The Review of Asset Pricing Studies

Price of Regulations: Regulatory Costs and the Cross-section of Stock Returns

Baris Ince

Michael Smurfit Graduate Business School, University College Dublin, Ireland

Han Ozsoylev

Ozyegin University, Turkey

Regulations introduce significant fixed costs and add to operating leverage. Fixed regulatory costs that contribute to operating leverage should generate a risk premium. To explore whether such a premium exists, we introduce a measure of "regulatory operating leverage" that reflects the importance of fixed regulatory costs in a firm's cost structure. Regulatory operating leverage predicts stock returns in the cross-section, and a zero-cost high-low regulatory operating leverage strategy generates positive and significant risk-adjusted return. Finally, the impact of regulatory operating leverage on returns is due to the (systematic) risk contribution of fixed regulatory costs. (*JEL* G12, G18, G28)

Received: October 31, 2022; Editorial decision: December 1, 2023
Editor: Zhiguo He
Authors have furnished an Internet Appendix, which is available on the Oxford University Press Web site next to the link to the final published paper online.

Benefits and costs of regulations have been widely discussed. Regulations enhance market safety and stability, and increasing levels of regulations can prevent the concentration of market power. Regulations also aim to protect consumers, even if it means lower profits for businesses. On the other hand, regulations can reduce overall social welfare. Opponents of regulations argue that free markets, dominated by rational actors, efficiently allocate resources and competition protects consumers. They believe that even if a company gains monopolistic power due to limited government interference, the market will eventually correct the issue.

We would like to thank Zhiguo He (the editor), two anonymous referees, Yigit Atilgan, Turan Bali, Hamza Demircan, Cem Demiroglu, Umit Gurun, Oguzhan Ozbas, and seminar participants at Bilkent University, Bogazici University, Durham University, Koc University, Koc Finance Day, and Sabanci University for helpful comments and suggestions. This research was supported by a TUBITAK 1001 grant from the The Scientific and Technological Research Council of Turkey [grant number 117K248]. Baris Ince would like to acknowledge the support of Science Foundation Ireland [grant number 16/SPP/3347]. Send correspondence to Baris Ince, baris.ince@ucd.ie.

The Review of Asset Pricing Studies 00 (2024) 1–47

https://doi.org/10.1093/rapstu/raae001 Advance Access publication 10 January 2024

Hahn and Hird (1991) are some of the first economists to analyze the costs and benefits of federal regulations. As many economists and policy makers attempt to quantify regulations with the number of pages in Federal Register, Goff (1996) introduces a measure of total regulation through factor analyses and finds a causal effect of regulation on economic activity. Subsequently, Nicoletti and Scarpetta (2003), Djankov et al. (2002), Bandiera et al. (2000), and Dawson and Seater (2013) estimate the effects of regulations on macroeconomic measures like real aggregate output, total factor productivity, capital, and labor. Additionally, Coffey, McLaughlin, and Peretto (2016) show that federal regulations have increased over the years, and if the level of regulations would had remained constant since 1980, the U.S. economy would have been 25% larger in 2012. Similarly, Crain and Crain (2014) estimated the total cost of U.S. federal regulations to be around $2 trillion in 2012.

In the context of asset pricing, despite a growing interest in the cross-sectional pricing of governmental policies and policy uncertainty (Pastor and Veronesi 2012, 2013, 2020; Kelly, Pastor and Veronesi 2016), no prior study has documented the relationship between regulations and subsequent stock returns.[1] This paper aims to fill that gap by (a) offering a firm-level measure of regulatory operating leverage that captures a firm's exposure to fixed regulatory costs, (b) documenting that regulatory operating leverage predicts stock returns, and (c) providing a rational risk-based explanation for this prediction: regulatory operating leverage contributes to risk.

Bradford (2004) and Crain and Crain (2014) document that most of regulatory costs, including capital expenditures, information costs, reporting, and record-keeping, are fixed. Smaller firms often struggle with regulatory compliance because of limited resources, making regulatory costs more burdensome for them. Additionally, regulatory costs are distributed unevenly across industries.[2] The size- and industry-dependent regulatory burden differences imply that the significant cross-sectional regulatory cost spreads might be an important factor in firms' risk exposure, which in turn affects their risk premiums. Building on this idea, this paper focuses on the cross-sectional pricing of firm-level regulatory fixed costs and contributes to the literature on regulatory framework and operating leverage.

Lev's (1974) seminal article is the first to mention that operating leverage can trigger systematic risk and, therefore, expected stock returns. Carlson, Fisher, and Giammarino (2004), Zhang (2005), and Cooper (2006) show that operating leverage is critical to the models that generate value premium, and value stocks generate higher returns due to systematic risk. Novy-Marx (2011) documents that

[1] Corporate finance literature generally focuses on the effects of regulations on corporate governance and the channels through which deregulation affects merger waves. Ince (forthcoming) introduces a measure of regulatory (in)flexibility and investigates its M&A implications.

[2] The amount and type of regulations that apply to a particular industry depend on a variety of factors, including the nature of the industry, the products or services the industry provides, and the potential risks or externalities associated with its activities.

interindustry differences in book-to-market are mainly driven by differences in operating leverage. In addition, operating margin differences within industry might give rise to book-to-market differences.[3,4]

The rationale behind the association between operating leverage and systematic risk is as follows. If a firm's costs are mostly fixed as opposed to variable, then it loses operating flexibility. During economic expansions, such a firm's revenues increase at a faster rate than its costs. As a result, it generates larger profits in comparison to a firm whose costs are mostly variable. Similarly, during recessions, a firm with high operating leverage experiences larger losses. Therefore, prospects of a firm with high operating leverage are more dependent on business cycles, and such a firm is more exposed to systematic risk. As a result, investors demand extra compensation in the form of higher expected returns to hold stocks with high operating leverage. This suggests that regulatory fixed costs, which contribute to operating leverage, should generate a risk premium. To explore whether such a risk premium exists, this paper introduces a measure of regulatory operating leverage (ROL) that captures the importance of regulatory fixed costs in a firm's cost structure and examines its cross-sectional pricing implications.

To generate a measure of regulatory operating leverage, the study utilizes the "RegData 4.0" database, which quantifies the incidence of regulatory restriction words imposed on industries based on a text analysis of federal regulatory code. Then, we estimate firm-specific time-series regressions of SG&A expenses on regulatory restrictions and sales, and introduce the ratio of fixed costs attributable to regulatory restrictions in the regression over the SG&A expenses as "regulatory operating leverage." ROL is a firm-specific measure that varies over time.

Common operating leverage measures imply profitability and growth prospects. As the long run trend of the U.S. economy has been positive, firms with a high operating leverage ratio tend to generate larger profits compared to those with a low fixed cost ratio (Chen, Harford, and Kamara 2019). Differing from common operating leverage measures, regulatory operating leverage (fixed costs) does not contribute to firms' profitability. Regulatory costs are considerably recurrent expenses that appear in firms' cost structure regularly, constraining their cost structure and decreasing profitability.[5]

3 Novy-Marx (2011) quantifies operating leverage as ((COGS+SG&A)/AT), whereas the operating leverage measure proposed by Chen, Harford, and Kamara (2019) is (SG&A/AT). Chen, Harford, and Kamara (2019) document that, because of the positive long-run trend of the U.S. economy, operating leverage has a significantly positive predictive power on a firm's profitability. On the other hand, if a firm with high fixed costs experiences a negative sales shock, it will generate greater losses since it cannot reduce its costs as much as the decline on its revenues.

4 Cohen, Polk, and Vuolteenaho (2003) show that that the value premium is significantly an intraindustry phenomenon.

5 Although Table 8 implies a positive association between regulatory operating leverage and operating margin, cross-sectional regressions of operating margin on regulatory operating leverage measures and control variables, such as natural logarithm of sales, market-to-book asset ratio, cash holdings scaled by assets, book leverage, cash dividends scaled by assets, and fixed assets scaled by assets, show that regulatory operating leverage negatively and significantly predicts firm-level profitability. The negatively significant relationship persists when operating leverage measures of Novy-Marx (2011) and Chen, Harford, and Kamara (2019) are added to the regression. Table A3 of the Internet Appendix reports the relevant regression results.

Building on the fixed cost channel, this study investigates the cross-sectional predictive power of federal-level regulations on the future stock returns. More specifically, we sort individual stocks into quintile portfolios based on their regulatory operating leverage measure during the previous quarter and examine the monthly returns on the resultant portfolios from April 1991 to December 2021. Stocks in the highest regulatory operating leverage quintile generate 6.48% (5.88%) more equal (value)-weighted annualized returns compared to the stocks in the lowest regulatory operating leverage quintile. After controlling for the well-known market, size, book-to-market, momentum, liquidity, investment, and profitability factors of Fama and French (1993, 2015), Carhart (1997), Pastor and Stambaugh (2003), and Hou, Xue, and Zhang (2015), we find that the difference between the returns on the portfolios with the highest and the lowest regulatory operating leverage remains significantly positive.

To ensure that the observed return differences are driven by regulatory operating leverage rather than other firm-specific characteristics and risk factors, we perform bivariate portfolio sort analyses and firm-level cross-sectional Fama-Macbeth (1973) regressions. We control for market beta, size and book-to-market (Fama and French 1992, 1993), intermediate-term-momentum (Jegadeesh and Titman 1993), short-term-reversal (Jegadeesh 1990), illiquidity (Amihud 2002), idiosyncratic volatility (Ang et al. 2006), maximum of daily returns (Bali, Cakici, and Whitelaw 2011), asset growth and return on equity (profitability) (Fama and French 2015; Hou, Xue, and Zhang 2015), and operating margin. After controlling for this large set of stock return predictors, we find the positive relation between the regulatory operating leverage and future returns remains economically and statistically significant.[6]

Value premium is driven by cross-industry operating leverage differences and intraindustry operating margin spreads. First, capital-intensive industries tend to carry a higher level of asset heaviness. As a result, firms within capital intensive industries tend to have higher book-to-market ratios because of their asset heaviness. Second, firms within the same industry with different levels of operating margin are exposed to industry-specific shocks in different degrees. A firm with a lower operating margin is more exposed to shocks; as a result, it would have a lower market value and higher book-to-market ratio in comparison to firms with higher operating margin within the same industry. Additionally, firms' hiring decisions and fixed labor expenses play important roles in firms' capital structure and operating leverage, and they are priced in the cross-section of stock returns (Rosett 2001; Danthine and Donaldson 2002; Donangelo et al. 2019). To ensure

[6] A true operating leverage measure should eliminate the cross-sectional pricing of regulatory operating leverage. In other words, once portfolios are constrained to be neutral toward operating leverage measures, a zero-cost regulatory operating leverage should fail to generate significant risk-adjusted return. To test this, we conduct additional bivariate portfolio sort analyses, in which we control for operating leverage measures of Novy-Marx (2011) and Chen, Harford, and Kamara (2019). First, we form quintile portfolios based on the level of each operating leverage measure. Then, within each measure, we create portfolios formed by sorting on ROL. Once portfolios are neutralized to each of the operating leverage measures, the alpha spreads between the extreme regulatory operating leverage measures are positively significant.

that our results are not driven by cross-sectional differences in operating margin, operating leverage, and labor expenses, we construct additional bivariate portfolio sorts. The results suggest that the cross-sectional relation between regulatory operating leverage and subsequent stock returns are robust to such controls. Additionally, we find a stronger relation between regulatory operating leverage and future stock returns within stock subgroups with low operating margin, high operating leverage, and high labor expenses.

We provide a risk-based explanation for the observed cross-sectional relation between regulatory operating leverage and stock returns. More specifically, we conduct Fama-Macbeth (1973) regressions of cash flow volatility (four-quarter forward volatility of EBITDA scaled by assets) on regulatory operating leverage and find the relation between the two to be strongly statistically significant.[7] Regression results document that regulatory operating leverage triggers future cash flow volatility both during recessionary and nonrecessionary periods. Furthermore, the positive association between regulatory operating leverage and cash flow volatility is stronger during recessions.[8] This finding supports the idea that systematic risk implications of regulatory operating leverage contributes to the positive relation between regulatory operating leverage and stock returns. Additionally, we find that the relation between regulatory operating leverage and cash flow volatility is stronger during decreasing CFNAI (Chicago Fed National Activity Index) and decreasing industrial production periods. This suggests that economic activity and industrial production growth are important macroeconomic state variables on the systematic risk exposure of stocks with high regulatory operating leverage. In addition, we find the relation between regulatory operating leverage and cash flow volatility to be more pronounced among small-cap and mid-cap firms since they lack economies of scale.

Finally, we investigate the robustness of the findings. We propose two alternative regulatory operating leverage measures based on our primary measure. Additionally, we estimate regulatory operating leverage from quarterly regressions of SG&A expenses on regulatory restrictions and sales using a 60-quarter fixed window estimation. The results consistently support the cross-sectional relationship between regulatory operating leverage and future stock returns. In other words, the cross-sectional predictive power of regulatory operating leverage over subsequent stock returns is robust to alternative specifications and estimation methods.

[7] The positively significant relationship between regulatory operating leverage and cash flow volatility persists when operating leverage measure of Novy-Marx (2011) is added to the regression. Similarly, regulatory operating leverage continues to predict future cash flow volatility significantly when operating leverage measure of Chen, Harford, and Kamara (2019) is accounted in the regression.

[8] As documented by Cooper (2006), positive investment is costly and difficult; hence, value firms significantly covary with economic booms. On the other hand, regulatory operating leverage does not imply any investment requirement (opportunity) during expansionary periods. Hence, regulatory operating leverage does not trigger cash flow volatility during economic booms besides idiosyncratic negative shocks.

1. Data and Variables

1.1 The Code of Federal Regulations and RegData

In this study, we utilize several data sets. To examine the cross-sectional predictive power of regulatory operating leverage, which represents the significance of regulatory fixed costs in a firm's cost structure, we first need to quantify the regulations specific to each firm. To achieve this, we rely on a database called "RegData 4.0.," developed by the Mercatus Research Center of George Mason University (Al-Ubaydli and McLaughlin 2017). This database quantifies regulatory exposure of two-, three-, and four-digit-level NAICS industries from 1970 to 2020 in the Code of Federal Regulations (CFR).

The CFR, published annually since 1969, contains all regulations issued at the federal level. It consists of 50 titles that represent various regulatory areas at the federal level, such as agriculture, commerce, environment, health, and transportation. Each title is further divided into chapters, parts, sections, and subsections. "RegData 4.0" employs a two-stage methodology involving text analysis and machine learning algorithms to create an industry-level data set. First, it counts regulatory restriction words in the CFR parts, such as "shall", "must", "may not", "prohibited", and "required". Second, a machine learning algorithm assigns a relevance score (ranging from 0 to 1) between the CFR parts and NAICS-level industries. These relevance scores quantify the relationship between each CFR title and the NAICS-level industries and scores reflect the extent to which the regulations in a CFR title are applicable or relevant to a specific industry. The scores are determined through a combination of expert judgment, textual analysis, and statistical techniques. The aim is to assess the degree of regulatory burden or exposure faced by different industries due to the regulations contained within a CFR title. Once the relevance scores are calculated for each CFR title and NAICS-level industry pairing, they can be aggregated to construct industry-level regulatory exposure. Aggregation involves summing up the relevance scores across the CFR titles that are applicable to a specific industry. This provides a cumulative measure of the regulatory impact on that industry, taking into account the relevance of multiple CFR titles. As a result, by aggregating all regulatory restriction words coming from different titles, an industry-specific regulatory restriction data set is constructed.[9]

Figure 1 plots the total number of regulatory restriction words (in thousands) in the CFR from 1990 to 2020 with gray-shaded areas indicating recessionary periods in the United States determined by the National Bureau of Economic Research (NBER). The total number of regulatory restrictions increased from 786,512 in

[9] For simplicity, we assume there are three CFR titles: Agriculture, Transportation, and National Defense, and the number of restriction words under the titles are a, b, and c, respectively. The number of total regulatory restriction words that "Agriculture, Forestry, Fishing and Hunting" are exposed to are quantified in two stages. In the first stage, RegData quantifies the number of regulatory restriction words under each title. In the second stage, RegData assigns a relevance score that varies between 0 and 1 from each title to each industry, where we can further assume the relevance score between "Agriculture, Forestry, Fishing and Hunting" and the mentioned titles are x, y, and z, respectively. In this case, the total number of regulatory restriction exposure of this industry simply would be $a^*x + b^*y + c^*z$.

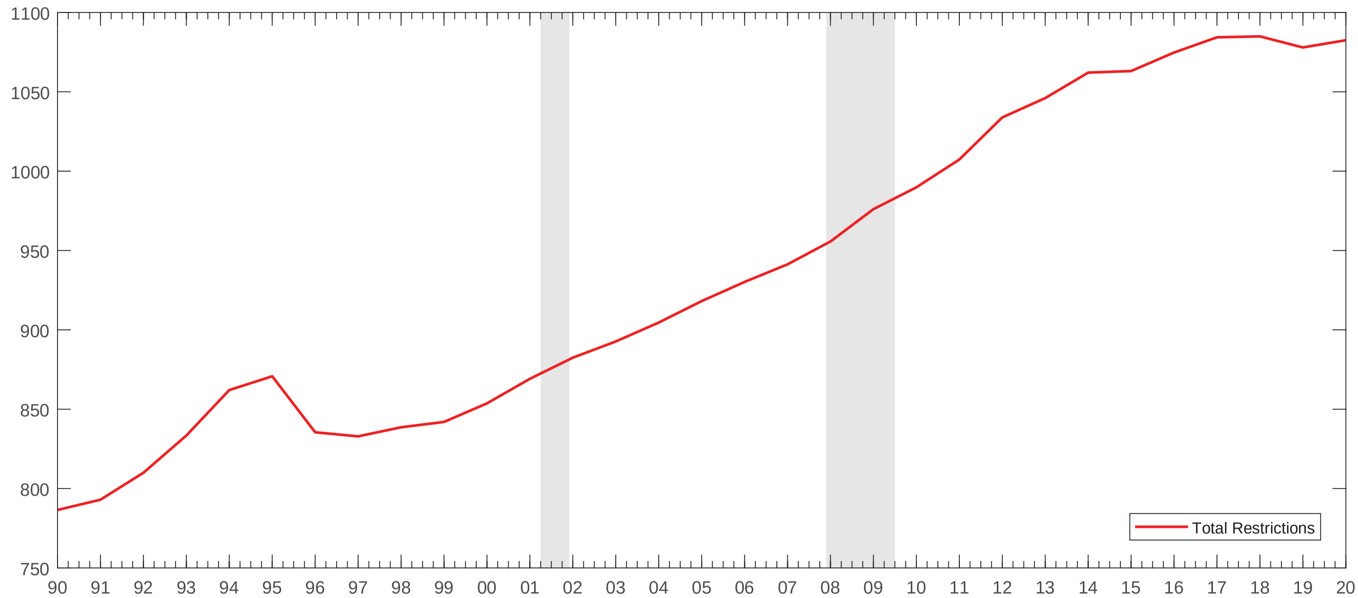

Figure 1
Total regulatory restriction words in the CFR
This figure plots the number of total regulatory restriction words in the Code of Federal Regulations from 1990 to 2020. The gray-shaded areas indicate recessionary periods in the United States determined by the National Bureau of Economic Research (NBER).

1990 to 1,082,486 in 2020. Although a slight decrease occurred between 1995 and 1996, the overall trend shows an upward trajectory. Moreover, the figure suggests that the growth of regulatory restrictions is not dependent on business cycles, as there is no observable change in their growth during recessionary and nonrecessionary periods.

Throughout the study, we focus on regulatory exposure of three-digit-level NAICS industries. To analyze interindustry differences in regulatory burden more comprehensively, Table 1 presents the 50 broad titles of the CFR and the NAICS-3-level industries most exposed to each title based on the relevance scores assigned by "RegData 4.0." To compute the industry-specific regulatory relevance, we compute the time-series averages of the yearly industry-specific regulatory restriction exposure to the CFR titles. To illustrate, "agriculture" (title 7) related regulations are updated every January. The food manufacturing industry is the industry most exposed to agricultural regulations, and the textile product mills industry is the one least exposed to federal-level agricultural regulations. "Transportation" (title 49) regulations are updated every October. As expected, transportation equipment manufacturing is the industry that is the most exposed to transportation-related regulations.

Additionally, Table A1 of the Internet Appendix provides information on the number of firms and selected moments of restriction count (mean, minimum, maximum) for each two-digit NAICS industry. The sample comprises 2,565 firms per year on average. The manufacturing industry represents half of the sample. Arts, entertainment, and the recreation industry; wholesale trade, retail trade are among the least regulated industries. Some of the highly regulated industries are educational services, administrative and support and waste management and remediation services. Subsectors such as waste collection, waste treatment, and disposal and waste management services increase regulatory exposure of administrative and support and waste management industry. The health care and social assistance industry has experienced increasing regulatory restrictions since 2010, partly because of the Patient Protection and Affordable Care Act (Obamacare).

1.2 Financial and accounting variables

We employ industry-level regulatory restriction data provided by "RegData 4.0" and take various business sectors that each firm operates in into consideration. Specifically, since firms often operate in multiple sectors, they are subject to different regulations specific to each sector. To create firm-level regulatory restriction data, we calculate the average restrictions weighted by sales for the various segments in which each firm operates. To accomplish this, we retrieve the primary three-digit NAICS code and segment sales data from the historical segments data of the CRSP/Compustat merged database.[10]

[10] For example, if a firm operates in three different industries, we calculate the firm's total sales by aggregating its segment-based sales. We compute each segment's contribution to the firm's total sales (sales weight) by dividing segment-based sales by its total sales. Then, we multiply the number of regulatory restriction words of each business segment by the

Table 1
Code of Federal Regulation titles and their revisions

Title	Subject	Most exposed industry
1	General Provisions	Food Manufacturing
2	Grants and Agreements	Chemical Manufacturing
3	The President	Miscallaneous Manufacturing
4	Accounts	Chemical Manufacturing
5	Administrative Personnel	Chemical Manufacturing
6	Domestic Security	Air Transportation
7	Agriculture	Food Manufacturing
8	Aliens and Nationality	Chemical Manufacturing
9	Animals and Animal Products	Animal Production
10	Energy	Professional, Scientific, and Technical Services
11	Federal Elections	Chemical Manufacturing
12	Banks and Banking	Credit Intermediation and Related Activities
13	Business Credit and Assistance	Utilities
14	Aeronautics and Space	Air Transportation
15	Commerce and Foreign Trade	Professional, Scientific, and Technical Services
16	Commercial Practices	Chemical Manufacturing
17	Commodity and Securities Exchange	Chemical Manufacturing
18	Conservation of Power and Water Resources	Utilities
19	Customs Duties	Support Activities for Transportation
20	Employees' Benefits	Food Manufacturing
21	Food and Drugs	Chemical Manufacturing
22	Foreign Relations	Chemical Manufacturing
23	Highways	Transportation Equipment Manufacturing
24	Housing and Urban Development	Real Estate
25	Indians	Oil and Gas Extraction
26	Internal Revenue	Professional, Scientific, and Technical Services
27	Alcohol, Tobacco Products and Firearms	Chemical Manufacturing
28	Judicial Administration	Chemical Manufacturing
29	Labor	Crop Production
30	Mineral Resources	Oil and Gas Extraction
31	Money and Finance: Teasury	Credigt Intermediation and Related Activities
32	National Defense	Chemical Manufacturing
33	Navigation and Navigable Waters	Water Transportation
34	Education	Educational Services
35	Panama Canal	Water Transportation
36	Parks, Forests, and Public Property	Transportation Equipment Manufacturing
37	Patents, Trademarks, and Copyrights	Chemical Manufacturing
38	Pensions, Bonuses, and Veterans' Relief	Ambulatory Health Care Services
39	Postal Service	Food Manufacturing
40	Protection of Environment	Chemical Manufacturing
41	Public Contracts and Property Management	Professional, Scientific, and Technical Services
42	Public Health	Ambulatory Health Care Services
43	Public Lands: Interior	Chemical Manufacturing
44	Emergency Management and Assistance	Food Manufacturing
45	Public Welfare	Ambulatory Health Care Services
46	Shipping	Support Activities for Transportation
47	Telecommunication	Telecommunications
48	Federal Acquisition Regulations System	Professional, Scientific, and Technical Services
49	Transportation	Transportation Equipment Manufacturing
50	Wildlife and Fisheries	Fishing, Hunting and Trapping

RegData 4.0. quantifies regulatory restriction words in the CFR and assigns a relevance score between CFR titles and NAICS level industries. This table reports the titles in the CFR, their subjects, and the three-digit NAICS industries most exposed to those titles.

sales weight. Finally, by summing all sales-weighted regulatory restriction words from each business segment that the firm operates in, we generate a firm-specific time-varying regulatory restriction measure.

To create a firm-specific quarterly-varying "regulatory operating leverage" measure, we estimate firm-specific time-series regressions of quarterly selling, general, and administrative expenses (XSAQ) on firm-specific regulatory restrictions and quarterly sales (SALEQ).[11] Quarterly selling, general, and administrative expenses (XSAQ), quarterly sales (SALEQ), quarterly cost of goods sold (COGSQ), quarterly total assets (ATQ), quarterly operating income after depreciation (OIADPQ), long-term debt (DLTT), debt in current liabilities (DLC), and annual total assets (AT) are from CRSP/Compustat merged database.

The stock sample includes all common stocks traded on the New York Stock Exchange (NYSE), American Stock Exchange (Amex), and Nasdaq exchanges from March 1991 to December 2021. The daily and monthly returns and the volume data are from the Center for Research in Security Prices (CRSP). We require at least 15 available daily observations for each stock-month observation. Stocks under $1 are excluded to ensure that our results are not driven by micro-cap/illiquid firms

Following Fama and French (1992), we estimate the market beta of individual stocks using monthly returns over the prior 60 months if available. Market capitalization (SIZE) is calculated as the stock's number of shares outstanding multiplied by its price per share. The book value of a firm is calculated as the sum of the book value of stockholders' equity (SEQ), deferred taxes (TXDB), and investment tax credit (ITCB) minus the book value of the preferred stock (PSTKRV, or PSTKL, or PSTK depending on availability). BM is the natural logarithm of the ratio of the book value of a firm to its market capitalization.

Following Jegadeesh and Titman (1993), intermediate-term momentum (MOM) is the cumulative return of a stock over the 11-month period before the portfolio formation month. Following Jegadeesh (1990), short-term reversal (REV) is the excess return generated over the portfolio formation month. We use the illiquidity (ILLIQ) measure proposed by Amihud (2002). Daily illiquidity is quantified as the ratio of daily absolute stock return scaled by its daily dollar trading volume. A stock's monthly illiquidity measure is computed as the average of its daily illiquidity within a month. Amihud illiquidity measure is scaled by 10^6.

Following Ang et al. (2006), we calculate idiosyncratic volatility (IVOL) as the monthly standard deviation of the daily residuals from a regression of daily excess stock returns on daily excess market returns, small-minus-big size factor, and high-minus-low book-to-market factor. Introduced by Bali, Cakici, and Whitelaw (2011), we use the average of the five highest maximum daily returns within a month (MAX) as a proxy for demand for lottery-type stocks.

Hou, Xue, and Zhang (2015) Q-factor model adds return on equity as a proxy for profitability and annual growth of assets to measure investment. Following their methodology, we quantify the annual growth of total assets (I/A) by the change in the book value of assets (Compustat item AT) divided by lagged AT.

[11] Throughout the paper, we winsorize all independent variables including regulatory operating leverage at the 1% and 99% levels.

To measure quarterly operating profitability (ROE), we divide income before extraordinary items (item IBQ) by one-quarter-lagged book equity.

The monthly excess market returns (MKT) and the small-minus-big size (SMB), high-minus-low book-to-market (HML), up-minus-down momentum (UMD), robust-minus-weak profitability (RMW), and conservative-minus-aggressive investment (CMA) factors of Fama and French (1993; 2015), Carhart (1997), and Fama-French-48 industry classifications are from Kenneth French's data library. The liquidity factor (LIQ) is from Lubos Pastor's data library. The Hou, Xu, and Zhang (HXZ) empirical Q-factor model factors (market, size, investment, and profitability factors) are supported by Lu Zhang upon our request. Stambaugh and Yuan (2017) mispricing factors (MGMT and PERF) are obtained from Robert Stambaugh's website. Daniel, Hirshleifer, and Sun (2020) short- and long-horizon behavioral factors (PEAD and FIN) are obtained from Kent Daniel's website. Quarterly institutional stock holdings data are from Thompson-Reuters' Institutional Holdings (13F) database. We obtain analyst coverage data from summary files of I/B/E/S.

2. Fixed Regulatory Costs: Regulatory Operating Leverage

Companies face fixed costs and variable costs, with Selling, General, and Administrative expenses (SG&A) being a quarterly reported cost structure. A significant portion of SG&A expenses is due to advertising expenses, bad debt expenses, commissions, directors' fees and remuneration, distribution expenses, engineering expenses, freight-out expenses, indirect costs, lease expenses, marketing expenses, pension, retirement, profit sharing, provision of bonus and stock options, employee insurance, and other employee benefit expenses, research and development expense, software and strike expenses. While Chen, Harford, and Kamara (2019) introduce SG&A expenses scaled by total assets (AT) as a measure of operating leverage (a proxy for fixed costs within total costs), they show that, on average, firms adjust their COGS (Cost of Goods Sold) by 0.86% and their SG&A expenses by 0.41% in response to a 1% decrease in sales revenue. This implies that SG&A expenses contain both fixed and variable cost components.

RegData 4.0 provides industry-specific regulatory restriction data based on the Code of Federal Regulations, which become available at the end of each year (beginning of the following year). Employing industry-level data, we generate firm-specific time-varying regulatory restriction measure. Before introducing measure of firm-level regulatory operating leverage, first, we need to document that regulations indeed add to firms' fixed cost burden. To do so, we estimate panel regressions of quarterly SG&A expenses on the natural logarithm of the most recently available (1-year-lagged) sales-weighted firm-specific regulatory restrictions and quarterly sales:

$$SG\&A_{i,t} = \alpha + \beta_{REG} * \log(REG)_{i,t-1} + \beta_{sale} * SALE_{i,t} + \epsilon. \tag{1}$$

Firm-specific sales accounts for the variable cost component of SG&A expenses. While $\beta_{sale} * SALE$ captures the variable part of SG&A expenses, the objective is to disentangle fixed regulatory costs.[12] Most of the regulatory compliance costs, expenses, such as bookkeeping, recording, and reporting, are recurrent. Hence, they appear in the firms' cost structure every time period.[13] As a result, this paper takes the levels of SG&A expenses and sales into account rather than the changes or logarithms.[14] β_{REG} captures the sensitivity of SG&A expenses to the regulatory restrictions while accounting for sales. The term $\beta_{REG} * log(REG)$ represents the fixed regulatory cost component of SG&A expenses. The natural logarithm of regulatory restrictions is used to account for regulatory changes. For instance, if two firms with different levels of regulatory restriction exposure experience a new regulatory reform, the new regulatory restriction will affect the firms' cost structures at distinct degrees.

Table 2 presents the regression results in which the dependent variable is the firm-specific quarterly-varying selling, general, and administrative expenses. The first column reports the bivariate regression results. As expected, sales positively and significantly explains the variation in SG&A expenses. The second row of the table reports the economic and statistical significance of the natural logarithm of regulatory restriction count. The results show that the regulations significantly increase SG&A expenses, with a slope coefficient for restrictions yielding a *t*-statistic of 6.74 according to the first column.

The remaining regression specifications account for NAICS-2-level industry and year fixed effects. The last column presents the full regression specification results. When we simultaneously control for the industry and year fixed effects, the natural logarithm of regulatory restrictions continues to significantly explain the variation in SG&A expenses. In other words, even after accounting for the variable component of SG&A expenses, and industry and year fixed effects, there is a positive and significant relationship between regulatory restrictions and SG&A expenses.

---

12 As a robustness test, we subtract R&D and advertising expenses from SG&A expenses and estimate the relationship between regulatory restrictions and SG&A expenses. Panel regression results document that while the slope coefficient for the quarterly sales decreases, the coefficient for the natural logarithm of restrictions increases. In addition, once regulatory operating leverage is defined as the portion of SG&A expenses less R&D and advertising expenses that are attributable to regulatory restrictions, regulatory operating leverage significantly predicts future stock returns.

13 The regressions in changes mainly capture the short-run response of costs to concurrent changes. On the other hand, a regression in levels would reflect the long-run expansion path of costs (Noreen and Soderstrom 1994). Most of the regulatory compliance costs are recurrent expenses, and they are reflected in the cost structure in the longer run.

14 Various regulations are reflected in firms' cost structure every time period. Accordingly, this paper investigates the importance of the level of regulatory operating leverage in the cross-section of stock returns. As a robustness test, we examine the cross-sectional relationship between innovations (changes) in regulatory operating leverage and 1-month-ahead stock returns. Both portfolio-level analyses and firm-level cross-sectional regressions show an insignificant relationship between firm-specific regulatory operating leverage innovations and stock returns. More specifically, a zero-cost high-low regulatory operating leverage innovations strategy generates 0.04% equal-weighted monthly raw return and 0.01% five-factor alpha.

Table 2
Fixed cost component of regulations

Dependent variable: SG&A	(1)	(2)	(3)	(4)
log(REG)	2.373	5.981	1.224	2.610
	(6.74)	(8.00)	(3.59)	(3.59)
SALE	0.131	0.130	0.131	0.130
	(56.55)	(56.10)	(56.39)	(56.01)
Industry fixed effect	NO	YES	NO	YES
Year fixed effect	YES	NO	YES	YES

Selling, general, and administrative expenses (SG&A) consist of both fixed and variable costs. To assess the impact of federal-level regulations on the fixed cost burden, we conduct panel regressions using quarterly SG&A expenses as the dependent variable. Our independent variables include the natural logarithm of sales-weighted firm-level regulatory restriction count and quarterly sales at the firm-level. Columns 2 and 4 include two-digit-level NAICS industry dummies as control variables. Columns 3 and 4 add year fixed effects. Standard errors are clustered at the firm level, and relevant *t*-statistics are reported in parentheses. The analysis covers the period from 1991 to 2021.

2.1 Stationarity

As a firm grows, it is expected that its costs and sales will increase. Additionally, Figure 1 documents a significant rise in regulations over the years. This raises concerns about stationarity issues. When the dependent variable and independent variables in a regression model exhibit trends or are nonstationary, it can lead to a spurious relationship and a misleadingly high correlation between them. To investigate this, we first test whether the dependent variable (SG&A expenses) and the independent variables (log(REG) and SALE) are stationary. Initially, we employ a Fisher unit root test on each variable separately and find that all three variables are nonstationary in their levels. Next, we test whether their first differences are stationary. As SG&A expenses and SALE vary quarterly and log(REG) varies yearly, we allow four quarterly lags for SG&A expenses and SALE and one lag for log(REG) to maintain consistency. The unit root tests confirm that the first differences of all variables are stationary. This suggests that the dependent and independent variables are integrated of order 1, denoted as I(1). Finally, we examine whether the variables are cointegrated or if the regression model is spurious. In our context, as all variables (dependent and independent) are I(1), if the error term is stationary, we can conclude that the dependent and independent variables are cointegrated.

Panel cointegration tests can be categorized into two groups: tests that examine the hypothesis of no cointegration and tests that assess the null hypothesis of integration. Kao (1999) investigates the residual-based tests for cointegration regression in panel data and examines the asymptotic null distribution of residual-based cointegration tests. More specifically, he investigates Dickey-Fuller (DF) tests and an augmented Dickey-Fuller (ADF) test to test the null of no cointegration. Adding to classical DF test, Kao (1999) discusses four additional modified DF tests: modified Dickey–Fuller, augmented Dickey–Fuller, unadjusted modified Dickey–Fuller, and unadjusted Dickey–Fuller statistics. The null hypothesis of these tests is H_0: $\rho = 1$, indicating no cointegration, while the alternative hypothesis is H_a: $\rho < 1$.

Table A2 of the Internet Appendix displays the test statistics and corresponding *p*-values for each test (Stata code: xtcointtest kao SGA log(REG) SALE). The results demonstrate that all four test statistics reject the null hypothesis of no cointegration. This provides evidence of cointegration among the variables in our model, indicating the presence of a long-term relationship between them.

2.2 Firm-level regulatory operating leverage

We have so far introduced a firm-level regulatory restriction measure and documented the fixed cost burden brought by regulations. Building on these, we propose a firm-level measure of regulatory operating leverage that quantifies the importance of fixed regulatory cost burden in a firm's cost structure. To do so, we employ firm-specific time-series regressions of quarterly SG&A expenses on regulatory restrictions and quarterly sales:

$$SG\&A_{i,t} = \alpha_i + \beta_{i,REG} * log(REG)_{i,t} + \beta_{i,sale} * \ SALE_{i,t} + + \gamma_i * t + \epsilon_{i,t}, \quad (2)$$

and estimate regulatory cost sensitivity beta and variable cost beta.[15] Based on the estimated betas, we construct a firm-specific quarterly-varying regulatory operating leverage (ROL) measure:

$$ROL_{i,t} = \frac{beta_{i,res} * \log{(res)}_{i,t}}{SG\&A_{i,t}}, \quad (3)$$

where ROL is defined as the ratio of fixed costs that are attributable to regulatory restrictions in the regression over the SG&A expenses. Put differently, ROL reflects the importance of regulatory fixed costs in a firm's cost structure.[16,17]

Figure 2 plots the regulatory operating leverage of a median ROL firm from 1991 to 2021. To do so, we compute the cross-sectional median of ROL across all the firms in the sample. The time-series average of the median ROL is 0.48. Although ROL exhibits significant volatility, no evident trend is observed between 1991 and 2021. The figure reveals an increasing trend in ROL during periods of economic recession. For instance, the regulatory operating measure slightly increased around 2001, while a substantial surge in ROL is observed during the 2008–2009 period. This suggests that during economic downturns, firms are

15 As the firms' cost structure, sales, and their regulatory burden could have an increasing time trend, the regression model adds a firm-level time trend. This approach allows the regression model to capture the systematic changes over time. To illustrate, time trend allows for the possibility that costs may change systematically over time due to factors not captured by regulations or sales alone. This helps to control for any underlying time-varying effects that may affect costs across firms.

16 Firms (industries) with missing regulatory restriction information are dropped from the analyses.

17 Firm-level segment data are available since 1990. In addition, the yearly-changing industry-specific regulatory restriction data are available until 2020. As regulatory restriction information becomes available beginning of the following year, our analyses cover the period between 1991 and 2021, which limits the regulatory restriction data points to 30. Hence, our main results depend on within sample estimation method where single regulatory restrictions and sales betas are estimated for each firm in the sample. Section 3.9 estimates regulatory operating leverage (ROL) through a 60-quarter rolling window approach to show that the cross-sectional predictive power of regulatory operating leverage on future stock returns is robust to alternative estimation methods.

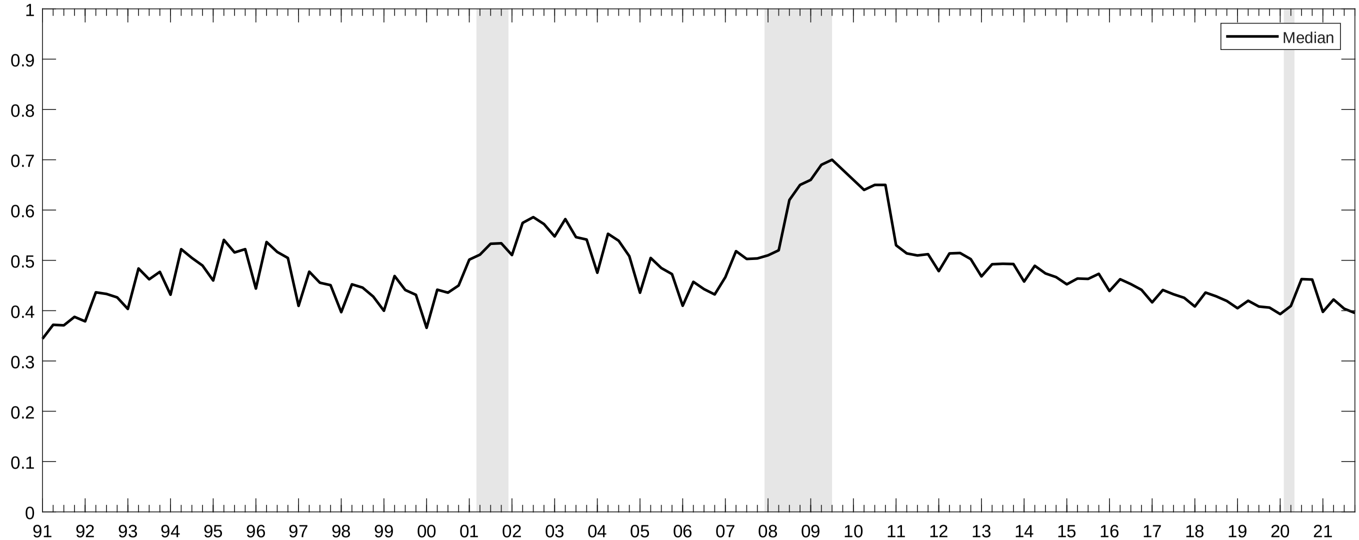

Figure 2
Cross-sectional median of regulatory operating leverage
This figure plots cross-sectional median of regulatory operating leverage (ROL) from 1991 to 2021. Firm-level ROL estimated through bivariate regressions of SG&A expenses on the natural logarithm of regulatory restrictions and sales (Equations (2) and (3), without the time trend). The gray-shaded areas indicate recessionary periods in the United States determined by the National Bureau of Economic Research (NBER).

unable to reduce their regulatory fixed costs, resulting in a higher proportion of their SG&A expenses being attributed to regulations. Similarly, ROL follows an upward trajectory during the COVID-19 pandemic crisis and the subsequent period. One plausible explanation is that although firms were able to cut some costs during this period, they still had to comply with the regulations to which they were exposed. Consequently, regulations constituted a larger share of the overall cost burden for firms throughout 2020.

2.3 Industry-level regulatory exposure

Table 3 presents additional findings regarding the differences in regulatory burden across industries and the average fixed regulatory costs faced by each industry. The table is organized by sorting all industries at the NAICS-3 level in descending order of their regulatory restriction count burdens, with each industry's NAICS-3-level code shown in parentheses.

The second column provides the average industry-specific regulatory restriction count, which represents the time-series average of the exposure to regulatory restriction words. According to this measure, the chemical industry (NAICS-3 code: 325) is identified as the industry most exposed to regulatory restriction words, with an average exposure of 64,575 words. Following this, the petroleum and coal products manufacturing industry (NAICS-3 code: 324), educational services (NAICS-3 code: 611), waste management and remediation services (NAICS-3 code: 562), air transportation (NAICS-3 code: 481), and credit intermediation and related activities (NAICS-3 code: 522) are among the highly regulated industries. Conversely, the industries with the lowest exposure to regulatory restriction words are data processing hosting and related services (NAICS-3 code: 518), real estate (NAICS-3 code: 531), and amusement gambling and recreation industries (NAICS-3 code: 713).

The third column presents the time-series average of the cross-sectional median of regulatory operating leverage (ROL) for each NAICS-3-level industry. Examining the median ROL values, we find that the industries with the highest median fixed regulatory cost burdens include electrical equipment, appliance, and component manufacturing; primary metal manufacturing; crop production; computer and electronic product manufacturing; merchant wholesalers nondurable goods; chemical manufacturing; and machinery manufacturing. In contrast, waste management and remediation services, ambulatory health care services, and animal production and aquaculture exhibit the lowest fixed regulatory cost burdens.

Furthermore, upon comparing the second and third columns, we observe that having an extreme exposure (highest or lowest) to regulatory restriction words does not necessarily imply carrying an extreme regulatory fixed cost burden for the relevant industries. While the amusement, gambling, and recreation industry has one of the lowest exposures to regulatory restriction words, its median ROL of 0.519 exceeds the cross-industry average. Similarly, although animal production and aquaculture industry faces high exposure to regulatory restriction words, its

Table 3
Industry-level regulatory exposure and SG&A expenses

INDUSTRY	REG	ROL	med(SG&A)	sum(SG&A)
Chemical Manuf. (325)	64,575	0.624	63.2065	487,295
Petroleum and Coal Products Manuf. (324)	57,784	0.535	778.85	86,324.5
Educational Services (611)	46,543	0.593	164.508	15,090.2
Waste Management and Remediation Services (562)	44,185	0.453	49.0115	5,398.17
Air Transportation (481)	42,829	0.422	296.076	22,076.9
Credit Intermediation and Related Activities (522)	37,598	0.392	75.979	368,121
Animal Production and Aquaculture (112)	32,114	0.295	198.631	198.631
Paper Manuf. (322)	30,976	0.488	528	22,596.3
Securities Commodity Contracts and Financial Inv. (523)	26,429	0.447	59.644	18,886.3
Transportation Equip. Manuf. (336)	25,914	0.432	200.226	156,261
Support Activities for Transportation (488)	24,337	0.457	67.285	1,011.39
Utilities (221)	24,065	0.357	48.922	811.716
Funds Trusts and Other Financial Vehicles (525)	17,152	0.297	29.9165	119.74
Social Assistance (624)	16,758	0.357	254.103	254.103
Beverage and Tobacco Product Manuf. (312)	16,138	0.393	740.618	105,565
Crop Production (111)	15,450	0.643	30.363	4,975.87
Food and Beverage Stores (445)	12,854	0.545	868.912	50,530.2
Mining (except Oil and Gas) (212)	12,441	0.483	35.2	11,071.4
Motion Picture and Sound Recording Industries (512)	11,996	0.390	80.6	5,149.93
Ambulatory Health Care Services (621)	11,937	0.225	117.411	68,398.1
Insurance Carriers and Related Activities (524)	11,511	0.337	173.9	111,413
Wood Product Manuf. (321)	11,242	0.462	246.797	7,116.73
Nonmetallic Mineral Product Manuf. (327)	11,221	0.543	99.398	12,162.9
Water Transportation (483)	9,958	0.422	29.13	8,082.4
Food Manuf. (311)	9,702	0.586	219.147	47,255.4
Telecommunications (517)	8,417	0.338	235.331	148,396
Primary Metal Manuf. (331)	7,187	0.668	185.352	17,005.3
Pipeline Transportation (486)	7,170	0.493	61	2,458.1
Oil and Gas Extraction (211)	6,456	0.380	53.617	13,864.8
Electrical Equip. Appliance and Component Manuf. (335)	3,927	0.675	80.879	39,607.6
Merchant Wholesalers Nondurable Goods (424)	3,648	0.635	238.376	48,943.8
Construction of Buildings (236)	3,418	0.429	390.619	15,058.7
Support Activities for Mining (213)	3,096	0.547	73.6005	6,850.19
Nonstore Retailers (454)	3,064	0.404	208.158	181,023
Merchant Wholesalers Durable Goods (423)	2,926	0.485	320.918	48,819.9
Wholesale Electronic Markets and Agents and Brokers (425)	2,079	0.517	185.611	185.611
Support Activities for Agriculture and Forestry (115)	1,642	0.507	6.916	6.916
Machinery Manuf. (333)	1,623	0.609	170.04	95,887.3
Computer and Electronic Product Manuf. (334)	1,161	0.640	131.034	371,863
Plastics and Rubber Products Manuf. (326)	887	0.545	341.54	8,666.38
Other Information Services (519)	725	0.320	265.546	244,612
Amusement Gambling and Recreation Industries (713)	465	0.519	166.469	10,010.4
Real Estate (531)	406	0.442	42.2235	28,174.1
Data Processing Hosting and Related Services (518)	317	0.570	201.626	248,030

RegData 4.0 quantifies the number of regulatory restriction words in the CFR (Code of Federal Regulations) and assigns a relevance score to three-digit NAICS industries. This table presents the industries for which both regulatory restriction and SG&A expenses information are available. The second column represents the time-series average of regulatory restriction words to which each industry is exposed. The third column shows the cross-sectional median of ROL (excluding firms with ROL smaller than zero and greater than one). In the fourth and fifth columns, we provide the median and sum of SG&A expenses for each industry in 2021.

median regulatory operating leverage is significantly lower than the sample average.

While real estate and amusement, gambling, and recreation industries are among the lowest with the lowest regulatory restriction exposures, their median regulatory operating leverage exposures are not. Additional potential reasons for them not carrying high regulatory exposures are (a) The real estate industry, while subject to regulations, primarily deals with property transactions, rentals, and management. The regulatory requirements are often related to property zoning, land use, and building codes. These regulations tend to remain relatively stable over time and do not necessarily scale linearly with the size of the real estate holdings. Therefore, as real estate firms expand, the incremental regulatory costs may not increase significantly, leading to a lower regulatory operating leverage measure, (b) while the gambling and casino sectors do face stringent regulations, the regulatory costs are typically associated with obtaining and maintaining licenses, ensuring fair gaming practices, and addressing issues related to addiction and responsible gaming. Once a casino or amusement facility is established, the regulatory costs may not grow at the same rate as the revenue, especially if the casino already complies with all necessary regulations. This can lead to a relatively lower regulatory operating leverage measure, (c) many firms within these sectors are often large and operate at scale. Larger companies may have the resources and expertise to navigate complex regulatory frameworks more efficiently. They can spread the cost of compliance over a larger revenue base, making the regulatory burden less significant in proportion to their size, (d) The regulatory environment can vary significantly by location and jurisdiction. Some states or regions may have more permissive regulatory frameworks, allowing businesses in these industries to operate with relatively lower regulatory costs, (e) certain industries, including real estate and gambling, may have a strong lobbying presence and political influence, which can shape regulatory conditions in their favor. This influence can lead to regulations that are perceived as more business-friendly.

Columns 4 and 5 present information on the median selling, general, and administrative (SG&A) expenses and the total SG&A expenses (in millions) for each industry in 2021. As this study measures the regulatory operating leverage (ROL) as the proportion of fixed costs attributed to federal-level regulations relative to a firm's SG&A expenses, multiplying the ROL (third column) by the median SG&A (fourth column) can be interpreted as the fixed regulatory burden of a typical firm. Similarly, multiplying the ROL by the sum of SG&A expenses (fifth column) can be viewed as the industry-level fixed regulatory burden as of 2021. Based on this analysis, firms in industries, such as petroleum and coal products manufacturing, paper manufacturing, air transportation, beverage and tobacco product manufacturing, food and beverage stores, educational services, animal production and aquaculture, and transportation equipment manufacturing, are likely to have a high regulatory operating leverage, indicating a significant portion of fixed regulatory costs within their SG&A expenses. Moreover, chemical manufacturing, credit intermediation and related activities, petroleum and coal products manufacturing, transportation equipment manufacturing, beverage and tobacco product manufacturing, insurance carriers and related activities, telecommunications, and air transportation are the industries with the highest fixed regulatory cost burden.

2.4 Major regulations and regulatory operating leverage

If Regulatory Operating Leverage (ROL) truly reflects a firm's regulatory cost burden, it would be expected that the ROL responds significantly to expensive regulatory reforms. To investigate this, we analyze the time-series changes in ROL for for firms following major regulations that impose substantial regulatory costs specific to their industry.

The Office of Management and Budget (OMB) provides annual reports to Congress on the benefits and costs of federal regulations. These reports include estimates of the benefits and costs of major final rules. We select major regulatory reforms from these reports, categorized by relevant departments, such as Agriculture, Energy, Health and Human Services, Homeland Security, Housing and Urban Development, and Justice, Labor, and Transportation. Detailed cost and benefit analyses of these regulations, including dollar amounts and sources, have been available since 1999. While we consider major regulations from various departments based on the reports, our focus is solely on the most expensive regulations.[18] Additionally, we include two regulatory reforms in our analysis: the Patient Protection and Affordable Care Act (Obamacare) and the Dodd-Frank Wall Street Reform and Consumer Protection Act. Panel A of Table 4 provides information on these major regulatory reforms and their introduction dates.

To demonstrate the changes in the ROL measure around the introduction of major regulations, panel B of Table 4 presents regression results of yearly changes in ROL using year dummies. We group firms belonging to industries most affected by the regulations and calculate yearly ROL changes around the regulatory reforms. Then, we regress these yearly ROL changes on year dummies, considering the 3 years before the announcement of the regulatory change and the 2 years after the announcement. We exclude the dummy variable for 3 years before the announcement to avoid multicollinearity issues. For instance, as the Dodd-Frank Wall Street Reform and Consumer Protection Act was announced in July 2010, we use the yearly ROL changes from 2007 to 2012 to capture the changes. Therefore, when calculating ROL changes around this regulation, we compare the ROL in the first quarter of 2011 with that of the first quarter of 2010, the second quarter of 2011 with the second quarter of 2010, and so on. The regressions include fixed effects for the year and four-digit SIC industry.

The regression results indicate a significant increase in ROL from one year before the regulatory reform to the reform year, as well as from the reform year to the following year. The increase in regulatory fixed cost burden from one year before the reform to the reform year is expected. Additionally, legislators allow for implementation delays in enforcing regulations in some cases. As a result,

[18] To illustrate, "Review of the National Ambient Air Quality Standards for Ozone," the costliest regulatory reform introduced by Environmental Protection Agency (EPA) between October 2001 and September 2011, is estimated to introduce an annual cost around $7.73 billion. Similarly, regulatory reform named as "National Emission Standards for Hazardous Air Pollutants From Coal-Fired Electric Utility Steam Generating Units," introduced on December 2011, which is estimated to be the costliest of the Environmental Protection Agency rules, has an annualized cost of $8.1 billion. In addition, the costliest rule introduced by Department of Transportation between October 2001 and September 2011 is "Tire Pressure Monitoring System," which has an estimated annual cost around $2.28 billion.

Table 4
Major regulatory reforms and regulatory operating leverage

A. Major regulations and their completion dates

Fama-French industry	Name of the regulation	Date completed
Agriculture (1)	Bovine Spongiform Encepthalopathy: Minimal Risk Regions and Importation of commodities	December 2004
Health (11)	Obama Care	March 2010
Textile (16), Machinery (21)	Review of the National Ambient Air Quality Standards for Ozone	March 2008
Coal (29), Utilities (31)	National Emission Standards for Hazardous Air Pollutants From Coal-Fired Electric Utility Steam Generating Units	December 2011
Transportation (40)	Tire Pressure Monitoring System	March 2005
Banking (44), Insurance (46), Real Estate (46), Trading (47)	Dodd-Frank Wall Street Reform and Consumer Protection Act	July 2010

B. Event study

	T-2	T-1	T	T + 1	T + 2
ROL	0.16 (0.94)	0.32 (1.49)	0.73 (3.52)	0.52 (2.39)	0.38 (1.35)
ROL—non. ROL	0.32 (0.98)	0.51 (1.33)	1.28 (3.42)	1.12 (2.33)	0.71 (1.29)

The Office of Management and Budget (OMB) presents annual reports to Congress regarding the benefits and costs associated with federal-level regulations. These reports contain estimates of the yearly benefits and costs of significant rules, along with the sources of those estimates. Panel A reports major regulatory reforms with significant cost implications and the Fama-French-48 industries most likely to be affected by those regulations. To evaluate the impact of these major regulatory announcements, we utilize event study regressions of the changes in the changes in ROL and the differences between changes in ROL and non-ROL on year dummies. Panel B reports the regression results (SIC four-digit-level industry fixed effects and year fixed effects are included).

regulatory costs may be reflected in cost structures with a delay. The event study regression results suggest that the change in the ROL measure is significantly positive only around the time of the major regulation, but not elsewhere.[19]

3. Empirical Results

So far, the fixed cost component of regulations and a measure of regulatory operating leverage, which reflects the importance of regulatory fixed costs in a firm's cost structure, are introduced. According to the well-established operating

[19] We additionally compute non-ROL as the component of SG&A that cannot be explained by regulatory restrictions and sales scaled by SG&A (α/SG&A). Regressions of the changes in the difference term between ROL and non-ROL, which can be interpreted as a difference-in-differences study, document that costly regulatory changes only magnifies the ROL measure. This suggests that regulatory reforms only amplify the regulatory fixed costs.

leverage hypothesis, firms with a high fixed cost ratio (operating leverage) are associated with low operating flexibility, and they are more exposed to business cycle risks. Therefore, a firm with higher operating leverage is more dependent on business cycles, making it more vulnerable to systematic risk. This suggests that fixed regulatory costs, which contribute to operating leverage, should generate a risk premium. To explore whether such a risk premium exists, we investigate the cross-sectional relation between regulatory operating leverage (ROL) and subsequent stock returns using univariate portfolio-level analyses, bivariate portfolio-level analyses, and firm-level cross-sectional regressions.

3.1 Univariate portfolio-level analyses

Table 5 presents univariate (panel A) and industry-controlled (panel B) equal- and value-weighted average excess monthly returns and risk-adjusted returns generated using three different factor models: (a) α_{FF5} is the intercept from the regression of the excess portfolio returns on a constant, and Fama and French (1992, 1993, 2015) market, size, book-to-market, investment, and profitability factors; (b) α_{FFCPS} the alpha relative to Fama and French (1992, 1993, 2015) market, size, book-to-market, investment, and profitability factors, Carhart's (1997) momentum factor, and Pastor and Stambaugh (2003) liquidity factor; and (c) α_Q is the alpha relative to Hou, Xue, and Zhang (2015) market, size, investment, and profitability factors.[20] Quintile portfolios are formed by sorting stocks based on their regulatory operating leverage (ROL) over the past quarter. Quintile portfolio 1 (5) consists of stocks with the lowest (highest) ROL. The last row presents the differences in excess returns and alphas between the extreme quintile portfolios. The results span the period from April 1991 to December 2021.

Panel A of Table 5 presents the univariate portfolio sort results. The highest ROL quintile generates the highest excess and risk-adjusted returns within both equal-weighted and value-weighted portfolios. Moving from the lowest to the highest ROL quintile, the equal (value)-weighted average monthly excess return increases from 75 (68) to 130 (117) basis points per month. A zero-cost high-low equal (value)-weighted strategy generates 54 (49) basis points return per month with a *t*-statistic of 6.30 (3.28). When we multiply by 12, the high-low equal (value)-weighted strategy generates a 6.48% (5.88%) annualized return.

The differences in returns between equal-weighted and value-weighted strategies can be considered as an indicator of economies of scale. Regulations significantly contribute to the cost rigidity of firms, particularly smaller ones. Larger firms have the advantage of spreading their fixed costs over a larger output, resulting in lower costs per unit of output. This implies that economies of scale reduce exposure to fixed (regulatory) costs. Since larger firms have larger weights in value-weighted strategies compared to equal-weighted strategies, moving from

20 Subsequent tables mainly report Fama-French-Carhart (1992, 1993, 2015) five-factor alphas (α_{FF5}). It is worth noting that the zero-cost high-low regulatory operating leverage strategy generates positive and significant α_{FFCPS} and α_Q within all portfolio-level analyses, thereby generating significant five-factor (FF5) alphas.

Table 5
Univariate portfolio-level analyses

A. UNIVARIATE

	EQUAL-WEIGHTED				VALUE-WEIGHTED			
Quintile	RET-RF	α_{FF}	α_{FFCPS}	α_Q	RET-RF	α_{FF}	α_{FFCPS}	α_Q
Low ROL	0.75	− 0.14	− 0.06	0.02	0.68	− 0.15	− 0.15	− 0.10
	(2.41)	(− 1.26)	(− 0.61)	(0.16)	(3.32)	(− 1.80)	(− 1.93)	(− 1.20)
2	0.65	− 0.18	− 0.06	− 0.03	0.62	− 0.14	− 0.13	− 0.09
	(1.94)	(− 1.81)	(− 0.68)	(− 0.27)	(2.93)	(− 2.49)	(− 2.34)	(− 1.42)
3	0.92	0.05	0.15	0.16	0.86	0.08	0.11	0.09
	(2.93)	(0.62)	(1.76)	(1.52)	(3.08)	(0.94)	(1.31)	(0.97)
4	1.16	0.30	0.38	0.37	0.96	0.08	0.10	0.02
	(3.68)	(3.85)	(4.64)	(3.61)	(3.30)	(0.81)	(0.94)	(0.21)
High ROL	1.30	0.41	0.44	0.49	1.17	0.25	0.20	0.25
	(4.24)	(3.53)	(4.02)	(3.77)	(4.64)	(2.34)	(1.95)	(1.98)
High-Low	0.54	0.55	0.50	0.47	0.49	0.40	0.35	0.35
difference	(6.30)	(6.42)	(5.80)	(5.34)	(3.28)	(2.86)	(2.49)	(2.35)

B. INDUSTRY-CONTROLLED

	EQUAL-WEIGHTED				VALUE-WEIGHTED			
Quintile	RET-RF	α_{FF}	α_{FFCPS}	α_Q	RET-RF	α_{FF}	α_{FFCPS}	α_Q
Low ROL	0.73	− 0.16	− 0.07	0.01	0.73	− 0.13	− 0.15	− 0.08
	(2.21)	(− 1.53)	(− 0.74)	(0.08)	(3.30)	(− 1.78)	(− 2.01)	(− 1.14)
2	0.73	− 0.11	− 0.01	− 0.01	0.55	− 0.18	− 0.15	− 0.14
	(2.37)	(− 1.33)	(− 0.18)	(− 0.05)	(2.58)	(− 2.62)	(− 2.31)	(− 1.96)
3	0.85	− 0.01	0.06	0.08	0.78	− 0.03	− 0.01	− 0.03
	(2.93)	(− 0.15)	(0.88)	(0.77)	(3.27)	(− 0.49)	(− 0.19)	(− 0.52)
4	1.08	0.19	0.27	0.27	0.88	0.04	0.06	0.04
	(3.53)	(2.29)	(3.43)	(2.58)	(3.25)	(0.38)	(0.61)	(0.42)
High ROL	1.41	0.55	0.61	0.66	1.32	0.51	0.45	0.62
	(4.22)	(5.92)	(6.74)	(6.66)	(4.65)	(4.94)	(4.31)	(4.53)
High-Low	0.68	0.71	0.69	0.65	0.59	0.64	0.60	0.60
difference	(8.83)	(9.51)	(9.18)	(8.00)	(3.90)	(4.68)	(4.45)	(4.29)

Quintile portfolios are constructed by sorting stocks based on their ROL during the previous quarter. Quintile portfolio 1 (5) consists of stocks with the lowest (highest) ROL. The table presents equal-weighted and value-weighted excess returns (RET-RF) and alphas. α_{FF5} is the alpha relative to Fama-French-5 factors, α_{FFCPS} is the risk-adjusted return relative to Fama-French-5 factors, Carhart's liquidity factor, and Pastor and Stambaugh liquidity factor, and α_Q is the alpha relative to Hou-Xue-Zhang Q-factor model. Panel A (B) reports univariate (two-digit NAICS industry controlled) portfolio returns. The last rows present the return differences between the extreme portfolios. Newey-West (1987) adjusted *t*-statistics are reported in parentheses.

equal-weighted ROL to value-weighted ROL sorts, the return spread between the extreme ROL quintile portfolios decreases.

In addition to the raw returns, Table 5 presents the magnitude and statistical significance of various risk-adjusted returns. Equal (value)-weighted α_{FF5} increases from − 14 (− 15) to 41 (25) basis per month, moving from the lowest to the highest ROL quintile portfolio. In addition, a zero-cost high-low equal (value)-weighted ROL strategy produces 50 (35) basis points α_{FFCPS} per month with a *t*-statistic of 5.80 (2.49). Similarly, a zero-cost equal (value)-weighted high-low ROL strategy produces 47 (35) basis points α_Q per month with a *t*-statistic of 5.34 (2.35). The results show that the positive relationship between ROL and future stock returns cannot be captured by common risk factor models.[21]

Next, we investigate the source of the significant alpha spreads between the extreme ROL quintiles. For this, we focus on the economic and statistical significance of the risk-adjusted returns generated by quintile 1 and quintile 5. As reported, while quintile 1 produces insignificant alphas, quintile 5 generates positive and significant risk-adjusted returns. The highest ROL quintile portfolio earns 41 (25) basis points equal (value)-weighted α_{FF5} per month with a t-statistic of 3.53 (2.34). Similarly, the highest ROL quintile portfolio produces positive and significant α_{FFCPS} and α_{Q}. Hence, the significantly positive alpha difference between extreme ROL stocks is due to the outperformance by high ROL stocks. In other words, investors demand a compensation in the form of higher expected returns to hold stocks with high ROL.[22]

Throughout the study, we exclude stocks with a price lower than \$1 to eliminate the effect of micro-cap/illiquid firms. Fama and French (2008) document that the returns on equal-weighted hedge portfolios can be dominated by tiny stocks, which are defined as stocks with market capitalization below the 20th NYSE percentile. After eliminating stocks with market capitalization below the 20th NYSE percentile, a zero-cost high-low ROL equal (value)-weighted strategy generates 42 (50) basis points excess return per month with a Newey-West-adjusted t-statistic of 4.55 (3.33) and 46 (42) basis points monthly α_{FF5} with a t-statistic of 5.58 (3.22).[23,24]

Novy-Marx (2011) introduces (COGS+SG&A)/AT as a proxy for operating leverage and shows that cross-industry book-to-market differences are driven by asset heaviness (operating leverage) differences between industries. Hence, operating leverage is critical to models that generate the value premium. To investigate whether interindustry ROL differences drive significantly positive alpha spread between the extreme ROL portfolios, panel B of Table 5 constructs NAICS-2-level industry controlled ROL-sorted quintile portfolios. Industry controlled high-low equal-weighted ROL strategy generates 68 (71) basis points subsequent

---

21 As a robustness test, we exclude utilities (NAICS-2 code 52) and financial firms (NAICS-2 code 52). The equal-weighted excess return (α_{FF5}) spread between the extreme ROL quintile portfolios is 0.75% (0.81%) per month with a Newey-West (1987) adjusted t-statistic of 7.02 (8.60). Similarly, a zero-cost high-low value-weighted ROL strategy produces 0.64% (0.71%) monthly excess return (α_{FFCPS}) with a t-statistic of 3.16 (4.10).

22 Stambaugh and Yuan (2017) introduce a four-factor model that introduces two mispricing factors in addition to market and size factors. Daniel, Hirshleifer, and Sun (2020) propose a three-factor model that augments the market factor with two factors that capture long- and short-horizon mispricing. To rule out possible mispricing-based explanations, we test the excess returns generated by ROL-sorted portfolios against Stambaugh and Yuan (SY, 2017) and Daniel, Hirshleifer, and Sun (DHS, 2020) models. The SY alpha spread between the extreme equal (value)-weighted ROL quintile portfolios is 0.52% (0.44%) per month with a Newey-West (1987) adjusted t-statistic of 5.63 (2.78). Similarly, the DHS risk-adjusted return spread between the highest and the lowest equal (value)-weighted ROL quintile portfolios is 0.51% (0.37%) per month with a t-statistic of 6.01 (2.43).

23 After eliminating stocks with market capitalization below the 20th NYSE percentile, a zero-cost equal (value)-weighted ROL strategy produces 40 (39) basis points α_{FFCPS} and 37 (35) basis points α_{Q} per month.

24 As an additional robustness test in which we attempt to eliminate the dominance of nonlarge stocks, we exclude stocks with market capitalization below the 50th NYSE percentile. Accordingly, a zero-cost value-weighted ROL strategy produces significantly positive returns: 46 basis points raw return and 39 basis points α_{FF5} per month.

excess return (α_{FF5}) with a *t*-statistic of 8.83 (9.51), while the industry controlled value-weighted raw return (α_{FF5}) spread between extreme ROL portfolios is 59 (64) basis points per month with a *t*-statistic of 3.90 (4.68). Additionally, the alternative equal- and value-weighted risk-adjusted return spreads are positive and significant. This provides evidence to the idea that the significant return differences between extreme ROL portfolios is not driven by cross-industry differences in ROL and the positive cross-sectional predictive power of ROL over future stock returns is robust to industry controls.

3.2 Size-dependent portfolio-level analyses

While some small businesses can be exempted from some regulations, regulations in general introduce fixed costs, such as capital expenditures, information costs, reporting, and compliance costs (Bradford 2004). Consistently, the equal-weighted alpha spread between the extreme ROL quintile portfolios is greater than the value-weighted spread. This suggests that there might be a stronger relationship between ROL and expected stock returns within smaller subsets of stocks, as regulations tend to increase (decrease) cost rigidity (flexibility) among smaller firms.

To investigate whether there is a size-dependent cross-sectional relation between ROL and stock returns, we group stocks into 20-60-20 percentile market capitalization (size) tiers. Then, within each size tier, quintile portfolios are formed by sorting stocks based on their ROL measure from April 1991 to December 2021. Table 6 reports excess returns and five-factor alphas generated by ROL-sorted quintiles. Panel A (B) constructs equal-weighted (value-weighted) portfolios.

There is a positive and significant relation between ROL and subsequent stock returns within all size subsamples. More specifically, within the small market capitalization subsample, equal (value)-weighted high-low ROL strategy generates 73 (83) basis points raw return and 71 (79) basis points risk-adjusted return per month. A zero-cost equal (value)-weighted high-low ROL strategy produces 62 (58) basis points raw return and 64 (63) points risk-adjusted return per month within the mid-cap stock subsample. Finally, while the return differences between the extreme ROL portfolios decrease further moving from the small- and mid-cap stock subsamples to the large-cap subsample, the same strategy continues to generate positive and significant return spreads. More specifically, the five-factor equal (value)-weighted alpha spread between the extreme ROL portfolios is 31 (38) basis points per month with a *t*-statistic of 3.42 (2.86).

The results are consistent with the economies of scale implications of fixed cost component of regulations. Regulations impose substantial fixed costs, and larger firms can leverage their larger output to benefit from economies of scale, unlike smaller firms. Put differently, smaller firms lack economies of scale. The presence of significant fixed regulatory costs significantly restricts firms' cost structures and adds to their riskiness. Consequently, risk-averse investors require a premium in the form of higher expected returns when investing in stocks with high ROL, particularly within smaller firm subgroups.

Table 6
Size-dependent portfolio sorts

A. EQUAL-WEIGHTED

	SMALL CAP		MID CAP		LARGE CAP	
Quintile	RET-RF	α_{FF}	RET-RF	α_{FF}	RET-RF	α_{FF}
Low ROL	0.67	−0.01	0.70	−0.27	0.82	−0.09
	(1.05)	(−0.07)	(2.19)	(−2.65)	(3.25)	(−1.02)
2	1.06	0.50	0.55	−0.36	0.65	−0.19
	(2.55)	(1.99)	(1.52)	(−3.98)	(2.37)	(−2.13)
3	1.18	0.56	0.86	−0.06	0.79	−0.12
	(3.24)	(2.84)	(2.59)	(−0.73)	(2.74)	(−1.17)
4	1.61	0.98	1.16	0.24	0.91	0.01
	(4.42)	(4.98)	(3.56)	(2.72)	(3.20)	(0.18)
High ROL	1.40	0.70	1.32	0.36	1.10	0.22
	(3.59)	(3.06)	(4.14)	(2.73)	(4.44)	(2.55)
High-Low	0.73	0.71	0.62	0.64	0.28	0.31
difference	(4.18)	(4.29)	(6.00)	(6.26)	(2.90)	(3.42)

B. VALUE-WEIGHTED

	SMALL CAP		MID CAP		LARGE CAP	
Quintile	RET-RF	α_{FF}	RET-RF	α_{FF}	RET-RF	α_{FF}
Low ROL	0.41	−0.26	0.68	−0.32	0.68	−0.13
	(1.14)	(−1.19)	(2.19)	(−3.37)	(3.56)	(−1.96)
2	0.77	0.17	0.59	−0.39	0.55	−0.14
	(2.00)	(0.79)	(1.74)	(−4.43)	(2.47)	(−1.98)
3	0.95	0.34	0.84	−0.14	0.87	0.11
	(2.85)	(1.97)	(2.56)	(−1.57)	(3.32)	(1.26)
4	1.31	0.66	1.12	0.17	0.95	0.09
	(3.81)	(3.72)	(3.51)	(2.23)	(3.34)	(0.82)
High ROL	1.24	0.53	1.27	0.30	1.13	0.24
	(3.37)	(2.39)	(4.21)	(2.50)	(4.38)	(2.37)
High-Low	0.83	0.79	0.58	0.63	0.45	0.38
difference	(4.93)	(5.00)	(5.05)	(5.44)	(2.90)	(2.86)

This table reports size-dependent relation between regulatory operating leverage and 1-month-ahead stock returns. Stocks are grouped into 20-60-20 percentile size (market capitalization) tiers. Then, within each size tier, quintile portfolios are constructed by sorting stocks based on their ROL. Portfolio 5 (1) is the portfolio of stocks with the highest (lowest) ROL. The table reports the time-series averages of the monthly equal-weighted (panel A) and value-weighted (panel B) excess returns (RET-RF) and alphas (α_{FF5}) generated by bivariate dependent sort portfolios. The last rows report the return differences between quintile 1 (Low) and quintile 5 (High). Newey-West (1987) adjusted *t*-statistics are reported in parentheses.

3.3 Average stock characteristics

This subsection examines the average characteristics of stocks with low vs. high ROL based on univariate portfolio-level analyses. Table 7 reports the time-series averages of the median values of firm-specific characteristics and risk factors, such as firm-specific regulatory restriction count, market capitalization, market beta, book-to-market ratio, intermediate-term momentum, illiquidity, idiosyncratic volatility, and operating margin after depreciation.

Table 7
Average characteristics of regulatory operating leverage-sorted portfolios

Quintile	REG	SIZE	BETA	B/M	MOM	ILLIQ	IVOL	OM
Low ROL	13611	410	0.929	0.581	9.50	0.206	0.021	0.089
	(49.34)	(10.92)	(41.35)	(49.46)	(5.87)	(4.84)	(37.58)	(53.99)
2	2972	606	1.000	0.503	9.06	0.078	0.020	0.077
	(26.81)	(9.32)	(122.71)	(39.42)	(5.74)	(6.45)	(30.23)	(43.65)
3	2693	466	1.052	0.502	10.06	0.091	0.020	0.086
	(17.99)	(11.33)	(83.42)	(46.05)	(6.51)	(6.03)	(31.23)	(60.18)
4	21442	406	1.051	0.542	11.56	0.088	0.020	0.117
	(14.50)	(11.51)	(52.67)	(42.41)	(7.24)	(7.29)	(31.03)	(42.61)
High ROL	31094	284	1.041	0.500	13.30	0.181	0.022	0.137
	(28.32)	(13.31)	(29.93)	(42.41)	(7.97)	(7.14)	(42.76)	(23.02)

Quintile portfolios are constructed every month from April 1991 to December 2021 by sorting stocks based on their regulatory operating leverage measure during the previous quarter. Quintile 5 (1) is the portfolio of stocks with the highest (lowest) ROL. The table reports the time-series averages of the median values of firm-specific characteristics and risk factors of regulatory operating leverage-sorted quintile portfolios, such as “REG” regulatory restriction count, “SIZE” market capitalization,” “BETA” market beta, “B/M” book-to-market ratio, “MOM” intermediate-term momentum, “ILLIQ” Amihud (2002) illiquidity mesure, “IVOL” idiosyncratic volatility, and “OM” operating margin after depreciation.

The first column documents the time-series average of the median values of firm-specific regulatory restriction exposures of ROL-sorted quintile portfolios. It is seen that ROL is not a monotonic transformation of regulatory restriction. Having a closer look, the regulatory restriction counts are the highest for the two highest ROL portfolios and for the lowest ROL portfolio. This shows the difference economic channels captured by the level of regulatory restriction words and the fixed cost component of regulations. Put differently, exposure to many “must”, “shall”, and other regulatory restriction words does not necessarily mean that a firm’s fixed regulatory cost exposure is a higher portion of its costs.

The market capitalization (size) increases from the first to the second ROL quintile. Then, size decreases monotonically from the second to the fifth ROL portfolio. As some small businesses are exempted from regulations and/or as certain regulations allows small firms to prepare for regulatory compliance gradually (staggered adoption) compared to larger firms, some small firms’ regulatory burden might be lower compared to larger ones. Hence, the increase in market capitalization from the first to the second ROL quintile is plausible. On the other hand, most of regulatory compliance costs are fixed and they fall disproportionately on smaller firms. As a result, small firms are significantly constrained by the regulations. This phenomenon explains the decrease in market capitalization from the second to the fifth quintile.

The third column reports the time-series average of median market beta. While the lowest ROL quintile has an average market beta of 0.929, the rest of the quintiles has significantly larger market betas. The third, fourth, and fifth ROL portfolios have a market beta of 1.052, 1.051, and 1.041, respectively. The results are consistent with the operating leverage literature according to which firms with high operating leverage are more dependent on business cycles and, hence, more exposed to systematic risks.

The time-series average of the median book-to-market ratios varies between 0.500 and 0.581. While the intermediate-term-momentum decreases from quintile 1 to 2, the two highest ROL quintiles generate the highest momentum. Similarly, there is no significant variation in Amihud (2002) illiquidity and idiosyncratic volatility from the lowest to the highest ROL portfolio.

Moving from the lowest to the highest ROL quintile portfolio, operating margin after depreciation tends to increase, albeit not monotonically. To examine the relation between operating margin and ROL, we estimate firm-level cross-sectional regressions of operating margin after depreciation on ROL and control variables including natural logarithm of sales, logarithm of market-to-book asset ratio, cash holdings scaled by assets, book leverage, dummy variable of cash dividend payments, cash dividends scaled by assets, and fixed assets scaled by assets. Table A3 of the Internet Appendix documents the regression results. The table suggests a significantly negative relation between regulatory operating leverage and operating margin. In addition, the results indicate a positive relation between operating leverage measures, such as ((COGS+SG&A)/AT) and (SG&A/AT), and operating margin. The long run trend of the U.S. economy gives rise to the positive association between operating leverage and profitability. However, fixed regulatory costs constrain firms' cost structure in a way that firms cannot cut them. As a result, ROL constrains firms' operating flexibility and decreases their profitability.[25]

3.4 Bivariate portfolio-level analyses

The recent literature provides cross-industry and intraindustry explanations to the value premium (Novy-Marx 2011). First, asset-level differences between industries contribute to cross-industry book-to-market spreads. To illustrate, firms in industries such as "utilities" tend to be asset-intensive, whereas firms in industries such as "information technology" are not. This phenomenon leads to firms in capital intensive industries to have higher book-to-market ratios as such firms have high book values compared to their market values. On the other hand, profit margin differences of different firms in the same industry can lead to book-to-market differences. For example, a firm with a 2% operating margin is more exposed to industry-level shocks than a firm with a 10% operating margin. Hence, the firm with a lower operating margin would carry a lower market value and higher book-to-market ratio compared to a firm with a higher operating margin within the same industry. Hence, asset heaviness differences between industries and operating margin differences in the same industry explain a significant portion of the value premium.

[25] Table A3 of the Internet Appendix introduces an interaction term between ROL and natural logarithm of sales as an independent variable and reports positive and significant coefficients for the interaction term. The positive sign can be interpreted as follows. First, the logarithm of sales can be considered as a proxy for size. As large firms are less constrained by regulatory burden, the interaction term increases profitability. Second, if a firm with high ROL experiences a negative sales shock, its revenue decreases at a faster rate than its costs; hence its operating margin decreases even further.

Additionally, the literature that provides labor expenses (leverage) based explanations to operating leverage and value premiums (Rosett 2001; Danthine and Donaldson 2002; Donangelo et al. 2019; Favilukis, Lin, and Zhao 2020). More specifically, Rosett (2001) and Danthine and Donaldson (2002) provide evidence to the cost rigidity and operating leverage implications of committed labor expenses. Hence, labor expenses (fixed labor costs) contribute to risk premium. Donangelo et al. (2019) document that firms' labor costs are significantly inflexible compared to their cash inflows and they are less variable than nonlabor costs.[26] Built on this idea, Donangelo et al. (2019) construct a firm-level measure of labor (operating) leverage that quantifies the level of labor expenses scaled by the firm's value-added and document that labor leverage is positively priced in the cross-section of stock returns. Favilukis, Lin, and Zhao (2020) introduce measures of labor expenses growth and labor share as proxies for labor market frictions. They show that both variables predict credit risk, debt growth, and financial leverage significantly.[27]

To ensure that the measures described do not fully explain the cross-sectional pricing of regulatory operating leverage, we perform bivariate portfolio sorts and reexamine the return and alpha differences between extreme ROL portfolios. To do so, we use a 5x5 dependent sort based on the control variables: operating margin, opeerating leverage, labor leverage, and labor share growth. To illustrate, first, we control for operating margin by forming quintile portfolios ranked based on the level of operating margin. Then, within each operating margin quintile, we sort stocks into quintile portfolios based on their ROL so that quintile 1 (quintile 5) consists of stocks with the lowest (highest) ROL. For brevity, we do not report returns for all 25 (5x5) portfolios. Instead, Table 8 presents excess returns and alphas averaged across the operating margin quintiles with dispersion in ROL. Naturally, we conduct the same analyses for operating leverage, labor leverage, and labor share growth.[28] Panel A (B) reports equal (value)-weighted returns.

First two columns of Table 8 reports excess and risk-adjusted returns generated by operating margin controlled ROL-sorted quintile portfolios. When operating margin is the first-stage sorting variable, the equal-weighted excess return and alpha spreads between the extreme ROL quintile portfolios are 58 and 57 basis points per month with Newey-West-adjusted t-statistics of 8.40 and 8.44, respectively. Similarly, a zero-cost operating margin controlled ROL strategy produces a

[26] Donangelo et al. (2019) show that a 1.0% reduction in sales is associated, on average, with 1.08% decrease in nonlabor costs and only 0.53% reduction in labor costs.

[27] Favilukis, Lin, and Zhao (2020) define labor share as labor expenses scaled by the sum of labor expenses and earnings before interest and depreciation (EBITDA). Their labor expenses growth measure reflects the yearly growth in total labor expenses. Total staff expenses measure is available for around 10% of firm-year observations. As the labor share and labor expenses growth measures require the availability of total labor expenses information for 2 consecutive years and EBITDA, the measures decrease the sample size further. Favilukis, Lin, and Zhao (2020) utilize the yearly growth in the number of employees as an additional measure of labor growth, which is available for almost 70% of the sample. Hence, this section introduces employee growth as a measure of labor share growth.

[28] The labor leverage measure of Donangelo et al. (2019) requires data on firm-level labor expenses for at least 10% of the bservations. Hence, while generating labor leverage-controlled ROL quintile portfolios, we divide our sample into three tiers based on the level of labor leverage rather than five quintiles.

Table 8
Operating margin, operating leverage measures, and ROL

A. EQUAL-WEIGHTED

	Operating margin		Cost/Asset		Labor LEV		Net hiring	
Quintile	RET-RF	α_{FF}	RET-RF	α_{FF}	RET-RF	α_{FF}	RET-RF	α_{FF}
Low ROL	0.80	− 0.11	0.73	− 0.15	0.79	− 0.33	0.73	− 0.16
	(2.62)	(− 1.14)	(2.27)	(− 1.52)	(2.17)	(− 1.71)	(2.30)	(− 6.62)
2	0.74	− 0.09	0.69	− 0.10	0.93	− 0.08	0.75	− 0.10
	(2.31)	(− 1.02)	(2.23)	(− 1.13)	(2.28)	(− 0.29)	(2.23)	(− 1.00)
3	0.93	0.05	0.85	− 0.01	0.75	− 0.13	0.93	0.03
	(3.01)	(0.65)	(2.82)	(− 0.09)	(2.15)	(− 0.57)	(2.92)	(0.44)
4	1.15	0.25	1.14	0.20	0.90	− 0.25	1.15	0.29
	(3.65)	(3.37)	(3.58)	(2.57)	(2.16)	(− 0.93)	(3.60)	(3.35)
High ROL	1.38	0.45	1.37	0.50	1.24	0.29	1.40	0.52
	(4.34)	(4.72)	(4.24)	(4.88)	(3.23)	(1.50)	(4.44)	(5.44)
High-Low	0.58	0.57	0.64	0.66	0.45	0.62	0.67	0.68
difference	(8.40)	(8.44)	(7.78)	(8.83)	(1.90)	(2.06)	(7.93)	(8.53)

B. VALUE-WEIGHTED

	Operating margin		Cost/Asset		Labor LEV		Net hiring	
Quintile	RET-RF	α_{FF}	RET-RF	α_{FF}	RET-RF	α_{FF}	RET-RF	α_{FF}
Low ROL	0.66	− 0.16	0.70	− 0.15	0.90	− 0.18	0.70	− 0.15
	(3.37)	(− 2.04)	(3.43)	(− 1.96)	(2.64)	(− 1.79)	(3.49)	(− 2.12)
2	0.63	− 0.10	0.57	− 0.14	0.72	− 0.32	0.60	− 0.12
	(2.91)	(− 1.86)	(2.63)	(− 2.35)	(2.18)	(− 2.48)	(2.71)	(− 1.88)
3	0.89	0.08	0.83	0.06	0.91	0.02	0.92	0.11
	(3.27)	(1.02)	(3.03)	(0.79)	(3.62)	(0.17)	(3.42)	(1.29)
4	0.98	0.06	1.04	0.09	1.04	0.04	0.93	0.04
	(3.62)	(0.64)	(3.77)	(0.86)	(3.48)	(0.32)	(3.20)	(0.41)
High ROL	1.15	0.25	1.16	0.29	1.23	0.13	1.17	0.28
	(4.46)	(2.43)	(4.49)	(2.73)	(3.22)	(1.40)	(4.47)	(2.60)
High-Low	0.49	0.41	0.46	0.44	0.33	0.31	0.47	0.43
difference	(3.30)	(3.14)	(3.16)	(3.32)	(2.18)	(2.14)	(3.14)	(3.22)

This table presents excess and risk-adjusted returns generated by the equal-weighted (panel A) and value-weighted (panel B) bivariate sorts based on dependent double sorts. First, quintile portfolios are formed by sorting on the relevant control variable: operating margin after depreication (Operating margin), total cost-to-asset ratio (Cost/Asset), labor leverage (Labor LEV), and net hiring. Then, within each control variable quintile, we sort stocks into quintile portfolios based on their ROL so that quintile 1 (quintile 5) consists of stocks with the lowest (highest) ROL. The last rows document the excess return and alpha spreads between the extreme ROL quintiles and their associated Newey-West-adjusted *t*-statistics.

value-weighted excess return of 49 basis points with a *t*-statistic of 3.30 and five-factor alpha of 41 basis points with a *t*-statistic of 3.14. The rest of the columns provide similar results. When we control for operating leverage measure of Novy-Marx (2011), the highest ROL quintile generate 66 basis points more equal-weighted alpha compared to the lowest ROL quintile. Similarly, the equal-weighted alpha spread between the extreme ROL quintiles is 62 basis points per month once we neutralize the portfolios to labor (operating) leverage measure of Donangelo et al. (2019). Finally, labor share growth (Favilukis, Lin, and Zhao 2020) controlled equal-weighted alpha difference between quintile 5 and quintile 1 is 68 basis points per month. Similarly, once we control for the first-stage sorting variables, the value-weighted excess return and alpha spreads between the extreme ROL portolios are positive and significant at 5% level.[29,30]

This subsection provides evidence to the fact that operating margin and operating leverage, potential drivers of intra- and cross-industry book-to-market differences, cannot capture the positive and significant cross-sectional relation between ROL and subsequent returns. Similarly, labor leverage, a significant contributor to operating leverage, fails to eliminate the predictive power of ROL on future stock returns. Finally, labor share growth controlled ROL-sorted portfiolios continue to generate positive and significant returns. This suggests that the effect of ROL on subsequent returns cannot be subsumed by potential factors that might give rise to operating leverage differences between stocks, which in turn generates significant risk premiums.

Additionally, we divide the sample of stocks into tiers based on the level of first-stage sorting variables and examine the return differences (not reported) between extreme ROL quintiles within each tier. The results show that ROL strategy generates larger return spreads within the subgroups of stocks with lower operating margin, higher operating leverage, higher labor leverage, and higher labor share growth. This provides further evidence to the idea that ROL is more binding for firms that are significantly constrained by their operating margin and their cost structures (i.e., higher labor expenses). As a result, investors demand a higher premium in the form of higher expected returns to invest in stocks with high ROL, particularly those with low operating margin, high operating leverage, high labor leverage, and high labor share.

3.5 Liquidity, institutional holdings, and analysts

It is essential to examine whether the significant cross-sectional pricing of ROL is only prominent among small stocks, illiquid stocks, stocks with low analyst coverage, and stocks with low institutional holdings. If so, the predictive power of ROL on future stock returns could be attributed to mispricing rather than a risk-based explanation. To investigate this, we analyze the association between ROL and future stock returns while accounting for liquidity, institutional holdings, and analyst coverage. Tables 9, 10, and 11 present the results.

Table 9 documents that the significant cross-sectional relation between ROL and subsequent returns is pronounced among all liquidity subgroups. While the value-weighted α_{FF5} spread between the extreme ROL quintile portfolios is 55 basis points per month within the most illiquid stock subsample (LIQ 1), a zero-cost high-low ROL strategy produces 58 (44) basis points alpha within the

[29] Additionally, when we use 5x5 dependent sorts based on the market beta, size, book-to-market, momentum, short-term reversal, illiquidity, idiosyncratic volatility, return on equity, investment, MAX, and return on equity, a zero-cost high-low ROL strategy continues to generate positively significant 1-month-ahead alphas. Once dependently controlled by the mentioned control variables, the equal-weighted and value-weighted alpha spreads between the extreme ROL portfolios vary between 0.34% and 0.72% per month (all significant at the 5% level).

[30] The following subsections report value-weighted returns.

Table 9
Liquidity and regulatory operating leverage

	LIQ 1		LIQ 2		LIQ 3	
Quintile	RET-RF	α_{FF}	RET-RF	α_{FF}	RET-RF	α_{FF}
Low ROL	0.68	0.00	0.75	−0.30	0.68	−0.16
	(2.46)	(0.02)	(2.46)	(−3.43)	(3.51)	(−2.32)
2	0.70	0.01	0.59	−0.36	0.57	−0.14
	(2.17)	(0.08)	(1.79)	(−4.56)	(2.63)	(−2.29)
3	0.77	0.15	0.80	−0.16	0.90	0.11
	(2.53)	(1.08)	(2.64)	(−2.12)	(3.29)	(1.09)
4	1.15	0.42	1.15	0.24	0.91	0.04
	(3.92)	(3.32)	(3.88)	(2.80)	(3.12)	(0.41)
High ROL	1.34	0.56	1.27	0.28	1.18	0.28
	(4.05)	(2.54)	(4.32)	(2.37)	(4.58)	(2.72)
High-Low	0.65	0.55	0.52	0.58	0.50	0.44
difference	(3.27)	(2.82)	(4.75)	(4.98)	(3.21)	(3.34)

This table reports value-weighted excess returns (RET-RF) and risk-adjusted (α) returns generated by bivariate dependent sort portfolios. Every month, stocks are grouped into 30-40-30 percentile liquidity tiers. Then, within each liquidity tier, quintile portfolios are constructed by sorting stocks based on their regulatory operating leverage measure. The last row presents excess return and alpha spreads between the extreme ROL quintiles within each liquidity tier and their associated Newey-West-adjusted *t*-statistics.

subgroup of stocks with medium (high) liquidity. Tables 10 and 11 yield similar results.

To measure institutional holdings (INST) of a particular stock, we use the percentage of total shares outstanding owned by institutional investors by the end of the last quarter. There is a significantly positive relationship between ROL and subsequent returns within all stock subgroups with different level of institutional holdings. The results document that the highest ROL portfolio generates both economically and statistically significant subsequent risk-adjusted returns within all institutional holdings tiers. The α_{FF5} difference between the highest and the lowest ROL quintiles is 35 basis points within the highest institutional holdings tier and 31 (78) basis points within the medium (lowest) institutional holdings tier.

Asymmetric (incomplete) information on some stocks might result in arbitrage opportunities. Hence, one might doubt that high ROL stocks generate high subsequent returns because of a lack of information. To test this, we conduct bivariate portfolio-level analyses. We measure analyst coverage (CVRG) as yearly average of the total number of analysts for each stock. Table 11 presents a significant relation between ROL and future stock returns within all analyst coverage subsamples. A zero-cost high-low ROL strategy produces 35 (31) basis points subsequent excess return (α_{FFC5}) within the lowest analyst coverage tier. Moving to higher analyst converage subsgroups, we see the excess and risk-adjusted return spreads between the extreme ROL quintiles increase. As an illustration, note that stocks with high ROL generate 50 basis points more excess return and 45 basis points more alpha compared to stocks with low ROL in the medium level of analyst coverage. Similarly, the excess return (alpha) difference between the

Table 10
Institutional holdings and regulatory operating leverage

	INST 1		INST 2		INST 3	
Quintile	RET-RF	α_{FF}	RET-RF	α_{FF}	RET-RF	α_{FF}
Low ROL	0.09	− 0.33	0.54	0.02	0.82	− 0.10
	(0.25)	(− 1.39)	(2.29)	(0.25)	(3.19)	(− 0.80)
2	− 0.36	− 0.98	0.58	0.06	0.53	− 0.27
	(− 0.84)	(− 4.01)	(2.55)	(0.52)	(1.82)	(− 2.16)
3	0.42	− 0.14	0.79	0.28	0.77	− 0.04
	(0.99)	(− 4.01)	(2.29)	(1.65)	(2.53)	(− 0.35)
4	0.47	− 0.14	0.75	0.25	0.80	− 0.04
	(1.51)	(− 0.73)	(2.13)	(1.41)	(2.57)	(− 0.33)
High ROL	1.16	0.45	1.00	0.33	1.18	0.25
	(3.63)	(1.84)	(3.67)	(2.01)	(4.29)	(1.86)
High-Low	1.07	0.78	0.45	0.31	0.36	0.35
difference	(3.27)	(2.50)	(2.13)	(1.94)	(2.59)	(2.46)

This table reports value-weighted excess returns (RET-RF) and risk-adjusted (α) returns generated by bivariate dependent sort portfolios. Every month, stocks are grouped into 30-40-30 percentile institutional holdings (INST) tiers. Then, within each INST tier, quintile portfolios are constructed by sorting stocks based on their regulatory operating leverage measure. The last row presents excess return and alpha spreads between the extreme ROL quintiles within each INST tier and their associated Newey-West-adjusted t-statistics.

Table 11
Analyst coverage and regulatory operating leverage

	CVRG 1		CVRG 2		CVRG 3	
Quintile	RET-RF	α_{FF}	RET-RF	α_{FF}	RET-RF	α_{FF}
Low ROL	0.74	− 0.07	0.68	− 0.05	0.63	− 0.10
	(2.29)	(-0.73)	(1.95)	(-0.48)	(3.03)	(-1.25)
2	0.73	− 0.01	0.46	− 0.35	0.44	− 0.09
	(1.82)	(-0.08)	(1.24)	(-3.05)	(1.82)	(-1.20)
3	0.95	0.08	0.68	− 0.13	0.73	0.14
	(2.48)	(0.60)	(1.93)	(-1.01)	(2.39)	(1.17)
4	1.10	0.42	0.89	0.07	0.70	0.03
	(3.39)	(3.10)	(2.60)	(0.69)	(2.26)	(0.24)
High ROL	1.09	0.24	1.18	0.39	1.15	0.37
	(3.29)	(2.22)	(4.25)	(3.51)	(4.28)	(3.09)
High-Low	0.35	0.31	0.50	0.45	0.52	0.47
difference	(2.06)	(2.42)	(3.15)	(3.30)	(2.94)	(3.01)

This table reports value-weighted excess returns (RET-RF) and risk-adjusted returns (α) generated by bivariate dependent sort portfolios. Every month, stocks are grouped into 30-40-30 percentile analyst coverage (CVRG) subgroups. Then, within each subgroup, quintile portfolios are constructed by sorting stocks based on their regulatory operating leverage measure. The last row presents excess return and alpha spreads between the extreme ROL quintiles within each analyst coverage subgroup and their associated Newey-West-adjusted t-statistics.

extreme ROL quintiles is 52 (47) basis points per month with a t-statistic of 2.94 (3.01) within the subsample of stocks high analyst coverage.

3.6 Firm-level cross-sectional regressions

So far, we test the cross-sectional relation between ROL and subsequent stock returns at portfolio-level. We now examine the cross-sectional relation between regulatory operating leverage, regulatory restriction counts, and expected returns at the firm level using Fama-Macbeth (1973) regression methodology. Firm-level cross-sectional regressions have two significant advantages over portfolio sorts. First, portfolio sorts hide a significant amount of information in the cross-section because of stocks accumulating in portfolios. Second, cross-sectional regressions have the advantage of being able to control for several simultaneous effects and factors.

Table 12 reports the time-series averages of the slope coefficients from the regressions of stock returns on regulatory operating leverage (ROL), the natural logarithm of firm-specific regulatory restriction count (REG), market beta (BETA), the natural logarithm of market capitalization (SIZE), the logarithm of book-to-market ratio (B/M), intermediate-term momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), asset growth (I/A), return on equity (ROE), maximum of daily returns (MAX), and operating margin after depreciation (OM) from April 1991 to December 2021.[31]

Columns (1) and (2) report slope coefficients of univariate regressions of 1-month-ahead stock returns on regulatory operating leverage and regulatory restrictions. The last two columns document the multivariate regression results in which the independent variables are regulatory operating leverage and the mentioned control variables (column 3) and the natural logarithm of firm-specific restriction count and control variables (column 4).

Consistent with univariate portfolio-level analyses, the first column suggests that the regulatory operating leverage (ROL) measure has a positively significant predicting power on future returns. The average slope from the univariate monthly regressions of 1-month-ahead stock returns on ROL is 0.023 with a Newey-West *t*-statistic of 4.73. According to the univariate regression of realized returns on the natural logarithm of regulatory restrictions, the coefficient for restriction count is negative albeit insignificant with a *t*-statistic of -0.96. The first two columns show that the overall effect of regulations on stock returns is distinctly different from the cross-sectional pricing of fixed cost component of regulations.[32]

Column 3 reports the multivariate regression results of excess returns on ROL and control variables. According to this specification, the average slope coefficient for ROL is 0.037 (t-stat. =6.04), larger than the univariate regression coefficient. The coefficient for the logarithm of regulatory restrictions is still negative and insignificant after accounting for all firm-specific characteristics and risk factors, which repeatedly documents the different economic channels captured by fixed cost component of regulations and the overall effect of regulations.

To examine the return differences between stocks with the extreme level of ROL, we create quarterly-varying quintile portfolios based on ROL measure and estimate firm-level cross-sectional regressions of excess returns on the dummy

[31] Our results are robust to controlling for operating margin before depreciation.

[32] Given the nature of regulations, there might be concerns about endogeneity. However, different economic channels implied by regulatory restrictions and the fixed cost component of regulations help to address this potential issue.

Table 12
Cross-sectional regressions based on regulatory operating leverage

Dependent variable: RET-RF	(1)	(2)	(3)	(4)
ROL	0.023		0.037	
	(4.73)		(6.04)	
REG		– 0.061		– 0.060
		(-0.96)		(-1.62)
BETA			0.322	0.285
			(1.77)	(1.72)
SIZE			– 0.076	– 0.074
			(-2.51)	(-2.45)
B/M			0.192	0.194
			(2.36)	(2.46)
MOM			0.005	0.005
			(3.47)	(3.52)
REV			– 0.031	– 0.032
			(-6.64)	(-6.77)
ILLIQ			0.261	0.263
			(1.75)	(1.78)
IVOL			– 0.079	– 0.084
			(-1.33)	(-1.47)
I/A			– 0.074	– 0.067
			(-3.97)	(-3.31)
ROE			0.426	0.388
			(2.73)	(2.46)
MAX			– 0.007	– 0.001
			(-0.05)	(-0.01)
OM			0.425	0.462
			(3.93)	(4.23)
n	928,786	928,786	744,401	744,401
Avg. R^2	.004	.003	.099	.098

This table reports univariate and multivariate firm-level cross-sectional regression results of 1-month-ahead excess returns on the subsets of lagged regulatory operating leverage (ROL), the natural logarithm of firm-level sales-weighted restriction count (REG), and control variables, such as market beta (BETA), the natural logarithm of market capitalization (SIZE), the logarithm of book-to-market ratio (B/M), intermediate-term momentum (MOM), excess return generated during the portfolio formation month (REV), Amihud (2002) illiquidity (ILLIQ), idiosyncratic volatility (IVOL), asset growth (I/A), return on equity (ROE), maximum of daily returns (MAX), and operating margin after depreciation (OM). The last two rows report the number of observations (n) and R^2. Newey-West-adjusted *t*-statistics are reported in parentheses.

variables indicating the ROL quintile that a particular stock belongs to and control variables. According to quintile sort Fama-Macbeth regressions, there is a significant monotonicity from the first to the fifth ROL quintile. More specifically, stocks in the fifth quintile generate 54 basis points return per month more than stocks in the lowest quintile. In other words, after accounting for a number of return predictors, a high-low zero-cost strategy, in which an investor takes a long position at high ROL stocks and a short position at low ROL stocks, generates around 6.5% annualized return.

3.7 Risk contribution of regulatory operating leverage

This section aims to provide further risk-based explanation for the observed positive relation between ROL and subsequent stock returns. Specifically, we examine whether stocks with high ROL generate higher returns compared to stocks with low ROL due to risk exposure.

To investigate this, we conduct firm-level cross-sectional Fama-Macbeth (1973) regressions of firm-level forward-looking cash flow volatility on ROL, along with a set of control variables. We quantify quarterly firm-level cash flows as EBITDA (earnings before interest, tax, depreciation, and amortization) scaled by assets (AT). We define cash flow volatility as firm-level four-quarter forward-looking volatility of EBITDA scaled by assets. Following Dou et al. (2021), we include the natural logarithm of asset value, the natural logarithm of book-to-market ratio, and the natural logarithm of debt-to-equity ratio as control variables. Additionally, we account for the operating leverage measure (SG&A/AT) proposed by Chen, Harford, and Kamara (2019) and operating margin after depreciation.[33] Table 13 presents the regression results.

The first column of Table 13 presents the univariate regressions results of firm-specific four-quarter forward-looking volatility of EBITDA scaled by assets on ROL. The results document that ROL alone positively and significantly predicts the forward-looking cash flow volatility. The second column adds size, book-to-market ratio, and financial leverage to the regression model. According to this specification, the estimated coefficient for ROL is positive and significant with a Newey-West-adjusted *t*-statistic of 2.40.

The findings in the first two columns demonstrate that firms experience increased cash flow volatility due to regulatory operating leverage. However, it is possible that this positive association is driven by the implications of operating leverage and operating margin related to ROL. In other words, the positive relation between ROL and future cash flows might be captured by the effects of operating leverage and operating margin. To address this, the third column adds the operating leverage measure proposed by Chen, Harford, and Kamara (2019) and operating margin as independent variables, alongside the variables from column 2. The third column reports an estimated coefficient of 0.0012 on ROL with a *t*-statistic of 4.17. This shows that the significantly positive cross-sectional relation between ROL and forward-looking cash flow volatility is robust to controls for operating leverage and operating margin.

Furthermore, the third column reports the estimated coefficients for operating leverage (OL) and operating margin (OM). Consistent with existing literature on operating leverage literature, the coefficient for the operating leverage (SG&A/AT) is positive and significant. This positive association can be explained by the fact that firms with higher fixed costs, compared to variable costs, have less flexibility in their operations. During economic expansions, these firms experience faster revenue growth compared to their costs, while during recessions, they incur larger losses. Consequently, firms with higher operating leverage are more exposed to systematic risk, leading to greater cash flow volatility. Additionally, there is a significantly negative relation between operating margin and future cash

[33] It is worth noting that the positive and significant relationship between regulatory operating leverage and future cash flow volatility remains robust after controlling for various firm-specific characteristics, such as market beta, idiosyncratic volatility, and illiquidity.

Table 13
Cash flow volatility and systematic risk

Dependent variable: VOL(CF)	(1)	(2)	(3)	(4)	(5)
ROL	0.0032	0.0023	0.0012		0.0118
	(2.84)	(2.40)	(4.17)		(3.26)
ROL*rec				0.0019	
				(3.20)	
ROL*non.rec				0.0010	
				(4.45)	
ROL*diff(rec-non.rec)				0.0009	
				(1.98)	
ROL*Δ(CFNAI)				– 0.0028	
				(-2.24)	
ROL*Δ(INDP)				– 0.0032	
				(-2.22)	
ROL*SIZE					– 0.0005
					(-3.21)
SIZE		– 0.0061	– 0.0032	– 0.0032	– 0.0032
		(-22.31)	(-31.16)	(-31.16)	(-25.69)
BM		– 0.0070	– 0.0029	– 0.0029	– 0.0028
		(-17.55)	(-6.67)	(-6.67)	(-5.62)
LEV		– 0.0065	– 0.0037	– 0.0037	– 0.0037
		(-5.66)	(-3.53)	(-3.53)	(-2.99)
OL			0.1056	0.1056	0.1058
			(15.51)	(15.51)	(13.57)
OM			– 0.0004	– 0.0004	– 0.004
			(-5.83)	(-5.83)	(-5.39)

This table presents firm-level cross-sectional Fama-Macbeth (1973) regressions results examining the relationship between future cash flow volatility and regulatory operating leverage, along with a range of firm-level characteristics. Cash flow volatility is defined as the four-quarter forward-looking volatility of EBITDA (earnings before depreciation) divided by asset value. The control variables include the natural logarithm of asset value (SIZE), the logarithm of book-to-market ratio (BM), the logarithm of debt-to-equity ratio (LEV), SG&A expenses scaled by assets (OL), and operating margin after depreciation (OM). Column 4 reports the regression results of estimated values of ROL in the first stage on recessionary and nonrecessionary quarter dummy variables (based on the NBER business cycle definitions), changes in CFNAI (four-quarter forward-looking average of CFNAI minus contemporaneous CFNAI), and changes in the logarithm of industrial production index (four-quarter forward-looking average of INDP minus contemporaneous INDP). Column 5 introduces the interaction term between ROL and the logarithm of asset base as an independent variable. Newey-West (1973) adjusted *t*-statistics are reported in parentheses.

flow volatility. As highlighted by Novy-Marx (2011), firms operating at low margins are more exposed to industry-level shocks compared to firms operating at high margins. Consequently, firms with low margins exhibit greater cash flow volatility compared to firms with high margins.

The fourth column intends to provide detailed explanations for the observed positive relation between ROL and future cash flow volatility. More specifically, we investigate whether ROL triggers future cash flow volatility due to systematic risk, idiosyncratic risk, or both. Then, we provide additional systematic shock explanations for the positive association between ROL and cash flow volatility. To do so, we first estimate cross-sectional regressions of cash flow volatility on ROL and control variables in column 3 for each quarter and obtain slope coefficients for ROL. Then, we estimate time-series regressions of the ROL coefficients for recessionary and nonrecessionary dummy variables, which are defined based on the recessionary periods of NBER (National Bureau of

Economic Research). If there is a recessionary month in at least one of the next four quarters, the recessionary dummy variable takes a value of one and otherwise zero. The estimated coefficient for the interaction variable between ROL and recessionary period dummy variable is 0.0019 with a *t*-statistic of 3.20. On the other hand, the estimated coefficient for the interaction term between ROL and nonrecessionary period dummy variable is 0.0010 with a *t*-statistic of 4.45. This means that there is a significantly positive relation between ROL and cash flow volatility during recessionary and nonrecessionary periods. The results suggest that ROL significantly contributes to systematic and idiosyncratic risk. Additionally, the economic magnitude of the estimated coefficient for ROL is higher during recessionary periods, almost double of the magnitude during nonrecessionary periods.[34] The fourth column also documents the difference in the estimated coefficients for ROL between recessionary and nonrecessionary periods. The coefficient for the difference term is significantly positive with a *t*-statistic of 1.98.

ROL increases future cash flow volatility, a proxy for risk, during both recessionary and nonrecessionary periods. Furthermore, the positive association between ROL and future cash flow volatility is significantly stronger during recessionary periods. This supports the idea that the impact of ROL on returns is driven by the (systematic) risk contribution of fixed regulatory costs. As regulatory fixed costs have a significant impact on operating leverage, which further triggers firms' exposure to fluctuations in business cycles, we anticipate that the relation between ROL and cash flow volatility is influenced by the state of the economy. Thus, we examine how macroeconomic state variables contribute to the extent to which ROL affects a firm's cash flow volatility.

To investigate this, we introduce bivariate interaction terms between ROL and changes in CFNAI (Chicago Fed National Activity Index) as well as the natural logarithm of industrial production. Specifically, we calculate forward-looking four-quarter averages of CFNAI and industrial production index, and compute changes in these variables (to illustrate, the changes in CFNAI is defined as mean $(CFNAI_{Q+1,Q+4}) - CFNAI_Q$). We then introduce time-series regressions of the ROL coefficients (obtained from the first-stage regression) on changes in CFNAI ($\Delta(CFNAI)$) and changes in industrial production index ($\Delta(INDP)$). In column 4, we present the estimated coefficients for the interaction terms. The estimated coefficient for the interaction term between ROL and changes in CFNAI (INDP) is -0.0028 (-0.0032) with a *t*-statistic of -2.24 (-2.22). This suggests that the association between ROL and future cash flow volatility fluctuates depending on the state of the economy (i.e., CFNAI and industrial production). Particularly, there is a stronger relationship between ROL and future cash flow volatility during periods of decreasing economic activity.

The underlying idea is that regulations impose significant fixed costs and add to operating leverage. As regulations significantly contribute to operating leverage,

[34] Because of shorter recessionary periods, the *t*-statistic on ROL during the recessionary periods is lower (3.20) than nonrecessionary periods.

firms with high ROL become more dependent on business cycles. Specifically, firms with high ROL are unable cut their regulation-driven fixed costs as much as firms with low ROL, making them more likely to generate more volatile cash flows, particularly during periods of decreasing economic activity. Consequently, firms with high ROL exhibit greater cash flow volatility compared to firms with low ROL during periods of decreasing economic activity and declining industrial production growth. In other words, CFNAI and industrial production are important macroeconomic state variables on the systematic risk implications of ROL.

Column 5 of Table 13 introduces a new independent variable, the interaction term between ROL and the natural logarithm of asset value (a measure of size). Consistent with the bivariate portfolio analyses (first on market capitalization, then on ROL), there is a size-dependent cross-sectional relation between ROL and future cash flow volatility. In particular, column 5 reports an estimated coefficient of 0.0118 on ROL (t-statistic = 3.26) and a coefficient of -0.0005 on the interaction term between ROL and size (t-statistic = -3.21). These results indicate that the positive association between ROL and future cash flow volatility (risk) triggers moving from large firms to small firms. In other words, the relationship between ROL and cash flow volatility is stronger within smaller stock subgroups. Hence, investors demand extra compensation in the form of higher expected returns to hold smaller stocks with high ROL as they generate more volatile future cash flows.

Specifically, the equal-weighted return spread between the extreme ROL quintiles is 73 (62) basis points per month with a t-statistic of 4.18 (6.00) within small-cap (mid-cap) stock subgroups. In the largest stock subsample, the equal-weighted alpha spread between extreme ROL quintiles decreases to 28 basis points per month with a t-statistic of 2.90. The value-weighted return spreads exhibit a similar pattern when moving from the smallest to the largest stock subsample. In summary, the findings in column 5 are consistent with the previous bivariate portfolio analyses. They suggest that economies of scale decrease the burden of regulatory fixed costs. In other words, large firms are less exposed to the negative implications of ROL. Hence, there is a stronger cross-sectional relation between ROL and future stock returns moving from large to small-cap firms as smaller firms lack economies of scale.

3.8 Regulatory operating leverage and economic mechanism

As the preceding subsections provide evidence of the association between regulatory operating leverage and systematic risk, this subsection investigates the importance of discount rate shocks in the cross-sectional pricing of ROL. To do so, we follow the approach of Dou, Ji, and Wu (2021) and estimate the exposure of ROL-sorted portfolio returns to discount-rate shocks. Specifically, we calculate the sum of ROL-sorted value-weighted portfolio excess returns over the past 36 months (from t-35 to t) and the sum of shocks to the earnings-price ratio over the same period using an AR(1) model. Following

Campbell and Shiller (1988, 1998), we employ the cyclically adjusted price-to-earnings ratio as a proxy for discount rates.[35] Then, we estimate return loadings on the discount rate shocks for the ROL-sorted portfolios and the return spread between the extreme portfolios. Panel A of Table 14 presents the discount rate exposures. The results show that the exposure to accumulated discount-rate shocks is negative and diminishes across portfolios sorted on ROL. Furthermore, the loading of the extreme ROL spread on the discount rate shocks is significantly negative.[36] This contributes to the notion that one reason that ROL is positively priced in the cross-section of stocks returns is the increased exposure to discount rate shocks as the ROL measure increases.

Substantial evidence indicates that costly regulations create barriers to entry, impede market entry, and pose challenges to new entrants attempting to displace market leaders (Djankov et al. 2002; Klapper, Laeven, and Rajan 2006; Suzuki 2013). In essence, the burden of regulatory compliance hardens barriers to entry, resulting in a reduced turnover rate of market leadership. This suggests that reduced entry rates lead to decreased competition and an increase in the monopoly rents enjoyed by incumbents. Dou, Ji, and Wu (2021) develop an asset pricing model and find that discount rates intensify product market competition. Furthermore, industries with a lower rate of leadership turnover are more exposed to fluctuations in discount rate. Consequently, the turnover rate of market leadership (and competition) emerges as an important characteristic in the cross-sectional pricing of ROL, given that exposure to discount-rate fluctuations increase with ROL (panel A of Table 14).

To test this hypothesis, panel B of Table 14 divide our sample based on measures of market turnover rate. Specifically, following the approach of Dou, Ji, and Wu (2022), we introduce a market turnover indicator dummy variable that takes a value of one if (a) the largest firm ranked by sales in the industry (three-digit NAICS industry) in year $t+1$ is not among the four largest firms in year t, or (b) any of the second- to fourth-largest firm ranked by sales in the industry in year $t+1$ are not among the four largest firms in year t and are large enough that their sales exceed 60% of the sales of the largest firm in year $t+1$; otherwise, it takes a value of zero. Panel B divides the sample of firms into two subgroups based on the values of market turnover indicator. The first (last) six columns of panel B report the returns generated by ROL-sorted quintile portfolios within industries with a market indicator of 1 (0). In other words, the first-six columns report the returns in industries characterized by high market turnover, while the remaining columns investigate return differences within industries with low market leader turnover.

35 Additionally, we examine the relationship between regulatory costs and discount rates by regressing yearly changes in average regulatory operating leverage of ROL-sorted quintile portfolios on the changes in earnings-price ratio. Given that ROL measurements are available at the quarterly level and earnings-price ratios are available at both the monthly and yearly levels, the regression specification could be noisy. Nevertheless, our regression results reveal a greater comovement between discount rates and regulatory costs as we move from the lowest to the highest ROL quintile.

36 Bustamante and Zucchi (2023) propose that discount rates act as barriers to entry by discouraging new market entrants.

Table 14
Regulatory operating leverage, discount rates, and market turnover

A. Univariate sorts and discount rates

Quintile	Q1	Q2	Q3	Q4	Q5	5-1
RET-RF	0.68	0.62	0.86	0.96	1.17	0.49
	(3.32)	(2.93)	(3.08)	(1.17)	(4.64)	(3.28)
β_{DR}	− 0.474	− 0.487	− 0.431	− 0.567	− 0.581	− 0.106
	(-6.00)	(-4.80)	(-4.16)	(-3.67)	(-7.87)	(-3.43)
R^2	.177	.142	.109	.185	.293	.032

B. Subsamples based on turnover indicator

	Turnover indicator = 1						Turnover indicator = 0					
Quintile	Q1	Q2	Q3	Q4	Q5	5-1	Q1	Q2	Q3	Q4	Q5	5-1
RET-RF	0.70	0.68	0.86	0.94	0.99	0.29	0.47	0.42	0.70	0.81	1.18	0.71
	(2.76)	(2.61)	(2.74)	(2.87)	(3.51)	(1.38)	(1.87)	(1.67)	(2.45)	(2.68)	(3.66)	(3.06)
α_{CAPM}	− 0.03	− 0.07	− 0.02	0.06	0.25	0.28	− 0.12	− 0.24	− 0.10	0.02	0.41	0.53
	(-0.31)	(-0.59)	(-0.15)	(0.44)	(1.37)	(1.25)	(-0.66)	(-1.61)	(-0.73)	(0.11)	(2.19)	(2.41)
α_{FF}	− 0.11	− 0.01	0.14	0.10	0.19	0.30	− 0.34	− 0.40	− 0.37	− 0.06	0.23	0.57
	(-0.95)	(-0.06)	(1.13)	(0.70)	(1.30)	(1.55)	(-2.04)	(-2.73)	(-2.72)	(-0.46)	(1.28)	(2.82)

Panel A reports the value-weighted excess returns generated by ROL-sorted quintiles and their exposure to discount-rate shocks. We estimate the return loadings (β_{DR}) by regressions of summation of ROL-sorted value-weighted portfolio excess returns for the past 36 months (from t-35 to t) on summation of shocks to the cyclically adjusted earnings-price ratio for the past 36 months using an AR(1) model. Panel B divides the sample based on market turnover indicator. Market turnover indicator is a dummy variable that takes a value of one if (a) the largest firm ranked by sales in the industry in year $t+1$ is none of the four largest firms in year t, or (b) if any of the second- to fourth-largest firm ranked by sales in the industry in year $t+1$ is none of the four largest firms in year t and it is large enough so that its sales are greater than 60% of the sales of the largest firm in year $t+1$, zero otherwise. The first (last) six columns report the returns and alphas (α_{CAPM} and α_{FF5}) generated by ROL-sorted quintiles within subsample of stocks with high (low) market turnover and their associated Newey-West (1987) adjusted t-statistics.

Panel B documents that the return spread between the extreme ROL quintiles decreases to 29 basis points per month among industries with high market turnover. Similarly, CAPM and five-factor alphas between the highest and lowest ROL portfolios are insignificant within this stock subgroup. In other words, the ROL premium disappears (becomes insignificant) within the subgroup characterized by low leadership turnover. The results provide evidence to the importance of market leadership turnover in the cross-sectional pricing of ROL.

On the other hand, the return and alpha spreads between the extreme ROL quintiles are positive and significant within subgroups of industries with low leadership turnover. Specifically, the excess return spread between the fifth and first quintiles is 71 basis points per month within low turnover. In other words, industries with lower leadership turnover imply that incumbents enjoy longer durations as market leaders and they are likely to face reduced competition and main their positions. This suggests that cash flows of firms (industries) with higher regulatory operating leverage are more susceptible to discount-rate shocks as regulations are likely to introduce significant costs, create barriers to entry, and reduce the turnover rate of market leaders. Consequently, firms (industries) with more costly regulations tend to have higher excess returns and risk-adjusted returns, as market leaders in such industries often secure their positions with longer durations.[37]

This subsection offers important insights into the literature on regulations, discount rates, and competition. Existing evidence highlights barriers to entry and increased concentration as externalities of regulations, resulting in fewer market entrants and participants, as well as reduced market leadership turnover. This additionally suggests that incumbents in such markets tend to secure their positions with longer durations. Dou, Ji, and Wu (2021) provide evidence of the relationship between market leadership turnover and exposure to discount-rate fluctuations. Specifically, they find that firms' profit margins in industries with lower turnover rate are highly exposed to discount-rate risk. Additionally, they show that, once they control for leadership turnover spread, the gross-profitability premium becomes insignificant. Building on Dou, Ji, and Wu (2021), Dou, Ji, and Wu (2022) show that the market leadership turnover rate and the cash flow loading on expected growth jointly determine exposure to fluctuations in discount rate and expected growth, where market turnover induces discount-rate risk exposure.

Our paper adds to the literature by showing that regulatory operating leverage contributes to exposure to systematic risks. More specifically, this subsection shows that discount-rate risk affects the risk premium across stocks with varying ROL measures. Given that market leadership turnover is a crucial factor in exposure to discount rate fluctuations, this study provides consistent explanations. As the ROL premium disappears in industries with high market leadership turnover, it remains significant in industries characterized by low leadership turnover. This suggests that firms (industries) with costly regulations generate higher returns in industries where market leaders secure their positions for longer durations. This subsection provides additional evidence that market leadership turnover is an important factor in the cross-sectional pricing of ROL.

3.9 Robustness check: Alternative regulatory operating leverage measures

This subsection introduces two alternative regulatory operating leverage measures and examines whether the cross-sectional relation between regulatory operating leverage and subsequent stock returns is robust to various specifications. Novy-Marx (2011) introduces an operating leverage measure that scales annual operating costs by assets (Compustat item AT), whereas Chen, Harford, and Kamara (2019) quantify operating leverage as selling, general, and administrative expenses (Compustat item SG&A) divided by assets. Similarly, we construct a regulatory operating leverage measure that scales regulatory fixed costs by quarterly-varying assets:

[37] Following Dou, Ji, and Wu (2022), we analyze the robustness of our results by testing the cross-sectional pricing implications of ROL, focusing on the top four firms (ranked by sales) in each industry. Table A4 of the Internet Appendix reports value-weighted returns generated by ROL-sorted quintile portfolios within the subgroup of top firms. The excess return, α_{CAPM}, and α_{FF} spreads between the extreme quintiles are 0.94%, 0.96%, and 0.60% per month, respectively. This reinforces the notion that the ROL premium is prominent within the group of market leaders, thus demonstrating that our results are not driven by small followers.

$$ROL_{i,t} = \frac{beta_{i,res} * \log(res)_{i,t}}{AT_{i,t}}. \tag{4}$$

Additionally, we create a regulatory operating leverage defined as fixed regulatory cots divided by quarterly operating costs (COGS+SG&A).

$$ROL_{i,t} = \frac{beta_{i,res} * \log(res)_{i,t}}{COGS_{i,t} + SGA_{i,t}} \tag{5}$$

Table 15 presents the univariate equal-weighted and value-weighted average excess monthly returns and five-factor alphas (α_{FF5}) of quintile portfolios that are formed by sorting stocks based on the alternative regulatory operating leverage (ROL) measures, which are estimated by Equations (4) and (5).

The results suggest that the cross-sectional predictive power of ROL on 1-month-ahead returns is robust to alternative ROL specifications. A zero-cost high-low equal (value)-weighted ROL strategy, in which ROL is generated through Equation (4), produces 67 (77) basis points monthly excess return and 73 (85) basis points α_{FF5} per month. Similarly, a zero-cost equal (value)-weighted ROL strategy, where ROL is estimated through Equation (5), generates 65 (52) basis points α_{FF5} per month with a Newey-West-adjusted *t*-statistic of 7.12 (3.92).

3.10 Robustness check: Rolling window estimation

So far, the cross-sectional relation between ROL and subsequent stock returns is tested where ROL is estimated through firm-specific time-series regressions where a constant regulatory cost beta is estimated for each firm in the sample. As a robustness test, this subsection estimates firm-specific quarterly-varying regulatory operating leverage measure using a 60-quarter fixed window estimation.[38] Regulatory operating leverage is defined as fixed regulatory costs that are attributable to regulations over SG&A expenses. Table 16 reports value-weighted excess returns and three sets of alphas (α_{FF}, α_{FFCPS}, and α_Q) generated by industry controlled ROL-sorted quintile portfolios.

The first column of Table 16 reports that stocks in the lowest ROL quintile (portfolio 1) have a monthly value-weighted average excess return of 58 basis points. On the other hand, stocks in the highest ROL quintile (portfolio 5) produce 125 basis point value-weighted excess return per month. As a result, the average return difference between the extreme ROL quintiles is 0.67% per month with a Newey-West-adjusted *t*-statistic of 2.65. When tested against common risk factors, the risk-adjusted return spread between quintile 5 and quintile 1 varies between 42 basis points and 56 basis points per month. More specifically, a zero-cost high-low value-weighted strategy produces 42 basis points α_{FF5}, 44 basis points α_{FFCPS}, and 56 basis points α_Q per month, where the *t*-statistics vary between 1.95 and 2.47.

[38] Because of the nature of rolling window regressions, the results span the period from April 2006 to December 2021.

Table 15
Robustness test: Alternative regulatory operating leverage measures

	ROL= β_{res}* log(res)/(COGS+SG&A)				ROL= β_{res}* log(res)/(AT)			
	EW		VW		EW		VW	
Quintile	RET-RF	α_{FF}	RET-RF	α_{FF}	RET-RF	α_{FF}	RET-RF	α_{FF}
Low ROL	0.72	− 0.11	0.70	− 0.09	0.74	− 0.14	0.72	− 0.10
	(2.27)	(-1.11)	(3.60)	(-1.08)	(2.21)	(-1.28)	(3.66)	(-1.20)
2	0.78	− 0.21	0.60	− 0.22	0.61	− 0.15	0.51	− 0.24
	(2.30)	(-1.88)	(2.72)	(-2.65)	(2.16)	(-1.62)	(2.16)	(-2.78)
3	0.93	− 0.01	0.81	− 0.01	0.89	− 0.02	0.69	− 0.10
	(2.85)	(-0.16)	(2.96)	(-0.09)	(2.98)	(-0.27)	(2.84)	(-1.46)
4	1.07	0.25	0.87	0.12	1.13	0.15	1.02	0.15
	(3.48)	(3.24)	(3.13)	(1.15)	(3.38)	(1.67)	(3.75)	(1.39)
High ROL	1.31	0.53	1.25	0.43	1.41	0.59	1.50	0.72
	(4.38)	(4.76)	(4.82)	(4.12)	(3.98)	(5.25)	(5.25)	(6.33)
High-Low	0.59	0.65	0.54	0.52	0.67	0.73	0.77	0.85
difference	(6.29)	(7.12)	(3.47)	(3.92)	(6.03)	(8.33)	(4.04)	(5.56)

This table constructs two alternative measures of regulatory operating leverage measures. The first measure the fixed regulatory costs over a firm's total cost structure (COGS+SG&A). The second measure is quantified as fixed costs that are attributable to the regulations over a firm's asset value. Quintile portfolios are constructed by sorting stocks based on their regulatory operating leverage measures during the previous quarter. Quintile portfolio 1 (5) consists of stocks with the lowest (highest) ROL. The table presents average equal-weighted (EW) and value-weighted (VW) excess returns (RET-RF) and five-factor alphas (α_{FF5}). The last row presents the differences in average monthly returns and alphas between quintile portfolios 5 (High) and 1 (Low). Newey-West (1987) adjusted *t*-statistics are reported in parentheses.

Table 16
Robustness test: Rolling window estimation

	VALUE-WEIGHTED			
Quintile	RET-RF	α_{FF5}	α_{FFCPS}	α_{Q}
Low ROL	0.58	− 0.22	− 0.23	− 0.30
	(1.70)	(− 2.43)	(− 2.49)	(− 2.54)
2	0.85	0.02	0.02	0.01
	(2.69)	(0.43)	(0.38)	(0.10)
3	0.92	0.07	0.07	0.07
	(3.02)	(0.77)	(0.78)	(0.72)
4	1.00	0.02	0.02	0.05
	(2.81)	(0.20)	(0.23)	(0.52)
High ROL	1.25	0.20	0.21	0.26
	(3.13)	(1.19)	(1.20)	(1.68)
High-Low	0.67	0.42	0.44	0.56
difference	(2.65)	(1.95)	(1.96)	(2.47)

This table estimates firm-level time-varying regulatory operating leverage (ROL) through rolling regressions of individual stocks' quarterly SG&A expenses on the natural logarithm of regulatory restrictions and quarterly sales using a 60-quarter fixed window estimation. Then, we construct NAICS-2-level industry controlled ROL-sorted quintile portfolios. Quintile portfolio 1 (5) consists of stocks with the lowest (highest) ROL. The table presents average value-weighted excess returns (RET-RF) and three sets of alphas (α_{FF}, α_{FFCPS}, and α_{Q}). The last row presents the differences in average monthly returns and alphas between quintile portfolios 5 (High) and 1 (Low). Newey-West (1987) adjusted *t*-statistics are reported in parentheses.

4. Conclusion

A significant portion of regulatory compliance costs are fixed, such as information costs, reporting, and recordkeeping, and they are mostly included in the SG&A expenses. Building on this idea, we first show that federal-level regulations indeed impose significant costs on firms' cost structure. Subsequently, we investigate the impact of regulatory costs in the cross-section of stock returns.

To do so, we introduce a firm-specific quarterly-varying measure, regulatory operating leverage, that captures a firm's exposure to fixed regulatory costs. We show that regulatory operating leverage predicts returns in the cross-section and that strategies formed by sorting on regulatory operating leverage earn significant excess returns. After controlling for a battery of firm-specific characteristics and risk factors, the relationship between ROL and future stock returns remains economically and statistically significant. Furthermore, the cross-sectional relation between ROL and stock returns is robust to controls for operating margin, operating leverage, labor leverage, and labor share. Additionally, we show that the effect of ROL on future returns is prominent in all liquidity, institutional holdings, and analyst coverage tiers.

To provide further insights into the pricing of regulatory operating leverage and its relation to stock returns, we conduct a regression analysis of cash flow volatility on regulatory operating leverage. The results indicate a statistically significant relation between the two variables, particularly during recessionary periods where the association is even stronger. This finding supports the idea that the impact of ROL on returns is due to the (systematic) risk contribution of fixed regulatory costs. To better understand the systematic shocks that contribute to this relation, we introduce interaction terms between ROL and innovations in macroeconomic state variables, such as the Chicago Fed National Economic Activity Index and industrial production growth. Our findings demonstrate a stronger relationship between ROL and cash flow volatility during periods of decreasing economic activity. Hence, the CFNAI and industrial production are important state variables that contribute to the systematic risk exposure of stocks with high ROL. We additionally find that the relation between ROL and cash flow volatility to be more pronounced among small-cap firms as they lack economies of scale.

Adding to the systematic risk explanations, we provide evidence of the importance of exposure to the discount-rate shocks of ROL-sorted portfolios. Specifically, we find that firms with higher ROL are more exposed to discount-rate shocks. Then, built on the recent literature on discount rates and competition, we provide market turnover based explanations to the observed ROL premium. As discount rate shocks affect market leadership turnover and market concentration, they are likely to play an important role in the cross-sectional pricing of ROL. To test this, we divide our sample into subgroups based on the market leadership turnover indicator. The economic and statistical significance between extreme ROL portfolios diminishes within the subgroup with high market leadership turnover. This contributes to the idea that incumbents in industries with reduced leadership turnover tend to secure their position for longer durations, hence, their cash flows are more exposed to discount rate shocks. As a result, firms (industries) with more costly regulations tend to have higher (risk-adjusted) excess returns, as incumbents in these industries often secure their positions for longer durations. Additionally, the stock characteristics (Table 7) show an increasing pattern in operating margin moving from the lowest to the highest ROL quintile. This might indicate that incumbent firms operating in industries with costly regulations tend to secure their positions for longer durations. As a result, such firms might generate higher profitability and be more exposed to discount rate shocks. Future research on the relation between regulations, competition (barriers to entry), and profitability might provide important insights on the importance of regulatory costs on leadership turnover and gross profitability premiums.

5. Code Availability Statement

The replication code is available in the Harvard Dataverse at https://doi.org/10.7910/DVN/CF7LBA.

References

Al-Ubaydli, O., and P. McLaughlin. 2017. RegData: A numerical database on industry-specific regulations for all U.S. industries and federal regulations, 1997-2012. *Regulation and Governance* 11:109–23.

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

Ang, A., R. Hodrick, Y. Xing, and X. Zhang. 2006. The cross-section of volatility and expected returns. *Journal of Finance* 61:259–99.

Bali, T. G., N. Cakici, and R. Whitelaw. 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics* 99:427–46.

Bandiera, O., G. Caprio, P. Honohan, and F. Schiantarelli. 2000. Does financial reform raise or reduce saving? *Review of Economics and Statistics* 82:239–63.

Bradford, C. S. 2004. Does size matter? An economic analysis of small business exemptions from regulation. *Journal of Small and Emerging Business Law* 8:1–37.

Bustamante, M. C., and F. Zucchi. 2023. Innovation, industry equilibrium, and discount rates. Working Paper, University of Maryland.

Calcagno, P. T., and R. S. Sobel. 2014. Regulatory costs on entrepreneurship and establishment employment size. *Small Business Economics* 42:541–59.

Campbell, J. Y., and R. J. Shiller. 1988. Stock prices, earnings, and expected dividends. *Journal of Finance* 43:661–76.

———. 1998. Valuation ratios and the long-run stock market outlook. *Journal of Portfolio Management* 24:11–26.

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

Carlson, M., A. Fisher, and R. Giammmarino. 2004. Corporate investment and asset price dynamics: Implications for the cross section of returns. *Journal of Finance* 59:2577–603.

Chen, Z., J. Harford, and A. Kamara. 2019. Operating leverage, profitability, and capital structure. *Journal of Financial and Quantitative Analysis* 54:369–92.

Coffey, B., P. McLaughlin, and P. Peretto. 2020. The cumulative cost of regulations. *Review of Economic Dynamics* 38:1–21.

Cohen, R. B., C. Polk, and T. Vuolteenaho. 2003. The value spread. *Journal of Finance* 58:609–42.

Cooper, I. 2006. Asset pricing implications of nonconvex adjustment costs and irreversibility of investment. *Journal of Finance* 61:139–70.

Crain, M., and N. Crain. 2014. The cost of federal regulation to the U.S. economy, manufacturing, and small business. *A Report for the National Association of Manufacturers* 35:1–25.

Daniel, K., D. Hirshleifer, and L. Sun. 2020. Short- and long-horizon behavioral factors. *Review of Financial Studies* 33:1673–736.

Danthine, J., and J. B. Donaldson. 2002. Labour relations and asset returns. *Review of Economic Studies* 69:41–64.

Dawson, J. W., and J. J. Seater. 2013. Federal regulation and aggregate economic growth. *Journal of Economic Growth* 18:137–77.

Djankov, S., R. LaPorta, F. Lopez-de-Silanes, and A. Shleifer. 2002. The regulation of entry. *Quarterly Journal of Economics* 117:1–37.

Donangelo, A., F. Gourio, M. Kehrig, and M. Palacios. 2019. The cross-section of labor leverage and equity returns. *Journal of Financial Economics* 132:497–518.

Dou, W. W., Y. Ji, D. Reibstein, W. Wu. 2021. Inalienable customer capital, corporate liquidity, and stock returns. *Journal of Finance* 76:211–65.

Dou, W. W., Y., Ji, and W. Wu. 2021. Competition, profitability, and discount rates. *Journal of Financial Economics* 140:582–620.

———. 2022. The oligopoly Lucas tree. *Review of Financial Studies* 35:3867–921.

Fama, E. F., and J. D. Macbeth. 1973. Risk, return, and equilibrium: empirical tests. *Journal of Political Economy* 81:607–36.

Fama, E. F., and K. R. French. 1992. The cross-section of expected stock returns. *Journal of Finance* 46:427–66.

———. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33:3–56.

———. 2008. Dissecting anomalies. *Journal of Finance* 63:1653–78.

———. 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116:1–22.

Favilukis, J., X. Lin, and X. Zhao. 2020. The elephant in the room: The impact of labor obligations on credit markets. *American Economic Review* 110:1673–712.

Goff, B. 1996. *Regulation and macroeconomic performance*. Boston: Kluwer.

Hahn, R. W., and J. A. Hird. 1991. The costs and benefits of regulation: review and synthesis. *Yale Journal on Regulation* 8:233–78.

Hou, K., C. Xue, and L. Zhang. 2015. Digesting anomalies: an investment approach. *Review of Financial Studies* 28:650–705.

Ince, B. Forthcoming. How do regulatory costs affect M&A decisions and outcomes? *Journal of Banking and Finance*.

Jegadeesh, N. 1990. Evidence of predictable behavior of security returns. *Journal of Finance* 45:881–98.

Jegadeesh, N., and S. Titman. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance* 48:65–91.

Kao, C. 1999. Spurious regression and residual-based tests for cointegration in panel data. *Journal of Econometrics*, 90:1–44.

Kelly, B., L. Pastor, and P. Veronesi. 2016. The price of political uncertainty: theory and evidence from the option market. *Journal of Finance* 71:2417–80.

Klapper, L., L. Laeven, and R. Rajan. 2006. Entry regulation as a barrier to entrepreneurship. *Journal of Financial Economics* 82:591–629.

Lev, B. 1974. On the association between operating leverage and risk. *Journal of Financial and Quantitative Analysis* 9:627–41.

Newey, W. K., and K. D. West. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55:703–708.

Nicoletti, G., and S. Scarpetta. 2003. Regulation, productivity and growth: OECD evidence. *Economic Policy* 18:9–72.

Noreen, E., and N. Soderstrom. 1994. Are overhead costs strictly proportional to activity?: evidence from hospital departments. *Journal of Accounting and Economics* 17:255–78.

Novy-Marx, R. 2011. Operating leverage. *Review of Finance* 15:103–34.

Pastor, L., and P. Veronesi. 2012. Uncertainty about government policy and stock prices. *Journal of Finance* 67:1219–64.

———. 2013. Political uncertainty and risk premia. *Journal of Financial Economics* 110:520–45.

———. 2020. Political cycles and stock returns. *Journal of Political Economy* 128:4011–45.

Pastor, L., and R. F. Stambaugh. 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111:642–85.

Rosett, J. G. 2001. Equity risk and the labor stock: the case of union contracts. *Journal of Accounting Research*, 39:337-64.

Singla, S. 2022. Regulatory costs and market power. Working Paper, London Business School.

Stambaugh, R. F., and Y. Yuan. 2017. Mispricing factors. *Review of Financial Studies* 30:1270–315.

Suzuki, J. 2013. Land use regulation as a barrier to entry: Evidence from the Texas lodging industry. *International Economic Review* 54:495–23.

Zhang, L. 2005. The value premium. *Journal of Finance* 60:67–103.