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EXTREME WEATHER EVENTS AND STOCK RETURNS IN THE INSURANCE INDUSTRY

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EXTREME WEATHER EVENTS AND STOCK RETURNS IN THE INSURANCE INDUSTRY

ABSTRACT

This thesis examines abnormal returns on insurance stocks listed on NYSE subsequent to an Atlantic hurricane making landfall in the U.S., using data from 2000 to 2018. We investigate if firm characteristics explain the abnormal return using panel data regression. We further elaborate by constructing high, medium, and low portfolios of stock sorted by various multiples, and testing if there is a difference in the abnormal return. To control for the extraordinary market conditions during the financial crisis, we conduct the analysis both with and without events occurring in this period. The goal of this thesis is to further add on to the existing research on extreme weather effects on the stock market by using panel data regression and multiples. We conclude that the insurance firms on the NYSE do not exhibit negative abnormal returns after hurricanes making landfall. Furthermore, we find the dividend yield, margin, and cash explains the abnormal returns and time dummy variables are significant in all events. When the financial crisis events are excluded, only time-dummy variables are significant. When testing between the constructed portfolios, we find no significant differences.

1. INTRODUCTION

Climate change has led to a substantial increase in the frequency and intensity of North Atlantic hurricanes since the 1980s (U.S. Global Change Research Program, 2014). Most parts of the economy will directly or indirectly be affected by a hurricane. According to World Economic Forum's report Global Risks Report 2019 (World Economic Forum, 2019), in terms of likelihood, extreme weather is the number one global risk, and third in terms of impact. Climate research indicates that the emission of greenhouse gas increases globally, and so will the severity and quantity of particular natural disasters (The Intergovernmental Panel on Climate Change [IPCC], 2012). The increased risk of natural disasters emphasizes the importance of having a greater understanding of how the economy is affected. Motivating us to further explore this subject. In this thesis, we will investigate the insurance industry, and examine how the stock return reacts when extreme weather events occur. Also, we will investigate the explanatory power of firm characteristics on abnormal returns. We will use hurricanes as a proxy for extreme weather events.

The hurricane season is an annual, recurring event, and thus predictable. Conventional disaster risk studies focus on unpredictable and rare events. However, hurricanes are unpredictable in size, movement pattern, and strength. Therefore, the hurricane season is a predicted period of unpredictable events. Boustan, Kahn, Rhode, and Yanguas (2017) find that extreme disasters lower housing prices and increase migration rates, especially in areas at high risk of disaster events, but milder disasters have little effect. Further, Rappaport and Sachs (2003) state that an increasing part of the American economic activity is clustering near the coast. Thus, the population and the economy are more exposed to natural disasters Boustan et al. (2017). We choose to investigate hurricanes of a certain strength, which leads to a higher probability of a significant impact on the economy.

When investigating the impact of an extreme event on the economy, there are several instruments to consider when conducting an analysis, such as bonds, stocks, options, and other derivatives. We believe that stock prices are the best measurement because it is a reflection of the current value of a firm. Furthermore, the stock market is well developed and highly liquid.

Previous research has shown that stock prices across certain industries in the U.S. are affected significantly in the event of a hurricane (Lanfear, Lioui, and Siebert, 2017, B). Lamb (1995) finds that property-liability stock had a significant negative return during hurricane Andrew. Lawless (2005) infer an increase in personal bankruptcy filings in affected areas, while Boustan et al. (2017) document a negative development in housing prices after a hurricane. Further, Dessaint and Matray (2017) find that a large proportion of firms in the U.S. will be affected by a hurricane strike. We choose to investigate the insurance industry because previous literature shows significant reactions to extreme weather events. Furthermore, the industry is tied up to almost all businesses, private households, and the public through underwritten premiums. Thus, it reflects the damages that a hurricane inflicts on the nation, making the insurance industry a proxy for the total economic impact.

Lanfear, Lioui, and Siebert (2017, A) find differences in their analysis when including stocks listed on Nasdaq, rather than only NYSE. Nasdaq firms are smaller, and the stocks tend to be more volatile. They state that NYSE/NYSE MKT and Nasdaq differ in market microstructure and trading volume, and this may lead to spurious patterns. Since our analysis has a limited scope, we choose only to use stock listed on NYSE, and in that way avoid potential spurious patterns.

After filtering for our selection criteria, we examine the returns of 38 companies. Stock data includes stock prices and firm characteristics, and event data includes dates and magnitude. Hurricane sample consists of all hurricanes category 2 or higher making landfall in the U.S. from 2000 – 2018, in total 15 hurricanes. We extend the analysis by controlling for extraordinary effects occurring due to the financial crisis.

Using the same event study approach as Lanfear et al. (2017, A/B), we investigate whether insurance firms exhibit negative abnormal after hurricanes make landfall. We estimate panel data regression models with eight firm characteristic variables in an attempt to explain abnormal returns. Furthermore, we rank the firms from high to low in each event after the firm-specific factors. Using this rank, we construct three portfolios; high medium and low. Differences between portfolios are tested using a non-parametric test. Our analysis is an extension of previous relevant research by including more specified factors. And we investigate more profound in one industry than other studies.

In our full sample, fixed effect model, we find three statistically significant factors, cash and margin, both negatively correlated with abnormal returns, and dividend yield, positively correlated. A positively correlated dividend yield is consistent with our expectations. Cash and margin, however, contradicts our expectation. When the financial crisis is excluded, these statistically significant effects disappear. The extraordinary financial conditions during this period might be the reason we find these unanticipated effects. Time effect is accounted for in both samples by adding time dummy-variables. For both samples the time-dummies are significant as we expected. The non-parametric portfolio analysis does not provide any significant results. This analysis shows that there are no significant differences between the three constructed portfolios.

Our thesis makes the following contribution to the disaster risk research: i) we expand the existing analysis by adding multiples as explanatory variables and conducting panel data regression. This extension increases the insight on what explains the return in the industry during an extreme event. ii) by adapting panel data methodology, we examine information both cross-sectionally and longitudinal. This methodology will enlighten if there is a firm characteristic that is preferred during extreme events.

2. INSURANCE INDUSTRY

The U.S. insurance industry is a multi-billion dollar industry. In 2017, net premiums written totaled to $1.2 trillion. Of this, 52% were life insurers, and 48% written by property and casualty. The industry is divided into two main parts, life/health (L/H) and property/casualty (P/C). The market is concentrated, in the P/C part the top five firms, in terms of direct premiums written have over 30% of the market, with State Farms being the biggest with 10% of the market (Moorcraft, 2016). The industry faced the most substantial losses so far due to natural catastrophe in 2017 with a net loss of $135 billion, with North America accounting for 93% of this loss (Insurance Information Institute, 2018). Mostly due to three major hurricanes (two of these hitting U.S.), the California wildfire, and an earthquake in Mexico. This loss was almost twice as large as the 10-year inflation adjusted average (EY, 2018).

The industry has been through comprehensive transformations in the last decades due to increased globalization and deregulation. The Gramm-Leach-Bliley act of 1999 allowed insurance companies, banks, and investment banks to consolidate. Allowing large financial institutions to provide a broader spectrum of products. It further failed to give the regulative agencies the authority to regulate large investment bank holding companies (SEC, 2008). The financial crisis showed that regulation in the industry is needed. It is important to emphasize that the industry still is regulated compared to other industries in terms of standardization of products and capital requirements. Regulation in the U.S. is regulated by each of the 50 states, and there are different regulations to different types of insurance firms.

There are two types of ownership structure in insurance companies, policyholder ownership, and publicly traded companies. In policy ownership constructed firms, the customers are the equity owners, and the equity is not tradeable. Over the last decade, the trend has a shift from policyholder-ownership to publicly traded firms. Only a small number remains as policyholder owned (Investopedia, 2019). We will only analyze the publicly traded insurance firms due to the availability of data, and because this will be sufficient regarding analyzing the industry, as the majority of the firms are publicly traded.

Insurance companies have large amount of money generated from premiums, invested in capital markets. Since they need to keep the risk low to be able to meet potential liabilities, they have a lot of their investments in interest rate sensitive securities, such as corporate and government bonds. Thus, the income is dependent on the interest rate. We expect stock returns vary in line with changes in the interest rate. Figure 1 shows the development in risk-free interest rates throughout the period of our analysis. Especially in the first nine years, the interest rates fluctuate. Thus, we expect the time of the event to affect the *Abnormal Returns (AR)*.

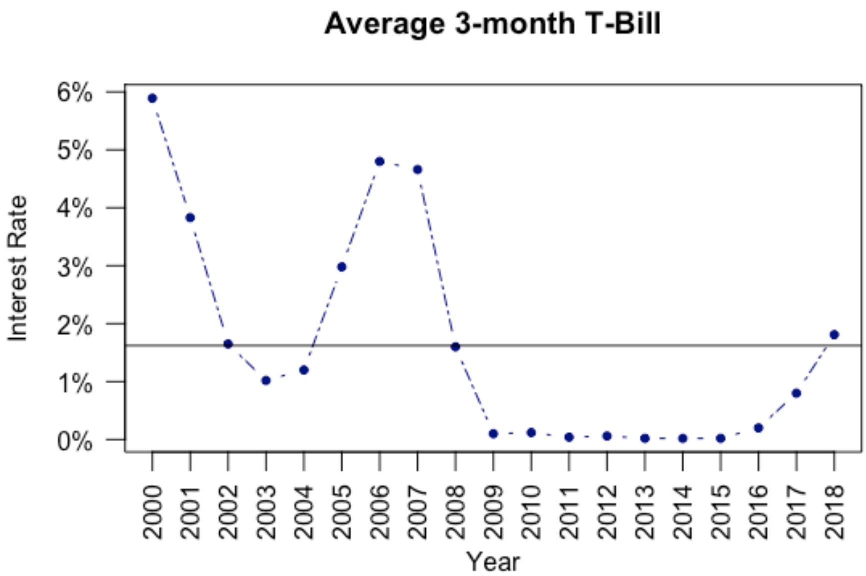

Figure 1 - Risk-free interest rates - 3-month treasury bills

Insurance companies protect their portfolio against losses due to extreme events by transferring risk to another party, through reinsurance. Risk reduction is done by insuring the policy portfolio for losses that exceed a certain amount. Reinsurance reduces the individual firm's potential losses when they encounter extreme events and makes them able to meet their liabilities from both policyholders and debt holders. Thus, reduce the bankruptcy risk related to hurricane events. As most insurance companies use reinsurance, we do not account for it in our analysis. We expect that reinsurance will reduce the abnormal returns on the industry during extreme events. Reinsurance firms are often large and global. Thus, some of the losses will apply for firms not listed on the New York Stock Exchange (NYSE).

3. LITERATURE REVIEW

In this section, we review the literature on disaster risk and the effect on stock returns. More specifically, the impact of hurricanes on the insurance industry. First, we present past studies on disaster risk and stock returns. Second, we introduce the literature studying returns in the insurance industry.

3.1 EVIDENCE FROM EXTREME WEATHER EVENTS

Using an event study approach Lanfear et al. (2017, A) examine whether value stocks (High Book Equity/Market Equity) are more exposed to disaster risk than growth stocks (Low Book Equity/Market Equity), and if any effect, what the impact on stock price is. Furthermore, this analysis is extended by considering variations in stock liquidity and tail risk across the decile portfolios, sorted by book-to-market and market equity, during the events. The study examined all 34 hurricanes making landfall in the U.S. from 1990 - 2014. Landfall is defined as the point when the center of a hurricane hits the coastline (National Hurricane Center [NHC], Glossary of NHC Terms). Lanfear et al. (2017, A) find that small firms experience more substantial negative abnormal returns, and the abnormal return is negatively related to firm size. In addition, they find that when Nasdaq stocks, which are smaller firms, are included statistical significance is increased for value stocks and reduced for growth stocks. In addition to examining abnormal returns, tests are performed to check if this is due to illiquidity and tail risk. They document a substantial reduction in the stock trading liquidity and of tail risk during the event window.

The study included all common stocks in the U.S. that have been trading from the start of 1990 and the end of 2014. The sample after filtering consists of close to 4000 stocks.

Lanfear et al. (2017, A) conclude, based on their findings, that value stocks are more exposed to disaster risk than growth stocks, and this affects the price. Growth and value stocks indicate more substantial negative abnormal returns than middle range firms, and small firms exhibit a larger effect than small firms. The inclusion of Nasdaq stocks leads to a reduction in the statistical significance of the impact on growth stocks and an increase for value stocks.

Based on the same data as their previous paper (Lanfear et al., 2017, A), Lanfear, Lioui and Siebert (2017, B) extended their study by examining whether gold-related stocks exhibit different returns than other industries during extreme weather events.

The paper document the economic impact on the stock market as a result of a hurricane making landfall. Lanfear et al. (2017, B) find that most industries, including insurance, exhibits a negative abnormal return, with a notable exception of gold-related stocks, which shows a positive abnormal return. Further, they conclude that this is not due to investors search for stock trading liquidity, as the decrease in liquidity is the same across all sectors. The article enlightens how different industries respond to hurricanes and how investors preferences change after hurricanes.

3.2 INSURANCE LITERATURE

Shelor, Anderson, and Cross (1992) examine property-liability insurance companies after the 1989 California earthquake. They find a positive abnormal return after the earthquake. The positive return was due to a substantial increase in demand for property insurance products. It's worth noting that at this time, only 30% of homes and businesses in California had earthquake insurance.

Lamb (1995) investigates the effect of property damage due to hurricane Andrew, on the property-liability insurance stocks. Results show that there is a negative stock price reaction on insurers with direct premiums written in the states affected by the hurricane. Further, there are no significant price changes in the unexposed firms stock price. This result indicates that the market is efficient and efficiently interpreted information.

During a hurricane event, the return on insurance stocks may vary as the characteristics of the hurricane change. Ewing, Hein, and Kruse (2006) use public hurricane data and an event study approach to study the impact of Hurricane Floyd. They find a negative return, but this is not consistent during the lifecycle of the hurricane. The market responds to the changes in the hurricane's characteristics, and daily returns change between negative and positive as the hurricane develops.

3.3 LITERATURE SUMMARY

The literature reviewed implies no consistent pattern in returns during extreme events. Shelor et al. (1992) document a positive AR after the earthquake in 1989 due to an increase in demand for insurance. Lamb (1995) concludes that exposed insurance firms exhibit negative abnormal returns after hurricane Andrew. Lanfear et al. (2017, B) document a negative abnormal return on all industries except gold-related during hurricane strikes. Ewing et al. (2006) find that insurance firms exhibit negative returns, but this is not consistent during the event.

In contrast to Lanfear et al. (2017, A/B), we do not conduct the same risk adjustments in terms of liquidity- and tail risk analysis. Instead, we exclude certain events that may be confounding. However, in resemblance to Lanfear et al. (2017, A), we investigate growth and value stocks, but through other underlying multiples. We use dividend yield and price-earnings rather than book to market ratio. Instead of focusing on only property-liability insurers like Shelor et al. (1992) and Lamb (1995), we focus on all insurance firms on NYSE. However, we do not consider stocks on both NYSE and Nasdaq like Lanfear et al. (2017, A/B). Unlike Shelor et al. (1992) and Ewing et al. (2006), that considered one event, we consider multiple events. Lanfear et al. (2017, A/B) include all hurricanes occurring in the period being studied, while we chose to include only hurricanes of a certain magnitude. To further distinguish our study from previous research, we add a panel data regression methodology. In this way, we extend the analysis by incorporating information across space and time.

4. THEORY

In this section, we will introduce some central theory that establishes the groundwork for our analysis. First, we present papers on methods for estimating returns before discussing theory concerning capital markets and stock pricing theory. Based on this, we formulate our research questions.

4.1 ESTIMATING EXPECTED RETURN

There are several methods to estimate expected returns on stocks. Practitioners usually favor the *Capital Asset Pricing Model* (CAPM), when estimating the expected return on a single stock, while they prefer the Fama-French three-factor model for estimations on portfolio returns (Bartholdy, Peare, 2004). CAPM is a single-factor model that estimates the relationship between the risk and the equilibrium expected return on a risky asset. The model makes some unrealistic assumptions, such as all investors are rational, mean-variance optimizers. All securities are publicly held and traded, and all investors may trade them (Sharpe, 1964). CAPM thus suggests that all investors will be passive and hold the market portfolio. The model has a relatively low explanatory power, explaining 3% of the variation in the market return (Bartholdy, Peare, 2004).

The Fama-French three-factor model is an extension of the CAPM, adding two more explanatory variables; size, and book-to-market value. Bartholdy and Peare (2004) find that the gain of including the additional size (Small-Minus-Big, SMB) and value premium (High-Minus-Low, HML) factors to the market model is small and thus the simple model is a better approach, especially when operating with individual stocks. However, Lanfear et al. (2017, A) find that smaller-sized stocks, measured by market capitalization are affected more by hurricane events than large stocks. Lanfear et al. (2017, A) also find differences between growth and value stocks. Therefore, we use the Fama-French three-factor model as this model takes the size and value factors in consideration, and this affects the calculated expected returns.

4.2 EFFICIENT MARKET HYPOTHESIS

The *Efficient Market Hypothesis* (EMH) lays the groundwork for modern financial and investment theory. Fama (1970) defines an efficient market as a state where the prices fully reflect all available information, meaning the stock price reflects the firm's intrinsic value, thus beating the market is impossible. To increase returns, the investors have to take on additional risk. The EMH assumes rational, utility-maximizing agents. Furthermore, it assumes that the entire population on average is right, even if no individual is. Thus, some may overestimate, and others underestimate the information. Last, it assumes that the agents make adjustments to its expectations when exposed to new information. The hypothesis is divided into three states, weak, semi-strong, and strong. Weak market efficiency states that the current prices reflect all information from previous prices. Semi-strong market efficiency states that the stock prices reflect all available public information. In a state with strong market efficiency, the stock prices reflect all information, both public and inside. For our hypothesis, we assume the market efficiency to be semi-strong. Implying that the public has full access to information about potential hurricanes, and utilizes this information.

4.3 CAPITAL STRUCTURE

The Modigliani and Miller Theorem (Miller, Modigliani, 1958) demonstrate that under the assumption of perfect capital markets, no transaction costs, no bankruptcy cost, and no taxes, the value of a firm unaffected by capital structure and payout policy. The value of a firm is the same, whether it is financed by equity or debt, or a combination. Furthermore, investors are indifferent to the payout policy. Thus, the wealth of an investor is unaffected whether the firm chooses to pay out free cash flow as dividends, repurchase stock, or invest in projects. The assumptions for this theorem are not adaptable for our study as we do have taxes and bankruptcy costs. Thus, the theorem states that the value of a firm is affected by the capital structure and payout policy. A firm with leverage will have tax deduction on its interest payments, increasing the value. High debt ratio will increase the bankruptcy cost. Furthermore, the payout policy of a firm will affect the wealth of its investors, as they face different tax rates on dividend and capital gains. To investigate this, we have added the multiples dividend yield, cash, and debt to our analysis.

4.4 HYPOTHESES

Based on financial theories and previous research, we formulate our research questions. We believe that the finding of Shelor et al. (1992) from the 1989 earth quake is not relevant for our data period, because a significant fraction of the property in California was uninsured at this time. Today, approximately 85% of all homeowners in the U.S. have homeowners insurance (Croll, 2018). Thus, there is not the same potential increase in insurance demand due to extreme events. Natural disasters are more likely to make the net cash flow negative and result in negative abnormal returns. We believe we will find differences because we have chosen multiples that should define how robust a firm is. While the finding of negative abnormal returns by Lamb (1995) and Lanfear et al. (2017, A/B) is a more likely scenario in our time frame.

Previous research has shown both positive and negative abnormal returns after disaster events. While based on EMH, one could argue that there are no opportunities to earn abnormal returns since losses to natural disasters already should be reflected in the stock price. Leading to the first research question we seek to answer throughout this thesis:

1. *Does insurance firms on the NYSE exhibit negative abnormal returns after hurricane strikes?*

Further, both the theory of Modigliani and Miller (1958) and previous research (Lanfear et al., 2017, B) indicate that capital structure and firm characteristics affect return, and further should affect abnormal returns during disaster events. Thus, if the industry exhibits any abnormal returns, we would expect firm characteristics to have explanatory power. Since market imperfections exist, we believe differences between firms will affect returns, and formulate the second research question:

2. *Do firm characteristics influence the abnormal return on insurance companies during hurricanes?*

5. METHODOLOGY

In this section, we elaborate on the methodology we use to examine abnormal returns in the event of a hurricane. We use an event study approach to estimate expected returns for each individual firm and subtract the actual return during the event window to obtain the abnormal returns. *Cumulative abnormal returns* (CAR) over the events are then compared between groups of firms. We use several criteria concerning firm characteristics to separate the firms. Testing the significance is done using panel data regressions and the non-parametric Kruskal-Wallis test. We estimate several panel models and conduct the Hausman-test to find the best fit. Further, the analysis is extended by repeating it without events occurring during the financial crisis, and controlling for time-specific effects.

5.1 EVENT STUDY

Event studies use financial market data to measure the impact of a specific event on the value of a firm (MacKinlay, 1997), here used to measure the impact of hurricanes on the prices of U.S. insurance stocks. First, we estimate abnormal returns before using and testing these in combination with firm characteristics.

5.1.1 ESTIMATION- AND EVENT WINDOW

There is no clear consensus in the literature regarding the optimal length of an estimation window when performing an event study using daily data. While Cummins and Lewis (2004) recommends 250 trading days as this constitutes a full year, McWillians, Siegel, and Teoh (1999) suggest anything between 50 and 250 trading days. Because of the nature of the Atlantic hurricane season, we decided to use the same framework as Lanfear et al. (2017 A/B). The Atlantic hurricane season lasts from June 1 until November 30 (NHC, Glossary of NHC Terms) thus, we use the period prior to the hurricane season as our estimation window. This estimation window makes our expected return unaffected by expectations of potential hurricanes. We estimate expected returns by using the three-factor model in the period December 1 to May 31, prior to the event we analyze. When measuring abnormal returns, we consider one event window, lasting from three days before landfall to five days after landfall, [-3, 5], where the event date, 0, is the date the hurricane makes landfall. NHC continuously issues hurricane forecasts including positions, wind fields, and intensities from 72 hours before a potential landfall (NHC, Tropical Cyclone Forecast/Advisory [TCM]). Market anticipations of possible impact are based on these forecasts. We chose to include three days (72 hours) prior to landfall to capture the adjustments in prices. After landfall, we believe that the market use, on average a couple of days to absorb the cumulative effect. We decided to end the event window five days subsequent to landfall, as this should be sufficient for the market to absorb the potential consequences of the hurricane. When the event occurs on a non-trading day, the event date is set to the next trading day as we expect most of the effect to appear here.

5.1.2 ESTIMATING ABNORMAL RETURNS

To examine the effect of hurricanes in the U.S., we estimate abnormal returns for individual stocks in the days subsequent to a hurricane making landfall. Using the Fama-French (1993) three-factor model, we calculate expected returns and further calculate abnormal returns in the occurrence of the events.

We use equation (5.1), Fama-French three-factor model to estimate the expected returns:

$$(5.1)\ r_i = r_f + \beta_1(r_m - r_f) + \beta_2(SMB) + \beta_3(HML) + \varepsilon$$

r_i is the adjusted excess return over risk-free rates for each stock i, r_f is the risk-free rate based on 3-month Treasury bill, r_m is the return on the market portfolio based on stock returns from NYSE and Nasdaq. The breakpoints for estimating SMB and HML portfolios is however based on solely on NYSE firms. Idiosyncratic return, the part of the excess return not explained by the three factors are represented by ε. Expected returns are based on an estimation window consisting of approximately 125 trading days.

After estimating expected returns individually for each firm over all events, we can calculate abnormal returns. AR for every day in the event window is calculated by subtracting actual returns from the estimated expected return. Thus, the excess return the firm exhibits over or under the expected return is abnormal. Equation (5.2) is used to calculate abnormal returns for all stocks i, and all events h.

$$(5.2)\ AR_{i,h} = R_i - r_i$$

where r_i is our estimated expected, and R_i is the actual return on each firm.

Further, we want to investigate the CAR over the event window. We expect the stock price effect to adjust over several days, dependent on the development of the hurricane. Thus, CAR will show the cumulative effect of the event window. Equation (5.3) is used to calculate CAR for each hurricane and each firm. Our CAR is estimated over a total of nine days, three days before landfall to five days after including the event date, 0. Accumulation over the event window is calculated from [t_1,t_2] ([-3,5]).

$$(5.3)\ CAR_{h,i} = \sum_{t_1=-3}^{t_2} AR_{h,i}$$

5.1.3 TESTING ABNORMAL RETURNS

To check whether abnormal returns are statistically significantly different from zero, we conduct a one-sample Wilcoxon signed rank, which is a non-parametric version of one sample t-test. The Wilcoxon signed-rank test is based on ranks. Thus, the location parameter is the median and not the mean value. Furthermore, it does not assume normality in the data, fitting our data set well. We use the one-sample Wilcoxon signed rank test to test if our estimated abnormal returns are statistically significantly different from zero. In the two-tailed test, the null hypothesis states the median is equal to zero, and the alternative hypothesis is different from zero. In the left-tailed test, the null hypothesis is stating that the median is ≤ 0. The alternative hypothesis states that the median is > 0

5.2 PANEL DATA

Panel data, also known as longitudinal data, is data where we have multiple entities, and each entity is observed two or more times (Stock, Watson, 2014). Before deciding what panel technique to use in our analysis, we identify whether we have a balanced or unbalanced panel. Our data sample is set up as a balanced panel because it has the same number of cross-sectional units at each point in time, rather than an unbalanced (Brooks, 2008), which has an unequal number of cross-sectional units at different points in time. Econometrically, our model can be written as equation (5.4), where i is the firm, which ranges from 1 to 38, and h refers to the event, which ranges from 1 to 15. Further, we have 8 explanatory variables.

$$(5.4)\ y_{ih} = \alpha + \beta x_{ih} + u_{ih}$$

Where α is the interception term, β is the coefficient, x_{ih} is the explanatory variable, and u_{ih} is the error term. The coefficient indicates the impact the explanatory variable has on the dependent variable. The error term represents the difference between observed and actual population data, which is the idiosyncratic return. The intercept term is not relevant to interpret in our analysis.

The simplest way to analyze our data is to pool the data and use ordinary least squared (OLS). When conducting OLS on the pooled data, we assume u_{ih} to be normally distributed, its mean value equal to zero and uncorrelated with our coefficients. The OLS model does not take into consideration that the data is panel data, thus treating all observation as individual.

Next, we extend the pooled OLS analysis by including time dummy variables. As our panel data set contains 15 events, we add 14 time-dummy variables, one less the number of events, to avoid the dummy variable trap. If we use the same number of time dummy variables as events, there will be a problem with multicollinearity. Each time-dummy variable will absorb variance particular to each event. Equation (5.5) shows the pooled OLS model with time dummy variables.

$$(5.5)\ y_{ih} = \beta x_{ih} + \lambda_1 D1_h + \lambda_2 D2_h + \cdots + \lambda_2 Dh_h + u_{ih}$$

Further, we conduct the fixed and random effect models, with and without time dummy variables. In the fixed effects model, the disturbance term can be written as $u_{ih} = \mu_i + v_{ih}$ Where μ_i is an individual specific effect that doesn't change over time, but across entities. v_{ih} captures the rest of the disturbance in y_{ih} that μ_i does not capture. Thus, we can rewrite equation (5.4), and we get equation (5.6)

$$(5.6)\ y_{ih} = \alpha + \beta x_{ih} + \mu_i + v_{ih}$$

Equation (5.6) is an entity fixed effects model, which is not the best fit for our data. Thus, we choose to use time fixed effects model. We change μ_i with λ_h, and get equation (5.7). λ_h is a time-varying intercept that captures all of the variables that affect y_{ih} and is constant cross-sectionally but vary over time (Brooks, 2008). v_{ih} will have the same function as in (5.6), but now capture the disturbance unexplained by λ_h.

$$(5.7)\ y_{ih} = \alpha + \beta x_{ih} + \lambda_h + v_{ih}$$

We extend this by adding time dummy variables to the fixed effects model, and get equation (5.8).

$$(5.8)\ y_{ih} = \beta x_{ih} + \lambda_1 D1_h + \lambda_2 D2_h + \cdots + \lambda_h Dh_h + v_{ih}$$

The next step in our analysis is to estimate the random effects model (5.9), before testing which model is the best. In the random effect model, $u_{ih} = \varepsilon_i + v_{ih}$, thus we rewrite equation (5.4) and get equation (5.9). εi captures the heterogeneity in the cross-sectional dimensions (Brooks, 2008). Assumptions for the random effect model is that ε_i is independent of the explanatory variables, has constant variance, and has a mean equal to zero. Further, ε_i and v_{ih} need to be independent of each other.

$$(5.9)\ y_{ih} = \alpha + \beta x_{ih} + \varepsilon_i + v_{ih}$$

We add time dummy variables to the random effect model as well, in the same manner as with the pooled OLS and fixed effect model, adding one less than the number of events. We then get equation (5.10)

$$(5.10)\ y_{ih} = \beta x_{ih} + \lambda_1 D1_h + \lambda_2 D2_h + \cdots + \lambda_h Dh_h + v_{ih}$$

To see which model is the best fit we use the Hausman test-statistics, given by equation (5.11). The Hausman-test is a test to check if the covariance between the explanatory variable x_{ih} and α is equal to zero. If this is the case, then both random- and fixed-effects are consistent, but the random will be more efficient, as the standard error is lower. The null hypothesis is that the covariance is zero, and the random effect is the best fit. The alternative hypothesis states that the fixed effect is the best fit.

$$(5.11)\ W = \frac{(\hat{\beta}_{FE*} - \hat{\beta}_{RE*})^2}{Var(\hat{\beta}_{FE}) - Var(\hat{\beta}_{RE})}$$

5.3 PORTFOLIO DIFFERENCES

The second analysis we conduct is to compare abnormal returns between groups of firms. We rank all firms based on each firm-specific variable and further divide all firms into three equal groups for each event. Creating portfolios consisting of firms with high, medium, and low values of the respected multiple. Since the multiple values change over time, firms are ranked every event. Each portfolio provides a *Portfolio Average Cumulative Abnormal Return* (PACAR), one for each of the 15 events. The PACAR is the average CAR of all stocks in the portfolio.

$$(5.12)\ PACAR_g = \frac{1}{S}\sum_{i=1}^{S} CAR_{h,i}$$

Equation (5.12) is used to calculate PACAR for group *g*, where *S* is the number of stocks.

5.3.1 TESTING DIFFERENCES

To avoid the assumptions of standard parametric tests, we chose to use the non-parametric alternative to a one-way ANOVA, Kruskal-Wallis test. Using this non-parametric test, we examine whether the abnormal return medians are different between PACAR over our 15 events. We use the Kruskal-Wallis test-statistics, *H*, in equation (5.13), to conduct the test and account for potential non-normality in our data (Elliot, Hynan, 2011). The Kruskal-Wallis test is based on values in the test set being ranked.

$$(5.13)\ H = \frac{12}{N(N+1)}\sum_{g=1}^{k}\frac{R_g^2}{n_g} - 3(N+1),\ N = \sum_{g=1}^{k} = n_g$$

For each group, g (g = 1, 2, ...k, k = 3) consisting of n_g firms, the rank R_g is calculated. The test statistics is an adjusted representation of the variance of ranks within the groups. We compare the test statistics to the chi-square critical values since the Kruskal-Wallis-test is considered to follow a χ^2 distribution (Hecke, 2012). The null hypothesis of the test is that there is no difference in the median value between the groups tested. This test is repeated for all of our firm-specific variables.

For the Kruskal-Wallis test to be valid, four assumptions must be met. Variables should be of a continuous scale, our AR is continuous values. Independent variables should consist of two or more categorical groups, we divide all multiples into three portfolios; *High, Medium,* and *Low*. There should be no relationship between groups or between observations in each group. All stocks are independent and occur only once at each point in time. Thus, there is independence both within the group and between the groups. The fourth assumption is that the group distributions have the same shape. Even though differences in firm characteristics might lead to different AR, we expect the various events to affect all firms in the same direction. The distributions should have the same shape.

5.4 FINANCIAL CRISIS

Before and during the financial crisis, which occurred between 2007-2009, insurance corporations sold complex insurance products on financial instruments. In this period a substantial fraction of these products were deemed worthless and insurance firms suffered losses that account for a significant fraction of the negative returns we see in this period.

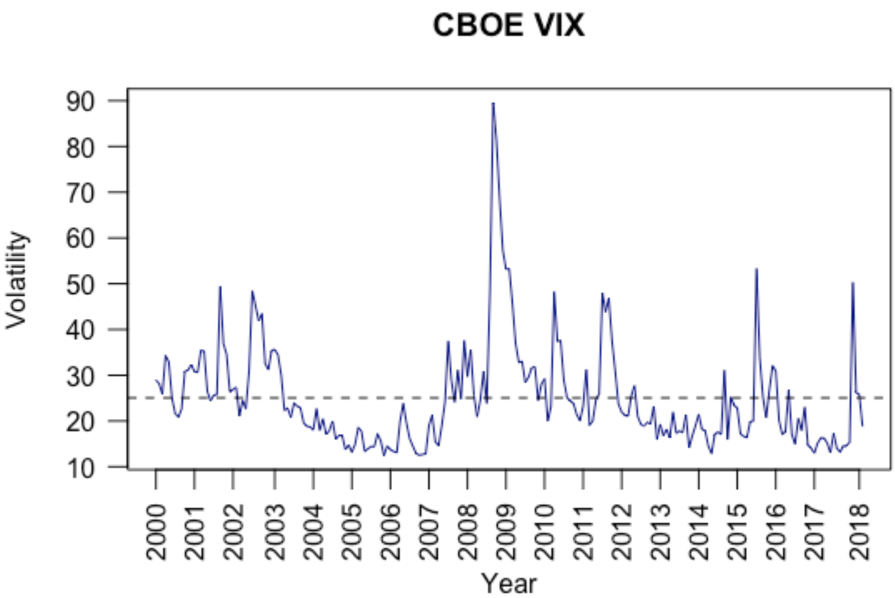

Figure 2 - CBOE Volatility Index

The Chicago Board Options Exchange (CBOE) volatility index (VIX) tracks the expected volatility on the S&P 500. It is calculated on the basis of the prices on the S&P 500 option market. This is why it is often referred to as the fear index or the investor fear gauge

(Whaley, 2000). A high value indicates high expected volatility. From Figure 2, constructed by monthly high prices, we can see that during the last 18 years, the VIX was at an all-time high at the end of 2008. Thus, leaving out the events occurring in 2008 is reasonable because of the unique market conditions. First, we carry out our regression and tests for all 15 events (Model 1). Further, we repeat this analysis without the two hurricanes that hit land during the financial crisis in 2008 (Model 2). We do this is to control for effects that the uncertainty of the financial markets had on returns in the insurance industry.

6. DATA

In this section, we present the data we use for our empirical analysis. The data consist of two main parts, stock data, and event data. In addition, data includes factors for the Fama-French three-factor estimation. Stock data is daily stock prices, multiples, and firm characteristics for the corresponding firms. Hurricane data contains dates of the event and the category and cost of the natural disaster. We use three databases to obtain data for our analysis. For stock data, we use Thomson Reuters Datastream, which provides a wide variety of historical stock market and securities time series data. To acquire event information, we *use National Oceanic and Atmospheric Administrations* (NOAA) list; *Continental United States Hurricane Impacts/Landfalls 1851-2017* to find events of interest and further gather more detailed information from respective hurricane reports provided by NOAA. Estimation factors are from Kenneth R. French´s website.

6.1 STOCK DATA

Our stock data are obtained from the *Thomson Reuters DataStream* database. The data set includes daily stock prices, multiples, and firm characteristics from January 2000 to December 2018 of all insurance companies on NYSE. Including specialty insurers, property-casualty insurers, life insurance, and accident & health insurance. Firms that went public after 2000 are not included in the sample, Lanfear et al. (2017, A) set some criteria as to which stocks to include in their study. Stocks had to trade at some point during the research at a price higher than $5 and under $1.000. We have chosen to exclude Berkshire Hathaway Inc. class A and class B. Class A is excluded due to the high price of $302.600 (December 2018), and it has at all times during our study traded above $7.000. Class B is excluded due to the correlation they have with the class A shares. We do this because the high price can lead to low liquidity, and thus, the stock might react differently to events. Only common shares are included in the data set. To be included, the stocks must be trading continuously, and have disclosed all used variables throughout the estimation window and the corresponding event window. Following these criteria, we end up with 38 stocks in the sample. To account for dividends and stock repurchases, we use the adjusted closing price. Stock prices are used to calculate logarithmic-returns. We use logarithmic returns to rescale data, and reduce potential problems with heteroscedasticity, transform positive skewness closer to the normal distribution. This transformation is usually done in finance research (Brooks, 2008).

On event 11 (Hurricane Ike, 2008), the AIG stock exhibits unusually large negative returns, resulting in our data showing high skewness and kurtosis. This observation is during the financial crisis, and the reason for the extreme negative return is most likely due to the Federal Reserve issued a loan of $85 billion to AIG, and took control over 80% of AIG's equity (Reuters, 2018). This equity takeover diluted current shares, and the stock price fell by 73% during our defined event window. As we have observed the AIG stock price development during several hurricanes, we conclude that this substantial drop is due to the equity takeover, and not the hurricane. Therefore, we decided to replace this observation from our with the average AR on that particular event.

To estimate the expected returns with the three-factor model, factor data for the corresponding period are obtained from Kenneth R. French´s website (Kenneth R. French, 2018). The factors included in this data set is HML, SMB, and market return (r_m), and the risk-free rate (r_f).

MULTIPLES

For each firm, we have considered eight variables concerning capital structure, stock- and accounting information. The first two variables contain information about the size of the firm's - market value, and the reported annual revenue. The remaining six variables are ratios, and in this way, we analyze variables independent of firm size. Multiple values are collected from the last trading day of our estimation window. This is the last day of outside the hurricane season, hence the last day before the multiple might be affected by hurricanes.

MARKET VALUE

Market value is the current stock price multiplied by the number of outstanding shares. This multiple is a measure of the size of the firm, as the stock price reflects the value of the firm's assets. We include this as it is the most basic and widely used multiple. Further, we expect it to be able to explain some of the abnormal returns. High market value will indicate a large portfolio of policies, and that the expected loss will be prominent during a hurricane. But as a firm grows, it becomes more robust, has greater cash reserves, and is more diversified than smaller companies. Therefore, we believe that a large firm will have less affected by disasters than a small company.

SALES

Sales are the total underwritten premiums. A firm with high sales will have higher liabilities when hurricanes occur due to a large portfolio. As for market value, high sales numbers will indicate a large portfolio of policies. Indicating significant possible losses, but again a more diversified portfolio. We expect this multiple to affect AR, but uncertain whether the effect is positive or negative.

DEBT RATIO

This ratio explains the leverage of a firm. It is estimated by dividing debt by common equity. A high debt ratio indicates higher financial risk due to more liabilities. During a disaster event, this increases the bankruptcy risk. Thus, we would expect a high debt ratio to be correlated with an increased negative abnormal return.

PRICE EARNINGS

Price-earnings, P/E, is one of the most commonly used multiples. P/E is the stock price divided by the earnings per share. A high P/E ratio is an indication that the firm has growth potential. Typically, young firms, yet to have high earnings while the stock price reflects future growth opportunities. Likewise, a low P/E is an indication that the firm is mature with high earnings and small future growth opportunities reflected in the stock price. We expect that a firm with a high P/E will be more sensitive to a hurricane event than firms with low P/E. Thus, high P/E should result in negative abnormal returns.

MARGIN

Margin is the firm's net income divided by net sales. Margin measures how much a firm makes on one dollar of sales. A high margin means that the firm generates more free cash to cover liabilities. A high margin is also a good indicator of how well the firm is managed. We choose to include this variable because it is an indicator of how well the firm can handle increased liabilities to cover matured policies after hurricane strikes.

VOLATILITY

Volatility is a measure on deviations of the stock price from the mean value. As we expect negative abnormal returns in the industry, we further expect firms with high volatility to exhibit more substantial negative returns.

DIVIDEND YIELD

The dividend yield is calculated by dividing the annual dividend by the share price. This multiple is an indicator of how well the firm operates and whether the firm has positive net investment opportunities. A high yield indicates that free cash flow generated is paid out to the owners and that the cash reserves are sufficient. We believe that a high yield indicates a solid firm, hence the firm will be less negatively affected by a hurricane event.

CASH

This variable is the ratio of cash and marketable securities to total assets. When a disaster event strikes and incurs losses, we expected a firm with a high amount of cash and marketable securities perform better.

6.2 EVENT DATA

When investigating the impact of hurricanes on the economy, Boustan et al. (2017) find that there needs to be a certain size of the event to have an impact on housing prices and migration. We argue that the same applies when investigating stock prices. The hurricane needs to be of a certain size to make a notable impact on the stock price. Thus, following the Saffir-Simpson Hurricane Wind Scale, we only include hurricanes making landfall as a category 2 or higher. The scale categorizes hurricanes from 1 to 5 based on the wind speeds and potential damage. Category 2 is described as "Extremely dangerous winds will cause extensive damage" (NHC, Saffir-Simpson Hurricane Wind Scale). Hurricanes categorized 3 or higher are considered to be major hurricanes. Table 1 shows the wind speed needed for a hurricane to obtain a certain category. The scale implicates the potential property damage the hurricane will inflict, and an increase in the category by one indicates an increase in damage cost by a factor of four.

Category	1	2	3 (major)	4 (major)	5 (major)
Sustained winds	74/95 mp/h 119-153 km/h	96-110 mph 154-177 km/h	111-129 mph 178-208 km/h	130-156 mph 209-251 km/h	157 mph or higher 252 km/h or higher

Table 1 - Saffir-Simpson Hurricane Wind Scale

Between the start of 2000 and to the end of 2017 there were 15 hurricanes category 2 or above, that made landfall in the United States over seven different years. The hurricane data is obtained from NOAA´s Continental United States Hurricane Impacts/Landfalls list (NOAA, 2018). Inflation-adjusted estimated costs of these hurricanes vary from $50 million and up to almost $140 Billion. Most of the hurricanes are category 2 and 3, while there are three category four hurricanes making landfall in the U.S. from 2000 to 2017. Table 2 provides descriptive statistics of our hurricane sample.

				Cost in Billion USD	
Name	*Year*	*Category*	*Landfall*	*Nominal*	*2018*
Isabel	2002	2	18.09.2002	$ 5.5	$ 7.8
Charley	2004	4	13.08.2004	$ 15.1	$ 21.1
Frances	2004	2	05.09.2004	$ 9.4	$ 12.5
Ivan	2004	3	16.09.2004	$ 18.8	$ 25.0
Jeanne	2004	3	26.09.2004	$ 7.7	$ 10.2
Dennis	2005	3	10.07.2005	$ 2.5	$ 3.2
Katrina	2005	3	25.08.2005	$ 108.0	$ 138.8
Rita	2005	3	24.09.2005	$ 12.0	$ 15.4
Wilma	2005	3	24.10.2005	$ 21.0	$ 27.0
Gustav	2008	2	01.09.2008	$ 4.3	$ 5.0
Ike	2008	2	13.09.2008	$ 29.5	$ 34.4
Arthur	2014	2	03.07.2014	$ 0.05	$ 0.05
Matthew	2016	2	07.10.2016	$ 10.0	$ 10.4
Harvey	2017	4	26.08.2017	$ 125.0	$ 128.0
Irma	2017	4	07.09.2017	$ 50.0	$ 51.2

Table 2 - Descriptive statistics hurricane sample

7. ANALYSIS

In this section, we will present our results from the analysis. First, we apply our described methodology to calculate abnormal returns. Further, we estimate several panel data regression models. Then examine differences between our constructed portfolios. We use a 5% significance level throughout the analysis. We will also present the limitations to our analysis

7.1 ABNORMAL RETURNS

To estimate abnormal returns throughout a disaster event, we must first forecast expected returns for every firm individually. Forecasting of expected returns is based on the Fama-French three-factor model. Table 3 provides descriptive statistics for cumulative abnormal returns over all events, and descriptive statistics excluding the two events during the financial crisis.

Descriptive statistics Cumulative AR	*Including 2008*	*Excluding 2008*
Mean	0,732 %	-0,123 %
Standard Error	0,0026	0,0022
Standard dev.	0,062	0,049
Kurstosis	14,589	16,633
Skewness	0,516	-2,461
Minimum	-40,730 %	-40,730 %
Maximum	45,251 %	18,561 %
Observations	570	494

Table 3 - Descriptive statistics cumulative abnormal returns

The mean CAR throughout all our events is 0.73% while it is -0.12% when 2008 events are excluded. Expected returns during the financial crisis were negative due to poor performance, especially in the insurance industry. The 2008 events are the only ones with expected negative returns. As long as firms exhibited positive returns in our event window, the AR would be positive as well. Positive returns during this period are the reason the mean values over all events are positive. To deal with these negative expected returns, we remove events occurring in 2008.

Including the 2008 events, there is a low positive skewness and high kurtosis. Excluding these events, the kurtosis remains high, but the skewness changes from positive to negative. This distribution is consistent with what we expected. Abnormal returns would in a regular period be expected to be zero, thus the high kurtosis. Negative skewness is also expected since we expect to see a negative abnormal return during hurricanes. Still, our data does not follow a normal distribution in either of the datasets. Thus, we use a non-parametric test when conducting the analysis. It's worth noting that the standard deviation also is reduced as the financial crisis is excluded. Figure 3 shows the CAR for each event.

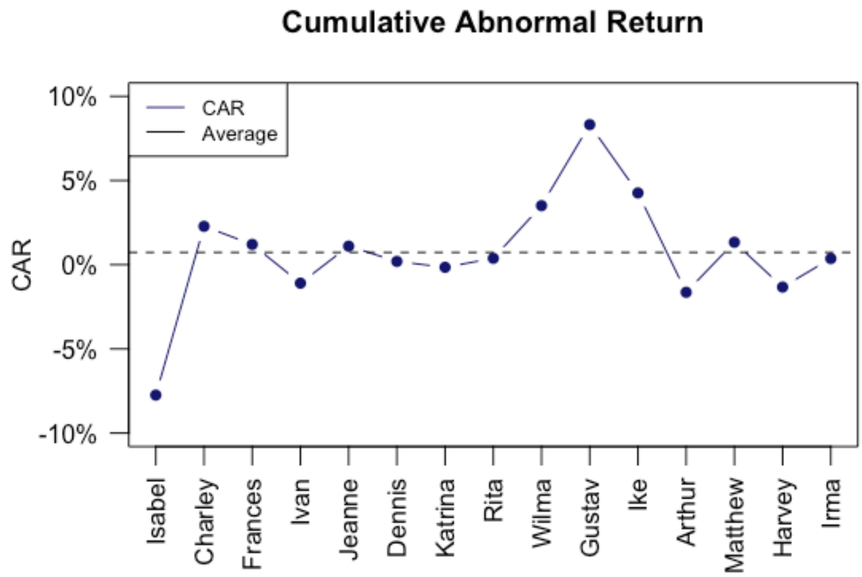

Figure 3 - Cumulative Abnormal Return over all events

We conduct the one-sample Wilcoxon signed rank test to investigate if the AR is significantly different from zero. The results from the test are listed in table 4. We start by conducting a two-tailed test on AR, including and excluding events in 2008. When 2008 is included, the test is significant. Thus, we reject the null hypothesis and conclude that the median not is equal to zero. When 2008 is excluded, the p-value is greater than 0.05. Thus, using a 5% significance level, we keep the null hypothesis. Further, we use a left-tailed test to see if the AR is less than zero. The test is not significant for both samples, thus we do not reject the null hypothesis, meaning that the median is not less than zero in both datasets.

Wilcoxon-test	*mu*	*Type*	*V*	*p-value*
Including 2008	0	"two.sided"	97901	2.634e-05
Excluding 2008	0	"two.sided"	97901	0.0563
Including 2008	0	"less"	67193	1
Excluding 2008	0	"less"	67193	0.9719
alternative hypothesis: true location is not equal to 0				

Table 4 - Wilcoxons-test

This result is not in line with our predictions. We believe this is due to the fact that there are some extreme negative observations, where the hurricane was not accounted for in the stock price. And many slightly positive, where the hurricane was accounted for in the stock price. Resulting in the median value being above zero.

After individually investigating the firms with maximum and minimum values during the event window, we have no reason to believe this is caused by anything else than the event we are considering.

7.2 PANEL DATA

In this section, we will present the results from our panel data regression. We construct a panel and run panel data regressions on two data sets. Also, each model is extended by including time dummy variables. This extension results in 6 estimated regression models. We will first present results from our pooled OLS model, with and without time dummies. Next, we will present the results from fixed- and random effect models, with and without time dummies.

From the pooled OLS regression, we find that volatility and margin are statistically significant, with a negative coefficient. The dividend yield is also statistically significant, but with a positive coefficient. When running the regression in STATA, we also get the F-statistics, which tests whether the coefficients are different from zero. The null hypothesis states that $\beta_1 = \beta_2 = \dots = \beta_\mathrm{i} = 0$. The p-value is > 0.05, thus we reject this hypothesis. This means that all explanatory variables explain some of the variations in the abnormal return. The added time dummy variables are all significant, thus absorbing the time effect. This means that the specific time period of the event explains some of the variations that is observed. Further, the dividend yield is no longer significant. Meaning when controlling for time effect, dividend yield does no longer explain the variation in AR.

The OLS model has several assumptions that have to be met for the estimate to be valid. This model assumes homoskedasticity and that the error term is uncorrelated with the coefficient (Brooks, 2008). Since the OLS regression does not recognize the fact that our data is structured as a panel, it pools the data instead. These assumptions are unrealistic in our case because we have the same firm appearing in all events. Therefore, we conclude that the pooled OLS model is not the optimal model. The next step is to run the fixed and random effect regressions, both with and without time dummies.

Next, we estimate the fixed and random effect models regression. We find that in the fixed effect model that dividend yield, debt, and margin are statistically significant. The F-statistics is not statistically significant with a p-value of 0.149. Thus, we cannot reject the null hypothesis, and some of the variables do not explain the variation in AR. We get three different R-squared values when conducting panel data regression. Within R-squared tells us how much of the variance between the separate units in the panel the model accounts for. Between shows how much of the variance within the panel units the model accounts for. And the R-squared overall is the weighted average of the within and between. We get the following result from this model; 0.076, 0.028, and 0.031.

When adding time dummy variables, we find that all are statistically significant, and that debt is no longer significant, and cash becomes significant. The p-value to the F-statistics is 0.016, and we can reject the null hypothesis, and conclude that the fixed effect model with time dummy variables is a good fit. The overall R-squared is 0.272, which is significantly higher than the same model without time dummy variables, telling us that this model is explaining more of the variance in AR when time dummy variables are added.

In the random effect, volatility, dividend yield, and margin are statistically significant. When adding time dummy variables, they are all statistically significant, but time dummies are added, dividend yield is no longer statistically significant.

We then conduct the Hausman test to see which model is the best fit. The Hausman-test is significant, and we can reject H_0, which states that the differences in coefficients are not systematic. Thus, the fixed effects model with time dummy variables is the best fit.

We run the best fit model, fixed effect with time dummy variables, on the model 2 dataset, excluding events occurring during the financial crisis.

15 events		13 events	
Fixed-effects (within) regression		*Fixed-effects (within) regression*	
Model 1		*Model 2*	
Group variable :	Stock	Group variable :	Stock
R-squared		R-squared	
Within	0.3689	Within	0.3810
Between	0.0026	Between	0.0760
Overall	0.2716	Overall	0.3131
Number of observations	*569*	*Number of observations*	*493*
Number of stocks	38	Number of stocks	38
Obs per group		Obs per group	
min	14	min	12
avg	15	avg	13
max	15	max	13
corr(u_i, Xb) = -0.3451		corr(u_i, Xb) = -0.2783	
F(22, 509)	=13.53	F(22, 509)	=13.39
Prob > F	=0.000	Prob > F	=0.000

AR	*Coef.*	Std. Err.	*P>t*	*Coef.*	Std. Err.	*P>t*
MV	-1.62e-7	3.28e-07	(0.623)	-2.83e-07	2.93e-07	(0.335)
Sales	-1.11e-10	6.61e-10	(0.867)	-1.05e-10	5.60e-10	(0.852)
Volatility	0.0255	0.0258	(0.323)	-0.0223	0.0221	(0.313)
DY	0.0055	0.0027	(0.040)**	0.0033	0.0030	(0.266)
PE	-3.91e-06	0.0000	(0.873)	-0.0000	0.0000	(0.424)
Debt	0.1394	0.0759	(0.067)	-0.0962	0.0708	(0.175)
Margin	-0.0003	0.0001	(0.005)***	-0.0001	0.0001	(0.119)
Cash	-0.2319	0.1031	(0.025)**	-0.1473	0.1089	(0.177)
Event						
2	0.1066	0.0116	(0.000)***	0.1079	0.0904	(0.000)***
3	0.0958	0.0116	(0.000)***	0.0971	0.0904	(0.000)***
4	0.0728	0.0116	(0.000)***	0.0741	0.0904	(0.000)***
5	0.0948	0.0116	(0.000)***	0.0970	0.0904	(0.000)***
6	0.0871	0.0117	(0.000)***	0.0860	0.0091	(0.000)***
7	0.0835	0.0117	(0.000)***	0.0825	0.0091	(0.000)***
8	0.0889	0.0117	(0.000)***	0.0879	0.0091	(0.000)***
9	0.1202	0.0117	(0.000)***	0.1192	0.0091	(0.000)***
10	0.1615	0.0123	(0.000)***	0.0649	0.0095	(0.000)***
11	0.1209	0.0123	(0.000)***	0.0911	0.0097	(0.000)***
12	0.0668	0.0123	(0.000)***	0.0659	0.0098	(0.000)***
13	0.0941	0.0123	(0.000)***	0.0828	0.0098	(0.000)***
14	0.0698	0.0124	(0.000)***			
15	0.0867	0.0124	(0.000)***			
_cons	-0.0978	0.0138	(0.000)***	-0.0775	0.0129	(0.000)***
sigma_u	0.0255				0.0180	
sigma_e	0.0499				0.0388	
rho	0.2069				0.1775	
F-test that all u_i=0: F(37, 509) = 1.60				F-test that all u_i=0: F(37, 435) = 0.86		
Prob > F = 0.0158				Prob > F = 0.6986		
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 5 - Fixed effects mode with time effects. Model 1 and Model 2

Table 5 presents regression results from the fixed-effects model with time-effect dummies. Model 1 is the sample, including all events and Model 2 excludes 2008-events. For model 1, there are two statistically significant coefficients on a 5% level, the dividend yield, and cash, while margin is significant on a 1% level. Cash is hard to interpret since we can not increase this ratio with one full unit. The highest cash ratio is one. But the results indicate a negative relation between cash/assets and CAR, inconsistent with our expectation. Increasing dividend yield by one should result in 55 basis points (BPS) higher CAR. Statistically significant on a 1% level an increase of one in the net margin indicates 3 BPS lower CAR. This result is contradictory to our expectation of net margins effect on AR. Consistent with our expectation all time dummies are statistically significant in both models. They indicate a positive relation significant on the 1% level.

In model 2, only the time dummy variables are statistically significant with positive coefficients. For both of the models, the first F-test shows significant values, and thus, all coefficients are deemed different from zero. We believe the unanticipated effects in Model 1 is due to the extraordinary conditions during the financial crisis, and these effects disappear in Model 2.

The intraclass correlation is presented as *rho* (ρ). This coefficient is calculated using sigma_u and sigma_e. A high rho indicates close similarity between values from the same stock. There are several scales concerning this coefficient. Cicchetti (1994) states that rho less than 0.4 is considered poor, while Koo and Li (2016) considered below 0.5 to be poor. We expect the intraclass correlation in our sample to low. As a stock reacts differently to each event because the hurricanes are different in strength, and they appear at different times, where the characteristics of the firm may have changed. For model 1, rho states that 20.7% of the variance is due to differences in panels, while it is 17.8% for model 2.

Table 6 shows the expected effect of our explanatory variables, and the results from our analysis.

Multiple	MV	Sales	Volatility	DY	PE	Debt	Margin	Cash
Expectation	+	+/-	-	+	-	-	+	+
Result model 1	-	-	+	+	-	+	-	-
Significant	No	No	No	Yes	No	No	Yes	Yes
Result model 2	-	-	-	+	-	-	-	-
Significant	No	No	No	No	No	No	No	No

Table 6 - Panel data regression

7.3 DIFFERENCE BETWEEN GROUPS

After ranking firms based on their multiples and separating them into three groups, we calculate a PACAR for each group on each event. Considering three groups, we get three PACAR for 15 events. The nonparametric test is conducted on these PACAR's. The test Kruskal-Wallis test-statistics are not significant for any of the multiples, and thus, H_0 is not rejected. We cannot conclude that there are different PACAR between groups. Figure 4 shows the PACAR for high, medium and low portfolios ranked after dividend yield. We can see small differences in the sorted portfolio, but they do not differ enough to be statistically significant.

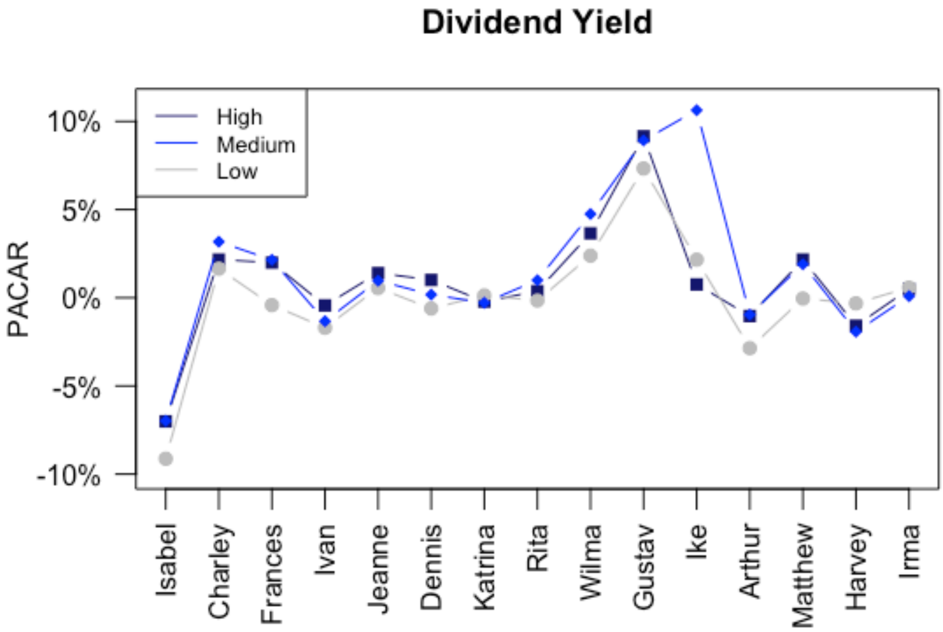

Figure 4 - Portfolio Average Cumulative Abnormal Return ranked by Dividend Yield

This analysis is only conducted with the sample, including the financial crisis events. Even with the full sample, we have few observations for each portfolio. Excluding events would further decrease the degrees of freedom and weaken the test. Thus, we choose only to analyze the full sample.

7.4 LIMITATIONS

Our data sample consists of NYSE insurance stocks exclusively. Combined with our other selection criteria, the sample size ends up with 38 stocks. To achieve greater statistical strength, we could have included Nasdaq insurance stocks. Another extension could be to include additional events by increasing the time frame or adding other types of natural disasters.

When testing the differences between groups, we calculated the PACAR. This calculation reduces the number of observations down to 1 per group, 3 in total for each event. By increasing the number of events we would increase the number of observations and with it the statistical power. Another way to improve this part of the analysis would be to divide the sample into more groups. More groups would increase the degrees of freedom of the Kruskal-Wallis test.

We use only one event window in this thesis. This is selected on the background of previous research, as the best fit, we believe. But to be certain that all effect in the abnormal return is accounted for, further testing on multiple event windows could be conducted.

This thesis is investigating only the insurance industry stocks listed on the NYSE. The insurance industry in the U.S. is regulated by the U.S. government (Federal Insurance Office [FIO], 2018). Regulations include licensing, preserving and monitoring the solvency of the insurance companies, and standardizing products. These regulations make the industry more homogenous, as the variation in cash reserves and debt are restricted by the regulation. This monotone structure might limit the results when investigating a single industry.

8. CONCLUSION

Inspired by the climatic changes the world is experiencing, we investigate the impact that extreme weather events have on the stock market, as we believe this to be increasingly important for the future

Using an event study approach, we have examined the insurance industry and how hurricanes affect the stock price. First, defining the perimeter for our thesis; investigating only insurance stocks listed on NYSE and using hurricanes category 2 or higher as events. After filtering for our selection criteria, we end up with 38 stocks and 15 events.

We calculate abnormal returns expecting to see negative AR, due to expectations of increased liabilities. Using the same approach as Lanfear et al. (2017, A/B), we estimate expected returns using the Fama-French three-factor model. Over a 9-day event window, we calculate cumulative abnormal returns. In model 1, the CAR is 0.73%, and for model 2, the CAR is -0.12%. The one-sample Wilcoxon signed rank left-tail test is not significant, and we cannot conclude that the median CAR is less than zero. Model 1 results contradict our expectations, but when looking at the data, it is clear that the positive abnormal return is a result of two hurricanes occurring in the financial crisis when the expected return was negative due to extreme market conditions. Model 2 shows a negative CAR, which is in line with our expectations. The Wilcoxon signed rank left-tail test shows that the median is greater than zero, which contradicts our expectation. Looking closer at the AR, we see that there is some large negative AR observation, and many slightly positive, thus the positive median. We believe this is a result of the market being able to efficiently anticipate the effect of most hurricanes.

Further estimating six different models, pooled OLS, fixed effects, and random effects, both with and without time dummy variables. We conclude that our data violates the pooled OLS model. Next, we estimate the fixed and random effect models and use the Hausman-test to find the fixed effects model with time effects to be the best fit. This result is further confirmed by the overall R-squared value, which was highest for this model. The model shows dividend yield, margin, and cash to be statistically significant explanatory variables, as well as all time-dummy variables. The significant variables have little impact on AR. Among the significant variables, only dividend yield showed a positive effect, while margin and cash had negative coefficients. The effects of margin and cash contradict our expectations, but when excluding the financial crisis, these effects disappear. Only the time dummy variables are significant when the financial crisis is excluded.

Further, in our analysis, we investigate whether firm characteristics affect the abnormal return on insurance companies. Ranking firms from high to low in multiple values, dividing firms into three equal portfolios and testing them against each other using the Kruskal-Wallis test. We expected to find differences in abnormal returns between the portfolios. The Kruskal-Wallis test results show no statistically significant differences between the medians in any of the portfolios. We believe this is due to the fact that the insurance industry is regulated and therefore, homogenous. An unregulated industry with more considerable differences between the firms' characteristics might have shown a different result.

We conclude that the insurance firms on the NYSE do not exhibit negative abnormal returns after hurricanes making landfall. Furthermore, we find that the difference in stock characteristics does not explain the abnormal returns on NYSE insurance stocks. There are no negative abnormal returns over the past 20 years when category 2 or higher hurricanes make landfall.

FURTHER RESEARCH

We find no economically significant results in our research. However, taking our analysis' limitations in consideration, there are multiple ways to study the disaster risk topic further. First, one could implement the panel data methodology with multiple values as explanatory variables to larger samples, including Nasdaq and more events. Conversely, the same analysis could be conducted in several industries in the same sample. In this way, the homogeneity in firm variables is reduced, and more predominant effects might appear.

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APPENDIX

Panel data regression results.

Pooled OLS model, full sample:

```
. regress AR MV Sales Volatility DY PE Debt Margin Cash
```

Source	SS	df	MS
Model	.152703666	8	.019087958
Residual	2.01846159	560	.003604396
Total	2.17116526	568	.003822474

Number of obs	=	569
F(8, 560)	=	5.30
Prob > F	=	0.0000
R-squared	=	0.0703
Adj R-squared	=	0.0571
Root MSE	=	.06004

AR	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
MV	-3.00e-07	2.83e-07	-1.06	0.291	-8.57e-07	2.57e-07
Sales	1.78e-10	4.04e-10	0.44	0.660	-6.15e-10	9.70e-10
Volatility	-.0613201	.0151542	-4.05	0.000	-.0910862	-.0315541
DY	.0043844	.0018996	2.31	0.021	.0006532	.0081157
PE	-.0000276	.0000278	-0.99	0.321	-.0000821	.0000269
Debt	.0106876	.0262853	0.41	0.684	-.0409422	.0623175
Margin	-.0003323	.0000974	-3.41	0.001	-.0005236	-.000141
Cash	-.0026753	.0480418	-0.06	0.956	-.0970394	.0916889
_cons	.0225181	.006647	3.39	0.001	.009462	.0355741

Pooled OLS model with time-dummy variables, full sample

```
. regress AR MV Sales Volatility DY PE Debt Margin Cash i.Event
```

Source	SS	df	MS			
				Number of obs	=	569
				F(22, 546)	=	13.31
Model	.757985433	22	.034453883	Prob > F	=	0.0000
Residual	1.41317983	546	.002588241	R-squared	=	0.3491
				Adj R-squared	=	0.3229
Total	2.17116526	568	.003822474	Root MSE	=	.05087

AR	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
MV	-2.13e-07	2.42e-07	-0.88	0.378	-6.88e-07	2.62e-07
Sales	6.03e-11	3.44e-10	0.18	0.861	-6.16e-10	7.37e-10
Volatility	-.0547388	.0136589	-4.01	0.000	-.0815693	-.0279083
DY	.002354	.0016383	1.44	0.151	-.0008642	.0055722
PE	3.57e-06	.0000239	0.15	0.881	-.0000434	.0000505
Debt	.0125832	.022352	0.56	0.574	-.0313232	.0564896
Margin	-.0002122	.0000848	-2.50	0.013	-.0003788	-.0000455
Cash	-.021049	.0411789	-0.51	0.609	-.1019374	.0598394
Event						
2	.1085523	.0117695	9.22	0.000	.0854332	.1316714
3	.097802	.0117695	8.31	0.000	.0746829	.120921
4	.0747811	.0117695	6.35	0.000	.0516621	.0979002
5	.096751	.0117695	8.22	0.000	.0736319	.11987
6	.0852197	.0117837	7.23	0.000	.0620728	.1083666
7	.0817269	.0117837	6.94	0.000	.05858	.1048738
8	.087057	.0117837	7.39	0.000	.0639101	.1102039
9	.1183507	.0117837	10.04	0.000	.0952038	.1414976
10	.1578734	.0120065	13.15	0.000	.1342887	.181458
11	.1173092	.0120065	9.77	0.000	.0937245	.1408938
12	.0641083	.0118689	5.40	0.000	.040794	.0874227
13	.0897536	.0119592	7.50	0.000	.066262	.1132453
14	.0617578	.0119397	5.17	0.000	.0383045	.0852111
15	.0786984	.0119397	6.59	0.000	.0552451	.1021517
_cons	-.0649621	.0099053	-6.56	0.000	-.0844194	-.0455049

```
. testparm i.Event

 ( 1)  2.Event = 0
 ( 2)  3.Event = 0
 ( 3)  4.Event = 0
 ( 4)  5.Event = 0
 ( 5)  6.Event = 0
 ( 6)  7.Event = 0
 ( 7)  8.Event = 0
 ( 8)  9.Event = 0
 ( 9)  10.Event = 0
 (10)  11.Event = 0
 (11)  12.Event = 0
 (12)  13.Event = 0
 (13)  14.Event = 0
 (14)  15.Event = 0

       F( 14,   546) =   16.70
            Prob > F =    0.0000
```

Fixed Effects Model, full sample:

```
. xtreg AR MV Sales Volatility DY PE Debt Margin Cash , fe

Fixed-effects (within) regression               Number of obs     =        569
Group variable: Stock                           Number of groups  =         38

R-sq:                                           Obs per group:
     within  = 0.0759                                         min =         14
     between = 0.0280                                         avg =       15.0
     overall = 0.0311                                         max =         15

                                                F(8,523)          =       5.37
corr(u_i, Xb)  = -0.6923                        Prob > F          =     0.0000

------------------------------------------------------------------------------
          AR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          MV |  -3.86e-07   3.85e-07    -1.00   0.317    -1.14e-06    3.71e-07
       Sales |   4.76e-10   7.67e-10     0.62   0.535    -1.03e-09    1.98e-09
  Volatility |  -.0050676   .0260368    -0.19   0.846    -.0562171    .0460818
          DY |   .0103052   .0031351     3.29   0.001     .0041462    .0164642
          PE |  -.0000366   .0000287    -1.28   0.203    -.0000931    .0000198
        Debt |    .191113   .0891693     2.14   0.033      .015939     .366287
      Margin |  -.0004133   .0001033    -4.00   0.000    -.0006162   -.0002103
        Cash |  -.2129433   .1206966    -1.76   0.078     -.450053    .0241664
       _cons |   -.012777   .0132272    -0.97   0.335    -.0387619     .013208
-------------+----------------------------------------------------------------
     sigma_u |  .02940423
     sigma_e |   .0595396
         rho |  .19607546   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(37, 523) = 1.25                     Prob > F = 0.1494
```

Random Effects Model, full sample:

```
. xtreg AR MV Sales Volatility DY PE Debt Margin Cash , re

Random-effects GLS regression                   Number of obs     =        569
Group variable: Stock                           Number of groups  =         38

R-sq:                                           Obs per group:
     within  = 0.0540                                         min =         14
     between = 0.3122                                         avg =       15.0
     overall = 0.0703                                         max =         15

                                                Wald chi2(7)      =          .
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =          .

------------------------------------------------------------------------------
          AR |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          MV |  -3.00e-07   2.83e-07    -1.06   0.290    -8.55e-07    2.56e-07
       Sales |   1.78e-10   4.04e-10     0.44   0.660    -6.13e-10    9.69e-10
  Volatility |  -.0613201   .0151542    -4.05   0.000    -.0910218   -.0316185
          DY |   .0043844   .0018996     2.31   0.021     .0006612    .0081076
          PE |  -.0000276   .0000278    -0.99   0.321     -.000082    .0000268
        Debt |   .0106876   .0262853     0.41   0.684    -.0408306    .0622059
      Margin |  -.0003323   .0000974    -3.41   0.001    -.0005231   -.0001415
        Cash |  -.0026753   .0480418    -0.06   0.956    -.0968355    .0914849
       _cons |   .0225181    .006647     3.39   0.001     .0094902    .0355459
-------------+----------------------------------------------------------------
     sigma_u |          0
     sigma_e |   .0595396
         rho |          0   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Fixed Effects Model time-dummies, full sample:

```
. xtreg AR MV Sales Volatility DY PE Debt Margin Cash i.Event, fe

Fixed-effects (within) regression               Number of obs     =        569
Group variable: Stock                           Number of groups  =         38

R-sq:                                           Obs per group:
     within  = 0.3689                                         min =         14
     between = 0.0026                                         avg =       15.0
     overall = 0.2716                                         max =         15

                                                F(22,509)         =      13.53
corr(u_i, Xb)  = -0.3451                        Prob > F          =     0.0000

------------------------------------------------------------------------------
          AR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          MV |  -1.62e-07   3.28e-07    -0.49   0.623    -8.07e-07    4.83e-07
       Sales |  -1.11e-10   6.61e-10    -0.17   0.867    -1.41e-09    1.19e-09
  Volatility |   .0255188   .0257941     0.99   0.323    -.0251572    .0761948
          DY |   .0055441   .0026914     2.06   0.040     .0002564    .0108318
          PE |  -3.91e-06   .0000245    -0.16   0.873     -.000052    .0000442
        Debt |   .1393885   .0758685     1.84   0.067    -.0096655    .2884425
      Margin |  -.0002537     .00009    -2.82   0.005    -.0004305   -.0000769
        Cash |  -.2318846   .1030554    -2.25   0.025    -.4343509   -.0294182
             |
       Event |
          2  |   .1065914   .0116117     9.18   0.000     .0837787    .1294041
          3  |    .095841   .0116117     8.25   0.000     .0730283    .1186537
          4  |   .0728202   .0116117     6.27   0.000     .0500075    .0956329
          5  |     .09479   .0116117     8.16   0.000     .0719773    .1176027
          6  |   .0870639   .0117025     7.44   0.000     .0640728     .110055
          7  |   .0835711   .0117025     7.14   0.000     .0605801    .1065622
          8  |   .0889012   .0117025     7.60   0.000     .0659101    .1118923
          9  |    .120195   .0117025    10.27   0.000     .0972039     .143186
         10  |   .1615031   .0122518    13.18   0.000     .1374328    .1855733
         11  |   .1209389   .0122518     9.87   0.000     .0968686    .1450091
         12  |   .0667714   .0120158     5.56   0.000     .0431647    .0903781
         13  |   .0941061   .0123251     7.64   0.000     .0698916    .1183205
         14  |   .0697848   .0124002     5.63   0.000      .045423    .0941466
         15  |   .0867254   .0124002     6.99   0.000     .0623636    .1110872
             |
       _cons |  -.0978483   .0138472    -7.07   0.000    -.1250531   -.0706436
-------------+----------------------------------------------------------------
     sigma_u |  .02547604
     sigma_e |  .04987408
         rho |  .20693083   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(37, 509) = 1.60                     Prob > F = 0.0158

. testparm i.Event

 ( 1)  2.Event = 0
 ( 2)  3.Event = 0
 ( 3)  4.Event = 0
 ( 4)  5.Event = 0
 ( 5)  6.Event = 0
 ( 6)  7.Event = 0
 ( 7)  8.Event = 0
 ( 8)  9.Event = 0
 ( 9)  10.Event = 0
 (10)  11.Event = 0
 (11)  12.Event = 0
 (12)  13.Event = 0
 (13)  14.Event = 0
 (14)  15.Event = 0

       F( 14,   509) =   16.88
            Prob > F =    0.0000
```

Random Effects Model time-dummies, full sample:

```
. xtreg AR MV Sales Volatility DY PE Debt Margin Cash i.Event, re

Random-effects GLS regression                   Number of obs     =        569
Group variable: Stock                           Number of groups  =         38

R-sq:                                           Obs per group:
     within  = 0.3511                                         min =         14
     between = 0.3432                                         avg =       15.0
     overall = 0.3491                                         max =         15

                                                Wald chi2(21)     =          .
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =          .

------------------------------------------------------------------------------
          AR |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          MV |  -2.15e-07   2.44e-07    -0.88   0.378    -6.92e-07    2.63e-07
       Sales |   6.15e-11   3.48e-10     0.18   0.860    -6.20e-10    7.43e-10
  Volatility |   -.053922   .0138343    -3.90   0.000    -.0810367   -.0268073
          DY |   .0023826   .0016565     1.44   0.150     -.000864    .0056292
          PE |   3.42e-06   .0000239     0.14   0.886    -.0000434    .0000503
        Debt |   .0129264    .022694     0.57   0.569    -.0315531    .0574058
      Margin |  -.0002142   .0000849    -2.52   0.012    -.0003806   -.0000478
        Cash |  -.0227976   .0418186    -0.55   0.586    -.1047606    .0591654
             |
       Event |
          2  |   .1085513   .0117512     9.24   0.000     .0855193    .1315833
          3  |   .0978009   .0117512     8.32   0.000     .0747689     .120833
          4  |   .0747801   .0117512     6.36   0.000     .0517481    .0978121
          5  |   .0967499   .0117512     8.23   0.000     .0737179    .1197819
          6  |   .0852525   .0117661     7.25   0.000     .0621913    .1083137
          7  |   .0817597   .0117661     6.95   0.000     .0586985     .104821
          8  |   .0870898   .0117661     7.40   0.000     .0640286     .110151
          9  |   .1183835   .0117661    10.06   0.000     .0953223    .1414448
         10  |   .1579078   .0119935    13.17   0.000      .134401    .1814145
         11  |   .1173436   .0119935     9.78   0.000     .0938368    .1408503
         12  |   .0641655   .0118536     5.41   0.000     .0409329    .0873982
         13  |   .0898239   .0119462     7.52   0.000     .0664098    .1132381
         14  |   .0618658   .0119277     5.19   0.000      .038488    .0852436
         15  |   .0788065   .0119277     6.61   0.000     .0554287    .1021843
             |
       _cons |   -.065237   .0099428    -6.56   0.000    -.0847246   -.0457495
-------------+----------------------------------------------------------------
     sigma_u |  .00264869
     sigma_e |  .04987408
         rho |  .00281247   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. testparm i.Event

 ( 1)  2.Event = 0
 ( 2)  3.Event = 0
 ( 3)  4.Event = 0
 ( 4)  5.Event = 0
 ( 5)  6.Event = 0
 ( 6)  7.Event = 0
 ( 7)  8.Event = 0
 ( 8)  9.Event = 0
 ( 9)  10.Event = 0
 (10)  11.Event = 0
 (11)  12.Event = 0
 (12)  13.Event = 0
 (13)  14.Event = 0
 (14)  15.Event = 0

           chi2( 14) =  234.47
         Prob > chi2 =    0.0000
```

Hausmann Test:

```
. hausman fixed random

Note: the rank of the differenced variance matrix (5) does not equal the number of coefficients
        being tested (8); be sure this is what you expect, or there may be problems computing the
        test.  Examine the output of your estimators for anything unexpected and possibly
        consider scaling your variables so that the coefficients are on a similar scale.

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference          S.E.
-------------+----------------------------------------------------------------
          MV |  -3.86e-07    -3.00e-07      -8.66e-08        2.61e-07
       Sales |   4.76e-10     1.78e-10       2.98e-10        6.52e-10
  Volatility |  -.0050676    -.0613201       .0562525        .0211722
          DY |   .0103052     .0043844       .0059208        .0024941
          PE |  -.0000366    -.0000276      -9.07e-06        7.40e-06
        Debt |    .191113     .0106876       .1804254        .0852071
      Margin |  -.0004133    -.0003323       -.000081        .0000345
        Cash |  -.2129433    -.0026753       -.210268        .1107233
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       19.15
                Prob>chi2 =      0.0018
```

Non Parametric Analysis for testing differences between portfolios. Using the Kruskal-Wallis test.

Margin:

Kruskal-Wallis equality-of-populations rank test

Group	Obs	Rank Sum
1	15	334.00
2	15	352.00
3	15	349.00

```
chi-squared =     0.072 with 2 d.f.
probability =     0.9647

chi-squared with ties =     0.072 with 2 d.f.
probability =     0.9647
```

Cash:

Kruskal-Wallis equality-of-populations rank test

Group	Obs	Rank Sum
1	15	328.00
2	15	362.00
3	15	345.00

chi-squared = **0.223** with **2** d.f.
probability = **0.8943**

chi-squared with ties = **0.223** with **2** d.f.
probability = **0.8943**

Debt:

Kruskal-Wallis equality-of-populations rank test

Group	Obs	Rank Sum
1	15	348.00
2	15	337.00
3	15	350.00

chi-squared = **0.038** with **2** d.f.
probability = **0.9812**

chi-squared with ties = **0.038** with **2** d.f.
probability = **0.9812**

Price/Earnings:

Kruskal-Wallis equality-of-populations rank test

Group	Obs	Rank Sum
1	15	339.00
2	15	349.00
3	15	347.00

chi-squared = **0.022** with **2** d.f.
probability = **0.9892**

chi-squared with ties = **0.022** with **2** d.f.
probability = **0.9892**

Dividend Yield:

Kruskal–Wallis equality-of-populations rank test

Group	Obs	Rank Sum
1	15	340.00
2	15	347.00
3	15	348.00

chi-squared = **0.015** with **2** d.f.
probability = **0.9927**

chi-squared with ties = **0.015** with **2** d.f.
probability = **0.9927**

Volatility:

Kruskal–Wallis equality-of-populations rank test

Group	Obs	Rank Sum
1	15	332.00
2	15	362.00
3	15	341.00

chi-squared = **0.183** with **2** d.f.
probability = **0.9125**

chi-squared with ties = **0.183** with **2** d.f.
probability = **0.9125**

Sales:

Kruskal–Wallis equality-of-populations rank test

Group	Obs	Rank Sum
1	15	335.00
2	15	361.00
3	15	339.00

chi-squared = **0.151** with **2** d.f.
probability = **0.9271**

chi-squared with ties = **0.151** with **2** d.f.
probability = **0.9271**

Market Value:

```
Kruskal-Wallis equality-of-populations rank test
```

Group	Obs	Rank Sum
1	15	343.00
2	15	343.00
3	15	349.00

```
chi-squared =     0.009 with 2 d.f.
probability =     0.9954

chi-squared with ties =     0.009 with 2 d.f.
probability =     0.9954
```