How Does the Introduction of the Sharing Economy Reshape the Financial Performance of Closely Related Incumbents?

by

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Abstract

In this study, we analyze the effects of sharing economy firms on the financial performance of closely related incumbents. We specifically investigate the effects the introduction of sharing economy firms has on the share price growth rate of these incumbents. These growth rates in share price are measured over time frequencies of six months, one year, two years, and three years in order to develop a deeper understanding of the true effect of these sharing economy firms over time. Using mainly a combination of Bloomberg data, the sharing firm introduction dates, and inference on close incumbents; we estimate that the introduction of sharing economy firms exhibits no statistically significant effects on the financial performance of their closely related incumbents. In particular, our main independent variable of interest $(ISF_f * CI_f)$ posed no statistically significant effects on our dependent variable (ΔSP_f^t) for any of the analyzed time frequencies *(t)*.

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Chapter 1

Introduction

In this modern-era of ever-changing technology, new business models are constantly being created based off of the new-found capabilities of these innovations. The development of big data technologies such as Hadoop and Spark, cloud systems such as AWS and Azure, and production ML/AI technologies such as TensorFlow and IBM Watson open increasingly expanding doors for business possibilities. Perhaps one of the most dominant new business models to be found in the past decade due to the developments of big data and other technologies is that of 'sharing economy' firms.

The term 'sharing economy' can often seem vague and it's definition readily changes upon who and when you ask. These firms can also be known as 'on-demand economy', 'collaborative consumption', and P2P or B2B models. Companies in this category such as Airbnb, Uber, Doordash, and Rover all offer very different services, but regardless can all be put under the umbrella of the 'sharing economy' using a common definition such as that posed by Gerwe and Silva (2020) in Clarifying the Sharing Economy: Conceptualization, Typology, Antecedents, and Effects. Gerwe and Silva (2020) contend that the four common features that define a sharing economy firm are having: online/digital platform organization, peer to peer/business to business transactions, emphasis of access over ownership, and reliance on underused supply of a service or product. The companies that encompass this variable list of P2P, B2B, and sharing firms can be an immense force upon their incumbent markets. By creating strong customer value propositions, fair pricing, and ease of use, the firms that follow this category of business model have the capability to be massive financial players in a wide range of sectors. The growth of firms encompassing this business model has been massive and widely documented. PWC (2015) predicts in the 5 sectors where the sharing economy is most relevant, total sales from sharing economy firms will reach 335 billion dollars by 2025 from a total of 15 billion dollars in 2013.

Coming with the introduction and growth of these sharing firms is their effect on incumbent firms financial performance. The effect that the introduction of major sharing firms such as Airbnb and Uber has had on their incumbent local markets has been previously studied. For example, Zervas (2017) concludes, “in Austin, where Airbnb supply is highest, its impact on hotel revenue averages in the -8%-10% range with lower-priced hotels and hotels that do not cater to business travelers being the most affected financially”. On Uber, Wallsten (2015) concluded that it’s introduction forced taxis in NYC, Chicago, and Long Beach, CA to improve their value of service by improving quality and/or lowering rates. Despite this previous literature on sharing firms effects on incumbents, there are many limitations to it. All the articles I have reviewed either only analyzed the quantitative financial performance impact on local markets (Zervas, Wallsten, CBRE Hotels) or only listed the impacts qualitatively. In order to bridge the gap in the literature and provide some quantitative insight into the effects of the sharing economy, this paper will explore how the introduction of sharing firms impacts the financial performance, measured as percent change in share price, of closely related incumbents. Understanding the relationship between the rise of sharing economy firms and the financial performance of their closely related incumbents will provide valuable insight to associated customers, investors, management, and government regulators.

In investigating the general relationship between the introduction of sharing economy firms and the financial performance of closely related incumbents, we hypothesize that the introduction of the sharing economy firms will have a significant effect on closely related incumbents percent change in share price over six month, one year, two year, and three year periods. This two-sided hypothesis test was chosen because of the possibility of the introduced sharing firms acting as either competitors with their closely related incumbents or as potential business partners. For example, it is most likely that a company like Airbnb is a competitor with a hotel company, causing a decrease in their revenues, and a negative effect on their financial performance. On the other hand, if some sort of deal was made between that hotel company and Airbnb for Airbnb to list their rooms on their website, it is possible that Airbnb could act as a business partner with the hotel company, increasing the company's revenues, and yielding a positive effect on its financial performance.

Chapter 2

Literature Review

Possibly due to their relative youth, past academic research on sharing economy firms has largely left out analysis on the effect these firms have had on the financial performance of related, publicly traded companies, let alone research on the financial performance of some of these public firms themselves. Most of the pre-existing work on sharing economy firms can be related to these four topics: 'what is the sharing economy?', 'why is the sharing economy so big?', 'what are the effects of the sharing economy?', and 'what are the future sectors of the sharing economy?'. On the topic of 'what is the sharing economy?', Oksana and Gerwe (2020) conceptualize the sharing economy, it's definition, and some of its perceived, qualitative effects. They summarize the common features of sharing economy firms as online platform organization, peer-to-peer transactions, emphasis of access over ownership, and reliance on underused capacity. Furthermore, they contend that future research of the sharing economy should focus on defining the different business models of the sharing economy, paying closer attention to the power dynamics of them with incumbents, and expanding quantitative research to firms outside of Airbnb and Uber.

On 'why the sharing economy is so big?', Lee et al. (2018) researches what users perceive as the biggest benefits to the sharing economy. Using responses from 294 Uber users in Hong Kong, it concludes that perceived user benefits, fair pricing, and perceived platform quality/trustworthiness are of the greatest importance in brewing demand for a specific sharing company. Also specifically on what generates consumer demand in the sharing economy, Zhang et al. (2019) identifies a specific Customer Value Proposition for the most successful sharing economy firms. It affirms that emotional and social values are more significant in driving customers to reuse/repurchase a sharing firms service/product than the economic and technical benefits of the company's business.

Out of all the topics, many of the papers that have been done have been related to 'what are the effects of the sharing economy?' Regardless, none truly show how they affect the financial performance of large, publicly traded companies. Zervas et al. (2017) analyzes the economic impact of the sharing economy on incumbent firms by studying Airbnb's effect on the Texas hotel industry. It concludes that in Austin, where the Airbnb supply is highest, it's impact on hotel revenue averages in the -8%-10% range. It also concluded that lower-priced hotels and hotels that do not cater to business travelers were the most negatively affected financially. In "An Analysis of Airbnb in the United States' by CBRE Hotel's America Research, the results show that the growth of average daily room rates will be curtailed by Airbnb as will the construction of new traditional hotels. CBRE believes that incumbent firms that are not able to compete with the lower prices and greater variety Airbnb offers will not be able to survive. Sundararajan (2014) summarizes the effects of P2P and Sharing Economy firms on the economy and business regulations. It concludes that these firms will have a positive impact on economic growth by catalyzing new forms of consumption, increasing efficiency, and stimulating entrepreneurial innovation. It also emphasizes the importance of "robust measurement of the economic impact of sharing firms". Regulation wise, it is concluded that balancing of the lowering of current barriers while also preventing market failure will be the key to the efficiency of the sharing economy.

Standing (2019) discusses the impact of the sharing economy on the transportation industry. It contends that the sharing economy is likely to be a part of the solution to transport problems such as lack of service and congestion, especially with the future onset of driverless cars. The paper additionally warns that future regulators must not under or over fit regulations of sharing firms. This will ensure an even balance of market power and prevent against market failures. Finally related to the impact/future impacts of sharing firms, Wallsten (2015) illustrates the competitive effects of the sharing economy on multiple local taxi industries including NY, Chicago, and Long Beach, CA. Using Uber search result and taxi complaint data, it concludes that in NY, taxis respond to the new competition by improving quality of service. In Chicago, it is again conferred that that Uber causes taxis to improve service. In Long Beach, CA, the results show cabs are beginning to offer variable fares in order to better compete with Uber.

The remainder of reviewed sharing economy literature focuses on the topic of 'what are the sectors/future sectors of the sharing economy?'. Geissinger et al. (2020) using data from Sweden, effectively maps out what sectors of the sharing economy are expected to gain traction in the future. It is concluded that with continued demand for sharing economies, "more sectors of society are likely to be characterized by abundance and increasing returns in the coming years due to the emergence of the sharing economy as a discontinuous innovation" (Geissinger, 2020). PWC's "Sharing or paring? Growth of the Sharing Economy" (2015), identifies the mobility, retail/consumer goods, tourism, entertainment, financial energy, and human resources as the 7 key sectors where the sharing economy is already strong or where there is high growth potential.

In comparison to the previous, primarily qualitative research done on the sharing economy this paper will look at the quantitative relationship between sharing economy firms and their sector-related public incumbents' share prices; something that has not been done in the research I have reviewed. All of the previous quantitative analyses on the effect sharing firms have on the financial performance of incumbents has been limited to local or regional markets such as in Zervas et al. (2017) and Wallsten (2015). This paper will prove to be vital in both predicting and controlling the future financial performance and success of these incumbent, public firms. These findings will provide important insight to a wide range of people from investors, management of incumbent firms, government regulators, to customers.

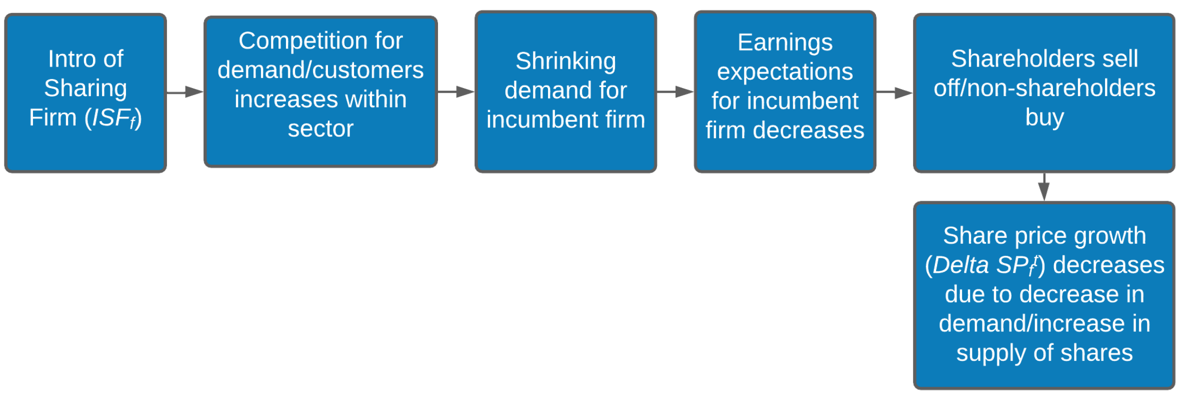
Chapter 3

Conceptual Framework

Although it is difficult to estimate the "true" relationship, the financial performance of a firm is often significantly affected by the financial performance and success of related firms in their sector, no matter if these firms are competitors or business partners. This being the case, it is quite possible that the unique business model of sharing economy firms may exhibit a specific effect on the financial performance of their sectoral incumbents. This paper will focus on the relationship between sharing economy firms and the financial performance of their incumbents. Specifically, we analyze and attempt to estimate the effect of the introduction of sharing economy firms on the share price growth rate of their closely related incumbents. In this day and age, with companies like Uber and Airbnb seemingly taking over and redefining whole industries, it will only become increasingly important for incumbent firm management, employees, investors, and government regulators to estimate the "true" effect this revolutionary new business model is having.

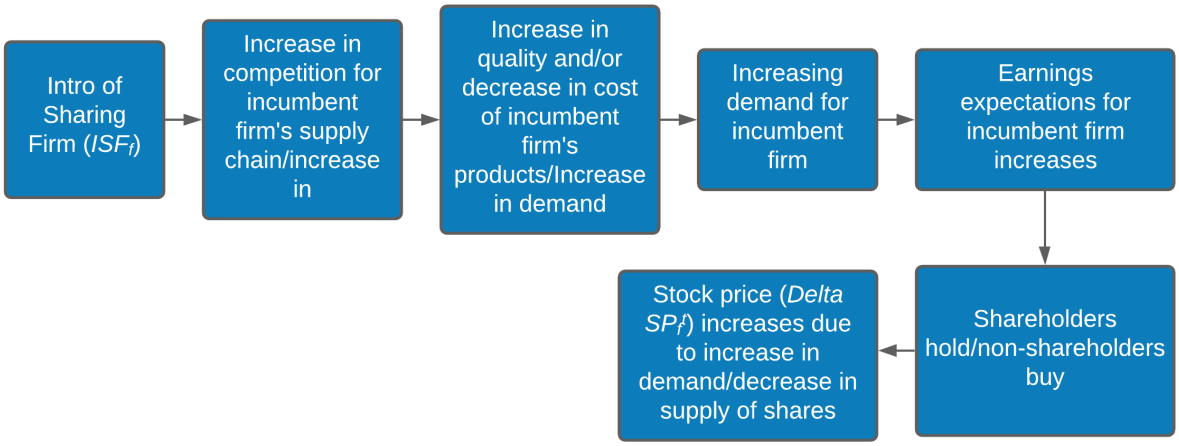
When analyzing the relationship between the introduction of a specific firm and the financial performance of its closely related incumbents, there are two potential scenarios that may take place if these firms exhibit any effect. The first scenario takes place if the introduced firm, in this case a sharing economy firm, is a competitor of the incumbent. The introduction of a "true competitor" into a sector will cause the financial performance of the incumbent firm to decline and should therefore decrease its share price growth rate. The logic for this scenario is illustrated in Figure 3.1 below:

Figure 3.1: Flowchart of Sharing Economy Firm = Competitor Effect on Incumbent Financial Performance



The second scenario takes place if the firm, again specifically a sharing economy firm in this case, is a business partner of the incumbent. The introduction of a "true business partner" into a sector will cause the financial performance of the incumbent firm to improve. The logic for this scenario is illustrated in Figure 3.2 below:

Figure 3.2: Flowchart of Sharing Economy Firm = Business Partner Effect on Incumbent Financial Performance



Considering these two scenarios, both the ratio of competitors to business partners among the sampled "closely related" sharing economy firms as well as the magnitudes of these firms effects will determine the estimated average effect the introduction of sharing economy firms has on the financial performance of closely related incumbents. This will allow our analysis to give us a logically robust estimate of whether the introduction of these firms generally tends to negatively, positively, or not exhibit an effect on the financial performance of their closely related incumbents.

The robust care taken in the models and data sampling as described in chapter 4 and chapter 5.2 will enable us to properly test our conceptual framework in as an experimental way as possible with the data we have available. By using the described models, data sample, and regression assumption checks, this analysis is given the best chance to pose potential statistical significance.

Chapter 4

Econometric Model

The main goal of my thesis is to estimate the causal relationship between the introduction of sharing economy firms and the share price growth rate of closely related incumbents. To explore this relationship, I will be conducting a series of five increasingly complex "Multiple Ordinary Least Square" (OLS) linear regressions for each of the frequencies of (t = 6, 12, 24, or 36 months).

Analyzing our research question over these different frequencies of time poses many benefits in any regression analysis. This is especially true for our analysis of share price growth rates that can be dependent not only on the time frequency (i.e. 1 minute, 3 days, 5 years etc.) that they are measured over, but also at the point in time they are (i.e. January 2017 ,Market Crash of 2008, COVID-19 Pandemic) like many other stock metrics. After originally running regressions with one month *(t=1)* (Table A.1) and three month *(t=3)* (Table A.2) data as well, the longer frequencies were selected for discussion in the 7.5 due to the difficulty of producing significant results at those shorter frequencies.

Predicting stock price growth rates in short term frequencies is notoriously difficult, especially with the relatively small dataset I was able to produce due to the lack of ability for my school's Cisco server backed Bloomberg Anywhere Terminal to integrate with Python's xbbg library for automated data extraction. This difficulty with small datasets and short frequencies is mainly due to the large size of the relative variance of short term growth rates. More complex, often non-linear models and larger datapools such as those used by quantitative asset managers are required for accurate and robust results at these frequencies. Although our time frequencies are not too long, longer-run analyses can often pose internal validity issues

In particular, using a six month frequency *(t=6)* will allow us to analyze any short term changes in the share price growth rate that could show that the effects of the sharing economy are quick to take effect and/or they create a lot of "hype" when they are first introduced. The one year frequency *(t=12)* will allow analysis of slightly longer term and potentially "more robust" effects that the introduction of the sharing economic exhibits. Consecutively, the two year frequency *(t=24)* will expand upon the power of the one year analysis. Finally, the three year frequency *(t=36)* poses the ability to produce the "most robust" results due to it's usually lower relative variance compared to the other time frequencies.

At the most basic level of our model for each time frequency *(t)*, I will use the % change in share price as the dependent variable (ΔSP_f^t) and the introduction of the sharing economy firm (ISF_f) as well as the relatedness of the incumbent firm (CI_f) as the independent variables. This regression will estimate the relationships between ISF_f, CI_f, ΔSP_f^t. The first regression will be structured as:

$$\Delta SP_f^t = \beta_0 + \beta_1 ISF_f + \beta_2 CI_f + \varepsilon_f \tag{4.1}$$

The dependent variable, % change in share price, will be abbreviated as "ΔSP_f^t". The primary independent variables, the introduction of the sharing firm as well as whether the incumbent firm is closely related will be abbreviated as "ISF_f". and "CI_f". respectively.

Although the above regression gives us insight into the general relationship between being a closely related incumbent and differences in % change in share price (ΔSP_f^t) upon the introduction of the sharing firm, there are many other potential variables as well as interactions that may significantly impact the relationships between our main dependent variables and our independent variable and therefore need to be controlled for.

These other independent variables include the % change in volume of the firm over the time period (ΔV_f^t), the exchange the firm is listed on ($NASDAQ_f, NYSE_f, Other_f$), and the % change in level of the S&P500 over the time period ($\Delta S\&P500_f^t$).

By including these additional independent variables, we are removing potential sources of endogeneity from our error term, thereby increasing the accuracy and potential statistical significance of our model as measured by R^2 and the t and F statistics respectively. By taking all potential "first order" interactions with the Introduction of the Sharing Firm "ISF_f", we filter through only the interactions that are of interest to our general research question of the impact of the introduction of the sharing economy on incumbents.

The models including these additional independent variables as well as interactions will be as follows:

$\underline{\boldsymbol{With\ \Delta V_f^t}}$

$$\Delta SP_f^t = \beta_0 + \beta_1 ISF_f + \beta_2 CI_f + \beta_3 \Delta V_f^t + \varepsilon_f \tag{4.2}$$

$\underline{\boldsymbol{With\ \Delta V_f^t, NASDAQ_f, NYSE_f}}$

$$\Delta SP_f^t = \beta_0 + \beta_1 ISF_f + \beta_2 CI_f + \beta_3 \Delta V_f^t + \beta_4 NASDAQ_f + \beta_5 NYSE_f + \varepsilon_f \tag{4.3}$$

$\underline{\boldsymbol{With\ \Delta V_f^t, NASDAQ_f, NYSE_f,\ and\ \Delta S\&P500_f^t}}$

$$\begin{aligned}\Delta SP_f^t = \beta_0 + \beta_1 ISF_f + \beta_2 CI_f + \beta_3 \Delta V_f^t + \beta_4 NASDAQ_f + \beta_5 NYSE_f \\ + \beta_6 \Delta S\&P500_f^t + \varepsilon_f\end{aligned} \tag{4.4}$$

With $\Delta V_f^t, NASDAQ_f, NYSE_f$, and Potential Interactions

$$\Delta SP_f^t = \beta_0 + \beta_1 ISF_f + \beta_2 CI_f + \beta_3 \Delta V_f^t + \beta_4 NASDAQ_f + \beta_5 NYSE_f + \beta_6 \Delta S\&P500_f^t$$
$$+\beta_7 ISF_f * CI_f + \beta_8 ISF_f * \Delta V_f^t + \beta_9 ISF_f * NASDAQ_f + \beta_{10} ISF_f * NYSE_f$$
$$+\beta_{11} ISF_f * \Delta S\&P500_f^t + \varepsilon_f \tag{4.5}$$

For my exchange dummy variables, although $OTHER_f$ is technically "included" in our model, it is a part of our y-intercept/constant (β_0) term and left out of our equation to avoid multicollinearity and the dummy variable trap. This is because we can infer whether the firm is a part of another stock exchange just by looking at our $NASDAQ_f$ and $NYSE_f$ dummies. If the values of $NASDAQ_f$ and $NYSE_f$ are both 0, we know that the firm is listed on another exchange and that the value of $OTHER_f$ is 1. Therefore when we are analyzing the coefficients on the exchange dummies, the interpretation for a coefficient of .23 for $NYSE_f$ would be: "All else constant, being listed on the NYSE increases the percent change in share price of a firm over time period t by .23 greater than being listed on another exchange."

Utilizing these independent and dependent variables in five increasingly complex models for each of our time frequencies/periods of analysis, the goal is to: improve the overall fit of our model as measured by R^2, the statistical significance of the overall fit as measured by our F-statistic, and our ability to pick up on any statistically significant coefficients produced by adding new terms including the interactions. The coefficient of the interaction of ISF_f and CI_f will be specifically important in its ability to directly answer my main question of interest; how does the introduction of sharing economy firms affect the share price growth rate of closely related incumbents?

Chapter 5

Data Description

In order to complete my main analyses of the effects of the introduction of sharing economy firms on the financial performance of their closely related incumbents, the simple percent change in share price (ΔSP_f^t) at time frequencies/periods (t) of six months, one year, two years, and three years are being used as my dependent variables in what can be best described as a cross-sectional "event study".

By conducting four separate regressions for each of these frequencies, I am improving the sensitivity and ability of our model to pick up on any possible differences in the effects of the introduction of these firms over different time periods. For example, we may find that six months after introduction is not enough time for sharing firms to exhibit an effect while one year is. Similarly as discussed in chapter 4, we may find that these firms produce a lot of "hype" when they introduced and although they might have some substantial short-term effects, they have a weak or no effect in the long run.

5.1 Data Sources

In the interest of data pedigree and reliability, ΔSP_f^t was derived from Bloomberg historical data. Utilizing closing daily price data ($Share\ Price_{Beginning\ of\ t/End\ of\ t}$) and Python, I transformed the original price data time series into the simple percent change in price for the time period using:

$$\Delta SP_f^t = \left(\frac{Share\ Price_{End\ of\ t} - Share\ Price_{Beginning\ of\ t}}{Share\ Price_{Beginning\ of\ t}} \right) \times 100 \qquad (5.1)$$

For my main dependent variables, I will be using the introduction of the sharing economy firm (ISF_f) as well as whether the incumbent is closely related or not (CI_f). For ISF_f, a value of 1 will denote that the related sharing economy firm was introduced and a value of 0 will denote that the related sharing economy firm has not been introduced. Encoded as dummy variables for the regression analysis, ISF_f or the date of introduction of the sharing economy firm was sourced through either the company websites and/or Google search. A value of 1 denotes that the related sharing economy firm was introduced and a value of 0 denotes that the related sharing economy firm has not been introduced. For all the sharing economy firms, I used either the last day of the month they were introduced or the last day of the year they were introduced (if monthly data could not be found) as the introduction dates. This will help to control for any random variation in the ”true” introduction date of the firms as many of these firms did not start ”full operations” right when they were introduced.

For CI_f, a value of 1 will denote that the incumbent is a closely related incumbent and a value of 0 will denote that the incumbent is not closely related. CI_f, or whether the incumbent is closely related or not was sourced through my own inference. A value of 1 signals that the incumbent is a closely related incumbent and a value of 0 signals that the incumbent is not as closely related.

Other than the two main dependent variables of ISF_f and CI_f, there are surely many other factors that can affect the share price growth rate of a firm. Because of this, we will also control for the simple percent change in volume (ΔV_f^t), the exchange the incumbent firm is listed on ($NASDAQ_f, NYSE_f, Other_f$), and the simple percent change in the level of the S&P500 ($\Delta S\&P500_f^t$) in our models. The percent change in volume ,the exchange the firm is listed, as well as the percent change in S&P500 were all sourced from Bloomberg. The percent change in volume for the time period (ΔV_f^t) was transformed similarly to the percent change in share price (ΔSP_f^t), through Python, except from daily volume data ($Volume_{Beginning\ of\ t/End\ of\ t}$) with the following formula:

$$\Delta V_f^t = \left(\frac{Volume_{End\ of\ t} - Volume_{Beginning\ of\ t}}{Volume_{Beginning\ of\ t}} \right) \times 100 \tag{5.2}$$

Likewise, the percent change in S&P500 for the time period ($\Delta S\&P500_f^t$) was transformed using:

$$\Delta S\&P500_f^t = \left(\frac{S\&P500_{End\ of\ t} - S\&P500_{Beginning\ of\ t}}{S\&P500_{Beginning\ of\ t}} \right) \times 100 \tag{5.3}$$

5.2 Sample Design

To create the dataset to analyze if the financial performance of closely related incumbents is affected differently from the introduction of the sharing firms compared to a random, unrelated firm, great care was put into my data design and sampling/assignment methodologies. Firstly, in order to integrate the "event study" piece of our research question and check for general, homogenous effects of the introduction of the sharing firm ISF_f, the (ΔSP_f^t) before and after the introduction of the sharing firm (ISF_f) was recorded for each of the incumbent firms in our analysis whether the firm was closely related or not. Without this crucial step of event study analysis, we would not have a "model of expected returns" created when $ISF_f = 0$ to use to analyze if returns when $ISF_f = 1$ are "abnormal returns".

The second piece that was of great importance in putting together solid data was the manual assignment of closely related incumbents ($CI_f = 1$) and the random sampling of the incumbent firms that where deemed not related ($CI_f = 0$). In this process, for each of the sharing economy firms in the analysis, I manually picked one firm that I deemed as closely related and randomly picked one firm that was not closely related.

In the manual picking process for the closely related incumbent, I selected from my own inference the first closely related firm that came to mind that also had share price data in the range required before and after ISF_f. Examples of close incumbent pairs selected include pairs like Airbnb and Marriott or Uber and Ford. In the random selection process for not closely related incumbents, a "Random US Stock Picker" (https://raybb.github.io/random-stock-picker/), was cycled through and again the first firm that had share price data in the range required before and after ISF_f was selected as the observation. Due to this process, the difference in the relatedness of the closely related and not closely related incumbent for each sharing economy firm should be consistent, enabling greater accuracy and homogeneity of our results.

For the other independent controls of ΔV_f^t, $NASDAQ_f, NYSE_f, Other_f$, and $(\Delta S\&P500_f^t)$, the respective values held by the observations selected and sampled in the ISF_f and CI_f processes were used.

Chapter 6

Descriptive Statistics/Exploratory Data Analysis

An important part of any data analysis is understanding the dataset you are working with. For its benefits to our understanding, this go through the descriptive statistics, exploratory data analysis plots, and OLS assumption checks for each regression analysis/time period together. Doing this enables us to effectively increase our understanding of the sampled data, clearly communicate differences between the data in each of the time periods ($t = 6,12,24,36$), and expose complications that our data may pose to the general assumptions of our multiple OLS regression.

6.1 Summary Statistics of Continuous Variables

Variable	N	mean	median	sd	min	max
% Change in Volume (t=6)	128	96.43	96.43	334.2	-93.03	2,580
% Change in Volume (t=12)	128	86.82	86.82	474.9	-95.13	4,828
% Change in Volume (t=24)	128	260.2	260.2	1,765	-99.32	18,849
% Change in Volume (t=36)	128	106.6	106.6	269.3	-95.54	1,877
% Change in Share Price (t=6)	128	6.719	6.719	28.32	-56.08	161.2
% Change in Share Price (t=12)	128	18.99	18.99	48.90	-77.36	213.5
% Change in Share Price (t=24)	128	41.81	41.81	169.2	-71.56	1,814
% Change in Share Price (t=36)	128	45.81	45.81	117.2	-83.73	915.0
% Change in S&P 500 (t=6)	128	3.320	3.320	11.04	-42.70	34.23
% Change in S&P 500 (t=12)	128	9.839	9.839	15.14	-38.49	36.12
% Change in S&P 500 (t=24)	128	17.96	17.96	22.73	-36.31	62.09
% Change in S&P 500 (t=36)	128	23.40	23.40	27.16	-38.38	74.02

Table 6.1: Summary Statistics for % Change in Share Price, Volume, and S&P 500

Table 6.1 above shows the observations, mean, median, standard deviation, minimum, and maximum for our continuous variables ΔV_f^t, ΔSP_f^t, and $\Delta S\&P500_f^t$ at our main frequencies of *t=6,12,24,36*. Firstly, the 128 throughout column N signifies that we have no missing observations in our dataset for the continuous data. Looking at the summary statistics for our ΔV_f^ts, the mean interestingly goes through values of around 96, 86, 260, and 106 as time increases. This along with the erratic scale of the standard deviations of these values in relation to the mean and the consistency in values across t make me believe that ΔV_f^t is not affected by the time frequency, t.

Moving on to our main dependent variable of analysis, ΔSP_f^t, one can see that the mean of the values goes from values of around 7, 19, 42, and 46 % in a logarithmic fashion. This makes sense because share price growth rates, unlike volume growth rates that have virtually no limits on their value, generally tend to not deviate too far (relative to volume) from what is considered their "fundamental growth rates" overtime. The less volatile nature of ΔSP_f^t relative to ΔV_f^t can additionally be seen in the size of it's relative standard deviations, minimum, and maximum values. For example, while $\Delta V_f^{t=24}$ exhibits maximum over 72 times larger than it's mean, the largest maximum size for all the ΔSP_f^t values is around 43.

Finally looking at our $\Delta S\&P500_f^t$s, the means follow a similar logarithmic growth pattern as seen in ΔSP_f^t, with respective more slowly increasing values of around 3, 10, 18, and 23 %. Of noticeable significance in the summary statistics for the S&P 500 growth rate are the extremely small relative standard deviations in comparison with those of ΔV_f^t and ΔSP_f^t. This is largely attributable to the fact the the S&P 500, as an actively managed stock market index, usually contains relatively consistent companies over the short term and weighted by market-cap weight.

6.2 Summary Statistics of Categorical Variables

Sharing Firm Introduced	No.	%
No	64.0	50.0
Yes	64.0	50.0
Total	128.0	100.0

(a) Frequency Table of Sharing Firm Introduced (ISF_f)

Exchange	No.	%
NASDAQ	34.0	26.6
NYSE	84.0	65.6
Other	10.0	7.8
Total	128.0	100.0

(b) Frequency Table of Exchange ($NASDAQ_f, NYSE_f, Other_f$)

Relatedness with Sharing Firm	No.	%
Closely Related	64.0	50.0
Less Closely Related	64.0	50.0
Total	128.0	100.0

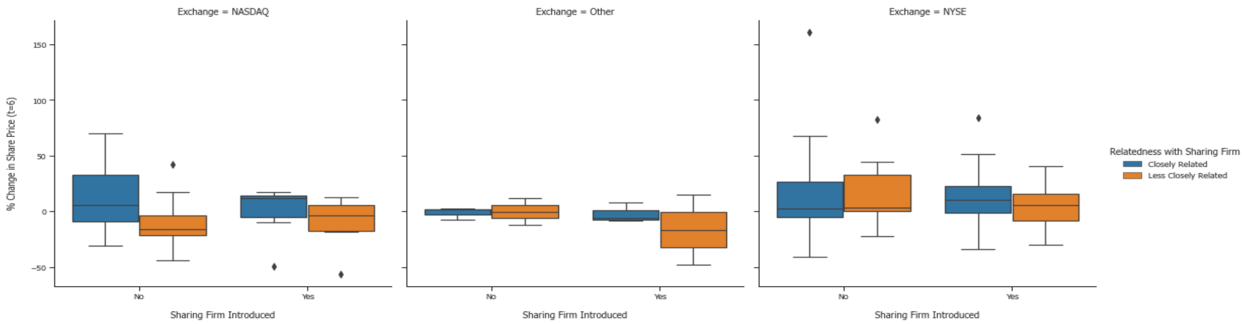
(c) Frequency Table of Relatedness with Sharing Firm (CI_f)

Table 6.2: Frequency Tables of ISF, Exchange, and CI

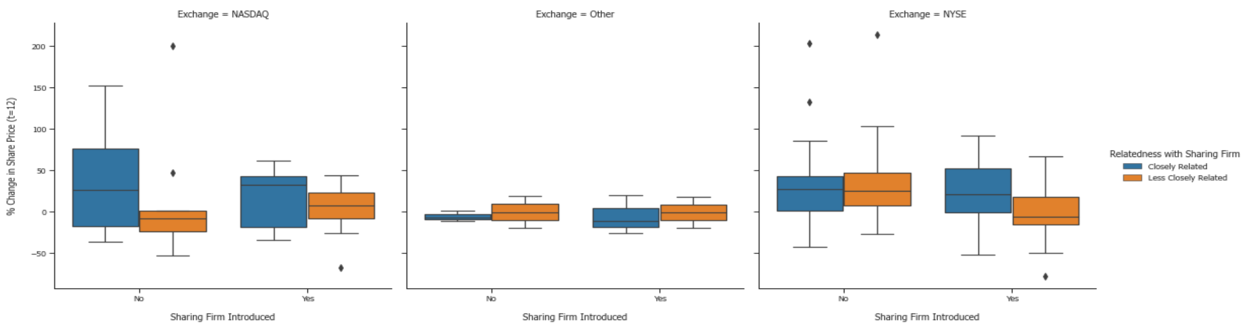
Table 6.2 above shows the frequency tables for our categorical variables of ISF_f, CI_f, and Exchange that are consistent over our time frequencies, t. Subtables 6.2a and 6.2c specifically show that we had an even balancing of samples for ISF_f and CI_f due to the process described in section 5.2. 6.2b shows the split of the exchanges of our incumbent firms with 34 observations on the NASDAQ, 84 on the NYSE, and 10 on Other.

6.3 EDA Plots

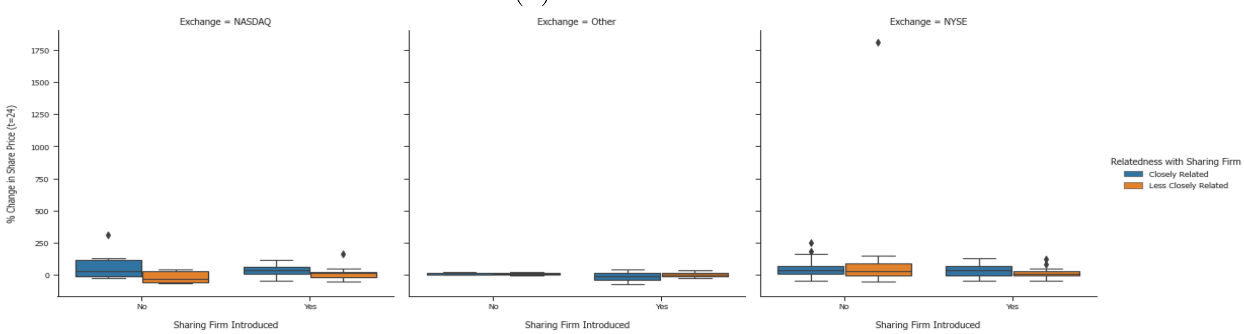
6.3.1 Boxplots of % Change in Share Price vs. Cat. Variables



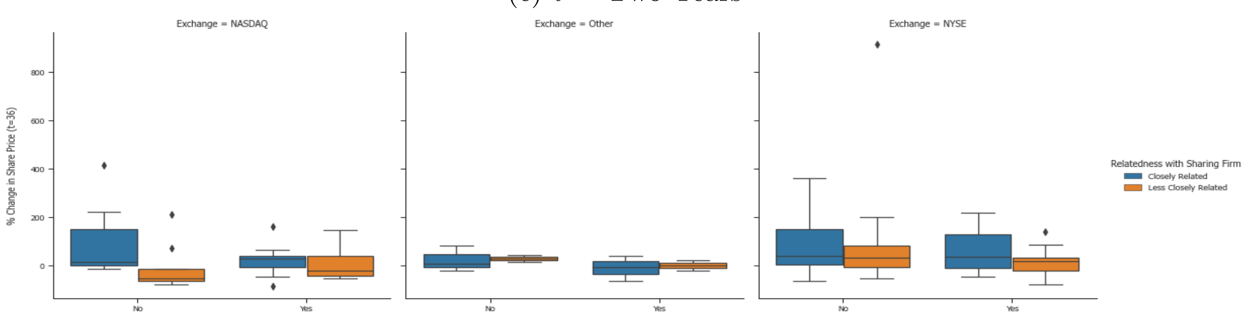
(a) t = Six Months



(b) t = One Year



(c) t = Two Years

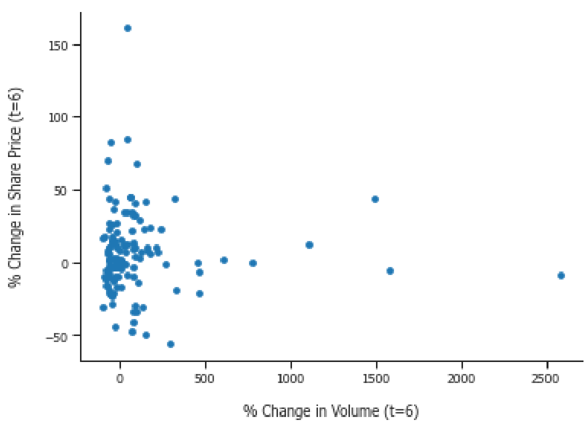


(d) t = Three Years

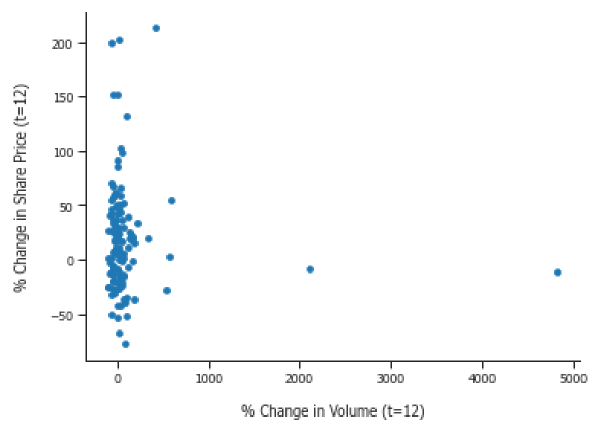
Figure 6.1: Boxplots of % Change in Share Price vs. Categorical Variables for $t = (6,12,24,36)$

Figure 6.1 shows grouped boxplots for each of our time frequencies with the lined columns splitting data by Exchange, the subcolumns splitting the data by ISF_f, box color splitting data by CI_f and the y axis being the ΔSP_f^t for each of the time frequencies of t. Looking at 6.1a, one can see that larger differences are to be seen between respective CI_f in comparison to ISF_f hinting that ISF_f does not display much effect on $\Delta SP_f^{t=6}$. 6.1b shows as to be expected, larger ranges in values due to the increase in t, but once again, no noticeable difference between ISF_f groupings. 6.1c and 6.1d for the two and three year data show much of the same except smaller ranges of values relative to the time frequency, t.

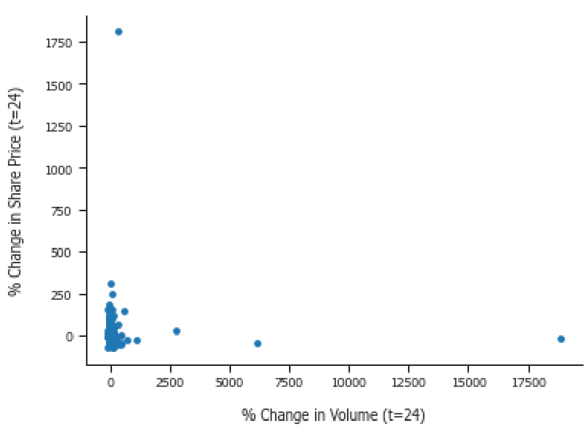
6.3.2 Scatterplots of % Change in Share Price vs. % Change in Volume



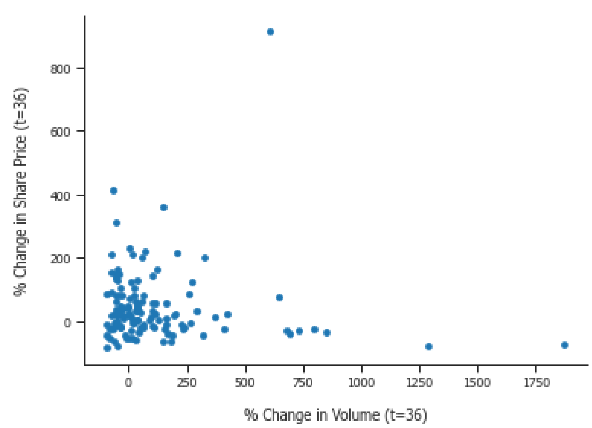
(a) t = Six Months



(b) t = One Year



(c) t = Two Years

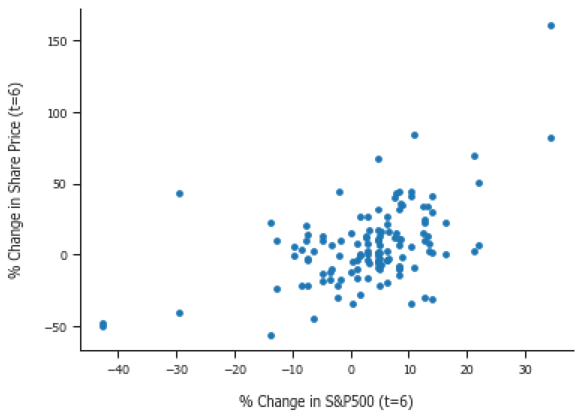


(d) t = Three Years

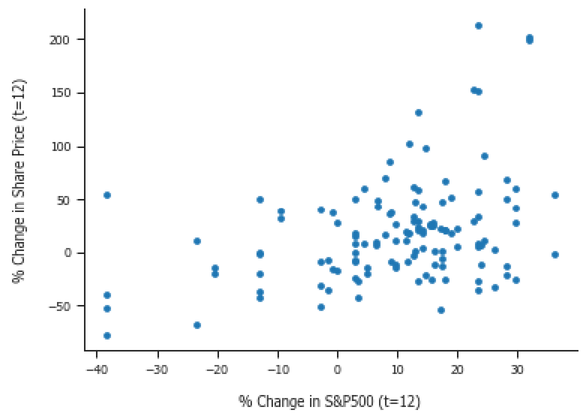
Figure 6.2: Scatterplots of % Change in Share Price vs. % Change in Volume for t = (6,12,24,36)

Figure 6.2 shows scatterplots of the % Change in Share Price (ΔSP_f^t) vs. % Change in Volume (ΔV_f^t) for each of our time frequencies, t. On top of showing that a linear relationship is plausible for the relationships between ΔSP_f^t and ΔV_f^t these plots show us the ranges, middle datapoints, and outliers for each of our models. 6.2a specifically shows it's large variation and large number of ΔV_f^t outliers to the right of the graph. 6.2b shows less large outliers for ΔV_f^t, but an increased range of values for ΔSP_f^t. 6.2c shows a couple of massive outliers, particularly for ΔV_f^t and an increased middle range of ΔSP_f^t. Lastly, 6.2d shows that it lacks large outlier values for ΔSP_f^t, but like the other plots displays large outliers for the proven erratic ΔV_f^t.

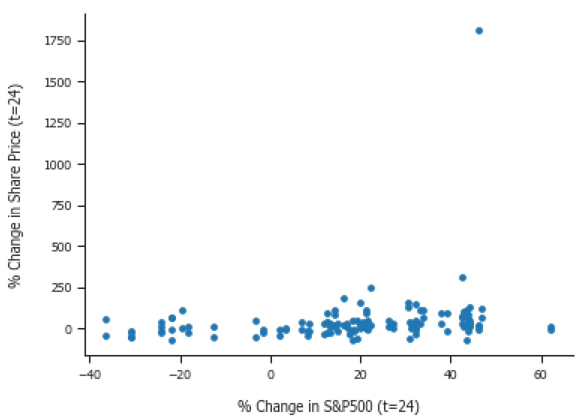
6.3.3 Scatterplots of % Change in Share Price vs. % Change in S&P 500



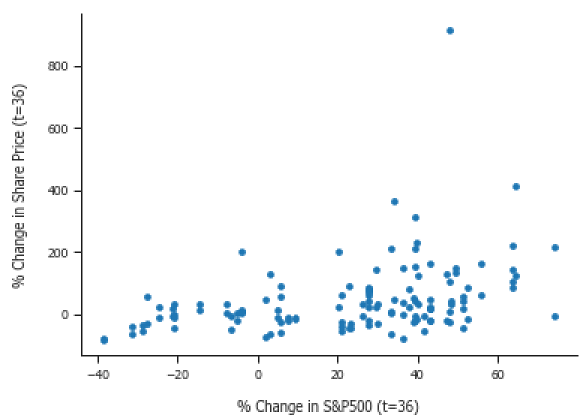
(a) t = Six Months



(b) t = One Year



(c) t = Two Years



(d) t = Three Years

Figure 6.3: Scatterplots of % Change in Share Price vs. % Change in S&P 500 for t = (6,12,24,36)

Figure 6.3 shows scatterplots of the % Change in Share Price (ΔSP_f^t) vs. % Change in the S&P 500 ($\Delta S\&P500_f^t$) for each of our time frequencies, t. In addition to illustrating that a linear relationship is plausible for the relationships between ΔSP_f^t and $\Delta S\&P500_f^t$, these plots show us the ranges, middle datapoints, and outliers for each of our models. 6.3a specifically shows and nicely positive correlation and few crazy outliers. 6.3b also shows a relatively close to 45 degree positive relationship, but an increased range of values for ΔSP_f^t. 6.3c again illustrates a positive correlation between ΔSP_f^t and $\Delta S\&P500_f^t$, but the ranges of the graph are distorted due to the presence of a high outlier for ΔSP_f^t. Finally, 6.3d, like the others shows that ΔSP_f^t is strongly correlated with the $\Delta S\&P500_f^t$.

6.3.4 Correlation Matrix/Heatmap

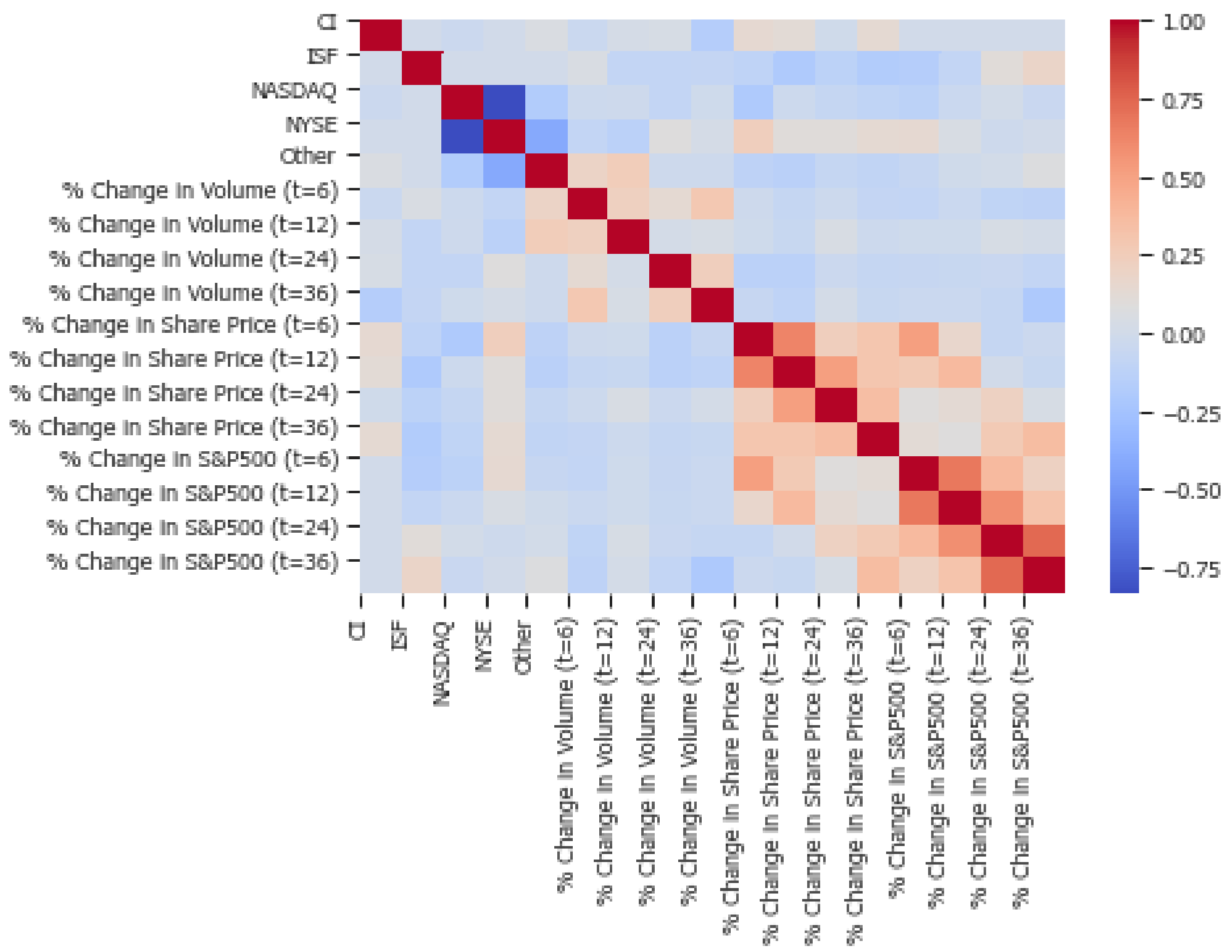
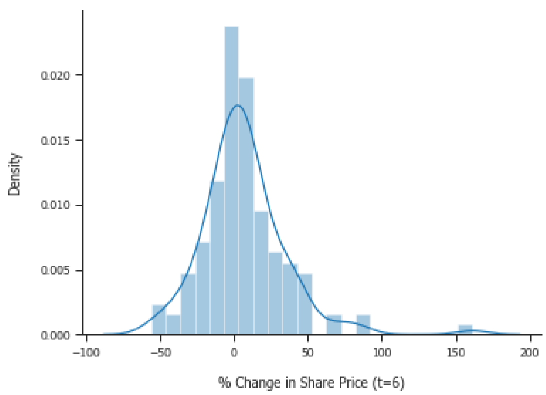


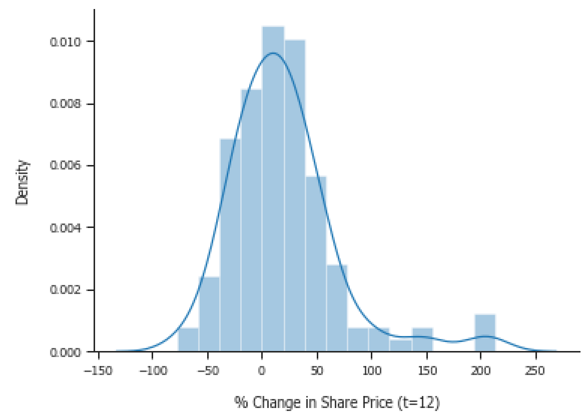
Figure 6.4: Correlation Matrix/Heatmap

Figure 6.4 above is a correlation matrix/heatmap of all of our variables. In a "sea of blue", the most noticeable thing on the graph are the relatively strong correlations between the individual ΔSP^t_fs, the individual $\Delta S\&P500^t_f$s, and each other. This further corroborates the evidence seen in Figure 6.3. The next "hotspot" of relatively strong correlations can be seen between each of the individual ΔV^t_fs although this is most likely mostly due to the general nature of volume growth rates and not a special circumstance of the dataset. Finally, strong negative correlations can be seen between our exchange dummy variables showing why the $Other_f$ term needs to be dropped from our models.

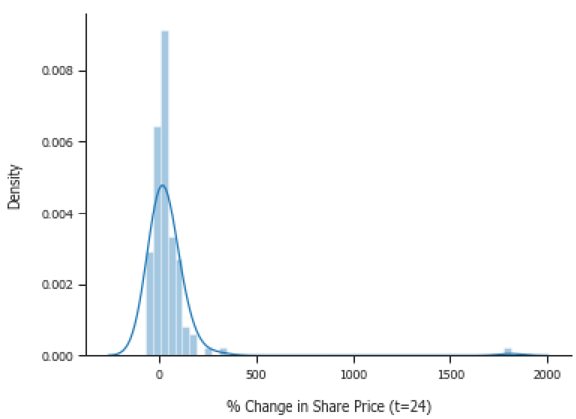
6.3.5 Distributions of % Change in Share Price



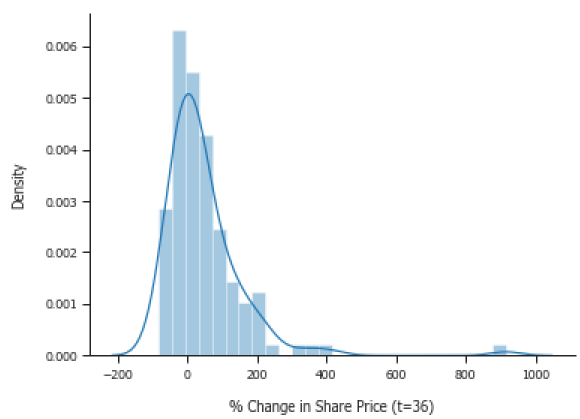
(a) t = Six Months



(b) t = One Year



(c) t = Two Years

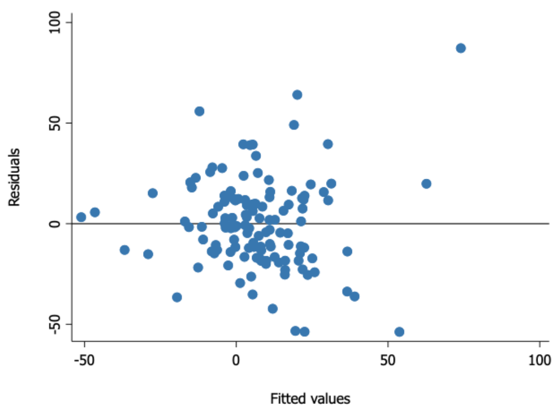


(d) t = Three Years

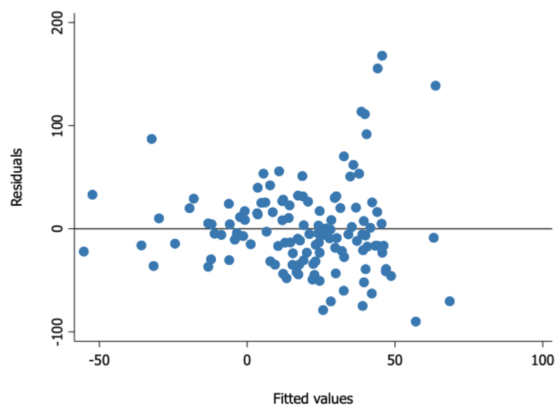
Figure 6.5: KDE Plots for t = (6,12,24,36)

Figure 6.5 above shows the distributions of ΔSP_f^t, visualized as Kernel Density Estimates for each of our time frequencies *(t)*. Figures 6.5a, 6.5b, 6.5c, and 6.5d all show relatively normal distributions for our values of ΔSP_f^t, with 6.5c and 6.5d only showing slight skewness to the left. This is largely due to the fact that if a company indeed had a negative share price growth rate, they wouldn't last with that financial performance until a two or three year time frequency was hit. On the other hand, short terms dips in share price growth rate are to be expected and are of little cause of concern for companies to stop operations as happens in a long term slowdown.

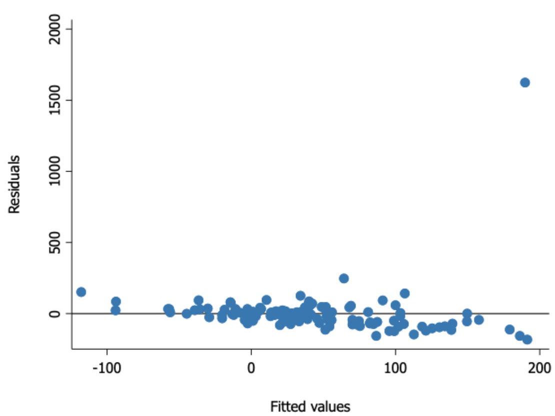
6.3.6 Scatterplots of Residuals vs. Fitted for Most Complex Model



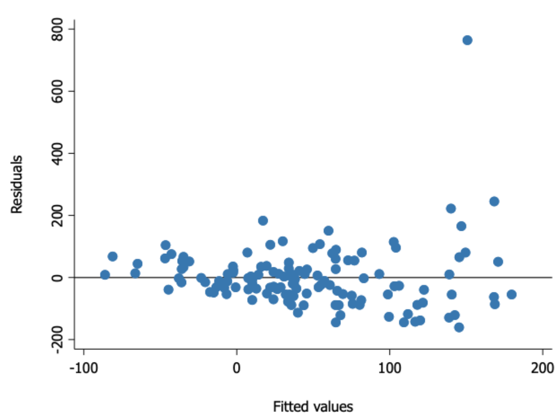
(a) t = Six Months



(b) t = One Year



(c) t = Two Years

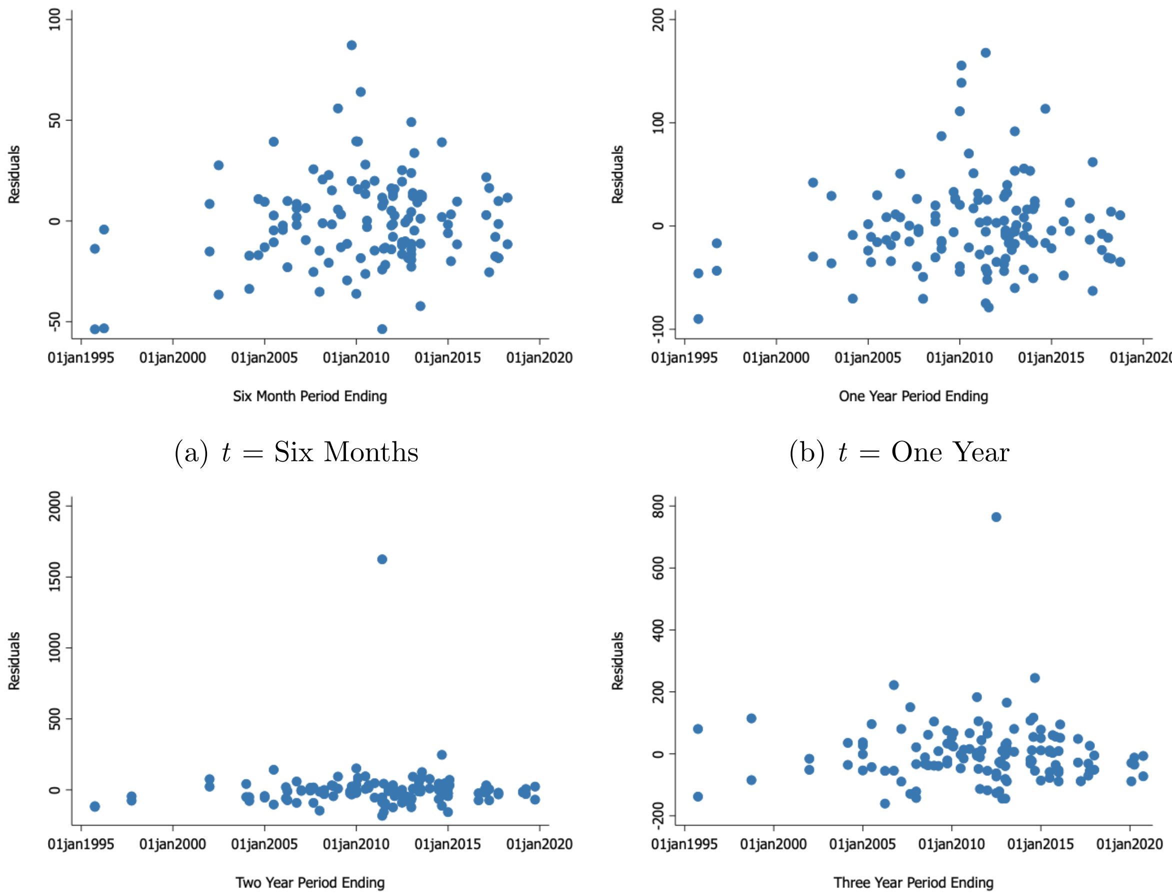


(d) t = Three Years

Figure 6.6: Scatterplots of Residuals vs. Fitted for t = (6,12,24,36)

Figure 6.6 above displays the residual vs fitted plots for the fifth, most complex, model for each of our time frequencies t. These plots show that for all our our frequencies, heteroskedacity of our residuals is a problem and hence our use of "STATA" a.k.a. "HC1" robust standard errors in our regression results. They also give us a decent view into the normality of the distribution of the residuals, further investigated in Figure 6.8.

6.3.7 Scatterplots of Residuals vs. Time for Most Complex Model



(a) t = Six Months

(b) t = One Year

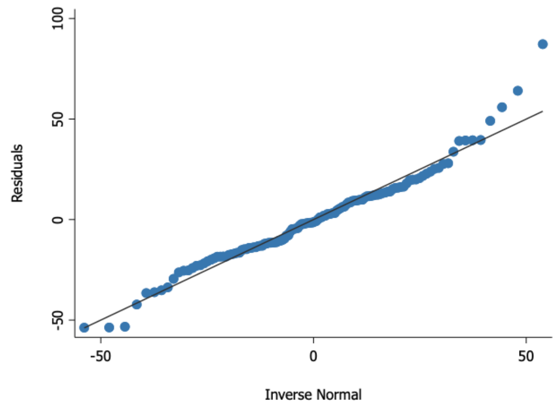
(c) t = Two Years

(d) t = Three Years

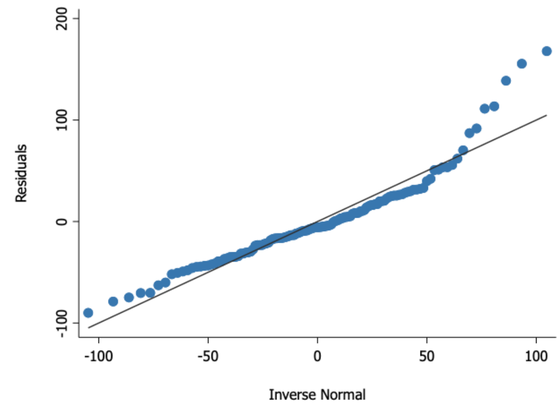
Figure 6.7: Scatterplots of Residuals vs. Time for t = (6,12,24,36)

Figure 6.7 above shows the residual vs time plots for the fight, most complex, model for each of our time frequencies t. These plots are traditionally used for the surveillance of autocorrelation in time-series models. For our analysis, these plots are of particular use in making sure we are controlling for effects at any given point in time. Before controlling for the S&P 500, there was some endogeneity present from not including some kind of measure the overall level of the stock market overtime. By including $\Delta S\&P500_f^t$, we controlled for some of that present endogeneity caused by the overall stock market performance being in the standard error. Before the inclusion of $\Delta S\&P500_f^t$, the empty bubbles in the graphs above the period ending on "01jan2010", right after the Market Crash of 2008, were much larger. This is likely due to the fact that because share prices of firms that existed during this market crash were very low at that point in time, the subsequent ΔSP_f^ts following the market crash were larger than normal, thus causing the model to consistently predicting lower than actual values for ΔSP_f^t at the time period around "01jan2010".

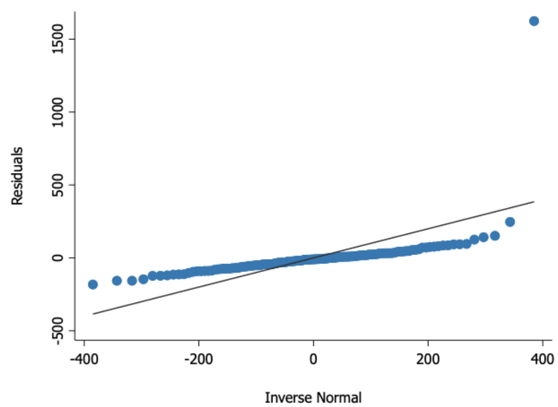
6.3.8 Normal Q-Q Plots for Most Complex Model



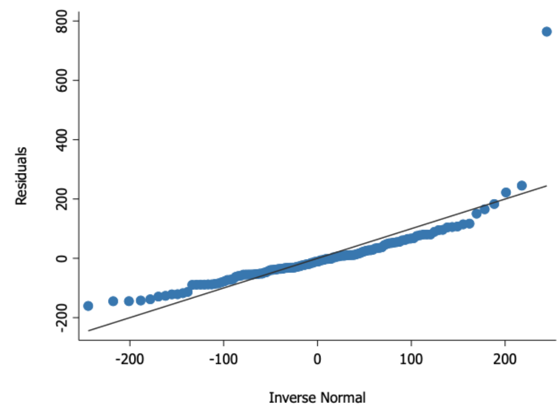
(a) t = Six Months



(b) t = One Year



(c) t = Two Years



(d) t = Three Years

Figure 6.8: Normal Q-Q Plots of Residuals for t = (6,12,24,36)

Figure 6.8 above displays our residuals vs. a theoretical normal distribution of our residuals. As can be seen in 6.8a and 6.8b, relative normality in the lower quantiles of the plots tails up away from normality towards the upper quantile end. Despite this, normality of the standard errors is not completely out of the question at these two frequencies. 6.8c slightly perpindicular to the normal quantiles and has a slight high quantile tail, but still does not stray too far from normal. Finally, 6.8d rotates back closer to the normal quantiles although there is a slight high low and high quantile tail. Despite this and similarly to the others, normality of residuals at the three year frequency should not be of much concern.

6.4 Regression Assumptions

The following list will go over each of the general assumptions of OLS regression and check for both cases of compliance and potential issues with the assumptions:

1. Linearity

   - Equations 4.1,4.2,4.3,4.4,4.5 all demonstrate linearity of the coefficients and error terms in our regression models for each of the time frequencies *(t)*.
   - Figures 6.2, 6.3, 6.6, and 6.8 in Section 6.3 all illustrate that a linear model is in fact plausible for each of the time frequencies *(t)*.

2. No Multicollinearity

   - Figure 6.4 clearly shows that multicollinearity is not a problem in our data with the exclusion of $Other_f$, using a typical threshold of correlations with an absolute value of .8 or greater posing a significant risk to our analysis.

3. Homoskedasticity

   - Despite the heteroskedasticity issues with our data illustrated in Figure 6.6, our use of "STATA"/"HC1" heteroskedasticity robust standard errors in the regression results should still allow our analysis to give accurate results with the given data.

4. Independent Error Terms

   - This assumption also known as the assumption of no autocorrelation is not an issues in our model because we are using cross-section rather than time-series data.

5. Normality of Error Terms

- Figures 6.6 and 6.8 both show that the small lack of normality of our residuals should not be a major cause for concern in our analysis.

6. Exogeneity

   - By implementing increasingly complex models as in Equations 4.2, 4.3, 4.4, and 4.5, potential sources of endogeneity that I had the ability to get data for should be controlled for and help to increase the overall fit and significance of our model.

Chapter 7

Regression Results

Analyzing the causal relationships between the percent change in share price of a firm (ΔSP_f^t) and our dependent variables over time periods of one, three, six, and twelve months; we utilize a Multiple Ordinary Least Squares (OLS) technique for each of the time periods as reported in the below tables. For each of the regression sets below (7.1, 7.2, 7.3, 7.4), columns 1 through 5 shows the regression results for equations 4.1, 4.2, 4.3, 4.4, and 4.5 respectively. External results for our initially run time frequencies of one month and three months are located in Tables A.1 and A.2.

7.1 Six Month Results

	(1)	(2)	(3)	(4)	(5)
Intercept	5.562	5.632	-6.997	-11.42**	-18.17**
	(1.35)	(1.36)	(-1.03)	(-2.34)	(-2.09)
ISF_f	-5.986	-5.960	-6.036	-1.657	8.783
	(-1.21)	(-1.19)	(-1.24)	(-0.38)	(0.85)
CI_f	8.298*	8.279*	8.453*	8.541**	8.175
	(1.67)	(1.66)	(1.72)	(2.02)	(1.25)
$\Delta V_f^{t=6}$		-0.001	0.001	0.004	0.03
		(-0.14)	(0.29)	(0.45)	(1.24)
$NASDAQ_f$			3.778	4.372	1.671
			(0.52)	(0.78)	(0.19)
$NYSE_f$			17.32**	13.66**	17.08**
			(2.59)	(2.45)	(2.21)
$\Delta S\&P500_f^{t=6}$				1.256***	1.911***
				(3.95)	(3.45)
$ISF_f{*}CI_f$					2.064
					(0.25)
$ISF_f{*}\Delta V_f^{t=6}$					-0.034
					(-1.38)
$ISF_f{*}NASDAQ_f$					2.678
					(0.25)
$ISF_f{*}NYSE_f$					-8.282
					(-0.86)
$ISF_f{*}\Delta S\&P500_f^{t=6}$					-0.941
					(-1.60)
N	128	128	128	128	128
adj. R^2	0.017	0.010	0.055	0.286	0.323
F	1.799	1.194	2.193	4.798	4.585

[1] t statistics in parentheses

[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[3] Standard Errors are 'STATA' heteroscedasticity robust

Table 7.1: Regression Output for t = Six Months

At the six month time frequency *(t=6)*, both models 4.1 and 4.2 display parallel individual statistical significance of CI_f with both having magnitudes and significance levels of 8.3% and 10%. Model 4.3, demonstrates individually significant effects on CI_f with a magnitude of 8.5% (10% sig. level) and $NYSE_f$ with a magnitude of 17.32% (5% sig. level). Model 4.4 poses more significant results with individually significant effects displayed for our coefficients of CI_f, $NYSE_f$, and $\Delta S\&P500_f^{t=6}$. The coefficient on $\Delta S\&P500_f^{t=6}$ displays noticeably significant effects at the 1% level. Our final and most complex model 4.5 that includes interaction terms with ISF_f, displays significant results on $NYSE_f$ and $\Delta S\&P500_f^{t=6}$ with magnitudes of 17% and 2% respectively. Interpreting the coefficient of $\Delta S\&P500_f^{t=6}$, a one percent increase in $\Delta S\&P500_f^{t=6}$ increases $\Delta SP_f^{t=6}$ by around 2% on average or all else constant. The coefficient on $NYSE_f$ can be interpreted as being listed on the NYSE increases the $\Delta SP_f^{t=6}$ by 17%.

7.2 One Year Results

	(1)	(2)	(3)	(4)	(5)
Intercept	22.180**	23.052***	-0.021	-12.715	-13.788
	(2.61)	(2.69)	(-0.00)	(-1.38)	(-1.36)
ISF_f	-18.437**	-19.030**	-18.749**	-15.821**	-14.648
	(-2.17)	(-2.23)	(-2.21)	(-2.07)	(-0.83)
CI_f	12.047	12.211	12.774	12.790	6.256
	(1.42)	(1.43)	(1.50)	(1.61)	(0.43)
$\Delta V_f^{t=12}$		-0.008**	-0.004	-0.003	-0.003
		(-2.12)	(-1.11)	(-0.76)	(-0.60)
$NASDAQ_f$			20.485*	21.421*	17.879
			(1.77)	(1.93)	(1.07)
$NYSE_f$			25.751***	24.985***	31.529**
			(2.89)	(2.77)	(2.55)
$\Delta S\&P500_f^{t=12}$				1.161***	1.250**
				(3.85)	(2.14)
$ISF_f{*}CI_f$					13.230
					(0.81)
$ISF_f{*}\Delta V_f^{t=12}$					0.003
					(0.38)
$ISF_f{*}NASDAQ_f$					6.269
					(0.28)
$ISF_f{*}NYSE_f$					-13.256
					(-0.71)
$ISF_f{*}\Delta S\&P500_f^{t=12}$					-0.079
					(-0.13)
N	128	128	128	128	128
adj. R^2	0.036	0.034	0.037	0.164	0.142
F	3.435	3.115	3.911	4.244	5.149

[1] t statistics in parentheses

[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[3] Standard Errors are 'STATA' heteroscedasticity robust

Table 7.2: Regression Output for t = One Year

At the one year time frequency *(t=12)*, model 4.1 displays individual statistical significance of ISF_f with a magnitude and significance levels of around -18% and 5%. Model 4.2 demonstrates individually significant effects on both ISF_f and $\Delta V_f^{t=12}$ with magnitudes of 19% (10% sig. level) and 0% respectively (10% sig. level). Model 4.3 poses more significant results with individually significant effects displayed for our coefficients on ISF_f, $NASDAQ_f$, and $NYSE_f$. Of noticeable statures are the coefficient on ISF_f and $NYSE_f$ with their size and significance of effects. Model 4.4 expands on Model 4.3 by adding a significant individual effect of the coefficient of $\Delta S\&P500_f^{t=12}$ with a magnitude and significance level of 1% and 1%. In Model 4.5, although the magnitudes of the effects of $NYSE_f$ and $\Delta S\&P500_f^{t=12}$ both increased, their statistical significance decrease due to effect being taken in by added interaction terms. Model 4.5 in this analysis overall poses the best predictive power for our dependent variable of $\Delta SP_f^{t=12}$ with an F statistic of 5.149.

7.3 Two Year Results

	(1)	(2)	(3)	(4)	(5)
Intercept	63.349	64.676	22.268	-6.059	-31.107
	(1.48)	(1.50)	(0.67)	(-0.28)	(-1.49)
ISF_f	-40.526	-41.666	-41.926	-50.218	-3.911
	(-1.35)	(-1.38)	(-1.39)	(-1.50)	(-0.14)
CI_f	-2.556	-1.987	-1.186	-1.267	-18.457
	(-0.09)	(-0.07)	(-0.04)	(-0.04)	(-0.32)
$\Delta V_f^{t=24}$		-0.004***	-0.005***	-0.004***	-0.005***
		(-4.13)	(-4.04)	(-3.97)	(-3.34)
$NASDAQ_f$			21.525	22.421	-2.527
			(1.20)	(1.22)	(-0.08)
$NYSE_f$			55.858**	57.616**	95.335*
			(2.51)	(2.51)	(1.87)
$\Delta S\&P500_f^{t=24}$				1.722**	2.744
				(1.98)	(1.50)
$ISF_f{*}CI_f$					33.971
					(0.57)
$ISF_f{*}\Delta V_f^{t=24}$					-0.002
					(-0.87)
$ISF_f{*}NASDAQ_f$					41.306
					(1.06)
$ISF_f{*}NYSE_f$					-65.820
					(-1.21)
$ISF_f{*}\Delta S\&P500_f^{t=24}$					-1.769
					(-0.96)
N	128	128	128	128	128
adj. R^2	-0.001	-0.008	-0.010	0.037	0.033
F	2.976	5.816	4.785	4.813	11.944

[1] t statistics in parentheses

[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[3] Standard Errors are 'STATA' heteroscedasticity robust

Table 7.3: Regression Output for t = Two Years

At the two year time frequency *(t=24)*, individual statistical significance is not displayed until model 4.2 unlike with the shorter time frequencies. The coefficient of $\Delta V_f^{t=24}$ in this model is predicted to be around 0 at a significance level of 1%. Model 4.3 adds $NYSE_f$ as a statistically significant term with an effect of an around 56% increase on $\Delta SP_f^{t=24}$ at the 5% significance level. This can be interpreted as all else constant, being on the NYSE increases $\Delta SP_f^{t=24}$ by around 56%. Model 4.4 demonstrates the addition of individually significant effects on $\Delta S\&P500_f^{t=24}$ with a magnitude of around 2% at the 5% level. Model 4.5 illustrates how statistical power was taken away from our standard terms with the addition of the interaction terms. Although none of these interaction coefficients are significant, as an example, $ISF_f * \Delta V_f^t$ can be interpreted as the effect a 1% increase in $\Delta V_f^{t=24}$ has after the sharing economy firm was introduced, all else constant.

7.4 Three Year Results

	(1)	(2)	(3)	(4)	(5)
Intercept	49.993**	53.440***	14.072	-36.999*	-70.253*
	(2.09)	(2.86)	(0.75)	(-1.69)	(-1.86)
ISF_f	-40.388**	-41.201**	-41.254**	-58.551***	10.359
	(-1.98)	(-2.13)	(-2.14)	(-2.85)	(0.23)
CI_f	32.024	30.280*	30.837*	34.355**	36.673
	(1.57)	(1.67)	(1.69)	(2.11)	(1.24)
$\Delta V_f^{t=36}$		-0.020	-0.022	0.014	0.030
		(-0.40)	(-0.43)	(0.25)	(0.36)
$NASDAQ_f$			21.430	37.223	49.383
			(0.98)	(1.55)	(1.23)
$NYSE_f$			51.146***	62.532***	87.142**
			(2.79)	(2.84)	(2.32)
$\Delta S\&P500_f^{t=36}$				1.817***	2.401***
				(4.07)	(2.94)
$ISF_f{*}CI_f$					-4.610
					(-0.14)
$ISF_f{*}\Delta V_f^{t=36}$					-0.047
					(-0.55)
$ISF_f{*}NASDAQ_f$					-20.745
					(-0.44)
$ISF_f{*}NYSE_f$					-43.883
					(-0.99)
$ISF_f{*}\Delta S\&P500_f^{t=36}$					-1.176
					(-1.37)
N	128	128	128	128	128
adj. R^2	0.034	0.028	0.035	0.198	0.187
F	4.886	3.469	3.798	7.615	5.311

[1] t statistics in parentheses

[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[3] Standard Errors are 'STATA' heteroscedasticity robust

Table 7.4: Regression Output for t = Three Years

At the three year time frequency *(t=36)*, individually statistically significant effects are displayed in model 4.1 by the coefficient of ISF_f with a magnitude of around -40% at the 5% level. 4.2 displays additional individually significant effects on CI_f, although at a weak significance level of 10%. The addition of $NYSE_f$ in model 4.3 poses an individual magnitude of 51% at a strong 1% level. All else constant, being on the NYSE increase share price growth rate at this frequency by around 51%. Model 4.4 follows the previous effects of models 4.2 and 4.3 except with the addition of a statistically significant $\Delta S\&P500_f^{t=36}$ term with a magnitude of around 2% and significance level of 1%. The introduction of the interaction terms parallels the problem faced at the $t = 24$ frequency where the introduction of the terms despite not being statistically significant themselves, redistributes the previous statistical significance in the model to the new terms, decreasing the power of our coefficients on ISF_f, CI_f, and $NYSE_f$ shown in models 4.3 and 4.4.

7.5 Main Results

Based on the overall regression results discussed above for the time frequencies of *t=6,12,24,36*, our main independent variable of interest $ISF_f * CI_f$ poses no individual statistical significance through any of the time frequencies. Because this interaction term has the power to directly answer our main research question of "How Does the Introduction of the Sharing Economy Impact the Financial Performance of Closely Related Incumbents", we fail to reject our null hypothesis that the coefficient of $ISF_f * CI_f$ is zero and conclude that $ISF_f * CI_f$ has no effects on ΔSP_f^t. Despite this, some interesting individually significant coefficients were produced for the coefficients on the controls we added such as those on $NYSE_f$ and $\Delta S\&P500_f^t$. These coefficients help to support often argued theories that metrics like the exchange a firm is listed on and the level of the growth rate of the S&P500 can significantly affect ΔSP_f^t.

Chapter 8

Conclusion

In this day and age of ever-changing technology, new business models are constantly coming on the block that redefine how we as humans do things. With the development of big data technologies such as Hadoop and Spark, cloud systems such as AWS and Azure, and production ML/AI technologies such as TensorFlow and IBM Watson open increasingly expanding opportunities and potential models for businesses. Perhaps one of the most dominant new business models to be found in the past decade due to the developments of big data and other technologies is that of 'sharing economy' firms.

The term 'sharing economy' can often seem vague and it's definition readily changes upon who and when you ask. Companies in this category such as Airbnb, Uber, Doordash, and Rover all offer very different services, but regardless can all be put under the umbrella of the 'sharing economy' using a common definition such as that posed by Oksana Gerwe and Rosario Silva in Clarifying the Sharing Economy: Conceptualization, Typology, Antecedents, and Effects. Gerwe and Silva argue that all firms within the "sharing economy" possess the four common features of: online/digital platform organization, peer to peer/business to business transactions, emphasis of access over ownership, and reliance on underused supply of a service or product. The companies that encompass this variable list of P2P, B2B, and sharing firms can be an immense force upon their incumbent markets. By creating strong customer value propositions, fair pricing, and ease of use, the firms that follow this category of business model have the capability to be massive financial players in a wide range of sectors.

Coming with the introduction and growth of these sharing firms is their effect on incumbent firms financial performance. The effect that the introduction of major sharing firms such as Airbnb and Uber has had on their incumbent local markets has been previously studied. For example, Zervas (2017) concludes, "in Austin, where Airbnb supply is highest, its impact on hotel revenue averages in the -8%-10% range with lower-priced hotels and hotels that do not cater to business travelers being the most affected financially". On Uber, Wallsten concluded that it's introduction forced taxis in NYC, Chicago, and Long Beach, CA to improve their value of service by improving quality and/or lowering rates. Despite this previous literature on sharing firms effects on incumbents, there are many limitations to it.

In order to bridge the gap in the literature and provide some quantitative insight into the effects of the sharing economy, this paper analyzed how the introduction of sharing firms impacts the financial performance, measured as percent change in share price, of closely related incumbents. Although we originally hypothesized that the introduction of the sharing economy firms will have a significant effect on closely related incumbents percent change in share price over the time frequencies *(t)* of six months, one year, two years, and three years; our predictions did not pan out.

Overall, the six month, one year, two year, and three year results of our analysis all show that both the introduction of the sharing economy firm and being a closely related incumbent do not generally have a statistically significant effect on the share price growth rate of a incumbent firms. Although these results are not conclusive and there is much work that can be done to improve our models, at this time we fail to conclude that $ISF_f * CI_f$ has a statistically significant effect on the financial performance of incumbent firms. Taking this into account, at this time and with our estimates, investors, management of incumbent firms, government regulators, and customers should have no reason to believe that the introduction of the sharing economy firm exhibits any homogenous, generalizable effects on the financial performance of its closely related incumbents.

Despite the results, potential improvements to the framework used to answer this research question could arise from the future usage of a larger dataset, different independent variables, and a new design matrix style. Doing this will enable increased statistical significance of the results as well as greater generalizability.

Appendix A

Appendix

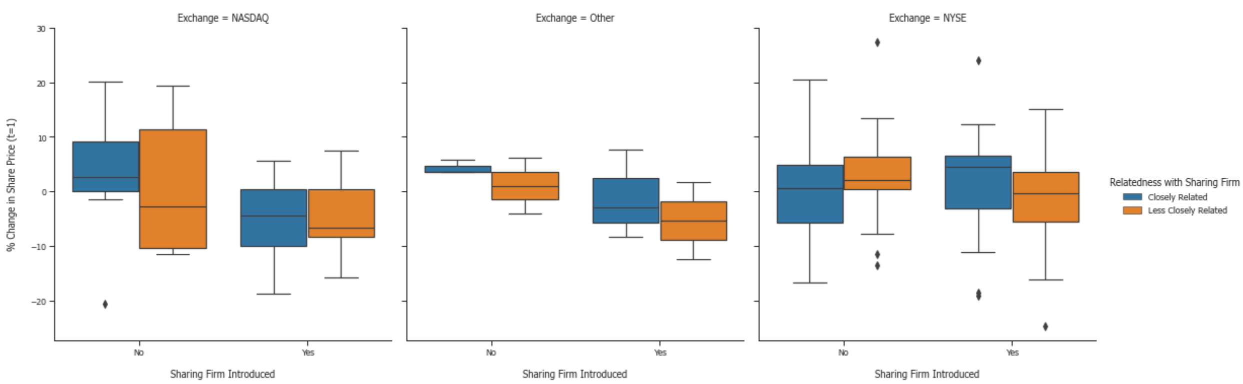


Figure A.1: Boxplot of % Change in Share Price vs. Categorical Variables for $t = 1$

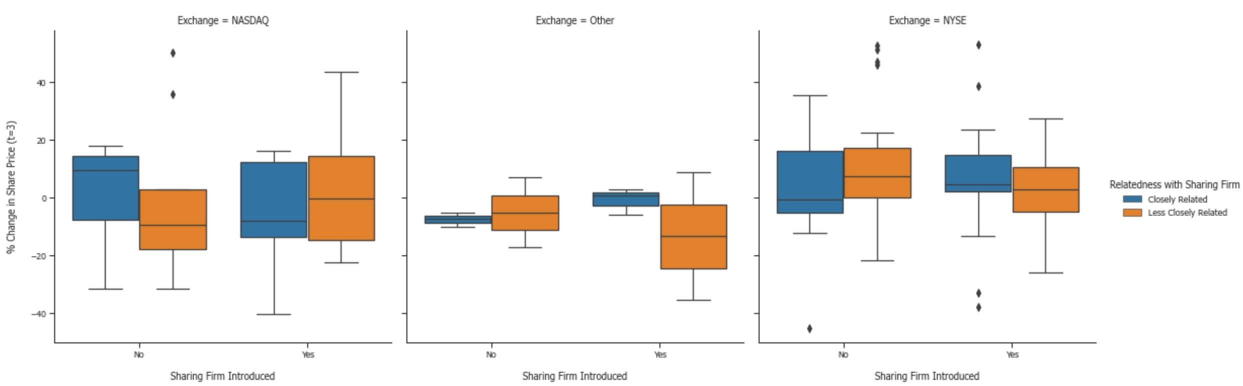


Figure A.2: Boxplot of % Change in Share Price vs. Categorical Variables for $t = 3$

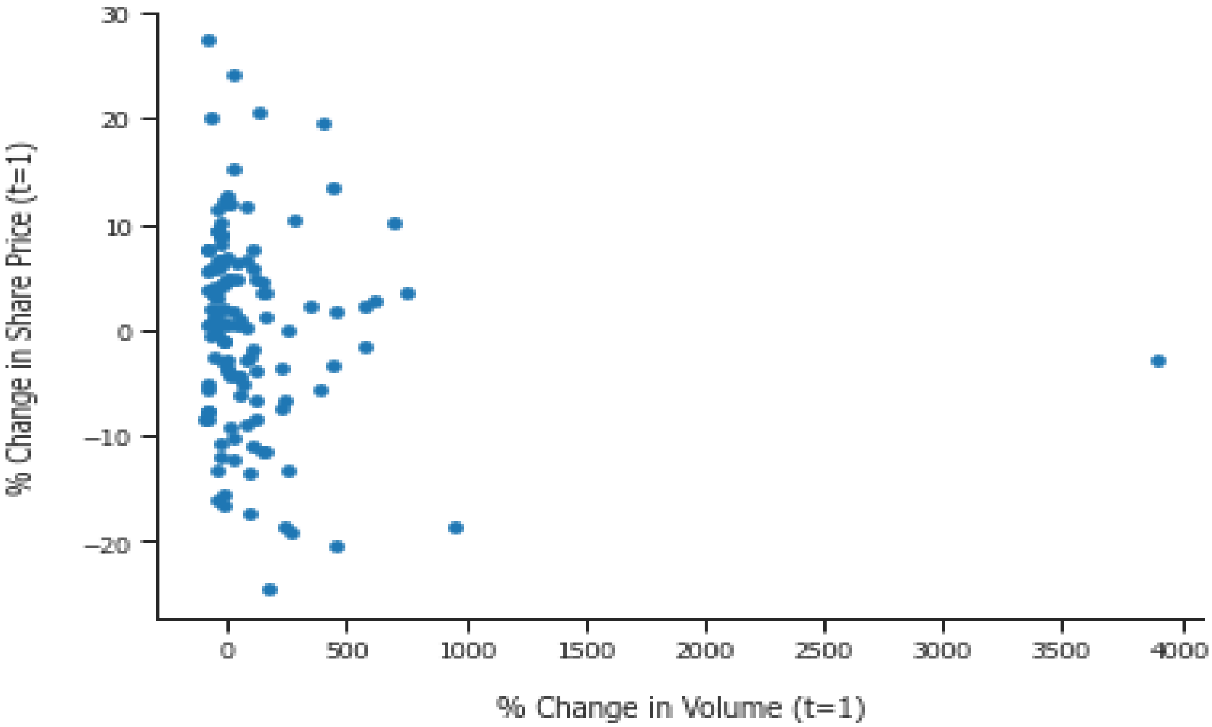


Figure A.3: Scatterplot of % Change in Share Price vs. % Change in Volume for $t = 1$

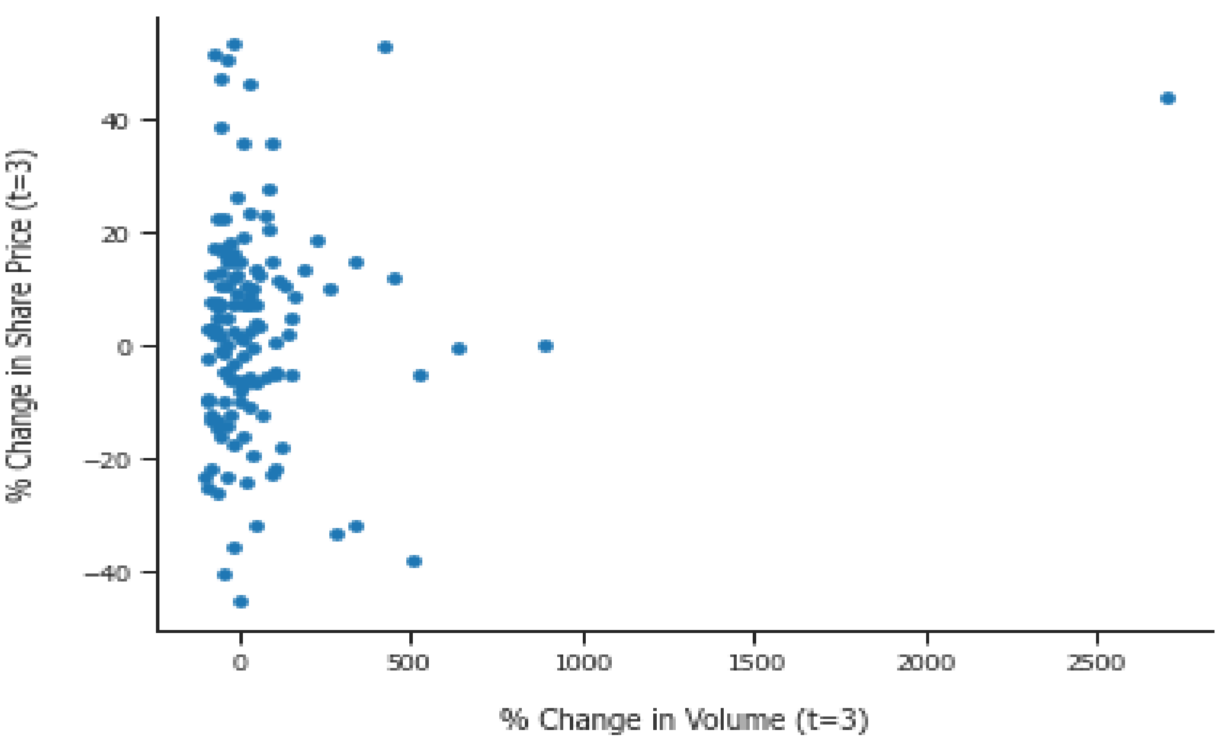


Figure A.4: Scatterplot of % Change in Share Price vs. % Change in Volume for $t = 3$

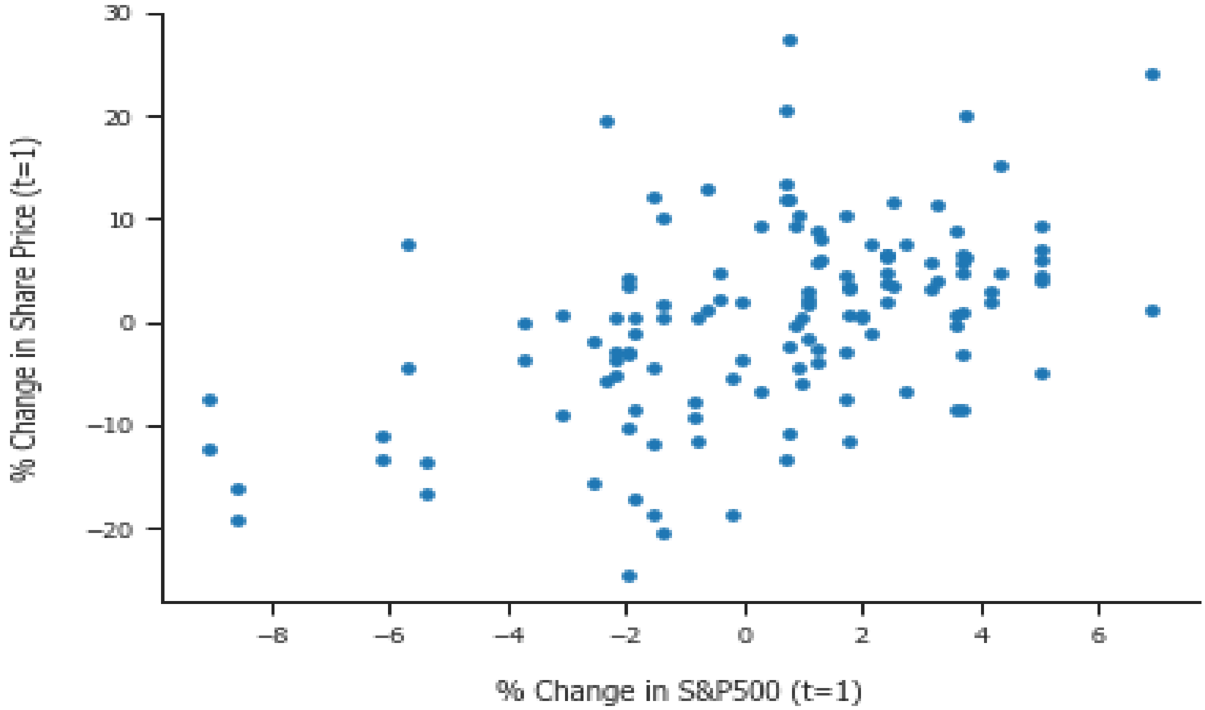


Figure A.5: Scatterplot of % Change in Share Price vs. % Change in S&P 500 for $t = 1$

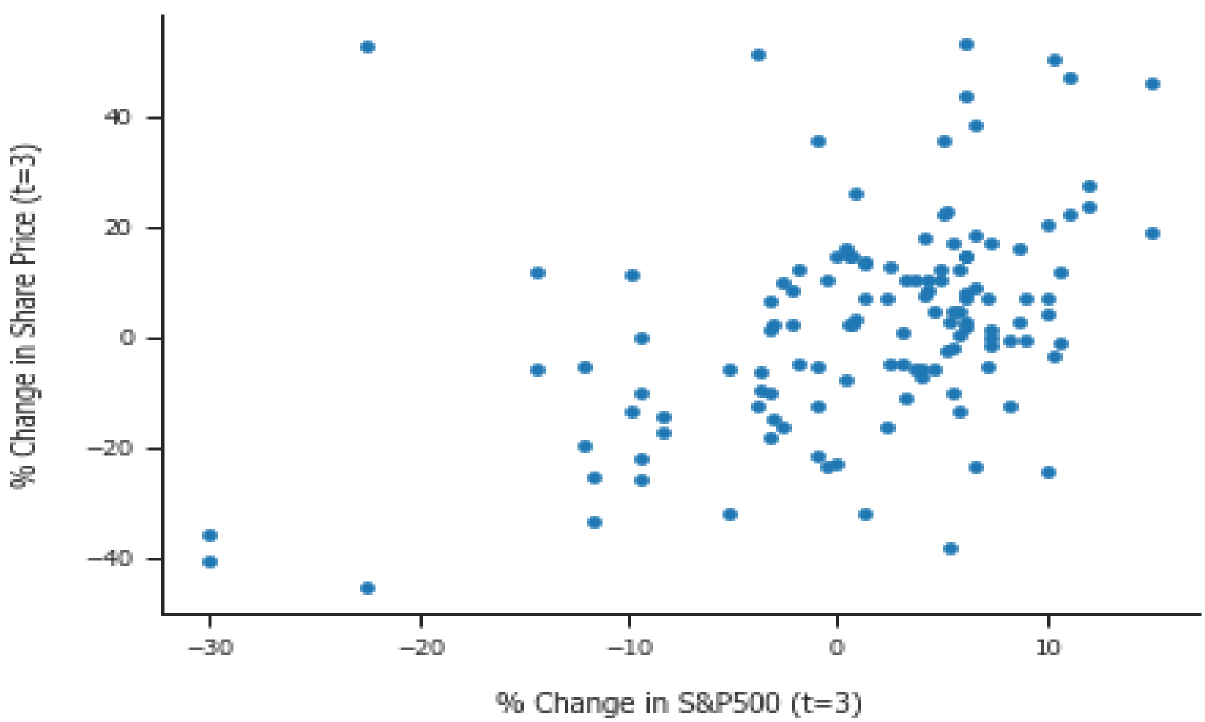


Figure A.6: Scatterplot of % Change in Share Price vs. % Change in S&P 500 for $t = 3$

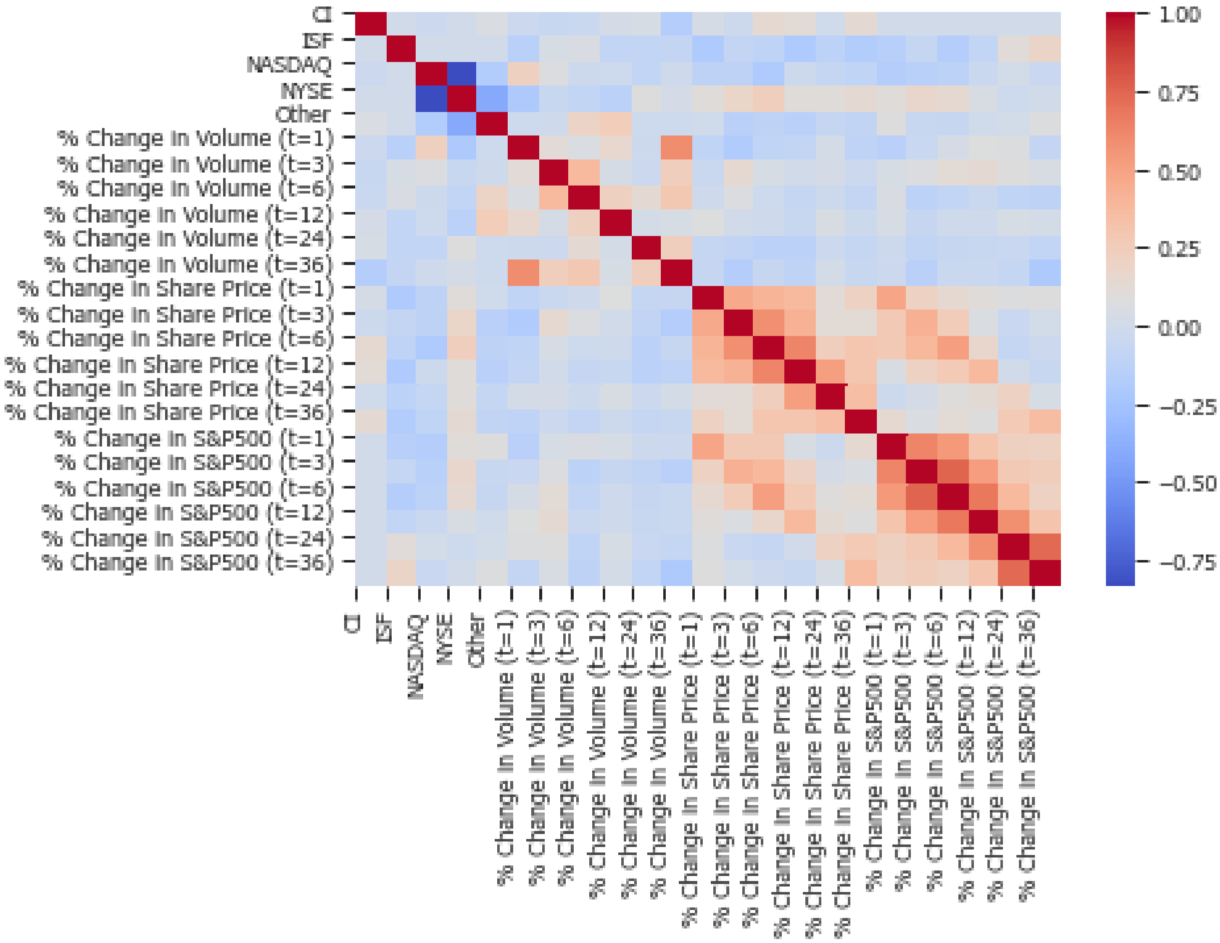


Figure A.7: Correlation Matrix/Heatmap of all the Data

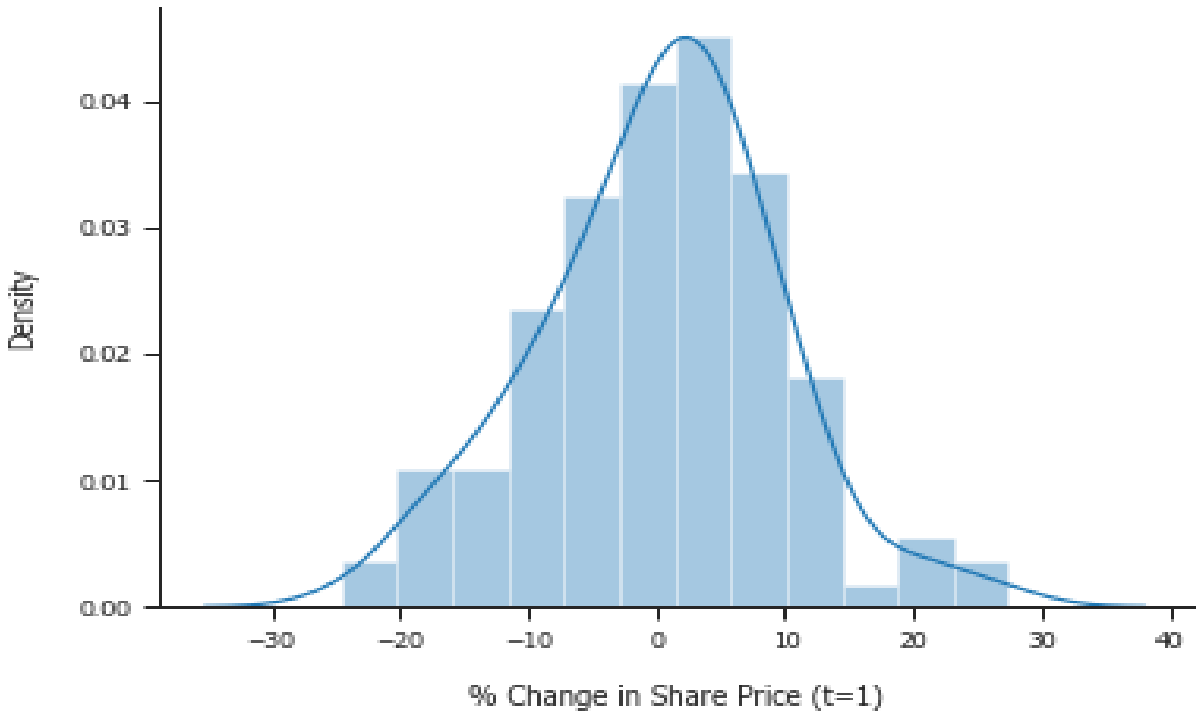


Figure A.8: KDE Plot for $t = 1$

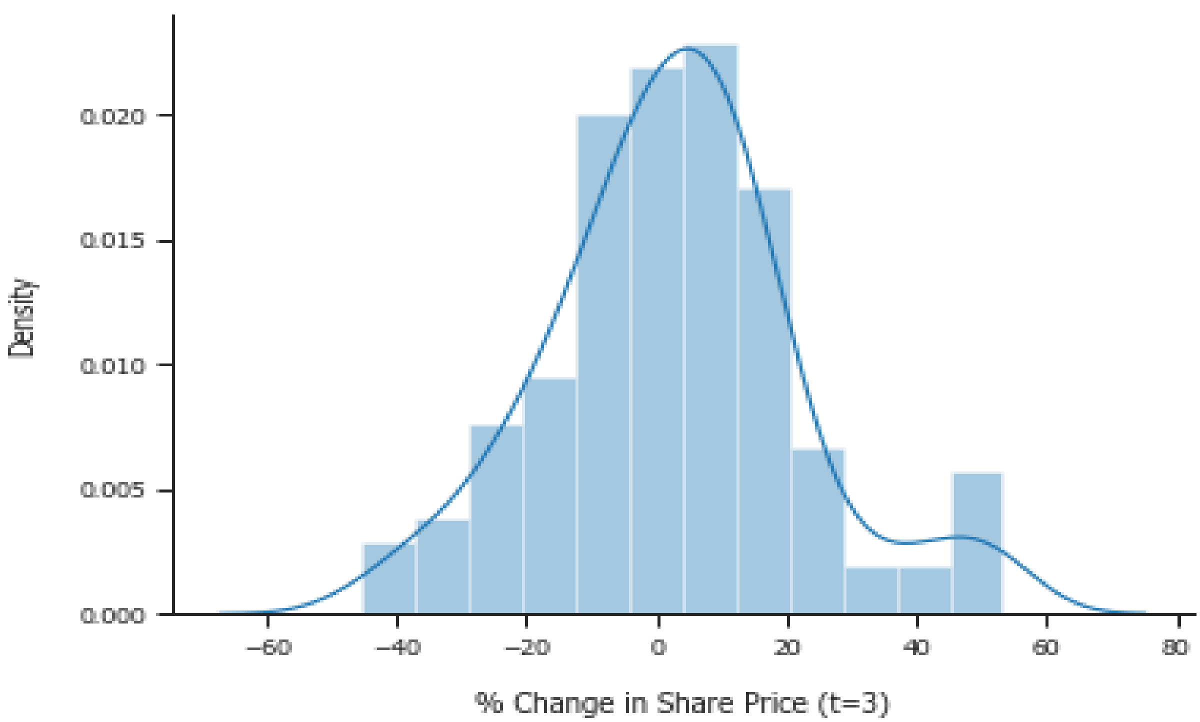


Figure A.9: KDE Plot for $t = 3$

	(1)	(2)	(3)	(4)	(5)
Intercept	1.693	2.198	1.885	-0.919	-0.745
	(1.20)	(1.49)	(0.83)	(-0.48)	(-0.29)
ISF_f	-3.495**	-3.813**	-3.762**	-2.301	-4.148
	(-2.14)	(-2.29)	(-2.24)	(-1.50)	(-1.01)
CI_f	0.551	0.483	0.460	0.566	-0.932
	(0.34)	(0.30)	(0.28)	(0.39)	(-0.41)
$\Delta V_f^{t=1}$		-0.003	-0.002	-0.001	-0.000
		(-1.66)	(-1.41)	(-0.72)	(-0.23)
$NASDAQ_f$			-1.068	1.216	2.480
			(-0.42)	(0.54)	(0.84)
$NYSE_f$			0.811	1.904	1.860
			(0.38)	(1.08)	(0.87)
$\Delta S\&P500_f^{t=1}$				1.364***	1.532***
				(6.35)	(3.15)
ISF_f*CI_f					3.895
					(1.32)
ISF_f*$\Delta V_f^{t=1}$					-0.015***
					(-2.67)
ISF_f*$NASDAQ_f$					-1.027
					(-0.22)
ISF_f*$NYSE_f$					1.732
					(0.45)
ISF_f*$\Delta S\&P500_f^{t=1}$					-0.373
					(-0.68)
N	128	128	128	128	128
adj. R^2	0.021	0.028	0.020	0.222	0.232
F	2.385	2.300	1.716	8.876	6.550

[1] t statistics in parentheses

[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[3] Standard Errors are 'STATA' heteroscedasticity robust

Table A.1: Regression Output for t = One Month

	(1)	(2)	(3)	(4)	(5)
Intercept	4.762	4.075	-4.926	-5.173	-4.427
	(1.39)	(1.18)	(-0.95)	(-1.52)	(-1.23)
ISF_f	-3.003	-3.230	-3.244	-2.168	-2.155
	(-0.87)	(-0.94)	(-0.96)	(-0.67)	(-0.42)
CI_f	-0.983	-0.652	-0.480	-0.537	-4.616
	(-0.29)	(-0.19)	(-0.14)	(-0.17)	(-0.97)
$\Delta V_f^{t=3}$		0.010^{*}	0.011^{*}	0.009	-0.005
		(1.85)	(1.77)	(1.31)	(-0.32)
$NASDAQ_f$			4.841	5.356	5.072
			(0.90)	(1.50)	(0.93)
$NYSE_f$			11.577^{**}	9.215^{***}	12.441^{***}
			(2.48)	(3.07)	(3.15)
$\Delta S\&P500_f^{t=3}$				0.966^{***}	0.943
				(3.33)	(1.55)
$ISF_f{*}CI_f$					7.991
					(1.29)
$ISF_f{*}\Delta V_f^{t=3}$					0.017
					(0.99)
$ISF_f{*}NASDAQ_f$					-0.973
					(-0.14)
$ISF_f{*}NYSE_f$					-7.212
					(-1.31)
$ISF_f{*}\Delta S\&P500_f^{t=3}$					0.060
					(0.09)
N	128	128	128	128	128
adj. R^2	-0.009	0.005	0.031	0.186	0.178
F	0.383	1.452	2.119	8.366	6.501

[1] t statistics in parentheses

[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[3] Standard Errors are 'STATA' heteroscedasticity robust

Table A.2: Regression Output for t = Three Months

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