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COMMON TECHNICAL INDICATORS AND THEIR IMPACT ON STOCK PRICES

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Abstract

In the following paper we will examine the effect of technical support and resistence levels on one-day U.S. equity returns. Moving averages and local minima/maxima of varying windows will be studied, as well as round numbers. Ultimately, we find that when an asset price closes arbitrarily near these technical indicators, its range of ensuing one-day returns changes in significant ways. The most notable observation was that moving averages (and to a lesser extent, round numbers) reduce volatility, sometimes substantially. Finally, we conclude by investigating how responsive U.S. equities have been to the studied technical indicators over time, finding that while the overall trend is positive, it has weakened since the Great Recession.

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CHAPTER 1

Introduction

Perhaps one of the most divisive studies in all of finance, technical analysis (TA) uses historical asset prices, volume, and/or open interest in an attempt to predict the direction of future prices. Its use was pioneered by Charles Dow in the late 19th century, whose work was synthesized to form the Dow theory. Dow introduced the concepts of trading ranges and trends, and gave investors a framework for assessing security prices in the absence of modern financial reporting.

Since, financial reporting has become more transparent, reliable, and widely-available. From this arose the study of fundamental analysis. Benjamin Graham is considered the the father of fundamental analysis, and his book *Security Analysis* (1934) the bible. In lieu of price and volume data, Graham advocated the use of balance sheet metrics and financial ratios to screen for undervalued securities.

Economists tend to prefer fundamental analysis as it fits the widely-accepted efficient market hypothesis (EMH) for describing financial markets. Conversely, the view that past prices contain information relevant to the future value of a security is squarely rejected by the EMH. As such, academics have taken an incredulous view toward the utility of TA.

This paper will make no attempt to advocate for or against technical analysis. It will especially avoid investigating the potential profitability of any TA-based trading strategy. Thankfully, this avoids the need to take into account transaction costs, cross-sampling data, and many other considerations typical of such a study.

Instead, this paper sets out on a less rigorous proof: that widely-monitored technical indicators have a consistent market impact. If this proves to be the case, then the argument for including TA in trading decisions – and to a lesser extent, investing decisions – makes itself.

On our way to this goal, we must first define what is meant by ”market impact”. In the context of this paper, ”market impact” refers to any persistent deviation in a given asset's distribution of one-day returns from how the asset has traded on a historical basis. In simpler English, this study will implement a method that compares selected one-day asset returns to the asset's entire history of returns. Each security will thus

The comparison will take note of measures of central tendency (e.g. mean, median, etc.) but otherwise focus entirely on measures of spread. Namely, our hypothesis test will determine whether the samples of returns on selected days have the same variance as the asset's overall distribution of returns.

Rather than make these comparisons using index-level data, we will take the more pragmatic approach of analyzing traded securities. More specifically, constituents of the S&P 500 will be used, giving us approximately 500 data points on any given trading day.

Exchange-traded funds were tempting to include in this study, but their relative newness would make it more difficult to draw any statistical conclusions, and their illiquidity (in some cases) and additional fees would serve as noise that would get in the way of applying TA rules.

Additionally, due to the market-cap weighted nature of the S&P 500, there is a clear geometric relationship between the strength of our findings and their relevance at the index-level. This allows us to avoid making any binary conclusions, and also facilitates deeper exploration of our results.

1.1 Review of the related literature

Simply put, there are no influential studies similar to the one about to be performed. The large majority of papers related to TA focus upon its profitability (or lack thereof) and/or ability to predict future price movements. This study will borrow elements from prior studies, but the research question appears to be novel.

In the first major study on the matter, Working (1956) concluded so-called ”turnaround signals” have greater predictive power in real agricultural commodity futures prices as compared to synthetic timeseries, whereas under the random-walk model, the timeseries' predictive power would be equivalent.

Sidney Alexander (1961) took this a step further, applying filter rules to the U.S. stock market for the first time. On one hand, Alexander's results corroborated Working's evidence against the random-walk model, although it was found that a simple buy-and-hold (BH) strategy produced significantly higher profits. Fama and Blume (1966) performed a similar study on Dow Jones Industrial Average components, which was met with identical results.

Likewise, Van Horne and Parker (1967) found serial correlation in U.S. equity prices, but demonstrated that moving average trading rules were also unprofitable net of transaction costs. And lastly, Jensen and Benington (1970) extended these results to relative strength trading rules.

It was these early studies (in addition to the popularity of the EMH) that soured the view of TA within academics. More recent results, however, have proven more favorable with regards to the profitability of technical trading rules (TTR), even if not entirely conclusively. Brock et al. (1992) provided the first popular study in favor of TA. The authors tested various momentum-based trading strategies on Dow Jones Industrial Average (DJIA) components, finding statistically significant profitability across most strategies compared to a BH portfolio. Strategies examined by Lukac et al. (1988) also achieved profitability in commodity markets, while Lo et al. (2000) and Neely (2002) achieved profitability in foreign exchange markets.

Reconciling both groups of studies, Taylor (2013) concluded that TTR performance has varied substantially across time. While the author concurred that TTR strategies tended to outperform the BH portfolio (on a risk-adjusted basis, and net of transaction costs) prior to the Brock et al. study, performance diminished soon thereafter, citing broadly higher liquidity as a potential factor.

Finally, a third group of studies attempts to apply information from TA to forecast risk premia. For example, Neely et al. (2010) confirms that TA signals do provide incremental information in predicting equity risk premia, capturing information that is distinct from macroeconomic variables. Goh et al. (2013) found the same results in forecasting U.S. sovereign bond yields. In fact, technical indicators based on forward bond spreads actually outperformed fundamental factors overall in forecasting both short-term and long-term yields, and a model using both technical and fundamental factors had the highest predictive ability.

Regardless, TTR strategy performance is not the focus of this paper. With this in mind, it is only important how frequently and in which ways TA is used among market participants. Survey results have been highly favorable in this dimension. For instance, Smidt (1965) found more than half of respondents stated they ”moderately” or ”exclusively” use charts when placing trades in the soybean futures market. Notably, the study fielded responses from an eclectic sample ranging from farmers and laborers to professional and clerical workers.

More recently, Taylor and Allen (1988) showed approximately two thirds of a sample of professional foreign exchange dealers in London utilize trend-following technical indicators in their analyses. Two-thirds also answered that their organizations regularly utilize online charting software in making trading decisions. And perhaps most importantly, the respondents weighed TA and fundamental analysis roughly equally in intraday analysis. Note that this is the time horizon of our study.

Cheung and Chinn (2002) later conducted a similar survey in which roughly 30% of foreign exchange dealing respondees indicated they were best characterized as technical traders. Menkhoff (1997) and Gehrig and Menkhoff (2003) are also frequently-cited studies in support of the popularity of TA, with up to 40% of foreign exchange traders citing TA as the major factor influencing exchange rates in the short-term.

Thus, while the body of literature surrounding TTR profitability may be hazy, it is clear that most market participants at least consider technical signals when trading or investing. This alone supports the notion that TA likely impacts asset prices in the short-run. The balance of this paper will concentrate on determining exactly what these effects are, if any, in the context of short-term equity returns.

CHAPTER 2

Methodology

2.1 Data

Separate analyses will be performed on each individual equity that has ever been a constituent of the S&P 500 for at least 201 days. Daily prices are examined dating from 03/01/1957 – 12/31/2018. All data is courtesy of the Center for Research in Security Prices (CRSP). CRSP data is adjusted for stock splits and for dividends where appropriate.

2.2 Technical indicators

The following three classes of technical indicators will be studied: moving averages (MA), rolling local minima/maxima (rolling minimum/maximum), and round numbers.

2.2.1 Moving average

The simple moving average is calculated as the equally-weighted mean of the previous n prices ranging from P_{t-1} to P_{t-n}. In general form, it can be expressed as:

$$\begin{aligned}\overline{P}_n &= \frac{P_{t-1} + P_{t-2} + \ldots + P_{t-n}}{n} \\ &= \frac{1}{n}\sum_{i=1}^{n-1} P_{t-i}\end{aligned}$$

We will also define a parameter j as the threshold at which the percentage difference between P_t and $\overline{P}_n$ is considered sufficiently small enough to generate a signal at time t. Said differently, the threshold at which an asset's price is considered arbirtarily "close" to its n-day moving average. For any time t, the state of our model $MA_n(t)$ is generalized as:

$$MA_n(t) = \begin{cases} 0, & (P_t - \overline{P}_n)/\overline{P}_n > j \\ 1, & j > (P_t - \overline{P}_n)/\overline{P}_n > -j \\ 0, & -j > (P_t - \overline{P}_n)/\overline{P}_n \end{cases}$$

Where 1 represents a positive signal and 0 represents no signal. For threshold j, we will use a value of 1%. And for the amount of days n, windows of 50, 100, and 200 will be used.[1]

[1]These windows are commonly used in practice, and thus should yield informative results.

2.2.2 Rolling maximum/minimum

The rolling maximum (minimum) evaluates whether P_t is greater than (less than) the highest (lowest) price over the previous P_{t-1}, P_{t-2}, . . ., P_{t-n} prices. In this case, the rolling maximum is generalized as:

$$Max_n(t) = \begin{cases} 1, & P_t > Max(P_{t-1}, P_{t-2}, \ldots, P_{t-n}) \\ 0, & P_t < Max(P_{t-1}, P_{t-2}, \ldots, P_{t-n}) \end{cases}$$

Similarly, the rolling minimum is generalized as:

$$Min_n(t) = \begin{cases} 1, & P_t < Min(P_{t-1}, P_{t-2}, \ldots, P_{t-n}) \\ 0, & P_t > Min(P_{t-1}, P_{t-2}, \ldots, P_{t-n}) \end{cases}$$

As above, windows of 50, 100, and 200 will be used for n. Returns will also be analyzed in totality.

2.2.3 Round numbers

Round numbers have been studied due to their purported psychological significance to market participants. Among others, Osler (2005) provides the following explanations for abnormal volume characteristics: 1) round numbers reduce the time taken to communicate with dealers, 2) round numbers reduce potential sources of communication error, and 3) round numbers are easier to perform mental calculations on.

Unfortunately, there is no consensus regarding what exactly a round number is in the context of equity prices. An exchange rate is considered round to the nearest "big figure" when it ends in two zeroes (e.g. a EURUSD rate of 1.1600, or a USDJPY rate of 114.00), and intermediate points (e.g. EURUSD 1.1650, or USDJPY 114.50) also experience elevated volume.

Using this as a guideline, we round prices using the following expression, where y is the security price's number of non-decimal digits:

$$[P] = \frac{P_t}{10^{\text{min(1, y-1)}}}$$

For securities priced in ones or tens of dollars, we will thus consider prices ending in $.00$ to be "round". Otherwise, securities are considered "round" after the first two digits. For example, an S&P price level of 2800 would be considered round, while Apple Inc. (NASDAQ: AAPL) stock would be considered round at either 170 or 180.

The model is generalized the same way as in the moving average – as a percent difference compared to a parameter j, except from the nearest round number $[P]$ rather than a simple MA:

$$Round_n(t) = \begin{cases} 0, & (P_t - [P])/[P] > j \\ 1, & j > (P_t - [P])/[P] > -j \\ 0, & -j > (P_t - [P])/[P] \end{cases}$$

Because the function is time-invariant, there is no need for a window parameter n.

2.2.4 Graphical example

The following figure depicts each aforementioned technical indicator:

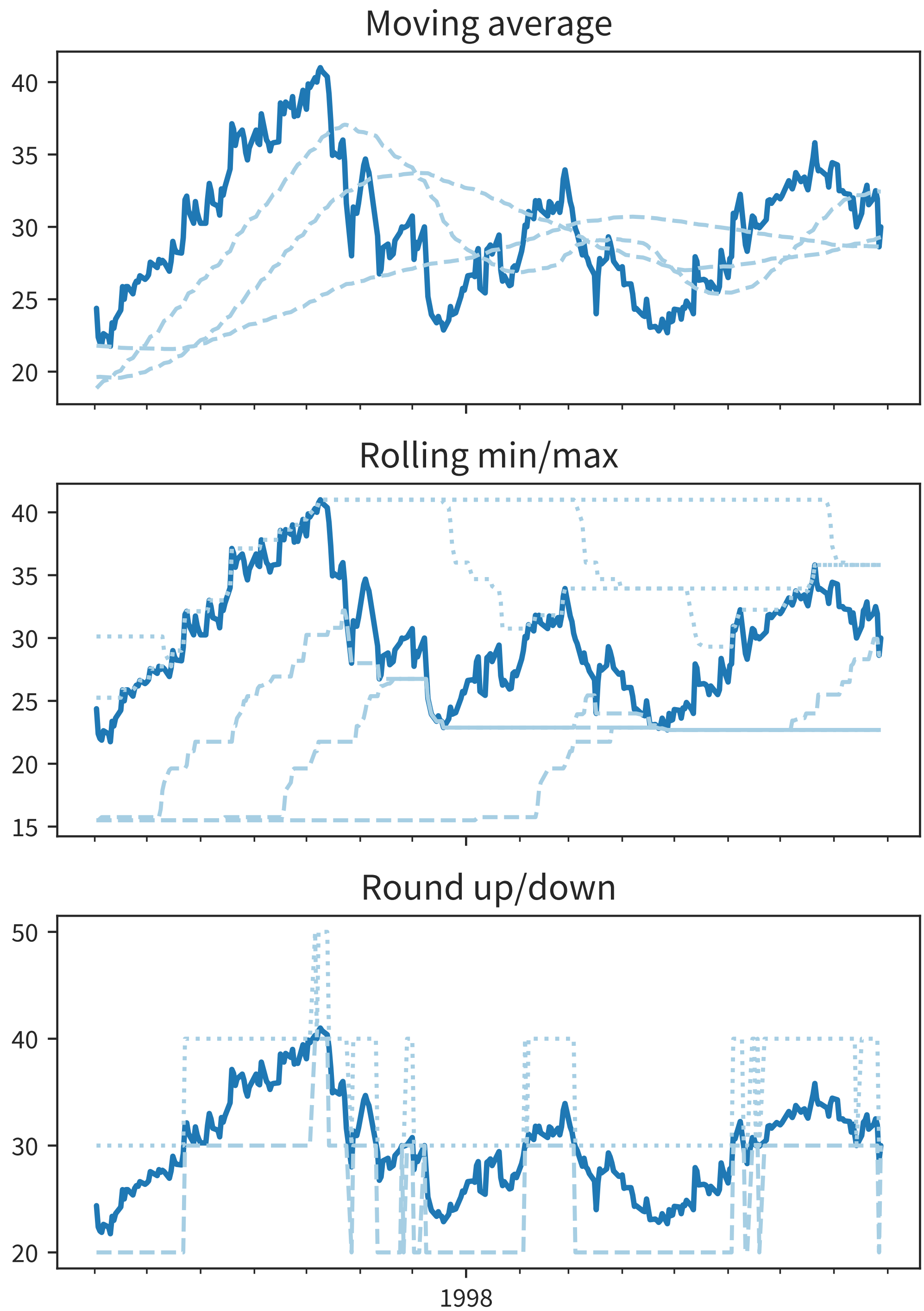

Figure 2.1: Sample of studied technical indicators for an arbitrary security

2.3 Sampling

Data will be analyzed ranging from March 4, 1957 – the inception of the S&P 500 index – to December 31, 2018. Originally, CRSP data was taken dating back to 1925; however, the results were substantially less robust up until the index's inception. Because of this sharp divergence it was more informative to drop the preceding period altogether. The original results containing all available data are made available in the appendix.

2.4 Procedure

2.4.1 Data preparation

First, CRSP data for each S&P 500 constituent was downloaded from WRDS in the following format:

```
”          PERMNO     start    ending  ...      PRC      ASK     BID”,
”0          27561  19251231  19661214  ...   93.875   94.000   93.75”,
”1          27561  19251231  19661214  ...   93.875   94.000   93.75”,
”2          16109  19251231  19851106  ...  106.750  107.000  106.50”,
”3          16109  19251231  19851106  ...  106.750  107.000  106.50”,
”4          16109  19251231  19851106  ...  106.750  107.000  106.50”,
”5          16109  19251231  19851106  ...  106.750  107.000  106.50”,
”             ...       ...       ...  ...      ...      ...     ...”,
”31309353   10145  19251231  20181231  ...  132.120  132.120  132.09”,
”31309354   10104  19890803  20181231  ...   45.150   45.160   45.15”,
”31309355   10104  19890803  20181231  ...   45.150   45.160   45.15”,
”31309356   10104  19890803  20181231  ...   45.150   45.160   45.15”,
”31309357   10107  19940607  20181231  ...  101.570  101.670  101.66”
```

All columns except for the following were dropped: PERMNO, start date, ending date, and price. Then, the data was transformed to index by date (row) and security (column) as follows:

```
”          49154      65541  32791  65568  ...  24563  81910  24571  90110”,
”DATE                                      ...                           ”,
”19251231    NaN        NaN    NaN    NaN  ...    NaN    NaN    NaN    NaN”,
”19260102    NaN        NaN    NaN    NaN  ...    NaN    NaN    NaN    NaN”,
”19260104    NaN        NaN    NaN    NaN  ...    NaN    NaN    NaN    NaN”,
”19260105    NaN        NaN    NaN    NaN  ...    NaN    NaN    NaN    NaN”,
”19260106    NaN        NaN    NaN    NaN  ...    NaN    NaN    NaN    NaN”,
”              ...        ...    ...    ...  ...    ...    ...    ...    ...”,
”20181224  61.55  232.70000    NaN    NaN  ...    NaN  15.71    NaN    NaN”,
”20181226  65.11  244.59000    NaN    NaN  ...    NaN  16.48    NaN    NaN”,
”20181227  64.71  252.17999    NaN    NaN  ...    NaN  16.71    NaN    NaN”,
”20181228  64.96  249.64999    NaN    NaN  ...    NaN  16.55    NaN    NaN”,
”20181231  66.09  254.50000    NaN    NaN  ...    NaN  16.74    NaN    NaN”
```

There are only prices for each security on days that security is one of the 500 members of the S&P 500 index. Otherwise, the price on that day is NaN.

Next, these prices are used to create the technical indicators to be studied. These technical indicators are the 50-, 100-, and 200-day moving average; the 50-, 100-, and 200-day rolling minima and maxima; and the nearest round number above and below the current price. For further details on how these calculations are performed, refer back to Section 2.2.

Using the 50-day moving average as an example, the data takes the same form as above:

```
"               49154        65541   32791   65568  ...  24563    81910  24571  90110",
"DATE                                                ...                              ",
"1926-01-30       NaN          NaN     NaN     NaN  ...    NaN      NaN    NaN    NaN",
"1926-02-01       NaN          NaN     NaN     NaN  ...    NaN      NaN    NaN    NaN",
"1926-02-02       NaN          NaN     NaN     NaN  ...    NaN      NaN    NaN    NaN",
"1926-02-03       NaN          NaN     NaN     NaN  ...    NaN      NaN    NaN    NaN",
"1926-02-04       NaN          NaN     NaN     NaN  ...    NaN      NaN    NaN    NaN",
"                 ...          ...     ...     ...  ...    ...      ...    ...    ...",
"2018-12-24   76.3430   258.376200     NaN     NaN  ...    NaN  19.8672    NaN    NaN",
"2018-12-26   75.9530   258.143600     NaN     NaN  ...    NaN  19.7980    NaN    NaN",
"2018-12-27   75.5552   258.127199     NaN     NaN  ...    NaN  19.7238    NaN    NaN",
"2018-12-28   75.1382   257.878799     NaN     NaN  ...    NaN  19.6440    NaN    NaN",
"2018-12-31   74.7716   257.683199     NaN     NaN  ...    NaN  19.5600    NaN    NaN"
```

Note that as an interim step, the date index was converted into a more readable format.

The next step we take is to convert these technical indicators into a binary signal that represents whether that day's closing price is within j% (we use a value of 1%) of the technical indicator in question. Again, the output takes the same form as above:

```
"             49154  65541  32791  65568  ...  24563  81910  24571  90110",
"DATE                                     ...                            ",
"1925-12-31       0      0      0      0  ...      0      0      0      0",
"1926-01-02       0      0      0      0  ...      0      0      0      0",
"1926-01-04       0      0      0      0  ...      0      0      0      0",
"1926-01-05       0      0      0      0  ...      0      0      0      0",
"1926-01-06       0      0      0      0  ...      0      0      0      0",
"               ...    ...    ...    ...  ...    ...    ...    ...    ...",
"2018-12-24       0      0      0      0  ...      0      0      0      0",
"2018-12-26       0      1      0      0  ...      0      0      0      0",
"2018-12-27       0      0      0      0  ...      0      0      0      0",
"2018-12-28       0      0      0      0  ...      0      0      0      0",
"2018-12-31       0      0      0      0  ...      0      0      0      0"
```

The above example, again, is for the 50-day moving average. The positive signal on December 26, 2018 for security 66541 means the security's price on that day is within j% of of the technical indicator's value on that day. All of the remaining visible values are 0, representing a negative signal, which tells us the security's price is more than j% away from the corresponding moving average value (or the security doesn't have a price on that day).

Our last step before analyzing is then to match the signals with the securities' corresponding returns. That is, using the matrices of 0 and 1 signals, we delineate returns for each security into two groups: "all" and "signal". As the names imply, the "all" group contains each day's return, while the "signal" group only contains returns where the signal value is 1 on that given day. The result is 1,830 pairs of distributions of returns for each 11 technical indicators tested. For example, here is the output for security 49154 with respect to its 50-day moving average:

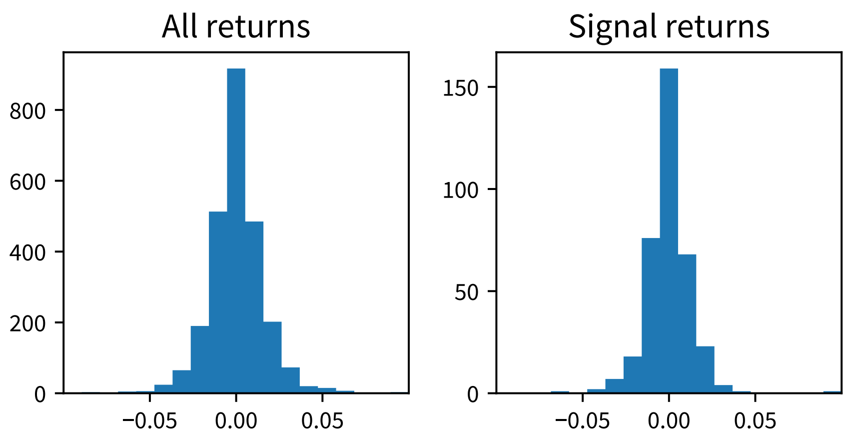

Figure 2.2: Distributions of returns for security 49154, unconditional (left) and conditional upon a positive 50-day moving average signal (right)

Finally, the data is ready to be analyzed. The following section will introduce the statistical tests used, and the results will be presented in Chapter 3.

2.4.2 Data analysis

2.4.2.1 Homogeneity of variance

The basis of our statistical analysis will be testing for homogeneity of variance (HOV) across each pair. Our null hypothesis for each security is that both samples – "all" and "signal" – have the same underlying distribution, or more specifically, the same variance:

$$\begin{aligned} H_0 &: \sigma^2_{\text{signal}} = \sigma^2_{\text{all}} \\ H_A &: \sigma^2_{\text{signal}} \neq \sigma^2_{\text{all}} \end{aligned} \tag{2.1}$$

We will test these hypotheses using the four common HOV statistics. Levene's test and the Brown-Forsythe test perform a one-way between-groups analysis of variance (ANOVA) on the absolute differences between each return and the subgroup's average from which the return came. Where they differ is in their measures of average. Levene's test uses the groups' mean returns in its calculation, making it more sensitive to departures from normality compared to the Brown-Forsythe test, which uses the median value instead.

Even more sensitive to non-normality is Bartlett's test, which follows a modified likelihood ratio test to yield a chi-square statistic. However, all of our data is assumed to be normal or roughly normal, so robustness to non-normality is inconsequential. Lastly, the fourth test is Fligner-Killeen's test, which differs by being non-parametric, and is considered robust to departure from normality. The results of these four tests will be analyzed in conjunction.

2.4.2.2 Addressing the multiple samples problem

When performing a hypothesis test multiple times, the ratio of false positives to total tests is directly proportional to the chosen alpha level. Since there are 1,830 securities, with an alpha value of 0.05, we would expect 91.5 false positives (V). This assumes p-values are uniformly distributed with $\bar{p} = 0.5$. Said differently, even if each security's pair of samples came from an identical underlying distribution (i.e. all null hypotheses are true in actuality), approximately 5% of the tests would reject the null hypothesis.

To combat these false positives, researchers attempt to minimize the false discovery rate (FDR), formally defined as:

$$E[\text{FDR}] = E[V/R] \tag{2.2}$$

Where R is the quantity of tests declared significant.

Each of these FDR control methods penalize p-values algorithmically. Whole research papers in the life sciences fields exist comparing these methods (e.g. Diz et al. 2011), with the general consensus that the Benjamini-Hochberg (BH) method provides a fair trade-off between strictness and power. The BH method involves ranking p-values in ascending order (i.e. most to least significant) and comparing them to the following scalar rather than solely a:

$$p_i \leq \frac{i}{m + 1 - i} * a \tag{2.3}$$

Where m equals the total number of tests. For all values p_i for which the above is true, we can reject the null hypothesis. Alternatively, one could divide p_i by the scalar term for each p-value to solve for a, the new effective level of significance for the test in question.

2.4.2.3 Interpreting the results

The final output will consist of 11 sets of 1,830 p-values. There is no unifying test that would allow us to declare the results either 'significant' or 'insignificant' altogether; rather, we will be drawing conclusions from the proportion of significant p-values to insignificant p-values for each technical indicator. These proportions can be thought of as the "information content" of each technical indicator. This will be discussed further in the conclusion.

CHAPTER 3

Results

3.1 Summary statistics

Table 3.1: Summary statistics for distrution of one-day returns among studied technical indicators

	Moving average			**Rolling minimum**			**Rolling maximum**			**Round numbers**		**Control**
	50d	*100d*	*200d*	*50d*	*100d*	*200d*	*50d*	*100d*	*200d*	*Up*	*Down*	
Median	0.00%	0.00%	0.00%	-0.96%	-1.05%	-1.14%	0.75%	0.72%	0.69%	0.00%	0.00%	0.00%
Standard deviation	1.58%	1.64%	1.69%	2.28%	2.53%	2.80%	1.92%	1.88%	1.82%	1.90%	1.92%	2.18%
Count	942,492	629,040	402,773	883,969	554,768	344,994	1,235,085	901,871	658,030	412,056	393,302	7,780,921
Skewness	0.57	0.56	0.54	-4.83	-4.97	-5.06	5.08	5.58	5.77	0.38	0.43	0.59
Kurtosis	8.88	9.44	9.34	64.06	63.39	61.92	87.98	109.42	115.36	18.69	23.78	35.90

Each technical indicator offers an acceptable sample size, with the smallest sample (round down) still registering on over 5% of trading days for S&P 500 constituents. We also notice that counts decrease as the window measured increases. Intuitively, assets are more likely to test short-term trends than medium- or longer-term trends.

The rest of the statistics vary across indicators in noteworthy ways. Obviously, indicators' means and medians differ substantially due to the natures of the indicators themselves. For instance, we would expect moving averages to be approximately zero mean and median (in-line with the control group) since these indicators are equally likely to be approached from above or below. The same holds for round numbers. However, the rolling minimum/maximum technical indicator clearly yields averages that suggest these indicators are much more likely to be approached from below (rolling maximum) or above (minimum).

However, the chief concern of this paper remains volatility. It is readily apparent that when an asset is arbitrarily ”near” round numbers and especially moving averages, volatility – as measured by standard deviation – is suppressed. Conversely, the rolling minimum indicator has a higher volatility by virtue of the fact that these levels are often tested in market sell-offs. Interestingly, the rolling maximum indicator actually appears to have a slightly lower volatility on average, which is an unexpected result. Perhaps rising markets tend to be more gradual (less volatile) than sell-offs.

3.1.1 Distributions of returns

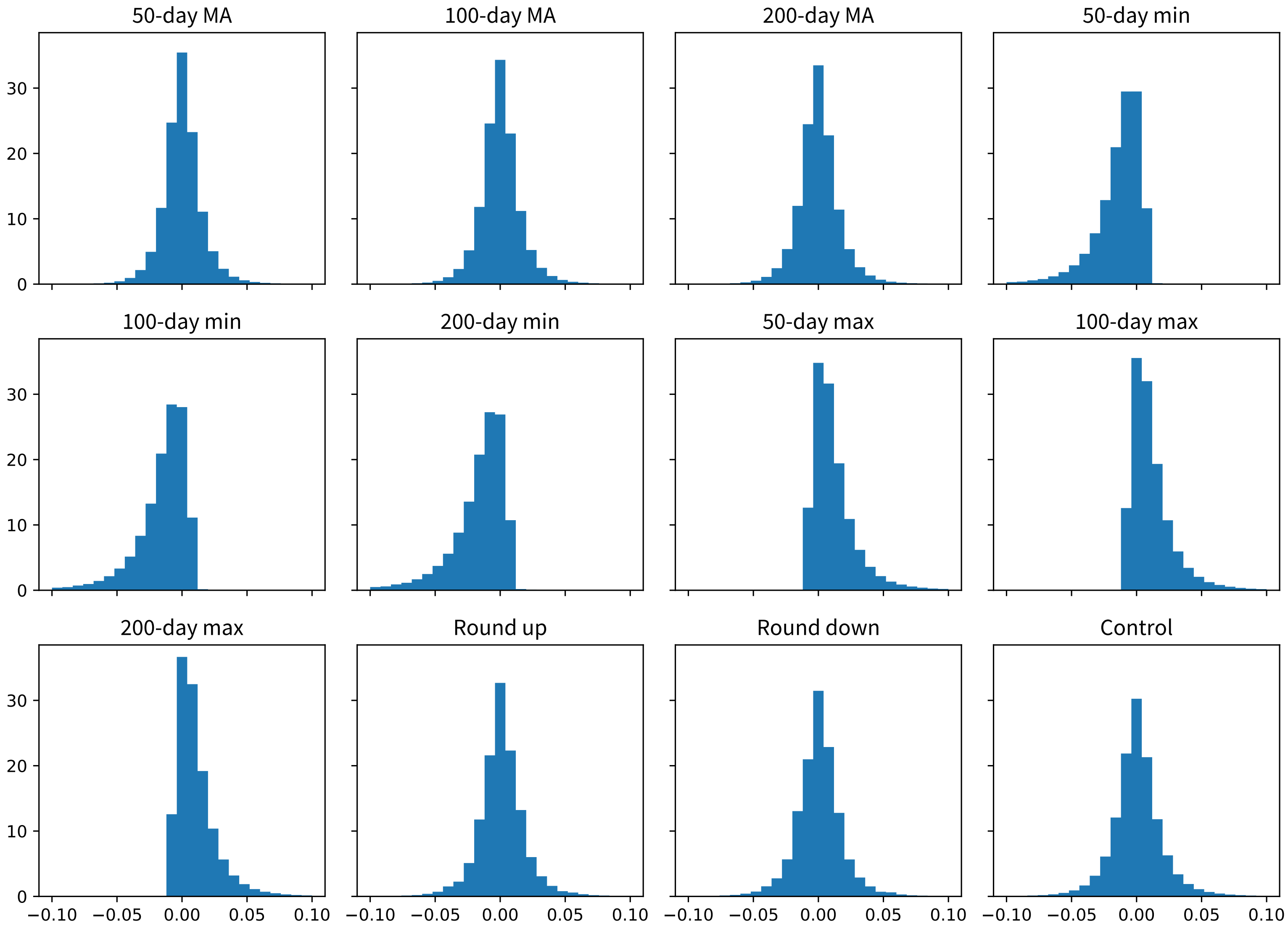

Figure 3.1: Combined distributions of returns across each security for each studied technical indicator

3.2 Hypothesis test

3.2.1 Unadjusted results

Table 3.2: Significant p-values as a proportion of all securities tested

	Moving average			**Rolling minimum**			**Rolling maximum**			**Round numbers**	
	50d	*100d*	*200d*	*50d*	*100d*	*200d*	*50d*	*100d*	*200d*	*Up*	*Down*
$a = .05$											
Brown-Forsythe	66.9%	47.6%	34.5%	37.6%	35.7%	42.3%	62.6%	62.0%	62.0%	21.4%	16.8%
Bartlett	86.4%	75.4%	66.6%	65.7%	64.7%	67.7%	75.8%	74.7%	76.2%	50.1%	44.6%
Levene	66.6%	47.9%	34.4%	39.7%	43.4%	48.7%	61.7%	61.0%	61.5%	21.7%	16.9%
Fligner-Killeen	66.0%	48.1%	34.3%	38.6%	33.0%	38.1%	67.4%	66.6%	66.5%	25.0%	19.4%
$a = .01$											
Brown-Forsythe	55.2%	34.5%	20.5%	24.1%	23.0%	29.3%	53.0%	52.8%	51.6%	11.1%	8.7%
Bartlett	80.9%	66.3%	56.2%	55.4%	55.5%	58.6%	68.7%	67.3%	68.4%	39.0%	34.6%
Levene	55.0%	35.0%	20.6%	27.2%	30.8%	37.1%	52.0%	51.0%	50.1%	11.2%	8.9%
Fligner-Killeen	55.0%	35.2%	20.4%	26.8%	20.3%	25.7%	59.6%	57.5%	56.1%	14.5%	10.0%
$a = .001$											
Brown-Forsythe	40.8%	21.8%	9.4%	14.1%	13.0%	19.4%	43.9%	42.4%	41.5%	5.0%	3.7%
Bartlett	74.4%	57.8%	44.4%	45.5%	45.2%	49.4%	60.7%	60.1%	61.2%	28.0%	24.9%
Levene	41.1%	22.4%	9.6%	15.5%	19.2%	27.0%	40.0%	40.1%	39.6%	4.6%	4.1%
Fligner-Killeen	41.7%	22.6%	11.1%	15.6%	11.9%	15.4%	51.0%	48.9%	48.1%	7.3%	5.4%

While this paper will conclude using an a value of 0.05, here we see many of our securities remain significant at a level of significance as low as 0.001. Results were especially robust for the 50-day moving average, and all windows of the rolling maximum.

3.2.2 Adjusted results

Table 3.3: Proportion of significant p-values, adjusted for multiple testing using the Benjamini-Hochberg procedure

	Moving average			**Rolling minimum**			**Rolling maximum**			**Round numbers**	
	50d	*100d*	*200d*	*50d*	*100d*	*200d*	*50d*	*100d*	*200d*	*Up*	*Down*
$a = .05$											
Brown-Forsythe	64.0%	40.4%	20.9%	26.2%	24.3%	32.2%	58.9%	58.6%	58.2%	7.4%	5.0%
Bartlett	85.9%	73.1%	63.9%	62.5%	61.5%	65.2%	74.4%	72.9%	74.9%	43.3%	38.3%
Levene	63.8%	40.8%	20.8%	30.0%	34.9%	40.6%	57.6%	57.0%	56.7%	8.1%	5.4%
Fligner-Killeen	63.2%	40.0%	20.7%	29.1%	20.6%	27.0%	65.4%	64.0%	62.4%	12.4%	7.0%
$a = .01$											
Brown-Forsythe	51.2%	26.3%	9.1%	15.5%	13.8%	22.6%	50.2%	49.1%	48.6%	3.4%	2.9%
Bartlett	80.3%	64.7%	52.0%	52.4%	51.6%	55.7%	66.9%	66.0%	67.2%	33.1%	29.1%
Levene	50.6%	26.8%	9.5%	17.9%	22.9%	31.6%	47.4%	46.3%	46.6%	3.2%	3.0%
Fligner-Killeen	50.5%	26.9%	11.4%	17.8%	12.6%	17.6%	57.8%	54.9%	53.5%	6.7%	4.5%
$a = .001$											
Brown-Forsythe	35.7%	14.5%	4.1%	7.8%	6.5%	14.1%	40.7%	39.1%	38.8%	1.2%	1.1%
Bartlett	73.3%	55.6%	39.8%	42.0%	41.7%	46.6%	59.0%	58.9%	59.9%	23.4%	19.3%
Levene	36.6%	14.6%	4.4%	9.4%	13.1%	22.5%	37.3%	36.4%	36.3%	1.2%	1.3%
Fligner-Killeen	37.0%	15.8%	4.9%	10.0%	4.8%	10.8%	49.2%	46.5%	45.2%	3.1%	1.9%

The results appear robust on an unadjusted basis, and generally remain robust after adjustment. A notable area of exception is with the round numbers indicator. Even taking into account this indicator's lesser sample size, its proportion of significant p-values is substantially smaller than the rest of the indicators. For instance, the 200-day rolling minimum substantially outperforms both round number indicators despite its smaller sample size. Therefore, one would conclude that round numbers (at least as defined by this study) carry little informational value as a technical indicator.

Similarly, and somewhat counter to expectations, significance decreases for the moving average indicator as window size increases. From purely a standpoint of sample size, this makes sense, although the rolling minimum/maximum indicators largely remain just as robust (in fact, the rolling minimum indicator becomes even more robust) as window size increases. As such, it appears moving average indicators have a larger market impact under shorter horizons.

CHAPTER 4

Conclusion

4.1 Results

As a whole, the results clearly demonstrate that return characteristics for S&P 500 constituents differ upon encountering ”support” or ”resistance” from a number of popular technical indicators. Some of these differences are expected; others, less so.

Most significantly, depending on the window measured, one-day realized volatility dropped 49-60 basis points for the average security when confronted with a moving average. This is also reflected in the drastically smaller kurtosis displayed on ”moving average days” compared with the control group. It can be said that moving averages are ”sticky” in a sense, which could have interesting implications in the options markets. The round numbers technical indicator had similar characteristics, although to a lesser extent.

It goes without saying that options prices are beyond the scope of this study, but in terms of real-life application, options are the most logical starting point. For instance, one may consider selling a straddle on a given stock that closes near its 50-day moving average if the options price fails to reflect the lower expected volatility. A strategy like this deployed across the S&P 500 and hedged for delta could be profitable on average.

It is more difficult to make any concrete, and potentially actionable conclusion regarding the rolling minimum/maximum indicators. By definition, these indicators will mostly be approached in trending markets, which skews the resulting distributions. Naturally these indicators will register strong results across our statistical tests due to this reason. Nonetheless, it could still be worthwile to examine how options prices behave when underlying security prices approach local minima/maxima.

Extending this study across other technical indicators could yield similar insights, and thus similar potentially profitable vega-based trading strategies – all without a shred of fundamental analysis.

4.2 Economic foundation

It would be worthwile to conclude by taking a deeper look into the economic significance of our results. To start, the graphic on the following page depicts the proportion of S&P 500 members that test significant across each technical indicator over time. Again, this proportion can be interpreted as the ”information content” of each technical indicator, serving as a proxy for the degree to which a given technical indicator influences index-level returns.

A caveat to this analysis, however, is that part of the increase may be attributed to survivorship bias. Over time, more securities have more data points, and overall significance increases. This effect may be partially negated by churn as securities’ prices are only included in the study on days they are S&P 500 constituents, regardless of prior trading history.

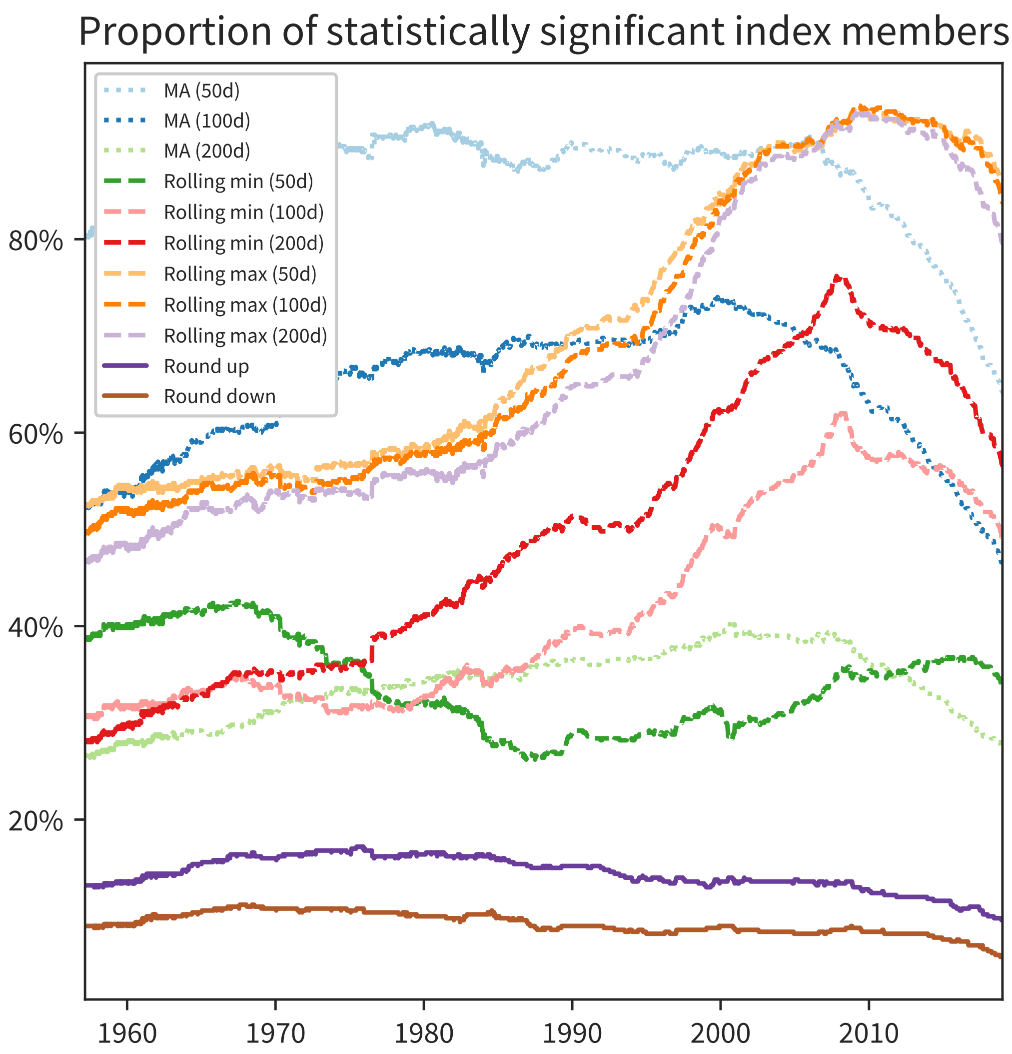

Figure 4.1: Proportion of S&P 500 members with significantly different distributions on "technical indicator days" over time

As can be seen, the overall trend is broadly positive (flat for some indicators, and positive for others) which supports the assumption that the impact of technical analysis has grown over time, perhaps owing to the proliferation of technological trading systems and high-frequency information.

However, over the past decade, this trend has interestingly pulled back. There are likely a variety of contributing factors (e.g. indiscriminant asset purchases by central banks) but the trend – which appears to have begun around the Great Recession – is certainly unexpected and merits further investigation.

APPENDIX A

Expanded results

As previously stated, we elected only to use data beginning at the inception of the S&P 500 in March 1959. However, CRSP begins providing data for an artificial S&P 500 as early as December 1925. The following tables show results using the full range of CRSP data instead.

A.1 Summary statistics

Table A.1: Summary statistics for distrution of one-day returns among studied technical indicators

	Moving average			**Rolling minimum**		
	50d	*100d*	*200d*	*50d*	*100d*	*200d*
Median	0.00%	0.00%	0.00%	-0.95%	-1.04%	-1.13%
Standard deviation	1.59%	1.64%	1.69%	2.34%	2.59%	2.85%
Count	1,057,688	703,580	447,230	978,757	612,298	381,332
Skewness	0.72	0.70	0.66	-4.69	-4.79	-4.85
Kurtosis	12.70	12.91	11.51	58.01	57.23	55.81
	Rolling maximum			**Round numbers**		**Control**
	50d	*100d*	*200d*	*Up*	*Down*	
Median	0.74%	0.72%	0.69%	0.00%	0.00%	0.00%
Standard deviation	1.98%	1.95%	1.86%	1.92%	1.94%	2.24%
Count	1,354,453	986,720	717,423	463,439	443,925	8,581,362
Skewness	5.61	6.12	6.11	0.46	0.42	0.77
Kurtosis	103.47	127.15	128.54	20.66	24.65	38.17

A.2 Adjusted p-values

Table A.2: Proportion of significant p-values, adjusted for multiple testing using the Benjamini-Hochberg procedure

	Moving average			**Rolling minimum**			**Rolling maximum**			**Round numbers**	
	50d	*100d*	*200d*	*50d*	*100d*	*200d*	*50d*	*100d*	*200d*	*Up*	*Down*
$a = .05$											
Brown-Forsythe	64.8%	42.5%	24.5%	25.2%	25.0%	33.6%	59.9%	59.5%	59.3%	9.7%	6.6%
Bartlett	86.0%	74.0%	64.8%	61.8%	61.3%	65.2%	74.4%	73.5%	75.4%	44.6%	39.2%
Levene	64.7%	42.9%	24.6%	29.6%	36.7%	42.8%	58.6%	57.7%	57.5%	9.9%	7.5%
Fligner-Killeen	64.1%	42.5%	24.9%	28.2%	21.8%	28.8%	66.1%	64.7%	63.4%	15.3%	9.6%
$a = .01$											
Brown-Forsythe	52.5%	29.5%	13.6%	14.4%	14.5%	24.2%	51.1%	50.0%	50.0%	5.3%	3.9%
Bartlett	80.5%	65.9%	53.8%	51.4%	51.7%	55.8%	67.1%	66.6%	68.0%	34.4%	30.3%
Levene	52.1%	30.4%	13.5%	17.4%	24.5%	33.7%	48.2%	46.9%	47.3%	5.2%	4.2%
Fligner-Killeen	52.1%	29.6%	15.5%	17.3%	13.1%	19.1%	58.6%	55.8%	54.7%	8.8%	6.7%
$a = .001$											
Brown-Forsythe	38.4%	18.5%	7.4%	7.3%	7.4%	15.3%	42.1%	39.9%	39.8%	2.4%	1.7%
Bartlett	74.0%	57.1%	42.3%	41.4%	41.7%	46.7%	59.5%	59.3%	60.9%	24.9%	20.7%
Levene	38.8%	18.5%	7.8%	9.3%	14.6%	24.7%	37.7%	36.9%	37.0%	2.4%	1.9%
Fligner-Killeen	39.4%	19.8%	8.2%	9.7%	5.2%	12.0%	50.2%	47.7%	46.1%	5.2%	3.7%

APPENDIX B

Source code

This research question was taken on in part to provide me a forum to learn how to program. All data manipulation, analysis, and visualization was performed in Python 3.7.2. I have elected to make the source code freely available on Github for two reasons: 1) reproducability of results, and 2) to help other new programmers trying to tackle similar projects.

As a word of warning, the source code is not well-documented, and it is at times disorganized as it was developed over the course of a changing research question. That being said, I made a deliberate effort toward explicitness while writing my code, and directions are provided in the 'readme.md' file. One should be reasonably able to replicate my results in roughly 30 minutes, depending on the strength of his/her computer.

Github: https://github.com/rdy1107/TA-thesis.git

Finally, I would like to acknowledge the following organizations for their free products/services used in the creation of this thesis: Python, SciPy, Matplotlib, TeX, JetBrains, and Atom.io. Thank you also to DTU Compute for this free-to-use LaTeX template.

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