Regulatory Intensity and Stock Liquidity

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January 16, 2025

Abstract

This study investigates the impact of regulatory intensity on stock liquidity. We show that regulatory intensity has a significant negative effect on stock liquidity, a finding that is robust after employing a quasi-natural experiment that exploits exogenous increases in regulatory intensity due to state ruling party changes. Further analysis shows that the effect is more pronounced for firms with higher financial constraints, firm-specific risks, and investment irreversibility. Overall, our evidence suggests that high regulatory intensity increases firm uncertainty, which causes a reduction in firm's stock liquidity.

Keywords: Stock Liquidity, Corporate Regulation, Economics of Regulation

JEL Codes: G12, G14, G18

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1 Introduction

Government regulation is a set of rules and requirements imposed on the market by various regulatory agencies through laws and regulations, with the core objective of balancing market efficiency and economic stability. Although the original intention of regulation is to maintain market order, protect investors' interests, and prevent systemic risks, the regulatory costs faced by companies have surged over the past forty years. According to statistics, since 1980, the regulatory costs borne by companies have increased by approximately $1 trillion (Singla, 2023). Along with the increasing compliance requirements, companies not only face direct financial expenditures but also have to invest substantial manpower and resources to meet these regulatory demands. This rise in costs has made it increasingly difficult to maintain the balance between regulation and market efficiency.

In theory, regulation can promote market transparency by reducing information asymmetry and curbing unfair trading behavior. However, in practice, companies not only bear the direct financial burden of compliance but also face the uncertainty caused by frequent policy changes (Gulen & Ion, 2016). This uncertainty directly impacts companies' future operational decisions and transmits through capital markets, affecting investor behavior and ultimately influencing stock liquidity. Therefore, understanding the impact of regulatory intensity on stock market liquidity has become a critical issue in current academic research.

A key question is whether investors are truly aware of and concerned about the regulatory burden faced by companies. Christensen et al. (2016) find that markets do react to policy changes such as the Market Abuse Directive (MAD) and the Transparency Directive (TPD), showing a link between stock liquidity and securities regulations. However, recent literature has taken a broader perspective, attempting to quantify the impact of regulatory costs on the stock market (e.g. Azevedo et al., 2024; Ewens et al., 2024; Ince & Ozsoylev, 2024). These studies reveal that investors also pay attention to the overall regulatory environment faced by companies, not just individual policies or regulations. This view differs from earlier studies, treating regulation as a more complex and dynamic factor rather than a singular legislative event.

While many studies have examined the short-term impact of specific policy changes on the stock market, existing literature still lacks in-depth empirical analysis of the broader perspectives through which regulatory intensity systematically affects stock market liquidity. Leuz and Wysocki (2016) point out that regulation should be dynamic rather than static. The effect of regulation should not be seen as a one-time event but rather as a long-term and continuous market factor. Inspired by these studies, we aim to reassess the average impact of the overall regulatory environment on stock market liquidity through the quantitative regulatory intensity indicators. By using the comprehensive regulatory intensity indicators developed by Kalmenovitz (2023), we can not only capture the benefits of increased transparency brought about by stronger regulation but also understand the pressure that increased compliance costs place on companies' operations. Thus, we propose competing hypotheses.

In earlier theories, significant literature has linked information to liquidity (e.g. Copeland & Galai, 1983; Glosten & Milgrom, 1985; Easley & O'hara, 1987). Strengthened government regulation is believed to enhance transparency in financial markets, thereby reducing information asymmetry among investors. Christensen et al. (2016), using empirical analysis, demonstrate that regulatory policies improve transparency and positively impact stock liquidity. Thus, we propose Hypothesis 1a, which posits that stronger regulation enhances stock liquidity.

In recent years, deeper research into regulation has highlighted the significant role of compliance costs. Baker et al. (2016) point out that policy changes often lead to delays in firms' investment decisions, increasing uncertainty about their future operations (Gulen & Ion, 2016). Recent studies on regulatory quantification further support this view (e.g. Kalmenovitz, 2023; Ince, 2024). In financial markets, Easley and O'Hara (2010) show that uncertainty about the future amplifies the ambiguity of transmitted information. When investors face ambiguous information, it increases information asymmetry, which ultimately impacts the firm's stock liquidity. This phenomenon is also evident in stock markets, as emphasized by So and Wang (2014) and Beaupain and Joliet (2011). Based on this theoretical framework, we propose Hypothesis 1b, which posits that stronger regulatory intensity increases the uncertainty of companies' future operations, thereby amplifying information ambiguity, increasing information asymmetry, and ultimately reducing stock liquidity.

To address potential endogeneity issues, we are inspired by Kalmenovitz (2023) to use state government party changes as a quasi-natural experiment. According to Kalmenovitz (2023), political party changes in the United States have a significant relationship with changes in regulatory intensity. Regulatory intensity tends to be lower under Republican administrations, while Democrats tend to implement stricter regulatory policies during their administrations. Williams III (2012) points out that state government regulations sometimes differ from federal government regulations, and conflicts may arise. This also demonstrates that state governments have the authority to cause changes in the regulatory intensity faced by companies. Based on this observation, we treat state government party changes as an external shock and use this political shift to measure the impact of regulatory intensity on stock liquidity. By constructing a stacked-cohort differences-in-differences (DID) model and combining it with Propensity Score Matching (PSM), we can accurately identify the causal relationship between these policy changes (i.e., changes in regulatory intensity) and their impact on stock liquidity.

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We establish two channel test frameworks to differentiate the heterogeneous responses of different types of companies to increased regulatory intensity, further exploring the impact of regulatory intensity on stock liquidity by examining information ambiguity between investors and companies. Information ambiguity implies that investors lack a clear understanding of the company's future operations, making the market more uncertain about these companies when regulatory intensity increases, thereby exacerbating the decline in liquidity. We primarily use two tests to analyze this ambiguity. First, the Earnings Surprise test measures the gap between a company's actual earnings and market expectations, reflecting the accuracy of investor predictions about the company's future operations and the market's uncertainty. Second, the Credit Rating test consists of comparing rated and unrated companies. Unrated companies have limited investor knowledge due to a lack of transparency. Through these two tests, we further reveal the critical role of information ambiguity in how regulatory intensity affects liquidity driven by future operation uncertainty.

In our further analysis, we divide the effects of uncertainty into three aspects: First, we examine financial constraints. Financial constraints refer to a company's limited ability to obtain external funding, forcing it to rely on internal resources, making highly constrained firms more vulnerable to regulatory changes. Second, we look at firm-specific risk, which refers to unique risks faced by a company, such as management decisions or market position. Firms with high firm-specific risk usually face greater future uncertainty. Lastly, we follow the Gulen and Ion (2016) approach to investigate the investment irreversibility. We highlight how companies adapt flexibly to the challenges brought about by regulatory changes in reallocating or transferring assets. This analysis further strengthens our baseline results and confirms that the impact of regulatory intensity on stock liquidity is driven by uncertainty about the company's future operations.

We use financial and stock market data from Compustat, incorporating the comprehensive regulatory intensity index developed by Kalmenovitz (2023). We use the effective spread as the main measure of stock liquidity (Korajczyk & Sadka, 2008; Hasbrouck, 2009; Hendershott et al., 2011), covering data from 1993 to 2019. In our empirical analysis, we introduce a series of control variables based on prior literature on stock liquidity (Gopalan et al., 2012; So & Wang, 2014; Qiu & To, 2022) to ensure the robustness of the results. Statistically, the four regulatory intensity measures constructed by Kalmenovitz (2023) are positively associated with the effective spread at the 1% level, indicating a negative impact on liquidity. Economically, the regulation indicator had the largest effect, with a one standard deviation increase in the regulation indicator of regulatory intensity associated with a 47.8 basis point increase in the effective spread, consistent with prior effective spread literature (Hendershott et al., 2011; Kahraman & Tookes, 2017). Our baseline results are significant both statistically and economically.

However, our results differ from those of Christensen et al. (2016). Their study focuses on specific securities market policies (TPD and MAD), which aim to reduce information asymmetry and improve market transparency. They find that increased securities market regulation positively impacted liquidity by enhancing transparency. In contrast, our study use Kalmenovitz (2023) comprehensive regulatory intensity index, captures broader and more complex regulatory burdens that companies face beyond financial market regulations. For example, companies in industries such as energy or technology must comply with a range of environmental regulations, which adds operational complexity and long-term uncertainty. Another reason for the differing results is that Christensen et al. (2016) analyse short-term market reactions to specific policies, while our study focuses on the average impact of regulatory intensity. While individual policies may reduce information asymmetry and improve liquidity in the short term, the long-term burden of increased compliance costs and operational complexity may outweigh these benefits, leading to a negative impact on liquidity.

In our channel tests, we explore the role of information ambiguity by examining earnings surprise and credit ratings. Companies with greater earnings surprises experience more pronounced liquidity declines under heightened regulatory intensity. Earnings surprise reflects the gap between a company's actual performance and market expectations, indicating investors disagreements. Under stricter regulatory conditions, this uncertainty is magnified, leading to reduced trading activity and lower liquidity. Similarly, we find that unrated companies suffer greater liquidity declines compared to rated companies, as the lack of transparency in unrated firms increases market uncertainty about the companies, especially under regulatory pressure. These findings underscore how uncertainty regarding a company's future operations, combined with information ambiguity from the investor's perspective, amplifies the negative impact of regulatory intensity on stock liquidity.

In our extended analysis, we find that companies with high financial constraints experience a more significant decline in liquidity when regulatory intensity increases. These firms, relying primarily on internal funding, have limited flexibility to handle rising compliance costs and operational pressures, leading to greater operational uncertainty and reduced stock liquidity. Additionally, companies with high firm-specific risk also face sharper declines in liquidity under heightened regulatory intensity. Firm-specific risk is positively associated with future uncertainty (Fink et al., 2010), and as regulatory intensity grows, this uncertainty is amplified, causing investors to act more cautiously, thereby reducing market trading activity and liquidity. Lastly, we observe that firms with higher levels of investment irreversibility experience a notable decrease in liquidity as regulatory intensity escalates. Investment irreversibility reflects the difficulty or inability of a company to reallocate or shift assets in response to external changes, such as regulatory adjustments. This inflexibility exacerbates uncertainty regarding future operations, heightening investor concerns and further impacting liquidity. These findings collectively support our baseline hypothesis that increased regulatory intensity raises uncertainty about a company's future operations, ultimately leading to a decline in liquidity.

In our robustness test, we replace the dependent variable with trading volume to verify the impact of regulatory intensity on stock liquidity. Three of the four regulatory intensity measures are significantly associated with a decline in trading volume, confirming that higher regulatory intensity increases investor uncertainty and reduces liquidity. These findings further confirm our baseline results that increasing regulatory intensity amplifies uncertainty regarding companies' future operations, leading to decreased liquidity. The decline in trading volume, which is a direct measure of market activity, further supported the robustness of our conclusions. Reduced trading volume indicates that investors are hesitant to engage in market transactions due to increased uncertainty about the company's future operations, reflecting how regulatory intensity negatively impacts liquidity.

Our research makes significant contributions to both regulatory and stock liquidity literature. We address the empirical gap in understanding the average effects of regulatory intensity on stock liquidity by using a comprehensive regulatory intensity index, offering a holistic view of how cumulative regulatory burdens impact firms—extending beyond the focus on singular policies in prior studies (Fernandes et al., 2010; Iliev, 2010; Kang et al., 2010). This approach reinforces the notion that regulation is dynamic rather than static (Leuz & Wysocki, 2016). Our novel identification strategy, leveraging state government party shifts as a quasi-natural experiment, strengthens causal inference on exogenous regulatory shocks. Furthermore, our analysis highlights how information asymmetry various through firm characteristics, like earning surprise, shape their responses to regulatory changes, offering new insights into the heterogeneous effects of regulatory intensity. Through competitive hypotheses, we demonstrate that the compliance costs induced by regulation have a significant negative impact on stock liquidity.

We also add to liquidity literature by providing empirical support for Easley and O'Hara (2010)'s uncertainty model, showing how uncertainty from regulatory intensity affects stock liquidity. Our findings diverge from Christensen et al. (2016) by measuring the regulatory environment more broadly, offering a new perspective on regulation and liquidity. Additionally, we use competitive hypotheses to show that the compliance burden from increased regulatory intensity exacerbates information ambiguity and asymmetry, thereby negatively influencing stock liquidity. Practically, these findings suggest policymakers should consider firm heterogeneity to reduce unnecessary liquidity risks and balance market stability with firms' operational burdens. This underscores that the stock market's development relies not only on securities regulation but also on collaborative efforts across regulatory bodies to drive comprehensive improvements.

The remainder of this study is organized as follows. Section 2 introduces the theoretical framework and develops the hypotheses. Section 3 describes the data sources, sample selection, and variable definitions used in the empirical analysis. Section 4 presents the baseline regression results, demonstrating the overall relationship between regulatory intensity and stock liquidity. Section 5 outlines the identification strategy employed to address potential endogeneity concerns. Section 6 discusses the channel tests, exploring the heterogeneous responses of firms with different characteristics. Section 7 focuses on the further analysis and robustness, where we also use competitive hypotheses to evaluate the negative effects of compliance costs on stock liquidity. Section 8 concludes.

2 Literature Review & Hypothesis Development

2.1 Quantitative Regulation

The relationship between regulation and market dynamics has long been a pivotal area of study in financial economics. Mulherin (2007) conducts a comprehensive review of regulatory economic theories spanning the past century, emphasizing the importance of exercising caution in empirical research on regulatory costs. In his review, Mulherin (2007) points out potential conceptual challenges in assessing the costs and benefits of regulation, which has since influenced much of the subsequent research in this area, particularly concerning regulatory costs in securities markets. Some researchers utilize event studies to investigate the impact of major regulatory enactments or updates on market outcomes. For instance, the passage of the Sarbanes-Oxley Act (SOX) has been extensively studied across different dimensions. These studies include its impact on foreign shareholders (Fernandes et al., 2010), its effect on corporate investment decisions (Kang et al., 2010), and its role in altering the cost of capital (Iliev, 2010). This body of work typically treats regulations as significant events, using market responses to quantify their impact at specific moments.

Building on these insights, Leuz and Wysocki (2016) review prior empirical studies on regulation, emphasizing the critical need for quantifying the costs associated with regulatory frameworks. Further research has since concentrated on measuring these regulatory costs. Al-Ubaydli and McLaughlin (2017) assess the industry-level constraints imposed by different regulations through the development of a regulatory restrictiveness model. Calomiris et al. (2020) construct a firm-level regulatory cost model using textual analysis, while Kalmenovitz (2023) compiles comprehensive federal regulatory data to quantify the compliance costs across different industries. Ewens et al. (2024) utilize a new bunching estimation method to quantify firm-level regulatory costs. Additionally, some scholars have already started using these newly quantified measures of regulatory costs in the financial and economics area (Chambers et al., 2022; Kalmenovitz, 2023; Singla, 2023; Ince, 2024; Ince & Ozsoylev, 2024), highlighting their applicability beyond general single policy analysis.

Although different methods are used to measure regulation, they yield consistent results. For example, increased regulation can have a negative impact on firms' innovation and investment behavior. Coffey et al. (2020) quantitative analysis for a government report shows that rising regulatory cost restricts corporate innovation. This finding aligns with the results of Gao and Zhang (2019), who used a quasi-natural experiment based on SOX to show that increased regulation has a negative impact on corporate innovation.

2.2 Regulatory and Stock Market

Pastor and Veronesi (2012) initially demonstrated through a theoretical model that the uncertainty of government policies enhances the volatility of stock prices. As the study of quantified regulation has gained traction, more literature has emerged discussing the relationship between regulation and the stock market. Ewens et al. (2024) use a regulatory cost model to explain the recent decline in the number of IPOs in the U.S., while Azevedo et al. (2024) examine how rising regulatory costs increase firms' concerns, leading to delistings. Ince and Ozsoylev (2024) argue that regulatory costs have already been factored into stock prices. These studies reinforce Leuz and Wysocki (2016) argument that regulation is dynamic rather than static, proving that regulation is not just a short-term market disturbance but a long-term barrier to firms entering the capital markets.

To explore regulation as a long-term factor in the stock market, liquidity is a key component. Liquidity not only reflects capital market expectations for a company but also signals the company's attractiveness to the market. Existing literature suggests that stock liquidity is influenced by various factors. Nielsson (2009) finds that stock market institutional development contributes to improved market liquidity. Additionally, factors such as corporate transparency (Lang & Maffett, 2011), company announcements (Siikanen et al., 2017) and corporate governance structures (Foo & Zain, 2010; Qiu & To, 2022) have been shown to significantly impact liquidity. Collectively, these studies suggest that stock liquidity is influenced by a combination of external and internal factors, including market structure, corporate transparency, governance systems, and information disclosure practices.

In addition to these studies, some scholars have focused on how regulatory changes or individual policy implementations impact stock liquidity. For instance, Cumming et al. (2011) compare trading rules across various exchanges, concluding that certain regulatory restrictions on specific behaviors can improve stock liquidity. Christensen et al. (2016), in their examination of the Market Abuse Directive (MAD) and the Transparency Directive (TPD) in the European Union, finds that these regulations reduced information asymmetry, thereby increasing market transparency and enhancing liquidity. Conversely, Fernández-Amador et al. (2013) and Hvozdyk and Rustanov (2016) show that both tightening and loosening regulatory policies could significantly impact liquidity in stock markets. Bai and Qin (2015) examine the relationship between market volatility and liquidity, concluding that higher volatility leads to lower liquidity levels. Despite these insights, a gap remains in quantifying the broader impact of regulatory intensity on stock liquidity, which could provide a more comprehensive understanding of how multiple regulations cumulatively affect firms.

Despite these substantial findings, there are still notable gaps in the literature. While certain studies have addressed the effects of specific regulatory policies on stock liquidity, there is a lack of detailed analysis regarding how overall regulatory intensity influences liquidity in stock markets. Traditional research often views regulation as the implementation or adjustment of individual policies, overlooking its role as a long-term market factor. Second, most studies focus on the direct effects of financial market regulations, failing to investigate how cross-industry and cross-sector regulations collectively influence firms' long-term performance and market liquidity. For instance, industries like energy or technology must comply with numerous environmental and technical regulations, and the cumulative effect of these regulations on corporate operations may far exceed the impact of financial market regulations.

To address these gaps, this study uses the comprehensive regulatory intensity index developed by Kalmenovitz (2023) to systematically assess the average impact of the overall regulatory environment on stock market liquidity. This index includes not only specific compliance costs but also the uncertainty introduced by frequent policy changes.

2.3 Baseline Hypothesis

Based on the existing literature and theoretical framework, this section discusses the hypotheses regarding the relationship between regulatory intensity and stock liquidity. While the primary goal of regulation is often to enhance market transparency, balance, and protect investor interests, the associated costs of regulation may also increase pressure on firms. Regulatory policies aim to reduce information asymmetry by improving market transparency, and the negative relationship between information asymmetry and stock liquidity has been well-documented in prior studies (Diamond & Verrecchia, 1991; Coller & Yohn, 1997). However, whether the increased compliance costs associated with regulation might also negatively affect stock markets remains an open question. In this section, we discuss both the positive and negative impacts of regulatory intensity on stock liquidity.

The debate over regulatory effectiveness, particularly in the realms of financial markets and corporate governance, has long been a focal point in academic discussions. Researchers have explored the balance between the benefits and costs of regulation. Starting with the positive effects, Admati and Pfleiderer (2000) argue that companies often fail to benefit from voluntary disclosure due to the "free-rider" problem, which deters many firms from disclosing information. In this context, Mandatory disclosure brought about by supervision has become particularly important. Verrecchia (2001) further demonstrates that mandatory disclosure significantly reduces information asymmetry and improves market pricing efficiency. Empirical evidence supports these theoretical assertions. For instance, Christensen et al. (2016) analysis the Market Abuse Directive (MAD) and Transparency Directive (TPD) in the European Union and found that these regulatory policies enhanced firms' disclosure levels, significantly reduced information asymmetry, and improved stock liquidity. Similarly, in the United States, the Sarbanes-Oxley Act (SOX) initially caused short-term market volatility but ultimately led to greater transparency through stricter regulatory and disclosure requirements, positively impacting stock liquidity in the long run (Jain et al., 2008).

Although increased regulation can enhance information disclosure and benefit stock liquidity, recent research highlights the importance of disclosure quality (Bushee & Noe, 2000; Hermalin & Weisbach, 2012; Leuz & Wysocki, 2016). Moreover, the compliance costs associated with regulation and the uncertainties it generates cannot be overlooked. The negative impact of regulatory costs may also affect stock liquidity. Gulen and Ion (2016) introduce the concept of policy uncertainty, highlighting how regulatory changes influence corporate decision-making. They found that such uncertainty prompts firms to delay investments due to the unpredictability of future policies, thereby increasing operational uncertainty and dampening capital expenditure and innovation activities. Baker et al. (2016) further demonstrate that economic policy uncertainty reduces corporate investment and exacerbates stock price volatility. Recent studies also analyze how regulatory costs impact corporate decisions. This perspective is further supported by Kalmenovitz (2023) and Ince and Ozsoylev (2024), who employed quantitative models to examine the relationship between regulatory intensity and firms' operational uncertainty. For instance, when new regulatory rules are introduced in an industry, companies often adopt a wait-and-see approach, postponing investment decisions until the implications of the new rules become clearer. This delay increases operational uncertainty during the year of regulatory implementation.

The uncertainty faced by firms extends beyond their operations and affects stock market, ultimately influencing stock liquidity. Easley and O'Hara (2010), using the Bewley (2002) uncertainty model, develop a framework showing that high uncertainty associated with underlying assets creates ambiguity, resulting in a high degree of ambiguity in the information available to investors. According to the investor demand model it is shown that the surface directly reduces investor confidence and trading volume. This weakens market liquidity as investors become hesitant to trade when risks are perceived as ambiguous rather than measurable. When a company faces high uncertainty about its future, it may obscure forward-looking disclosures or avoid discussing its strategies, making it difficult for investors to evaluate its true condition.

Easley and O'Hara (2010) (the other paper) demonstrate that reducing information ambiguity benefits both investors and stock markets by fostering transparency and improving liquidity. Mukerji and Tallon (2001) first introduce the concept of ambiguity aversion, which Trojani and Vanini (2004) further support by showing that ambiguity functions similarly to an increase in risk aversion. Bossaerts et al. (2010) also find evidence indicating that in asset markets, ambiguity aversion likes risk aversion, and investors exhibit heterogeneity in their levels of aversion. Dimmock et al. (2016) and Brenner and Izhakian (2018) provide empirical evidence of the impact of ambiguity on stock markets. These studies collectively suggest that investors with varying levels of ambiguity aversion interpret ambiguous information differently, thereby increasing information asymmetry among investors. This implies that the uncertainty about a company's future induced by regulatory intensity increases the company's information ambiguity. This, in turn, amplifies information asymmetry among investors, ultimately harming stock liquidity.

Based on the above theoretical framework, we propose the following competing hypotheses:

Hypothesis 1

Higher regulatory intensity positively impacts stock liquidity.

Hypothesis 2

Higher regulatory intensity negatively impacts stock liquidity.

3 Data and Sample Construction

3.1 Key Variables

3.1.1 Measuring Firm-Level Regulatory Intensity

We use the regulatory intensity measure developed by Kalmenovitz (2023) as our measure of regulatory intensity, and the data from Kalmenovitz's website[1]. Kalmenovitz (2023) manually collects data on all federal regulations from the Office of Management and Budget (OMB) between 1980 and 2020 to estimate the regulatory burden these regulations impose on the public. The OMB estimates include detailed information about the paperwork required,

[1]Kalmenovitz's website: https://sites.google.com/view/jkalmenovitz/home

the time firms need to comply, and the financial costs associated with adherence to these regulations.

To translate regulatory burdens into firm-level data, Kalmenovitz (2023) applies machine learning methods to analyze firms' 10-K filings. These filings often reference specific regulations that impact the firm. By linking regulatory data from the Office of Management and Budget (OMB) to the text in the 10-K reports, Kalmenovitz (2023) develops a set of firm-level regulatory intensity indicators. He constructs 4 firm-level regulatory intensity indicators: the number of regulations (Regulations), the paperwork required (Response), the time spent (Time) and the dollar spent (Dollar). This measurement is based on the construct of all regulations' formula submitted to the government. The fact-based measurement not only reflects the impact of 'Supply' (regulators) but also considers the real-time response of 'Demand' (firms).

3.1.2 Measuring Firm-Level Stock Liquidity

The primary measure of stock liquidity utilized in this study is the natural logarithm of the average daily effective bid-ask spread for the given year. Compared to other measures, the daily of effective bid-ask spread high frequency is a more accurate indicator of stock liquidity(Fink et al., 2010; Ee et al., 2022). Previous literature considers the effective spread to be one of the best measures of the liquidity indicator (Korajczyk & Sadka, 2008; Hasbrouck, 2009; Hendershott et al., 2011). We follow Holden and Jacobsen (2014) to construct the effective spread.

For robustness, we also use trading volume as alternative measure of stock liquidity in Section 7.

3.2 Data Source and Summary Statistics

3.2.1 Baseline Regression Data

This study uses firm-level regulatory intensity as independent variable, and the data range from 1993 to 2019[2] on yearly basis, alongside stock data and company fundamental data from Compustat for the same period. The definitions and sources of control variables are shown in Appendix Table A1.

Table 1 shows the summary statistics are comparable to prior literature (Gopalan et al., 2012; Fang et al., 2014; So & Wang, 2014; Qiu & To, 2022). The dollar indicator is available from 1997. After merging all variables, we have a total of 86,251 observations, covering 7,841 firms. For the dollar indicator, there are 69,852 observations from 6,827 firms.

[Insert Table 1 about here]

3.2.2 Identification Strategy Data

Our identification strategy relies on state elections. We manually collect election dates and the winning party for each U.S. state governor from sources including the Almanac of American Politics and the Stateline database. In the process of collecting this data, we found that not all states time their gubernatorial elections to coincide with the U.S. presidential election cycle. However, we utilized monthly data to include all states in our analysis. While this alignment does not significantly affect our results, we ensured the stability and robustness of the control group by excluding data from the first cycle of state election changes. This allows us to maintain the integrity of the sample.

Appendix Table A2 illustrates the changes in state governance from Republican to Democratic control between 1997 and 2019. For this study, the control group consists of states where the governing party did not change during the study period (1997–2017). These

[2] Our sample starts from 1993 due to the availability of regulatory intensity measures and ends in 2019 to avoid the impact of Covid-19.

states, represented by their abbreviations, include DE (Delaware), FL (Florida), ID (Idaho), NE (Nebraska), NV (Nevada), ND (North Dakota), OR (Oregon), SD (South Dakota), TX (Texas), UT (Utah), WA (Washington), and WV (West Virginia). By focusing on these states, we ensure that the control group remains stable and unaffected by political party shifts, allowing for a clearer comparison of treatment effects in states where the governing party changed.

4 Empirical analysis

We use the following fixed effects regression model to examine the effect of regulatory intensity on stock liquidity:

$$\ln(\text{EffectiveSpread}_{i,j,t+1}) = \alpha + \beta \cdot \ln(\text{RegIn}_{i,j,t}) + \gamma \cdot \text{Control}_{i,j,t} + X_i + \lambda_{j,t} + \epsilon_{i,j,t} \tag{1}$$

where $\ln(\text{EffectiveSpread}_{i,j,t+1})$ is the natural logarithm of the effective spread, representing the liquidity measure of company i at time t, and j denotes the SIC 2-digit industry. Our key variable of interest is $\ln(\text{RegIn}_{i,j,t})$, representing the natural logarithms of the four regulatory intensity measures: Dollar, Response, Time and Dollar. We follow the prior literature to include a series of standard firm-level controls (Copeland & Galai, 1983; Black et al., 2012; Gopalan et al., 2012; So & Wang, 2014; Qiu & To, 2022). Specifically, these controls capture various aspects of firm characteristics known to influence liquidity, including firm size (measured by the logarithm of total assets), leverage ratio, cash holdings, return on assets (ROA), market-to-book ratio, stock return volatility, and property, plant, and equipment (PPE) to assets ratio. X_i represents firm fixed effects for capturing the unobserved heterogeneity across firms, and $\lambda_{j,t}$ represents industry times year fixed effects for capturing the unobserved heterogeneity across industries in each year. We cluster standard errors at the firm level.

[Insert Table 2 about here]

Table 2 presents the baseline regression results, examining the impact of regulatory intensity on stock liquidity. We include firm-level and time $\times$ industry fixed effect. We find that all four regulatory intensity indicators are positively related to the effective spread and are significant at the 1% level, indicating that higher regulatory intensity is associated with lower stock liquidity. This supports our hypothesis 3. Regarding the firm-level control variables, we find that firms with higher profitability, higher market-to-book ratios, lower stock return volatility, and lower PPE-to-asset ratios tend to have stronger stock liquidity. These findings are consistent with prior literature(Copeland & Galai, 1983; Black et al., 2012; Gopalan et al., 2012; So & Wang, 2014; Qiu & To, 2022).Firms facing higher regulatory intensity experience increased uncertainty in their future business and financial planning, leading to greater information ambiguity. This, in turn, reflects an increase in information asymmetry between external investors and the company, ultimately reducing stock liquidity. This finding aligns with recent research exploring the negative impacts of regulatory uncertainty on firms (Kalmenovitz, 2023; Azevedo et al., 2024; Ince & Ozsoylev, 2024). And we are consistent with Goldstein and Yang (2019) that the disclosed information channels brought about by regulation bring about more negative than positive impacts. In the channel test, we further prove the negative effect driven by increasing information asymmetry.

In terms of economic significance, Column 4 of Table 2 shows the impact of Regulations indicator on the effective spread. A one-standard-deviation increase in regulatory Regulations is associated with an increase of 47.8 basis points(coefficient $\times$ SD/Mean) in the effective spread[3]. These results demonstrate the economically and statistically significant negative impact of regulatory intensity on stock liquidity, in line with previous studies on effective spread variations (Hendershott et al., 2011; Kahraman & Tookes, 2017).

Although our findings differ from those of Christensen et al. (2016), who argue that increased securities market regulation reduces information asymmetry through the implemen-

[3]Dollar: 43.6 basis points. Response: 39.8 basis points. Time: 36.1 basis points.

tation of transparency regulations, thus enhancing stock liquidity, our analysis encompasses a broader scope of long-term regulatory intensity across various industries, not limited to financial markets. Our results do not conflict; enhanced securities regulation leads to better liquidity, but the cumulative regulatory costs across different sectors have a negative impact.

Our baseline result demonstrates the statistically and economically significant effects of increased regulatory pressure on stock liquidity. It shows that under stricter regulatory scrutiny, companies face considerably greater liquidity challenges. This finding also reinforces the conclusion that regulation is dynamic rather than static (Leuz & Wysocki, 2016).

5 Identification

This study aims to empirically analyze the relationship between regulatory intensity and stock liquidity. However, our results may be subject to endogeneity issues through two channels. The first is reversal causality. While strict regulation might enhance stock liquidity, companies with poor liquidity could also attract stricter regulation. We addressed this issue by considering the dependent variable at time t+1 in Equation 1. These may affect both regulatory intensity and stock liquidity. This issue represents an empirical challenge for this study, and the following sections will primarily discuss the strategy to address it. Therefore, we use the government change party as an exogenous shock to regulatory intensity[4].

5.1 Identification Design

The political ideologies of parties differ across U.S. states. The Republican Party is right-wing, supporting market liberalization and reducing government intervention, which corresponds to less regulation. The Democratic Party is left-wing, supporting government intervention in the economy, which corresponds to more regulation. Williams III (2012) also demonstrates that the power of state governments in the U.S. can significantly influence

[4] Considering that regulatory intensity is imposed on companies by the government, changes in the strength of each regulation cannot be easily explained through instrumental variables.

regulation. States governed by different parties represent different ideologies. It is common for states to switch governing parties, from red (Republican) to blue (Democrat). Kalmenovitz (2023) also shows that overall regulatory intensity (yearly) has a negative relationship with Republican control at the federal level. We develop the hypothesis that when state governments switch from red to blue, regulatory intensity will increase[5].

We treat each election where a state's governing party changes as a separate stacked cohort. States that switched from red (Republican) to blue (Democrat) in state elections are considered the treated group, while states that remained either red or blue throughout the data period (1997 to 2017) serve as the control group. We conduct stacked cohort DID tests (red to blue) and use Propensity Score Matching (PSM) based on firm fundamentals to obtain comparable individual treatment effects. It is worth noting that, to mitigate the influence of additional unknown factors, we use monthly data in the stacked cohort DID, specifically focusing on data 1 month and 2 months before and after the election. Notably, we excluded data from the election month (November) to avoid any confounding effects. Consequently, we estimate equation (3).

$$\ln(\text{EffectiveSpread}_{i,j,t,c}) = \alpha+\beta_1\text{Treated}_{i,j,c}\times\text{Post}_{t,j,c}+\beta_2\text{Treated}_{i,j,c}+\beta_3\text{Post}_{t,j,c}+\gamma_{i,c}+\delta_t+\theta_{j,c}+\epsilon_{i,j,t,c} \tag{2}$$

$\ln(\text{EffectiveSpread}_{i,j,t})$, is the natural logarithm of monthly effective spread as the dependent variable, representing the liquidity measure of company i in election cohort c at time t, and j denotes the state where the firm is located. We define each election as a cohort, the dynamic treatment effects are measured through dummy variables indicating a change in political party control in the state where the company is located and post-election timing (i.e., Treated = 1 if the company is located in a state where the political party changed in election c and Post = 1 after the election. Treated = 0 if the state in which the company is

[5] For robustness, we also do alternative test to change from blue to red, and the results are shown in Appendix Table A4.

located has no political party changed during the data period). We cluster standard errors at the cohort level.

Our fixed effects model incorporates company and state fixed effects at the cohort level, and Year fixed effect. Specifically, $\gamma_{i,c}$ represents company fixed effects located state change color election cohort, capturing the individual characteristics of companies within the cohort that do not change over time. δ_t is the time fixed effect, which controls for time-level influence. $\theta_{j,c}$ represents state fixed effects for each cohort, accounting for state-specific factors (such as macro-level economic uncertainty) within different cohorts.

5.2 PSM and DID Analysis

To control for potential differences between companies in different states that could impact our results, we apply Propensity Score Matching (PSM) to ensure comparability between the treatment and control groups. First, we calculate propensity scores based on baseline control variables to estimate the probability of each company being in the control group (main and alternative results are in Appendix Table A3). Using nearest-neighbor matching, each treatment group company is matched with a control group counterpart, keeping the propensity score difference below 0.01.

[Insert Table 3 about here]

Next, we test for average differences in matched characteristics between the groups. Panel A of Table 3 confirms no statistically significant differences, indicating high comparability and reducing sample selection bias, thus strengthening our basis for causal inference.

The DID analysis, shown in Panel B of Table A3, examines the impact of a state's governing party switch from Republican to Democrat on stock liquidity, using data from 1-month and 2-month windows around the election. The positive and statistically significant coefficient for Treated $\times$ Post in both columns suggests that firms' effective spreads increase when the governing party shifts, indicating a decline in liquidity. This quasi-natural experiment highlights how increased regulatory intensity, associated with party shifts, tends to reduce stock liquidity, as evidenced by the rise in Effective Spread.

6 Economic Mechanism

In this section, we introduce an interaction term between regulatory intensity and a binary classification of specific subset firms in the baseline regression model. First, we consider the higher-earing surprise firms. Finally, we consider the credit-rated firms. We adopt all indicators of regulatory intensity as the key test variables in our channel tests.

6.1 Earnings Surprise

Past literature suggest that analysts' forecast errors and disagreements are used as one of the best measures of the information environment(Zhang, 2006; Loughran & McDonald, 2014). We measure information ambiguity using the accuracy of earnings surprise and dispersion. The forecast error represents the discrepancy between the actual earnings of a company and the analyst forecasts, where a higher forecast error reflects increased uncertainty in the company's future operations. This increased uncertainty amplifies the ambiguity of information, leading to a greater information asymmetry between the company and external investors, which can ultimately reduce stock liquidity under greater regulatory intensity. The higher dispersion of the forecast indicates greater uncertainty and ambiguity of information, thus increasing the greater uncertainty about the future operational prospects of the company in the market (Diether et al., 2002).

Under increased regulatory intensity, the uncertainty surrounding future operations of a company increases, driven by stricter compliance requirements and additional operational costs. This heightened uncertainty amplifies information ambiguity, especially when significant earnings surprises reveal a substantial gap between actual earnings and market expectations. Such earnings surprises exacerbate the asymmetry of information between the company and external investors, reducing their ability to accurately assess the firm's future performance. This dual impact—greater regulatory pressure and amplified information ambiguity—intensifies information asymmetry, ultimately placing downward pressure on the company's stock liquidity.

Hypothesis 3

Firms with higher forecast error or forecast dispersion, reflecting greater information ambiguity, experience a stronger negative impact of regulatory intensity on stock liquidity.

we classify firms based on their forecast error or forecast dispersion, with those in the highest quartile considered to have high information ambiguity and those in the other quartiles considered to have low information ambiguity.

[Insert Table 4 about here]

Table 4 presents the interaction results between regulatory intensity and measures of information ambiguity. Columns (1) to (4) show that the coefficient of the interaction term between forecast error and regulatory intensity is significant at the 1% level. This demonstrates that higher forecast errors, combined with increased regulatory intensity, lead to a significant widening of the effective spread, indicating a substantial decline in stock liquidity. Similarly, Columns (5) to (8) reveal that the coefficient of the interaction term between forecast dispersion and regulatory intensity is also significant at the 1% level. This suggests that firms with greater forecast dispersion, reflecting higher information ambiguity, experience a more pronounced negative impact on stock liquidity under heightened regulatory intensity. These findings align with our hypothesis 3 that firms with higher information ambiguity, as captured by greater forecast errors or forecast dispersion, face amplified declines in stock liquidity in a high regulatory intensity environment.

6.2 Credit Rating

Credit ratings are a key measure of a company's credit risk, reflecting external agencies' assessments of its financial stability and ability to repay debt. These ratings serve as critical signals in financial markets, particularly for uninformed investors. Boot et al. (2006) demonstrate through an equilibrium model that credit ratings act as "focal points" for investors, influencing their market decisions. Similarly, An and Chan (2008) highlight that credit ratings provide valuable information about a company's value, reducing information asymmetry between firms and investors. Thus, credit ratings not only offer a clear assessment of a company's risk profile but also reduce information asymmetry by shaping investor expectations about the company's future operations.

We classify companies based on their S&P long-term domestic issuer credit ratings. We categorize companies into "rated" and "unrated" groups. Rated companies are those with credit ratings assigned by S&P, while unrated companies lack such ratings. Unrated firms typically exhibit lower transparency, leaving investors with less information about their future risks. This lack of transparency can amplify information ambiguity and uncertainty, especially under heightened regulatory intensity.

Hypothesis 4

Unrated firms, due to higher information ambiguity, experience a stronger negative impact of regulatory intensity on stock liquidity compared to rated firms.

Hypothesis 4 aligns with the broader premise that higher information ambiguity exacerbates information asymmetry, particularly in a high regulatory intensity environment, ultimately reducing stock liquidity. The interaction analysis will test whether the lack of credit ratings amplifies this negative effect by comparing the liquidity impacts between rated and unrated firms.

[Insert Table 5 about here]

Table 5 reports the results of the interaction between regulatory intensity and unrated firms. Columns (1) to (4) show that the interaction term is significant at the 1% level, supporting the hypothesis 4 that unrated firms, characterized by higher information ambiguity, experience a more pronounced decline in stock liquidity under greater regulatory intensity. The absence of credit ratings heightens information asymmetry by limiting the transparency of these firms' risk profiles. This increased uncertainty discourages trading activity and exacerbates liquidity pressures for unrated firms.

In contrast, rated firms benefit from the risk clarity provided by credit ratings, which reduces information asymmetry and fosters greater investor confidence. As a result, rated firms are better positioned to maintain higher stock liquidity levels, even in the face of heightened regulatory intensity. These findings underscore the critical role of credit ratings in mitigating the negative impact of regulatory intensity on stock liquidity for firms with lower information ambiguity.

7 Further and Robustness

7.1 Further analysis

7.1.1 Financial Constraints

Financial constraints refer to the inability of companies to obtain external funding at reasonable costs to support their operations and investments (Fazzari et al., 1988). Financially constrained firms typically face higher financing costs and limited access to capital markets, forcing them to rely more heavily on internal funds. This reliance restricts their flexibility in responding to changes in the external environment, particularly under increased regulatory intensity. Almeida and Campello (2007) point out that financial constraints significantly reduce a company's future investments, thereby affecting its operational stability. When new regulatory requirements are introduced, financially constrained firms must allocate more resources to compliance, resources that could otherwise be used for investment or operational expansion.

Additionally, Korajczyk and Levy (2003) indicate that financially constrained firms are unable to quickly adjust their capital structures. Increased regulatory intensity can have profound effects on a company's long-term capital structure. For these firms, prolonged regulatory pressure may force them to abandon original investment plans or even lead to downsizing or exiting certain markets. As a company's size and profitability decline, the market's expectations of its liquidity also decrease. This long-term impact further amplifies the interaction between financial constraints and regulatory intensity.

In this study, we measure the degree of financial constraints faced by firms using the Whited-Wu (WW) index developed by Whited and Wu (2006) and credit ratings. Firms with high-yield credit ratings (below BB+) are classified as financially constrained, as these ratings indicate higher credit risk and limited access to low-cost financing. Similarly, firms in the top quartile of the WW index are categorized as financially constrained. Firms with investment-grade credit ratings or in the bottom three quartiles of the WW index are considered financially unconstrained, reflecting lower credit risk and greater access to external funding.

[Insert Table 6 about here]

Table 6 presents the estimated results of the interaction between financial constraints and regulatory intensity. The findings indicate that the interaction term between regulatory intensity and the binary classification of financial constraints has a significant positive impact on the effective spread, reflecting a negative effect on stock liquidity. The heightened uncertainty surrounding financially constrained firms amplifies investor concerns, further reducing their confidence in the firm's future operations. Consequently, this leads to a more significant decline in stock liquidity for financially constrained firms compared to their unconstrained counterparts. These findings are consistent with our baseline conclusion that regulatory intensity exacerbates the future uncertainty faced by financially constrained firms, thereby amplifying its negative impact on stock liquidity.

7.1.2 Firm-specific Risk

Firm-specific risk, or idiosyncratic risk, plays a critical role in shaping a company's response to regulatory intensity. Research consistently shows that idiosyncratic volatility reflects uncertainty about a company's future operations (Ang et al., 2006, 2009; Fu, 2009). Ai and Kiku (2016) suggest that idiosyncratic volatility signals information about future investments, while Fink et al. (2010) highlight that increased idiosyncratic risk often stems from market uncertainty regarding a firm's future profitability. This implies that firms with higher specific risk face greater vulnerability to external changes.

Under heightened regulatory intensity, the role of firm-specific risk becomes especially significant. High-risk firms experience amplified uncertainty as regulatory demands increase, exacerbating market concerns about their future operations. This dual pressure not only intensifies internal challenges but also weakens investor confidence, leading to a sharper decline in stock liquidity.

We measure firm-specific risk using idiosyncratic volatility and, as an alternative, cash flow volatility calculated over a five-year rolling window following Ince and Ozsoylev (2024). Firms in the top quartile of these measures are classified as high-risk, while others are considered low-risk.

[Insert Table 7 about here]

Table 7 presents the estimated results for the interaction effects between firm-specific risk and regulatory intensity. The findings reveal that the interaction terms are highly significant, indicating that firms with higher specific risk experience a much stronger negative impact on stock liquidity under heightened regulatory scrutiny. Specifically, high-risk firms face a more substantial decline in liquidity as regulatory intensity increases, reflecting the compounded uncertainty they face.

Additionally, the interaction terms using cash flow volatility as an alternative measure are also statistically significant, further supporting the robustness of our findings. These results underscore the critical role of firm-specific risk in shaping the impact of regulatory intensity on liquidity. Firms already burdened with high uncertainty are disproportionately affected by increasing regulatory demands, as the combination of specific risk and regulatory intensity exacerbates market concerns.

7.2 Alternative Stock liquidity measure

To ensure the robustness of the impact of regulatory intensity on stock liquidity, we conducted a robustness test by replacing the dependent variable with an alternative liquidity measure: Trading Volume. Trading volume measures market activity and indicates how easily assets can be traded without affecting their prices. By incorporating this measure, we aim to determine whether the influence of regulatory intensity on liquidity remains consistent.

Our baseline results indicate that increased regulatory intensity raises uncertainty regarding a company's future operations, which in turn negatively affects stock liquidity. Investor behavior is critical in this context. Inspired by Statman et al. (2006), who find that trading volume reflects investor sentiment, and Lou and Shu (2017), who noted that the Amihud (2002) ratio is influenced by trading volume, we employ trading volume as an additional test to determine if liquidity concerns persist. Furthermore, Chordia et al. (2001) suggest that liquidity is a key component of market efficiency, and trading volume can reflect market trading activity and friction. The definition of this alternative stock liquidity measurement is shown in Appendix Table A1.

[Insert Table 9 about here]

Table 9 presents the results, examining the effect of regulatory intensity on alternative stock liquidity metrics, specifically focusing on trading volume. We find that three of the four regulatory intensity indicators are positively associated with trading volume, supporting our hypothesis that higher regulatory intensity decreases trading volume. These findings support our baseline conclusion that higher regulatory pressures increase investor uncertainty about firms' future operations, consistent with Lou and Shu (2017), who find that reduced trading activity signals market concerns about firms' future performance. These robustness test results support our main findings and reveal how regulatory intensity influences market performance through decreased trading volume, reflecting heightened investor uncertainty.

8 Conclusion

This study provides a comprehensive analysis of the impact of regulatory intensity on stock liquidity, filling a significant gap in the existing literature by exploring not just the short-term effects of specific policies but also the broader, cumulative impact of regulatory intensity on market behavior. Employing the regulatory intensity index developed by Kalmenovitz (2023), our findings contribute a dynamic perspective to the regulatory landscape, revealing how ongoing regulatory burdens shape firm behavior and influence market liquidity.

We have demonstrated that increased regulatory intensity exacerbates the uncertainty surrounding firms' future operations, increasing information ambiguity, leading to significant reductions in stock liquidity. This is particularly pronounced in firms with high earning surprise and credit unrated. These firms have higher information asymmetry, which is reflected in a more pronounced liquidity decline. Furthermore, our study reveals that companies already grappling with high levels of uncertainty suffer more substantial damage. For instance, firms with larger financial constrained, , elevated firm-specific risks, and substantial investment irreversibility face sharper declines in liquidity under heightened regulatory conditions.

Our research advances the understanding of how regulatory intensity affects stock liquidity by utilizing a novel identification strategy that leverages state government party shifts as a quasi-natural experiment. This methodological approach has strengthened our causal inferences, highlighting the utility of political cycles as tools for examining the impact of regulatory changes on market dynamics.

Moreover, this study broadens the regulatory perspective for future research and offers practical guidance for policymakers. It underscores the importance of considering firm heterogeneity when crafting regulations to mitigate undue liquidity risks and balance market stability with firms' operational challenges.

Despite its contributions, this study faces limitations, primarily the geographical focus on the United States, which might limit the applicability of findings to other regulatory and market contexts. Future research could expand this scope to include other countries, which would enrich our understanding of regulatory impacts across different legal and economic frameworks.

In conclusion, by providing new insights into how different types of firms respond to changes in regulatory intensity and the resulting effects on market liquidity, this study not only enriches academic discourse but also offers valuable implications for market regulators and participants striving to optimize regulatory frameworks in an increasingly complex global market environment. This work paves the way for further empirical research into the nuanced interactions between regulation, corporate behavior, and market liquidity, continuing to build on the foundational theories of market dynamics and regulatory impacts.

References

Admati, A. R., & Pfleiderer, P. (2000). Forcing firms to talk: Financial disclosure regulation and externalities. *The Review of Financial Studies*, *13*(3), 479–519.

Ai, H., & Kiku, D. (2016). Volatility risks and growth options. *Management Science*, *62*(3), 741–763.

Almeida, H., & Campello, M. (2007). Financial constraints, asset tangibility, and corporate investment. *The Review of Financial Studies*, *20*(5), 1429–1460.

Al-Ubaydli, O., & McLaughlin, P. A. (2017). Regdata: A numerical database on industry-specific regulations for all u.s. industries and federal regulations, 1997-2012. *Regulation and Governance*, *11*, 109–123.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31–56.

An, H. H., & Chan, K. C. (2008). Credit ratings and ipo pricing. *Journal of Corporate Finance*, *14*(5), 584–595.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance*, *61*(1), 259–299.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2009). High idiosyncratic volatility and low returns: International and further us evidence. *Journal of Financial Economics*, *91*(1), 1–23.

Azevedo, A., Colak, G., El Kalak, I., & Tunaru, R. (2024). The timing of voluntary delisting. *Journal of Financial Economics*, *155*, 103832.

Bai, M., & Qin, Y. (2015). Commonality in liquidity in emerging markets: Another supply-side explanation. *International Review of Economics & Finance*, *39*, 90–106.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593–1636.

Beaupain, R., & Joliet, R. (2011). Corporate drivers of market liquidity on the warsaw stock exchange. *International Economics*, *125*, 83–104.

Bewley, T. F. (2002). Knightian decision theory. part i. *Decisions in Economics and Finance*, *25*, 79–110.

Black, B. S., De Carvalho, A. G., & Gorga, É. (2012). What matters and for which firms for corporate governance in emerging markets? evidence from brazil (and other brik countries). *Journal of Corporate Finance*, *18*(4), 934–952.

Boot, A. W., Milbourn, T. T., & Schmeits, A. (2006). Credit ratings as coordination mechanisms. *The Review of Financial Studies*, *19*(1), 81–118.

Bossaerts, P., Ghirardato, P., Guarnaschelli, S., & Zame, W. R. (2010). Ambiguity in asset markets: Theory and experiment. *The Review of Financial Studies*, *23*(4), 1325–1359.

Brenner, M., & Izhakian, Y. (2018). Asset pricing and ambiguity: Empirical evidence. *Journal of Financial Economics*, *130*(3), 503–531.

Bushee, B. J., & Noe, C. F. (2000). Corporate disclosure practices, institutional investors, and stock return volatility. *Journal of Accounting Research*, 171–202.

Calomiris, C. W., Mamaysky, H., & Yang, R. (2020). Measuring the cost of regulation: A text-based approach. *Working Paper*.

Chambers, D., McLaughlin, P. A., & Richards, T. (2022). Regulation, entrepreneurship, and firm size. *Journal of Regulatory Economics*, *61*(2), 108–134.

Chordia, T., Roll, R., & Subrahmanyam, A. (2001). Market liquidity and trading activity. *The Journal of Finance*, *56*(2), 501–530.

Christensen, H. B., Hail, L., & Leuz, C. (2016). Capital-market effects of securities regulation: Prior conditions, implementation, and enforcement. *The Review of Financial Studies*, *29*(11), 2885–2924.

Coffey, B., McLaughlin, P. A., & Peretto, P. (2020). The cumulative cost of regulations. *Review of Economic Dynamics*, *38*, 1–21.

Coller, M., & Yohn, T. L. (1997). Management forecasts and information asymmetry: An examination of bid-ask spreads. *Journal of Accounting Research*, *35*(2), 181–191.

Copeland, T. E., & Galai, D. (1983). Information effects on the bid-ask spread. *the Journal of Finance*, *38*(5), 1457–1469.

Cumming, D., Johan, S., & Li, D. (2011). Exchange trading rules and stock market liquidity. *Journal of Financial Economics*, *99*(3), 651–671.

Diamond, D. W., & Verrecchia, R. E. (1991). Disclosure, liquidity, and the cost of capital. *The Journal of Finance*, *46*(4), 1325–1359.

Diether, K. B., Malloy, C. J., & Scherbina, A. (2002). Differences of opinion and the cross section of stock returns. *The Journal of Finance*, *57*(5), 2113–2141.

Dimmock, S. G., Kouwenberg, R., Mitchell, O. S., & Peijnenburg, K. (2016). Ambiguity aversion and household portfolio choice puzzles: Empirical evidence. *Journal of Financial Economics*, *119*(3), 559–577.

Easley, D., & O'Hara, M. (2010). Microstructure and ambiguity. *The Journal of Finance*, *65*(5), 1817–1846.

Easley, D., & O'Hara, M. (2010). Liquidity and valuation in an uncertain world. *Journal of Financial Economics*, *97*(1), 1–11.

Easley, D., & O'hara, M. (1987). Price, trade size, and information in securities markets. *Journal of Financial Economics*, *19*(1), 69–90.

Ee, M. S., Hasan, I., & Huang, H. (2022). Stock liquidity and corporate labor investment. *Journal of Corporate Finance*, *72*, 102142.

Ewens, M., Xiao, K., & Xu, T. (2024). Regulatory costs of being public: Evidence from bunching estimation. *Journal of Financial Economics*, *153*, 103775.

Fang, V. W., Tian, X., & Tice, S. (2014). Does stock liquidity enhance or impede firm innovation? *The Journal of Finance*, *69*(5), 2085–2125.

Fazzari, S., Hubbard, R. G., & Petersen, B. (1988). Investment, financing decisions, and tax policy. *The American Economic Review*, *78*(2), 200–205.

Fernandes, N., Lel, U., & Miller, D. P. (2010). Escape from new york: The market impact of loosening disclosure requirements. *Journal of Financial Economics*, *95*(2), 129–147.

Fernández-Amador, O., Gächter, M., Larch, M., & Peter, G. (2013). Does monetary policy determine stock market liquidity? new evidence from the euro zone. *Journal of Empirical Finance*, *21*, 54–68.

Fink, J., Fink, K. E., Grullon, G., & Weston, J. P. (2010). What drove the increase in idiosyncratic volatility during the internet boom? *Journal of Financial and Quantitative Analysis*, *45*(5), 1253–1278.

Foo, Y.-B., & Zain, M. M. (2010). Board independence, board diligence and liquidity in malaysia: A research note. *Journal of Contemporary Accounting & Economics*, *6*(2), 92–100.

Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics*, *91*(1), 24–37.

Gao, H., & Zhang, J. (2019). Sox section 404 and corporate innovation. *Journal of Financial and Quantitative Analysis*, *54*(2), 759–787.

Glosten, L. R., & Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, *14*(1), 71–100.

Goldstein, I., & Yang, L. (2019). Good disclosure, bad disclosure. *Journal of Financial Economics*, *131*(1), 118–138.

Gopalan, R., Kadan, O., & Pevzner, M. (2012). Asset liquidity and stock liquidity. *Journal of Financial and Quantitative Analysis*, *47*(2), 333–364.

Gulen, H., & Ion, M. (2016). Policy uncertainty and corporate investment. *The Review of Financial Studies*, *29*(3), 523–564.

Hasbrouck, J. (2009). Trading costs and returns for us equities: Estimating effective costs from daily data. *The Journal of Finance*, *64*(3), 1445–1477.

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does algorithmic trading improve liquidity? *The Journal of Finance*, *66*(1), 1–33.

Hermalin, B. E., & Weisbach, M. S. (2012). Information disclosure and corporate governance. *The Journal of Finance*, *67*(1), 195–233.

Hoberg, G., & Maksimovic, V. (2015). Redefining financial constraints: A text-based analysis. *The Review of Financial Studies*, *28*(5), 1312–1352.

Holden, C. W., & Jacobsen, S. (2014). Liquidity measurement problems in fast, competitive markets: Expensive and cheap solutions. *The Journal of Finance*, *69*(4), 1747–1785.

Hvozdyk, L., & Rustanov, S. (2016). The effect of financial transaction tax on market liquidity and volatility: An italian perspective. *International Review of Financial Analysis*, *45*, 62–78.

Iliev, P. (2010). The effect of sox section 404: Costs, earnings quality, and stock prices. *The Journal of Finance*, *65*(3), 1163–1196.

Ince, B. (2024). How do regulatory costs affect mergers and acquisitions decisions and outcomes? *Journal of Banking & Finance*, *163*, 107156.

Ince, B., & Ozsoylev, H. (2024). Price of regulations: Regulatory costs and the cross-section of stock returns. *The Review of Asset Pricing Studies*, raae001.

Jain, P. K., Kim, J.-C., & Rezaee, Z. (2008). The sarbanes-oxley act of 2002 and market liquidity. *Financial Review*, *43*(3), 361–382.

Kahraman, B., & Tookes, H. E. (2017). Trader leverage and liquidity. *The Journal of Finance*, *72*(4), 1567–1610.

Kalmenovitz, J. (2023). Regulatory intensity and firm-specific exposure. *The Review of Financial Studies*, *36*(8), 3311–3347.

Kang, Q., Liu, Q., & Qi, R. (2010). The sarbanes-oxley act and corporate investment: A structural assessment. *Journal of Financial Economics*, *96*(2), 291–305.

Kim, H., & Kung, H. (2017). The asset redeployability channel: How uncertainty affects corporate investment. *The Review of Financial Studies*, *30*(1), 245–280.

Korajczyk, R. A., & Levy, A. (2003). Capital structure choice: Macroeconomic conditions and financial constraints. *Journal of Financial Economics*, *68*(1), 75–109.

Korajczyk, R. A., & Sadka, R. (2008). Pricing the commonality across alternative measures of liquidity. *Journal of Financial Economics*, *87*(1), 45–72.

Lang, M., & Maffett, M. (2011). Transparency and liquidity uncertainty in crisis periods. *Journal of Accounting and Economics*, *52*(2-3), 101–125.

Leuz, C., & Wysocki, P. D. (2016). The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research. *Journal of Accounting Research*, *54*(2), 525–622.

Linn, M., & Weagley, D. (2023). Uncovering financial constraints. *Journal of Financial and Quantitative Analysis*, 1–36.

Lou, X., & Shu, T. (2017). Price impact or trading volume: Why is the amihud (2002) measure priced? *The Review of Financial Studies*, *30*(12), 4481–4520.

Loughran, T., & McDonald, B. (2014). Measuring readability in financial disclosures. *The Journal of Finance*, *69*(4), 1643–1671.

Mukerji, S., & Tallon, J.-M. (2001). Ambiguity aversion and incompleteness of financial markets. *The Review of Economic Studies*, *68*(4), 883–904.

Mulherin, J. H. (2007). Measuring the costs and benefits of regulation: Conceptual issues in securities markets. *Journal of Corporate Finance*, *13*(2-3), 421–437.

Nielsson, U. (2009). Stock exchange merger and liquidity: The case of euronext. *Journal of Financial Markets*, *12*(2), 229–267.

Pastor, L., & Veronesi, P. (2012). Uncertainty about government policy and stock prices. *The Journal of Finance*, *67*(4), 1219–1264.

Qiu, B., & To, T. Y. (2022). Board reforms, stock liquidity, and stock market development. *Review of Corporate Finance Studies*, cfac030.

Siikanen, M., Kanniainen, J., & Valli, J. (2017). Limit order books and liquidity around scheduled and non-scheduled announcements: Empirical evidence from nasdaq nordic. *Finance Research Letters*, *21*, 264–271.

Singla, S. (2023). Regulatory costs and market power. *Working Paper*.

So, E. C., & Wang, S. (2014). News-driven return reversals: Liquidity provision ahead of earnings announcements. *Journal of Financial Economics*, *114*(1), 20–35.

Statman, M., Thorley, S., & Vorkink, K. (2006). Investor overconfidence and trading volume. *The Review of Financial Studies*, *19*(4), 1531–1565.

Trojani, F., & Vanini, P. (2004). Robustness and ambiguity aversion in general equilibrium. *Review of Finance*, *8*(2), 279–324.

Verrecchia, R. E. (2001). Essays on disclosure. *Journal of Accounting and Economics*, *32*(1-3), 97–180.

Whited, T. M., & Wu, G. (2006). Financial constraints risk. *The Review of Financial Studies*, *19*(2), 531–559.

Williams III, R. C. (2012). Growing state–federal conflicts in environmental policy: The role of market-based regulation. *Journal of Public Economics*, *96*(11-12), 1092–1099.

Zhang, X. F. (2006). Information uncertainty and stock returns. *The Journal of Finance*, *61*(1), 105–137.

Tables

Table 1: **Summary Statistics**

Table 1 presents the summary statistics of our study. The final sample is from 1993 to 2019. Definitions of the variables are provided in Table A1 in the Appendix. All continuous variables are winsorized by year at the 1^{st} and 99^{th} percentiles.

	Mean	Standard Deviation	25^{th} Percentile	Median	75^{th} Percentile	Observations
ln(Effective Spread)	-3.701	0.718	-4.148	-3.709	-3.266	86251
ln(Regulations)	4.547	0.294	4.530	4.602	4.655	86251
ln(Response)	4.512	0.351	4.411	4.543	4.727	86251
ln(Time)	4.527	0.331	4.457	4.570	4.702	86251
ln(Dollar)	4.494	0.374	4.376	4.538	4.703	69852
ln(Asset)	5.275	2.309	3.670	5.252	6.868	86251
Leverage	0.279	0.448	0.019	0.191	0.386	86251
Cash holding	0.200	0.233	0.027	0.102	0.294	86251
ROA	-0.025	0.634	-0.001	0.096	0.159	86251
Market to book	2.954	5.823	1.045	1.938	3.580	86251
Stock volatility	0.139	5.980	0.023	0.036	0.055	86251
PPE	0.248	0.235	0.067	0.168	0.362	86251

Table 2: **Regulatory Intensity and Stock Liquidity**

Table 2 presents the impact of regulatory intensity on stock liquidity. The dependent variable is the natural logarithm of the effective spread. Columns (1), (2), (3), and (4) represent different regulatory intensity measures. We used year × industry and firm-level fixed effects. Definitions of the variables are in Table A1 in the Appendix. t-statistics are from robust standard errors clustered at the firm level. *p < 10%; **p < 5%; ***p < 1%.

	ln(Effective Spread)			
	(1)	(2)	(3)	(4)
ln(Dollar)	0.052***			
	(3.43)			
ln(Response)		0.051***		
		(3.05)		
ln(Time)			0.049***	
			(2.87)	
ln(Regulations)				0.074***
				(3.76)
ln(Asset)	-0.114***	-0.107***	-0.106***	-0.107***
	(-16.38)	(-17.30)	(-17.29)	(-17.39)
Leverage	0.042***	0.045***	0.045***	0.045***
	(2.70)	(2.99)	(3.00)	(2.99)
Cash holding	-0.172***	-0.136***	-0.137***	-0.133***
	(-6.86)	(-5.81)	(-5.83)	(-5.67)
ROA	-0.014	-0.019*	-0.019*	-0.020**
	(-1.42)	(-1.94)	(-1.93)	(-2.07)
Market to book	-0.001***	-0.001**	-0.001**	-0.001**
	(-3.00)	(-2.50)	(-2.51)	(-2.50)
Stock volatility	0.381***	0.423***	0.423***	0.423***
	(6.08)	(7.04)	(7.06)	(7.06)
PPE	0.112**	0.097**	0.098**	0.095**
	(2.51)	(2.45)	(2.45)	(2.39)
Firm FE	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.671	0.648	0.647	0.648
Observations	69852	86251	86251	86251

Table 3: **Identification Test Results**

Table 3 presents the results from two different analyses. Panel A reports the mean differences between the treatment and control groups after applying Propensity Score Matching (PSM). Panel B shows the results from the stacked cohort DID analysis.

Panel A: Differences between treatment and control groups after PSM

Panel A presents the mean differences between the treatment and control groups after applying Propensity Score Matching (PSM). It reports the mean values for key financial variables such as lnAsset, Leverage, Cashholding, ROA, Market to Book, Stock Volatility, and PPE for both groups, along with the differences between the two groups and the corresponding t-statistics. The treatment group includes firms affected by the regulatory change, while the control group includes matched firms. Definitions of the variables are provided in Table A1 in the Appendix.

Variable	**Treatment group**	**Control group**	**Difference**	**t-statistics**
ln(Asset)	5.932	5.948	-0.016	-0.833
Leverage	0.269	0.299	-0.029	-0.621
Cash holding	0.223	0.218	0.004	0.250
ROA	-0.016	0.010	-0.026	-0.688
Market to book	2.760	2.811	-0.051	-0.088
Stock volatility	0.044	0.039	0.005	1.430
PPE	0.206	0.207	-0.001	-0.141

Panel B: Stacked Cohort DID Results

Panel B presents the regression results from a stacked cohort Difference-in-Differences (DID) analysis, examining the effect of state political transitions (from red to blue) during the post-election period. Column (1) and Column (2) display the DID results using data from 1 month and 2 months before and after the election, respectively. The stacked cohort approach is based on state elections where the political party in power shifts, reflecting the increase of regulatory intensity. The dependent variable is monthly log(Effective Spread). The key independent variables include the interaction term (Treated × Post), which captures the effect of the state political transition during the post-election period, as well as the treatment (treated) and post-event period (post) variables. The table also reports the inclusion of fixed effects: Year, State × EventCohort, and Firm × EventCohort. t-statistics are calculated from robust standard errors clustered at the firm-level in parentheses. *p < 10%; **p < 5%; ***p < 1%.

	ln(Effective Spread)	
	(1)	(2)
Treated×Post	0.077**	0.069*
	(2.85)	(2.19)
State × Event Cohort FE	Yes	Yes
Firm × Event Cohort FE	Yes	Yes
Year FE	Yes	Yes
Adj. R-squared	0.717	0.785
Observations	520	1024

Table 4: **Earnings Surprise**

Table 4 presents the interaction regression results analyzing the impact of regulatory intensity and information ambiguity on stock liquidity. Columns (1)–(4) use Forecast Error, while Columns (5)–(8) use Forecast Dispersion as information ambiguity proxies. Key explanatory variables include ln(Dollar), ln(Response), ln(Time), and ln(Regulations) interacted with information ambiguity. The dependent variable is ln(Effective Spread). Control variables follow the baseline, with year $\times$ industry and firm-level fixed effects. Definitions are in Table A1. t-statistics are in parentheses. *p $<$ 10%; **p $<$ 5%; ***p $<$ 1%.

	ln(Effective Spread)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Forecast Error				*Forecast Dispersion*			
ln(Dollar) $\times$ Information Ambiguity	0.009***				0.006***			
	(14.53)				(9.63)			
ln(Response) $\times$ Information Ambiguity		0.009***				0.006***		
		(15.73)				(10.42)		
ln(Time) $\times$ Information Ambiguity			0.009***				0.006***	
			(15.86)				(10.46)	
ln(Regulations) $\times$ Information Ambiguity				0.009***				0.006***
				(15.73)				(10.42)
Information Ambiguity	0.088***	0.085***	0.086***	0.086***	0.092***	0.090***	0.091***	0.091***
	(14.29)	(14.09)	(14.21)	(14.24)	(14.50)	(14.62)	(14.79)	(14.85)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year $\times$ Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.812	0.801	0.801	0.801	0.820	0.811	0.811	0.811
Observations	48014	55927	55927	55927	42290	48457	48457	48457

Table 5: **Unrated Firms**

Table 5 presents the interaction regression results analyzing the impact of regulatory intensity and credit ratings on stock liquidity. Columns (1)–(4) use different measures of regulatory intensity: ln(Dollar), ln(Response), ln(Time), and ln(Regulations). The explanatory variables include interaction terms with Unrated firms. The dependent variable is ln(Effective Spread). Control variables follow the baseline. Year times industry and firm-level fixed effects are used. Standard errors are clustered at the firm level. Definitions are in Table A1. t-statistics are in parentheses. *p < 10%; **p < 5%; ***p < 1%.

	ln(Effective Spread)			
	(1)	(2)	(3)	(4)
ln(Dollar) × Unrated	0.193***			
	(7.25)			
ln(Response) × Unrated		0.291***		
		(8.90)		
ln(Time) × Unrated			0.285***	
			(7.45)	
ln(Regulations) × Unrated				0.477***
				(6.46)
Unrated	-0.884***	-1.349***	-1.320***	-2.212***
	(-7.24)	(-8.98)	(-7.51)	(-6.49)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year × Industry	Yes	Yes	Yes	Yes
Adj. R-squared	0.686	0.686	0.666	0.666
Observations	68294	68294	80722	80722

Table 6: **Financial Constraints**

Table 6 presents the interaction regression results analyzing the impact of regulatory intensity and financial constraints on stock liquidity. Columns (1)–(4) use the WW index for financially constrained companies, while Columns (5)–(8) use the credit rating high yield companies. Key explanatory variables include ln(Dollar), ln(Response), ln(Time), and ln(Regulations) interacted with financial constraints. The dependent variable is ln(Effective Spread), reflecting stock liquidity. Control variables follow the baseline, with year × industry and firm-level fixed effects. Definitions are in Table A1 in the Appendix. t-statistics are in parentheses. *p < 10%; **p < 5%; ***p < 1%.

	ln(Effective Spread)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	WW Index				*High Yield*			
ln(Dollar) × Financially constrained	0.064***				0.002			
	(3.11)				(0.07)			
ln(Response) × Financially constrained		0.172***				0.207***		
		(7.13)				(4.49)		
ln(Time) × Financially constrained			0.217***				0.202***	
			(7.42)				(3.91)	
ln(Regulations) × Financially constrained				0.279***				0.467***
				(5.23)				(4.24)
Financially constrained	-0.286***	-0.778***	-0.989***	-1.275***		-0.890***	-0.869***	0.467***
	(-3.05)	(-7.04)	(-7.34)	(-5.20)		(-4.21)	(-3.67)	(4.24)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.686	0.674	0.674	0.674	0.691	0.672	0.672	0.672
Observations	76337	76337	76337	76337	71541	71541	71541	71541

Table 7: **Firm Specific Risk**

Table 7 presents the interaction regression results analyzing the impact of specific risk and regulatory intensity on stock liquidity. Columns (1)–(4) focus on idiosyncratic volatility, while Columns (5)–(8) focus on cash flow volatility. Key variables include ln(Dollar), ln(Response), ln(Time), and ln(Regulations) interacted with specific risk. The dependent variable is ln(Effective Spread). Control variables follow the baseline, with year × industry and firm-level fixed effects. Definitions are in Table A1. t-statistics are in parentheses. *p < 10%; **p < 5%; ***p < 1%.

	ln(Effective Spread)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Idiosyncratic Volatility				*Cash Flow Volatility*			
ln(Dollar) × Specific risk	0.068***				0.113***			
	(3.30)				(4.64)			
ln(Response) × Specific risk		0.096***				0.161***		
		(4.47)				(5.52)		
ln(Time) × Specific risk			0.125***				0.189***	
			(3.33)				(3.56)	
ln(Regulations) × Specific risk				0.125***				0.189***
				(3.33)				(3.56)
Specific risk	-0.0969	-0.216**	-0.134	-0.358**	-0.441***	-0.666***	-0.759***	-0.801***
	(-1.05)	(-2.22)	(-1.17)	(-2.07)	(-4.00)	(-4.98)	(-4.71)	(-3.28)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.764	0.751	0.751	0.751	0.691	0.686	0.686	0.686
Observations	61352	73340	73340	73340	63250	66800	66800	66800

Table 8: **Asset Redeployability**

Table 8 presents the interaction regression results analyzing the impact of asset redeployability and regulatory intensity on stock liquidity. Columns (1)–(4) use Redeployability, while Columns (5)–(8) use Redeployability_R2. Key variables include ln(Dollar), ln(Response), ln(Time), and ln(Regulations) interacted with redeployability. The dependent variable is ln(Effective Spread). Control variables follow the baseline, with firm and year fixed effects. Definitions are in Table A1 in the Appendix. t-statistics are in parentheses. *p < 10%; **p < 5%; ***p < 1%.

	ln(Effective Spread)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Redeployability				*Redeployability_R2*			
ln(Dollar) × Redeploy	0.074***				0.088***			
	(2.98)				(3.53)			
ln(Response) × Redeploy		0.070**				0.088***		
		(2.27)				(3.53)		
ln(Time) × Redeploy			0.086**				0.078**	
			(2.45)				(2.31)	
ln(Regulations) × Redeploy				0.083				0.065
				(1.58)				(1.31)
Redeploy	-0.312**	-0.312**	-0.386**	-0.386**	-0.306**	-0.306**	-0.349**	-0.349**
	(-2.24)	(-2.24)	(-2.42)	(-2.42)	(-2.30)	(-2.30)	(-2.26)	(-2.26)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.727	0.712	0.727	0.712	0.727	0.712	0.727	0.712
Observations	60125	72304	72304	72304	59986	72103	72103	72103

Table 9: **Alternative Liquidity Measure: Trading Volume**

Table 9 presents the regression results analyzing the impact of regulatory intensity on trading volume as a liquidity measure. Columns (1), (2), (3), and (4) present different regulatory intensity measures. The dependent variable is trading volume, with control variables following the baseline. We used year × industry and firm-level fixed effects. Definitions of the variables are provided in Table A1 in the Appendix. t-statistics are calculated from robust standard errors clustered at the firm level in parentheses. *p < 10%; **p < 5%; ***p < 1%.

	Trading Volume			
	(1)	(2)	(3)	(4)
ln(Dollar)	-0.924			
	(-1.33)			
ln(Response)		-1.335*		
		(-1.82)		
ln(Time)			-1.381**	
			(-1.98)	
ln(Regulation)				-2.180***
				(-3.08)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.812	0.764	0.764	0.764
Observations	69854	86262	86262	86262

Appendix

Table A1: **Variable Definition**

Variable	Definition	Source
Regulations	This indicator measures the total number of regulatory acts a firm must comply with, reflecting the complexity of its regulatory environment.	Kalmenovitz (2023)
Response	This indicator quantifies the administrative burden by tracking the number of forms and reports firms must submit to comply with regulations.	Kalmenovitz (2023)
Time	This indicator estimates the total hours firms dedicate to compliance-related activities, capturing both direct and opportunity costs.	Kalmenovitz (2023)
Dollar	This indicator represents the financial costs of compliance, including fees and investments needed to meet regulatory standards.	Kalmenovitz (2023)
Assets	Natural logarithm of market value of equity at the end of the year.	Compustat
Leverage	Book value of debt (DLTT+DLC) scaled by the book value of total assets (AT).	Compustat
Cash holding	Cash holding (CHE) scaled by the book value of total assets (AT).	Compustat
ROA	Operating income before depreciation (OIBDP) scaled by the book value of total assets (AT).	Compustat
Market to Book	Market value of equity divided by Book value of equity (CEQ).	Compustat
Stock volatility	Natural logarithm of annualized standard deviation of stock returns.	Compustat
PPE	The ratio of property, plant, and equipment (PPE) to total assets.	Compustat
Effective spread	Average of the daily dollar-volume weighted average of effective spreads in a given year.	Compustat
Trading Volume	Average of the daily dollar-volume ($1,000,000) in a given year.	Compustat
WW Index	Based on a range of financial characteristics proposed by Whited and Wu (2006), constructed by us.	Compustat
LW Index	Constructed using a random forest model by Linn and Weagley (2023), using Hoberg and Maksimovic (2015) indicators as the training sample.	Linn and Weagley (2023)
Idiosyncratic Volatility	Natural logarithm of idiosyncratic volatility (IVOL) of stock returns, calculated by the standard deviation of residuals from the Fama-French three-factor model.	CRSP
Cash Flow Volatility	Standard deviation of a company's cash flow relative to its assets over a five-year rolling window.	Compustat
Redeployability	Based on firm-level measures, using market values of firms in each BEA industry as weights Kim and Kung (2017).	Kim and Kung (2017)
Redeployability_R2	Extends Redeployability by incorporating output correlation between companies within the same industry.	Kim and Kung (2017)
Forecast Error	Average absolute difference between analysts' earnings forecasts and actual EPS, scaled by the absolute stock price at the end of the previous quarter.	IBES
Forecast Dispersion	Standard deviation of analysts' earnings forecasts, scaled by the absolute stock price at the end of the previous quarter.	IBES
Unrated	The company was not given a long-term domestic issuer credit rating by S&P in a given year.	Capital IQ

Table A2: **States that Changed from Red to Blue or Blue to Red**

Panel A: States that Changed from Red to Blue

Year	**Red to Blue**
1999	MS
2001	NJ, VA
2002	AZ, IL, KS, NM, OK, PA, TN, WI, WY
2003	LA
2004	MT
2006	AR, CO, MD, MA, NY, OH
2007	KY
2008	MO
2010	CA, CT, HI, MN
2013	VA
2014	PA
2015	LA
2016	NC

Panel B: States that Changed from Blue to Red

Year	**Blue to Red**
2002	AL, AK, GA, HI, MD, SC
2003	KY, MS
2004	IN, MO
2006	CA
2007	LA
2009	NJ, VA
2010	AZ, IA, KS, ME, MI, NM, OH, OK, PA, TN, WI, WY
2012	NC
2014	AR, IL, MD, MA
2015	KY
2016	MO

Table A3: **Pre-PSM Probability Estimate**

Table A3 shows the results of the pre-PSM probability estimate for both red-to-blue and blue-to-red transitions. Column (1) represents the red-to-blue probability regression, while Column (2) represents the blue-to-red probability regression. The dependent variable in each event cohort is included in the treated group. The independent variables include company characteristics such as assets, leverage, cash holdings, return on assets (ROA), market-to-book ratio, stock volatility, and property, plant, and equipment (PPE) dividend asset. Definitions are in Table A1 in the Appendix. *p < 10%; **p < 5%; ***p < 1%.

	Treated	
	(1)	**(2)**
ln(Asset)	0.026***	0.049***
	(3.66)	(5.92)
Leverage	-0.039	-0.046
	(-1.18)	(-1.21)
Cash holding	0.192***	0.339***
	(2.68)	(4.27)
ROA	-0.021	-0.024
	(-0.87)	(-0.89)
Market to book	-0.001	-0.002
	(-0.37)	(-0.61)
Stock volatility	-0.719***	-0.451*
	(-3.23)	(-1.73)
PPE	-0.813***	-0.904***
	(-13.08)	(-12.60)
Pseudo R-squared	0.0255	0.0345
Observations	10200	8123

Table A4: **Alternative Test of Identification**

Table A4 presents the results from two different analyses. Panel A reports the mean differences between the treatment and control groups after applying Propensity Score Matching (PSM). Panel B shows the results from the stacked cohort DID analysis. The coefficient for Treated × Post is negative and statistically significant, suggesting that after a state's governing party switches from blue (Democrat) to red (Republican), effective spread decreases, implying an increase in stock liquidity in the state where the firm is located.

Panel A: Differences between treatment and control groups after PSM

Panel A presents the mean differences between the treatment and control groups after applying Propensity Score Matching (PSM). The table reports the mean values for key financial variables such as lnAsset, Leverage, Cashholding, ROA, Market to Book, Stock Volatility, and PPE for both groups, along with the differences between the two groups and the corresponding t-statistics. Definitions of the variables are provided in Table A1 in the Appendix. The treatment group includes firms affected by the regulatory change, while the control group includes matched firms.

Variable	Treatment group	Control group	Difference	t-statistics
ln(Asset)	5.649	5.679	-0.029	0.183
Leverage	0.231	0.195	0.036	0.460
Cash holding	0.289	0.263	0.026	0.174
ROA	-0.116	0.040	-0.076	0.275
Market to book	2.951	2.099	0.852	0.159
Stock volatility	0.041	0.041	0.000	0.965
PPE	0.175	0.167	0.008	0.3681

Panel B: Stacked Cohort DID Results

Panel B shows the stacked cohort DID results. Column (1) and Column (2) display the DID results using data from 1 month and 2 months before and after the election, respectively. The dependent variable is monthly log(Effective spread). t-statistics are calculated from robust standard errors clustered at firm-level in parentheses. *p < 10%; **p < 5%; ***p < 1%.

	ln (Effective Spread)	
	(1)	(2)
Treated × Post	-0.048**	-0.028**
	(-2.77)	(-2.90)
Year FE	Yes	Yes
State × EventCohort FE	Yes	Yes
Firm× EventCohort FE	Yes	Yes
Adj. R-squared	0.721	0.779
Observations	492	973