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Abstract

The Dodd-Frank Wall Street Reform and Consumer Protection Act, which forced large banks to meet the standard minimum regulatory ratios of equity to assets under several adverse economic scenarios, was passed in 2009 after the financial crisis. The main purpose of this paper is to discuss whether the financial crisis in 2007 changed the regional and large banks in terms of volatility and asset pricing model. Volatility model and asset pricing models would be used to test the volatility and asset pricing differences between the control group (regional banks) and treated groups of bank holding companies (large banks). Minimal evidence was found that there were changes to returns and volatility for these companies due to the implementation of this act (confirming previous analysis of market analysis and economists).

Introduction

The Dodd Frank Wall Street Reform and Consumer Protection Act (DFA) is a financial reform legislation passed by the Obama administration in July, 2010 as a response to the financial crisis that ended in 2009. Having more than 360,000 words and 2300 pages in length, the Dodd-Frank Act represents "the longest and the most complex piece of financial legislation in the American history" (Peirce and Broughel 2012). DFA targeted the financial firms and the sector of the financial system which were believed to have caused the 2007 financial crisis, including mortgage lenders, banks, and credit rating agencies.

The goal of DFA was to prevent the economy from experiencing the financial crisis like 2007 again, and protect the consumers from many abuses that contributed to the financial crisis. Under DFA, all bank holding companies (BHC) which have total assets of $50 billion assets or more are required to submit detailed resolution plans which describe how BHC would unwind their balance sheets when the potential crisis comes. The DFA also requires banks which have total assets of $10 billions or less to conduct annual stress tests. The Dodd-Frank Act Stress Tests requires all banks to conduct a semi-annual and annual "stress test" (Board of Governors 2013). The stress test includes estimating how much equity banks will lose under several scenarios, as well as capital planning procedures in response to economic shocks.

This paper adds to a body of research surrounding the Dodd Frank Act; it is a detailed study which mainly compares the volatilities changes and asset pricing differences between the regional banks and bank holding companies before and after the financial crisis to see whether there was a change on volatility or asset pricing because of the implementation of the Dodd-Frank Wall Street Reform and the Consumer Protection Act.

Literature Review

The Dodd Frank Act was made for the purposes of ensuring financial institutions can stay afloat during adverse economic scenarios. As was seen in 2007, this is extraordinarily important for the overall wellbeing of our country; hence there is extensive research performed on whether or not the CCAR stress testing actually makes an impact on the robustness of a financial institution. John C. Coffee (Coffee 2011) states that the financial crisis mainly occurred because of "a flawed system of executive compensation" which incentivized increased leverage and the "acceptance of undue risk".

When it was first passed, many experts opposed this legislation. Even though Dr. Coffee called for regulation, he believed the Dodd Frank act was more of a nuisance than good. He thought this legislation was enacted too little, too late, and points out that since the government had already set a strong precedent of bailing out such institutions during times of crisis, the banks are still going to operate at higher risk levels as the "market believes these banks are still protected by the government". Wharton Professor Jeremy Siegel suggested that the newly formed Financial Stability Oversight Council could become "overbearing" and would significantly increase the cost of data collections (Wharton, 2011). The Wall Street Journal Published an article in 2010 (WSJ 2010) talking about how the angel investing market would disappear as a result of this legislation, and none of the investing risks that were taken to start Facebook, Google, and Amazon would be possible when the bank's risk management is being so tightly regulated.

Meghan Milloy of the American Action Forum points out that the rules put in place involve an extraordinary amount of resources to properly comply with ($20 Billion and 60 million paperwork hours) (Milloy, 2015). It was found that since it was enacted, the act might actually have caused a decreased rate of GDP growth. (Holtz-Eakin, 2015).

Sarin and Summers(2016) compared various market risk measurement indicators and asset pricing models before and after the 2007 financial crisis (2002~2007 bs. 2010~2015) to provide the largest domestic and fireign banks. By comparing these two time periods, Sarin and Summers(2016) found that, for large banks in the United States, the volatility, Beta and risk levels of most measures were the same or higher than the post-crisis period.

Overall, it seems like the Dodd Frank Act had its fair share of critics; a vast majority of professionals and researchers claim this act did not help the financial sector.

Methodology

Asset Pricing Models:

Data was collected from Yahoo Finance using Pandas_DataReader in python. 54 Bank Holding Companies (BHC) were chosen for this study, with a mean holding assets of greater than $10 Billion over the years 2003 - 2015. The monthly log returns for each company was returned, as well as the corresponding Fama French Factors retrieved from (French, 2020).

For each stock, 4 different regressions were performed; A traditional Capital Asset Pricing Model (CAPM) (Eq. 2), a Fama French 3 Factor Model (Eq. 1), a CAPM with the dummy variables for the Dodd frank act included (Eq. 3).

$$R_{i,t} = \alpha_{0,t} + \alpha_{1,t}\beta_{i,t} + \alpha_{2,t}MV_{i,t} + \alpha_{3,t}BTM_{i,t} + u_{i,t}$$

Equation 1: Fama French 3 Factor Model

$$\overline{R}_i = R_F + \beta_i \times (\overline{R}_M - R_F)$$

Equation 2: CAPM Model

$$Dit * Tit + Dit + Tit$$

Equation 3: The dummy variables added to the pricing model. Dit is a dummy variable that equals 1 during the time period where the Dodd Frank act was in effect (2011 and later) and it equals 0 when the Dodd Frank act was not yet implemented (2010 and earlier). Tit is a dummy variable representing the size of the bank. It is equal to 1 when the mean assets of the bank is $50 Billion or later, and it is equal to 0 when the bank's assets are between $10 and $50 Billion.

For each stock, the intercept, the excess market returns coefficient, and the dummy variable coefficient were returned along with their p-value for all four models. The average p value for each coefficient was estimated to understand whether or not the coefficient is statistically significant overall across all banks.

Volatility Models:

With regards to volatility, three banks were utilized(randomly selected from our data) and conducted subsequent Autocorrelation and Partial Autocorrelation functions to generate the given volatility parameters. From the given data output in these tests, it can be seen that the optimal parameters for the tests were the following:

ARCH(1), GARCH(1,1), ARCH(1) + GARCH(1,1). each volatility model was then employed on each of the given banks, storing the volatility values in a subsequent table. After running all of the models, the volatility values were then annualized, and then they were averaged for each subsequent quarter for each year. Before running any linear models on our data, two columns of dummy variables needed to be added. One column would represent if a bank was a Large bank (greater than or equal to $50 billion in assets) or a Regional bank (between $50 billion and $10 billion in assets); where the other outlined if it was a specific period of time before or after the implementation of the Dodd-Frank Act (2006-2010 would be value of 0, 2011-2015 would be value of 1). After adding in these variables to the data set, the following formulas were utilized to create panel linear models (on each subsequent volatility model output):

$$Equation\ 3: \quad Y_{ijt} = constant + D_{it} + error_{ijt}$$

$$Equation\ 4: \quad Y_{ijt} = constant + T_{it} * D_{it} + D_{it} + T_{it} + error_{ijt}$$

In the equations above, “Y_ijt” is the volatility values generated by the three models above (ran three times for separate results). The “D_it” value was the Large bank/Regional Bank dummy variable; and “T_it” represented the Dodd-Frank time identifier. The important terms to view within the equations are the following: “D_it” for equation 1; “T_it * D_it” for equation 4.

Results

Asset Pricing Models:

Figure 1.1 shows the average p value for each coefficient after the linear regression is run. It can be seen that none of the intercept values were statistically significant. The market returns, however, were statistically significant in all the regressions, whether or not the dummy variable was applied. Figure 1.2 shows the mean p values for the coefficients when the banks were split into small and large cap banks. As can be seen, the results are the same; the Dodd Frank Act and the fact that it is a large bank does not seem to make a difference in the Asset Pricing model. Figure 1.3 shows the distribution of intercept coefficients for all the pricing models. Overall, it can be seen that these values are not different from 0, meaning the BHCs are not performing better or worse than the broader market, whether or not we incorporate dummy variables. In Figure 1.4, we can see the excess market returns, which mostly range between 1 and 2 for the BHCs (with a few outliers). This shows that for every % change in the market, we might expect a 1-2% change in the BHC returns, although this value doesn’t seem to change when the Dodd Frank Dummy variable was incorporated. Figures 1.5 and 1.6 show the Dummy variable coefficients. As can be seen, for the most part, these coefficients hovered around 0, showing that the act doesn’t seem to have an impact on the returns for these BHCs.

Volatility Models:

Figures 2.1 to 2.3 highlights the model output on equation 1, while Figure 2.4 to 2.6 highlights the output on equation 3. A summarization of key values can be seen in Figure 2.7, which highlights the key variable output for each equation and volatility model (with significance value star identifiers). For equation one, it can be seen that there is a negative relationship between both the Regional Bank and Large Bank identifiers against volatility. However, these values seemed to be more effective and variant for the Regional Banks compared to the Large bank (which seemed more stable across all the tests). Furthermore, the intercept values showed a strong, significant variance estimator. For equation 4, it can be seen that the key variables are not significant (excluding the intercept). However, a positive relationship appears with Regional banks and the Dodd-Frank Act here, unlike before in the first equation. We also see diminished effects for Large banks compared to equation 3 (but holding a negative relationship still). Lastly, it is seen that the variance estimator has increased through adding the new dummy variable, meaning that more variance can be explained due to the addition of the intercepts.

Implications

Asset Pricing Model:

The results obtained in this study seem to support the growing body of evidence that the Dodd Frank Act didn't have much of an impact on financial institutions. In the Literature Review, experts were found saying the Dodd Frank act and the corresponding stress tests were much more of a hindrance to these financial institutions than they were an asset. These rules were very difficult to comply with as they were highly cost and labor intensive, reducing the effectiveness of these Bank Holding Companies.

Volatility Models:

From the results, it can be seen that the inclusion of the Dodd-Frank Act Identifier increased the intercept value by approximately two percent on each test (for equation two). From the given values in Figure 2.7, it shows there could possibly be a negative, yet weak effect on bank volatility given that the bank was Large and was in the Dodd-Frank Act period. This effect can be identified as weak due to the overall non-significance of the identified important estimated coefficients. However, this act did not affect Regional banks (as stated in the literature review as well), as the identifier showed a positive relationship. As such, the notion that there was a negative relationship and effect on Large bank volatility can be held. However, these banks are less risky with the inclusion of the Dodd-Frank Act (equation 4) compared to excluding this key factor (equation 3), meaning this regulation was able to potentially minimize this relationship by approximately 2.5%. However, this lingering amount of volatility could be driven to stay due to the strong connection of the government and bailing out banks when in need/trouble.

Conclusion

Overall, it can be concluded that the Dodd Frank Act, and the implementation of the CCAR stress tests was not too impactful on the returns of banks. From the asset pricing model, it is shown that the implementation of this act had no significant impact on the returns for the banks, whether they were large (>= $50 Billion in assets) or they were regional (between $10 and $50 Billion in assets). The volatility models showed weak evidence that the volatility of the stock returns decreased by a little bit, but overall it wasn't enough to claim the act had a significant impact on the bank stock returns. This is also confirmed in an extensive literature review, where a multitude of financial and economic experts showed both empirically and through studies that the Dodd Frank didn't have much of an impact on the activity of these financial institutions.

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Appendix

Appendix 1: Asset Pricing Model Results

CAPM_Intercept	CAPM_Intercept_Dummies	FF_Intercept	FF_Intercept_Dummies	CAPM_Market_Rets	CAPM_Market_Rets_Dummies	FF_Market_Rets	FF_Market_Rets_Dummies	CAPM_LargeDodd_Dummies	FF_LargeDodd_Dummies
0.3211905	0.3645311	0.4499818	0.4117193	3.639911e-07	3.414273e-07	6.758344e-05	9.531957e-05	0.6432957	0.5316145

Figure 1.1: The average p values for all the coefficients across all the banks.

CAPM_Intercept	CAPM_Intercept_Dummies	FF_Intercept	FF_Intercept_Dummies	CAPM_Market_Rets	CAPM_Market_Rets_Dummies	FF_Market_Rets	FF_Market_Rets_Dummies	CAPM_LargeDodd_Dummies	FF_LargeDodd_Dummies	IsLargeBank
0.3929014	0.3929014	0.5080257	0.5080257	6.543310e-07	6.543310e-07	1.209063e-04	1.209063e-04	0.6118074	0.4638103	0
0.2315520	0.2817276	0.3774271	0.4008609	1.066088e-09	1.464257e-09	9.298785e-07	1.945088e-06	0.6826561	0.6163699	1

Figure 1.2: The average p values for all the coefficients across banks, split by small and large

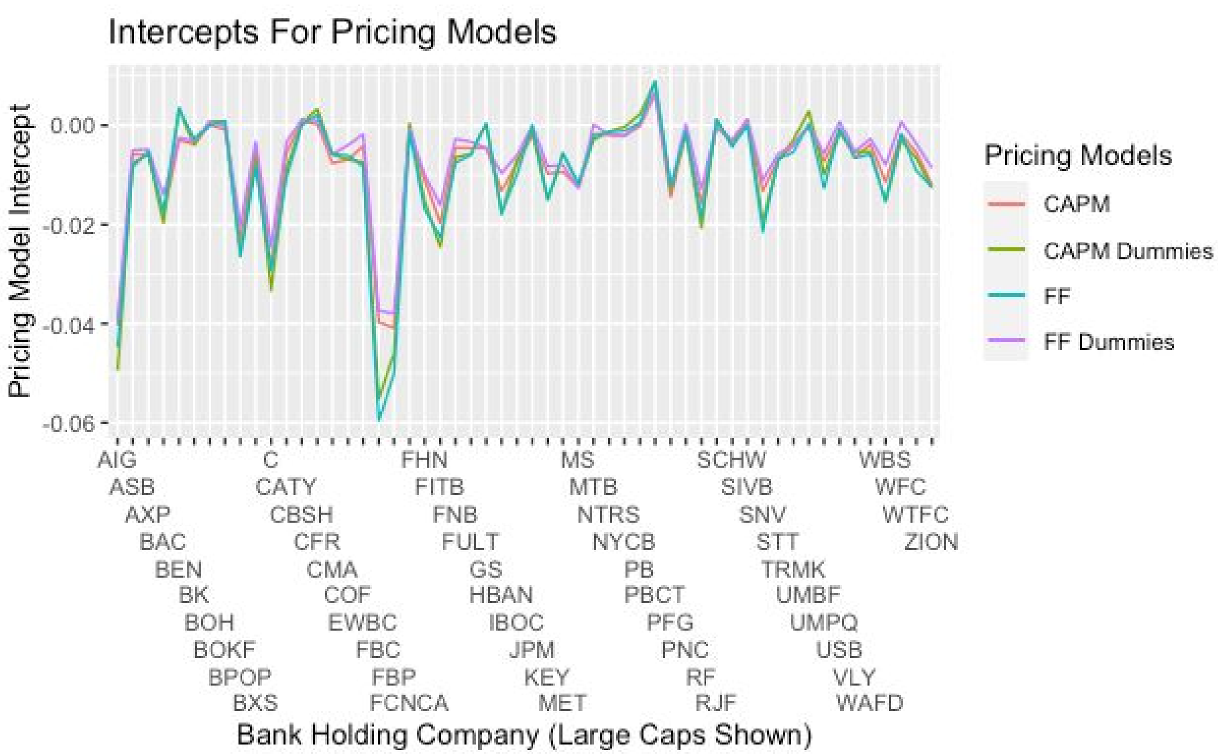

Figure 1.3: Intercept for the Asset Pricing Models

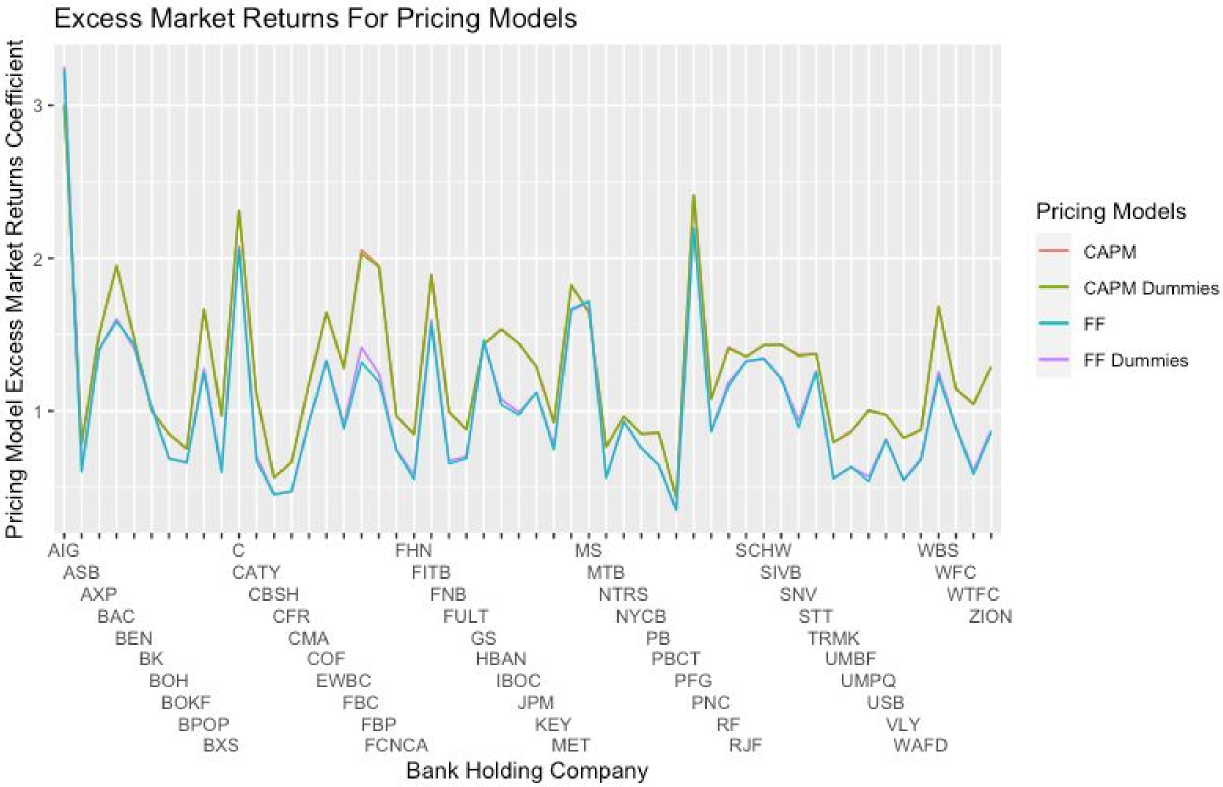

Figure 1.4: Excess Market Returns for Asset Pricing Models. The Dummies had almost no impact here.

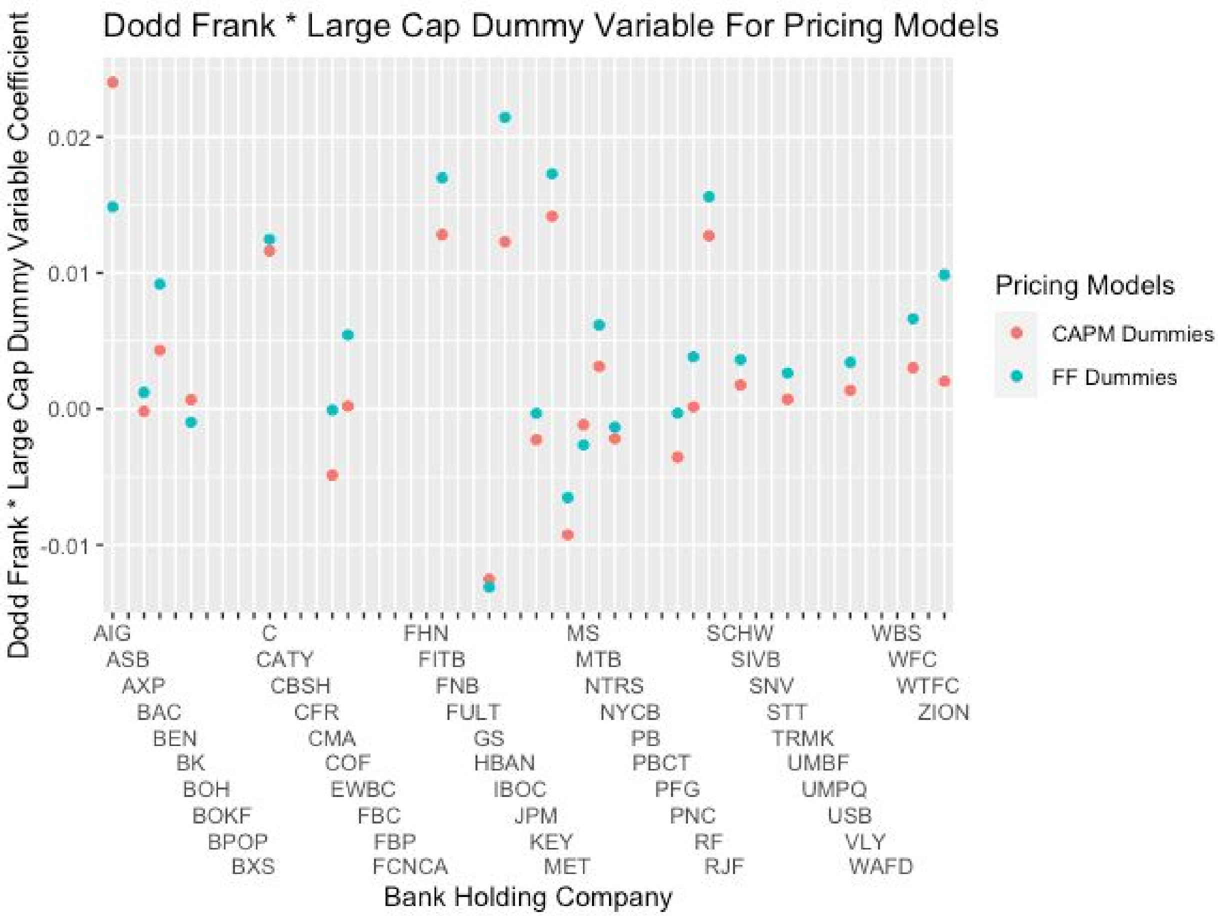

Figure 1.5: Coefficient for the Dodd Frank * Large Cap variable

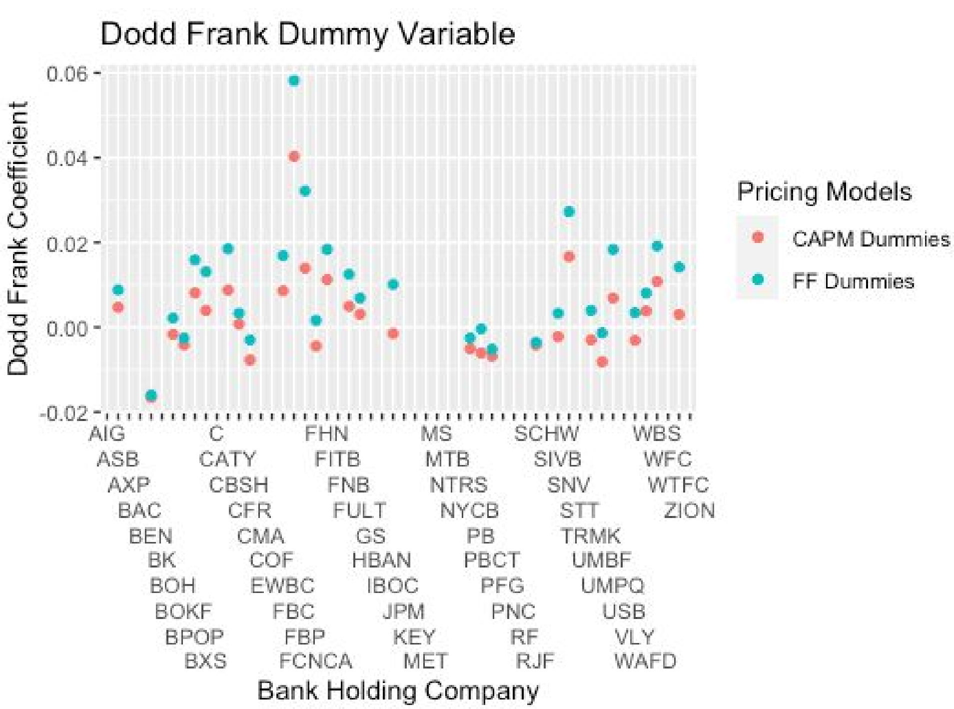

Figure 1.6: Coefficient for the Dodd Frank Variable

Appendix 2: Volatility Model Results

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = Volatility ~ Large, data = archLarge, model = "rando
m",
    index = c("Ticker", "Date"))

Balanced Panel: n = 54, T = 40, N = 2160

Effects:
                   var  std.dev share
idiosyncratic 0.073641 0.271369 0.929
individual    0.005628 0.075021 0.071
theta: 0.5035

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-0.363508 -0.143091 -0.087393  0.028004  1.876983

Coefficients:
             Estimate Std. Error z-value  Pr(>|z|)
(Intercept)  0.454624   0.022478 20.2251 < 2.2e-16 ***
Large0      -0.110651   0.024368 -4.5407 5.606e-06 ***
Large1      -0.076636   0.025580 -2.9960  0.002736 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    160.51
Residual Sum of Squares: 158.98
R-Squared:      0.0095588
Adj. R-Squared: 0.0086404
Chisq: 20.8173 on 2 DF, p-value: 3.0171e-05
```

Figure 2.1: ARCH Model And Large/Regional Firm Dummy Variable

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = Volatility ~ Large, data = garchLarge, model = "rando
m",
    index = c("Ticker", "Date"))

Balanced Panel: n = 54, T = 40, N = 2160

Effects:
                   var  std.dev share
idiosyncratic 0.077201 0.277850 0.928
individual    0.006006 0.077496 0.072
theta: 0.5068

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-0.387434 -0.145492 -0.089045  0.028632  1.885265

Coefficients:
             Estimate Std. Error z-value  Pr(>|z|)
(Intercept)  0.461533   0.023081 19.9966 < 2.2e-16 ***
Large0      -0.114846   0.025001 -4.5936 4.356e-06 ***
Large1      -0.079247   0.026250 -3.0190  0.002536 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    168.28
Residual Sum of Squares: 166.64
R-Squared:      0.0097794
Adj. R-Squared: 0.0088613
Chisq: 21.3026 on 2 DF, p-value: 2.367e-05
```

Figure 2.2: GARCH Model And Large/Regional Firm Dummy Variable

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = Volatility ~ Large, data = argarchLarge, model = "rand
om",
    index = c("Ticker", "Date"))

Balanced Panel: n = 54, T = 40, N = 2160

Effects:
                   var  std.dev share
idiosyncratic 0.075435 0.274655 0.933
individual    0.005386 0.073387 0.067
theta: 0.4907

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-0.360396 -0.146120 -0.088384  0.028184  1.862458

Coefficients:
             Estimate Std. Error z-value  Pr(>|z|)
(Intercept)  0.454021   0.022499 20.1794 < 2.2e-16 ***
Large0      -0.109626   0.024464 -4.4811 7.424e-06 ***
Large1      -0.075139   0.025658 -2.9285  0.003406 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    164.39
Residual Sum of Squares: 162.86
R-Squared:      0.0092828
Adj. R-Squared: 0.0083642
Chisq: 20.2107 on 2 DF, p-value: 4.086e-05
```

Figure 2.3: ARCH+GARCH Model And Large/Regional Firm Dummy Variable

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = Volatility ~ Dodd * Large + Dodd + Large, data = archL
arge,
    model = "random", index = c("Ticker", "Date"))

Balanced Panel: n = 54, T = 40, N = 2160

Effects:
                   var  std.dev share
idiosyncratic 0.064539 0.254046 0.914
individual    0.006094 0.078066 0.086
theta: 0.5425

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-0.421032 -0.119055 -0.041128  0.023981  1.755813

Coefficients:
              Estimate Std. Error z-value  Pr(>|z|)
(Intercept)  0.4757669  0.0238060 19.9852 < 2.2e-16 ***
Dodd        -0.1795422  0.0352786 -5.0893 3.595e-07 ***
Large0      -0.0316462  0.0276459 -1.1447    0.2523
Large1       0.0222291  0.0284665  0.7809    0.4349
Dodd:Large0  0.0093422  0.0391817  0.2384    0.8115
Dodd:Large1 -0.0486987  0.0400152 -1.2170    0.2236
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    159.94
Residual Sum of Squares: 138.79
R-Squared:      0.1322
Adj. R-Squared: 0.13019
Chisq: 328.141 on 5 DF, p-value: < 2.22e-16
```

Figure 2.4: ARCH Model Against Dodd-Frank & Large/Regional Firm Dummy

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = Volatility ~ Dodd * Large + Dodd + Large, data = garch
Large,
    model = "random", index = c("Ticker", "Date"))

Balanced Panel: n = 54, T = 40, N = 2160

Effects:
                   var  std.dev share
idiosyncratic 0.067756 0.260299 0.913
individual    0.006486 0.080534 0.087
theta: 0.5449

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-0.447637 -0.122551 -0.041704  0.023037  1.811914

Coefficients:
             Estimate Std. Error z-value  Pr(>|z|)
(Intercept)  0.483505   0.024442 19.7819 < 2.2e-16 ***
Dodd        -0.185072   0.036155 -5.1189 3.073e-07 ***
Large0      -0.035436   0.028366 -1.2492    0.2116
Large1       0.021263   0.029210  0.7279    0.4667
Dodd:Large0  0.013010   0.040155  0.3240    0.7460
Dodd:Large1 -0.047961   0.041009 -1.1695    0.2422
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    167.69
Residual Sum of Squares: 145.72
R-Squared:      0.13102
Adj. R-Squared: 0.129
Chisq: 324.756 on 5 DF, p-value: < 2.22e-16
```

Figure 2.5: GARCH Model Against Dodd-Frank & Large/Regional Firm Dummy

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = Volatility ~ Dodd * Large + Dodd + Large, data = argar
chLarge,
    model = "random", index = c("Ticker", "Date"))

Balanced Panel: n = 54, T = 40, N = 2160

Effects:
                   var  std.dev share
idiosyncratic 0.066001 0.256907 0.919
individual    0.005839 0.076415 0.081
theta: 0.5306

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-0.417570 -0.121131 -0.042193  0.025001  1.738674

Coefficients:
              Estimate Std. Error z-value  Pr(>|z|)
(Intercept)  0.4755668  0.0238455 19.9436 < 2.2e-16 ***
Dodd        -0.1797786  0.0356431 -5.0439 4.563e-07 ***
Large0      -0.0297368  0.0277743 -1.0707    0.2843
Large1       0.0260979  0.0285882  0.9129    0.3613
Dodd:Large0  0.0068665  0.0395846  0.1735    0.8623
Dodd:Large1 -0.0535309  0.0404291 -1.3241    0.1855
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    163.8
Residual Sum of Squares: 141.94
R-Squared:      0.13343
Adj. R-Squared: 0.13142
Chisq: 331.653 on 5 DF, p-value: < 2.22e-16
```

Figure 2.6: ARCH+GARCH Model Against Dodd-Frank & Large/Regional Firm Dummy

	ARCH(1)	GARCH(1,1)	ARCH(1)+GARCH(1,1)
Regional Bank	-0.1107***	-0.1148***	-0.1096***
Large Bank	-0.0766**	-0.0792**	-0.0751**
Intercept (Equation 1)	0.4546***	0.4615***	0.4540***
Dodd, Regional	0.00934	0.0130	0.00687
Dodd, Large	-0.04870	-0.0480	-0.05353
Intercept (Equation 2)	0.4758***	0.4835***	0.4756***

Figure 2.7: Key Variable Output Table