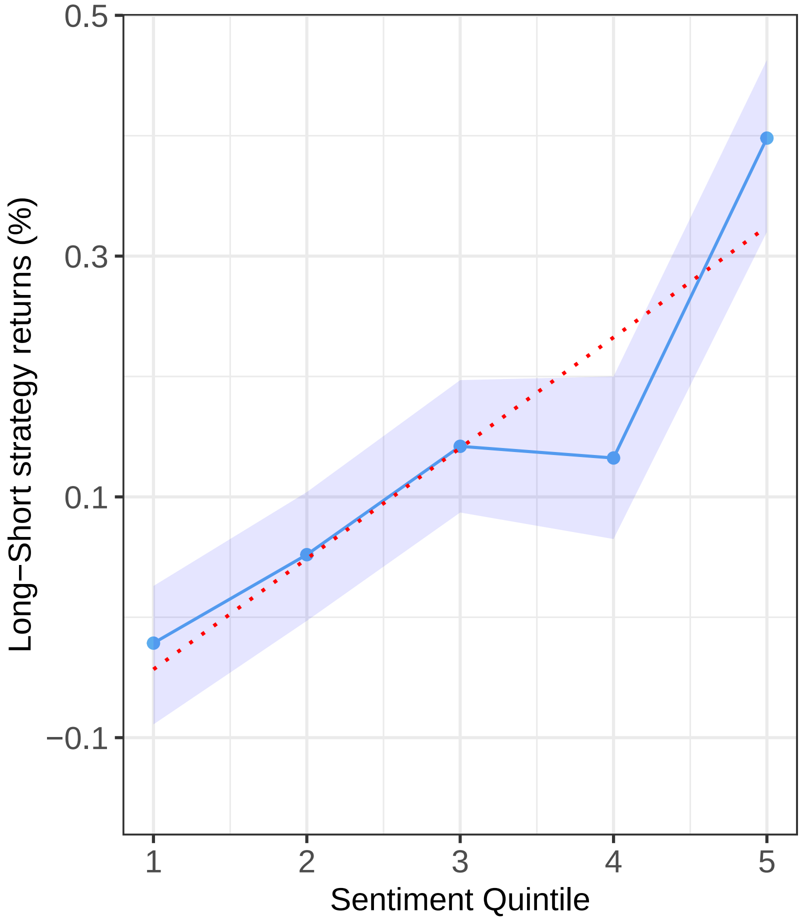
Dep. Variable (R^{mkt}_{t+1})	β	$t(\beta)$	R-squared	Constant?
VWR_TBL	**-0.96*** **	**-3.68**	0.02	Yes
EWR_TBL	**-0.56** **	**-2.14**	0.01	Yes

Panel B: Market Returns Conditional on Sentiment Levels

	VWR_TBL			EWR_TBL		
Sentiment Sorts	(1)	(2)	(3)	(4)	(5)	(6)
	mean returns	t-stat	n	mean returns	t-stat	n
Above Median	-0.37	-0.10	330	1.10	0.23	330
Below Median	**9.59*** **	**3.70**	330	**11.94*** **	**3.14**	330
Difference	**9.96** **	**2.29**	-	**10.84* **	**1.71**	-
Top decile	**-19.10*** **	**-3.86**	66	**-23.20*** **	**-3.40**	66
Bottom decile	**11.64* **	**1.95**	66	**28.57*** **	**3.26**	66
Difference	**30.76*** **	**3.96**	-	**51.78*** **	**5.27**	-

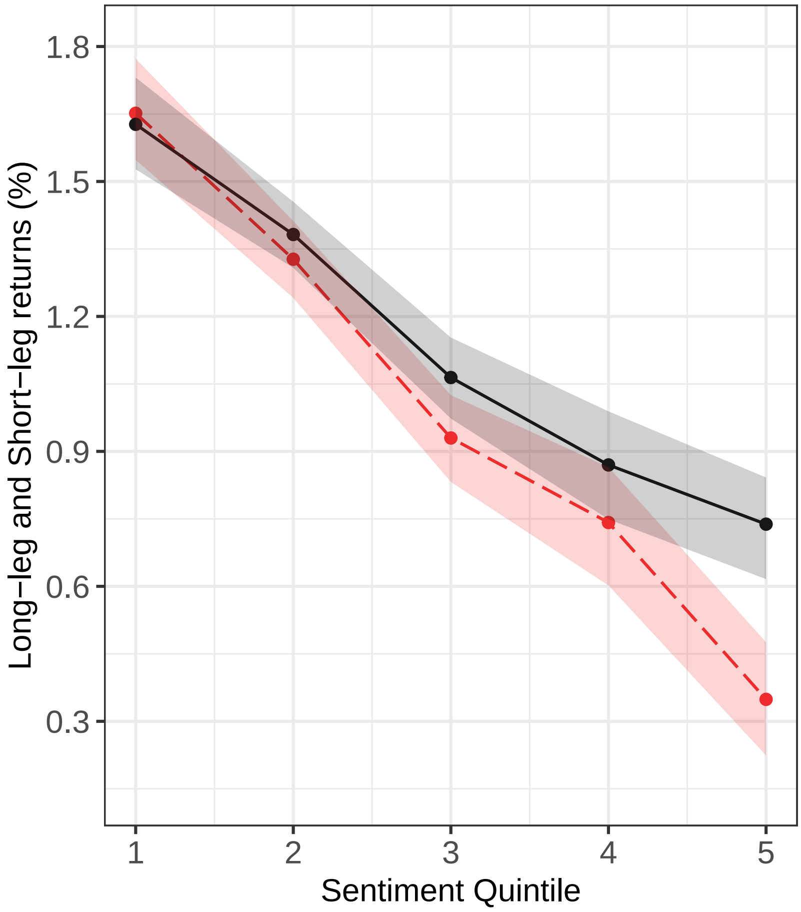
Note: This table records stock market returns conditional on sentiment levels. We use one-month lagged value of Huang et al. (2015), and value-weighted excess stock returns (VWR_TBL) as well as equally-weighted excess stock returns (EWR_TBL) in both panels. Panel A presents predictive regression results. Panel B provides average stock returns, t-statistics, and number of months that fall into each sentiment levels. Above/Below Median indicates that the sentiment during the full-sample is above/below the median value. We similarly define quintile/decile sorts on sentiment levels. In both Panel A and B, we adjust t-statistics using Newey-West procedure with 6 lags.

Figure 3.2: **Average Long-Short Portfolio Returns across Sentiment Quintile**



Note: This figure illustrates the average monthly returns of 100 number of long-short portfolio strategy. We take average monthly return of cross-sectional signals across sentiment quintiles (Quintile 1: lowest sentiment, Quintile 5: highest sentiment). Sentiment measure is one month lag of equity market sentiment (see Section 3.3.1). The shaded areas are 95% Confidence Intervals using 1,000 bootstrapped samples with replacement, and the red dotted line is the regression line that fits the graph. Approximately 40% of anomalies switch long-leg characteristics with short-leg characteristics in order to assign safe (risky) firm characteristics to the long- (short-) legs.

Figure 3.3: **Average Long Portfolio Returns and Short Portfolio Returns across Sentiment Quintile**



Note: This figure illustrates the average monthly returns of 100 number of long-leg returns and short-leg returns. We take average monthly return of cross-sectional signals' long-leg returns or short-leg returns across sentiment quintiles (Quintile 1: lowest sentiment, Quintile 5: highest sentiment). The solid black line indicates average of long-leg returns, and the red dotted line indicates average of short-leg returns. Sentiment measure is one month lag of equity market sentiment (see Section 3.3.1). The shaded areas are 95% Confidence Intervals using 1,000 bootstrapped samples with replacement. Approximately 40% of anomalies switch long-leg characteristics with short-leg characteristics in order to assign safe (risky) firm characteristics to the long- (short-) legs.

Figure 3.3 illustrates the central finding of this paper. Similar to Figure 3.2, we plot the mean returns of all available long- or short-leg strategy returns across sentiment quintile. This figure provides three empirical patterns that deserve further attention: First, the returns of both the long-leg (represented by a black solid line) and the short-leg (depicted by a red dashed line) portfolios increase as they transition from the highest to the lowest sentiment quintile. Since lower sentiment leads to less demand for securities that results in higher returns for holding risky assets, this is the anticipated direction of the market. Second, the magnitude of this pattern is more severe in the short-leg. The higher the sentiment, more unsophisticated investors arrive at the market, and their demand is concentrated on stocks that are more sentiment-elastic, which tends to be short-legs. The figure illustrates a significant drop in short-leg returns, shrinking from 1.65% to 0.35% per month. This remarkable decrease in short-leg returns in the highest sentiment group is clearly seen in the bootstrapped confidence intervals. When the sentiment is low (sentiment quintile 1 and 2), the upper bootstrapped intervals of short-leg returns intersect much with the lower bootstrapped interval of long-leg returns. But as sentiment increases, moving to sentiment quintile 3 and 4, they overlap significantly less. At the peak of the sentiment, the spread between long-leg returns and short-leg returns is so significant that the boostrapped intervals never intersect. In sum, we establish $\beta_1^m > \beta_2^m > 0$.[15]

The long-short portfolio strategy returns in Figure 3.2, which is $R_t^{cs} = R_{t,2} - R_{t,1}$, is the gap between black solid line and the red dotted line in Figure 3.3. Aggregate market returns, $R_t^{mkt} = (R_{t,2} + R_{t,1})/2$, across sentiment quintile is also established using the same figure. Putting together, we arrive at Corollary 3.2.3.

As a robustness check, we use the Baker-Wurgler macroeconomics-orthogonalized sentiment, and alter the sentiment bucket to either median or quartile. We find that results remain robust (see Appendix for details).

3.3.4 The Long-leg results

In Figure 3.3, we showed that sentiment also plays a significant role in the variation of long-leg returns. The long-leg returns have shrunk in half moving from the lowest to highest sentiment, from 1.63% to 0.74% per month across sentiment quintile. Bootstrapped intervals also tell us that a wide range of long-leg returns become unprofitable as market sentiment elevates, establishing $\beta_2^m > 0$.

To further validate this finding, we employ a simple regression framework in Table 3.3. Here, we run predictive regressions with the average returns across 100 anomalies as the dependent variable, separately examining long-side returns (R^{long}), short-side returns (R^{short}), and long-short strategy returns ($R^{\text{long-short}}$). The independent variable is the market sentiment measure from Huang et al. (2015).

[15] We obtain the same quantitative result when we use 63 (out of 100) cross-sectional signals that contain safe characteristics in their long-legs and risky characteristics in their short-legs. Since these signals match with our sentiment model, they should provide the upward-sloping pattern of long-short strategy returns as sentiment increases, which we confirm in an unreported exercise. For 37 (out of 100) anomalies that contain safe characteristics in their short-legs and risky characteristics in their long-legs (i.e., they have the ‘flipped’ legs), the long-short returns are the highest when the sentiment is at the lowest quintile.

Table 3.3: **Sentiment affects all of long-leg, short-leg and long-short strategy returns**

Panel A: Using the anomalies as they are

Regression is of the form $R_{t+1}^{\text{portfolio}} = \alpha + \beta s_t + \varepsilon_{t+1}$
where portfolio $= \{\text{long},\ \text{short},\ \text{long-short}\}$

Dep. Variable	β	$t(\beta)$	Adj. R-squared (%)	Constant?
R_{t+1}^{long}	**-0.58****	**-2.55**	0.9	Yes
R_{t+1}^{short}	**-0.71*****	**-3.10**	1.2	Yes
$R_{t+1}^{\text{long-short}}$	**0.13*****	**3.00**	2.5	Yes

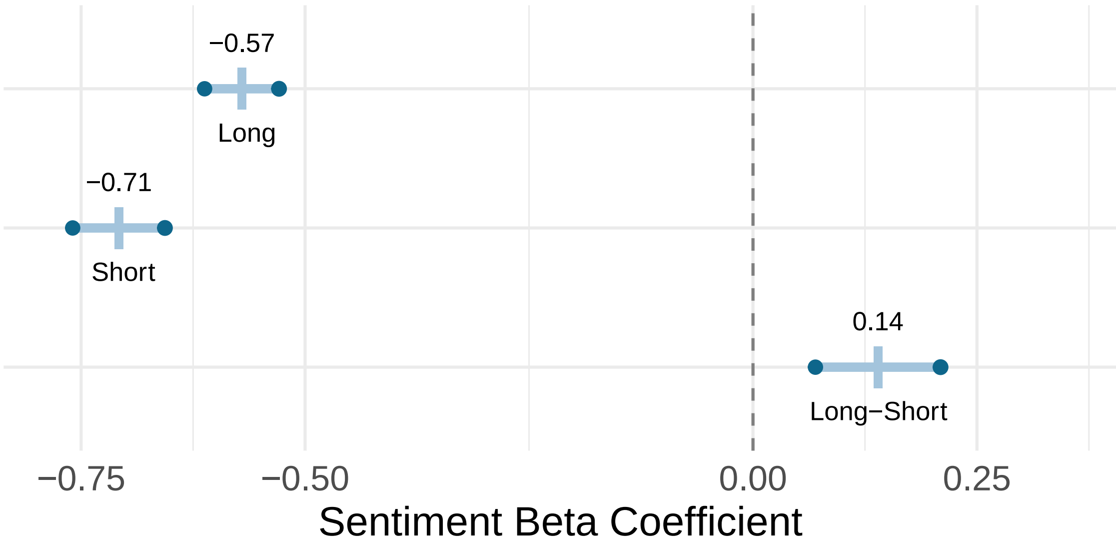
Panel B: Using the anomalies as proposed in this paper

Regression is of the form $R_{t+1}^{\text{portfolio}^*} = \alpha + \beta s_t + \varepsilon_{t+1}$
where portfolio$^* = \{\text{long}^*,\ \text{short}^*,\ \text{long-short}^*\}$

Dep. Variable	β	$t(\beta)$	Adj. R-squared (%)	Constant?
R_{t+1}^{long}	**-0.56****	**-2.57**	0.9	Yes
R_{t+1}^{short}	**-0.73*****	**-3.10**	1.3	Yes
$R_{t+1}^{\text{long-short}}$	**0.18*****	**4.55**	2.7	Yes

Note: This table examines the impact of sentiment on the performance of long-leg, short-leg, and long-short strategy returns. We use a one-month lagged sentiment measure based on Huang et al. (2015) and analyze the average returns across 100 anomalies, focusing separately on long-side returns, short-side returns, and the combined long-short strategy returns. In Panel A, we calculate a composite measure by averaging the long-leg returns, short-leg returns, and long-short strategy returns across all 100 anomalies, resulting in R^{long}, R^{short}, and $R^{\text{long-short}}$, respectively. In Panel B, we repeat this procedure, but with one-third of the anomalies' long- and short-legs reversed to ensure that the long side of the portfolio represents safer firm characteristics. The resulting composite measures are indicated with an asterisk (*). Each panel presents the estimated coefficients and corresponding t-statistics, adjusted for autocorrelation using Newey-West standard errors with six lags.

Figure 3.4: **Distribution of Sentiment Beta**



Note: This figure illustrates the distribution of sentiment beta for 100 anomalies: the long side of portfolio returns (Long), the short side of portfolio returns (Short), and the long-short strategy portfolio returns (Long-Short). The numbers in each dumbbell plot represent the mean of the sentiment beta estimate, and the distribution is shown with a 95% confidence interval.

In Panel A, we find that market sentiment negatively predicts composite long-leg returns, with a coefficient of -0.58 and a significant Newey-West adjusted t-statistic of -2.55. The effect on short-leg returns is even stronger, with a coefficient of -0.71 and a Newey-West adjusted t-statistic of -3.10, indicating that sentiment has a more substantial negative predictive power for short-leg returns. As a result, the predictive ability of market sentiment on the long-short strategy return is positive, with a coefficient of 0.13 and a t-statistic of 3.00. In Panel B, we rerun the predictive regressions using our modified methodology, which constructs average returns based on firm characteristics. In this approach, the long side of the portfolio is designed to capture firms with safer characteristics, while the short side represents riskier characteristics, achieved by flipping the long-side and short-side returns for approximately one-third of the anomalies. We denote these modified composite measures with an asterisk (R^{long^*}, R^{short^*}, and $R^{\text{long-short}^*}$). The results in Panel B mirror those in Panel A, reinforcing our main conclusion that long-leg returns are indeed influenced by market sentiment. This finding contrasts with the results of Stambaugh et al. (2014) and Chu et al. (2020). Finally, the distribution of sentiment beta for each anomaly, as shown in Figure 3.4, confirms that the long side of portfolio returns is also sensitive to market sentiment. This is evidenced by the distribution of sentiment betas for 100 anomalies being significantly different from zero, supporting our regression findings.

3.4 Discussion

3.4.1 Mechanism

In the previous section, we demonstrated that higher equity market sentiment leads to temporary overpricing in both the long and short legs of portfolio returns. This overpricing subsequently reverses in the following month, resulting in lower returns. Notably, this effect is more pronounced for the short-leg portfolios, which enhances the returns of the long-short strategy.

This relationship between market sentiment and portfolio returns can be understood through the lens of trading activity, liquidity, and short-selling constraints. When sentiment is low, fewer noise traders participate in the market, reducing excess trading activity and, consequently, market liquidity. With less speculative trading, price distortions are minimized, and stocks tend to reflect their fundamental values more accurately, so that the long-short strategy returns is not statistically different from zero.

Conversely, when sentiment is high, an influx of noise traders drives up demand, pushing stock prices higher, particularly for speculative and overvalued stocks (which tend to be placed on the short side of a portfolio strategy). However, increased demand also makes it more difficult and costly to borrow stocks for short-selling, as available shares become scarce. This constraint exacerbates price distortions, leading to greater overpricing, especially in the short leg of the portfolio. Jones and Lamont (2002) provide empirical evidence from the 1926–1933 period showing that stocks with high shorting costs tend to be overvalued and subsequently deliver lower future returns. They find that stocks that are difficult to short or newly enter the loan market exhibit a negative pattern. This supports the idea that short-sale constraints allow mispricing to persist longer than it otherwise would, leading to stronger reversals once these constraints ease.

3.4.2 Resolving puzzles

Empirical finance literature has developed a vast array of cross-sectional signals aimed at consistently generating statistically significant positive returns. This *statistical* approach reflects a *positive economics* perspective, which focuses on describing observed patterns without necessarily providing an economic rationale for their existence. In contrast, this paper adopts a *normative economics* approach by offering an *economic* interpretation of long-short portfolio strategies that justifies the positive return performance of stock market signals that do not conform to the standard risk-return tradeoff framework.

A number of well-documented anomalies challenge the traditional risk-return paradigm in asset pricing. In an influential study, Ang et al. (2006b) document that stocks with lower volatility earn higher average returns—an empirical finding that contradicts the fundamental principle that riskier assets should be compensated with higher expected returns. They characterize this as a puzzle, noting that *"[...] the cross-sectional expected return patterns found by sorting on idiosyncratic volatility present something of a puzzle."* Similarly, Campbell et al. (2008) identify the *distress-risk puzzle*, demonstrating that firms with higher probabilities of financial distress earn lower—not higher—returns. While a positive economics approach can document the historical performance of these anomalies, it falls short of explaining *why* they persist. The conventional risk-return framework suggests that investors should demand a premium for bearing higher levels of risk, yet empirical evidence contradicts this notion.

The theoretical model introduced in this paper provides a guiding principle for investors, offering an economically grounded portfolio construction strategy. Specifically, shorting stocks with riskier firm characteristics (e.g., high idiosyncratic volatility, high distress risk) rather than taking long positions can generate positive returns conditional on sentiment. This perspective helps resolve the puzzles observed in volatility and distress risk by providing an explanatory mechanism rather than merely identifying statistical irregularities. This result complements Stambaugh et al. (2015), who attribute the idiosyncratic volatility puzzle to arbitrage asymmetry and arbitrage risk. However, our framework extends beyond volatility, applying more broadly to a wide range of firm characteristics and offering a unified, normative approach to understanding return anomalies.

3.4.3 Exceptions

As discussed in Section 3.3.1, we are left with an explanation on how some of 100 anomalies have switched signs. The model framework laid out in Section 3.2 suggests that we identify safer (riskier) firm characteristics as long (short) legs. We find that, among 100 anomalies considered in this work, about 2/3 of them are already constructed in this way. However, the remaining 1/3 of anomalies are in opposite direction. We discuss them in more detail.[16]

Size and Beta-related anomalies

We find that size and beta-related anomalies work in the opposite direction across the sentiment quintile. Examples for beta related anomalies include beta itself; examples for size related anomalies include firm size (Fama and French, 1992) and firm listing age (Barry and Brown, 1984), illiquidity (Amihud, 2002a) and the bid ask spread (Amihud and Mendelson, 1986a). This is not surprising that these cross-sectional signals contain risky and harder-

[16] See Appendix 3.6.1 for full investigation on each anomaly.

to-arbitrage stock in their long-legs (see a related discussion in Birru, 2018). In such case, high sentiment environment is associated with low performance in the stocks assigned to the long-legs, generating the inverse relationship.

Value (BM)-related anomalies

We also find that portfolios sorted on book-to-market (Fama and French, 1992 and relevant concepts such as growth in book equity in Lockwood and Prombutr, 2010) show a similar pattern. While we did not directly examine Fama-French type risk factor[17], the results here and the above subsection clearly tell us that 'distressed' or riskier stocks are assigned to long-side of the portfolio returns (which are small firms and value firms, respectively), justifying their inverse relationship with sentiment.[18]

Momentum and aggregate stock returns

Factors based on past stock price, most prominently the past 2-12 months momentum (Jegadeesh and Titman, 1993), are simply strategies that bet on past winning stocks. We opt for not including these signals since it is extremely hard to associate past winners and losers with risky and safe legs. In other words, investors simply bet on past winners regardless of their safe or risky traits. In fact, it seems that most momentum strategies do well in both high and low sentiment regimes (undocumented but results are available upon request). We hence pull out 23 number of strategies formed on momentum.

Table 3.4: **Momentum and Aggregate Stock Market**

Regression is of the form $R_t^{mkt} = \alpha + \beta mom_t + \varepsilon_{t+1}$

1. Full Sample (1927:01 - 2020:12)

Dep. Variable	α	$t(\alpha)$	β	t(β)
VWR_TBL	**11.18*** **	**6.15**	**-4.71*** **	**-12.33**
EWR_TBL	**12.95*** **	**5.66**	**-7.25*** **	**-15.07**

Note: This table records relationship between momentum and aggregate returns.

Nevertheless, our explanation can connect the contemporaneous relationship between market anomalies and the aggregate stock market to momentum strategies. Ehsani and Lin-

[17] SMB and HML are two-way sorts on firm size and book-to-market ratio. A clear test for cross-sectional signals related to firm size and book-to-market would be to do a single sort on firm size and book-to-market ratio, respectively. We use these signals rather than SMB and/or HML.

[18] Gârleanu et al. (2012) also propose that value stocks are riskier since they are harder to hedge against "displacement risk".

nainmaa (2022) show that most factors are positively autocorrelated, suggesting that momentum is not a distinct risk factor: rather, it times other factors. Based on our findings, that would suggest a negative relationship between aggregate stock market returns and momentum, a result that we verify in Table 3.4, in line with the literature (see Daniel and Moskowitz, 2016).

3.5 Conclusion

This paper develops a sentiment-based framework to jointly explain the contemporaneous negative relationship between aggregate stock market returns and cross-sectional anomaly returns. By extending the classic noise trader model of De Long et al. (1990), we introduce a two-risky-asset setting where investor sentiment amplifies mispricing in the short-leg of long-short portfolio strategies. When sentiment is high, noise traders push prices further from fundamental values, disproportionately inflating the valuations of riskier stocks. As a result, aggregate market returns decline, while cross-sectional anomaly returns become more pronounced. Conversely, when sentiment is low, both long- and short-leg returns increase, but the effect is more pronounced in the short-leg, reducing the profitability of long-short strategies. This framework provides a novel, unified explanation for both time-series and cross-sectional asset pricing patterns.

Our framework also helps justify well-documented asset pricing puzzles that challenge traditional risk-return logic. Specifically, it provides an economic rationale for the *low-volatility puzzle* (Ang et al., 2006b) and the *distress-risk puzzle* (Campbell et al., 2008), which demonstrate that riskier stocks tend to earn lower, not higher, returns. The model suggests that these anomalies arise because sentiment-driven mispricing distorts risk premia: during high-sentiment periods, noise traders overvalue high-volatility and high-distress stocks, causing their future returns to be lower than predicted by standard risk-based models. This insight aligns with our empirical findings that short-leg anomaly returns decline disproportionately in high-sentiment environments, reinforcing the idea that sentiment influences the pricing of risky stocks beyond what conventional risk-return frameworks predict.

Empirically, we validate our theoretical predictions using U.S. stock market data and 100 cross-sectional anomalies. We establish that market sentiment negatively predicts aggregate returns while positively predicting anomaly returns, confirming the proposed inverse relationship. Additionally, we show that both long-leg and short-leg portfolio returns decline as sentiment rises, but the effect is significantly stronger for short-leg stocks, reinforcing the role of sentiment-driven mispricing in the formation of asset pricing anomalies.

Beyond providing a mechanism for linking time-series and cross-sectional anomalies, our results have broader implications for portfolio construction and the interpretation of anomaly-based investing strategies. Specifically, our findings suggest that strategies that assign riskier firm characteristics to the short leg, rather than the long leg, can yield positive returns conditional on sentiment, and offers a normative perspective on anomaly formation. Taken together, our framework highlights the central role of investor sentiment in shaping return dynamics across both the aggregate market and the cross-section. By bridging these two domains, this paper provides a novel contribution to the literature on behavioral asset pricing and deepens our understanding of how mispricing interacts with market-wide fluctuations.

3.6 Appendix

3.6.1 List of Anomalies

This section enumerates the full list of published risk factors used in the empirical section in the main body of the paper. The 100 number of anomalies are listed in an alphabetical order of their factor label, followed by their description. The asset pricing literature has generated anomalies that are exclusively focused on generating statistically significant positive returns (i.e., firm characteristics that are associated with future positive returns go to the long-legs, while those associated with future negative returns go to the short-legs). However, there has been less focus on identifying the placement of safe or risky characteristics in the long or short positions. We add to the empirical asset pricing literature by assigning an economic interpretation to them: cross-sectional signals identified with a check mark (✓) contain risky (safe) firm characteristics in the long (short) positions, which we ultimately interchange in our main analysis.

1. ✓ **Accruals (accruals, Sloan, 1996)**: firms with relatively high (low) levels of accruals (defined as net income (IB) minus operating cash flow (oancf) scaled by lagged total assets) experience negative (positive) future abnormal stock returns. This means that firms with safe characteristics (high accruals) are placed in the short-legs.

2. ✓ **Accruals-BM (book-to-market and accruals, Bartov and Kim, 2004)**: Firms with low accruals and high B/M ratio goes to long-legs, while high accruals and low B/M ratio goes to short-legs. Since the former characteristics (both accruals and B/M ratio) are associated with risky characteristics, long-legs are risky legs.

3. ✓ **Beta (CAPM beta, Fama and MacBeth, 1973)**: firms with higher market beta are more influenced by the market movement, hence riskier. Since they tend to obtain higher returns, they are placed in the long-legs.

4. ✓ **Beta-Liquidity-PS (Pastor-Stambaugh Liquidity beta, Pastor and Stambaugh, 2003)**: firms with low liquidity tends to earn high future returns. This indicates that high liquidity firms, which are well-known corporate identities with strong fundamentals, are placed in the short-legs.

5. ✓ **Beta-Tail-Risk (tail risk beta, Kelly and Jiang, 2014)**: firms with high loadings on past tail risk (hence riskier) earn high returns. In this vein, long-legs are risky legs.

6. ✓ **Bid-Ask-Spread (bid-ask spread, Amihud and Mendelson, 1986b)**: liquid stocks would have bid-ask spread close to zero. Hence, more illiquid and riskier stocks are placed in the long-legs.

7. ✓ **BM (book-to-market ratio, Rosenberg et al., 1985)**: B/M ratio can be considered as a distress measure, so firms with higher B/M (that goes to the long-legs) are riskier firms.

8. ✓**BM-Dec (book-to-market ratio where book assets used are from December last year, Fama and French, 1992)**: Same as above.

9. ✓ **Brand-Invest (brand capital investment, Belo et al., 2014b)**: Brand capital, an intangible asset, *"helps firms increase sales through, for example, increased customer loyalty or visibility [...] [,] allows firms to differentiate their goods and services from those of competitors and thus it is a potential source of competitive advantage."* Since firms with low brand capital investment rates have higher average stock returns and go to long-legs, risky traits are placed to the long-legs.

10. ✓ **Cash-Prod (cash productivity, Chandrashekar and Rao, 2006)**: productivity of cash is defined as firm's economic rents per dollar of cash holdings. The authors argue that cash productivity is negatively related to future returns, so a portfolio strategy would place firms with less cash productivity to the long-legs.

11. **CB-Oper-Prof (cash-based operating profitability, Ball et al., 2016)**: This measure is created by purging accruals from operating profitability. Since higher cash-based operating profitability relates to stronger firm performance, and higher stock returns, long-legs are firms with safe characteristic.

12. **CF (cash flow to market, Lakonishok et al., 1994)**: Higher cash flows produce higher returns, and this is a good sign for company management.

13. **CFP (operating cash flow to price, Desai et al., 2004)**: operating cash flow, defined as earnings plus depreciation minus working capital accruals, positively predicts future abnormal returns. Since higher operating cash flow firms are equipped with safe characteristics, long-legs are safe legs.

14. **Ch-Asset-Turnover (change in asset turnover, Soliman, 2008)**: Asset Turnover (ATO) is defined as sales divided by net operating assets. The asset turnover ratio can be used as an indicator of the efficiency with which a company is using its assets to generate revenue. The paper documents that higher asset turnover predicts positive returns. Hence, long-legs contain safe assets.

    Net Non-Current Operating Assets (NNCOA) is defined as change in total assets (COMPUSTAT ITEM #6) - current assets (#4) - investment and advances (#32). Net Working Capital (NWC) is the change in current operating assets minus current operating liabilities; see Table 3 of the paper.

15. ✓ **Ch-EQ (growth in book equity, Lockwood and Prombutr, 2010)**: high sustainable growth firms (measured by ratio of book equity to book equity in the previous year) tend to have low default risk, low BM ratios, and low subsequent returns. This indicates that high sustainable growth firms, which are safer than low sustainable growth firms, are placed in the short-legs.

16. ✓ **Ch-Inv (inventory growth, Thomas and Zhang, 2002)**: change in inventory, defined as 12 month change in inventory over average total assets, negatively predicts future stock returns. The paper documents a profitability reversal argument based on shift in demand, which indicates that past high performing firms suffer from profitability reversals and hence are placed in the short-legs.

17. ✓ **Ch-Inv-IA (change in capital investment, industry adjusted, Abarbanell and Bushee, 1998)**: Change in Investment with industry adjustment, which the article denotes as RCAPX, is constructed to test the notion that it is good news for future earnings when firm-specific capital expenditures outpace industry average capital expenditures. The result is the opposite, indicating that firms with higher capital investment relative to given industry earns negative subsequent returns.

18. **Ch-NNCOA (change in net noncurrent operating assets, Soliman, 2008)**: see discussions in Ch-Asset-Turnover

19. **Ch-NWC (change in net working capital, Soliman, 2008)**: see discussions in Ch-Asset-Turnover

20. **Ch-Tax (change in taxes, Thomas and Zhang, 2011)**: firms with high seasonally differenced quarterly tax expense earn positive future returns. Since firms with strong fundamentals tend to pay high tax, long-legs are safe legs.

21. **Comp-Equ-Iss (composite equity issuance, Daniel and Titman, 2006)**: *"composite share issuance variable measures the amount of equity the firms issues (or retires) in exchange for cash or services. Thus, seasoned issues, employee stock option plans, and share-based acquisitions increase the issuance measure, while repurchases, dividends, and other actions that take cash out of the firm reduce the issuance measure."* The paper argues that composite equity issuance captures intangible information. Since composite share issuance variable is significantly negatively related to future returns, and firms tend to place themselves in a riskier position by conducting share issuance at the sacrifice of, for instance, dilution of ownership stake, short-legs contain riskier firms.

22. ✓ **Coskew-ACX (coskewness using daily returns, Ang et al., 2006a)**: see below for coskewness. The logic works the same way.

23. ✓ **Coskewness (coskewness, Harvey and Siddique, 2000)**: *"Everything else being equal, investors should prefer portfolios that are right-skewed to portfolios that are left-skewed. This is consistent with the Arrow-Pratt notion of risk aversion. Hence, assets that decrease a portfolio's skewness are less desirable and should command higher expected returns."* Since higher skewness produces low future returns, short-legs contain firms with relatively safe characteristics.

24. ✓ **Del-COA (change in current operating assets, Richardson et al., 2005)**: Table 1 and 2 of the paper describes variables in details. Changes in current operating assets negatively predicts stock returns. Since higher operating assets indicate positive signals for the future activity, short-legs are safe legs.

25. **Del-COL (change in current operating liabilities, Richardson et al., 2005)**: see Del-COA. Changes in current operating liabilities negatively predicts stock returns. Higher operating liabilities indicates riskier business activities, so firms with riskier characteristics are placed in the short-legs.

26. **Del-FIN-L (change in financial liabilities, Richardson et al., 2005)**: see Del-COA. Changes in financial liabilities (Del-FIN-L) negatively predicts future stock returns. So, firms with more liabilities (hence riskier) are placed in the short-legs.

27. **Del-LT-I (change in long term investment, Richardson et al., 2005)**: see Del-COA. Changes in long term investment negatively predicts stock returns. Since higher investment results in negative subsequent returns, risky characteristics are placed in the short-legs.

28. **Del-Net-Fin (change in net financial assets, Richardson et al., 2005)**: see Del-COA. Increases in net financial assets positively predicts returns. Since higher financial assets provide greater investment opportunities as well as firm fundamentals, long-legs contain safe firms.

29. **Div-Init (dividend initiation, Michaely et al., 1995)**: Changes in dividends can provide insight into a company's future prospects. Dividend initiations is good news, whereas dividend omissions is bad news. The paper documents that firms with dividend initiations have positive future returns, so that long-legs contain firms with stronger future prospects.

30. **Div-Omit (dividend omission, Michaely et al., 1995)**: similar to Div-Init above, firms that omit dividend payments earn negative future returns. Since firms that are not omitting dividends go to long-legs, firms with safe characteristics are placed in the long-legs.

31. **Div-Season (dividend seasonality, Hartzmark and Solomon, 2013)**: firms predicted to issue a dividend earn positive abnormal returns. Since dividend-paying firms tend to have better future prospects, long-legs contain safe characteristics.

32. **Div-Yield-ST (predicted dividend yield next month, Litzenberger and Ramaswamy, 1980)**: higher predicted dividend yield next month would indicate firms with better future prospects, so long-legs would have firms with stronger future prospects.

33. ✓**Dol-Vol (past trading volume, Brennan et al., 1998)**: stocks with higher trading volume indicate higher liquidity and thus are associated with safer features. Since these stocks produce negative returns, they are placed in the short-legs.

34. ✓ **Earnings-Consistency (earnings consistency, Alwathainani, 2009)**: Firms consistently ranking in the lowest 30% of past financial growth (risky firms) have greater rates of future returns. So, riskier firms go to the long-legs.

35. **Earnings-Surprise (earnings surprise, Foster et al., 1984)**: firms with positive earnings surprise are those associated with better (safer) future prospects, so long-legs contain firms with safe characteristics.

36. **Earn-Sup-Big (earnings surprise of big firms, Hou, 2007)**: same logic as above.

37. **Ent-Mult (enterprise multiple, Loughran and Wellman, 2011)**: firms with low Enterprise Multiple (EM is defined as equity value plus debt plus preferred stock less cash, divided by EBITDA) outperform high EM firms. So, long-legs contain firms with safer characteristics.

38. **EP (earnings-to-price ratio, Basu, 1977)**: in a given industry, high E/P ratio firms compared to low E/P ratio firms typically indicates that the former are well-performing in the market. Since EP positively predicts stock market returns, long-legs contain firms with safe characteristics.

39. **Equity-Duration (equity duration, Dechow et al., 2004)**: long duration equities that tend to be sensitive (thus riskier) generate lower average returns. This indicates that firm with long equity duration are placed in the short-legs.

40. **Exch-Switch (exchange switch, Dharan and Ikenberry, 1995)**: stocks that move trading platform generally earn poor returns. Since firms with strong fundamentals will generally not switch their listings, short-legs are risky legs.

41. ✓ **Firm-Age (firm age based on CRSP listings, Barry and Brown, 1984)**: firm age, proxied as a period of listing, negatively predicts future stock returns. Since firms that

spent less time in CRSP have less public information, hence riskier, long-legs contain firms that are relatively riskier.

42. **GP (gross profits-to-total assets, Novy-Marx, 2013)**: profitable firms generate significantly higher returns than unprofitable firms, although the are less prone to distress, have longer cash flow durations, and have lower levels of operating leverage. Hence, firms with safe feature (highly profitable) go to long-legs.

43. ✓ **Gr-LT-NOA (growth in long term operating assets, Fairfield et al., 2003)**: The paper argues that, after controlling for current profitability, growth in long-term net operating assets has negative associations with future returns, consistent with conservative accounting and diminishing marginal returns on investments. Hence, safe characteristic is assigned to the short-legs.

44. **Gr-Sale-To-Gr-Inv (sales growth over inventory growth, Abarbanell and Bushee, 1998)**: Percentage growth in sales less percentage growth in inventory positively predicts subsequent stock returns. Since higher sales relative to industry signals safe traits, long-legs are safe legs.

45. **Gr-Sale-To-Gr-Overhead (sales growth over overhead growth, Abarbanell and Bushee, 1998)**: Similar to above, Gr-Sale-To-Gr-Overhead (defined as percentage growth in sales relative to average sales of past two years, minus percentage growth in administrative expenses relative to average administrative expenses of last two years) positively predicts stock returns.

46. ✓ **Herf (Herfindahl industry concentration using sales, Hou and Robinson, 2006)**: firms in more concentrated industries earn lower returns, as highly concentrated industries are less risky because they engage in less innovation. This indicates that firms that go to long-legs are those in industries with high herfindahl index (less concetrated industry) and riskier.

47. ✓ **Herf-Asset (Herfindahl industry concentration using assets, Hou and Robinson, 2006)**: see Herf.

48. ✓ **Herf-BE (Herfindahl industry concentration using book equity, Hou and Robinson, 2006)**: see Herf.

49. **Hire (employment growth, Belo et al., 2014a)**: firms with high hiring rates are expanding firms that incur high adjustment costs, hence riskier firms. Since the paper documents that hiring rate is negatively associated with future stock returns, risky legs are short-legs.

50. **Idio-Vol-3F (idiosyncratic risk using Fama-French 3 factor model, Ang et al., 2006b)**: stocks with high idiosyncratic volatility receive low average returns. Hence, short-legs are risky legs.

51. **Idio-Vol-AHT (idiosyncratic risk using AHT model, Ali et al., 2003)**: similar to above (Idio-Vol-3F), reciprocal of Ivolatility, defined as standard deviation of residuals from CAPM regression using daily data, positively predicts future stock returns. Since low volatility stocks earn higher returns than high volatility counterparts, long-legs are safe legs.

52. ✓ **Illiquidity (Amihud's illiquidity, Amihud, 2002b)**: stock returns increase in illiquidity (daily ratio of absolute stock return to its turnover average over the past 12 months). Since illiquid assets tend to be risky, long-legs are risky legs.

53. **Ind-IPO (initial public offerings, Ritter, 1991)**: firms that go through initial public offerings underperform for the next three years. Since IPO firms are riskier than mature firms in the secondary market, short-legs are risky legs.

54. **Ind-Ret-Big (industry return on big firms, Hou, 2007)**: intra-industry lead-lag effects where top 30% size firms take the long-legs. Since these firms tend to come with strong and stable characteristics, long-legs are safe legs.

55. **Intan-CFP (intangible return using cash-flow-to-price, Daniel and Titman, 2006)**: see discussions in Comp-Equ-Iss.

56. **Intan-EP (intangible return using earnings price, Daniel and Titman, 2006)**: see discussions in Comp-Equ-Iss.

57. **Intan-SP (intangible return using sales-to-price, Daniel and Titman, 2006)**: see discussions in Comp-Equ-Iss.

58. ✓ **Investment (investment to revenue, Titman et al., 2004)**: higher investment expenditures should be viewed favourably as they are likely to be associated with greater investment opportunities. Since higher investment expenditures result in negative future returns, safe characteristics are assigned to the short-legs.

59. ✓ **Invest-PPE-Inv (change in PPE and investment-to-assets, Lyandres et al., 2008)**: investment factor that longs low-investment firms and shorts high-investment firms earn significantly positive average returns. The logic is similar to above.

60. ✓ **Inv-Growth (inventory growth, Belo and Lin, 2012)**: similar to Ch-Inv, inventory growth negatively predicts future stock returns.

61. **Mean-Rank-Rev-Growth (revenue growth rank, Lakonishok et al., 1994)**: The anomaly is defined as mean rank based on firms' annual revenue growth in the past 5 years. Since higher revenue indicates firms performing well, which earns higher stock returns, long-legs are firms with safe characteristics.

62. **MS (mohanram G-score, Mohanram, 2005)**: GSCORE is a combination of 8 existing signals related to earnings and cash flow fundamentals, extrapolation, and accounting conservatism. Since higher values of individual signals generally indicate firms with stronger performance, and since firms with higher GSCORE earn higher returns, long-legs contain firms with safe characteristics.

63. ✓ **Net-Debt-Price (net debt to price, Bradshaw et al., 2006)**: $\Delta DEBT$, defined as #111 - #114 + #301 (COMPUSTAT annual data item) negatively predicts future stock returns. This indicates that firms with less debt are placed in the long-legs (so that safe firm characterstics goes to the long-legs).

64. **Net-Payout-Yield (net payout yield, Boudoukh et al., 2007)**: payout yields (dividends plus repurhcases) as well as net payout yields (dividends plus repurchases minus issuances) mirror firms' performance. Since higher payout yields (as well as net payout yields) predicts positive future returns, safe firms are assigned to long-legs.

65. **Num-Earn-Increase (earnings streak length, Loh and Warachka, 2012)**: a consistent earnings (streak) positively predicts future stock returns. Since a series of positive earnings indicate good performance, hence associated with safe features of a given firm, long-legs are safe legs.

66. **Oper-Prof (operating profits to book equity, Fama and French, 2006)**: firms with higher operating profitability predict higher stock returns. Since firms with higher profitability tends to be those with strong fundamentals, long-legs are safe legs.

67. **Oper-Prof-RD (operating profitability, R&D adjusted, Ball et al., 2016)**: This is the operating profitability less Research and Development Expenses, which bears the same meaning as CB-Oper-Prof. See discussions there.

68. **OP-Leverage (operating leverage, Novy-Marx, 2011)**: firms with levered assets earn higher returns than non-levered assets. The leverage in this context is operating leverage, defined as (COGS + XSGA)/AT (note that this is not financial leverage. In fact, page 110 says that operating leverage and financial leverage are negatively correlated). Since firms that sell more are generally viewed as those performing well, long-legs contain safe firms.

69. ✓ **Org-Cap (organizational capital, Eisfeldt and Papanikolaou, 2013)**: firms with more organization capital (defined as a durable input in production that is distinct from physical capital) earn higher average returns than firms with less organization capital. *"Since shareholders can appropriate only a fraction of the cash flows from organization capital, investing in firms with high organization capital exposes them to additional risks."* In this sense, long-legs are risky-legs.

70. **Payout-Yield (payout yield, Boudoukh et al., 2007)**: see Net-Payout-Yield.

71. ✓ **Pct-Acc (percent operating accruals, Hafzalla et al., 2011)**: from the standard definition of accruals (where the numerator is earnings less operating cash, and the denominator is the total assets), percent accruals replace the denominator with earnings. Since the predicted patterns remain the same, the same logic as mentioned earlier in the anomaly Accruals apply here.

72. ✓**Price (stock price, Blume and Husic, 1973)**: similar to firm size, log of absolute value of stock price negatively predicts stock returns.

73. **QMJ (quality of a stock, Asness et al., 2019)**: quality characteristics, including profitability, growth, and safety, are a safe characteristics that *"investors should be willing to pay a higher price for."* Since they earn positive future returns, long-legs are safe legs.

74. **RD-Ability (R&D ability, Cohen et al., 2013)**: long-short portfolio strategy that longs the past R&D winners and that shorts the past R&D losers earns significant profits. R&D activities can be viewed as risky behavior, but this paper focuses on R&D winners and losers . In that manner, past R&D winners who produce positive returns are safe firms.

75. **RD-IPO (IPO and no R&D spending, Guo et al., 2006)**: firms that do not spend on R&D activity nor who went through IPO earn higher returns. Since these are relatively stable firms than their counterparts (i.e., those that invested in R&D or those that were recently IPO-ed), long-legs are safe legs.

76. **Realized-Vol (realized total volatility, Ang et al., 2006b)**: see Idio-Vol-3F.

77. **Return-Skew (return skewness, Bali et al., 2016)**: return skewness.

78. **Return-skew-3F (idiosyncratic skewness based on Fama-French 3 factor model, Bali et al., 2016)**: See above.

79. **Revenue-Surprise (revenue surprise, Jegadeesh and Livnat, 2006)**: revenues reported during preliminary earnings announcement positively predicts future stock returns. Since these are firms with better fundamentals and prosperous future prospects, long-legs contain firms with safe characteristics.

80. **RIO-MB (institutional ownership and market to book, Nagel, 2005)**: institutional owernship (Residual Institutional Ownership, or RIO, defined as the percentage of shares held by institutions controlling for firm size, see equation 2 of the paper) is used as a supporting proxy for short-sale constraints hypothesis. For a given level of institutional ownership, high market to book firms are relatively safer firms and go to long-legs.

81. **RIO-Turnover (institutional ownership and turnover, Nagel, 2005)**: similar logic to RIO-MB. For a given level of institutional ownership, high turnover firms are relatively safer firms and go to long-legs.

82. **RIO-Volatility (institutional ownership and idiosyncratic volatility, Nagel, 2005)**: similar logic to RIO-MB. For a given level of institutional ownership, low idiosyncratic volatility firms are relatively safer firms and go to long-legs.

83. **RoE (net income to book equity, Haugen and Baker, 1996)**: return on equity positively predicts stock returns, which is a safe characteristic placed in the long-legs.

84. **Share-Iss-1Y (share issuance 1 year, Pontiff and Woodgate, 2008)**: annual share issuance, defined as log difference between month t adjusted shares less month $t-11$ adjusted shares, negatively predicts future stock returns. Since share issues tend to be related to the demand for cash at the sacrifice of dilution of ownership stake, it indicates that firms are riskier. So, short-legs are risky legs.

85. **Share-Iss-5Y (share issuance 5 years, Daniel and Titman, 2006)**: same as above.

86. **Share-Repurchase (share repurchases, Ikenberry et al., 1995)**: When the management team believes their firm is undervalued, they would choose to buy back their own stocks to signal economic agents that the firm is a good investment. Since firms that repurchase their own shares earn significant subsequent returns, long-legs contain firms that are undervalued, hence (relatively) safe characteristics than the firms in the short-legs.

87. **Share-Vol (share volume, Datar et al., 1998)**: the statement *"The negative sign on the turnover rate variable confirms that illiquid stocks offer higher average returns than liquid stocks."* (page 210) indicates that more risky (illiquid) firms are assigned to long-legs.

88. ✓ **Size (firm size, Fama and French, 1992)**: small size firms tend to be risky for many reasons. Hence, long-legs are risky legs.

89. **SP (sales-to-price, Barbee et al., 1996)**: since higher annual sales (per share) would lead to stable firm performance, long-legs are safe legs.

90. ✓ **Spinoff (spinoffs, Cusatis et al., 1993)**: the paper shows that *"both the spinoffs and their parents offer significantly positive abnormal returns for up to three years beyond the spinoff announcement date."* Since spinoff-ed firms relative to their parent firms are new and risky, long-legs contain firms with riskier characteristics.

91. **Std-turn (share turnover volatility, Chordia et al., 2001)**: the paper documents a negative cross-sectional relationship between stock returns and volatility of share turnover (as well as dollar trading volume). Since higher liquidity volatility is associated with riskier characteristic, long-legs are safe assets that have lower liquidity volatility.

92. **Tang (tangibility, Hahn and Lee, 2009)**: The paper examines the marginal effect of tangibility on stock returns. The empirical measure of tangibility is debt capacity since *"a firm's debt capacity increases with asset tangibility as higher tangibility implies higher value of collateral for lenders."* While the paper shows that tangibility positively affect stock returns to constrained firms only, this still suggests that long-legs contain firms with safe characteristics relative to firms in the short-legs.

93. **Tax (taxable income to income, Lev and Nissim, 2004)**: firms with higher tax ratio, which produces higher subsequent returns, tend to be big, less volatile, and growth firms. Hence, firms that go to long-legs are relatively safer.

94. ✓ **Total-Accruals (total accruals, Richardson et al., 2005)**: see Del-COA.

95. **Vol-Mkt (volume to market equity, Haugen and Baker, 1996)**: trading volume over market equity negatively predicts mean returns. This indicates riskier firms with higher trading volume are placed in the short-legs.

96. **Vol-SD (volume variance, Chordia et al., 2001)**: See the anomaly Std-turn.

97. **Volume-Trend (volume trend, Haugen and Baker, 1996)**: similar to Vol-Mkt, five-year time trend in monthly trading volume, which is a risky firm characteristic, is negatively related to stock returns.

98. ✓ **Zero-trade (days with zero trades, ?)**: The paper defines turnover-adjusted number of zero daily trading volumes over the prior n months. $n = 1$. Since firms with

more number of no trading records (zero trades) are those accompanied with more illiquidity and higher future stock returns, long-legs contain more risky firms.

99. ✓ **Zero-trade-Alt-1 (days with zero trades, alternative specification, ?)**: Same as above, but $n = 6$.

100. ✓ **Zero-trade-Alt-2 (days with zero trades, alternative specification, ?)**: Same as above, but $n = 12$.

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