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The Effects of the 1933 Bank Holiday and the Emergency Banking Act of 1933 on the Systematic Risks of Various Industries

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Abstract

Utilizing the industry portfolio classifications that Fama and French provide in their data library, I analyze the specific effects that the 1933 Bank Holiday has on various industries. My empirical results go beyond what Silber (2009) determines to be significantly positive abnormal market returns on March 15, 1933, which is the day after the Bank Holiday and the largest ever one-day increase in the stock market. I use the CAPM and the Fama-French 3-factor Model to find significant systematic risk decreases after the Bank Holiday in the Coal and Transportation industries, as well as systematic risk increases in Consumer Goods and Apparel. To determine the driving factors behind these changes in systematic risk and abnormal returns, I test the correlation between industry leverage ratios and differences in systematic risk changes after the Bank Holiday. The Bank Holiday helps stabilize the economy and the nation's banking system, which I expect industries with larger debt obligations will benefit more after the Bank Holiday. Inconsistent with my expectations, I don't find significant evidence that the systematic risks of highly leveraged industries decreases more than industries with lower leverage ratios. I develop my argument to leave room for changes in the model used to estimate systematic risks in order to identify the variables that are the true drivers of the systematic risk changes that I observe.

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I. Introduction

Friedman and Schwartz (1963 cited Bordo 2010) mark the period from August 1929 through Roosevelt's 1933 Bank Holiday as the Great Contraction, and considered it to be possibly the worst "business-cycle contraction" in U.S. history. The U.S. stock market crashed on October 24, 1929, and by March 1933, the stock of money in the U.S. fell by more than one-third (Friedman and Schwartz 1963). The instability of the U.S. economy created instability and panic in the nation's banking system. Friedman and Schwartz (1963) describe the banking panics as "a contagion of fear" in which depositors became fearful that their money was not safe in banks. These fears lead to bank runs and banking panics that would spread across geographical regions and the ultimately the entire nation. The number of commercial banks in the U.S. fell by more than one-third at the beginning of the Great Contraction (Friedman and Schwartz 1963). In addition to regional banking panics, Wicker (1996 cited Bordo 2010) identified the 2,293 bank suspensions in fall 1931 and the 4,000 bank suspensions in winter 1933 as the two national baking panics of the Great Contraction. Figure 1 displays the number of all bank suspensions in the U.S. from 1921 to the year 1936.

Immediately following President Roosevelt's inauguration, and in the midst of the second national banking panic of the 1930s, Roosevelt ordered all the nation's banks to cease banking activities starting on March 6, 1933 (Silber 2009 and Wicker 1996). The 1933 Bank Holiday lasted from March 6, 1933 through March 14, 1933. The nation's stock exchanges were also closed during the Bank Holiday. Before the banks and stock exchanges reopened on March 15th, the Emergency Banking Act of 1933 was signed by President Roosevelt. The Act essentially the government promising to insure deposits

(Silber 2009). On March 15, 1933 the New York Stock Exchange rose by over 15 percent. It was the largest ever one-day increase by the New York Stock Exchange. In addition to the record one-day jump in the stock market, figure 2 shows evidence of the turnaround when two-thirds of the currency that had been withdrawn by the public since the banking panic began was re-deposited into banks by the end of the month (Silber 2009).

To understand why Roosevelt felt the urgent need to order the 1933 Bank Holiday, the prior month-long period of bank closures must be examined. Awalt (1969 cited Silber 2009) marks February 14, 1933, as the day the nationwide banking system began to crumble. On that day, in order to stop the Union Guarding trust Company of Detroit from failing, a state-wide banking holiday was ordered by Michigan Governor William A. Comstock, which caused a ripple effect across the country over the course of the next month (Silber 2009). Evidence of the public withdrawing their money in cash is easily seen through the 30% increase in currency held by the public between February 8th and March 8th (Silber 2009).

“On Sunday, March 5th, after a month-long run on American banks, the newly inaugurated President of the United States, Franklin Delano Roosevelt, proclaimed a four-day suspension of all banking transactions, beginning the following day” (Silber 2009). The Bank Holiday also meant that the nations’ stock exchanges would temporarily cease all trading (Silber 2009). Roosevelt would ultimately extend the suspension for an additional three days through Tuesday, March 14th (Silber 2009). Roosevelt’s goal of the Bank Holiday was to stop the panic and communicate to the American people that their money was safe in American banks (Silber 2009). In order to instil confidence in

America's banking system and calm the panic of the American people, Roosevelt also implement the Emergency Banking Act of 1933 as concrete policy action to stabilize the nation's banking system (Silber 2009). He needed to show the people that they were better off depositing their money, rather than holding it in cash.

Roosevelt targeted two different audiences through his first Fireside chat, "On the Bank Crisis," when he publically explained his decision to order the 1933 Bank Holiday (Silber 2009). This would be the first of 30 Fireside chats he would deliver to the American people over the course of his presidency. The following quote is the opening excerpt of "On the Bank Crisis," delivered over the radio to the American people on Sunday, March 12, 1933:

> I want to talk for a few minutes with the people of the United States about banking -- with the comparatively few who understand the mechanics of banking but more particularly with the overwhelming majority who use banks for the making of deposits and the drawing of checks. I want to tell you what has been done in the last few days, why it was done, and what the next steps are going to be. I recognize that the many proclamations from State Capitols and from Washington, the legislation, the Treasury regulations, etc., couched for the most part in banking and legal terms should be explained for the benefit of the average citizen. I owe this in particular because of the fortitude and good temper with which everybody has accepted the inconvenience and hardships of the banking holiday. I know that when you understand what we in Washington have been about I

> shall continue to have your cooperation as fully as I have had your sympathy and help during the past week. ("On the Bank Crisis")

Roosevelt's first target audience was the financiers who understood how the banking system functioned (Silber 2009). He told them that the nation's banks would be rehabilitated through the Emergency Banking Act of 1933, and the twelve Federal Reserve Banks would be able to "supply unlimited amounts of currency to reopened banks" (Silber 2009). Silber (2009) explains how the unlimited supply of currency to reopened banks "created de facto 100 percent deposit insurance," and was a key factor in the stock market's sharp jump when security exchanges reopened on March 15th. The Act is the concrete policy action that helped America's financiers feel more comfortable making deposits and knowing it was insured by the government.

Roosevelt's second target audience was the average American, who needed reassurance that the nation's banking system was strong and there was no need for panic (Silber 2009). Silber (2009) explains that the Bank Holiday was needed to allow the nation's banking system time to breathe, and Roosevelt helped calm the American people through the way he spoke. Allen (1939) attributes the success of the reopening to Roosevelt's ability to persuade the American people to trust him. Silber (2009) describes how Roosevelt informed the public in his first Fireside chat that the U.S. treasury would be evaluating the solvency of the banks, and that only financially healthy banks would be allowed to reopen. He said to the American people, "I can assure you that it is safer to keep you money in a reopened bank than under the mattress" (New York Times 3 Mar. 1933, cited Silber 2009). The importance of Roosevelt's persuasive communication skills is further reiterated by Alter (2006 cited Silber 2009) by saying "[Roosevelt] made everyone understand it, even the bankers."

II. Hypothesis Development

Hypothesis 1: Leverage ratios show how companies use a combination of debt and equity to finance their operations ("Leverage Ratio"). Highly leveraged firms have a greater risk of insolvency due to market downturns that may affect their ability to pay back creditors ("Solvency"). President Roosevelt's rhetoric during the Bank Holiday and the backing of deposits through the Emergency Banking Act helped stabilize the nation's banking system, as well as the economy (Silber 2009). The stabilization of the economy as a result of the Bank Holiday and the Emergency Baking Act is why I expect the systematic market risk of highly leveraged industries to decrease more after the Bank Holiday. In addition to estimating the Capital Asset Pricing Model's systematic market beta risk, I estimate the Fama-French 3-Factor Model to measure the independent effects of each of the three risk factors on the outcome (LaMorte). Small and value firms tend to have less systematic risk than large and growth firms, which is why I expect the systematic size and value risk factors to decrease less in industries with high leverage ratios, as compared to large and growth firms (Acharya 2010).

Hypothesis 2: My argument is that the 1933 Bank Holiday and the Emergency Banking Act of 1933 decreases systematic risks for industries that rely heavily on financing through debt. I expect that the effects of the systematic risk changes after the Bank Holiday are reflected through stock returns after the Bank Holiday. I expect that the stock returns of highly leveraged industries are more likely to have significantly positive abnormal returns, and that stock returns of industries with less leverage are more likely to have significantly negative abnormal returns. I calculate abnormal returns before and after the Bank Holiday using the CAPM and Fama-French 3-Factor Model. Silber (2009) tests for changes in the systematic risk of the market after Roosevelt's election by using Temin and Wigmore's (1990 cited Silber 2009) argument, that after Roosevelt was elected his inflationary policies caused the increase in the stock market. I expect that the one-day changes in stock returns on March 15^{th} have more to do with the effects of the systematic risk changes resulting from the Bank Holiday and the Emergency Banking Act, and that the effects vary by industry due to differences in industry leverage ratios.

III. Previous Literature

Bordo (2010) examines the causes of the two national banking panics in the U.S. from 1930-1933, and how banking panics were common-place in the U.S. before the 1933 Bank Holiday. Banking panics weren't something new to the early 1930s and the Great Depression. Banking panics occurred in the U.S. every decade between the early nineteenth century and 1914 (Bordo 2010). Bordo (2010) argues that unit banking and the absence of an effective lender of last resort are the two main factors contributing to the instability of the U.S. banking system.

Branch banking was considered by the American people in the 1930s to be a dangerous precedent for fear of the concentration of economic power, and interstate banking didn't become the norm in America until the mid-1900s (White 1983, cited Bordo 2010). Unit banks did not have branches spread across multiple states. Because the portfolios of unit banks are concentrated in a confined geographical area, there is increased risk that these banks would fail in times of a market downturn (Bordo 2010). The system of branch banking would allow banks to spread their portfolios across wide geographical areas, and decrease risk through increased diversification (Bordo 2010). Empirical studies connecting unit banking to banking panics have been thoroughly researched going back to the nineteenth century (White 1983, cited Bordo 2010). The analysis of Grossman (1994 cited Bordo 2010) and Grossman (2010 cited Bordo 2010) shows through cross-country regression evidence that there is a significant positive correlation between unit banking and banking instability.

Carlson and Michener (2009 cited Bordo 2010) show evidence that contradicts the argument that branch banking sets a dangerous precedent due to the concentration of economic power. California is one of the few states in the 1930s that allowed branch banking (Carlson and Michener 2009, cited Bordo 2010). They argued that their empirical data showed evidence that the increased market competitiveness of large networks of bank branches actually increased the probability of bank survivorship (Carlson and Michener 2009, cited Bordo 2010). However, they don't argue that the increased diversification that comes with bank branching would have been the reason "that the U.S. banking system would have been less fragile in the 1930s" (Carlson and Michener 2009, cited Bordo 2010). Instead, they propose that branch baking would have had more efficient banks, and thus, would have created a more stable U.S. banking system in the late 1930s (Carlson and Michener 2009, cited Bordo 2010).

Bordo (2010) explains how the lack of a lender of last resort in America "since the demise of the Second Bank of the United States until the establishment of the Federal Reserve in 1914," is one of the main reasons that banking panics had been common place in America for decades. The go-to solution for ending banking panics had been to temporarily suspend the convertibility of deposits into currency (Bordo 2010). This practice of suspending the convertibility of deposits into currency was not healthy for the nation's financial system. Ultimately, a reliable lender of last resort is needed for the country's people to have confidence that their deposits were safe in banks. Even though one of the functions of the Federal Reserve when it was established in 1914 was to act as a lender of last resort, it's obvious that it failed at this task between 1930 and 1933 when banking panics were occurring more frequently than in decades past.

There is evidence that Roosevelt's Bank Holiday and the Emergency Banking Act were successful. Silber (2009) determined that the 15.34 percent jump in the Dow Jones Industrial Average is significant after accounting for the trading suspension. Silber (2009) concluded this by running a simple t-test on the continuously compounded return of 14.27 percent on March 15, 1933.

While Silber's (2009) study does show that the market increase on March 15th is statistically significant, it does not examine what industries are driving the market increase the most. This leaves room to provide statistical evidence that addresses the research question related to which industries of the market benefited from increased consumer confidence. Investors were able to look at the new policies and see that they benefited the economy, as well as specific industries. While many of the previous authors are correct that President Roosevelt's comforting Fireside chats helped spur confidence in the American economy, it's likely that investors recognized that the new deposit insurance benefited specific industries. Hence, in this paper, I contribute to the previous literature by studying the specific industry effects associated with the 1933 Bank Holiday.

Temin and Wigmore (1990) argue that Roosevelt's new policy regime after he took office in March 1933 is the cause of the stock market increase. Temin and Wigmore (1990) don't attribute the one-day rise in the stock market on March 15th to the Bank Holiday or the Emergency Banking Act of 1933. Instead, they attribute the changes in the stock market to "Roosevelt's devaluation of the dollar and the resulting rise in farm prices and incomes" (Temin and Wigmore 1990). Roosevelt's policy changes successfully devalued the dollar within six weeks after he took office as he sought to use inflation to boost the economy (Temin and Wigmore 1990).

Taking into account Temin and Wigmore's (1990) argument attributing regime changes and Roosevelt's inflationary policies to the stock market increase, Silber (2009) uses an F-Test to analyze difference in the standard deviation of returns comparing before and after the election of President Roosevelt. Silber (2009) uses Temin and Wigmore's (1987) argument to justify using November 8, 1932, the day Roosevelt was elected, as the split date for the estimation periods of systematic risk. Silber (2009) used an estimation period from January 4, 1932 through March 3, 1933 to estimate the normal standard deviation of excess returns. Silber (2009) split the estimation period of systematic risk on November 8, 1932, the date Roosevelt was elected President. Silber (2009) is interested in determining if there is a significant difference in the variability of the Dow Jones Industrial Average before and after Roosevelt's election to office. Silber (2009) uses an F-test to determine that the pre-election standard deviation of 3.45 percent is significantly different from the post-election standard deviation of 2.48 percent.

IV. Data Construction

To study industry-specific effects surrounding the 1933 Bank Holiday, I use the Fama-French data library, which has stock return data categorized by industry dating back to 1926. CRSP SIC codes are used for industry classification.[1] For the purposes of my event study, I use daily data because the event windows that I analyze are either one-day or cumulative two-day returns. I use the Fama-French 30 industry portfolios daily data in my empirical tests for my event study ("Detail for 30 Industry Portfolios"). By choosing to use 30 industry portfolios classifications, instead of one of the data sets with fewer and broader industry classifications, I'm able to analyze and precisely estimate the effects of the Bank Holiday on the 30 industries.[2]

IV.1 Event Windows

My empirical tests aim to find the effects on the Fama-French 30 industry portfolios classifications due to the 1933 Bank Holiday and the implementation of the Emergency Banking Act of 1933 by President Roosevelt. My event study looks at a total of four different event windows before and after the nine-day long Bank Holiday. The first event window I look at is March 3, 1933, the day before the Bank Holiday. My event study aims to identify how different industries react on this day due to possible information leakage. The second event window that I look at is March 15, 1933, the day after the Bank Holiday and the first day of trading after the reopening of exchange markets. Silber (2009) showed using a simple t-test, that the 15.34 percent one-day increase in the Dow Jones Industrial Average is statistically significant. For this reason,

[1] Full industry titles and details of the SIC codes can be found in the Appendix or reference ("Detail for 30 Industry Portfolios")
[2] The justifications for the parameters I use to select my data are located in the Appendix.

March 15th is probably the most interesting and important one-day event windows that my empirical research looks to analyze. The third event window that I consider is March 16, 1933, the second day of trading after the Bank Holiday. This event window is important to look at because all of the Bank Holiday's effects on daily stock returns may not have been realized on March, 15, 1933 due to market inefficiencies. It's possible that significant effects persist in some industries into the second day of trading after security exchanges reopened. The fourth event window is the cumulative two days after the Bank Holiday, March 15th and March 16th. Because it's possible that significant effects persist in some industries into the second day of trading after security exchanges reopened, it's important to study the cumulative two days after the 1933 Bank Holiday. It's difficult to determine which event window is the most important, which is why the relevance of the statistically significant results of each event window must be considered.

IV.2 Estimation Periods of Systematic Risk

My event study focusses on the differences in industry-specific returns before and after the 1933 Bank Holiday. This is why I choose to use the Bank Holiday to split my estimation period of systematic risk. Awalt (1969 cited Silber 2009) marks February 14, 1933, as the day the nationwide banking crisis began to crumble. I used Awalt's (1969 cited Silber 2009) claim to justify selecting October 13, 1932 through February 11, 1933 as the pre-event period to estimate systematic risk. I decided that a pre-event period of 100 daily returns is enough data points to estimate a normal distribution by conventional standards. I wanted to set the pre-event estimation period for systematic risk before the nationwide banking crisis began to crumble, which is why the pre-event estimation period does not include any daily returns between February 14, 1933 and the beginning of the Bank Holiday on March 6th. I also used a post-event period of 100 daily returns to estimate the systematic risk after the Bank Holiday. Because I use a buffer of 15 daily returns between the pre-event estimation period of systematic risk and the 1933 Bank Holiday, I decided it is appropriate to also use a buffer of 15 daily returns between the Bank Holiday and the post-event estimation period of systematic risk. The post-event estimation period of systematic risk runs from April 14, 1933 through July 31, 1933. The post-event buffer allows time for the market to fully realize and reflect the effects of the event.

IV.3 Leverage Ratios

I test my hypothesis that the systematic risk factors of highly leveraged industries will decrease more after the Bank Holiday by computing the leverage ratio of each industry, and then estimating the relationship of each industry's leverage ratio to their corresponding systematic risk factors and abnormal returns.

I started by looking at Moody's Manuals, which provides financial reports back to 1909. However, it does not provide industry averages of the company financial reports. Instead of sorting through each individual scanned report to create a database of leverage ratios, I used recent Compustat data to estimate leverage ratios for each industry. Also, I use long-term debt in my leverage ratio calculations, and that kind of specificity is not provided in 1933 financial reports. I do make sure to note the possibility that using a proxy for leverage ratios could possibly affect my results if the capital structure of industries changes over long periods of time.

The most common leverage ratio is the debt-to-equity ratio (“leverage ratio”):

Debt-to-Equity Ratio = Total Debt / Total Equity

However, I decide not to use the debt-to-equity ratio in my analysis. I use long-term debt instead of total debt to better measure the capital structure of each company (“Leverage Ratio”). I also chose to use market value of equity instead of the book value of equity to calculate leverage ratios. Using the book value of equity is problematic when calculating average leverage ratios in years where companies report negative book value of equity. Negative equity values make it difficult to accurately calculate average industry leverage ratios. I choose to use the long-term debt-to-market value ratio as the leverage ratio in my analysis (“Leverage Ratio”):

Long-term Debt to Market Value Ratio = Long-term Debt / (Share Price × Number of Shares)

Compustat data on long-term debt and market value only overlaps back to 1998. I separate the Compustat data using the SIC codes of the 30 industry classifications that are used to separate the Fama-French industry returns data (“Detail for 30 Industry Portfolios”). I excluded the companies who’s SIC codes were not explicitly labeled in the Fama-French SIC code details from the industry leverage ratio calculations in order to stay consistent with the Fama-French industry classifications. I calculate each industry’s market value weighted average leverage ratio of each fiscal year-end from 1998-2014. I then take the average of each year to estimate a proxy for each industry’s average leverage ratio.

V. Statistical Analysis

The first goal of my empirical research is to find how the systematic risk of each industry changed after the Bank Holiday. As stated in my hypothesis, I expect that the systematic risk of credit-hungry industries to decrease more than industries that are less credit-hungry. This is my expectation if President Roosevelt instilled confidence in the American people that the nation's banking system was stable and that their current and future deposits were safe and secure in banks. The Emergency Banking Act of 1933 is the concrete action that provided unlimited government backing to deposits in banks, which helped add stability to the economy and banking system (Silber 2009).

The second goal of my empirical research is to determine the Bank Holiday's effects on industry stock returns by analyzing which industries show evidence of abnormal returns over various event windows. I analyze abnormal returns to complement my empirical research on the effects of leverage on the systematic risks of different industries.

V.1 Differences in Risk Factors

The first objective of my event study is to identify how the systematic risk of the Fama-French 30 industry classifications are affected differently by comparing the difference of their beta estimates from before and after the 1933 Bank Holiday. I estimate the Capital Asset Pricing Model (CAPM) regression formula:

$$(r_{ind,t}-r_{f,t})=\widehat{B}(r_{m,t}-r_{f})+e_{ind,t}$$

In this CAPM regression formula $r_{ind,t}$ represents the return on the industry on the event window, $r_{f,t}$ represents the risk free rate of return on the event window, $\widehat{B}$

represents the beta systematic risk estimate over the corresponding estimation period, $r_{m,t}$ represents the return on the market on the event window, and $e_{ind,t}$ represents the random error of the industry regression on the event window. I use the CAPM regression to estimate the systematic beta risk for each of the 30 industries over the pre-event 100 daily returns estimation period, as well as the post-event 100 daily returns estimation period. I chose not to include alpha in my regression formula because the constant, or intercept, is not pertinent to my regression output. I subtracted the post-event beta estimate from the pre-event beta estimate. I use two-tail t-tests to determine the significance of the differences between the pre- and post-event beta estimates. The t-statistic for the difference in beta estimates is calculated by dividing the differences in pre- and post-event beta estimates by the standard error of the difference between pre- and post-event beta estimates. I used the variance of the difference formula:

$$var(\hat{B}_1-\hat{B}_2)=var(\hat{B}_1)+var(\hat{B}_2)+2cov(\hat{B}_1,\hat{B}_2)$$

In this variance of the difference formula var represents variance, $\hat{B}_1$ represents the pre-event industry beta estimate, $\hat{B}_2$ represents the post-event industry beta estimate, and cov represents covariance. In this case, $2cov(\hat{B}_1,\hat{B}_2)=0$. Because I need to find the SE of the difference, I took the square root of both sides of the previous formula for the standard error of the difference:

$$SE_{diff}=sqrt[(SE\hat{B}_1)^2+(SE\hat{B}_2)^2]$$

In this standard error of the difference formula SE_{diff} represents the standard error of the difference between the pre- and post-event beta estimates for each industry, sqrt represents square root, $SE\hat{B}_1$ represents the standard error of the pre-event beta estimate, and $SE\hat{B}_2$ represents the standard error of the post-event beta estimate. Using the standard error of the beta estimates from before and after the event window, which were shown in the CAPM regression outputs, I divide the difference of the pre- and post-event beta estimates by the standard error of the difference of the pre- and post-event beta estimates to calculate a t-statistic for each of the 30 industries.

In addition to using the regression estimates of the CAPM to determine how the systematic risk of the Fama-French 30 industry portfolios changes after the event window, I analyze the Fama-French 3-Factor Model to determine how the Fama-French market, size, and value risk factors changed after the Bank Holiday. By analyzing the Fama-French 3-Factor Model alongside the CAPM, I am able to control for other systematic risks by measuring the independent effect of each of the three risk factors on the outcome (LaMorte). I estimate the Fama-French 3-Factor regression formula:

$$(r_{ind,t}-r_{f,t})=\widehat{b}(r_{m,t}-r_{f,t})+\hat{c}(SMB_t)+\hat{d}(HML_t)+e_{ind,t}$$

In this Fama-French 3-Factor regression formula $r_{ind,t}$ represents the return on the industry on the event window, $r_{f,t}$ represents the risk free rate of return on the event window, $\widehat{b}$ represents the estimate of the market risk coefficient over the corresponding estimation period, $r_{m,t}$ represents the return on the market on the event window, $\hat{c}$ represents the estimate of the size risk coefficient over the corresponding estimation period, SMB_t represents the size premium on the event window, $\hat{d}$ represents the estimate of the value risk coefficient over the corresponding estimation period, HML_t represents the value premium on the event window, and $e_{ind,t}$ represents the random error of the industry regression on the event window. To estimate each risk factor before the event window, I estimate the Fama-French 3-Factor regression just as I did for the CAPM regressions for each of the 30 industries over the pre- and post-event 100 daily return estimation periods. I chose not to include alpha in my Fama-French 3-Factor regression formula, just as I didn't include alpha in my CAPM regression. Just as I did to determine which industries had significant changes in systematic risk after the event window, I use the differences between the pre- and post-event risk factor estimates and the standard error of the difference between pre- and post-event risk factor estimates to calculate a t-statistic for each risk factor in each of the 30 industries.

V.2 Abnormal Returns

The second goal of my empirical research is to determine the Bank Holiday's effect on industry stock returns by analyzing which industries show evidence of abnormal returns over various event windows. To calculate the CAPM abnormal returns, I estimate the same CAPM regression formula that I did when estimating the differences in beta:

$$(r_{ind,t}-r_{f,t})=\widehat{B}(r_{m,t}-r_f)+e_{ind,t}$$

I use the estimated beta regression output in the CAPM abnormal return formula:

$$AR_{ind,t}=r_{ind,t}-(\widehat{B}(r_{m,t}-r_{f,t})+r_{f,t})$$

In this CAPM abnormal returns formula $AR_{ind,t}$ represents the abnormal return of the industry on the event window, $r_{ind,t}$ represents the return of the industry on the event window, $\widehat{B}$ represents the beta systematic risk estimate over the corresponding estimation period, $r_{m,t}$ represents the return on the market on the event window, and $r_{f,t}$ represents the risk free rate of return on the event window. I calculated CAPM abnormal returns for all four event windows, first using pre-event beta estimates, and again using post-event beta estimates. The t-statistic for the abnormal return is calculated by dividing the industry abnormal return by the corresponding estimation period's standard deviation of normal excess returns.

I estimate the Fama-French 3-Factor Model abnormal returns using the same regression formula that I did when finding differences in the Fama-French risk factors:

$$(r_{ind,t}-r_{f,t})=\hat{b}(r_{m,t}-r_{f,t})+\hat{c}(SMB_t)+\hat{d}(HML_t)+e_{ind,}t$$

I use the estimated risk factor regression outputs in the Fama-French 3-Factor abnormal return formula:

$$AR_{ind,t}=r_{ind,t}-[\hat{b}(r_{m,t}-r_{f,t})+r_{f,t}]-\hat{c}(SMB_t)-\hat{d}(HML_t)$$

In this Fama-French 3-Factor abnormal return formula $AR_{ind,t}$ represents the abnormal return of the industry on the event window, $r_{ind,t}$ represents the return of the industry on the event window, $\hat{b}$ represents the estimate of the market risk coefficient over the corresponding estimation period, $r_{m,t}$ represents the return on the market on the event window, $r_{f,t}$ represents the risk free rate of return on the event window, $\hat{c}$ represents the estimate of the size risk coefficient over the corresponding estimation period, SMB_t represents the size premium on the event window, $\hat{d}$ represents the estimate of the value risk coefficient over the corresponding estimation period, and HML_t represents the value premium on the event window. I calculate Fama-French 3-Factor abnormal returns for all four event windows, first using pre-event beta estimates, and again using post-event beta estimates. The t-statistic calculation is the same for Fama-French 3-Factor abnormal returns as it is for CAPM abnormal returns.

VI. Results

I calculate the t-statistics for each industry to determine if the CAPM beta and Fama-French systematic risk factor differences are significant. I also test the significance of the industry abnormal returns. Because I test for both positive and negative differences in risk factors, as well as positive and negative abnormal returns, I use two-tailed t-tests. I use 5% significance levels in my event study explinations. My tables include significance levels at the 5%, 2%, and 1% level.

The first goal of my empirical research is to determine the Bank Holiday's effect on the systematic risks of the 30 Fama-French industries. I compare the difference of the CAPM systematic risk factor estimates, as well as the Fama-French systematic risk factor estimates, before and after the Bank Holiday. I subtracted the post-event beta and Fama-French risk factor estimates from the pre-event estimates, meaning that a negative difference in estimates shows evidence that the systematic risks of the industries increased after the Bank Holiday. Likewise, a positive difference in estimates shows evidence that the systematic risks of the industries decreased.

Table 1 shows which industries there is evidence that the CAPM beta and Fama-French 3-Factor systematic risk estimates change after the Bank Holiday. I use the Fama-French 3-Factor Model in addition to the CAPM to measure the independent effect of each of the three risk factors on the outcome, which allows me to adjust for other sources of systematic risk other than the market (LaMorte). Table 1 shows that the CAPM systematic beta risk after the Bank Holiday significantly decreased for five of the 30 industries, and significantly increased for ten of the 30 industries. I compare the 3-Factor model to the CAPM to strengthen my argument for my significant results (LaMorte). I find that Coal and Trans show evidence of a significant systematic market risk decrease using both the CAPM and the 3-Factor Model. I also find that Hshld and Clths have significant systematic market risk increases in both models. There is evidence of a significant systematic size risk increase in Coal and BusEq. My 3-Factor analysis also shows evidence of a systematic value risk decrease in Food, Steel, and Util. There is also evidence of a systematic value risk increase in Meals and Other.

The second goal of my empirical research is to determine the Bank Holiday's effect on industry stock returns by analyzing which industries show evidence of abnormal returns over various event windows. Table 2 shows which industries there is evidence that the CAPM and Fama-French 3-Factor Model abnormal returns are statistically significant.

Kupiec and Mathios (1986) identify a problem with the "event test" methodology when post-event abnormal returns are calculated using a pre-event period to estimate systematic risk. They argue that changes in systematic risks "confound" abnormal returns and cause the measures to be biased (Kupiec and Mathios 1986). In their methodology, Kupiec and Mathios (1986) claim that using a post-event estimation period to estimate systematic risks corrects for this bias when calculating post-event abnormal returns, and vice-versa for pre-event abnormal returns. My event study uses both pre- and post-event periods to estimate systematic risks. I also calculate both pre- and post-event abnormal returns. I explain my empirical results of abnormal returns in table 2 using the event study methodology that Kupiec and Mathios (1986) claim corrects for the systematic risk sensitivity bias. Kupiec and Mathios (1986) claim that it actually over-corrects, but that the correction does provide more accurate empirical evidence.

I test for abnormal returns on March 3, 1933, the last trading day before the Bank Holiday, in order to observe possible information leakage before Roosevelt issued the Bank Holiday. I do not find any significant abnormal returns on March 3, which means I find no evidence of information leakage before the Bank Holiday. This is the case for both the CAPM and Fama-French 3-Factor Model results. This allows me to be confident in the accuracy of the rest of my abnormal returns data after the Bank Holiday.

VII. Summary

On March 15th, the day after the Bank Holiday, I find that Books and Hshld have significantly positive abnormal returns using both the CAPM and the 3-Factor Model, and that Steel has a significantly positive abnormal return only in the 3-Factor Model. I calculate abnormal returns on March 16th, the second day after the Bank Holiday, to account for market inefficiencies. I find that Books have a significant positive abnormal return on March 16th only in the CAPM. The cumulative two-day abnormal return after the Bank Holiday accounts for immediate market reactions on March 15th, as well as possible market inefficiencies extend the effects of the Bank Holiday past March 15th. I find that Books and Hshld have significantly positive cumulative two-day abnormal returns after the Bank Holiday.

In order to include results where a systematic risk sensitivity correction may not be appropriate, table 3 does not use a systematic risk-sensitivity correction when calculating abnormal returns using opposite-of-the-event estimation periods of systematic risk. The number of abnormal returns that are statistically significant is drastically fewer when I use the systematic risk sensitivity correction suggested by Kupiec and Mathios

(1986), as compared to when I don't use the correction. This difference in the quantity of significant results is in line with what Kupiec and Mathios (1986) mention, that the systematic risk sensitivity correction actually over corrects for the bias resulting from changes in systematic risks, but that the correction provides a more accurate estimations overall. Consistent with the Kupiec and Mathios's (1986) argument, I am able to explain the abnormal returns when only three industries have significant results when I use their correction, compared to the difficult task of explaining the significant results of 15 industries when I don't use the correction.

I am able to determine that some of the systematic risk changes and abnormal returns of certain industries are statistically significant after the Bank Holiday. I want to know what factors are driving these significant results, which is why my hypothesis aims to find the relationship between leverage ratios and systematic risk factors. To test this relationship, I need to find the correlation between the industry leverage ratios and the differences in each systematic risk factor. I use the following correlation formula to calculate the correlation coefficient of leverage ratios and each systematic risk factor ("PreMBA Analytical Methods"):

$$r_{(x,y)}=COV(x,y)/s_x s_y$$

In this correlation formula $r_{(x,y)}$ represents the correlation of the leverage ratios x and differences in systematic risk factors y, COV(x,y) represents the covariance of the leverage ratios x and differences in systematic risk factors y, s_x represents the sample standard deviation of the leverage ratios, and s_y represents the sample standard deviation of the differences in systematic risk y ("PreMBA Analytical Methods"). Table 4 shows the correlation results of systematic risk factors and leverage ratios. The risk coefficient shows how much each systematic risk factor is expected to change given a change in the leverage ratio. The r-value is the correlation measure and shows the relationship of the systematic risk factors and leverage ratios. The p-value measures significance of the correlation. I find that the r-value is extremely low for all four of the systematic risk factors. There is no evidence of correlation of the systematic risk factors and leverage ratios at the 5% level given the extremely high p-values for each of the factors. This does not support my hypothesis and I see no significant evidence that the market factors of highly leveraged industries decrease significantly more, or that the size and value factors of highly leverage industries decrease significantly less.

Table 5 shows the correlation results of abnormal returns on different event windows and leverage ratios. None of the correlation results for abnormal returns are significant either. The closest to significance are the abnormal returns of the CAPM and the 3-Factor Model the day before the Bank Holiday, both of which have p-values of 0.11 and 0.12 respectively. However, there are no significant differences in systematic risk factors or significant abnormal returns that I can use these almost significant results to explain. Because none of the risk factors were significantly correlated with leverage ratios, it is difficult to determine what changes in risk factors are driving the significant abnormal returns after the Bank Holiday. Until a significant correlation between the changes in systematic risks and a variable like leverage ratios can be found, it’s difficult to know what specific factors are driving abnormal returns as an effect of the Bank Holiday and the Emergency Banking Act.

VIII. Discussion

By calculating multiple event periods and multiple estimation periods of systematic risk, I was able to observe specific differences in systematic risk factors and abnormal returns after the Bank Holiday. My significant findings of abnormal returns and differences in risk factors do show evidence that the 1933 Bank Holiday and the Emergency Banking Act of 1933 did benefit certain industries more than others. However, I am not able to explain the specific driving factors behind the changes in systematic risk and the significantly positive abnormal returns because there ended up being almost no statistical significance in the correlation tests.

Figures 3 through 6 show the plotted trend line of the correlation of the differences in risk factors and leverage ratios. While none of the correlation results are significant, the risk coefficients of all four risk factors align with my hypothesis. The slope of the CAPM beta risk trend line in figure 3 is 0.03, just slightly positive. The slope of the Fama-French market factor trend line in figure 4 is also slightly positive at 0.12. Even though these aren't significant figures, they directionally align with my hypothesis, which is that I expect systematic risk to decrease more in highly leveraged industries. Even though the correlation results of the Fama-French size and value factors are not statistically significant, their risk coefficients of -0.14 and -0.12 respectively also directionally align with my hypothesis.

Since the risk coefficients in table 4 show almost no significance by conventional standards to support my hypothesis, but the risk coefficients directionally align with my hypothesis, there is the possibility that using a model other than the CAPM or the 3-Factor Model may be appropriate. Another possible improvement to the model could be creating a database of historical debt and equity values for each public company in the U.S. for certain periods before and after the 1933 Bank Holiday. Then the leverage ratios for each company could be calculated and then sorted by SIC industries the same way I did. This would allow the correlations to be calculated using leverage ratios from the same estimation period as the risk factor estimations, which was not what I chose to do by using a proxy to estimate leverage ratios with more recent data. By using a proxy for leverage ratios, my calculations assume that the capital structure of firms is consistent over long periods of time. This could have been a factor limiting the number of my significant results. Additional modeling beyond the factors analyzed in my research might find variables that significantly affect systematic risk exposure and abnormal returns in certain industries.

IX. Works Cited

Acharya, Viral V., Christian Brownlees, Robert Engle, Farhang Farazmand, and Matthew Richardson. "Measuring Systemic Risk." *Handbook on Systemic Risk* (2010). Print.

Allen, Frederick. *Since Yesterday: The 1930's in America, September 3, 1929-September 3, 1939*. New York: Perennial Library, Harper & Row, 1972. Print.

Alter, Jonathan. *The Defining Moment: FDR's Hundred Days and the Triumph of Hope.* New York: Simon & Schuster, 2006. Print.

Awalt, Francis Gloyd. "Recollections of the Banking Crisis in 1933." *Business History Review* (1969): 349. Print.

Bordo, Michael, and John Landon-Lane. "The Lessons from the Banking Panics in the United States in the 1930s for the Financial Crisis of 2007-2008." *National Bureau of Economic Research* (2010): 3-16. Print.

Carlson, Mark, and Kris James Mitchener. "Branch Banking as a Device for Discipline: Competition and Bank Survivorship During the Great Depression." *Journal of Political Economy* (2009). Print.

"Daily Stock File." *The Center for Research and Security Prices.* Accessed via Wharton Research Data Services. 1932-1933. Web. <https://wrds-web.wharton.upenn.edu/wrds/ds/crsp/stock_a/dsf.cfm>.

"Detail for 30 Industry Portfolios." *The Fama and French Data Library*. 1932-1933. Web. <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_30_ind_port.html>.

Friedman, Milton, and Anna J. Schwartz. "The Great Contraction, 1929-33." *A Monetary History of the United States, 1867-1960*. Princeton UP, 1963. Print.

Grossman, Richard S. "The Shoe That Didn't Drop: Explaining Banking Stability During the Great Depression." *The Journal of Economic History* (1994): 654-82. Print.

Grossman, Richard. "Unsettled Account." Princeton University Press, (2010). Print.

Kupiec, Paul, and Alan Mathios. "Mergers, Event Studies And Systematic Risk." *The Financial Review* (1986): 76. Print.

LaMorte, Wayne. "Regression Analysis: Controlling for Confounding." *Boston University School of Public Health*. Web. <http://sphweb.bumc.bu.edu/otlt/MPH-Modules/EP/EP713_Regression/EP713_Regression_print.html>.

"Leverage Ratio." *Investopedia*. Web. This article is a definition located in the main website's "Dictionary" section. Web. <http://www.investopedia.com/terms/l/leverageratio.asp>.

"*New York Times"* 13 Mar. 1933: P. 1 Cont. Print.

"North America: Fundamentals Annual." *Compustat from Standard & Poor's.* Accessed via Wharton research Data Services. 1998-2014. Web. <https://wrds-web.wharton.upenn.edu/wrds/ds/crsp/stock_a/dsf.cfm>.

"On the Banking Crisis." *Fireside Chats of Franklin D. Roosevelt*. Franklin D. Roosevelt. District of Columbia, 12 Mar. 1933. Radio.

"PreMBA Analytical Methods." *PreMBA Analytical Methods*. Columbia Business School, 2003. Web. <http://ci.columbia.edu/ci/premba_test/c0331/s7/s7_5.html>.

Silber, William L. "Why Did FDR's Bank Holiday Succeed?" *SSRN Electronic Journal SSRN* (2009). Print.

"Solvency." *Investopedia*. Web. This article is a definition located in the main website's "Dictionary" section. <http://www.investopedia.com/terms/s/solvency.asp>.

Temin, Peter, and Barrie A Wigmore. "The End of One Big Deflation." *Explorations in Economic History* (1990): 483-502. Print.

White, Eugene. "The Regulation and Reform of the American Banking System, 1900-1929." (1983). Print.

Wicker, Elmus. "Banking Panics in the US: 1873-1933." *EHnet*. Edited by Robert Whaples, 4 Sept. 2001. Web.

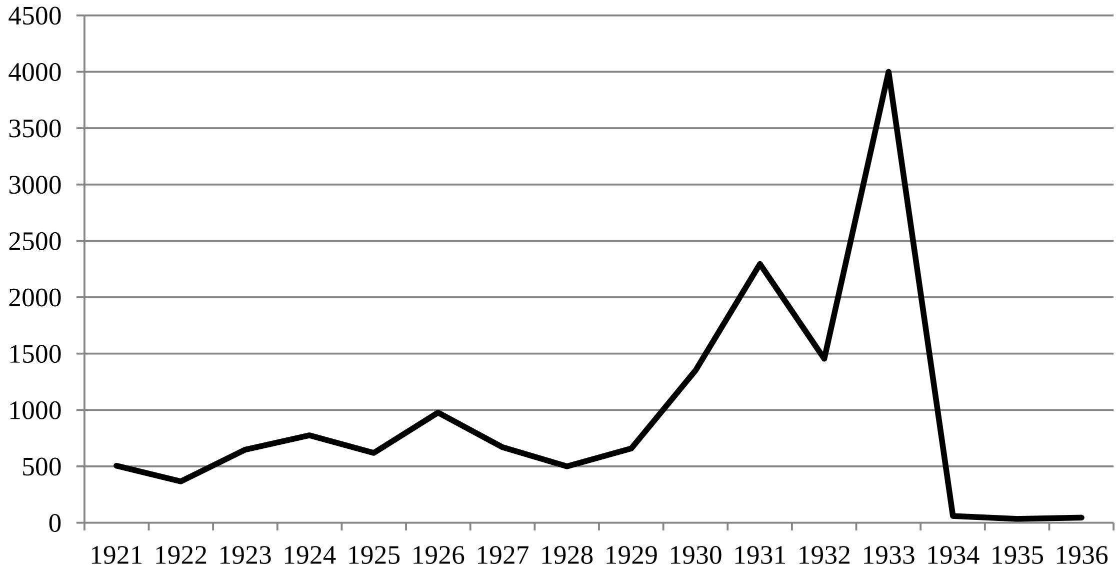
Wicker, Elmus. "The Banking Panics of the Great Depression." *EHnet*. Edited by John Wood, 1 May 1997. Web.

Wicker, Elmus. *Banking Panics of the Gilded Age*. New York: Cambridge University Press, 2000. Web.

Wicker, Elmus. *The Banking Panics of the Great Depression*. New York: Cambridge University Press, 1996. Web.

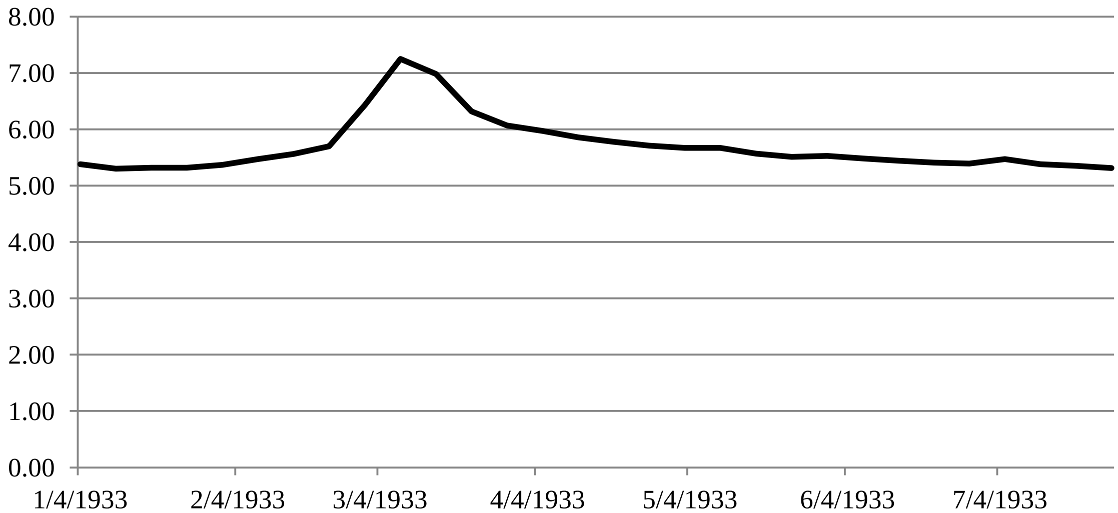
X. Appendix

Figure 1: This figure shows the total number of all bank suspensions in the U.S. from 1921-1936.



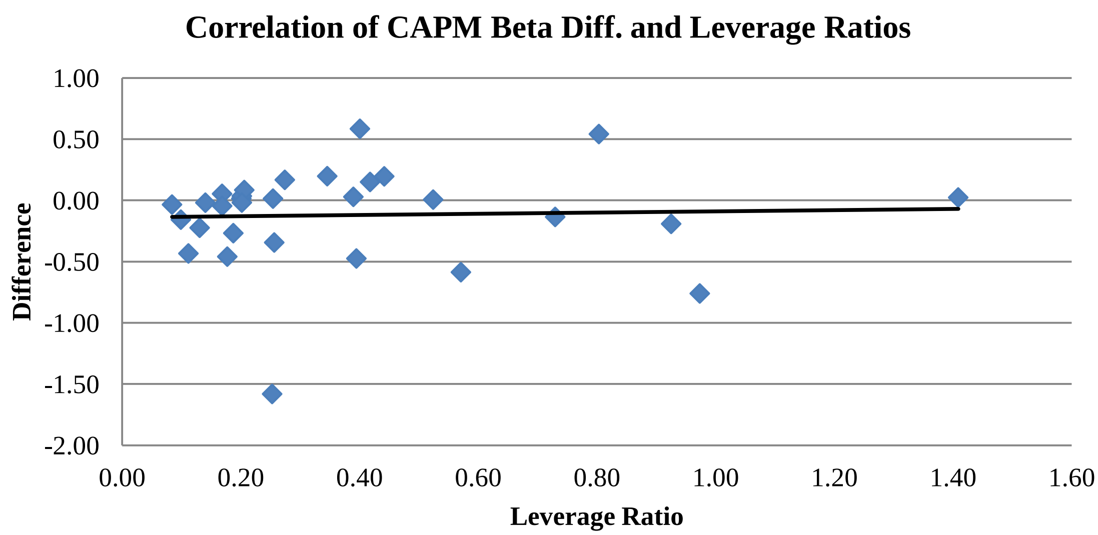
Source: Board of Governors of the Federal Reserve System (U.S.) , 1935-. "Bank Suspensions, 1921-1936." *Fraser Federal Reserve Archive*. Federal Reserve Bulletin, 1 Sept. 1937. Web.

Figure 2: This figure shows the amount of money (in billions) in circulation from January 4, 1933 through July 26, 1933.



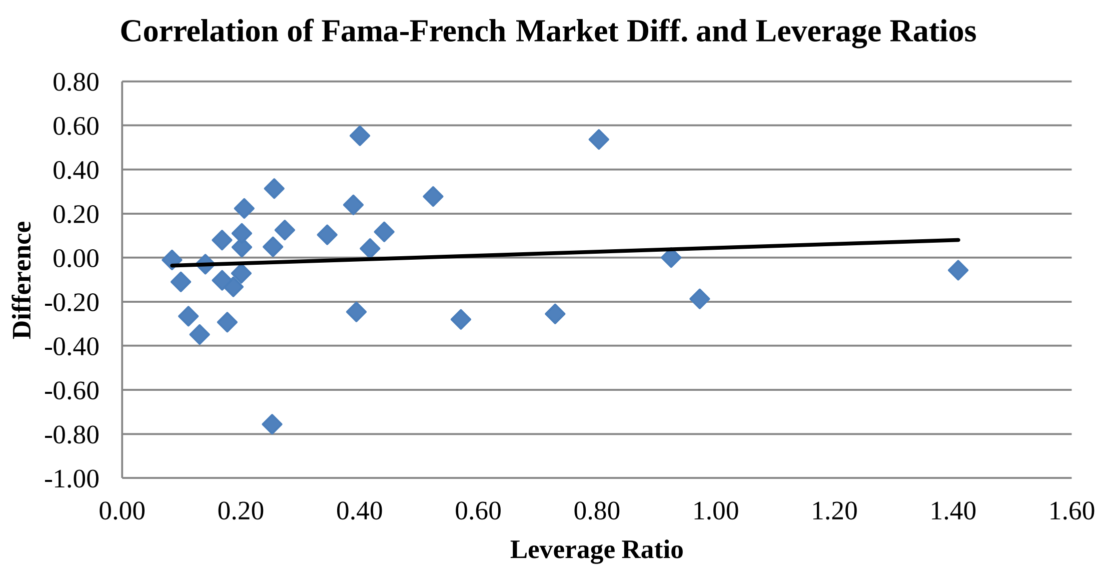
Source: Board of Governors of the Federal Reserve System (U.S.) , 1935-. "Banking and Monetary Statistics, 1941-1970." *Fraser Federal Reserve Archive*. Federal Reserve Bulletin, 1 Sept. 1937. Web. (Cited Silber 2009).

Figure 3: This figure shows the correlation and trend line of the difference in the pre- and post-event CAPM beta risk estimates for each of the 30 industry portfolios. Table 4 shows the correlation statistics of this figure.



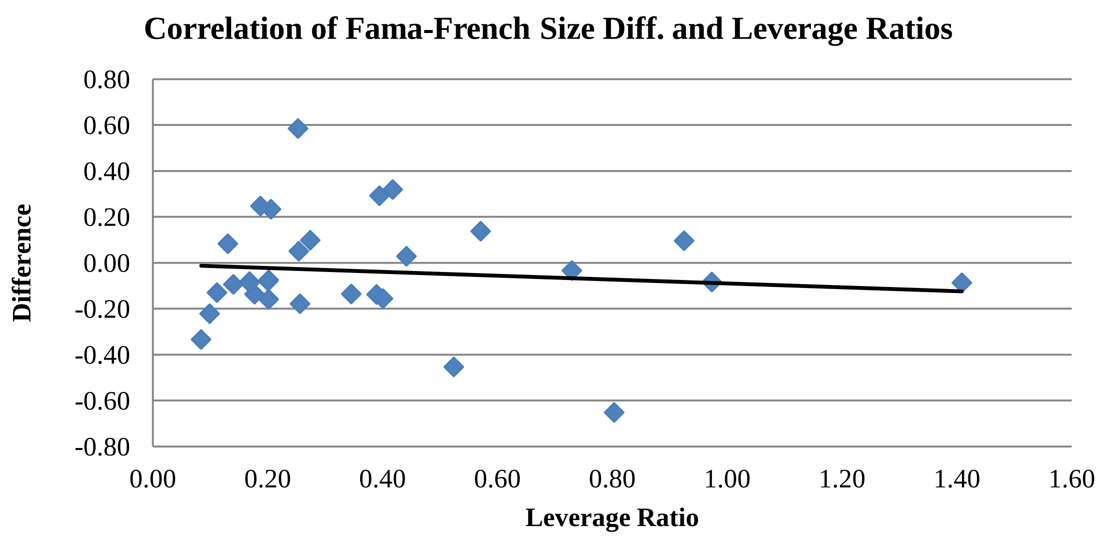
Data collected from the following sources to construct figure: ("Daily Stock File"), ("Detail for 30 Industry Portfolios,") and ("North America: Fundamentals Annual")

Figure 4: This figure shows the correlation and trend line of the difference in the pre- and post-event Fama-French market risk estimates for each of the 30 industry portfolios. Table 4 shows the correlation statistics of this figure.



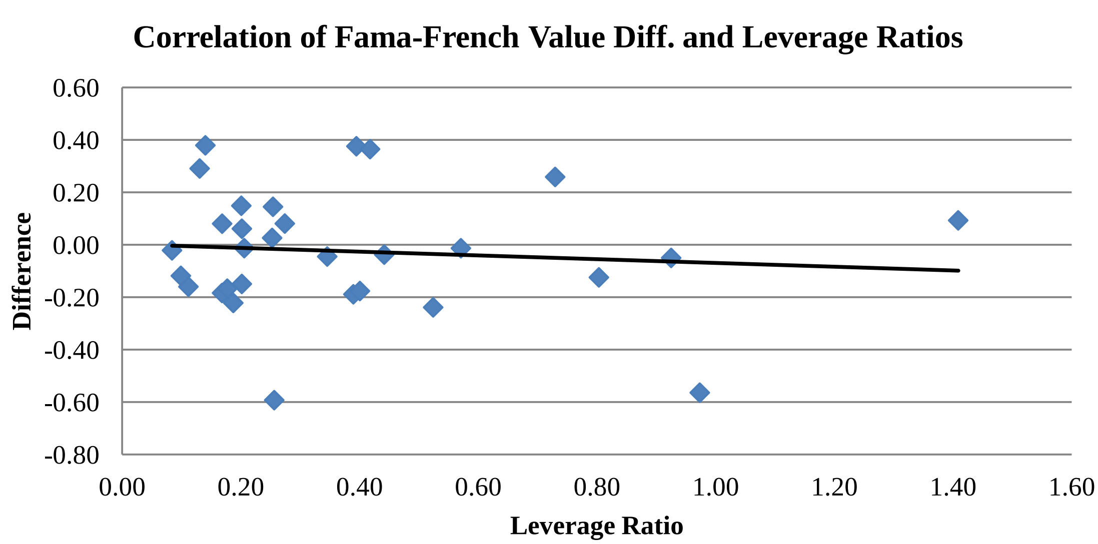
Data collected from the following sources to construct figure: ("Daily Stock File"), ("Detail for 30 Industry Portfolios,") and ("North America: Fundamentals Annual")

Figure 5: This figure shows the correlation and trend line of the difference in the pre- and post-event Fama-French size risk estimates for each of the 30 industry portfolios. Table 4 shows the correlation statistics of this figure.



Data collected from the following sources to construct figure: ("Daily Stock File"), ("Detail for 30 Industry Portfolios,") and ("North America: Fundamentals Annual")

Figure 6: This figure shows the correlation and trend line between the difference in the pre- and post-event Fama-French value risk estimates for each of the 30 industry portfolios. Table 4 shows the correlation statistics of this figure.



Data collected from the following sources to construct figure: ("Daily Stock File"), ("Detail for 30 Industry Portfolios,") and ("North America: Fundamentals Annual")

Table 1: This table shows the market value weighted average leverage ratio (1998-2014) for each industry displayed alongside the difference in systematic risk factors before and after the Bank Holiday for each industry. The standard errors are shown in parentheses below the corresponding systematic risk factor estimates. A 2-tailed t-test was run to determine significance for the differences in pre- and post-event risk factors. *, **, and *** denote significance at the 5%, 2%, and 1% levels, respectively.

		CAPM Beta Risk Factor			Market Risk Factor			Size Risk Factor			Value Risk Factor		
Industry	**Leverage Ratio**	**Pre-event**	**Post-event**	**Difference**	**Pre-event**	**Post-event**	**Difference**	**Pre-event**	**Post-event**	**Difference**	**Pre-event**	**Post-event**	**Difference**
Food	0.20	0.77	0.76	0.02	0.75	0.82	-0.07	-0.03	0.05	-0.08	0.01	-0.14	0.15 *
		(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)	(0.06)	(0.08)	(0.05)	(0.05)	(0.07)
Beer	0.14	1.30	1.32	-0.02	1.41	1.43	-0.03	0.33	0.42	-0.09	0.13	-0.25	0.38
		(0.10)	(0.15)	(0.18)	(0.17)	(0.20)	(0.26)	(0.20)	(0.31)	(0.37)	(0.18)	(0.27)	(0.33)
Smoke	0.17	0.60	0.54	0.05	0.62	0.54	0.08	-0.11	-0.03	-0.08	-0.17	0.02	-0.18
		(0.06)	(0.03)	(0.06)	(0.10)	(0.04)	(0.10)	(0.11)	(0.06)	(0.13)	(0.10)	(0.05)	(0.11)
Games	0.52	1.34	1.33	0.01	1.42	1.14	0.28	0.31	0.77	-0.45	0.16	0.40	-0.24
		(0.11)	(0.14)	(0.18)	(0.19)	(0.17)	(0.26)	(0.23)	(0.27)	(0.35)	(0.20)	(0.24)	(0.31)
Books	0.39	0.55	1.03	-0.47 ***	0.73	0.98	-0.25	0.79	0.49	0.29	0.48	0.11	0.38
		(0.13)	(0.11)	(0.17)	(0.20)	(0.14)	(0.25)	(0.24)	(0.22)	(0.32)	(0.21)	(0.20)	(0.29)
Hshld	0.13	0.69	0.92	-0.22 ***	0.66	1.01	-0.35 **	0.02	-0.06	0.08	0.09	-0.20	0.29
		(0.07)	(0.05)	(0.08)	(0.12)	(0.07)	(0.14)	(0.14)	(0.10)	(0.18)	(0.12)	(0.09)	(0.15)
Clths	0.11	0.24	0.67	-0.43 ***	0.29	0.55	-0.27 *	0.18	0.31	-0.13	0.09	0.25	-0.16
		(0.05)	(0.07)	(0.08)	(0.08)	(0.09)	(0.12)	(0.10)	(0.14)	(0.17)	(0.09)	(0.12)	(0.15)
Hlth	0.20	0.79	0.75	0.04	0.86	0.81	0.05	0.08	0.16	-0.07	-0.06	-0.12	0.06
		(0.06)	(0.06)	(0.09)	(0.11)	(0.08)	(0.14)	(0.13)	(0.12)	(0.18)	(0.11)	(0.11)	(0.16)
Chems	0.27	1.25	1.08	0.17 ***	1.28	1.15	0.13	-0.01	-0.11	0.10	-0.08	-0.16	0.08
		(0.03)	(0.04)	(0.05)	(0.06)	(0.05)	(0.08)	(0.07)	(0.09)	(0.11)	(0.06)	(0.08)	(0.10)
Txtls	0.57	0.63	1.21	-0.59 ***	0.84	1.12	-0.28	0.58	0.45	0.14	0.19	0.20	-0.01
		(0.07)	(0.07)	(0.10)	(0.12)	(0.09)	(0.15)	(0.14)	(0.14)	(0.19)	(0.12)	(0.12)	(0.17)
Cnstr	0.39	1.17	1.14	0.03	1.35	1.11	0.24 *	0.24	0.38	-0.14	-0.11	0.08	-0.19
		(0.05)	(0.05)	(0.07)	(0.09)	(0.06)	(0.10)	(0.10)	(0.09)	(0.13)	(0.09)	(0.08)	(0.12)
Steel	0.42	1.46	1.31	0.15	1.30	1.26	0.04	0.12	-0.20	0.32	0.47	0.11	0.36 *
		(0.08)	(0.06)	(0.10)	(0.13)	(0.08)	(0.15)	(0.15)	(0.12)	(0.19)	(0.13)	(0.10)	(0.17)
FabPr	0.25	1.29	1.28	0.01	1.34	1.29	0.05	0.20	0.15	0.05	0.11	-0.04	0.14
		(0.05)	(0.04)	(0.06)	(0.08)	(0.05)	(0.10)	(0.10)	(0.08)	(0.12)	(0.08)	(0.07)	(0.11)
ElcEq	0.21	1.42	1.34	0.08	1.58	1.35	0.22	0.26	0.03	0.23	-0.05	-0.03	-0.01
		(0.06)	(0.05)	(0.08)	(0.10)	(0.07)	(0.12)	(0.12)	(0.11)	(0.16)	(0.10)	(0.10)	(0.14)
Autos	1.41	1.47	1.44	0.02	1.44	1.50	-0.06	-0.07	0.02	-0.09	-0.03	-0.12	0.09
		(0.06)	(0.05)	(0.08)	(0.11)	(0.06)	(0.13)	(0.13)	(0.10)	(0.17)	(0.11)	(0.09)	(0.15)
Carry	0.20	1.18	1.19	-0.02	1.26	1.15	0.11	0.11	0.27	-0.16	-0.05	0.10	-0.15
		(0.05)	(0.05)	(0.07)	(0.09)	(0.07)	(0.11)	(0.10)	(0.11)	(0.15)	(0.09)	(0.09)	(0.13)
Mines	0.18	0.41	0.87	-0.46 ***	0.49	0.78	-0.29	0.17	0.31	-0.14	0.01	0.18	-0.17
		(0.08)	(0.08)	(0.11)	(0.14)	(0.10)	(0.18)	(0.17)	(0.16)	(0.23)	(0.15)	(0.14)	(0.20)
Coal	0.80	1.78	1.24	0.54 ***	1.47	0.93	0.54 ***	-0.12	0.53	-0.65 ***	0.54	0.67	-0.12
		(0.09)	(0.09)	(0.13)	(0.16)	(0.10)	(0.19)	(0.18)	(0.16)	(0.24)	(0.16)	(0.14)	(0.22)
Oil	0.19	0.73	1.00	-0.27 ***	0.75	0.88	-0.13	0.06	-0.19	0.25	0.01	0.24	-0.22
		(0.05)	(0.06)	(0.07)	(0.08)	(0.07)	(0.11)	(0.10)	(0.11)	(0.15)	(0.09)	(0.10)	(0.13)
Util	0.73	0.96	1.09	-0.13	1.05	1.30	-0.25 ***	0.01	0.04	-0.03	-0.18	-0.44	0.26 *
		(0.03)	(0.07)	(0.07)	(0.05)	(0.08)	(0.10)	(0.06)	(0.13)	(0.14)	(0.05)	(0.11)	(0.12)
Telcm	0.44	0.82	0.62	0.20 ***	0.79	0.67	0.12	-0.19	-0.22	0.03	-0.14	-0.11	-0.04
		(0.03)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.07)	(0.09)	(0.05)	(0.06)	(0.08)
Servs	0.10	0.02	0.17	-0.16	0.02	0.13	-0.11	-0.01	0.21	-0.22	-0.03	0.09	-0.12
		(0.04)	(0.10)	(0.10)	(0.07)	(0.13)	(0.15)	(0.09)	(0.20)	(0.22)	(0.08)	(0.18)	(0.19)
BusEq	0.08	0.89	0.93	-0.03	0.89	0.90	-0.01	0.03	0.36	-0.33 **	0.03	0.05	-0.02
		(0.04)	(0.05)	(0.07)	(0.08)	(0.06)	(0.10)	(0.09)	(0.10)	(0.13)	(0.08)	(0.09)	(0.12)
Paper	0.35	0.95	0.75	0.20 ***	0.86	0.76	0.10	-0.22	-0.09	-0.14	-0.06	-0.02	-0.04
		(0.04)	(0.03)	(0.05)	(0.07)	(0.05)	(0.08)	(0.08)	(0.07)	(0.11)	(0.07)	(0.06)	(0.10)
Trans	0.40	1.52	0.93	0.58 ***	1.24	0.69	0.55 ***	-0.22	-0.07	-0.16	0.33	0.51	-0.18
		(0.05)	(0.06)	(0.07)	(0.08)	(0.07)	(0.10)	(0.09)	(0.11)	(0.14)	(0.08)	(0.09)	(0.12)
Whlsl	0.25	0.25	1.83	-1.58 ***	0.81	1.56	-0.76	1.62	1.04	0.58	0.59	0.57	0.03
		(0.42)	(0.19)	(0.46)	(0.73)	(0.24)	(0.77)	(0.85)	(0.38)	(0.93)	(0.75)	(0.33)	(0.82)
Rtail	0.17	0.88	0.93	-0.05	0.85	0.95	-0.10	-0.04	0.05	-0.09	0.03	-0.05	0.08
		(0.03)	(0.03)	(0.04)	(0.06)	(0.04)	(0.07)	(0.07)	(0.06)	(0.09)	(0.06)	(0.05)	(0.08)
Meals	0.26	0.56	0.90	-0.34 *	0.93	0.62	0.31	0.74	0.92	-0.18	0.02	0.61	-0.59 *
		(0.12)	(0.11)	(0.16)	(0.21)	(0.13)	(0.24)	(0.24)	(0.21)	(0.32)	(0.21)	(0.18)	(0.28)
Fin	0.92	1.03	1.22	-0.19 ***	1.16	1.16	0.00	0.33	0.23	0.10	0.09	0.14	-0.05
		(0.04)	(0.05)	(0.06)	(0.07)	(0.06)	(0.09)	(0.09)	(0.09)	(0.12)	(0.07)	(0.08)	(0.11)
Other	0.97	0.28	1.04	-0.76 ***	0.69	0.87	-0.19	0.60	0.69	-0.08	-0.21	0.35	-0.56 *
		(0.10)	(0.10)	(0.14)	(0.17)	(0.13)	(0.21)	(0.19)	(0.20)	(0.28)	(0.17)	(0.17)	(0.24)

Data collected from the following sources to construct figure: (“Daily Stock File”), (“Detail for 30 Industry Portfolios,”) and (“North America: Fundamentals Annual”)

Table 2: This table shows the market value weighted average leverage ratio (1998-2014) for each industry displayed alongside the abnormal returns using the estimation periods suggested in the systematic risk sensitivity correction from Kupiec and Mathios (1986). Pre-event abnormal returns are shown using pre-event systematic risk estimations and post-event abnormal returns using post-event systematic risk estimations. The "Day Before" is March 3, 1933. The "Day After" is March 15, 1933. The "Second Day After" is March 16, 1933. The "Cum. Two Days After" is the cumulative two-day abnormal return of March 15 through March 16, 1933. A 2-tailed t-test was run to determine significance of abnormal returns. *, **, and *** denote significance at the 5%, 2%, and 1% levels, respectively.

		CAPM Model Abnormal Returns				Fama-French 3-Factor Model Abnormal Returns			
Industry	**Leverage Ratio**	**Day Before**	**Day After**	**Second Day After**	**Cum. Two Days After**	**Day Before**	**Day After**	**Second Day After**	**Cum. Two Days After**
Food	0.20	1.10	4.08	1.06	3.64	1.08	4.11	1.26	3.79
Beer	0.14	-0.05	-0.86	0.20	-0.46	-0.11	-1.30	-0.57	-1.32
Smoke	0.17	0.29	2.21	1.62	2.71	0.39	2.25	1.69	2.79
Games	0.52	-1.11	-7.51	1.37	-4.34	-1.19	-8.95	-2.27	-7.93
Books	0.39	-5.11	16.13***	10.11**	18.55***	-5.38	15.31***	8.15	16.59***
Hshld	0.13	-0.28	11.40***	0.12	8.14***	-0.35	11.64***	0.85	8.83***
Clths	0.11	-0.03	0.32	0.63	0.67	-0.07	-0.33	-1.07	-0.99
Hlth	0.20	0.98	0.15	-0.37	-0.15	1.03	0.01	-0.57	-0.40
Chems	0.27	0.66	-0.12	-2.22	-1.65	0.71	0.16	-1.43	-0.90
Txtls	0.57	0.19	-6.25	6.82	0.40	0.11	-7.06	4.79	-1.61
Cnstr	0.39	0.39	4.72	1.11	4.13	0.49	4.10	-0.38	2.63
Steel	0.42	-0.23	7.95	-1.42	4.61	-0.55	8.17*	-1.03	5.05
FabPr	0.25	2.20	6.03	3.10	6.46	2.14	5.83	2.69	6.03
ElcEq	0.21	-1.38	3.36	2.44	4.10	-1.32	3.35	2.45	4.10
Autos	1.41	-4.26	5.11	0.29	3.82	-4.25	5.17	0.56	4.05
Carry	0.20	1.77	-0.27	0.37	0.07	1.82	-0.75	-0.81	-1.10
Mines	0.18	0.34	1.53	-3.69	-1.53	0.35	0.93	-5.21	-3.02
Coal	0.80	-0.17	-0.10	-0.44	-0.38	-0.56	-1.38	-3.98	-3.79
Oil	0.19	-0.26	-2.47	-0.62	-2.18	-0.26	-2.36	-0.60	-2.10
Util	0.73	1.22	-6.30	-1.36	-5.42	1.34	-6.03	-0.33	-4.50
Telcm	0.44	-0.01	-2.51	0.04	-1.74	0.07	-2.11	1.05	-0.75
Servs	0.10	0.85	-2.39	0.55	-1.30	0.86	-2.77	-0.40	-2.24
BusEq	0.08	-0.79	-2.49	1.42	-0.76	-0.81	-3.07	0.04	-2.14
Paper	0.35	0.19	0.70	0.52	0.87	0.21	0.84	0.86	1.20
Trans	0.40	-1.64	3.82	-0.99	2.00	-1.90	3.55	-2.11	1.02
Whlsl	0.25	3.22	-9.79	-4.30	-9.96	2.96	-11.76	-9.32	-14.91
Rtail	0.17	0.65	3.20	2.58	4.08	0.63	3.16	2.54	4.03
Meals	0.26	-2.35	5.21	4.37	6.78	-2.29	3.39	-0.35	2.15
Fin	0.92	1.86	0.33	1.63	1.39	1.83	-0.12	0.48	0.26
Other	0.97	-0.32	-4.70	-0.67	-3.79	-0.11	-5.98	-3.93	-7.01

Data collected from the following sources to construct figure: ("Daily Stock File"), ("Detail for 30 Industry Portfolios,") and ("North America: Fundamentals Annual")

Table 3: This table shows the market value weighted average leverage ratio (1998-2014) for each industry displayed alongside the abnormal returns using the opposite estimation periods than are suggested in the systematic risk sensitivity correction from Kupiec and Mathios (1986). Pre-event abnormal returns are shown using post-event systematic risk estimations and post-event abnormal returns using pre-event systematic risk estimations. The "Day Before" is March 3, 1933. The "Day After" is March 15, 1933. The "Second Day After" is March 16, 1933. The "Cum. Two Days After" is the cumulative two-day abnormal return of March 15 through March 16, 1933. A 2-tailed t-test was run to determine significance of abnormal returns. *, **, and *** denote significance at the 5%, 2%, and 1% levels, respectively.

		CAPM Model Abnormal Returns				Fama-French 3-Factor Model Abnormal Returns			
Industry	**Leverage Ratio**	**Day Before**	**Day After**	**Second Day After**	**Cum. Two Days After**	**Day Before**	**Day After**	**Second Day After**	**Cum. Two Days After**
Food	0.20	1.14	3.85*	1.04	3.46*	1.32	4.12**	1.13	3.71*
Beer	0.14	-0.11	-0.56	0.23	-0.24	0.77	-3.80	-1.48	-3.74
Smoke	0.17	0.45	1.37	1.54	2.06	0.38	2.61	2.46	3.58*
Games	0.52	-1.09	-7.62*	1.37	-4.42	-0.09	-10.73***	-0.35	-7.83*
Books	0.39	-6.57	23.60***	10.81***	24.33***	-5.82	15.69***	6.27*	15.53***
Hshld	0.13	-0.97	14.92***	0.45	10.87***	-0.93	14.63***	0.11	10.42***
Clths	0.11	-1.36	7.15***	1.27	5.95***	-1.01	5.34***	0.29	3.98***
Hlth	0.20	1.08	-0.41	-0.42	-0.59	1.43	-1.14	-0.60	-1.23
Chems	0.27	1.17	-2.76	-2.46	-3.70	1.11	-2.62	-2.22	-3.42
Txtls	0.57	-1.61	2.99	7.68***	7.55***	-1.01	-2.75	4.78**	1.44
Cnstr	0.39	0.48	4.26	1.07	3.77	1.06	2.06	0.36	1.71
Steel	0.42	0.24	5.58	-1.64	2.78	-0.18	4.07	-3.39	0.48
FabPr	0.25	2.25	5.80*	3.08	6.28*	2.52	3.79	1.96	4.07
ElcEq	0.21	-1.12	2.03	2.32	3.07	-1.05	-0.41	1.37	0.68
Autos	1.41	-4.19	4.73	0.26	3.53	-4.08	5.43	0.62	4.28
Carry	0.20	1.71	0.00	0.40	0.29	2.10	-1.05	0.07	-0.70
Mines	0.18	-1.06	8.76***	-3.01	4.07*	-0.67	7.10***	-3.76*	2.36
Coal	0.80	1.49	-8.64*	-1.23	-6.98	1.91	-7.89	-2.15	-7.10
Oil	0.19	-1.08	1.74	-0.22	1.08	-1.56	1.17	-0.50	0.47
Util	0.73	0.80	-4.17*	-1.16	-3.77	1.17	-4.09	-0.71	-3.39
Telcm	0.44	0.59	-5.60***	-0.25	-4.14*	0.31	-3.69*	0.91	-1.97
Servs	0.10	0.37	0.09	0.78	0.62	0.65	0.24	0.91	0.81
BusEq	0.08	-0.90	-1.95	1.47	-0.35	-0.33	-2.27	1.26	-0.72
Paper	0.35	0.80	-2.41	0.23	-1.54	0.67	-0.24	1.32	0.76
Trans	0.40	0.15	-5.39	-1.85	-5.12	-0.32	-3.52	-1.81	-3.76
Whlsl	0.25	-1.63	15.12	-1.97	9.29	-0.29	-0.91	-10.27	-7.91
Rtail	0.17	0.51	3.91*	2.64	4.63**	0.63	4.24*	2.72	4.92**
Meals	0.26	-3.41	10.63***	4.88	10.96***	-2.30	3.53	1.77	3.75
Fin	0.92	1.27	3.35	1.91	3.72	1.56	0.14	0.32	0.33
Other	0.97	-2.65	7.28***	0.45	5.47**	-1.75	1.68	-1.49	0.14

Data collected from the following sources to construct figure: ("Daily Stock File"), ("Detail for 30 Industry Portfolios,") and ("North America: Fundamentals Annual")

Table 4: This table shows the correlation of leverage ratios and differences in CAPM beta and Fama-French 3-Factor Model systematic risk factors.

	CAPM Beta	**FF Market**	**FF Size**	**FF Value**
Risk Coefficient	0.03	0.12	-0.14	-0.12
r-value	0.04	0.1	0.11	0.09
p-value	0.84	0.59	0.57	0.62

Data collected from the following sources to construct figure: ("Daily Stock File"), ("Detail for 30 Industry Portfolios,") and ("North America: Fundamentals Annual")

Table 5: This table shows the correlation of leverage ratios and abnormal returns using the CAPM and Fama-French 3-Factor Model.

	CAPM Model Abnormal Returns				Fama-French 3-Factor Model Abnormal Returns			
	Day Before	**Day After**	**Second Day After**	**Cum. Two Days After**	**Day Before**	**Day After**	**Second Day After**	**Cum. Two Days After**
Risk Coefficient	-0.05	-0.01	0.00	0.00	-0.05	-0.01	-0.01	-0.01
r-value	0.29	0.10	0.00	0.08	0.29	0.11	0.05	0.10
p-value	0.11	0.58	0.99	0.68	0.12	0.56	0.79	0.60

Data collected from the following sources to construct figure: ("Daily Stock File"), ("Detail for 30 Industry Portfolios,") and ("North America: Fundamentals Annual")

Data Selection Process

To study industry-specific effects surrounding the 1933 Bank Holiday, I use the Fama-French data library, which has stock return data categorized by industry dating back to 1926. "[Kenneth French and his team] assign each NYSE, AMEX, and NASDAQ stock to an industry portfolio at the end of June of year t based on its four-digit SIC code at that time. ([They] use Compustat SIC codes for the fiscal year ending in calendar year t-1. Whenever Compustat SIC codes are not available, [they] use CRSP SIC codes for June of year t.) [They] then compute returns from July of t to June of t+1" ("Detail for 30 Industry Portfolios"). Compustat only reports daily security data back to 1983. As it pertains to my event study, where I'm only using data security returns between 1932 and 1933, the CRSP SIC codes are used for industry classification. The Fama-French industry returns are available in both monthly and daily data. For the purposes of my event study, I use daily data because the event windows that I analyze are either one-day or cumulative two-day returns. The industry portfolios are available in broad data sets that assign all NYSE, AMEX, and NASDAQ stocks to just five industry portfolios. The industry portfolios are also available in industry assignments as specific as 48 portfolios. The Fama-French 30 industry portfolios data is the most specific industry assignment that has returns data for all the industries classification back to 1932, which is what I need to run the empirical tests for my event study. This is why I chose the Fama-French 30 industry portfolios daily data in my empirical tests for my event study. By choosing to use the 30 industry portfolios classification, instead of one of the Fama-French data sets with fewer and broader industry classifications, I will be able to analyze most precisely estimate how each of the 30 industries are affected by the Bank Holiday.

Sic Codes - 30 Industries ("Detail for 30 Industry Portfolios"):

1 Food - Food Products
2 Beer - Beer & Liquor
3 Smoke - Tobacco Products
4 Games - Recreation
5 Books - Printing and Publishing
6 Hshld- Consumer Goods
7 Clths- Apparel
8 Hlth - Healthcare, Medical Equipment, Pharmaceutical Products
9 Chems - Chemicals
10 Txtls - Textiles
11 Cnstr - Construction and Construction Materials
12 Steel - Steel Works Etc
13 FabPr - Fabricated Products and Machinery
14 ElcEq - Electrical Equipment
15 Autos - Automobiles and Trucks
16 Carry - Aircraft, ships, and railroad equipment
17 Mines - Precious Metals, Non-Metallic, and Industrial Metal Mining
18 Coal - Coal
19 Oil - Petroleum and Natural Gas
20 Util - Utilities
21 Telcm - Communication
22 Servs - Personal and Business Services
23 BusEq- Business Equipment
24 Paper - Business Supplies and Shipping Containers
25 Trans - Transportation
26 Whlsl -Wholesale
27 Rtail - Retail
28 Meals - Restaraunts, Hotels, Motels
29 Fin - Banking, Insurance, Real Estate, Trading
30 Other - Everything Else