Analysis of Vehicle Recalls: Impact on Equity Value and Its Volatility

CSE6242 Team #71: Michael Cardenas, Sviatoslav I Dotsenko, Mark McDuffie, Cao Ky Duyen McKany, Sreelekshmi Sheela

Introduction

We are employing a novel approach to detect the effect of recalls on underlying equity value, and consider both volatility and potential insider trading activity while interpreting the results. Investors and stakeholders need to know whether recall-related activity affects the value of their equity and the impact that it has on the stock's risk level, and detecting insider trading prior to recall announcements could inform both trading and portfolio management decisions.

Problem Definition

Existing research has shown contradictory results on whether recall announcements have an impact on the issuing company's stock price, or has predicated those results on certain attributes of each specific company, such as its size or "respectability" level. As such, current results are conflicting or depend on subjective criteria, and could benefit from a more inclusive, objective analysis. It is also clear that while existing work has concentrated on the impact of recalls on equity value, less attention has been paid to the effect that recall announcements have on equity price volatility - which, as a measure of risk, is also an important consideration for any stockholder. Adding to the omissions from current research, we point out that insider trading activity may have pre-emptively affected the stock price, thus smoothing out or nullifying any apparent impact of recalls on the day they are announced.

Thus, we are faced with a three-pronged problem: recall events are not definitely linked to stock value fluctuations; the effects that recalls may have on the stock's standard deviation / price variance and thus risk levels and Sharpe ratios of containing portfolio, are unknown; and insider trading might be deflating the price before a recall is made public, thus muddying up the results of previous research.

Literature Survey

Pruit et al. (1986) demonstrated that the market's reaction to similar recall announcements supports a semi-strong version of the efficient market hypothesis, meaning that recall announcements have negligible effects on a company's share price. Hoffer et al. (1988) found that recall announcements have no significant effects on automotive company stock prices or their competitors. More recently, Kim at al. (2020) found no statistical significance between recalls and stock prices. Mahfuja and Fatima (2023) explored the connection between product recalls and CEO pay, noting that initial market downturns due to recalls are often an overreaction that later corrects.

Conversely, Eilert et al. (2017) found that increased defect severity leads to longer recall times, and recall delays may negatively impact stock prices. Confirming a negative relationship between equity prices and recalls, Singh (2018) found that recalls involving replacements had a more significant impact on stock prices than those involving repairs. Bernon et al. (2018) investigated the influence of product recalls on manufacturing firms' shareholder wealth across various sectors, revealing significant negative effects on share values, especially concerning industry type and hazard levels. Ngwakwe (2023) found a significant negative effect on stock prices within one to three days of the recall announcement. To add to this view, Astvansh and Eshghi (2023) found a statistically significant negative effect on stock prices in the two days surrounding the announcement. Also, longer regulatory investigation prior to recalls led to more negative market reactions, whereas recalls involving older product lines moderated the negative impact on returns.

Treading middle ground, Gokhale et al. (2014) revealed that only major recall events negatively affected Toyota’s stock returns.

Rounding up the wide range of results, Park (2011) discovered that auto recall announcements positively influenced Hyundai Motors and KIA Motors' stock prices using an event study methodology, while Liu and Varki (2021) evaluated the impact of a product recall on the market value of competitors in the US, finding that recalls from firms with high corporate product reliability negatively affect the market value of their competitors. Liu (2020) arrived at a similar finding: to suffer the negative effects, competitors had to be lower on the perceived reliability scale. Singh and Grewal (2023) found that lobbyists tend to delay the impacts of vehicle recalls, which helps mitigate the impact on their stock prices.

Proposed Method

Instead of seeking direct cause-and-effect relationships between recalls and stock price, we are employing a more “neural” approach: recall data is converted to a probability indicator, and this indicator is then used to augment an existing stock price prediction model. An increase in the model’s accuracy would signal the relevance of this recall information to the equity’s price, allowing us to abstract away from specific interactions and potential feedback loops that recall announcements may be responsible for, and instead concentrate on the final impact: does accounting for a recall probability help us make better pricing decisions? If it does, then we know that recalls do affect equity price, whether those effects are immediately obvious, or not.

Our analysis will also consider the impact of recalls on the volatility of an equity's price, by examining the strength of the correlation between the two, in order to account for potential impacts on risk levels associated with the stock, and the role that insider trading may play in recall-related price movements. Accounting for both should increase the accuracy of our research into the question of recalls and their effects on equity value.

Data: We obtained stock data for the six selected auto manufacturers (Ford and GMC from the American sector, Volkswagen and Mercedes from the European sector, and Honda and Toyota from the Asian sector) from Yahoo Finance (*Yahoo*). Stock data was limited to 2016 and newer, to better align it with recalls data among the six chosen manufacturers. Recall data itself was pulled from the US Department of Transportation (*USDOT*), and all recalls that were made by these manufacturers since January 1st, 2016 were included in this analysis.

To build our baseline regression and random tree forest models, we picked seven different technical indicators recommended by Investopedia (*Investopedia*): on-balance volume, accumulation / distribution line, average directional index, Aroon oscillator, moving average convergence divergence, relative strength index and stochastic oscillator. Python's '*ta*' library (*Padial*) was used to calculate these indicators for each of the stocks. Python's library '*pandas*' was used for all of the remaining calculations. A 30-day rolling standard deviation was used for ARIMA and volatility calculations. Reasoning that the closer we can get to predicting the next day's closing value, the better the decision we will be able to make today, we have chosen next-day close as the target number to predict with our regression models.

Recall Indicator: In order to incorporate the recall data into regression analysis, we needed to form a metric for recall probability. This was necessary because it is difficult to integrate count data that occurs at random events into a predictive model over a continuous period of time. To do so, we modeled the recall data through a poisson distribution, taking the manufacturer, date, and number of vehicles recalled as x parameters. The model allowed us to predict an estimated recall count, which we then normalized and scaled to [0-1] for each data point.

Regression Models: We employed two regression models using the 'LinearRegression' class from the 'sklearn.linear_model' module in Python. The first model used the seven baseline technical indicators as the independent variables. The second model used the recall indicator in addition to the baseline indicators, resulting in eight total independent variables to predict next day's close. Two regression models were then created for each of the six auto manufacturers, one model that included the recall indicator, and one that did not. This was done to isolate the effect of recall announcements on stock prices and quantify their significance.

Random Forests: In addition to regression, we ran a series of experiments with decision tree models, including random forests. While regression is better suited to predicting numerical values, we wanted to see if a more "human-like" reasoning of a decision tree would perform better or worse in this situation. For this, we created a new set of data labels, based on a simple rule: if the next day's closing price is lower than today's, then the label is a zero (0); otherwise, it's a one (1). The rest of the set up was identical to that of the regression model. Training was accomplished utilizing python's `klearn.model_selection.GridSearchCV` to tune hyperparameters, and `sklearn.ensemble.RandomForestClassifier` and `sklearn.tree` to build the actual models. We were hoping to see a significant improvement in the buy/sell decisions (1/0 labels) once recall information was made available to the models.

Correlation Analysis: In order to determine whether recalls have any impact on the volatility of a stock's price, we calculated a 30-day rolling standard deviation (via *pandas.rolling.std()*) for each of the stocks, and found the coefficient of correlation between it and the recall indicator. A non-trivial correlation would mean that recall events have an impact on the stock's price, therefore affecting all portfolios that contain that stock by way of impacting the Sharpe ratio.

ARIMA Model: We used *pmdarima's auto_arima()* function in Python to predict each stock's 30-day rolling standard deviation, and auto tune hyperparameters p, d, and q to produce the most robust models.We used the index column instead date to filter out weekends, holidays and other odd days. We were seeking a way to predict recall events before they happened via ARIMA's change detection mechanisms as a way of hunting for proof of insider trading.

Experiments / Evaluation

Experiment A: "Do recalls affect stock price?"

1. Identify several technical indicators to be used in a baseline model for predicting stock price, and select 6 automotive stocks from the North American, European and Asian markets.
2. Calculate the values of these indicators for each stock from 2016 to 2023.
3. Train regression and random forest models on those indicator values.
4. Quantify the recall data for each manufacturer via a new recall indicator
5. Add this indicator to the regression and random tree training data and re-train the models.
6. Observe whether predictive power, as measured by the model's R^2 score, has improved.

Experiment B: "Do recalls affect stock volatility?"

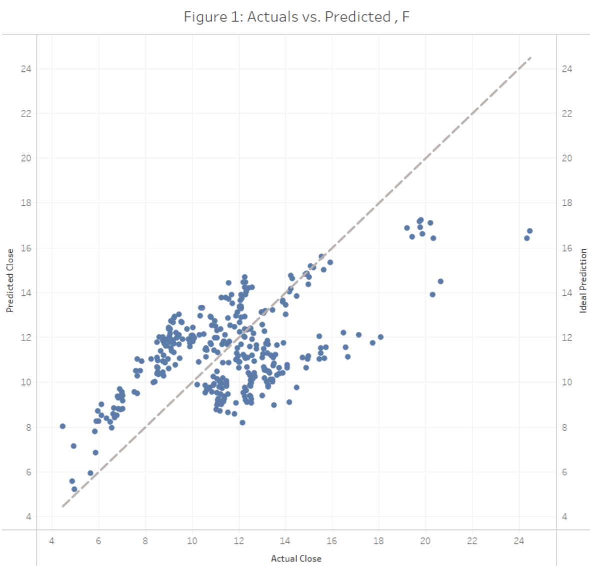
1. Calculate the value of a 30-day rolling standard deviation for each of the stocks.
2. Calculate the coefficient of correlation between each of the technical indicators from Experiment A, including the recall one, and the stock's standard deviation values.
3. Draw conclusions regarding possible correlation between recalls and stock volatility

Experiment C: "Is recall announcements' impact smoothed out by early insider trading?"

We will attempt to fine-tune an ARIMA model to report a change in price before recall announcements are made. If we are successful in creating such a model, an argument could be

made that the pre-announcement price shift is due to insider trading activity, and is possibly responsible for a blunted price response later on, after the actual announcement.
Results

Decision tree models did not live up to expectations. The average model accuracy of buy/sell decisions went from 0.5006 to 0.5099 after the recall indicator was included, which is hardly significant or useful, being right at the cusp of a 50/50 random decision boundary.



Experiment A: Comparing the two models for each of the stocks using F-statistics and p-values, we found that Honda (HMC) and Mercedes-Benz (MBGAF) both showed extremely high F-statistics (200.04 and 259.91, respectively) and p-values close to zero indicating a significant impact of the recall indicator. Ford (F) and Toyota (TM) both showed moderately high F-statistics (23.88 and 14.52, respectively) and statistically significant p-values, suggesting a significant impact of the recall indicator. General Motors (GM) and Volkswagen (VWAGY) both showed no significant impact from the recall indicator. This may be explained by brand resilience and consumer loyalty, and there is room for further research here to parse out the positive effects of consumer sentiment and the negative impacts of recalls using sentiment analysis. Overall, recall announcements generally seem to have a significant impact on the stock prices of automotive manufacturers.

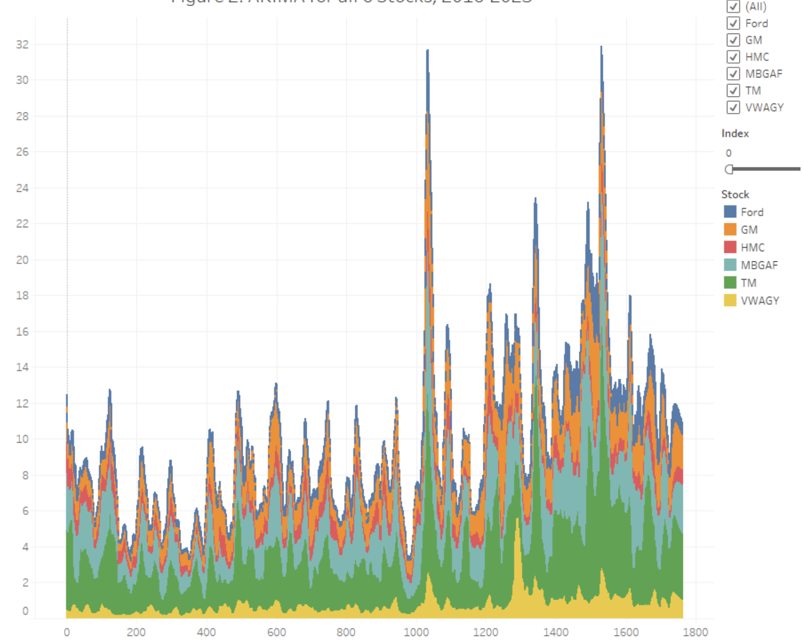
Experiment B: In examining the relationship between recall events and stock volatility, as quantified by the standard deviation of stock prices, our analysis revealed a strong negative correlation for five out of the six companies studied. Thus, recalls seem to reduce a stock's variance even while lowering its value. This suggests a potential moderation of the negative impact on the Sharpe ratio for stocks experiencing a decline in price due to recalls. We also found the average directional index (ADX) indicator to have a substantial positive correlation with volatility across all six companies, which would be an interesting subject for further exploration.

Table 2. Correlation Coefficients (compared with standard deviation)

Stock	Recall Factor	OBV	ADI	ADX	ARI	MAC	RSI	STO
F	-0.206	-0.042	-0.475	0.528	-0.01	0.051	0.005	-0.028
GM	-0.361	0.51	0.106	0.48	0.045	-0.006	0.03	0.002
HMC	0.074	0.037	-0.025	0.569	0.011	0.002	0.032	0.041
MBGAF	-0.217	-0.383	0.063	0.547	-0.092	-0.292	-0.101	0.014
TM	-0.171	0.462	0.441	0.356	0.014	-0.066	0.005	-0.033
VWAGY	-0.197	0.352	0.437	0.49	-0.007	0.27	-0.011	-0.081

Experiment C: We observed that the AIC values of all the six models produced were negative, in the range of -8000 to -2000, indicating that the chosen models were indeed strong . When comparing the recall data with the standard deviation from the ARIMA models, we did not see any big variation in the standard deviation based on future recall events for a 30 day period. We did see a dip in the stock price during the period of the major recalls, reinforcing earlier findings. Based on the model results and visualization, we are forced to conclude that insider trading is not a significant factor in recall equity dynamics after all.

Figure 2: ARIMA for all 6 Stocks, 2016-2023



Conclusions

Regression analysis shows that models that include recall information perform better than those that do not: Honda and Mercedes-Benz stock prices show a strong dependence on recall event probability, while Ford and Toyota showed a moderate, but significant, dependence. Curiously, GMC and Volkswagen appear to not be affected by recalls: it’s possible that factors like brand resilience and market trust are driving this behavior. Thus, recalls certainly do affect the price of underlying securities, but outside factors specific to each stock may exert a buffering influence.

A correlation analysis of recalls and stock price volatility found a moderately strong negative correlation between them for all companies, except for Honda. This finding implies that as the likelihood of a recall event rises, a stock’s volatility lowers. Therefore, a likely negative pressure on the stock’s price is balanced out by its lowered standard deviation, which potentially negates or even improves the Sharpe ratio of affected portfolios - something that investors need to take into account. Honda’s outlier result should be investigated further.

ARIMA analysis has failed to detect any meaningful traces of insider trading leading up to recall announcements. We conclude that insider trading is either non-existent or small enough in its extent as to not have a noticeable impact on the share value before a recall announcement.

Statement of Participation

All team members contributed equally to this project.

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