VOLATILE FINANCIAL CONDITIONS, ASSETS PRICES AND INVESTMENT DECISIONS: ANALYSIS OF DAILY DATA OF DJIA AND S&P500, FROM JANUARY TO APRIL OF 2022

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Abstract
This paper is a logical outgrowth of empirical work in a *Securities Analysis and Portfolio Management* course at Houghton University between the start of January 2022 and end of April 2022. Remarkably, the exposure of global financial markets to two unmistakable events (shocks), the COVID-19 pandemic and the Russo-Ukrainian war (February 24, 2022)—sources of systematic risk—coincided with our empirical inquiry. The dual shocks, which exacerbated negative investment prospects for multiple product and financial sectors, heightened the uncertainty of profitable returns from investments in financial markets. The performance of eight publicly traded companies in the US and composite indices—the Dow Jones Industrial Average (DJIA) and the S& P 500—were tracked on a daily basis from January 10, 2022 to April 29, 2022, generating a total of 77 observations. Using the superior performance of a moving average model and the Holt-Winters algorithm, we found that profitable investment prospects existed during the period of systematic risk. We conclude that technical analysis provided time sensitive information for leveraged financial investments during turbulent periods of systematic risk.

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Keywords: Dollar Cost Averaging, Dow Jones Industrial Average, S& P 500, Forecasting, Fundamental Analysis, Option Pricing, Systematic Risk

1. Introduction

This paper is a logical outgrowth of empirical work in a *Securities Analysis and Portfolio Management* course at Houghton College between the start of January 2022 and end of April 2022. Remarkably, the exposure of global financial markets to two unmistakable events (shocks), the COVID-19 pandemic and the Russo-Ukrainian war (February 24, 2022)—sources of systematic risk—coincided with our empirical inquiry. The dual shocks, which exacerbated negative investment prospects for multiple product and financial sectors, including the airline industry, financial sector, the retail sector, agriculture, and the technology sector, heightened the uncertainty of profitable returns from investments in financial markets for both shareholders and stakeholders (those who would otherwise be beneficiaries of the successful performance of public corporations apart from shareholders).

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The next section provides a historical overview of the literature on asset prices, market efficiency, assorted categories of financial shocks, and investment risk exposures occasioned by the COVID pandemic.

The subsequent section (Section III) provides some data analytics that are cognizant of competing financial hypotheses (fundamental and technical analyses) but also pertinent to the issues of asset prices and scientific projections. We have used the Black-Scholes algorithm to show how investors can leverage their risks during periods of financial turbulence. Section IV presents forecasting methodologies that are capable of augmenting the preference for fundamental analysis. The empirical results of 14 weeks of observations are presented in Section VI and a comprehensive analysis and summary of the most salient aspects of the empirical inquiry in this paper are provided at the end of the paper.

2. Review of the relevant literature on asset prices and crisis/virus economics

Over the years, the prospects of financial market volatility have been extensively documented. Pointedly, financial volatility is not a new phenomenon. Conspicuously, shocks and man-made financial shenanigans have heightened the occurrence of financial market volatility with concomitant results for asset prices in distant and recent years.

When it comes to asset prices, the financial literature has prominently considered the random walk and efficient market hypotheses. The random walk hypothesis underscores the futility of using historical information to forecast asset prices, even with explanatory models. The theory maintains that the factors affecting asset prices are multifariously random, including government policies, interest rates or monetary policies, the fluctuations of corporate earnings, innovation, and unemployment. A good historical overview of the random walk hypothesis can be found in the work of Dimson and Mussavian (1998). However, the literature on the random walk hypothesis is curiously dichotomous; partly suggesting that the time series of successive returns are independent or serially uncorrelated (Kendall, 1953; Fama, 1965) while also conceding that there might be evidence of some correlation in the subset of stock and commodity prices (Cowles and Jones, 1937, and Kendall, 1953).

Yet the random walk hypothesis could hardly be separated (cleanly) from market efficiency when scientifically anticipated prices ("properly anticipated prices") and the rational foresight of economic risk in the marketplace fluctuate randomly in competitive markets (Samuelson, 1965). Of course, the concept of efficiency is based on the intensity of information dispersion and readjustments to available information. That is, financial markets and asset prices readjust in self-corrective ways to historical information, publicly available information, and privileged information in order to attain weak, semi-strong, and strong efficiencies respectively; suggesting that financial markets could not persistently return abnormal profits (Fama, 1970). Shiller (1981) discovered that stock price volatility for over a century was excessively high for it to be attributed to new information about future dividends.

Global financial markets and returns have been disturbed by capital account liberalization, sovereign debt crisis, and esoteric securitization; most recently, the mortgage-backed securities (MBS). The unsurprising outcomes of financial disturbances have enticed some economists to extensively examine why and how financial markets fail disastrously—a failure that has been succinctly characterized as "crisis economics" (Roubini and Mihm). The problem with market exposure to indebtedness has a long history, which Hyman Minsky attributed to assorted categories of financial preconditions (hedge finance, speculative finance, and ponzi finance); the most egregious being ponzi finance in which serial debtors cannot make interest and principal payments without contracting new debts.[1] The COVID-19 pandemic became an incremental addition to the growing literature on crisis economics.

A comprehensive analysis of the economic effects of the pandemic can be found in the work of Padhan and Prabheesh (2021). By extending the work of Maliszewska et al. (2020) to include the stock market, exchange rate, and oil market as the conduit of economic consequences, they discuss policy implications—monetary policy, macroprudential regulation, fiscal policy, and policy coordination—in response to the COVID-19 pandemic. Notably, they broadly characterized the effects of the pandemic on investment in terms of supply and demand conditions—the supply conditions emanating from the loss of working hours, and the decline in aggregate demand that was attributable to the decline in income as a result of unemployment and lockdowns.

The interdependence of the real and financial sectors was not lost in the discussions of Maliszewska et al. (2020). They identify four transmission channels that also connect the real and financial sectors: (i) the direct effect of a reduction in employment, (ii) the increase in international transaction costs, (iii) the sharp decline in travel, and (iv) the decline in demand for services requiring proximity between people; pointedly, the reduction in employment that leads to lower demand for capital (or loss of output), the rising costs of imports and exports for goods and services resulting in loss

[1] See the work of Mehrling (1999); see also the work of Roubini and Mihm, p.51, and Krugman, pp.41-53. Comprehensive discussions of the MBS can be found in the work of Stiglitz (2010). Reinhart and Rogoff (2009) provide historical renditions of sovereign debt and financial market crises.

of productivity and a reduction in the volume of trade, and the decline in tourism and household consumption. Prior to the outbreak of the COVID pandemic, and in the tradition of interdependent analysis of the real and financial sectors, the effects of the velocity of money on a depressed economy were empirically investigated (Warburton, 2013). Empirical findings revealed that government consumption expenditure and gross investment, real personal consumption expenditure, and the velocity of money provide robust possibilities for improving economic growth after the failure of financial and real markets.

Risk exposures in financial markets underscore a common theme of the COVID pandemic and investment decisions. Of course, systematic risk was heightened by the Russo-Ukrainian war of 2022. Global systematic risk reduced capital flows; partly as a result of financial market uncertainty, which created investment uncertainties and unsurprising illiquidity problems in the global financial system. The empirical evidence suggests that the pandemic negatively affected stock market return and increased the volatility of stock return (Padhan and Prabheesh). Corbet et al. (2020) find a stronger correlation between financial contagion and the volatility of stock market return. Yet the lackluster performance of the stock market could also be attributed to risk aversion or lagging investment decisions (Goodell, 2020).

This paper extends the financial analysis of the pandemic by investigating the conditions under which investors could have leveraged or optimized their returns through investment strategies that are sensitive to fundamental and technical analyses. Naturally, the two approaches have not been in perfect harmony whenever they have been considered to be mutually exclusive rather than mutually inclusive. However, some recent studies have endorsed the inclusive nature of the two approaches.

Fundamental analysis profiles the earnings and dividend payments of a company and its industrial affiliation to make predictions about future prospects of asset prices. Financial statements, general economic conditions, and industry performance are integral to the decisions of the fundamentalists. On the contrary, the *modus operandi* of technical analysts (chartists) is to study charts (trends) and various technical indicators that propel the demand for assets. The basic principle of technical analysis is that patterns related to past prices (historical information) of assets that are traded in financial markets could be used to forecast the direction of future prices. However, implicit in the charts are the broader subterranean economic conditions that captivate the minds of the fundamentalists.

Realistically, the profitability of technical analysis has been favorably applied to global stock markets; for example, Silva de Souza et al. (2018) applied the chartist approach to the financial markets of Brazil, Russia, India, China, and South Africa (collectively known as “BRICS”). In the process, the authors searched for evidence in support of the complementarity of fundamental and technical analyses in the financial markets of the countries by creating a comprehensive portfolio containing the assets that were separately traded in the markets of each of the countries. They subsequently found that technical analysis augmented fundamental analysis to identify the most dynamic companies in the stock markets. We have subjected various aspects of the empirical literature to a comprehensive analysis by studying 77 days of closing stock prices (data) for various companies in different industries during a period of financial turbulence. We focused on the prospects of leveraged (successful) investment during a crisis period.

3. Data analytics

The performance of eight publicly traded companies and composite indices—the Dow Jones Industrial Average (DJIA) and the S&P 500—were tracked on a daily basis from January 10, 2022 to April 29, 2022. Two companies were selected from four sectors/industries for comparative analysis—all of which could be clearly identified as large capitalized publicly traded companies, meaning that they have market value in excess of US $10 b. The four sectors considered for empirical evaluation were: (i) the technology sector, (ii) the financial services sector, (iii) the airline industry, and (iv) the retail division. The firms from each of the industries are anonymously denoted herein as *Tech 1* and *Tech2* (for the technology sector); *Fin1* and *Fin2* (for the financial sector); *Air1* and *Air2*, (for the airline sector), and *Disc1* and *Disc2* (for the discount stores or retail sector).[2]

In effect, this study is deliberately probative and didactic, reflecting the investment choices of ordinary investors who are resource constrained; that is, investors who are constrained by available financial or investment grade resources during a period of economic and financial turbulence (a period of systematic or *nondiversifiable* risk) and uncertainty. As a result, we have reasonably reached the conclusion that the units of analysis and sample size (77 observations) are adequate for probative investment decisions and outcomes under the assumption of normality in an abnormal condition.

The S&P 500, which consists of 500 stocks that are supposed to approximate the value of financial markets, is a value-weighted index rather than a price-weighted index of the DJIA variety. Therefore, the S&P indicates value—the product of prices and number of shares outstanding. The discrepancy between stock prices and value of publicly traded companies necessitate some amount of adjustment (standardization of S&P values) for econometric valuation and comparative trend analysis. We scaled the S&P values by 10.[3] The DJIA gives the average of closing prices of 30 blue-chip stocks, also assumed to be representative of market performance. The value of the index is also scaled by 10 for comparative or trend analysis.

3 (a) The risk exposures of the companies

The perceived levels of risk exposures of the companies were intuitively and theoretically impractical to stratify during a period of systematic risk. However, some companies are less exposed than others because of their capitalization and nature of business operations in financial markets. Accordingly, the standard deviation of asset prices and financial ratios provide a general framework for comparative analysis.

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[2] We prefer to maintain the anonymity of the institutions in order to discourage prejudicial or biased investment decisions with unintended consequences.

[3] Notably, stock splits and stock dividends do not affect the S&P value.

Surprisingly, the closing stock prices of firms in the technology and retail industries registered more volatility (see Table 1).

It is instantly revealing that the dollar-cost-average (DCA) methodology increased the magnitude of positive returns and reduced the margin of negative returns. The DCA worked favorably across all the sampled industries. We caveat these observations by noting that the DCA methodology did not control for elusive intermittent transaction costs and the effects of those costs on the margins of profits or losses.

Compared to the other sectors of our econometric analysis, the firms in the retail and airline sectors were not similarly affected by the war in Europe (in relative terms). The technology and financial sectors were adversely and conspicuously affected more so than the overall reversals in the composite indices; suggesting that the technology and financial sectors were more positively correlated with the composite indices, albeit to asymmetric degrees. However, unemployment in the financial sector has been determined to be less volatile relative to the manufacturing, construction, transportation, and utilities sectors (Warburton, 2021, p. 58).

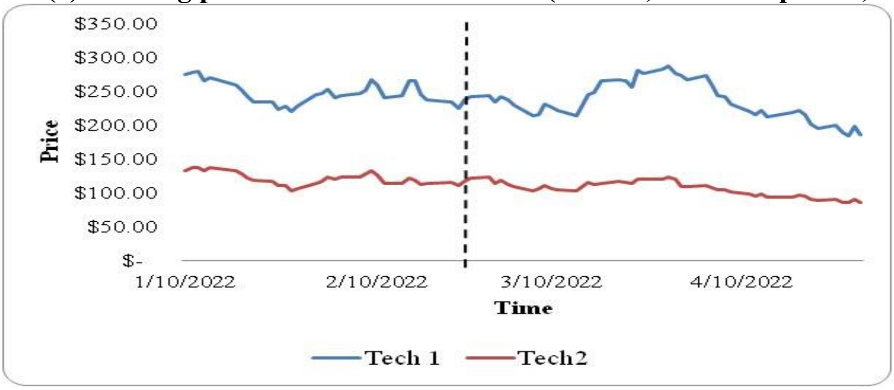
Table 1: Percentage changes of closing prices January to April 2022 (except otherwise stated)

	Percentage Change	Percentage change after the Russian war	Dollar Cost Average (DCA)	Highest Closing Price*	Lowest Closing Price*	Standard Deviation
Tech1	-32.31%	-21.90%	-22.88%	$286.56	$184.15	24.80
Tech2	-35.21%	-26.66%	-23.59%	$137.47	$84.91	12.91
Fin1	-21.17%	-17.23%	-15.97%	$59.06	$43.63	4.07
Fin2	-27.08%	-18.17%	-17.53%	$49.38	$35.68	3.76
Air1	-0.11%	10.67%	8.61%	$20.22	$12.84	1.56
Air 2	3.27%	5.37%	5.40%	$48.38	$37.19	2.14
Disc 1	5.79%	13.72%	5.91%	$159.87	$133.53	7.58
Disc2	0.54%	19.37%	3.98%	$249.32	$189.9	12.04
S&P500	-11.53	-3.66%	-6.67%	$4726.35	$4131.93	135.79
DJIA	-8.57	-0.74%	-4.33%	$36290.32	$32632.64	849.55

Notes: The dollar cost average (DCA) strategy presumes that a multiple of fixed amount of money could be invested at fixed intervals, say a day or month, over a period of time rather than lumpsum investment for an indeterminate or variable period of time. The prices from the start of January to the end of April are averaged out to determine the mean value of investment at inception (the proxy value of DCA). Values for S&P 500 denote composite capitalization values.

Closing stock prices for all of the companies that were considered for this study are graphically depicted by industry in Figure 1. The companies in the airline and retail sectors performed marginally better in March than the firms in the technology and financial sectors. However, lackluster financial performance did not foreclose the prospects of profitable investments in March 2022. Fundamental analysis provides opportunities for insights into earnings and managerial efficiencies in relatively less dynamic ways because of reporting schedules.

Figure 1 (a): Closing prices for *Tech1* and *Tech2* (Jan. 10, 2022 to April 29, 2022)



Notes: Vertical broken lines denote Russian invasion of Ukraine (Feb.24, 2022)
Data source: Yahoo finance

Figure 1 (b): Closing prices for *Fin1* and *Fin2* (Jan. 10, 2022 to April 29, 2022)

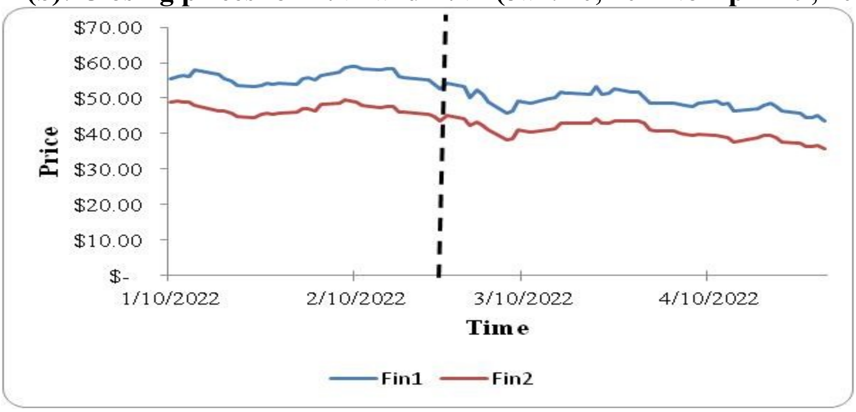


Figure 1 (c): Closing prices for *Air1* and *Air2* (Jan. 10, 2022 to April 29, 2022)

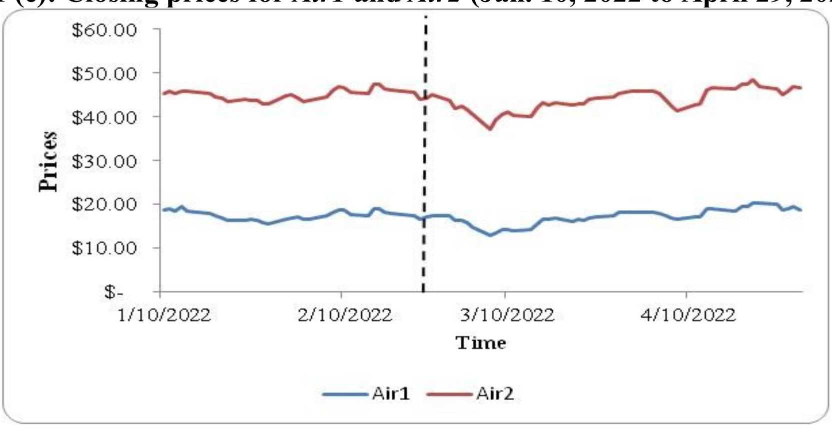


Figure 1 (d): Closing prices for *Disc1* and *Disc2* (Jan. 10, 2022 to April 29, 2022)

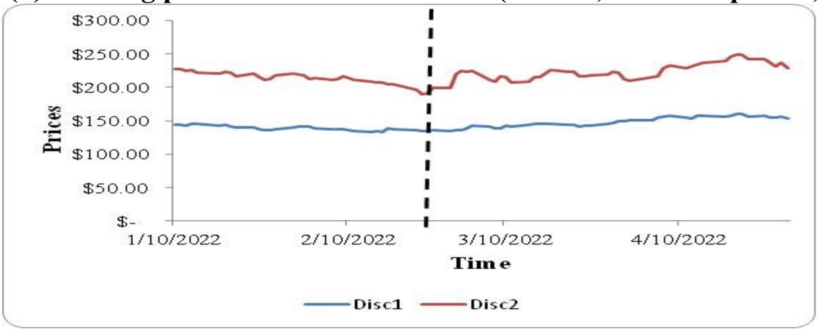
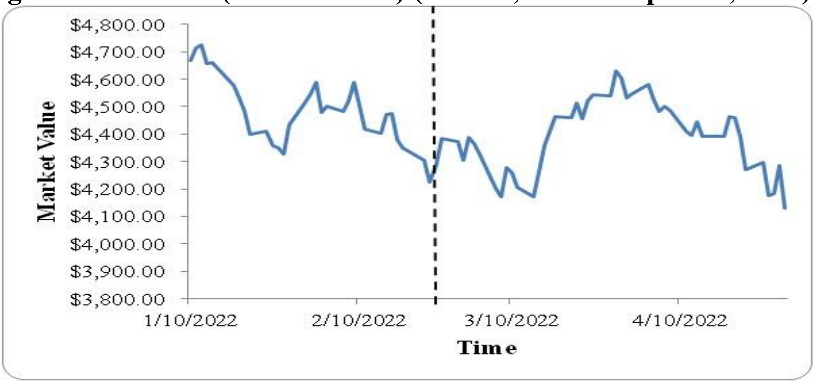


Figure 2: S&P 500 (market value) (Jan. 10, 2022 to April 29, 2022)



3 (b) Fundamental analysis

The analytical dispositions of a company's financial health and potential to grow could be obtained from fundamental analysis. Therefore, information about income, managerial efficiency, and operations of public companies, which can be readily obtained from financial statements, provides valuable information of the financial viabilities of public companies in normal and abnormal times. Since information about cash flows is conventionally derived from income statements and the balance sheets of publicly traded companies, the income statements and balance sheets provide the avenues of standardized information (financial ratios) for inter- and extra-industrial analyses. Given the nature and objectives of the businesses, we examined some of the appropriate and comparable ratios. We parsimoniously identified some financial ratios that could be exploited to analyze the prospects of profitability and managerial efficiencies of the subjects of our empirical inquiry. The price-earnings (PE) ratio, dividend ratio (Div/Ratio), profit margin (PM), Days sales in inventory (DSI)[4] and current ratio (CR, a ratio that measures liquidity in terms of current assets and liabilities) were deemed to be adequate for our empirical evaluation.

[4] It should be noteworthy that not all firms maintain inventory for operations.

The PE ratio, which is the prevailing market price per share relative to earnings per share, provides information about how investors are evaluating the value of a stock relative to others. Higher PE ratios are prima facie indicators of better earnings growth potential. The profit margin is a net income-to-sales ratio. It relates the profitability of a company to the sales of a company. Ideally, managers want to earn as much profit as possible after paying taxes so that they can project financial strength to investors. Dividend ratio (Div/ratio) is an indication of dividend payments per share in relation to earnings per share. Companies generally make dividend payments on a quarterly basis and not on a bi-weekly basis. Therefore, the data for this variable are less dynamic and generally retained for reference purposes.

The dividend ratios indirectly provide information about levels of indebtedness, cash flow, and long-term capital plans of public companies. DSI is a measurement of inventory turnover measured in terms of the number of days in a year that it takes for firms to replace their inventories.

Therefore, DSI is the reciprocal of the inventory turnover ratio (the cost-of-goods-sold-to-inventory) multiplied by the number of days in a year; lower DSI ratios indicate higher turnovers or increasing demand for the product of a company. Significantly, not all companies generate revenues by selling goods; meaning that some companies may not necessarily have inventories of goods (service-oriented businesses should immediately come to mind).

The current ratio of a company provides information about the liquidity of a company, since it tracks the ratio of liquid assets in the possession of a company relative to the liabilities that a company must pay within a year. Table 2 reports the results of the fundamentals.

The ratings of the companies remained unchanged during the period of analysis, implying that there were no significant internal drawbacks or unfavorable news about the internal operations of the companies that could have significantly disturbed investor perceptions of the financial stability of the companies.

During the period of turbulence, the retail stores turned over their inventory at a much faster rate than the technology companies. In Week 8 of our analysis, the stock price of *Tech 1* started to readjust to its earnings capacity as the rate of inventory turnover lagged behind the performance of previous weeks; such an observation is consistent with financial results during periods of sluggish consumer absorption. However, *Tech 2* improved on its disposal of inventory, suggesting that there might have been important responses to the competitive posture and managerial efficiency of the firms.

Additionally, the liquidity situation of *Tech 1* deteriorated during the Week (losing about $2 worth of current assets for every dollar worth of current liabilities). The PE ratio manifests the most dynamic results of the financial multiples but it is not necessarily a sufficient indicator of the probable scientific movement of asset prices.

Notably, the relatively stagnant fundamentals do not reveal unambiguous prospects of financial rewards or losses. The leveraging strategies of technical analysis could only augment the inadequacies of relatively static fundamentals.

Table 2: The fundamentals

	Tech 1	Tech 2	Fin 1	Fin 2	Air 1	Air 2	Disc 1	Disc 2
Week 4 (January 31 to February 4, 2022)								
	Tech 1	***Tech 2***	***Fin 1***	***Fin 2***	***Air 1***	***Air 2***	***Disc 1***	***Disc 2***
Rating	A3	Baa1	Aa2	Aa2	Baa1	Baa2	Aa2	A2
PE	70.43	32.46	10.95	12.85	N/A	N/A	48.42	16.02
Div/ Ratio	0.16 (0.07%)	N/A	0.80 (1.38%)	0.84 (1.75%)	N/A	N/A	2.20 (1.54%)	3.60 (1.63%)
PM	0.26	0.26	N/A	N/A	-1.29	-0.75	1.57	1.69
DSI	57	94	N/A	N/A	N/A	N/A	39.	59
CR	7.67	2.54	N/A	N/A	0.67	2.02	0.79	0.89
Week 6 (February 14 to February 18, 2022)								
	Tech 1	***Tech 2***	***Fin 1***	***Fin 2***	***Air 1***	***Air 2***	***Disc 1***	***Disc 2***
Rating	A3	Baa1	Aa2	Aa2	Baa1	Baa2	Aa2	A2
PE	73.85	44.04	11.78	13.42	N/A	N/A	47.65	15.57
Div/ Ratio	0.16 (0.07%)	N/A	1.00 (1.71%)	0.84 (1.75%)	N/A	N/A	2.20 (1.63%)	3.60 (1.70%)
PM	0.26	0.26	N/A	N/A	-1.29	-0.75	1.57	1.69
DSI	57	94	N/A	N/A	N/A	N/A	39	59
CR	7.67	2.54	N/A	N/A	0.67	2.02	0.79	0.89
Week 8 (February 28 to March 4, 2022)								
	Tech 1	***Tech 2***	***Fin 1***	***Fin 2***	***Air 1***	***Air 2***	***Disc 1***	***Disc 2***
Rating	A3	Baa1	Aa2	Aa2	Baa1	Baa2	Aa2	A2
PE	55.46	40.06	9.25	10.74	N/A	N/A	29.09	14.97
Div/ Ratio	0.16 (0.07%)	N/A	1.00 (2.18%)	0.84 (2.05%)	N/A	N/A	2.24 (1.57%)	3.60 (1.61%)
PM	0.26	0.19	0.25	0.36	-0.07	0.06	0.02	0.05
DSI	77	84	N/A	N/A	N/A	N/A	39	59
CR	4.09	2.02	N/A	N/A	0.91	1.97	0.97	1.03
Week 10 (March 14 to March 18, 2022)								
	Tech 1	***Tech 2***	***Fin 1***	***Fin 2***	***Air 1***	***Air 2***	***Disc 1***	***Disc 2***
Rating	A3	Baa1	Aa2	Aa2	Baa1	Baa2	Aa2	A2
PE	68.89	44.66	10.79	12.38	N/A	N/A	29.53	15.8
Div/ Ratio	0.16 (0.06%)	N/A	1.00 (1.87%)	0.84 (1.90%)	N/A	N/A	2.24 (1.56%)	3.60 (1.62%)
PM	0.26	0.19	0.25	0.36	-0.07	0.06	0.02	0.05
DSI	77	84	N/A	N/A	N/A	N/A	39	59
CR	4.09	2.02	N/A	N/A	0.91	1.97	0.97	1.03
Week 12 (March 28 to April 1, 2022)								
	Tech 1	***Tech 2***	***Fin 1***	***Fin 2***	***Air 1***	***Air 2***	***Disc 1***	***Disc 2***
Rating	**A3**	**Baa1**	**Aa2**	**Aa2**	**Baa1**	**Baa2**	**Aa2**	**A2**
PE	71.06	43.01	9.79	11.44	N/A	N/A	31.01	15.21
Div/ Ratio	0.16 (0.06%)	N/A	1.00 (2.05%)	0.84 (2.05%)	N/A	N/A	2.24 (1.48%)	3.60 (1.71%)
PM	0.26	0.19	0.25	0.36	-0.07	0.06	0.02	0.05
DSI	77	84	N/A	N/A	N/A	N/A	39	59
CR	4.09	2.02	N/A	N/A	0.91	1.97	0.97	1.03

Table 2: The fundamentals (contd.)

Week 14 (April 11 to April 14, 2022)								
	Tech 1	***Tech 2***	***Fin 1***	***Fin 2***	***Air 1***	***Air 2***	***Disc 1***	***Disc 2***
Rating	**A3**	**Baa1**	**Aa2**	**Aa2**	**Baa1**	**Baa2**	**Aa2**	**A2**
PE	56.58	36.53	9.53	10.88	N/A	N/A	32.01	16.98
Div/ Ratio	0.16 (0.08%)	N/A	1.00 (2.06%)	0.84 (2.16%)	N/A	N/A	2.24 (1.43%)	3.60 (1.54%)
PM	0.26	0.19	0.25	0.36	-0.07	0.06	0.02	0.05
DSI	77	84	N/A	N/A	N/A	N/A	39	59
CR	4.09	2.02	N/A	N/A	0.91	1.97	0.97	1.03

Notes: PE= price-earnings ratio, Div/Ratio= dividend ratio, PM= profit margin, DSI=Days sales in inventory, and CR= current ratio (a ratio that measures liquidity in terms of current assets and liabilities). Percentage changes reflect changes from the benchmark results of Week 2 (not shown here). Earnings per share (EPS) (not reported here) remain relatively constant for the companies from Week 8 through Week 14 (the period for which the ratio was tracked).

4. Leveraging losses in turbulent periods (the Black-Scholes option pricing algorithm)

It is rather surprising that the two technology firms were highly exposed to systematic risk and losses. The losses of the financial firms could have been predicted because of dwindling savings, lower investments, and financial sanctions that were almost comprehensive. So what if the bullish investors of *Tech1* had used a long-call as an investment strategy to leverage their losses by tolerating a 5% loss of the initial price of $274 on January 10, 2022 (an aggressive risk posture that could arguably be characterized as exorbitant)?

The investors would have purchased an option to strike at $260, but there could not have been prospective gain if the option was exercised after the first day of the third month (April, 2022). Notably, unlike European options, American options can be exercised at any time prior to the expiration date. Table 3 gives a list of dates when the call option for *Tech1* could have been in the money (positive intrinsic value).[5]

An option is generally considered to be the right (but not the obligation) to buy or sell a stock at a predetermined price (say a hypothetical price of $260 in this case to tolerate a subjective 5% loss of the initial closing price of *Tech1*)—a risk tolerance that could arguably be aggressive for risk-loving investors who are predisposed to invest a huge amount of money.

The value of the option is a derivative—derived from the market value of the underlying security—the market price coinciding with the initiation of the option contract ($274)—for which the investor acquires a right to buy or sell shares at a certain price within a given (expiration) period of time. Options take multiple representations of rights to buy a specified number of shares (*calls*), to sell a specified number of shares (*puts*), and to buy pre-owned (corporate) stock at a predetermined price and time (warrants). Contemporary pricing strategies are variegated and somewhat complex but

[5] Substantive discussions of options can be found in the work of Mayo, pp.625 to701.

this empirical and didactic exercise should suffice. We did not factor dividend payments into the Black-Scholes model because of the vagaries of such payments and the limited time dimension of our study.[6]

Table 3 provides some useful information about the intrinsic value of *Tech1*, contingent on a loss of 5% of initial (underlying) value. For the most part, the option could have been in the money (positive intrinsic value) in March of 2022 with a minimum value of $4.53 on March 18, 2022.

Table 3: The Long-Call and Intrinsic Values for *Tech1* (February 2022 to April, 2022)

Date	Market Price	Strike Price	Intrinsic Value	Date	Market Price	Strike price	Intrinsic Value
1-Apr-22	$ 267.12	$260	$ 7.12	2/9/2022	$ 267.05	$260	$ 7.05
4-Apr-22	$ 273.60	$260	$ 13.60	2/15/2022	$ 264.95	$260	$ 4.95
5-Apr-22	$ 259.31	$260	$ (0.69)	2/16/2022	$ 265.11	$260	$ 5.11
6-Apr-22	$ 244.07	$260	$(15.93)	3/18/2022	$ 264.53	$260	$ 4.53
7-Apr-22	$ 242.08	$260	$ (17.92)	3/21/2022	$ 267.34	$260	$ 7.34
8-Apr-22	$ 231.19	$260	$ (28.81)	3/22/2022	$ 265.24	$260	$ 5.24
11-Apr-22	$ 219.17	$260	$ (40.83)	3/24/2022	$ 281.50	$260	$ 21.50
12-Apr-22	$ 215.04	$260	$ (44.96)	3/25/2022	$ 276.92	$260	$ 16.92
13-Apr-22	$ 222.03	$260	$ (37.97)	3/28/2022	$ 282.19	$260	$ 22.19
14-Apr-22	$ 212.58	$260	$ (47.42)	**3/29/2022***	**$ 286.56**	**$260**	**$ 26.56**
18-Apr-22	$ 217.83	$260	$ (42.17)	3/30/2022	$ 276.90	$260	$ 16.90
19-Apr-22	$ 221.98	$260	$ (38.02)	3/31/2022	$ 272.86	$260	$ 12.86
20-Apr-22	$ 214.82	$260	$ (45.18)				
21-Apr-22	$ 201.83	$260	$ (58.17)				
22-Apr-22	$ 195.15	$260	$ (64.85)				
25-Apr-22	$ 199.02	$260	$ (60.98)				
26-Apr-22	$ 187.88	$260	$ (72.12)				
27-Apr-22	$ 184.15	$260	$ (75.85)				
28-Apr-22	$ 197.82	$260	$ (62.18)				
29-Apr-22	$ 185.47	$260	$ (74.53)				

The Black-Scholes pricing strategy realistically assumes that asset prices cannot be negative (asset prices are bounded by zero). Therefore, the truncated normal distribution, which shows the positive segment of the symmetric normal distribution (the lognormal distribution), is the preferred pricing methodology—hence, a series of curves that are skewed to the right with variations in means and standard deviations.

The values for pricing the call option of *Tech1*, the riskiest of the stocks, can be obtained from available data. Netcials.com provides the annual returns of *Tech1* from 2013 to May 13, 2022. The data are very useful to estimate the standard deviation of returns for *Tech1*. We estimated the standard deviation of its returns to be 0.93%. The minimum intrinsic value for this category of stock (for the period under review) is estimated to be $4.53. The strike price that tolerates a 5% loss relative to the initial price

[6] The classical representation adopted herein can be found in the work of Mayo, pp.670-679. The Greek alphabet soup is most notable for pricing options; see *Macroption,* https://www.macroption.com/option-greeks/

of the stock—the underlying value of $274—is $260, the standard deviation of returns for *Tech1* is estimated to be 0.93%, and the annual risk free rate, which is the Fed Funds Rate that coincided with the maturity of the option (Three Month Treasury Bill Rate is 1.04%.[7] We considered a-three-month (0.25) lifespan for the expiration of the option contract. The option price, presumed to be $20 in this case, is usually exogenously determined or quoted by an exchange, say the Chicago Board of Options Exchange (CBOE). The foregoing asset prices and assessments of risk provide sufficient information to estimate the value or trajectory of the call option for *Tech1* at the prevailing market price of $286.56. Though the option is conveniently presumed to be purchased naked in this case, nothing precludes the seller from leveraging the transaction with a covered call.

Table 4 provides a summary of the parameters of the Black-Scholes. We note that the maximum price at which the option could have been exercised is $286.56 on March 29, 2022. Unfortunately, investors do not always have a crystal ball, and investment is contingent on trials and errors or scientific guesses. Forecasting, which will be dealt with more extensively in the next section, could imprecisely enhance the levels of investors' intelligence about prospective trends and asset prices.

Table 4: Parameters of the Black-Scholes' call option

Parameters	Value
Stock price (P_S)	$286.56
Strike price (P_E)	$260
Time to expiration (T)	0.25
Annual standard deviation of returns (σ)	0.93
Risk free rate of comparable maturity(r)	1.04%

The call option pricing model for *Tech1* could then be stipulated as:

$$V_0 = P_S * F(d_1) - \left(\frac{P_E}{e^{rT}}\right) * F(d_2); \qquad (1)$$

where P_S is for a prevailing stock market price, $F(d_1)$ and $F(d_2)$ are for relative stock prices and volatility associated with the terminal value of the option (areas under the normal distribution), e is for the base of a natural log (2.71828), P_E is for the strike price, r is for the risk free rate coinciding with the maturity of the option contract, and T is for the terminal value of the option contract; (d_1) and (d_2) can be further defined more clearly as:

$$d_1 = \frac{\ln\left(\frac{P_S}{P_E}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} = 0.4473 \qquad (2)$$

[7] This information could be obtained from YCharts, https://ycharts.com/indicators/3_month_t_bill or FRED.

$$d_2 = d_1 - \sigma\sqrt{T} \;=\; (0.01773) \tag{3}$$

The main arguments of the option profile can be graphically posited for clarification and ease of reference (see Figure 3(a)).

Figure 3(a) : A naked call-option for *Tech1* (profits and stock price)

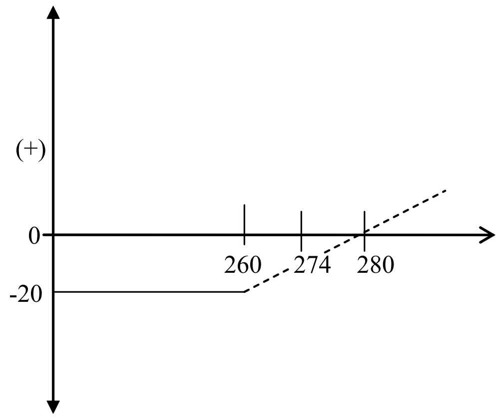
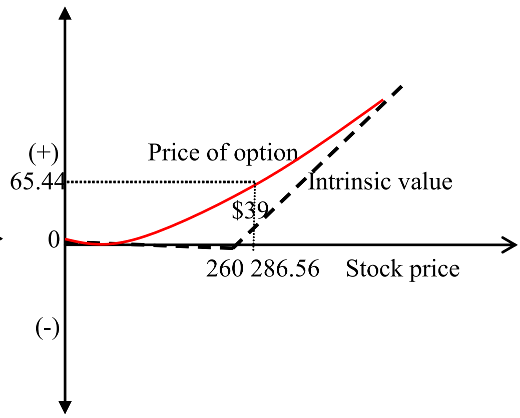


Figure 3(b) Stock price and intrinsic value



The Black-Scholes model shows that the value of the option for a *Tech1* stock of \$286.56 per share would have been \$65.44 cents (see Figure 3(b)), an improvement on the purchased price and realization of profit in turbulent financial times.

$$V_O = \$286.56 * 0.6736 - \left(\frac{\$260}{2.71828^{(1.04*0.25)}}\right) * 0.492 = \$65.44\,; \qquad \text{where}$$

$F(d_1)=0.4473 \rightarrow 0.6736$, and $F(d_2)= -0.01773 \rightarrow 0.492$. The time premium, which is equal to the option price (\$65.44) less the intrinsic value (\$26.56), would have been \$38.88 cents (≈\$39). However, the projection of stock prices is ordinarily challenging in times of relative stability and daunting periods of financial instability. Scientific algorithms assist investors to make informed and measured decisions. The mere perceptions of scientific trends could give investors indicators of price movements for informed investment decisions in bounded time periods. For example, Figure 1(a) provides an ocular representation of the upward trending stock prices of *Tech1* during March. Naturally, this trend could have been forecasted without beneficial hindsight. Three forecasting tools, albeit with some limitations, could be considered for prospective investment decisions; we have considered two of the three—moving averages and the seasonal and trend decomposition using Loess (STL)—for the sake of brevity (we exclude regression (explanatory) analysis with a trend).

5. Forecasting the stock prices of *Tech1*: Models and financial diagnoses

Forecasting is an inexact science for scientific projection of values. It is a realistic combination of art and science. Since investors are not omniscient, it is impossible for them to pinpoint the most lucrative price for the exercise of an option as depicted in Figure 3(b). However, investors can study trends and the fundamental properties of data, even in troubled times, to make quantitative forecasts.

The preliminary challenge confronting forecasters is to determine the appropriate forecasting model for scientific projection; such a decision is partly dependent on studying the time series and the properties of the relevant data for quantitative forecasts. Figure 1(a) shows two downward trends for *Tech1* and an upward trend during the month of March (the month that has been designated for the exercise the option). Evidently, Table 3 corroborates such an observation.

The diversity of forecasting objectives elicits a wide range of options that are contingent on the forecasting goals and available data.[8] It is conventionally strenuous to evaluate forecast errors that are associated with quantitative forecasting methodologies.[9] Yet it is probably more instructive and beneficial to evaluate the models against actual available data—"new data that were not used when fitting the model" (Hyndman and Athanasopoulos, p.62).

The time series of *Tech1* (see Figure 1(a)) does not clearly show the combinations of seasonal, trend, and irregular patterns that should be extrapolated for informed investment decisions.

However, the data provide sufficient information to determine the type of decomposition that is reasonably plausible. Decomposition of a time series data is generally contingent on patterns of the relevant data or series.

Data with amplified seasonal patterns and increasing trends are generally good candidates for multiplicative decomposition; a reasonably good representation of this

[8] Methods may include models with little quantitative information (qualitative models), intuitive/ad hoc (including naïve forecasts that replicate the most recent results) or formal quantitative techniques that rely on statistical principles, explanatory models (regression specifications), or time series methodology. Time series forecasting does not rely on exogenous factors that suggest correlative or causative relationships. Therefore, under the presumption that the correlative factors are less important or refractory to discern, time series forecasting relies on past historical values and errors. A comprehensive discussion of forecasting methodologies can be found in the work of Makridis et al., pp.6-12.

[9] Ascertaining the magnitude of scientific errors is equally challenging. Multiple methods requiring adequate precaution could be utilized to measure forecasting error: (i) the root mean squared error (RMSE), (ii) the mean absolute error (MAE), (iii) the mean absolute percentage error (MAPE), (iv) the symmetric mean absolute percentage error (SMAPE) and (v) the Theil inequality coefficient. The RMSE and MAE are scale sensitive (same series but different models) and dependent on the scale of the dependent variable used for comparative analysis. The MAPE and Theil are scale insensitive, with the Theil, which ranges from 0 to 1, showing a strong preference for numbers that hover around zero.

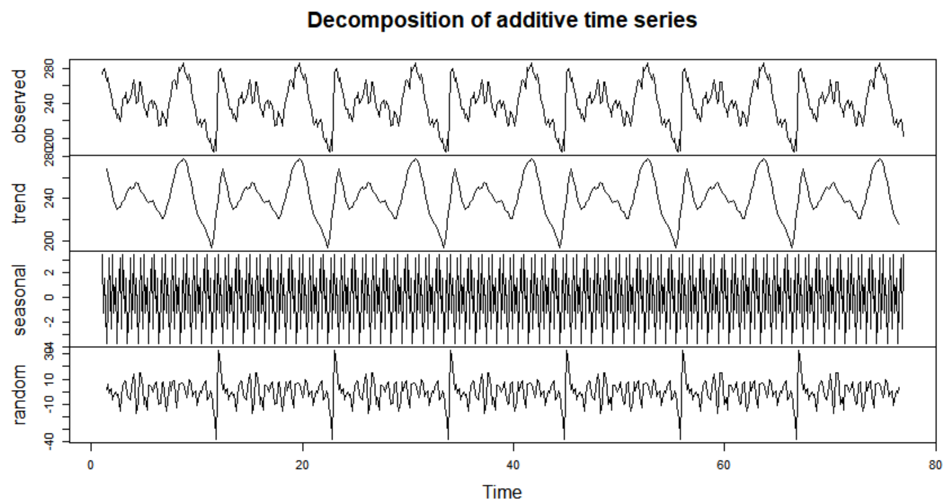
form of data can be found in Hyndman and Athanasopoulos p.30, depicting Antidiabetic drug sales.[10]

Stock prices are generally known to follow very irregular trends and patterns that lack evident seasonality of the amplified classification or even clear seasonal patterns; especially because the determinants of stock prices are generally and multifariously imprecise, including the "irrational exuberance" of investors or the Keynesian "animal spirits." Stock prices are therefore good candidates for the additive decomposition:

$$y_t = S_t + T_t + R_t\,; \qquad (4)$$

where y_t is for the stock prices of *Tech1*, S_t is for the seasonal component, T_t is for the trend-cycle component, and R_t is for the irregular, random, or residual component of the series. We utilized the R programming language to decompose the *Tech 1* series and report our findings as Figure 3.

Figure 3: Additive decomposition of the *Tech 1* series



The additive decomposition is most appropriate if the magnitude of the seasonal fluctuations, or the variation around the trend-cycle, does not vary with the level of the time series. When the variation in the seasonal pattern, or the variation around the trend-cycle, appears to be proportional to the level of the time series, the multiplicative decomposition is more appropriate. (Hyndman and Athanasopoulos, 2018, p. 158)

[10] See also Makridakis, Wheelwright, and Hyndman (1998) *Forecasting: methods and applications*, for monthly airline passenger data from 1949 to 1960, p.112.

The random and seasonal vacillations are generally constant in size over time and are not dependent on the level of the time series. The random component consists of residuals after removing the trend and seasonal components. Equation 5 depicts the multiplicative decomposition, which does not describe the series of interest in this case:

$$y_t = S_t * T_t * R_t \ . \tag{5}$$

Eviews 12 was preferentially utilized to test the significance of a latent trend in the series—the trend cycle for scientific guesses—and report our findings in Table 5. In the presence of a negative (-0.45) and strong trend (t-Stat of -3.89), we had to reject the null hypothesis that the latent trend is insignificant (see Table 5). Accordingly, the trend diagnosis suggests that the presence of a trend could not be ignored in the forecasting models. We considered three forecasting algorithms: (i) The centered moving average, (ii) a simple moving average of order 3, and (iii) the exponential smoothing algorithm (error, trend, and seasonality, (ETS) proposed by Holt and Winters.

Table 5: A significant trend test ($\beta_T = 0$)

Dependent Variable: TECH
Method: Least Squares
Date: 05/30/22 Time: 14:52
Sample: 1 77
Included observations: 77

Variable	Coefficient	Std. Error	t-Statistic	Prob.
T	-0.454449	0.116766	-3.891971	0.0002
C	258.2063	5.241476	49.26213	0.0000

R-squared	0.168030	Mean dependent var	240.4827
Adjusted R-squared	0.156937	S.D. dependent var	24.80246
S.E. of regression	22.77325	Akaike info criterion	9.114681
Sum squared resid	38896.55	Schwarz criterion	9.175559
Log likelihood	-348.9152	Hannan-Quinn criter.	9.139031
F-statistic	15.14743	Durbin-Watson stat	0.193157
Prob(F-statistic)	0.000214		

The ultimate objective of the moving average algorithm is to derive trend-cycles—the main movements of time series data without the pronounced intervening gyrations (for example, see 2M and 3M of Figure 4). The smoothness of the trend-cycles has been reported to be contingent on the order of the moving averages. In general, a larger order is indicative of a smoother curve.[11]

[11] For example, see Hyndman and Athanasopoulos, p.163.

Aforesaid, we utilized very high frequency data of daily closing stock prices, necessitating a moving average of a smaller order. For the purpose of symmetry, simple moving averages are conventionally represented in odd orders of 3, 5, 7, 9 etc.[12] We ambitiously subjected the series to a centered moving average evaluation that combines higher and lower orders for symmetry under the presumption that hidden cycles could significantly affect the forecasting result. The results of our findings and performances of the forecasting models are reported in Table 6. We have followed the representation of Hyndman and Athanasopoulos to denote the underlying principle of the trend estimate:[13]

$$\widehat{T}_t = \frac{1}{m}\sum_{j=-k}^{k} y_{t+j} \; ; \qquad (6)$$

where m = 2k+1 or the order of the moving average that estimates the trend cycle by averaging the value of the series within k periods of time. The elimination of oscillations in the series provides a trend cycle of the moving average order (m).

Our ambitiously probative inquiry produced a weighted (centered/symmetric) moving average of the order 2*4-MA that has been provided by Hyndman and Athanasopoulos, p.165:

$$\widehat{T}_t = \frac{1}{2}\left[\frac{1}{4}(y_{t-2} + y_{t-1} + yt + y_{t+1}) + \frac{1}{4}(y_{t-1} + y_t + y_{t+1} + y_{t+2}\right], \qquad (7)$$

$$\widehat{T}_t = \frac{1}{8}y_{t-2} + \frac{1}{4}y_{t-1} + \frac{1}{4}y_t + \frac{1}{4}y_{t+1} + \frac{1}{8}y_{t+2}\,.$$

The empirical findings associated with Equations 6 and7 are reported in Figure 4 and Table5. We compared the empirical findings and the performance of the models to that proposed by Holt (1957) and Winters(1960).

Holt-Winters extended Holt's method to capture seasonal variations. The Holt-Winters seasonal method consists of the forecast equation and three smoothing equations—one for the level (l_t) (with a smoothing parameter notation of α), another for the trend (b_t) (with a smoothing parameter notation of β*), and a third equation for the seasonal component (s_t) (with a smoothing parameter notation of γ). The additive method of Holt and Winters could also be found in the work of Hyndman and Athanasopoulos, p.199.

$$\widehat{y}_{t+h|t} = l_t + hb_t + s_{t+h-m(k+1)} \; ; \qquad (8)$$

[12] Ibid.
[13] See Hyndman and Athanasopoulos, p.161.

$$l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}); \qquad (9)$$

$$b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1} \quad ; \quad \text{and} \qquad (10)$$

$$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m} \ ; \qquad (11)$$

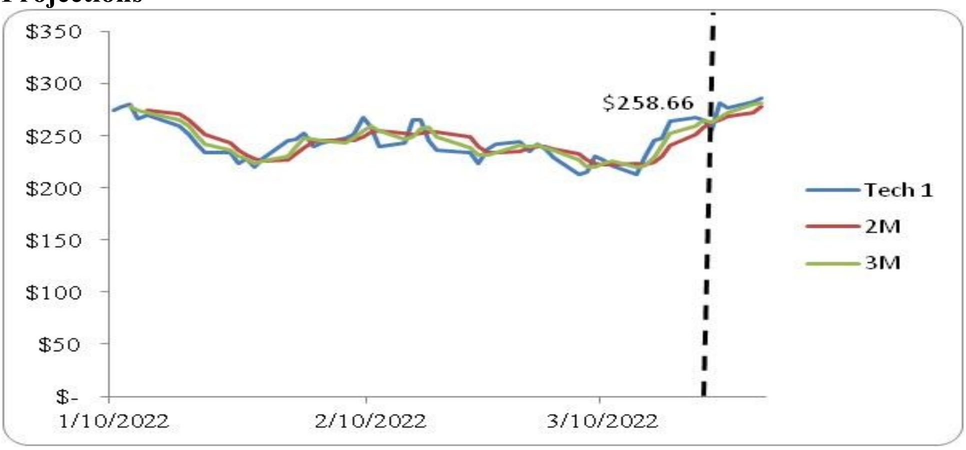
where Equation 8 is the forecasting equation, Equation 9 specifies the equation for the level, the trend and seasonal equations are provided by Equations 10 and 11 respectively, *h* is for the forecast horizon, *m* is for the number of seasons (repeated patterns) that could be detected, and *k* is for the integer part of h-1/m, which ensures that the estimates of the seasonal indices utilized for forecasting come from the final value of the sample.

The level equation depicts a weighted average between the seasonally adjusted observations (y_t-s_{t-m}) and the non-seasonal forecast (l_{t-1}+b_{t-1}) for time *t*. Equation 8 estimates the linear trend and the seasonal equation (Equation 9) shows a weighted average between the current seasonal index (y_t-l_{t-1}-b_{t-1}) and the seasonal index of the same season in the previous period (*m*) (see Hyndman and Athanasopoulos, p.199).

6. Empirical findings

The moving average results consistently support the upward trend of stock prices for *Tech 1* by the end of March 2022 though the efficiencies of the models are not identical. The moving average of order 3 outperforms the centered moving average on the bases of forecast accuracy ($4.67 difference) and the margins of scientific errors (RMSE of 7.72 and SMAPE of 3%); see Table 5.

Figure 4: The Moving Average (3-M) and Centered Moving Average (2*4-M) Projections



Notes: The 2M (centered moving average, 2*4-MA) and 3M are moving average projections. The forecasting period (March23-March 29) occurs after the vertical broken line; see Table 6 for the results.

Table 6: Models and forecasted results for *Tech 1* stock prices (US$) (March 23-March29)

Date (2022)	Actual stock price	2*4-MA	3-MA	ETS (upper bound)	ETS Actual	ETS (lower bound)
23 March	256.34	262.28	262.97	278.43	250.61	265.24
24 March	281.50	265.48	267.69	278.90	250.21	222.79
25 March	276.92	268.80	271.59	279.35	249.82	221.53
28 March	282.19	272.12	280.20	279.78	249.42	220.29
29 March	286.56	278.02	281.89	280.20	249.03	219.07
Error Measurements						
RMSE	N/A	11.89	7.92	18.22	18.22	18.22
SMAPE	N/A	0.04	0.03	0.06	0.06	0.06

Notes: March 29, 2022, is the empirical exercise date of the call option. The centered moving average is denoted by 2*4-MA (moving average of orders 4 and 2), 3-MA is for the moving average of order 3, and ETS is for "error, trend, and seasonality," which is alternatively known as exponential smoothing..

The actual ETS forecasted values are $RMSE = \sqrt{\frac{1}{n}\sum\left(Y_t - \widehat{Y}_t\right)^2}$; where n is for the number of observations considered, sigma is the usual summation operator, Y_t is for the actual values, and $\widehat{Y}_t$ is for the forecasted values. The RMSE measures the deviation of forecasted values from actual values in a standardized way but is usually sensitive to scale. It considers all the values in the high frequency time series data against the forecasted values. In essence, it is a reasonable representation of the unpredictable parts of the models.

The symmetric mean absolute percentage error (SMAPE) reports relative or percentage errors—the absolute error divided by the size of the exact value. Armstrong (1985, p. 348) has been widely credited for the introduction of the test to empirical analysis.[14] It incorporates bounded values and it is generally insensitive to the scale of time series data, which makes it useful for comparative analysis across models and datasets:

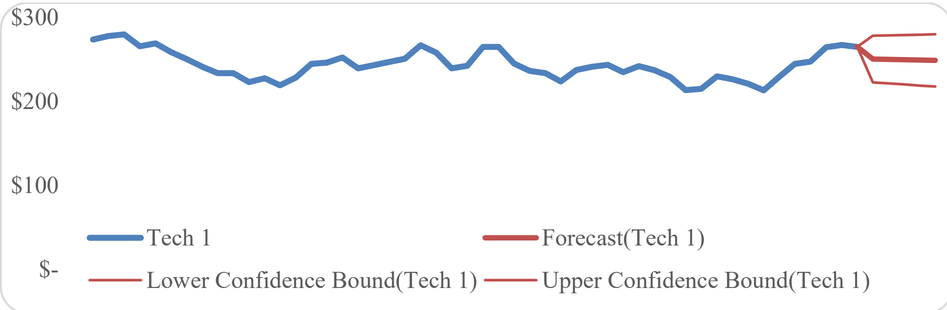
$SMAPE = \frac{1}{n} * \sum \left[\left(|\, \widehat{Y}_t - Y_t \,|\right) * \left(\frac{2}{|\, Y_t + \widehat{Y}_t \,|}\right)\right] * 100$. Notably, this paper uses a consistent scale.

The 3-M model also outperforms the ETS, which optimally smooths the level (α=0.25) but not the trend and seasonal components of the series. The ETS' upper bound of the 95% confidence interval is more aligned with the actual values than the forecasted values or the more pessimistic values. Notably, the ETS records higher margins of errors

[14] See Hyndman and Athanasopoulos, p.65. Hyndman and Koehler (2006) propose the use of scaled errors when comparing forecast accuracy across series with different units.

relative to the moving average models. The RMSE, which suggests standard deviation units of errors, are much more refractory to put into perspective. Therefore, the SMAPE, which is based on percentages that are insensitive to units or scale of data, provides a more insightful and meaningful framework for model evaluation.

Figure 5: The ETS Results (March 23-March 29, exercise date)



Notes: Smoothing parameters: α =0.25, β*=0, and γ=0.

We close this section with an unavoidable precaution:

> It is important to evaluate forecast accuracy using genuine forecasts. Consequently, the size of the residuals is not a reliable indication of how large true forecast errors are likely to be. The accuracy of forecasts can only be determined by considering how well a model performs on new data that were not used when fitting the model. (Hyndman and Athanasopoulos, p.62).

7. Discussion and conclusion

This paper affirms the theory that firms are exposed to various levels of risks in normal and abnormal times. It subscribes to the view that fundamental and technical analyses are not mutually exclusive. Though the theories are not mutually exclusive, technical analysis provides an expeditious framework to discern profitable trends in financial markets. We found that systematic risk does not foreclose the prospect of profitable investment during periods of financial turbulence. We therefore consider the leveraging effects of the dollar cost averaging technique and the call option pricing strategy proposed by Black and Scholes. Significantly, both measures provide leveraging opportunities albeit with imprecise preferential costs.

Though it is conceivable that stock prices follow a random walk, trend cycles and scientific projections provide algorithms to imprecisely forecast the general trajectory of asset prices. In this study, we evaluated the efficacy of moving averages (trend cycles) and Holt-Winters with the realization that trend cycles could still provide reasonable and superior opportunities to determine the general trajectory of asset prices. The technical ascertainment of the general direction of asset prices in normal and abnormal times may not necessarily be an exercise in futility after all.

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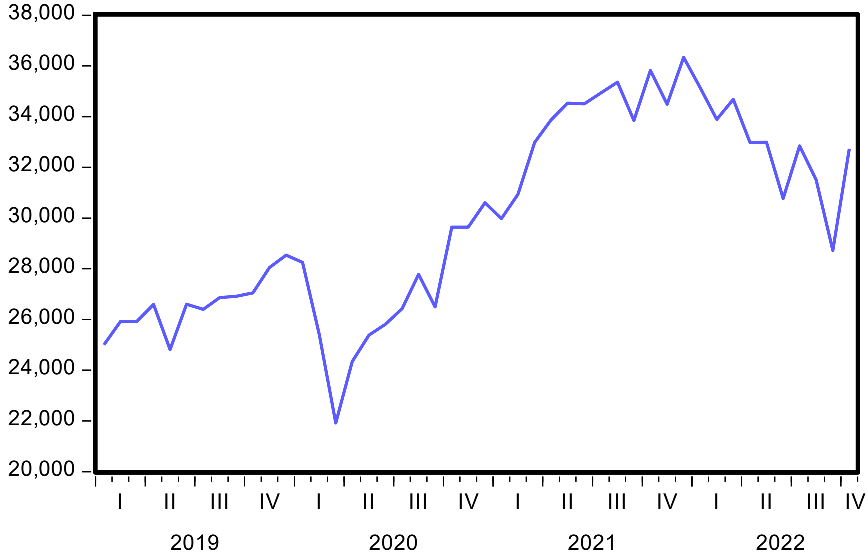
Annex: Evolution of DJIA, 2019.01-2022.10

Evolution of DJIA, monthly averages for the period January 2019 to October 2022



Source. Elaborated from data of the Dow Jones Industrial Average at Statista: https://www.statista.com/statistics/261690/monthly-performance-of-djia-index/