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Industry regulation and the comovement of stock returns

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ABSTRACT

Existing research highlights that observed levels of comovement among the returns of stocks exceed the levels predicted by theory. We develop and test the hypothesis that the degree of regulation in a particular industry can explain, at least in part, the comovement observed in the data. We find that stocks within industries that are most heavily regulated tend to exhibit the greatest levels of comovement. In a series of difference-in-differences tests, we examine comovement surrounding exogenous implementations of new regulations. Our results show that new regulatory environments for particular industries disproportionately influence the comovement of stocks in those industries.

1. Introduction

The theory of efficient markets suggests that prices of individual stocks should move as relevant information becomes publicly available (Fama, 1970). As information that affects multiple stocks is revealed, prices for all the affected stocks should move and adjust simultaneously to that new information. For example, industry-specific news affects the stock prices of all the firms in that industry in a correlated way. However, Shiller (1989) and Shiller and Beltratti (1992) suggest that the observed levels of comovement in asset prices exceed the levels predicted by the theory of efficient markets. Comovement can be caused by a variety of factors.[1] For instance, Pindyck and Rotemberg (1993) indicate that the prices of different stocks can move together in response to common movements in earnings, changes in firm-level fundamentals, or changes in macroeconomic variables. Barberis et al. (2005) find that comovement among asset prices stems from either market frictions or changes in investor sentiment.

While the market frictions described in Barberis et al. (2005) include trading costs and information asymmetries, perhaps another important friction that might affect the comovement of stocks is regulation. In this paper, we develop and test the hypothesis that regulation increases the comovement of stock returns. The amount of regulatory oversight varies dramatically across industries. At one extreme, utilities face regulation across many aspects of their business and must rely on regulators to approve changes in pricing, the construction of new facilities, and the raising of capital. At the other end of the spectrum, many technology firms have historically faced little or no regulatory oversight. At a minimum, the constraints faced by firms in heavily regulated industries could cause operational frictions that result in correlated cash flows, which would increase the comovement of stocks within that industry. Even if the regulation does not directly affect the individual cash flows, the fact that all firms in the industry face similar regulatory frictions might cause stocks in that industry to incorporate information similarly. If regulation causes expenses to be higher for given stock within a particular sector, rational investors might assume that other stocks in that same industry will face

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[1] Several studies examine comovement across domestic and foreign markets and across various asset classes. See, for example, Kaplanis (1988), Morck et al. (2000), Jang and Sul (2002), Johnson and Soenen (2002, 2003), Brooks and Del Negro (2004), Engsted and Tanggaard (2004), Brooks and Negro (2006), Pirinsky and Wang (2006), Connolly et al. (2007), Greenwood (2008), Albuquerque and Vega (2009), Kallberg and Pasquariello (2008), Green and Hwang (2009), Kizys and Pierdzioch (2009), Rua and Nunes (2009), Norden and Weber (2009), Lucey and Zhang (2010), Beine and Candelon (2011), Boyer (2011), Baker and Wurgler (2012), Lin (2012), Wahal and Yavuz (2013), Anton and Polk (2014), Buraschi et al. (2014), Muslu et al. (2014), and Hameed et al. (2015).

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that same challenge, even if it turns out to be false. Additionally, regulatory uncertainty can act as a friction that can make it more difficult for investors to estimate future fundamentals. To the extent that regulation makes information acquisition costlier or opaquer, information revealed about one stock could be extrapolated to other stocks, which would result in more comovement in their prices.

To assess our research question, we use three different proxies for stock price comovement. First, we estimate an industry-level R-squared (see e.g., Croux et al., 2001; Jin and Myers, 2006) from time-series regressions of single factor models in which the only factor is a value-weighted industry factor. Second, we use average pairwise correlations between each stock in each industry (see e.g., Longin and Solnik, 2001; Ang and Chen, 2002; Bae et al., 2003; Hong et al., 2007). Third, we introduce a novel measure of comovement, which we denote as beta dispersion that is calculated by estimating the difference between a firm's value-weighted industry beta and the average industry beta. Firms with betas closer to the average industry beta have more comovement.

We begin by examining whether any time-series correlation exists between regulation and stock return comovement. We obtain the number of economically significant federal regulations by year from the Regulatory Studies Center. We find that the returns of stocks tend to comove more during years with a greater number of passed regulations. In fact, after controlling for firm- and industry-specific factors, we find that stock return comovement increases – depending on the measure of comovement – between 5.44 and 7.04 percentage points more during years with 70 or more regulations, relative to other years.

Next, we examine if stock return comovement varies within the cross-section. From the RegData Industry Regulation Index[2] (RegData IRI), we identify the top five most heavily regulated industries, i.e., oil, utilities, automobile, banking, and airline. We find that firms within these industries experience much greater comovement in their stock returns than other firms. For example, in our multivariate regressions that hold constant other firm- and industry-specific characteristics, we find that the average comovement in the stock return of firms in the most regulated industries is – depending on the proxy of comovement – between 2.50 and 5.77 percentage points higher than other firms.

To more cleanly examine the relation between regulation and comovement, we set up our final set of tests in a difference-in-differences (DID) framework. More specifically, we attempt to determine whether new regulation that affects a particular industry increases the level of comovement of stocks within that industry. We identify treatment firms as those belonging to the top five most heavily regulated industries according to the RegData IRI, and control firms from all other industries not included in the top five. We examine several different regulatory changes that impacted specific industries. We generally find that shocks to the level of regulation in a particular sector cause higher stock return comovement for treatment firms vis-à-vis control firms.

These findings have important practical implications. For instance, to the extent that comovement represents fundamental changes in stock values, the increased comovement induced by regulation highlights the notion that regulation is becoming a more important factor in determining the fundamental value of assets. Alternatively, if comovement is primarily driven by investor sentiment, then the observed increase in comovement suggests that regulation significantly impacts the level of sentiment. Perhaps a fruitful avenue for future research might be to examine how regulation and investor sentiment interact to affect financial markets.

Outside of the practical implications, our study also contributes to the existing literature by highlighting how regulation influences investors' ability to value firms. While existing studies (see e.g., Pindyck and Rotemberg, 1993; Barberis et al., 2005) indicate that comovement is affected by the flow of industry-specific news, responses to common movements in earnings, changes to firm-level and macroeconomic fundamentals, and market frictions, our results suggest that regulation also plays an important role. Our study also contributes to the literature on frictions that impact market efficiency (see e.g., Rösch et al., 2017). As markets continue to evolve in response to new technologies and regulatory changes, it is important to understand the impact on prices and valuations. Comovement and its relationship to regulation is an example of this ever-changing dynamic between markets and governments.

2. Data

The data used in the empirical analysis come from several sources. From the Center for Research in Security Prices (CRSP), we obtain, for the universe of stocks between 1980 and 2021, daily closing prices, open and high prices, close-to-close returns, shares outstanding, and share volume. From the Regulatory Studies Center (RSC), we obtain the number of economically significant regulations issued by executive branch agencies.[3] From RegData Industry Regulation Index (IRI), which is a numerical database on industry-specific regulations for all U.S. industries, we identify the five most federally regulated sectors, i.e., oil, utilities, automobile, banking, and airline.[4] Since the purpose of the paper is to examine the role of regulation as a broader market friction that could influence the comovement of stock returns, we separate securities into those that are highly regulated (treatment) and those that are not (control). We utilize the standard industrial classification codes (SIC) reported in CRSP to categorize stocks into industries. We exclude stocks with prices less than $5 and winsorize all variables, defined in the following subsection, at the 99th and 1st percentile levels.

[2] The RegData Industry Regulation Index is a database compiled by The Mercatus Center and George Mason University that quantifies federal regulation. The database analyzes the text of federal regulations to create novel and objective measures of the accumulation of regulations in the economy overall and across different industries in the United States. A more detailed description of the data can be found at https://www.mercatus.org/research/working-papers/regdata with datasets located at https://www.reghub.ai/data/bulk.

[3] The definition of economic significance comes from the Executive Order 12 866, which reads "have an annual effect on the economy of $100 million or more or adversely affect in a material way the economy, a sector of the economy, productivity, competition, jobs, the environment, public health or safety, or State, local, or tribal governments or communities". These data are available from the George Washington Regulatory Studies Center in the Columbian College of Arts & Sciences at https://regulatorystudies.columbian.gwu.edu/reg-stats.

[4] The regulation data come from the Mercatus Center RegData database available at https://www.mercatus.org/research/working-papers/regdata.

2.1. Empirical measures

To measure comovement in the prices of stocks within a particular industry, we employ the following three methods. First, we follow existing literature (see e.g., Jin and Myers, 2006) and estimate comovement by stock-year as the R-squared values (R^2_*Ind*) from the following regression equation:

$$Ret_{i,j,t} = \alpha + \beta_1 VWRet_{j,t} + \varepsilon_{i,j,t}, \tag{1}$$

where the dependent variable is the Wednesday-to-Wednesday return for stock *i* during week *t* and the independent variable is the Wednesday-to-Wednesday value-weighted return across stocks in industry *j*. The higher (lower) this measure, the greater (lesser) the comovement among stock returns in a particular industry.

Second, we follow extant research (see e.g., Longin and Solnik, 2001; Ang and Chen, 2002; Bae et al., 2003; Hong et al., 2007) and measure comovement by stock-year as the average pairwise correlation coefficient between stock *i* and stock *j* in each industry (*PW_Corr*). The correlations are produced using weekly Wednesday-to-Wednesday returns. The higher (lower) this measure, the greater (lesser) the comovement among stock returns in a given industry.

Lastly, we estimate comovement by stock-year using a new measure, which we denote as beta dispersion (β_Disp). Specifically, we estimate Eq. (1) for each stock during each year and then take the absolute difference between a firm's estimated beta and the average industry beta. This latter measure inversely captures the level of comovement between a particular stock and its industry. Therefore, when stocks in a particular industry have low beta dispersion, we can infer that the particular industry generally has stocks with prices that move together, such that individual betas are closely clustered around the average industry beta. In contrast, when stocks in a particular industry have high beta dispersion, the industry does not have stocks that move closely together.

The following variables are used as controls throughout the analysis, which are estimated at the daily level by stock and averaged over the year. *Size* is the average daily market capitalization, or closing price times shares outstanding. *Price* is the average daily closing price. *Turn* is the average daily share turnover or the ratio of trade volume to shares outstanding. *Illiq* is the average daily (Amihud, 2002) illiquidity or the absolute daily return to dollar volume scaled by 10^6. Volatility is the average daily range-based volatility measure of Alizadeh et al. (2002), or the log of the daily high price minus the log of the daily low price. NYSE is an indicator variable equal to one if the stock is listed on the New York Stock Exchange (NYSE) and zero otherwise. *Industry_Size* is the market cap of all firms within an industry each year. *Industry_#Firms* is the total number of firms in each industry in each year. *Industry_Volt* is the standard deviation of daily returns for each stock in each industry by year.

2.2. Summary statistics

In Table 1, we report summary statistics that describe the data. For all observations, the average R^2_*Ind* is 0.1948 with a standard deviation of 0.1922. The average R^2_*Ind* is 0.3004 for oil stocks, 0.2919 for utilities, 0.2476 for the automobile industry, 0.1712 for banks, and 0.2776 for airlines. Similarly, we find that the average *PW_Corr* for all observations is 0.1538 with a standard deviation of 0.1290. The average *PW_Corr* is 0.2410 for oil stocks, 0.2131 for utilities, 0.2221 for automobiles, 0.1383 for banks, and 0.2217 for airlines. Furthermore, we show that the average β_Disp across all observations is 0.4456 with a standard deviation of 0.3909. The average β_Disp is 0.5107 for oil stocks, 0.3511 for utilities, 0.3388 for automobile stocks, 0.3845 for banks, and 0.3564 for airlines. Hence, it seems that the R^2_*Ind* and *PW_Corr* are generally higher than average, and the beta dispersion is lower than average, for stocks in more regulated industries.

The average stock in the sample has a market capitalization of $2.4398 billion and a share price of $26.30. The average daily share turnover for a stock in the sample is 0.59%, with a standard deviation of 0.66%. The average daily illiquidity for a stock in the sample is 0.0093, with a standard deviation of 0.0276. The average stock-day volatility is 3.72%, with a standard deviation of 2.76%. We also show that 35.92% of the sample stocks are listed on the NYSE and 47.98% are listed on the NASDAQ.

In Table 2 we report a Pearson correlation matrix for the stock-specific variables used throughout the analysis. A few results are noteworthy. We find a strong positive correlation of 0.7018 between R^2_*Ind* and *PW_Corr*, which is expected given that both measures positively capture the level of comovement of stocks within a particular industry. We find a slight positive correlation of 0.0694 between R^2_*Ind* and β_Disp, but a negative correlation of −0.1089 between *PW_Corr* and β_Disp. The latter correlation is more expected given that β_Disp inversely measures the level of comovement of stocks within a given industry. We also find positive correlations between R^2_*Ind* and *Size*, *Price*, and *Turn*. We also show strong negative correlations between R^2_*Ind* and both *Illiq* and *Volatility*. Similar correlations are documented between *PW_Corr* and *Size*, *Price*, *Turn*, *Illiq*, and *Volatility*. When focusing on the cross-correlations between β_Disp, we find positive correlation coefficients for *Price*, *Turn*, *Illiq*, and *Volatility* but a negative correlation for *Size*.

3. Empirical results

3.1. Regulation and comovement: Time series variation

In this subsection, we empirically examine how regulation might impact comovement over time. We begin by documenting how average comovement and regulation correlate across years. In particular, in Fig. 1 we show the time-series averages for each measure of comovement and the number of new regulatory rules that were introduced in the U.S. during a particular year. The figure shows that in 2020, approximately 140 new rules were introduced. Nearly 110 new rules were introduced in 2016, which is

Table 1
Summary statistics.

	All Observations		Oil		Utilities		Automobile		Banking		Airline	
	Mean [1]	Std. Dev. [2]	Mean [3]	Std. Dev. [4]	Mean [5]	Std. Dev. [6]	Mean [7]	Std. Dev. [8]	Mean [9]	Std. Dev [10]	Mean [11]	Std. Dev. [12]
R^2_Ind	0.1948	0.1922	0.3004	0.2374	0.2919	0.2217	0.2476	0.2102	0.1712	0.2027	0.2776	0.2428
PW_Corr	0.1538	0.1290	0.2410	0.1595	0.2131	0.1345	0.2221	0.1490	0.1383	0.1435	0.2217	0.1553
β_Disp	0.4456	0.3909	0.5107	0.4348	0.3511	0.2938	0.3388	0.2904	0.3845	0.3281	0.3564	0.3012
Size	2.4398	7.6356	3.8824	9.7617	3.4076	6.9012	2.8510	7.7262	1.5459	6.4466	6.2560	13.9050
Price	26.30	25.33	26.03	23.26	30.11	17.93	28.27	23.65	22.72	18.65	40.84	34.72
Turn	0.0059	0.0066	0.0070	0.0076	0.0032	0.0033	0.0056	0.0055	0.0031	0.0039	0.0047	0.0046
Illiq	0.0093	0.0276	0.0063	0.0232	0.0025	0.0105	0.0046	0.0166	0.0215	0.0431	0.0058	0.0221
Volatility	0.0372	0.0217	0.0382	0.0196	0.0212	0.0120	0.0321	0.0161	0.0325	0.0215	0.0294	0.0166
NYSE	0.3592	0.4798	0.5883	0.4922	0.7946	0.4040	0.6717	0.4697	0.1542	0.3612	0.6586	0.4745

The table reports statistics that describe the sample. *R^2_Ind* is the R-squared from the weekly market model over a stock-year where the independent variable is the value-weighted industry return. *PW_Corr* is the average pairwise correlation coefficient between stock *i* and stock *j* in each industry in each year, where correlation is estimated using weekly returns. *β_Disp* is the absolute value of the difference between the industry beta for a particular stock and the mean industry beta in each year using weekly returns. *Size* is the average daily market capitalization in $billions on the last day of each year. *Price* is the average daily closing share price on the last trading day of each year. The following three variables are measured at the daily level by stock and then averaged over the year. *Turn* is the average daily share turnover or the ratio of trade volume to shares outstanding. *Illiq* is the average daily measure of Amihud's (2002) illiquidity or the ratio of the absolute value of daily returns scaled by daily dollar volume. *Volatility* is the average daily difference between the natural log of the daily high price and the natural log of the daily low price. *NYSE* is an indicator variable that is equal to one if a particular stock is listed on the NYSE and zero otherwise.

Table 2
Correlation matrix.

	R^2_Ind [1]	*PW_Corr* [2]	*β_Disp* [3]	*Size* [4]	*Price* [5]	*Turn* [6]	*Illiq* [7]	*Volatility* [8]
R^2_Ind	1.0000	0.7018	0.0694	0.4009	0.3418	0.1979	−0.2496	−0.1622
PW_Corr		1.0000	−0.1089	0.2245	0.2565	0.2410	−0.2468	−0.0827
β_Disp			1.0000	−0.0395	−0.0794	0.1919	0.0576	0.2316
Size				1.0000	0.4995	0.0844	−0.1048	−0.1546
Price					1.0000	0.1103	−0.1873	−0.2650
Turn						1.0000	−0.2129	0.3010
Illiq							1.0000	0.2351
Volatility								1.0000

The table reports the Pearson correlation matrix for the variables used in the sample. *R^2_Ind* is the R-squared from the weekly market model over a stock-year where the independent variable is the value-weighted industry return. *PW_Corr* is the average pairwise correlation coefficient between stock *i* and stock *j* in each industry in each year, where correlation is estimated using weekly returns. *β_Disp* is the absolute value of the difference between the industry beta for a particular stock and the mean industry beta in each year using weekly returns. *Size* is the average daily market capitalization in $billions on the last day of each year. *Price* is the average daily closing share price on the last trading day of each year. The following three variables are measured at the daily level by stock and then averaged over the year. *Turn* is the average daily share turnover or the ratio of trade volume to shares outstanding. *Illiq* is the average daily measure of Amihud's (2002) illiquidity or the ratio of the absolute value of daily returns scaled by daily dollar volume. *Volatility* is the average daily difference between the natural log of the daily high price and the natural log of the daily low price.

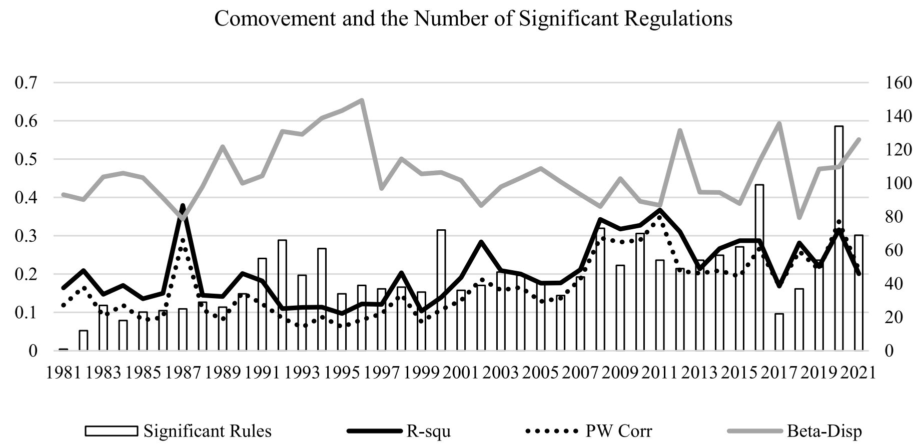

Fig. 1. The figure reports several measures of comovement *R^2_Ind*, *PW_Corr*, and *β_Disp* as well as the number of economically significant rules made each year according to the Regulatory Studies Center.

Table 3
Differences in comovement across years with more regulation and rules.

Dependent variable:	R^2_Ind		PW_Corr		β_Disp	
	[1]	[2]	[3]	[4]	[5]	[6]
70 + *Rules*	0.0843***	0.0544***	0.1049***	0.0704***	−0.0121***	−0.0425***
	(50.40)	(40.57)	(86.87)	(70.15)	(−3.71)	(−13.16)
Ln(Size)		0.0508***		0.0065***		0.0204***
		(48.93)		(11.00)		(11.26)
Ln(Price)		−0.0119***		−0.0036***		−0.0226***
		(−8.79)		(−3.91)		(−8.57)
Ln(Turn)		0.0100***		0.0114***		0.0451***
		(14.30)		(25.06)		(30.22)
Ln(Illiq)		−0.0082***		−0.0094***		0.0111***
		(−35.31)		(−53.85)		(17.75)
Volatility		0.3114***		0.0377*		4.3056***
		(12.02)		(1.94)		(49.16)
NYSE		0.0364***		0.0212***		0.0143***
		(16.80)		(15.04)		(3.77)
Ln(Industry_Size)		−0.0260***		0.0120***		−0.0210***
		(−37.00)		(26.15)		(−13.00)
Ln(Industry_#Firms)		0.0146***		−0.0248***		0.0448***
		(13.65)		(−36.35)		(17.80)
Ln(Industry_Volt)		−1.2325***		−0.5344***		−2.0786***
		(−21.38)		(−14.87)		(−15.24)
Constant	0.1863***	−0.1574***	0.1433***	−0.1486***	0.4468***	0.6811***
	(114.84)	(−8.71)	(187.37)	(−12.39)	(254.25)	(19.41)
Adj. R^2	0.0174	0.4096	0.0597	0.3165	0.0001	0.0768
N	156,397	156,397	156,397	156,397	156,397	156,397

The table reports the results from estimating the following equation on stock-year data:

$$Comovement_{i,t} = \alpha + \beta_1 70 + Rules_t + \beta_2 Ln(Size_{i,t}) + \beta_3 Ln(Price_{i,t}) + \beta_4 Ln(Turn_{i,t}) + \beta_5 Ln(Illiq_{i,t}) + \beta_6 Volatility_{i,t} + \beta_7 NYSE_{i,t} + \beta_8 Ln(Industry\_Size_{j,t}) + \beta_9 Ln(Num\_Firms_{j,t}) + \beta_{10} Ln(Industry\_Volt_{j,t}) + \varepsilon_{i,t},$$

where the dependent variable is set to one of three measures of comovement: R^2_Ind, *PW_Corr*, or β_Disp. R^2_Ind is the R-squared from the weekly market model over a stock-year where the independent variable is the value-weighted industry return. *PW_Corr* is the average pairwise correlation coefficient between stock *i* and stock *j* in each industry in each year, where correlation is estimated using weekly returns. β_Disp is the absolute value of the difference between the industry beta for a particular stock and the mean industry beta in each year using weekly returns. The independent variable of interest is the indicator variable, 70 + *Rules*, which equals one if a particular year in our sample period had 70 or more economically significant rules according to the RSC and zero otherwise. The control variables have previously been defined. We report *t*-statistics in parentheses obtained from robust standard errors clustered at the stock level. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

the second-highest number of rules introduced in a single year during our sample. It is also worth noting that regulation is often a one-way street. New regulations are introduced but old regulations are rarely repealed. Sometimes a new piece of regulation replaces or enhances an old regulation but it is rare for regulations to be removed without some sort of replacement. Thus, changes in the regulatory environment are quite persistent. Though difficult to see visually, there does appear to be an increase in comovement in some of the years with more regulatory rules. For instance, in 2008, approximately 70 new rules were introduced, and R^2_Ind and *PW_Corr* both increased, while β_Disp decreased. These results suggest that the comovement of stocks increased during that year. Similarly, there appears to be a slight increase in R^2_Ind and *PW_Corr* in 2000, 2010, and 2020 as well. However, much more needs to be done empirically before drawing any meaningful conclusions.

To better isolate the effects of new regulatory rules on the level of comovement, we estimate the following equation on stock-year observations:

$$\begin{aligned} Comovement_{i,t} &= \alpha + \beta_1 70 + Rules_t + \beta_2 Ln(Size_{i,t}) + \beta_3 Ln(Price_{i,t}) \\ &+ \beta_4 Ln(Turn_{i,t}) + \beta_5 Ln(Illiq_{i,t}) + \beta_6 Volatility_{i,t} + \beta_7 NYSE_{i,t} \\ &+ \beta_8 Ln(Industry\ Size_{j,t}) + \beta_9 Ln(Industry\_\#Firms_{j,t}) \\ &+ \beta_{10} Ln(Industry\ Volt_{j,t}) + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

where the dependent variable is one of three measures of comovement: R^2_Ind, *PW_Corr*, or β_Disp. The independent variable of interest is the indicator variable, *70+Rules*, which equals one if a particular year in our sample period had 70 or more economically significant new rules according to the RSC and zero otherwise.[5] The control variables have previously been defined. We report *t*-statistics in parentheses obtained from robust standard errors clustered at the stock level. We report the results of this analysis in Table 3.

In columns [1] and [2] of Table 3, we report the results of estimating Eq. (2) when R^2_Ind is the dependent variable. In column [1], we show the results from the model, which only includes our variable of interest and none of the control variables. Here we find

[5] There are five years with more than 70 new regulations according to the RSC: 2000, 2008, 2010, 2016, and 2020.

that R^2_*Ind* is 8.41 percentage points higher in years when there are at least 70 economically significant rules that are introduced, relative to other years during the sample period. In column [2] of Table 3, we find similar results when we control for other stock- and industry-specific variables. The coefficient on *70+Rules* is 0.0544, which suggests that during years with more rules introduced, R^2_*Ind* is 5.44 percentage points higher than normal. These findings suggest that the average comovement of stock returns is higher when more regulatory rules are introduced.

In columns [3] and [4] of Table 3, we display the results of estimating Eq. (2) when inserting *PW_Corr* as the left-hand-side variable. In Column [3], we find that the average *PW_Corr* is 10.49% higher in years when there is more regulation than in other years. Similarly, in column [4], after controlling for other stock-specific and industry-specific factors, we find that the average *PW_Corr* is 7.04 percentage points higher in years with more rules introduced, relative to other years. Again, these findings suggest a positive relation between stock comovement and regulation.

In columns [5] and [6] of Table 3, we show the results of estimating Eq. (2) when β_Disp is used as the dependent variable. We find that the coefficient on *70+Rules* is negative and significant in each specification. This is true whether or not we control for stock- and industry-specific characteristics. In column [6], for instance, we find that the average β_Disp is about 4.25 percentage points lower in years with more regulation compared to years with less regulation, other factors held constant.

Combined, the findings in this subsection highlight a strong time-series association between regulation and the comovement of stock returns. These results are consistent with our hypothesis that regulatory frictions might cause stocks to incorporate information similarly, perhaps because their cash flows or expenses have been affected in like manner.

3.2. Regulation and comovement: Highly regulated industries

Next, we examine whether the relation between regulation and comovement varies in the cross-section of stocks. More specifically, we analyze if stocks in heavily regulated industries exhibit greater comovement than stocks in less regulated industries. We use RegData IRI to categorize stocks into the top five federally regulated industries. To control for other factors that might influence the level of comovement among stock prices, we estimate specifications of the following regression equation on stock-year observations:

$$\begin{aligned} Comovement_{i,t} &= \alpha + \delta_t + \beta_1 Regulated_i + \beta_2 Ln(Size_{i,t}) + \beta_3 Ln(Price_{i,t}) \\ &+ \beta_4 Ln(Turn_{i,t}) + \beta_5 Ln(Illiq_{i,t}) + \beta_6 Volatility_{i,t} + \beta_7 NYSE_{i,t} \\ &+ \beta_8 Ln(Industry\_Size_{j,t}) + \beta_9 Ln(Industry\_\#Firms_{j,t}) \\ &+ \beta_{10} Ln(Industry\_Volt_{j,t}) + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

where the dependent variable is one of three measures of comovement: R^2_*Ind*, *PW_Corr*, or β_Disp. *Regulated* is a categorical variable equal to one if the stock belongs to one of the five most regulated industries according to the RegData IRI and zero otherwise. The control variables have previously been defined. To control for time-series variation in comovement, documented in the previous subsection, we include year fixed effects, δ_t. We report t-statistics in parentheses obtained from robust standard errors clustered at the stock level. The results of this analysis are reported in Table 4.

In the first two columns of Table 4, we report the results when R^2_*Ind* is the dependent variable in Eq. (3). In the restricted model in column [1], where only the year fixed effects and the variable *Regulated* are included on the left-hand side of the equation, we find that the coefficient on the categorical variable, *Regulated,* is 0.0299 and significant at the 0.01 level. This implies that holding constant only yearly trends, the average R^2_*Ind* for stocks in the most regulated industries is 2.99 percentage points higher than for stocks in industries that are not ranked in the top five in terms of regulatory burdens. In the full model specification in column [2], we find that the coefficient on the indicator variable, *Regulated,* is 0.0577, which is also significant at the 0.01 level. The results indicate that holding constant firm characteristics and time trends, the average R^2_*Ind* for stocks in the most regulated industries is 5.77 percentage points higher than for stocks in other industries.

In the third and fourth columns of Table 4, we show the results from estimating Eq. (3) when inserting *PW_Corr* as the dependent variable. In the restricted model in column [3], where only the year fixed effects and the variable *Regulated* are included as independent variables, we find that the average pairwise correlation is about 2.50 percentage points higher for stocks in more heavily regulated industries than stocks in other industries. In the full model specification in column [4], which holds constant other stock- and industry-specific factors, we find that the average pairwise correlation is 3.63 percentage points higher for stocks in the most regulated industries, relative to stocks in other industries.

In the final two columns of Table 4, we report the estimated coefficients from Eq. (3) when β_Disp is used as the dependent variable, which inversely captures the level of comovement. In the restricted model in column [5], where only the year fixed effects and the variable *Regulated* are included as explanatory variables, we show that the average beta dispersion for stocks in the most regulated industries is 5.88 percentage points lower than for stocks in less regulated industries, holding constant yearly trends. In the full model specification in column [6], we find that the average beta dispersion is 3.0 percentage points lower for stocks in the most regulated industries, relative to stocks in other industries.

Next, we examine the top five most regulated industries separately. Specifically, we re-estimate Eq. (3) for stocks in the oil, utilities, automobile, banking, and airline industries, each relative to stocks in industries not ranked in the top five according to RegData IRI. For brevity, we only report the estimated coefficients for the indicator variable *Regulated*. To avoid violating the full column rank assumption for consistent estimation, we do not include the industry variables, *Industry_Size*, *Industry_#Firms*, or *Industry_Volt*, in this analysis. Again, we report t-statistics in parentheses obtained from robust standard errors clustered at the stock level.

Table 4
Differences in comovement among most regulated industries.

Dependent variable:	R^2_Ind		PW_Corr		β_Disp	
	[1]	[2]	[3]	[4]	[5]	[6]
Regulated	0.0299***	0.0577***	0.0250***	0.0363***	−0.0588***	−0.0301***
	(6.31)	(23.36)	(10.89)	(23.93)	(−14.75)	(−6.90)
Ln(Size)		0.0527***		0.0090***		0.0202***
		(51.63)		(15.91)		(10.97)
Ln(Price)		−0.0072***		−0.0010		−0.0271***
		(−5.41)		(−1.16)		(−9.90)
Ln(Turn)		0.0145***		0.0148***		0.0451***
		(20.25)		(32.42)		(28.21)
Ln(Illiq)		−0.0067***		−0.0066***		0.0105***
		(−25.80)		(−33.81)		(14.83)
Volatility		0.3274***		−0.0173		4.3860***
		(12.51)		(−0.90)		(49.41)
NYSE		0.0283***		0.0181***		0.0187***
		(13.67)		(13.88)		(4.90)
Ln(Industry_Size)		−0.0207***		0.0123***		−0.0176***
		(−18.60)		(18.06)		(−7.94)
Ln(Industry_#Firms)		0.0103***		−0.0232***		0.0427***
		(8.11)		(−31.48)		(15.54)
Ln(Industry_Volt)		−0.9157***		−0.0915*		−2.3051***
		(−10.94)		(−1.81)		(−11.43)
Constant	0.1792***	−0.2659***	0.1534***	−0.1464***	0.3706***	0.6111***
	(70.89)	(−9.50)	(99.32)	(−8.62)	(74.62)	(12.49)
	0.1554	0.5170	0.3416	0.5038	0.0275	0.1011
Adj. R^2	156,397	156,397	156,397	156,397	156,397	156,397
Year FE	0.0299***	0.0577***	0.0250***	0.0363***	−0.0588***	−0.0301***
N	(6.31)	(23.36)	(10.89)	(23.93)	(−14.75)	(−6.90)

The table reports the results from estimating the following equation on stock-year data:

$$Comovement_{i,t} = \alpha + \delta_t + \beta_1 Regulated_i + \beta_2 Ln(Size_{i,t}) + \beta_3 Ln(Price_{i,t}) + \beta_4 Ln(Turn_{i,t}) + \beta_5 Ln(Illiq_{i,t}) + \beta_6 Volatility_{i,t} + \beta_7 NYSE_{i,t} + \beta_8 Ln(Industry\_Size_{j,t}) + \beta_9 Ln(Num\_Firms_{j,t}) + \beta_{10} Ln(Industry\_Volt_{j,t}) + \varepsilon_{i,t},$$

where the dependent variable is set to one of three measures of comovement: *R^2_Ind*, *PW_Corr*, or *β_Disp*. *R^2_Ind* is the R-squared from the weekly market model over a stock-year where the independent variable is the value-weighted industry return. *PW_Corr* is the average pairwise correlation coefficient between stock *i* and stock *j* in each industry in each year, where correlation is estimated using weekly returns. *β_Disp* is the absolute value of the difference between the industry beta for a particular stock and the mean industry beta in each year using weekly returns. The independent variable of interest is the indicator variable, *Regulated*, which equals one if a firm belongs to one of the five most regulated industries and zero otherwise. The control variables have previously been defined. We also include year fixed effects, δ_t, and report t-statistics in parentheses obtained from robust standard errors clustered at stock level. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

In Panel A of Table 5, we report the estimated coefficients from the modified Eq. (3) on the partitioned samples where the dependent variable is *R^2_Ind*. In all of the model specifications, we find that the coefficient on the indicator variable, *Regulated*, is positive and significant at the 0.01 level. For instance, the average industry R-squared values for stocks in the oil, utilities, automobile, banking, and aircraft sectors are 9.66, 3.48, 2.36, 5.66, and 3.51 percentage points higher than for stocks in other industries, holding constant firm-specific characteristics and year fixed effects.

In Panel B of Table 5, we display the estimated coefficients from the modified Eq. (3) where *PW_Corr* is the dependent variable and the sample is partitioned by heavily regulated industries. Again, we find that the coefficient on *Regulated* is positive and significant across the heavily regulated industries. More specifically, the average pairwise correlation for stocks in the oil, utilities, automobile, banking, and airline sectors are 7.18, 3.14, 4.03, 2.43, and 1.48 percentage points higher than for stocks in other industries — other factors held constant.

In Panel C of Table 5, we display the estimated coefficients from the modified Eq. (3) where *β_Disp* is the dependent variable and the sample is partitioned by the level of regulation. We find that the coefficients on the dummy variable, *Regulated*, are negative and significant at the 0.01 level in three of the five industries — i.e., utilities, automobile, and banking. For stocks within these industries, the average beta dispersions are 4.74, 6.80, and 5.60 percentage points lower than for stocks in other industries. Surprisingly, the estimated coefficient on *Regulated* is positive and significant in the oil specification, but negative and insignificant in the aircraft model.

Together, the results in this subsection provide substantive evidence that the level of comovement among stock returns is affected by regulation in the cross-section. This is consistent with the notion that firms in regulated industries face operational frictions that may result in correlated cash flows and, consequently, greater comovement in their asset prices.[6]

[6] In tests that are provided in the internet appendix, we replicate Tables 3 and 4 and include annual systematic risk factors as additional control variables. These factors in the (value-weighted) market-risk premium, the Small-minus-Big factor, the High-minus-Low factor, and the Up-minus-Down factor. Given that we

Table 5
Differences in comovement among most regulated industries: Industry-level analysis.

	Oil [1]	Utilities [2]	Automobile [3]	Banking [4]	Aircraft [5]
Panel A. Dependent variable: R^2_Ind					
Regulated	0.0966***	0.0348***	0.0236***	0.0566***	0.0350**
	(15.58)	(5.48)	(3.12)	(19.90)	(2.09)
Adj. R^2	0.5087	0.5030	0.5026	0.5071	0.5021
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	131,089	131,875	128,234	142,798	126,917
Panel B. Dependent variable: *PW_Corr*					
Regulated	0.0718***	0.0314***	0.0403***	0.0243***	0.0148**
	(20.32)	(9.49)	(9.42)	(12.36)	(2.20)
Adj. R^2	0.4952	0.4894	0.4884	0.4870	0.4854
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	131,089	131,875	128,234	142,798	126,917
Panel C. Dependent variable: β_Disp					
Regulated	0.0711***	−0.0474***	−0.0680***	−0.0560***	0.0138
	(7.00)	(−5.37)	(−6.91)	(−10.72)	(0.76)
Adj. R^2	0.0995	0.1025	0.1010	0.1017	0.1004
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	131,089	131,875	128,234	142,798	126,917

The table reports the results from estimating the following equation on stock-year data:

$$Comovement_{i,t} = \alpha + \delta_t + \beta_1 Regulated_i + \beta_2 Ln(Size_{i,t}) + \beta_3 Ln(Price_{i,t}) + \beta_4 Ln(Turn_{i,t}) + \beta_5 Ln(Illiq_{i,t}) + \beta_6 Volatility_{i,t} + \beta_7 NYSE_{i,t} + \varepsilon_{i,t},$$

where the dependent variable is set to one of three measures of comovement: R^2_Ind, *PW_Corr*, or β_Disp. R^2_Ind is the R-squared from the weekly market model over a stock-year where the independent variable is the value-weighted industry return. *PW_Corr* is the average pairwise correlation coefficient between stock i and stock j in each industry in each year, where correlation is estimated using weekly returns. β_Disp is the absolute value of the difference between the industry beta for a particular stock and the mean industry beta in each year using weekly returns. The independent variable of interest is an indicator variable capturing one of the five most regulated industries. For instance, in column [1], the indicator variable, *Regulated*, is equal to one if the firm is in the oil industry and zero if the firm is in any industry that is not ranked in the top five according to the RegData IRI. The control variables have previously been defined. We also include year fixed effects, δ_t, and report t-statistics in parentheses obtained from robust standard errors clustered at stock level. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

3.3. Regulation and comovement: Diff-in-diff tests

While the results in the previous two subsections provide evidence of a strong correlation between regulation and comovement, both across time and stocks, we have yet to document a causal link. To provide greater evidence supporting our hypothesis, we perform a series of difference-in-differences (DID) regressions. The general model for our DID is outlined as follows:

$$\begin{aligned} Comovement_{i,t} &= \alpha + \beta_1 Treat_i + \beta_2 Event_t + \beta_3 Treat_i \times Event_t + \beta_4 Ln(Size_{i,t}) \\ &+ \beta_5 Ln(Price_{i,t}) + \beta_6 Ln(Turn_{i,t}) + \beta_7 Ln(Illiq_{i,t}) + \beta_8 Volatility_{i,t} \\ &+ \beta_9 NYSE_{i,t} + \beta_{10} Ln(Industry_{Size_{j,t}}) + \beta_{11} Ln(Industry_{\#Firms_{j,t}}) \\ &+ \beta_{12} Ln(Industry_{Volt_{j,t}}) + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where the dependent variable is one of three measures of comovement: R^2_Ind, *PW_Corr*, or β_Disp. The categorical variable *Treat* is equal to one if the stock belongs to an affected regulated industry and zero if the stock belongs to any of the industries that are not ranked in the top five according to the RegData IRI. *Event* is a dummy variable equal to one if the observation is during the two years following the enactment of a regulatory change and zero if during the two years before the change. We exclude the calendar year in which the law was being considered by regulators.[7] The interaction term between *Event* and *Treat* is the DID estimator and the variable of interest. Since we include the *Event* dummy variable, which is time-invariant, we do not include year fixed effects as doing so would violate the full column rank assumption required for consistent estimation. The remaining control variables have

do not observe cross-sectional variation when including these factors, we do not include year fixed effects. Results from these robustness tests are qualitatively similar to those reported in Tables 3 and 4. In addition to including systematic risk factors as controls, we have also replicated Tables 3 and 4 including lagged dependent variables to account for the possibility of autocorrelation in comovement. When controlling for lagged dependent variables in our panel tests, we still find results that are consistent with those reported in the manuscript.

[7] In unreported tests, we include the years the laws were enacted and obtain qualitatively similar results to those that are reported in the text.

Table 6
Difference-in-differences in comovement around energy regulation.

Dependent variable:	R^2_Ind [1]	PW_Corr [2]	β_Disp [3]
Treat	0.0945***	0.0571***	−0.0330**
	(11.43)	(11.08)	(−2.00)
Event	−0.0403***	−0.0265***	−0.0355***
	(−14.26)	(−13.84)	(−4.27)
Treat × Event	0.0414***	0.0273***	−0.0566***
	(4.46)	(4.83)	(−3.03)
Adj. R^2	0.4643	0.3184	0.1372
Controls	Yes	Yes	Yes
N	12,758	12,758	12,758

The table reports the results from estimating the following equation on stock-year data for our sample of treated and control stocks for the four-year period surrounding the 2005 Energy Policy Act:

$$Comovement_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Event_t + \beta_3 Treat_i \times Event_t + \beta_4 Ln\left(Size_{i,t}\right) + \beta_5 Ln\left(Price_{i,t}\right) + \beta_6 Ln\left(Turn_{i,t}\right) + \beta_7 Ln\left(Illiq_{i,t}\right) + \beta_8 Volatility_{i,t} + \beta_9 NYSE_{i,t} + \beta_{10} Ln(Industry\_Size_{j,t}) + \beta_{11} Ln(Industry\_\#Firms_{j,t}) + \beta_{12} Ln(Industry\_Volt_{j,t}) + \varepsilon_{i,t},$$

where the dependent variable is set to one of three measures of comovement: R^2_Ind, *PW_Corr*, or β_Disp. R^2_Ind is the R-squared from the weekly market model over a stock-year where the independent variable is the value-weighted industry return. *PW_Corr* is the average pairwise correlation coefficient between stock i and stock j in each industry in each year, where correlation is estimated using weekly returns. β_Disp is the absolute value of the difference between the industry beta for a particular stock and the mean industry beta in each year using weekly returns. The independent variables of interest are *Treat*, *Event*, and the interaction between the two. *Treat* is equal to one if the firm is in the oil, automobile, or utilities industries and zero if the firm is in any industry that is not ranked in the top five according to the RegData IRI. *Event* is equal to one in the years 2006 and 2007 and zero in the years 2003 and 2004. The control variables have previously been defined. We report t-statistics in parentheses obtained from robust standard errors clustered at stock level. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

previously been defined. For brevity, we suppress the output for the control variables throughout each event.[8] We report t-statistics in parentheses obtained from robust standard errors that are clustered at the stock level.

Typically, DID tests attempt to identify an abrupt change in some defined outcome variable to time-dependent regime changes. However, we choose to remain agnostic on how abruptly the level of comovement changes in response to the regulation. Instead, we only attempt to show that new regulation eventually influences the level of comovement of stocks in a particular industry. Therefore, in the tests that follow, we examine comovement in the two years before the introduction of the new regulation and the two years following the passage of the new regulation. Because of the slow legislative process, we choose to utilize calendar years as opposed to event years since the timing of the events is ambiguous. Laws can be drafted and debated in a particular chamber of Congress for weeks or months before they pass in one chamber and move on to the next. Months and even years might go by before the U.S. president signs a bill into law.[9] Therefore, we are less inclined to identify exactly when comovement changes and instead, we focus on the trend in comovement in the years before and after the enactment of the various laws.

3.3.1. 2005 Energy Policy Act

The first regulatory change that we examine is the Energy Policy Act (EPA), which was introduced into the U.S. House of Representatives on April 18, 2005, and signed into law on August 8th, 2005. The bill provided both tax incentives and loan guarantees for U.S. energy production firms. We use the passing of this act as a plausibly exogenous shock to the regulatory environment in the oil, automobile, and utilities industries. The justification for including firms in these three industries is based on several provisions within the bill, which increased regulations for these specific industries. For instance, one provision authorized the Department of Interior to grant leases for drilling activities in certain areas of the country. Another provision required utilities to provide net metering information to customers at their request. Finally, one of the objectives of the bill was to improve fuel competition among automakers.

In this analysis, the categorical variables in Eq. (4) are defined as follows: *Treat* is equal to one if the stock is classified as an oil, automobile, or utilities firm, and zero if it belongs to any other industry that is not ranked in the top five regulated industries according to the RegData IRI. *Event* is equal to one in the years 2006 and 2007 and zero in the years 2003 and 2004. We remove the event year 2005 from the sample. The results of the EPA analysis are found in Table 6.

In the first column of Table 6, we present the estimated coefficients from Eq. (4) where R^2_Ind is the dependent variable. We find that the average industry R-squared increases by 4.14 percentage points for treatment stocks, relative to control stocks, after the increase in regulation from the EPA. In the second column of Table 6, we show the results from estimating Eq. (4) when inserting *PW_Corr* as the dependent variable. In economic terms, the average pairwise correlation for treatment stocks, relative to control stocks, increases by 2.73 percentage points after the increase in regulation associated with the EPA. In the final column of Table 6, we display the coefficient from Eq. (4) when β_Disp is the dependent variable. The average beta dispersion for stocks in the treated industries, relative to stocks in the control industries, decreases by 5.66 percentage points after the increase in regulation from the EPA. To the extent that the passing of the EPA in 2005 serves as an exogenous shock to the level of regulation in the oil, automobile, and utilities industries, our results indicate that regulation leads to greater stock return comovement.

[8] The estimated coefficients on the control variables are similar to those reported in Table 3, and are available upon request.

[9] Given the uncertainty introduced by the legislative process, volatility in affected stocks could be affected, which might influence the confound the comovement of stock prices and adversely affect our ability to observe a change in comovement overtime.

Table 7
Difference-in-differences of comovement around banking regulation.

Dependent variable:	1987 Competitive Equality Banking Act			1991 FDIC Improvement Act			1999 Gramm–Leach–Bliley Act		
	R^2_Ind [1]	PW_Corr [2]	β_Disp [3]	R^2_Ind [4]	PW_Corr [5]	β_Disp [6]	R^2_Ind [7]	PW_Corr [8]	β_Disp [9]
Treat	0.0078	−0.0019	−0.0286	0.0136**	−0.0210***	−0.1089***	0.0463***	0.0109***	−0.0404***
	(1.53)	(−0.78)	(−1.60)	(2.48)	(−8.02)	(−7.42)	(9.33)	(4.07)	(−3.35)
Event	0.0020	0.0069***	0.0579***	−0.0782***	−0.0704***	0.0820***	−0.0147***	−0.0210***	−0.0047
	(0.94)	(5.53)	(8.30)	(−27.90)	(−44.90)	(9.21)	(−5.96)	(−13.47)	(−0.62)
Treat × Event	0.0159***	0.0018	−0.0772***	0.0258***	0.0326***	−0.0232	−0.0378***	−0.0232***	−0.0089
	(2.89)	(0.63)	(−3.96)	(4.42)	(10.92)	(−1.13)	(−7.36)	(−7.66)	(−0.65)
Adj. R^2	0.5022	0.2293	0.0727	0.4664	0.2818	0.0968	0.4218	0.2719	0.1112
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13,943	13,943	13,943	13,988	13,988	13,988	17,703	17,703	17,703

The table reports the results from estimating specifications of the following equation on stock-year data for our sample of treated and control stocks for the four-year periods surrounding the 1987 Competitive Equality Banking Act, the 1991 FDIC Improvement Act, and the 1999 Gramm–Leach–Bliley Act:

$$Comovement_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Event_t + \beta_3 Treat_i \times Event_t + \beta_4 Ln\left(Size_{i,t}\right) + \beta_5 Ln\left(Price_{i,t}\right) + \beta_6 Ln\left(Turn_{i,t}\right) + \beta_7 Ln\left(Illiq_{i,t}\right) + \beta_8 Volatility_{i,t} + \beta_9 NYSE_{i,t} + \beta_{10} Ln(Industry\_Size_{j,t})$$
$$+\beta_{11} Ln(Industry\_\#Firms_{j,t}) + \beta_{12} Ln(Industry\_Volt_{j,t}) + \varepsilon_{i,t},$$

where the dependent variable is set to one of three measures of comovement: R^2_Ind, PW_Corr, or β_Disp. R^2_Ind is the R-squared from the weekly market model over a stock-year where the independent variable is the value-weighted industry return. *PW_Corr* is the average pairwise correlation coefficient between stock i and stock j in each industry in each year, where correlation is estimated using weekly returns. β_Disp is the absolute value of the difference between the industry beta for a particular stock and the mean industry beta in each year using weekly returns. The independent variables of interest are *Treat*, *Event*, and the interaction between the two. *Treat* is equal to one if the firm is in the banking industry and zero if the firm is in any industry that is not ranked in the top five according to the RegData IRI. For the CEBA, *Event* is equal to one in the years 1988 and 1989 and zero in the years 1985 and 1986. For the FDICIA, *Event* is equal to one in the years 1992 and 1993 and zero in the years 1989 and 1990. For the GLBA, *Event* is equal to one in the years 2000 and 2001 and zero in the years 1997 and 1998. The control variables have previously been defined. We report t-statistics in parentheses obtained from robust standard errors clustered at stock level. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

3.3.2. 1987 Competitive Equality Banking Act, 1991 FDIC Improvement Act, and 1999 Gramm–Leach–Bliley Act

The next three regulatory changes that we examine all impacted the banking industry. First, The 1987 Competitive Equality Banking Act (CEBA) amended the 1956 Bank Holding Company Act to redefine a bank to include any entity that accepts demand deposits and engages in making commercial loans. Here, many financial institutions that might not be considered a bank before 1987, would be reclassified as a bank and subject to the rules of the 1956 Bank Holding Company Act. Second, the 1991 FDIC Improvement Act (FDICIA), which was passed at the height of the savings and loan crisis included provisions that raised the FDIC's line of credit with the U.S. Treasury, improved the auditing and evaluation standards of member banks, and introduced the Truth and Saving Act. Third, the Gramm–Leach–Bliley Act (GLBA) of 1999, which repealed parts of the 1933 Glass-Steagall Act, thus allowing a single bank to engage in multiple banking-type activities, including (but not limited to) investment banking, commercial banking, and insurance coverage. While both the 1987 CEBA and 1991 FDICIA were likely to increase regulation in the banking sector, the 1999 GLBA was likely to reduce it. We use the passing of these acts as plausibly exogenous shocks to the level of regulation in the banking industry.

In this analysis, the indicator variables in Eq. (4) are defined as follows: *Treat* is equal to one if a stock belongs to the banking sector and zero if it belongs to any other industry that is not ranked in the top five regulated industries according to the RegData IRI. For the CEBA, *Event* is equal to one in the years 1988 and 1989 and zero in the years 1985 and 1986. For the FDICIA, *Event* is equal to one in the years 1992 and 1993 and zero in the years 1989 and 1990. For the GLBA, *Event* is equal to one in the years 2000 and 2001 and zero in the years 1997 and 1998. We note that we exclude the law passing years in the analysis to avoid confounding effects during the legislative process. The results of this analysis surrounding these regulatory changes in the banking sector are reported in Table 7.

In columns [1], [4], and [7] of Table 7, we report the estimated coefficients from Eq. (4) where R^2_Ind is the dependent variable. Our results in column [1] show that the average industry R-squared for stocks in the banking sector, relative to stocks in the control group, increased by 1.59 percentage points after the passing of the CEBA, which positively shocked regulation in the banking sector. Similarly, we show in column [4] that the average industry R-squared for stocks in the banking industry, relative to control stocks, increased by 2.58 percentage points after the passing of the FDICIA, which increased regulation in the treated industry. Furthermore, we find in column [7] that the average industry R-squared decreased by 2.41 percentage points for bank stocks, relative to control stocks, after the passing of the GLBA, which reduced regulation in the banking sector.

In columns [2], [5], and [8] of Table 7, we show the results from estimating Eq. (4) where *PW_Corr* is the dependent variable. In column [2], we do not find a significant change in the average pairwise correlation coefficient between stocks in the banking sector, relative to those in the control group, around the passing of the CEBA, which increased regulation in the banking industry. We do, however, show, in column [5] that the average *PW_Corr* increased by 3.26 percentage points for treatment stocks, relative to control stocks, around the passing of the FDICIA, which increased the amount of regulation in the banking sector. Additionally, we document in column [8] that the average pairwise correlation decreased by 2.74 percentage points for bank stocks than control stocks after the passing of the GLBA, which reduced regulation in the treated industry.

Table 8
Difference-in-differences of comovement around airline regulation.

Dependent variable:	R^2_Ind [1]	PW_Corr [2]	β_Disp [3]
Treat	0.0254	−0.0154	0.0600
	(0.82)	(−1.23)	(0.85)
Event	0.0734***	0.0875***	−0.0105
	(20.54)	(40.35)	(−1.02)
Treat × Event	0.0585**	0.0632**	−0.1209
	(2.04)	(2.48)	(−1.58)
Adj. R^2	0.4577	0.3454	0.1278
Controls	Yes	Yes	Yes
N	12,845	12,845	12,845

The table reports the results from estimating the following equation on stock-year data for our sample of treated and control stocks for the four years surrounding the 2001 and 2002 Transportation and Security Act and Homeland Security Act:

$$Comovement_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Event_t + \beta_3 Treat_i \times Event_t + \beta_4 Ln\left(Size_{i,t}\right) + \beta_5 Ln\left(Price_{i,t}\right) + \beta_6 Ln\left(Turn_{i,t}\right) + \beta_7 Ln\left(Illiq_{i,t}\right) + \beta_8 Volatility_{i,t} + \beta_9 NYSE_{i,t} + \beta_{10} Ln(Industry\_Size_{j,t}) + \beta_{11} Ln(Industry\_\#Firms_{j,t}) + \beta_{12} Ln(Industry\_Volt_{j,t}) + \varepsilon_{i,t},$$

where the dependent variable is set to one of three measures of comovement: R^2_Ind, PW_Corr, or β_Disp. R^2_Ind is the R-squared from the weekly market model over a stock-year where the independent variable is the value-weighted industry return. PW_Corr is the average pairwise correlation coefficient between stock i and stock j in each industry in each year, where correlation is estimated using weekly returns. β_Disp is the absolute value of the difference between the industry beta for a particular stock and the mean industry beta in each year using weekly returns. The independent variables of interest are *Treat*, *Event*, and the interaction between the two. *Treat* is equal to one if the firm is in the aircraft industry and zero if the firm is in any industry that is not ranked in the top five according to the RegData IRI. *Event* is equal to one in the years 2003 and 2004 and zero in the years 1999 and 2000. The control variables have previously been defined. We report t-statistics in parentheses obtained from robust standard errors clustered at stock level. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

In columns [3], [6], and [9] of Table 7, we tabulate the results from estimating Eq. (4) when β_Disp is the dependent variable, which inversely proxies the level of stock comovement. In column [3], we find that the average beta dispersion for stocks in the banking sector, relative to the control stocks, decreased by 7.72 percentage points after the passing of the CEBA, which increased regulation in the treated sector. We do not find a significant coefficient on the interaction term in columns [6] and [9].

Together, the results in Table 7 provide some evidence that more regulation in the banking industry leads to greater comovement in the industry's stock returns. We note the need to raise caution when drawing too strong of inferences regarding the results from the event study since the results are not robust across each column. However, the findings are generally consistent with the predictions of our hypothesis that regulation increases stock price comovement.

3.3.3. 2001 Aviation and Transportation Security Act and 2002 Homeland Security Act

The next regulatory change that we examine is the combined 2001 Aviation and Transportation Security Act (ATSA) and the 2002 Homeland Security Act (HSA), which directly affected the airline sector. Following the September 11, 2001, terrorist attacks, the U.S. Congress passed the ATSA in an attempt to standardize the pre-flight passenger and cargo screening processes. Shortly thereafter, in 2002, the HSA was passed. Both of these legislative bills overhauled the airline industry. Here, we utilize the passing of the ATSA and the HSA combined as an arguably exogenous shock to the level of regulation in the airline industry.

In this analysis, the indicator variables in Eq. (4) are defined as follows: *Treat* is equal to one if the stock belongs to the aircraft industry and zero if it belongs to any other industry that is not ranked in the top five regulated industries according to the RegData IRI. *Event* is equal to one in the years 2003 and 2004 and zero in the years 1999 and 2000. We exclude the calendar years 2001 and 2002 given the legislative activities were implemented during these two years. The results of this analysis around the ATSA and the HSA are reported in Table 8.

In the first column of Table 8, we report the estimated coefficients from Eq. (4) where R^2_Ind is the dependent variable. We find that the coefficient on the DID estimator is positive and significant at the 0.05 level. In economic terms, this means that the average comovement, as measured by R-squared, for stocks in the airline industry, relative to stocks in the control group, increased by 5.85 percentage points after the ATSA and HSA were passed, other factors held constant. Since these changes increased the regulatory burden in the airline sector, these results indicate that regulation and comovement are positively related.

In the second column of Table 8, we show the results from estimating Eq. (4) when inserting PW_Corr as the dependent variable. We show that the estimated coefficient on the DID interaction term is positive and significant at the 0.05 level. Again, this result suggests that the average comovement, proxied by pairwise correlations, for stocks in the airline industry, relative to stocks in the control group, increased by 6.32 percentage points after the bills were passed that increased regulation in the treated industry.

In the final column in Table 8, we tabulate the estimated coefficient from Eq. (4) when β_Disp is the dependent variable, which inversely captures the level of stock comovement. The average beta dispersion for stocks in the airline industry, relative to stocks in the control group, decreased by 12.09 percentage points after the passing of the ATSA and HSA, which increased the regulatory burden in the airline sector. We note, however, that the estimated coefficient on the DID interaction term is not quite significant at the 0.10 level.

In summary, the results in this subsection provide evidence that increased regulation in the airline industry led to greater comovement in the stock returns among firms in that industry. Again, these findings support our hypothesis that regulation might induce greater stock return comovement.

Table 9
Difference-in-differences around SOX.

Dependent variable:	R^2_Ind [1]	PW_Corr [2]	β_Disp [3]
Treat	0.0610*** (10.70)	0.0442*** (13.61)	−0.1193*** (−8.03)
Event	0.0296*** (7.66)	0.0612*** (25.34)	−0.0365*** (−3.42)
Treat × *Event*	−0.0144*** (−3.11)	−0.0340*** (−10.93)	0.0545*** (4.39)
Adj. R^2	0.4903	0.3791	0.1153
Controls	Yes	Yes	Yes
N	15,732	15,732	15,732

The table reports the results from estimating the following equation on stock-year data for our sample of treated and control stocks for the four years surrounding the 2002 Sarbanes–Oxley (SOX) Act:

$$Comovement_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Event_t + \beta_3 Treat_i \times Event_t + \beta_4 Ln\left(Size_{i,t}\right) + \beta_5 Ln\left(Price_{i,t}\right) + \beta_6 Ln\left(Turn_{i,t}\right) + \beta_7 Ln\left(Illiq_{i,t}\right) + \beta_8 Volatility_{i,t} + \beta_9 NYSE_{i,t} + \beta_{10} Ln(Industry\_Size_{j,t}) + \beta_{11} Ln(Industry\_\#Firms_{j,t}) + \beta_{12} Ln(Industry\_Volt_{j,t}) + \varepsilon_{i,t},$$

where the dependent variable is set to one of three measures of comovement: R^2_Ind, PW_Corr, or β_Disp. R^2_Ind is the R-squared from the weekly market model over a stock-year where the independent variable is the value-weighted industry return. PW_Corr is the average pairwise correlation coefficient between stock i and stock j in each industry in each year, where correlation is estimated using weekly returns. β_Disp is the absolute value of the difference between the industry beta for a particular stock and the mean industry beta in each year using weekly returns. The independent variables of interest are *Treat*, *Event*, and the interaction between the two. *Treat* is equal to one if the firm is in one of the top five most regulated industries and zero if the firm is in any industry that is not ranked in the top five according to the RegData IRI. *Event* is equal to one in the years 2003 and 2004 and zero in the years 2000 and 2001. Given that the legislative activity occurred during the first half of 2002, we have deleted the year 2002 to avoid confounding effects. The control variables have previously been defined. Each of the continuous control variables is in natural log form. We report t-statistics in parentheses obtained from robust standard errors clustered at stock level. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

3.3.4. 2002 Sarbanes–Oxley Act

Until now, we have attempted to show how comovement changed around several different regulatory episodes that affected industries that are most heavily regulated. While it is not feasible to identify every regulatory instance that affects one of our five heavily regulated industries during our sample period, we would be remiss without including the 2002 Sarbanes–Oxley Act (SOX), which increased the regulatory burden on nearly all firms. Fig. 1 shows that the year 2002 did not have an abnormally high number of new economically meaningful rules. However, several studies argue that SOX increased regulation that adversely affected stock returns (Zhang, 2007), improved the disclosure of publicly-traded firms (Coates and John, 2007), and led to an exodus of firms that "went private" to avoid the potential burden (Engel et al., 2007).

In this analysis, we estimate Eq. (4) surrounding SOX but the predictions – according to our hypothesis – are a bit different. Here, the most regulated industries are likely to be less affected by the passage of SOX than those that are least regulated, since those more regulated firms were likely already in compliance or perhaps insulated slightly from the regulatory burden at least initially (see e.g., Filbeck et al., 2011). Therefore, we expect that relative to stocks in the most regulated industries, those that are in less regulated sectors will experience a larger increase in comovement in response to SOX. The indicator variables in Eq. (4) are defined as follows: *Treat* is equal to one if a particular stock is in one of the five most regulated industries according to RegData IRI and zero otherwise. *Event* is equal to one in the calendar years 2003 and 2004 and zero in the calendar years 2000 and 2001. We exclude the year 2002, which included the legislative activity leading up to the passage of SOX. The results of this analysis around SOX are reported in Table 9.

In column [1] of Table 9, we show the results from estimating Eq. (4) when inserting R^2_Ind as the dependent variable. As expected, we find that the estimated coefficient on the DID interaction term is negative and significant at the 0.01 level. In economic terms, this result implies that for stocks in the top five most heavily regulated industries according to the RegData IRI, relative to all other stocks, average comovement, as measured by R-squared, decreased by 1.90 percentage points after SOX is passed.

In column [2] of Table 9, we report the results from estimating Eq. (4) where PW_Corr is the dependent variable. Again, we find that the coefficient on the DID interaction term is negative and significant at the 0.01 level. More specifically, the average level of comovement, as proxied by pairwise correlations, for treatment stocks, relative to control stocks, decreased by 2.26 percentage points after the passing of SOX.

In column [3] of Table 9, we display the results from estimating Eq. (4) when inserting β_Disp in as the dependent variable, which inversely captures the level of stock price comovement. Consistent with the results discussed previously, the coefficient on the DID interaction term is positive and significant at the 0.01 level. Economically, this result indicates that for stocks in the top five most heavily regulated industries according to the RegData IRI, relative to all other stocks, average beta dispersion decreased by 5.45 percentage points after SOX is passed.

Collectively, these findings support the notion that the passing of SOX led to more comovement among stocks in less regulated industries compared to those in more heavily regulated industries. Again, we believe that these results support our hypothesis that regulation leads to more return comovement, as the less regulated firms were likely to be more burdened by the act than the already heavily regulated firms.

4. Concluding remarks

In this study, we develop and test the hypothesis that regulation increases the level of comovement in stock returns. We estimate three proxies of return comovement, one being a novel measure, i.e., beta dispersion. We first analyze stock return comovement and regulation across time. To do so, we obtain annual regulation numbers from the Regulatory Studies Center. We find that stock return comovement is highest in years with the most rules. Next, we analyze comovement and regulation in the cross-section of stocks. To achieve this, we gather data from RegData Industry Regulation Index that allows us to identify the five industries that face the most regulation, i.e., oil, utilities, automobile, banking, and airline. We show that stocks in the five most regulated industries experience significantly more return comovement than stocks in other industries. These tests only allow us to draw a strong association between regulation and comovement.

To identify a more causal link between regulation and return comovement, we conduct a series of difference-in-differences (DID) tests. More specifically, we identify plausibly exogenous shocks to the regulatory environment of specific industries and then examine the comovement of stocks within those industries, relative to a group of control stocks not in the five most regulated industries. In each of these tests, we find fairly consistent evidence that, relative to other stocks, those from industries that experience shocks to their regulatory environments exhibit higher increases in the levels of return comovement pre-to-post.

Taken together, our findings contribute to the existing literature that attempts to explain the presence of return comovement. While the frictions described in Barberis et al. (2005) may indeed generate comovement, our findings show that regulation may also be an important economic driver. Given the unprecedented increase in regulatory intervention since the 2008–2009 financial crisis, it becomes important to document the various impacts regulation may have on financial markets (Trebbi and Xiao, 2019). Our study shows a strong directional flow from regulation to stock return comovement, which may have real economic consequences (see e.g., Brenner et al., 2009).

CRediT authorship contribution statement

Benjamin M. Blau: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Project administration. **Todd G. Griffith:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Project administration. **Ryan J. Whitby:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jempfin.2023.06.005.

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