Introduction

Hurricanes are some of nature's most extreme weather events, with the potential to devastate coastlines, batter civilian infrastructure and endanger the lives of local residents. Given the potential severity, many homeowners in the path of the hurricane often mobilize to mitigate damages of the hurricane's landfall. These efforts may involve covering up windows with plywood to prevent shattered glass from entering homes and purchasing emergency supplies (e.g. water, generators) to prepare for prolonged periods of disruption to local convenience. Following landfall, these same homeowners may also purchase materials to repair damages to their property. We argue that such activities are stimulative for home improvement retail stocks, namely Home Depot (NYSE: HD) and Lowe's (NYSE: LOW), which should benefit from the increased sales activity induced from the hurricane landfall.

We will leverage publicly available stock data, alongside information on the continental United States hurricane landfalls to test our hypotheses, regarding how home improvement stocks perform in relation to hurricanes. In our analysis, we segment our examination into two distinct periods: (a) the pre-hurricane preparation phase, and (b) the post-hurricane recovery phase, defined as 1-month before and after the hurricane landfall, respectively.

Data

We restrict our sample of hurricanes h_t occurring in month t to those recorded from the National Oceanic and Atmospheric Administration's (NOAA) hurricane research division[1], to exclude tropical storms that aren't relevant for the discussion of US equities. The data tracks historical landfalls between 1851-2022, organized by year and month of occurrence, which we limit from 2000-2022 to align with our stock observation period.

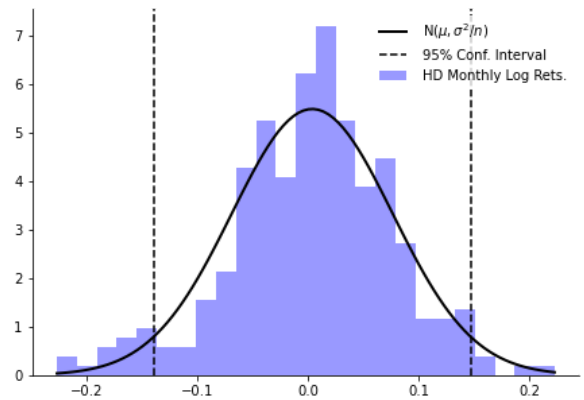
In selecting our stocks, we choose the largest home improvement retail companies in the S&P 500[2] by market capitalization[3], namely Home Depot (HD) and Lowe's (LOW). Given their overall size and industry presence, we expect for these stocks to have better liquidity[4] and price discovery relative to their smaller peers, which may be more prone to idiosyncratic catalysts. Daily price data was retrieved from Yahoo Finance for the periods 1/3/2000–11/24/2023 and used to compute our monthly log-returns. More formally, the month end return at time t for stock S_i is given by the following

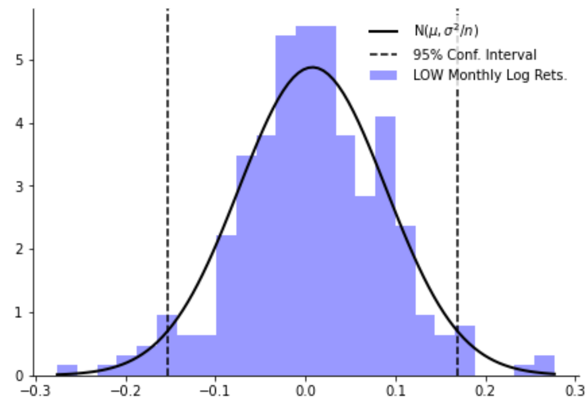
$$r_{i,t} = log(\frac{S_{i,t}^{close}}{S_{i,t}^{open}}),$$

[1] United States hurricane landfalls found at: https://www.aoml.noaa.gov/hrd/hurdat/All_U.S._Hurricanes.html
[2] The S&P 500® is widely regarded as the best single gauge of large-cap U.S. equities. The index includes 500 leading companies and covers approximately 80% of available market capitalization.
[3] Market capitalization (market cap) refers to the value of all of a company's public shares
[4] Liquidity is the feature of an asset to be readily bought or sold without creating a disruption in the market

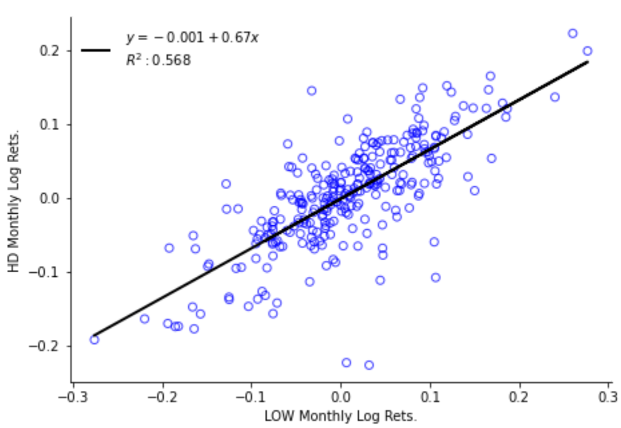
where the $S_{i,t}^{close}$ and $S_{i,t}^{open}$ reflect the open and close price on the first and last business days of the month, respectively.

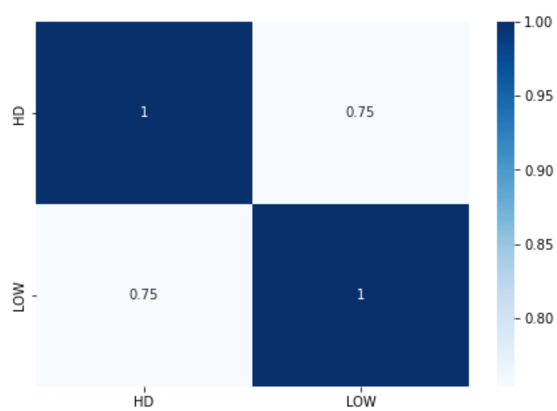
Observing the distribution of each stock's monthly returns, we see a slight deviation from normality, with greater mass centered at the mean and marginally *fat-tails*, i.e. the probability of large moves is greater than would be implied by the normal distribution. This observation is consistent with empirical finance literature, which notes the presence of this *fat-tailed* phenomena in almost every financial return series (Haas and Pigorsch, 2007).





Further examining the distribution of monthly log-returns for each stock, we note their similarity in shape. Intuitively, we assume that the returns for both HD and LOW should track closely, given their shared industry and market presence in the home improvement sector. This is confirmed when computing the pairwise correlation coefficient for the log returns of the stocks, where a value of 0.75 indicates a strong, positive relationship. We extend this initial correlation assessment by regressing the monthly log returns of HD against LOW, confirming with statistical significance (t-stat of 19.325) a positive linear relationship between either stock's monthly returns. However, given an R^2 of 0.568, we are cognizant of company specific idiosyncrasies (e.g. earnings report) that may result in deviations from the expected trendline, which in turn may create divergent response functions when examining the impact of hurricane landfalls.





Results

In order to evaluate our premise that hurricanes induce positive returns for home-improvement stocks, we will regress our monthly returns against the periods of hurricane occurrences. More specifically, our regression framework will distinguish between two disjoint time events (a) the pre-hurricane preparation phase and (b) the post-hurricane recovery phase, which we define with a dummy variable h_t that equals 1 when a hurricane occurs on a lagged basis – where h_{t-1} points to the month prior to hurricane landfall, and h_{t+1} is the month post. This construction is formalized in our equation below

$$r_{i,t} = \beta_0 + \beta_1 t + \beta_2 h_{t-1} + \epsilon_t \qquad \text{and} \qquad r_{i,t} = \beta_0 + \beta_1 t + \beta_2 h_{t+1} + \epsilon_t$$

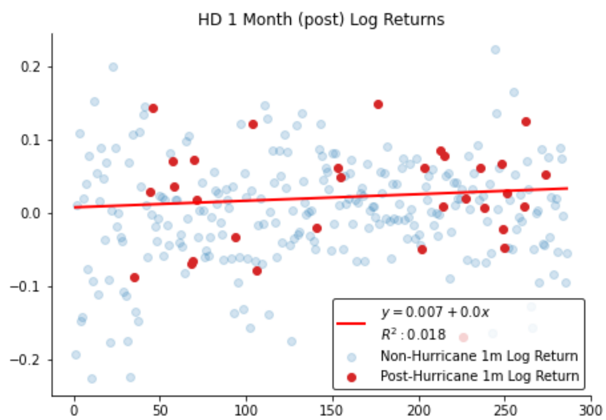
with an $\epsilon \sim N(0, \sigma^2)$ for the standard error term. Surprisingly, our results yield little convincing evidence of a hurricane induced price appreciation, in either the pre or post-hurricane phases. Additionally, while the coefficients on our binary are positive for both HD and LOW in the post-phase, the behavior in the pre-phase is conflicting – HD exhibits a negative bias, while LOW is positive. Nonetheless, in all of these observed relationships, our statistical significance[5] is quite poor, with the majority of our exogenous variables yielding insignificant *p*-values. We highlight this in our regression output below for the post-hurricane phase of HD's log-returns, where a *p*-value of 0.175 for our dummy variable prevents us from rejecting the null-hypothesis.

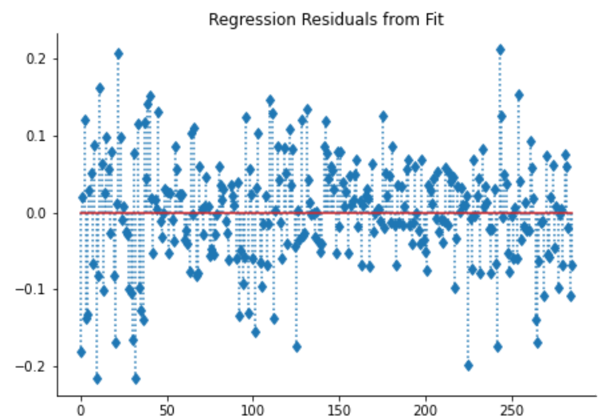
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                     HD   R-squared:                       0.018
Model:                            OLS   Adj. R-squared:                  0.011
Method:                 Least Squares   F-statistic:                     2.632
Date:                Sun, 03 Dec 2023   Prob (F-statistic):             0.0737
Time:                        09:37:16   Log-Likelihood:                 346.51
No. Observations:                 286   AIC:                            -687.0
Df Residuals:                     283   BIC:                            -676.0
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================================
                           coef    std err          t      P>|t|  [0.025000000000000022      0.975]
----------------------------------------------------------------------------------------------
const                   -0.0110      0.009     -1.278      0.202                 -0.028      0.006
Time                  8.998e-05   5.21e-05      1.729      0.085              -1.25e-05      0.000
Post-Hurricane Month     0.0185      0.014      1.359      0.175                 -0.008      0.045
```

We also highlight, that while our time (t) condition is closer in proximity to our significance threshold (0.085), the variable is disingenuous, as we make no effort to strip away base effects from the underlying growth of US stocks over the observation period from 2000-2023. As such, the argument that monthly log-returns are positive for any given stock with respect to time, does not comport with the economic reality of financial markets – i.e. stocks are not conditioned to attribute positive returns indefinitely.

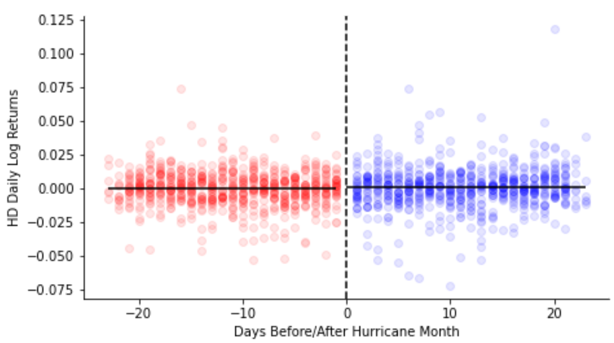
[5] All regressions were run with a 95% significance level for the confidence intervals

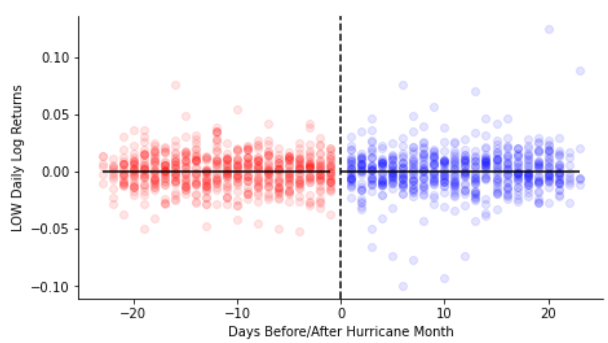
When plotting this relationship and segregating the monthly returns according to the post-hurricane and "non-hurricane" periods, we also see no discernible trend with respect to our dummy variable. In particular, we note that while there exists a slight compression in standard deviation for the post-hurricane (0.07156) period relative to the non-hurricane (0.07253) period, we do not exhibit a positive bias or directional skew. Furthermore, we see that our least-squares line is more a reflection of the overall time trend component, as noted earlier in our output table.





We attempt to further decompose this observation through introduction of higher frequency log-returns, leveraging the existing methodology outlined over a daily time τ interval. However, such decomposition yielded no additional insight, rather we found a stark similarity in both the average returns and shape of the distribution for both periods following a hurricane event. Given this similarity, we perform a quick mean-equality test and again can't reject our null hypothesis, implying that the average returns are comparable between both periods.





Conclusions

To conclude, we found no convincing evidence to support the hypothesis that home-improvement stocks were positively influenced by hurricanes, either in the preparation phase or the recovery phase. There are some limitations in our approach, namely in the return variable being examined and the observation window explored. As it relates to the return construct, we perform our regression on the absolute return of each stock, with no consideration to the broader market returns. Given that both stocks are members of the S&P 500, it is reasonable to assume that there exists systematic risk priced into the daily return of each equity. A cumulative aggregated abnormal return (CAAR) model, could be leveraged in subsequent analysis to measure the additional return of each stock relative to the benchmark returns (Schuh and Jaeckle, 2022). In doing so, we'd separate the idiosyncratic risk from the underlying equity to discern phenomena unique to the stock in question. Additionally, given that our hurricane dataset only provided the month of occurrence, rather than the date of landfall, we were restricted to examining monthly log-return intervals. An alternative construction, leveraging higher-frequency data could have been used, alongside a smaller examination window to narrow our regression scope to the immediacy of landfall. Given the relatively short-lived nature of stock volatility (Schwert, 2011), it would be reasonable to measure against this shorter-window of log-returns to more closely measure the influence of shocks on select equities.

Future research may benefit from incorporating these additional specifications, with the understanding that extreme weather events, while disruptive for economic activity, may not direct price action for stocks as expected.

References

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Schwert GW (2011) Stock volatility during the recent financial crisis. European Financial Management 17(5): 789–805.