Deregulation and Risk with a Multifactor Model

Thomas Shores

Our goal is to examine the impact of deregulation on the risk of firms in affected industries. Following the market crisis in 2008, the impact of deregulation on financial markets was scrutinized heavily. Given a lack of theoretical consensus regarding the impact of deregulation on risk, it follows that an empirical analysis of the market's reaction to deregulation is of high value. We examine the variation in stock returns of firms affected by deregulation in a set of different industries. Using the Carhart four factor model[1] *we decompose risk into systematic and idiosyncratic factors in order to examine the change in risk composition of affected firms post deregulation. We find that relative idiosyncratic to systematic risk may increase in the first year to two years following deregulation, after which it reverts, and usually decreases below pre-deregulation levels.*

---

1. Introduction

Following the 2008 financial crisis the effect of deregulation on risk became an area of interest for academics and market participants alike. The Gramm-Leach-Bliley Act (GLBA), which was implemented in response to the Great Depression, was repealed in 1999. In 2007 and 2008, the market experienced its first comparable setback to that of the 1930's, the Great Recession. The timing of the GLBA repeal relative to the financial crisis was enough to convince many people of a causal relationship.

Deregulation is intended to open industry to greater competition, which is, theoretically, associated with a more economically efficient market. Additionally, with greater competition, firms are encouraged to innovate, which leads to increased output and elevated quality of life. However, economic theory regarding the impact of deregulation on risk remains unclear. One theory posits that regulation provides a buffer for companies in a given industry against competition. In the event of deregulation, this buffer goes away, exposing firms to more supply and demand fluctuations and, subsequently, greater variation in both profits and stock price returns. This is called *buffering theory* and associates deregulation with increases in volatility[2].

A conflicting argument suggests that the approval process inherent to regulation increases business risk because it makes firms unable to respond to changing market conditions at a competitive rate[3]. Inability to adapt to changes in supply and demand makes a regulated firm more likely to experience greater stock price fluctuations if that same firm were unregulated. Moreover, in cases where some firms in an industry are regulated and others are not, changing market conditions present an opportunity for unregulated firms to outperform regulated competitors: leading to profit spikes and

---

[1] See Carhart (1997)
[2] See Peltzman (1976)
[3] See Joskow and Macavoy (1975) and Keran (1976)

drops respectively. This is called *regulatory lag* theory, and it suggests deregulation should be correlated with a decrease in the variance of stock returns.

Yet another theory is that regulation involving rate approval impedes firms from engaging in high-risk investments. If it is difficult to raise rates, then when investments pay off, the shareholders and customers will both benefit. However, when investments fail, the shareholders bear the entirety of the cost because the approval process impedes timely rate increases. As a result, shareholders are less eager to invest in high risk projects, where the ability to realize large profits is shared and the cost of failure is born entirely by themselves. In this case, deregulation will encourage investment in riskier projects, increasing the volatility of affected firms[4].

Since the theoretical impacts of deregulation on risk lack consensus, an empirical study is required to understand how the market truly reacts to deregulation. We attempt to do this by examining the volatility of stock returns of firms impacted by deregulation. In doing so we separate risk into idiosyncratic and systematic components using a multi-factor model consistent with the Carhart four factor model, which builds on the Fama-French model[5] with the addition of a momentum factor. Moreover, we examine deregulation of affected firms across three broad industries, trucking, telecommunications and financial services, to account for industry specific risk responses to deregulation.

This research builds on the work of previous literature by analyzing the impact of risk over varying time ranges and industries using a model with more relevant systematic risk factors than in any previous studies. It will provide a thorough and comprehensive analysis that could help policy makers predict the drawbacks of deregulation with more accuracy: allowing them to pursue deregulatory legislation with greater confidence in outcomes. In Section 2 we look at previous literature and evidence on deregulation and risk. We present our hypotheses in Section 3 and describe the data and methodology we use in Section 4. In Section 5 we present our results, and we provide our conclusions in Section 6.

2. Literature

There has been significant research into the overall time trend of idiosyncratic volatility. Campbell et al. (2001) documented an increase in firm specific risk from 1962 to 1997, while market risk remained relatively unchanged. Similarly, Morck et al. (2000) find a rise in the ratio of idiosyncratic to systematic risk in American stock markets. However, in response to the assertion that idiosyncratic risk has been rising over time, a deluge of literature has been published refuting this finding. One such paper is from Pontiff and Irvine (2009), who argue that idiosyncratic risk has risen due to an increasingly competitive business environment.

One piece of evidence Irvine and Pontiff (2009) use in their argument is that firms in deregulated, thus more competitive, industries experience higher idiosyncratic volatility. They take a long-term average of volatility using data from 1964 to 2003 and find that average idiosyncratic volatility increased in five of seven industries following deregulation. Semaan and Drake (2011) examined the impact of deregulation on risk using smaller time windows in their analysis. They find that initial rises in risk following deregulation are largely idiosyncratic and tend to revert back to the pre-deregulation mean

[4] Discussed in Guthrie (2006)

[5] See Fama, French (1993)

over time. Moreover, Pennathur et al. (2014) found that most regulation introduced during the financial recession increased systematic risk.

3. Hypotheses

Pontiff and Irvine (2009) found a long term rise in idiosyncratic risk following deregulation. Similarly, Semaan and Drake (2011) found a rise in the idiosyncratic over total risk in seven of nine industry portfolios tested over a 600-day window. However, when measured over a 4000-day window, idiosyncratic over average risk decreased in five of the nine industries under examination. Moreover, systematic risk decreased in the majority of industries 2000 days after deregulation. Both papers find that rise in risk is largely idiosyncratic and possibly temporary.

This is logical given that following deregulation, industries become more competitive. As a result, firms must learn how to contend with new market participants and investors must similarly re-evaluate their expectations for the future cash flows of firms. This process was termed the learning period by Semaan and Drake (2014).

We expect to find a similar rise in idiosyncratic volatility in the short-term following deregulation in our own study. However, our model includes more systematic factors then both Semaan and Drake's and Pontiff and Irvine's. Accordingly, we expect any rise in idiosyncratic volatility, and decrease in systematic volatility, following deregulation to be smaller in magnitude than those found in their study. Following a short-term increase in relative idiosyncratic volatility we expect reversion to pre-enactment levels in the long term.

4. Data and Methodology

We focus on three deregulatory acts to assess the impact of deregulation on the variance of firms affected. The event date of concern is the day the legislation is enacted. It is understood that in anticipation of deregulation, some of the impact that we are trying to capture will occur prior to the enactment date. A portion of the methodology below uses a daily time series that will capture some of the anticipatory effects that may exist. For the portions of methodology that do not capture these effects, such as comparing risk averages before and after enactment, our results will be mitigated. This is because averages taken from the before-enactment time period will encapsulate some of the effect we are attempting to identify. Thus, any results yielded from these tests will be more robust than if we attempt to account for legislative anticipation. A table with the acts, enactment date, and SIC codes of affected firms in our data set is provided in Table 1. The description of industries associated with each SIC code follows in Table 2.

Table 1: Acts, Enactment Dates and SIC Codes		
Deregulation Act	**Enactment Date**	**SIC Codes of Affected Firms**
Motor Carrier Regulatory Reform and Modernization Act	July 1, 1980	4213
Telecommunications Act of 1996	January 3, 1996	4813
Gramm-Leach-Bliley Financial Services Modernization Act	November 4, 1999	60,61,62,63,64,6712

Table 2. Industry Associated with SIC Codes	
SIC Code	**Description**
4213	Trucking, except local
4813	Telephone Communications, Except Radiotelephone
60	Depository institutions
61	Nondepository credit institutions
62	Security and commodity brokers, dealers exchanges and services
63	Insurance carriers
64	Insurance agents, brokers, and services
6712	Bank holding companies

We examine multiple measures of firm risk using two methodologies explained below.

i. Measuring Shifts in Beta

We build portfolios of the value weighted portfolio excess returns (R_{pt}) for each industry SIC code under examination over 3000 trading days centered on the enactment date:

$$R_{pt} = \frac{\sum_{i=1}^{n_t} v_{it} r_{it}}{v_{pt}} \tag{1}$$

where v_{it} is the market value, r_{it} is the excess return of the ith stock, and v_{pt} is the value of the industry specific portfolio *p* at time *t*. We then estimate the following regression:

$$R_{pt} = \propto_p + \beta_{1p} R_{Mt} + \beta_{2p} SMB + \beta_{3p} HML + \beta_{4p} UMD + \beta_{1ps}(D_p R_{Mt}) + \beta_{2ps}(D_p SMB) + \beta_{3ps}(D_p HML) + \beta_{4ps}(D_p UMD) + \gamma_p(D_p) + e_{pt} \tag{2}$$

where R_{Mt} is the Center for Research in Security Prices (CRSP) value-weighted returns including distributions at time *t*. SMB and HML are the small minus big and high minus low parameter from the Fama-French model, and UMD is the monthly momentum factor from the Carhart four factor model. β_{1ps}, β_{2ps}, β_{3ps} and β_{4ps} are the average shifts in the four beta parameters on market return, small-minus big and high minus low respectively following enactment, while D_p is a post-enactment dummy variable.

ii. Estimating Changes in Industry's Average Risk Components

Next, we look to decompose risk into idiosyncratic and systematic elements in order to measure the average risk components for each industry. We regress the excess return of portfolio *p*, R_{pt}, on market excess returns, high minus low, small minus big and up minus down parameters, for the trading day *t* using the 300 trading days prior to *t*.

$$R_{pt} = \alpha_i + \beta_{1p}R_{Mt} + \beta_{2p}SMB + \beta_{3p}HML + \beta_{4p}UMD + e_{it} \tag{3}$$

where α_i is the intercept, β_{1i}, β_{2i}, β_{3i} and β_{4i} are stock i's betas, and e_{it} is the stock specific residual. Next, we separate the variance of each stock's returns into systematic and idiosyncratic components.

The R^2 parameter from the regression above is interpreted as the amount of variation in returns explained by the systematic variables in the model. We will therefore use the R^2 as a measurement for systematic risk. The remaining variation in returns is unexplained by the systematic factors in our model, so are specific to the firm, or idiosyncratic.

$$SYS_{pt} = R^2 \tag{4}$$

$$IDIO_{pt} = 1 - R^2 \tag{5}$$

Given that we are interested in examining the relationship between idiosyncratic and systematic risk, we construct a 300-day moving window of each portfolio's ratio of average idiosyncratic over average systematic risk (δ_{pt}) for portfolio, *p,* over each trading day, *t*, in the 3000 day window:

$$\delta_{pt} = \frac{IDIO_{pt}}{SYS_{pt}} \tag{6}$$

Next, we regress δ_{pt} on dummy variables for four time periods defined below (Equation (7)).

Period 1: The first 300 trading days including and following the enactment date.
Period 2: The second 300 trading days following the enactment date.
Period 3: The third 300 trading days following the enactment date.
Period 4: The remaining 600 trading days in the sample.

Following Campbell et al. (2001) reporting a positive time trend for idiosyncratic volatility over much of our sample period, we add a parameter to control for time, τ. Evidence from Semaan and Drake (2011) showed that including a parameter for market concentration in a similar regression did not improve the model, so we omit such a parameter in our own analysis. D_{1p}, D_{2p}, D_{3p}, and D_{4p}, are dummy variables taking a value of 1 when the trading day *t* falls in the corresponding period, and 0 otherwise.

$$\delta_{pt} = \alpha_p + \tau_p(T) + \phi_{1p}(D_{1p}) + \phi_{2p}(D_{2p}) + \phi_{3p}(D_{3p}) + \phi_{4p}(D_{4p}) + e_{pt} \tag{7}$$

The coefficient τ_p will capture any temporal trend in our volatility ratio, δ_{pt}. Moreover, the coefficients on the dummy variables for each time period, ϕ_1, ϕ_2, ϕ_3 and ϕ_4, will capture the change in δ_{pt} over each of the four time periods compared to pre-deregulation. Therefore, Equation (7) will allow us to analyze the change in our industry specific ratio of systematic over idiosyncratic volatility for specific time periods following deregulation.

5. Results

i) Measuring Shifts in Beta

We perform the regression described in Equation 2 and display the results below in Table 3. We examine the beta shift parameters and find that the beta for market excess return is negative and significant in seven of eight industry portfolios and positive and significant in the trucking industry only. Similarly, the beta shift on up minus down is negative and significant in seven of eight industries and positive and significant in trucking. The beta shift on small minus big is positive and significant in communication, but otherwise yields the same results. The beta on up minus down is positive and significant in trucking, insignificant at the 5% level for the communication and insurance brokers industries and negative and significant in all other industries. We then construct daily betas using a 300-day moving window across the 3000 trading day sample and add each of the four betas together to make a 'cumulative beta' parameter. We present the time series of the cumulative beta in Figure 4 to visually present the findings from Table 3. This technique is flawed in that it weights each beta by absolute value, rather than weighting the betas equally. However, the visual representation is invariant to weighting given the consistency of the negative shift parameters across portfolios.

ii) Estimating Changes in Industry's Average Risk Components

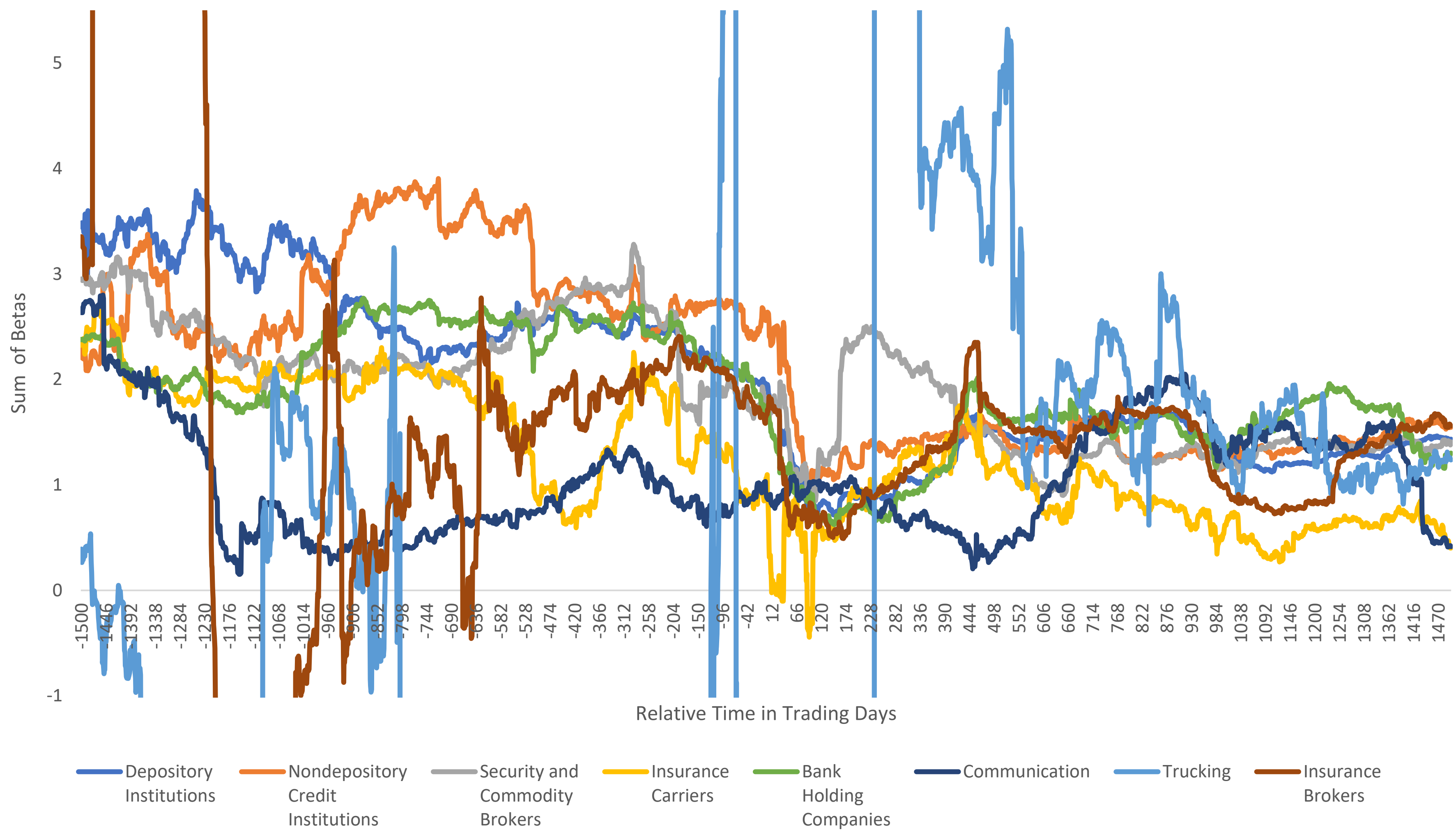
Descriptive statistics for delta, the ratio of systematic over idiosyncratic variance, are displayed in Table 5 for the entire sample period of 3000 days centered around the enactment date. The difference in pre and post enactment deltas is positive in six of eight industries and negative in the Insurance Carriers and Bank Holding Companies industries. We then restrict the sample to 600 trading days, centered on the enactment date, in Table 6. The difference is negative in seven portfolios and positive in the Communication industry. A negative difference implies relative idiosyncratic risk is increases post deregulation, as it is in the denominator of the delta parameter. These differences are in line with the findings of Semaan and Drake (2011) that relative idiosyncratic risk initially rises following deregulation, and then reverts back to pre-deregulation levels, or lower, in the long run.

We then present the difference between the average value of the delta parameter in the four time periods 4 and the 1500 days prior to enactment in Table 7. The difference between average deltas in the first 300 trading days prior to enactment is negative and significant in four of eight industries at the 0.01 level. Of the remaining industries, all four differences are positive: three are significant at the 0.01 level, and one is significant at the 0.1 level. Again, since idiosyncratic risk is in the denominator, a negative difference implies relative idiosyncratic risk has decreased Thus, relative idiosyncratic risk increased in four of eight industries in the first 300 trading days post-enactment. In each of the remaining time periods the difference is negative in two industries, Bank Holding Companies and Insurance Carriers, and positive in the other six industries. Moreover, all differences in Period 2 through Period 4 are significant at the 0.01 level, except Trucking in Period 3. A visualization of the differences is displayed in Figure 8.

Table 3: Impact of Deregulation on Betas of Affected Industries								
Estimated Parameter	**Industry**							
	Trucking	**Communication**	**Depository Institutions**	**Non-depository Credit Institutions**	**Security and Commodity Brokers**	**Insurance Carriers**	**Insurance Brokers**	**Bank Holding Companies**
α	-0.00441	0.00020	0.00023	0.00028	0.00022	0.00021	0.00023	0.00024
	(0.0044)	(0.0009)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0082)	(<.0001)
γ	0.01262	0.00021	0.00003	-0.00004	0.00003	0.00002	-0.00004	0.00007
	(<.0001)	(0.0019)	(0.1224)	(0.4849)	(0.6196)	(0.5667)	(0.7562)	(0.3591)
β_1	-1.99742	0.97580	0.87847	0.87962	0.88521	0.89441	0.88804	0.94033
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
β_2	-5.07706	-0.08501	0.28425	0.28661	0.29686	0.32466	0.29648	0.43206
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
β_3	-2.77765	0.21340	0.58461	0.57893	0.59229	0.59437	0.59210	0.61860
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
β_4	-1.97541	-0.08662	-0.00605	0.00268	0.00076	0.00973	0.00374	0.05487
	(<.0001)	(<.0001)	(0.0419)	(0.7406)	(0.9335)	(0.092)	(0.843)	(<.0001)
β_{1S}	4.46025	-0.09373	-0.38882	-0.38298	-0.40102	-0.41554	-0.42328	-0.42250
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
β_{2S}	6.37854	0.22940	-0.36601	-0.37752	-0.37486	-0.39434	-0.35651	-0.52476
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
β_{3S}	3.22914	-0.24486	-0.28422	-0.27359	-0.29490	-0.30042	-0.30035	-0.30360
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
β_{4S}	2.58357	-0.00587	-0.01686	-0.03055	-0.02563	-0.03522	-0.03418	-0.06747
	(0.0002)	(0.7199)	(<.0001)	(0.0007)	(0.0088)	(<.0001)	(0.0954)	(<.0001)

Table 3 follows from Equation 2: $R_{pt} = \propto_p + \beta_{1p}R_{Mt} + \beta_{2p}SMB + \beta_{3p}HML + \beta_{4p}UMD + \beta_{1ps}(D_pR_{Mt}) + \beta_{2ps}(D_pSMB) + \beta_{3ps}(D_pHML) + \beta_{4ps}(D_pUMD) + \gamma_p(D_p) + e_{pt}$ where α is the intercept, γ is the average abnormal daily return post enactment, and β_1, β_2, β_3 and β_4 are the coefficients on market return, small minus big, high minus low and up minus down. β_{1s}, β_{2s}, β_{3s} and β_{4s} measure the shift in respective betas following enactment. P-values for regular standard errors are reported in parentheses.

Figure 4: Sum of Industry Portfolio Moving Betas



We calculate betas using Equation (3), $R_{pt} = \alpha_t + \beta_{1pt} R_M + \beta_{2pt} SMB + \beta_{3pt} HML + \beta_{4pt} UMD + e_{it}$ on a 300 day moving window. The cumulative beta parameter is then calculated at trading day t as $\beta_{Cpt} = \beta_{1pt} + \beta_{2pt} + \beta_{3pt} + \beta_{4pt}$. The time series of cumulative betas is displayed.

Table 5: Descriptive Statistics on the Daily Ratio of Average Systematic Over Idiosyncratic Variance per Industry for 3000 Days Centered on Enactment

Industry	Pre-enactment N = 1 500		Post-enactment N = 1 500		Difference	Total Sample N = 3 000	
	Mean	Standard Deviation	Mean	Standard Deviation		Mean	Standard Deviation
Trucking	0.04029	0.05258	0.27431	0.30958	0.23402	0.15730	0.25096
Communication	0.96581	0.31732	1.69579	0.45281	0.72998	1.33080	0.53486
Depository institutions	1.90452	1.70970	4.51903	2.19771	2.61452	3.21177	2.36320
Non-depository credit institutions	1.21714	0.92905	1.70948	0.65794	0.49234	1.46331	0.84167
Security and commodity brokers	1.35025	0.71289	3.98892	2.22853	2.63867	2.66958	2.11603
Insurance carriers	0.77645	0.62381	0.15819	0.03467	-0.61826	0.46732	0.53916
Insurance brokers	0.18769	0.27953	1.19989	0.97411	1.01219	0.69379	0.87725
Bank holding companies	2.17498	0.88125	1.22238	0.39015	-0.95260	1.69868	0.83138

All differences are significant at the 0.01 percent level.

Table 6: Descriptive Statistics on the Daily Ratio of Average Systematic Over Idiosyncratic Variances per Industry for 600 Days Centered on Enactment

Industry	Pre-enactment N = 300		Post-enactment N = 300		Difference	Total Sample N = 600	
	Mean	Standard Deviation	Mean	Standard Deviation		Mean	Standard Deviation
Trucking	0.03604	0.01932	0.01736	0.00368	-0.01740	0.02670	0.01675
Communication	0.82091	0.13165	1.04713	0.19583	0.05841	0.93402	0.20152
Depository institutions	4.52862	0.70709	1.98335	0.35200	-0.15598	3.25598	1.39058
Non-depository credit institutions	2.65060	0.45817	0.93392	0.22655	-0.24522	1.79226	0.93187
Security and commodity brokers	1.91981	1.00688	1.16970	0.37000	-0.09640*	1.54475	0.84575
Insurance carriers	0.28154	0.10835	0.15796	0.03531	-0.07889	0.21975	0.10152
Insurance brokers	0.72992	0.09510	0.31796	0.08314	-0.41197	0.52394	0.22464
Bank holding companies	3.37516	0.24322	1.15977	0.35491	-2.21539	2.26747	1.14954

*Significant at the 0.1 level.
All other differences are significant at the 0.01 percent level.

Next, we present the results from the regression outlined in Equation (7) in Table 9 below. The ϕ_1 parameter, which measures the impact on delta of being in Period 1, is negative and significant in five of eight industries, and positive and significant in two. The parameter is insignificantly different from zero for the trucking industry. The ϕ_2 and ϕ_3 parameter are negative and significant in three industries, positive and significant in four industries, one at the 0.05 level, and insignificant for the Trucking industry. The coefficient for Period 4, ϕ_4, is positive and significant in five industries and negative and significant in 3. These results support the trend of diminishing idiosyncratic risk relative to systematic risk over the four time periods following deregulation. However, they do not support the finding of a consistent initial increase in idiosyncratic risk following enactment. A time series of the delta parameter over the 3000 day sample, centered on enactment, is provided in Figure 10 to aid in visualizing the results of Table 9.

6. Conclusion

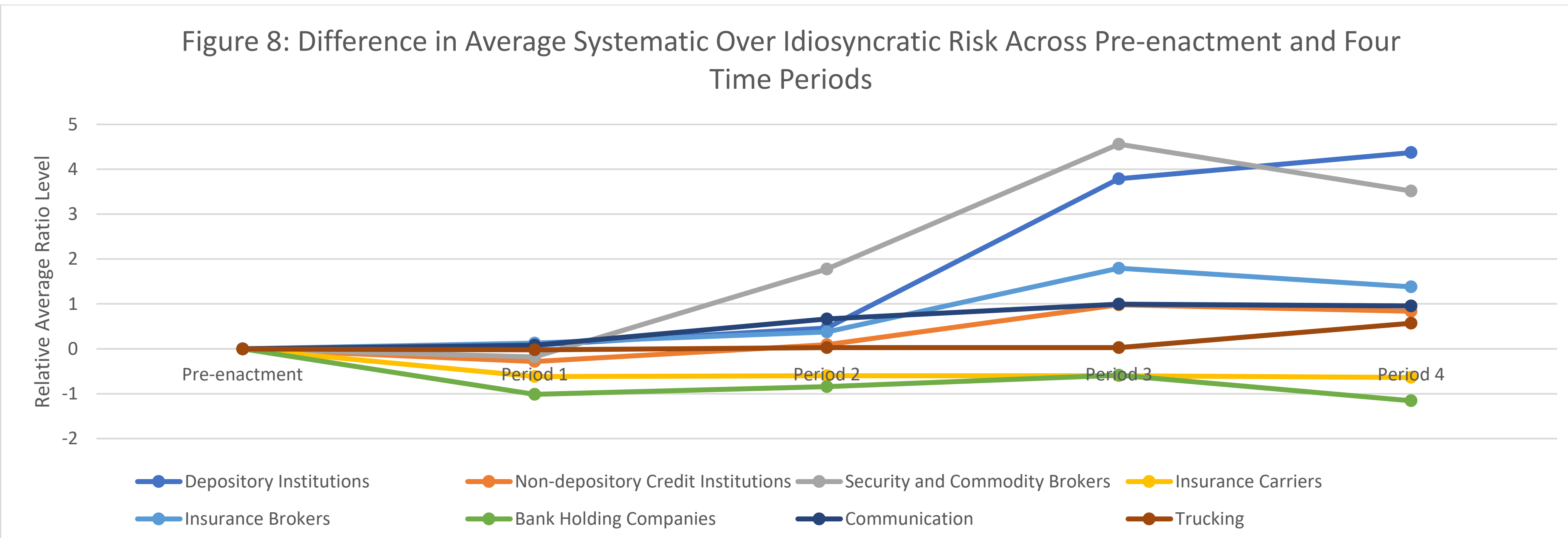
We find little evidence of a general upward trend in idiosyncratic volatility as proposed by Irvine and Pontiff (2009). Our results do support the findings of Semaan and Drake (2011) that relative idiosyncratic to systematic risk decreases over time following deregulation. However, our findings deviate in that the initial increase in idiosyncratic risk in the short run post enactment is far less pronounced, and the reversion to pre-enactment levels is accentuated, leading to a decrease in relative idiosyncratic risk in the 1500 trading days post enactment. We conclude in support of the theory proposed by Semaan and Drake (2011) that firms endure a learning period following deregulation in which they learn to deal with competition. However, our evidence shows that this period may last one to two years, rather than three, and that increases to idiosyncratic risk are modest, if present at all. Following this period, firms adjust to new competition and relative idiosyncratic risk tends to decrease in the long run.

While our research focusses on the relationship between systematic and idiosyncratic risk, more work is needed to assess the behavior of total risk following deregulation. Furthermore, applying our methodologies to more deregulation acts is needed to determine whether our results are generally robust, or specific to our selection of legislation.

Table 7: Means of Average Systematic Over Idiosyncratic Variance by Industry, Prior to Enactment and Under Four Periods Post Enactment

Industry	Pre-enactment	Regime 1		Regime 2		Regime 3		Regime 4	
	Mean	Mean	Difference	Mean	Difference	Mean	Difference	Mean	Difference
Trucking	0.04029	0.01736	-0.02293	0.06723	0.02694	0.06673	0.02644*	0.61011	0.56982
Communication	0.96581	1.04713	0.08132	1.63043	0.66462	1.96081	0.99500	1.92029	0.95448
Depository institutions	1.90452	1.98335	0.07883	2.36805	0.46353	5.69179	3.78727	6.27599	4.37147
Non-depository credit institutions	1.21714	0.93392	-0.28322~	1.30728	0.09015	2.19827	0.98113	2.05395	0.83681
Security and commodity brokers	1.35025	1.16970	-0.18055~	3.12930	1.77905	5.91036	4.56011	4.86762	3.51737
Insurance carriers	0.77645	0.15796	-0.61849	0.17770	-0.59875	0.17864	-0.59781	0.13833	-0.63812
Insurance brokers	0.18769	0.31796	0.13026	0.56168	0.37399	1.98428	1.79659	1.56776	1.38007
Bank holding companies	2.17498	1.15977	-1.01522	1.33024	-0.84475	1.58565	-0.58933	1.01813	-1.15685

*Significant at the 0.1 level.
~Insignificant at the 0.1 level.
All other differences are significant at the 0.01 level.



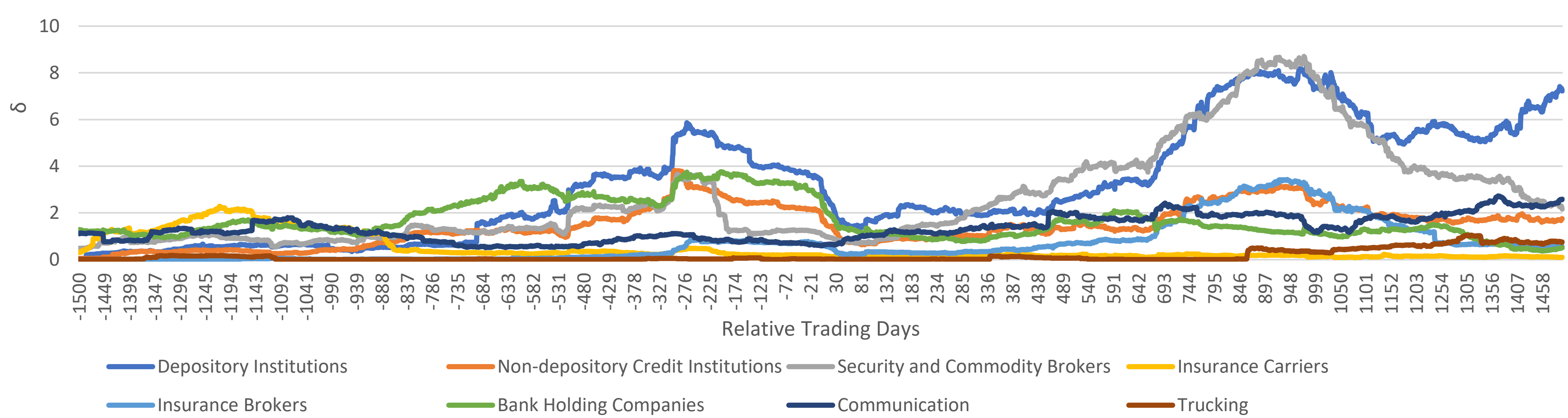
The vertical axis captures the difference in average systematic over idiosyncratic risk in each period (Pre-enactment N = 1500, Period 1 N = 300, Period 2 N = 300, Period 3 N = 300, Period 4 N = 600).

Table 9: Changes in the Ratio of Average Systematic Over Idiosyncratic Risk Following Deregulation by Industry

Estimated Parameter	Industry							
	Trucking	Communication	Depository Institutions	Non-depository Credit Institutions	Security and Commodity Brokers	Insurance Carriers	Insurance Brokers	Bank Holding Companies
α	0.02392	1.13183	-0.51916	-0.07200	0.97373	1.54174	0.02329	0.97049
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.397)	(0.000)
γ	0.00002	-0.00022	0.00323	0.00172	0.00050	-0.00102	0.00022	0.00160
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ϕ_1	-0.04256	0.28041	-2.82764	-1.82915	-0.63208	0.29924	-0.06689	-2.45965
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.135)	(0.000)
ϕ_2	0.00077	0.93007	-3.41177	-1.97110	1.17702	0.62489	0.11112	-2.77066
	(0.939)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.030)	(0.000)
ϕ_3	-0.00628	1.32681	-1.05685	-1.59543	3.80757	0.93174	1.46801	-2.99672
	(0.583)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ϕ_4	0.52730	1.38584	-1.92589	-2.51271	2.53907	1.35030	0.95291	-4.28646
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.8178	0.6917	0.8299	0.6856	0.7057	0.6944	0.6085	0.742

P-values are displayed in parentheses.

Figure 10: Moving Ratio of Systematic Over Idiosyncratic Risk



The δ parameter is calculated as described in Equation (6) using the R^2 parameter from the regression model in Equation (3) on a 300 moving window. The parameter is calculated for each day in the 3000 trading days centered on enactment and the time series is presented above.

References

Bakaert, G., R.J. Hodrick, and X. Zhang, 2008, "Is There a Trend in Idiosyncratic Volatility?" Columbia University

Bennett, James A., et al. “Greener Pastures and the Impact of Dynamic Institutional Preferences.” *The Review of Financial Studies*, vol. 16, no. 4, 2003, pp. 1203–1238. *JSTOR*, www.jstor.org/stable/1262741.

Brandt, M.W., A. Brav, J.R. Graham, and A. Kumar, 2010, "The Idiosyncratic Volatility Puzzle: Time Trend or Speculative Ep

Campbell, John Y., et al. “Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk.” *The Journal of Finance*, vol. 56, no. 1, 2001, pp. 1–43. *JSTOR*, www.jstor.org/stable/222462.

Carhart, Mark M. "On Persistence In Mutual Fund Performance". *The Journal Of Finance*, vol 52, no. 1, 1997, p. 57. *JSTOR*, doi:10.2307/2329556.

Fama, Eugene F., and Kenneth R. French. "Common Risk Factors In The Returns On Stocks And Bonds". *Journal Of Financial Economics*, vol 33, no. 1, 1993, pp. 3-56. *Elsevier BV*, doi:10.1016/0304-405x(93)90023-5.

Fink, Jason and Grullon, Gustavo and Fink, Kristin and Weston, James Peter, IPO Vintage and the Rise of Idiosyncratic Risk (February 2005). 7th Annual Texas Finance Festival Paper. Available at SSRN: https://ssrn.com/abstract=661321 or http://dx.doi.org/10.2139/ssrn.661321

Guthrie, Graeme. “Regulating Infrastructure: The Impact on Risk and Investment.” *Journal of Economic Literature*, vol. 44, no. 4, 2006, pp. 925–972. *JSTOR*, www.jstor.org/stable/30032390.

Irvine, Paul J. and Pontiff, Jeffrey, Idiosyncratic Return Volatility, Cash Flows, and Product Market Competition (March 2009). The Review of Financial Studies, Vol. 22, Issue 3, pp. 1149-1177, 2009. Available at SSRN: https://ssrn.com/abstract=1359528 or http://dx.doi.org/hhn039

Joskow, Paul L., and Paul W. MacAvoy. “Regulation and the Financial Condition of the Electric Power Companies in the 1970's.” *The American Economic Review*, vol. 65, no. 2, 1975, pp. 295–301. *JSTOR*, www.jstor.org/stable/1818868.

Keran, Michael W. “Inflation, Regulation, and Utility Stock Prices.” *The Bell Journal of Economics*, vol. 7, no. 1, 1976, pp. 268–280. *JSTOR*, www.jstor.org/stable/3003202.

Morck, Randall et al. "The Information Content Of Stock Markets: Why Do Emerging Markets Have Synchronous Stock Price Movements?". *Journal Of Financial Economics*, vol 58, no. 1-2, 2000, pp. 215-260. *Elsevier BV*, doi:10.1016/s0304-405x(00)00071-4.

Peltzman, Sam. "Toward A More General Theory Of Regulation". *The Journal Of Law And Economics*, vol 19, no. 2, 1976, pp. 211-240. *University Of Chicago Press*, doi:10.1086/466865.

Paul J. Irvine and *Jeffrey Pontiff*, (2009),Idiosyncratic Return Volatility, Cash Flows, and Product Market Competition, *Review of Financial Studies*, **22**, (3), 1149-1177

Semaan, Elias, and Pamela Peterson Drake. “Deregulation and Risk.” *Financial Management*, vol. 40, no. 2, 2011, pp. 295–329. *JSTOR*, www.jstor.org/stable/41237906.