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High Frequency Return and Risk Patterns in U.S. Sector ETFs during COVID-19

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ABSTRACT

This study investigates intraday patterns in the eleven sectors of the United States (U.S.). Key contributions are (i) risk and return patterns at specific trading periods on the New York Stock Exchange (NYSE), (ii) whether a specific day return model can predict the next 15-min positive return, and (iii) the impact of the first vaccination rollout in the U.S. on intraday Exchange-Traded-Funds (ETF) returns. Time-dependent regressions capture risk and return relationships, decision trees in machine learning compare return models, and impulse responses capture the effect of the 2019 coronavirus (COVID-19) vaccine rollout in U.S. 15-min Standard and Poor's Depository Receipts (SPDR) Select Sector ETF data is used over 12th March 2020-23rd February 2021. Findings support sector ETF returns fluctuate the most in the first and last 15 min. Average returns in the first 15 min are the highest, converging to near zero as the trading session continues. Overnight returns contribute the most to volatility. U-shaped patterns into both return and risk exist, especially on Mondays. Mondays and Fridays have the most significant positive returns 15 min after the open. Prediction scores using an all-return model were superior to any specific day return model. The first vaccination rollout has a positive effect only in energy, technology, and financial sector ETFs, however with a short-lasting effect on ETFs returns.

Keywords: U.S. Sectors, COVID-19, High Frequency Trading, Risk, Return, ETF, Machine Learning
JEL Classifications: G11, G12, G14, G15

1. INTRODUCTION

With an average trading volume nearing $85 billion per day and representing roughly 30% of the total U.S. equities volume, ETFs play a vital role in price discovery. Various studies such as Ernst (2021), Hasbrouck (2013), Sağlam, Tugkan and Wermers (2020) emphasize the benefits of ETFs in terms of improved liquidity, hedging and increased pricing efficiency for stocks. While there is an extensive literature on stock market return predictability (e.g. Rapach and Zhou (2013) for a broad survey), machine learning applications in Finance (Kamalov et al., 2021; Kamalov, 2020a; Smail and Gurrib, 2020b), studies on industry and sector ETFs are scarce, and studies on the major U.S. sector ETFs at high frequency are even more scarce. ETFs have been used extensively to specify returns in a portfolio (market, size or value). For example, Chinco et al. (2017) use 1-min iShares market ETF for market return, and iShares Russell 1000 and growth ETFs for size and value returns. Jiang et al. (2020) use 30-min returns for 226 sectors and find predictive power in the first 30 min. Lachance (2021) finds order imbalances increase overnight returns in ETFs and are exploitable. While we do not predict return or risk in this study, we go one step back by providing useful insights into the risk and return behavior of the 11 U.S. sectors using 15-min frequency information, in a period characterized by unprecedented events like COVID-19. We include both order imbalances at close and overnight returns to better understand ETFs risk and return.

We are the first to propose to look at intraday risk and return behavior patterns in 11 U.S. sectors, using 15-min frequency

ETF data. Our use of high frequency data is motivated by recent studies like Gao et al. (2018) who use intraday S&P500 ETF data and find intraday momentum patters during the first and last half hour, and Ambros et al. (2020) who use 30-min tick returns to examine the impact of COVID-19 news onto global markets. Further, to support the use of high frequency data in our sector ETF study, we borrow from Fama (1998) who justifies that market responses over a short time window provide more insights into market efficiency. Similar to expected returns on individual stocks being small during a short window and not very sensitive to model specifications (Fama, 1970), sector ETFs returns are also expected to be small since the sector ETFs are based on stocks. In our study, we consider large-cap stocks listed in the S&P500. We use Select Sector SPDR Funds due to the superiority of ETFs in their respective sectors, in terms of their solid tracking of U.S. sector indices, trading volume, asset under management, low expense ratios, and fund flows. The eleven Select Sector Indexes upon which the Select Sector SPDR Funds are based together constitute all the companies in the S&P 500.

World Bank (2020) characterized the impact of COVID-19 on financial markets as price adjustments with investors flight to safer assets and waning investors' risk appetite for riskier assets such as equities. Estrada et al. (2020) study ten major markets and caution that the current crisis can result in damages comparable to the 1929 crisis, with a 9–12-month recovery period. Eichenbaum et al. (2020) estimate that aggregate consumption and GDP in the U.S. will fall up to 20%. This impact is similar in various countries where governments ordered businesses to shut and families to stay at home except for essential activities. Shehzad et al. (2020) find the conditional variance of stock markets to be bigger during the COVID-19 compared to the global financial crisis of 2007–2008. Gurrib (2021) similarly find shocks to the number of COVID-19 cases affected healthcare sector companies but lasted only a few days.

Contributions of this study are four-folds. We are the first to investigate high frequency risk and return intraday patterns of 11 ETFs which are representative of the 11 sectors in the U.S. economy. By using high frequency data of 15-min intervals we can analyze the volatility and return behavior, both at the open and close of the core trading session on the NYSE. We include a 15-min interval data post the close at 4pm ET, to capture order imbalances which take place at the close due to the closing auction. Since 9 of the select ETF have American options which trade until 4.15 pm, this provides us with some information as to whether the risk and return of these sector ETFs are affected by trades occurring between 4 and 4.15 pm. The decomposition of the analysis into 15-min intervals provides valuable insights to financial players as to the volatility and return to expect during a particular part of the day for any of the 11 sectors in the U.S. and allows us to compare risk and return behavior across all the sectors in the U.S. economy. This also reasserts diffusion of information across sectors in the economy (Hong et al., 2007). Findings also allow financial regulators to be more informative of the price discovery process of what can be expected in terms of risk and return during the open, close and post close trading session periods.

Second, we break the analysis further to a day-by-day basis. This enables us to gauge if any significant risk and return behavior at 15-min intervals is observed during specific trading days of the week. This study adds to the existing literature on sector risk and return anomalies of the Efficient Market Hypothesis (EMH), specifically at high frequency. For example, McLean and Pontiff (2016) show that popular stock price anomalies tend to disappear or weaken after anomalies are highlighted and studied in academia. Comparatively, Jiang et al. (2021) find stronger market underreaction to Friday news.

Third, we make sure of machine learning to capture the predictability power of return models for sector ETF returns. Specifically, we use decision tree classifiers as a machine learning algorithm to obtain the scores of predicting the next 15-min positive returns for all the 11 sector ETF returns. Since our analysis include a day-by-day basis analysis, we can compare if any specific day return model is superior to a model which encompass all-returns. This also allows us to compare how each ETF prediction scores vary under each return model.

Fourth, we are, to our knowledge, the first to provide fresh light into whether the first vaccine rollout in the U.S. had a significant impact on the risk and return of the 11 sector ETFs, including important sectors like healthcare. Our findings provide some guidance in terms of whether events like COVID-19 first vaccination rollout can affect return of ETFs or even portfolios which include ETFs as risky assets. Specifically, we provide insights into the short or long last lasting impact on sector ETFs risk and return.

The rest of the paper is structured with a literature review section which investigates the risk and return relationship in ETFs and equity market, particularly at high frequency levels; the impact of COVID-19 on ETFs and equity market; and anomalies of the efficient market hypothesis such as the day of the week effect. The data and methodology sections then follow, before laying down the research findings. We rest our case with some conclusive remarks.

2. LITERATURE REVIEW

2.1. Returns and Risk Relationships on ETFs

Ackert and Tian (2008) investigate U.S. ETFs including SPDRs and find them to be closely related to their net asset values compared to country ETFs. Similarly, Buetow and Henderson (2012) find daily returns on U.S. ETFs to track closely their benchmarks. Israeli et al. (2017) find ETFs lead to an increase in the correlations of underlying security returns. Kuok-Kun Chu (2011) supports that large ETFs have lower trading costs. Efimova and Serletis (2014) argue that using low frequency data in finding volatility of financial asset prices may ignore a large amount of in-market information about intraday trading. This is in line with Andersen and Bollerslev (1998) who find high frequency intraday returns to reduce noise dramatically, relative to daily returns. Lachance (2021) however finds the ETF market is susceptible to distortions due to its rapid growth which is accompanied by order imbalances exceeding 10%. Ben-David et al. (2018) find ETFs can attract short term uninformed traders which can affect the non-fundamental price volatility of underlying stocks.

2.2. Impact of COVID-19 on ETFs

There are various studies covering the impact of COVID-19 onto equity markets, with however scarce evidence on ETFs. Polemis and Soursou (2020) examine the impact of the pandemic on Greek companies' returns, showing it affected the returns of most firms negatively, with however dissipating effect post the announcement date of the national lockdown. Albulescu (2020) similarly assesses the impact of COVID-19 on oil prices and found only a marginal effect on crude oil, after controlling for economic policy uncertainty and U.S. market volatility. Bakas and Triantafyllou (2020) study the impact of pandemics uncertainty on the volatility of commodity markets, and found a significant negative effect on crude oil, with the shock lasting about 1 year. Billio et al. (2021) use minute data for 12 country-specific ETFs and find the COVID-19 outbreak increased the centrality and connectedness of China on the global financial network. However, daily returns data failed to capture the rise in centrality of China economy.

2.3. Anomalies of EMH

With Kyle (1985) pioneering the study on the importance of asymmetric information, others like Admati and Pfleiderer (1988), Foster and Viswanathan (1996), Wang (1998) and Back and Pedersen (1998) provide plausible explanations on the behavior of risk and returns such as U-shaped patterns, based on the involvement of liquidity and informed traders. For instance, while liquidity traders receive asset information from overnight and trade aggressively during the open session, informed traders acquire and process information during the trading session and are more active as the market approaches the close, resulting in a U-shape pattern in risk and return. McInish et al. (1985) use 15-min data and find returns follow a U-shaped pattern in both risk and return of U.S. stocks. Ozenbas et al. (2002) support the same in international markets attributing it to price discovery and momentum trading. Similarly, Harris (1986) finds significant positive returns at the open and close of trading on the NYSE. This was observed on all trading days except for Monday. More recently, Heston et al. (2010) examine intraday patterns in U.S. stock returns and report a continuation pattern of returns at half-hour intervals. Pagano et al. (2013) find that the volatility of NASDAQ follows a U-shape with significant jumps in the first and last 5 min of trades. Hussain (2011) finds Germany equity returns to display a J-shaped pattern with the aggregate trading volume following the L-shaped pattern. L-shaped pattern in return volatilities was also observed in Tian and Guo (2007) for the Shanghai Composite market index. Karmakar and Paul (2016) use high frequency data for 16 global market indices and find that volatility is higher at the open and close. Studies like Padhi (2010), Seif et al. (2017) and Arora (2017) confirm significant day of the week effects. Other anomalies of EMH have also been evidenced in literature where technical analysis or cross market information have been used for individual security or index movement predictions (Gurrib et al., 2022; Gurrib, 2016; Gurrib, 2018a; Gurrib, 2018b; Gurrib, 2019; Gurrib and Kamalov, 2019).

2.4. Machine Learning Applications in Finance

The recent improvements in machine learning algorithms together with the increased computing power have led to the adoption of machine learning methods in various fields including finance (Henrique et al., 2019). Machine learning algorithms are capable of learning complex, nonlinear relationships directly from the data without the aid of an expert. One of the main applications of machine learning in finance is in price prediction which includes stocks, energy, cryptocurrencies, exchange rates, and other assets. In stock prediction, a deep neural network together with a custom feature selection algorithm was employed by Long et al. (2019) to predict the Chinese stock market index CSI 300. Gurrib and Kamalov (2021) compared a linear discriminant analysis model which includes sentiment analysis and asset specific information such as daily prices, with a support vector machine model, to predict tomorrow's price of bitcoin. A combination of the classical Auto Regressive Integrated Moving Average (ARIMA) model together with the modern neural networks was proposed by Sun et al. (2019) to capture intra-day patterns for stock market shock forecasting. Experiments on S&P 500 data confirm the efficacy of the method. One of the main machine learning models used in time series forecasting is Long Short-Term Memory (LSTM) network. It is a neural network designed to handle sequential data. It was used by Kamalov (2020) to forecast significant changes in stock price. For cryptocurrencies, a 2-stage approach based on LSTM network was proposed by Chen et al. (2021) to forecast the exchange rate of Bitcoin. LSTM network has also been applied to oil price prediction by Cen and Wang (2019). The results suggest efficacy of the LSTM- based forecasting models.

The above literature supports the use of high frequency data in analyzing risk and returns, including the existence of some anomalies at specific times of the day or days of the week. This study helps to bridge the gap in understanding the behavior of sector ETFs risk and return at high frequency. We are also the first to breakdown the 15-min interval analysis to a day-by-day level, thereby providing further insights to the day-of-the week effects on sector ETFs. The use of machine learning algorithm allows us to predict if any specific day can yield a better prediction of the next 15-min return for the 11 U.S. sectors ETFs. Finally, this study provides fresh information onto the effect of the COVID-19 vaccination rollout in the U.S. onto the risk and return of the 11 U.S. sectors.

3. RESEARCH METHODOLOGY

In addition to correlation analysis and analysis of variance (ANOVA), the methodology includes return and volatility regressions and impulse responses.

3.1. Return and Risk over Time

Based on the return relationships observed at the 15-min intervals, we use a time-dependent regression to capture any significant behavior in intraday returns. We include an autoregressive term of order one to adjust for the serial correlation. The model is stated as follows:

$$R_t = \sum_{f=1}^{F} \theta_f \Omega_{f,t} + \gamma R_{t-1} + \varepsilon_t \tag{1}$$

R_t represents 15-min returns, f represents each of the 15-min interval within a core trading session. We include 15 min after the core session ends to capture closing auction imbalances which might occur since 9 of the 11 sector ETFs have American ETF options trading until 4.15 pm (F=28). We also include the return from the previous close till the open on the next day to capture the return at the open. $\Omega_{f,t}$ is a dummy variable with a value of 1 for the specific 15-min interval of the data, or 0 otherwise. γ captures the effect of the autoregressive lag and ε_t is the stochastic error term.

In line with Schwert (1989) who estimated volatility as the sum of squared period returns after subtracting the average return, we estimate the volatility for each 15-min period intervals. This allows us to understand the impact of the volatility present at each 15-min intervals, towards determining the volatility in returns during the trading session.

3.2. Decision Trees Classifier in Machine Learning

A decision tree classifier is a popular machine learning algorithm. It is used in a variety of applications including stock price prediction (Kamble, 2017). It is a simple yet effective approach to modeling data. The decision tree algorithm is based on repeatedly splitting the data along its features. At each iteration, the feature that produces the maximum information gain is used to further split the data. The main advantage of a decision tree classifier over the more exotic algorithms is that the decision tree structure allows us to visualize the functioning of the algorithm. Unlike neural networks, which are often called black box models, a decision tree can be examined for purposes of validation. Another advantage of a decision tree is the low computational complexity. Thus, a decision tree classifier can handle large amounts of data. Specific implementations of decision trees exist such as ID3, C4.5, and CART. A detailed discussion of the algorithms can be found in Grus (2019).

The basic decision tree algorithm consists of iteratively splitting the training data into halves to obtain purer (homogeneous) subsets. Concretely, given a decision tree node and the corresponding subset of data, the features are evaluated based on an information criterion. In our model, we use the Gini coefficient to measure the level impurity given by the equation.

$$G = \Sigma p_{mk}(1 - p_{mk}) \tag{2}$$

where p_{mk} is the proportion of class k observations at node m. The feature that yields the lowest amount of impurity is selected and the data is split according to the threshold value of selected feature. This process is continued until each node contains points from a single class or another user-specified criterion is satisfied. In order to reduce overfitting, various techniques such as pruning and feature randomization are applied. Decision tree-based ensemble classifiers such random forest are also used to reduce the variance of the estimator.

3.3. Impulse Responses

Jordà (2005) provides a breakdown of the methodology of impulse responses by local projections. The impulse response function of the selected sector ETF returnsR_t to the introduction of the first COVID-19 vaccination rollout in the U.S. since 14th December 2020 Φ_t, that is, up to 1 day after its occurrence, is calculated as the residual between the following two forecasted estimations:

$$IRF(z) \equiv E\left[R_{t+z-1} \middle| \Phi_{t-1} = 1, R_s, \Phi_{t-1}, s > t\right]$$
$$E\left[R_{t+z-1} \middle| \Phi_{t-1} = 0, R_s, \Phi_{t-1}, s > t\right] \tag{3}$$

Where the impulse responses are based on the best mean squared multi-step-ahead forecasts. Several proponents of the use of impulse response by local projections onto financial markets include Gurrib et al. (2019) who analyze the response of major cryptocurrencies to one standard deviation shock on Bitcoin's returns and Bernal-Verdugo et al. (2013) who analyze the effect of labor reforms and bank crises onto unemployment.

4. DATA

While there are various industry classifications in the U.S., we adopt the Global Industry Classification Standard (GICS) as the framework for sector classifications. GICS was instilled as a retort to the international financial community's need for accurate, complete and standard industry definitions (SP Global, 2018). It currently consists of 11 sectors, 24 industry groups, 69 industries and 158 sub-industries. For each of the 11 sectors of our study, we use Select Sector SPDR Funds due to the superiority of ETFs in their respective sectors, in terms of their solid tracking of U.S. sector indices, trading volume, Asset Under Management, low expense ratios, and fund flows (SSGA, 2021). The eleven Select Sector Indexes upon which the Select Sector SPDR Funds are based together constitute all the companies in the S&P 500. The ETFs are energy (XLE), technology (XLK), healthcare (XLV), utilities (XLU), consumer staples (XLP), consumer discretionary (XLY), financial (XLF), communication services (XLC), industrial (XLI), materials (XLB) and real estate (XLRE). We use 15-min interval prices for each sector, covering the period 12th of March 2020 – 23rd of February 2021, for the core trading session 9.30 am-4 pm Eastern Time. We also include 15 min following the end of the core trading session to capture closing auction imbalances. Return values are calculated based on the percentage change from the previous period. ETF prices are quoted on the NYSE Arca. Data is sourced from Factset.

5. RESEARCH FINDINGS

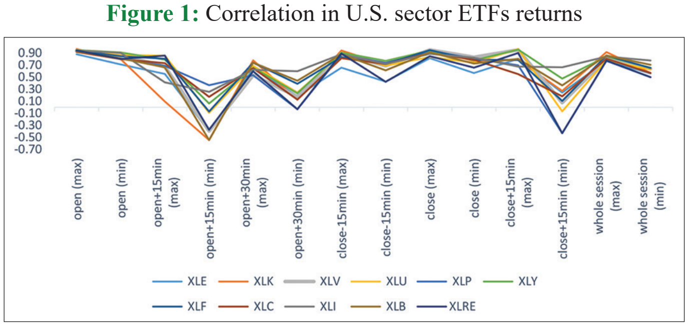
5.1. Descriptive Statistics

Using 6466 observations, all the eleven sectors have average returns, mode and median values close to zero. The energy and materials sector ETFs reported the lowest and the highest 15-min interval returns of –10.7% and 23.4%, respectively. Interestingly, the highest returns recorded for each sector took place on the same day at close on the 14th of March 2020. This shows that all the sectors' returns were all positively affected, regardless of the different economic activities provided by different constituents of each sector. However, the lowest negative returns for each sector did not occur at the same time, suggesting negative news affecting each sector differently. An un-tabulated ANOVA F-test (with 71115 degrees of freedom) support that the 11 sectors' average returns are not significantly different from each other. Standard deviation values ranged between 0.34% and 0.67%, with the consumer staples (energy) sector ETF returns having the lowest (highest) risk. This is in line with Davide et al. (2021) Contu, Elshareif & Gurrib (2021) who found positive sentiment from social media on energy sources. All sectors had leptokurtic return distributions with kurtosis ranging from energy sector ETF (70.9) and materials sector ETF (678.1). This can be attributed to the high number of 15-min returns around nearly zero average returns. All return distributions were also positively skewed ranging from the energy (0.9) to information technology (7.5). As reported widely in literature, none of the returns were normally distributed using the Jarque-Bera normality test. Both Augmented Dickey-Fuller (ADF) and Phillips-Perron unit root tests at 1%, 5% and 10% level support all sectors' returns are stationary at levels.

Due to the high frequency of the data, as expected, except for the energy ETF which shows no serial correlation at one lag at 1% level, all other returns series were serially correlated at 1%, 5% and 10% level, using the Ljung-Box Q statistics (up to 10 lags). In line with Yao (1988) and Liu et al. (1997) (LWZ) who support that the number of breaks which minimizes the Schwarz Information Criterion (SIC) is a reliable estimator of the true number of breaks, we also test for potential structural breaks. Although not tabulated here, multiple breakpoint tests using the global information criteria of Schwarz and LWZ support the existence of no structural breaks in the returns of the 11 U.S. sector ETF returns between March 2020 and February 2021.

To capture the relationships among the 11 U.S. sectors ETF returns, we include a summary of the return correlations in Figure 1. For brevity, we report only results for each of the 15-min intervals in the first 30 min at the open and close of the session. These include the overnight return, the return after the 1st 15-min of trading (open+15 min), 2nd 15-min (open+30 min), return at 15-min before the close (close-15 min), returns at close (close), and the 15-min returns after the close (close+15 min). We provide both minimum and maximum Pearson correlation values for each of the 11 U.S. sectors ETFs at the specific time of the trading session, including correlation values for the whole trading session. As expected, correlation values for a regular trading session show all the sectors' ETF returns were positively correlated, ranging from 0.51 to 0.91. This is consistent with Rapach et al. (2019) who find diffusion of information across economically linked industries. The technology sector shared strong correlations with other sectors' returns, with the highest correlation observed with communication services. Correlations, both at the open and close were consistently positive among all sector ETFs returns. However, the stable

Figure 1: Correlation in U.S. sector ETFs returns



relationship among the different sectors was not observed at the 15-min return periods after the open and close, at 9.30–9.45 am and 4–4.15 pm, with negative correlations observed among a few sector ETFs returns. Except for communication services, industrial, and consumer discretionary which always observed positive correlation with any sector, all other sectors witnessed a drop in the positive relationship, with technology and materials sharing the highest negative correlation value of –0.54 between their returns 15 min after the open. A negative correlation value of –0.4 was also observed between technology and the energy sector at the same time of the day. Negative correlations were less pronounced at 15-min period post close, with only real estate and consumer staples posting a –0.43 correlation. Differences in magnitude between the maximum and minimum values at the open +15 and close +15 periods suggest more volatility in returns across sectors during those periods, particularly at the open +15 period where correlations ranged from –0.43 to 0.66.

Figure 1 provides the Pearson correlation coefficients for 15-min interval periods around the open and close of a trading session. These are based on returns at the open (open), returns after the first 15-min of trading (open + 15 min), 2nd 15-min (open + 30 min), returns at 15-min before the close (close-15 min), returns at close (close), and the 15-min returns after the close (close + 15 min). The 15-min returns after the close captures order imbalances. We provide both minimum and maximum Pearson correlation values for each of the 11 U.S. sectors ETFs at these specific periods of the trading session, including correlation values for the whole trading session.

While a look at a regular trading day for any financial product like stocks or ETFs would, on average, show price and return fluctuations in a random fashion, by grouping the returns, based on the time of the day, we can extract possible returns patterns during specific time of the day. While most returns are close to zero, as expected, due to the high frequency data and gives some support to the efficient market hypothesis that intraday returns should not be significantly different from each other, three more important behavioral patterns are also noticeable. Firstly, the returns of both the first and last 15 min of the core session tend to fluctuate more than for the rest of the day. This is consistent to findings of Berkman et al. (2012) who find positive returns during the overnight period to be followed by reversals during the trading day for U.S. equities. This is similar to the U-smile pattern observed in equity markets in various studies including Pagano et al. (2013) and Harris (1986), with however most of the fluctuations appear towards in the opening hour. The behavior of returns at the opening can be attributed to the execution of the core open auction which is the first trade of the core trading session. New limit orders that are not eligible to trade in the early trading session and market orders are accepted to offset any imbalance between buying and selling volume.

Because the core auction takes place at a single auction price (indicative match price), this creates the potential for an opening session price which can be much different from the previous trading price at close. This results in subsequent returns which are higher or lower than the rest of the day, except for the last

15 min. The core open auction takes place at a single auction price (indicative match price) and any unexecuted orders are released into the core trading session. The returns in the last 15 min can be attributed to institutions trading at the close of the day or day-traders closing their positions. We also need to point that the end of the closing session is also subject to the closing auction at 4pm, where any imbalance between buying and selling volume are cleared. Imbalances, both at the start and close of the core session, due to excess buy or selling volume, result in prices which deviate from the average seen during the day. The prices can also deviate due to 9 of the select ETFs trading American ETF options which close at 4.15 pm. These prices when used to calculate returns, result in return values which deviate from average returns seen during the day.

Secondly, the average returns in the first 30 min (two slots of 15 min) of the core session tend to deviate from the average returns observed at other times. 10 of the 11 sector ETFs (except for technology) average returns in the first 15 min were higher than other times. The average returns in the last 15 min were lower in all sector ETFs, compared to the average return observed at 4 p.m. This can be attributed to the sector ETF prices 4.15 pm, mostly being lower than the prices at close. Thirdly, all average returns converge to values approaching zero as we progress through later part of a trading session, suggesting information accumulated throughout the day is absorbed and reflected in later prices of the day.

An ANOVA test for the equality of 11 sector ETF average returns in the first 15-min interval reported F-test values of 1.8653 with a probability of 0.0454. This suggests the average returns among the different U.S. sectors in the first quarter of the trading session are significantly different only at 1% level. A similar test was conducted for average return in the last 15-min interval of the core session, with F-test values of 0.2486 (with degree of freedom of 2585) and supported that there is no significant difference in the average returns among the 11 sector ETF returns during the last 15 min of trading in the core session. An ANOVA test was also carried out to test if the average return for every 15-min intervals were significantly different from each other. With 6438 degrees of freedom, F-test probability values found 6 out of 11 sectors (XLE, XLV, XLP, XLY, XLI and XLRE) with average returns for every 15-min intervals returns to be significantly different.

Figure 2 captures the behavior of intraday returns on NYSE Arca from 9.30 am to 4.15 pm (Eastern time), using 15-min intervals, for each of the eleven U.S. sectors. The first return (overnight return) at the open is based on the percentage change between the previous close and current opening price. We include 15 min following the end of the core trading session to capture closing auction imbalances. The period covered is 12th of March 2020–23rd February 2021. The average returns for each 15-min period are also displayed on the secondary vertical axis. The performance of the 11 U.S. sectors is represented by the returns under each of the Select sector SPDR funds as follows: energy (XLE), technology (XLK), healthcare (XLV), utilities (XLU), consumer staples (XLP), consumer discretionary (XLY), financial (XLF), communication services (XLC), industrial (XLI), materials (XLB) and real estate (XLRE).

5.2. Intraday Seasonality in Return

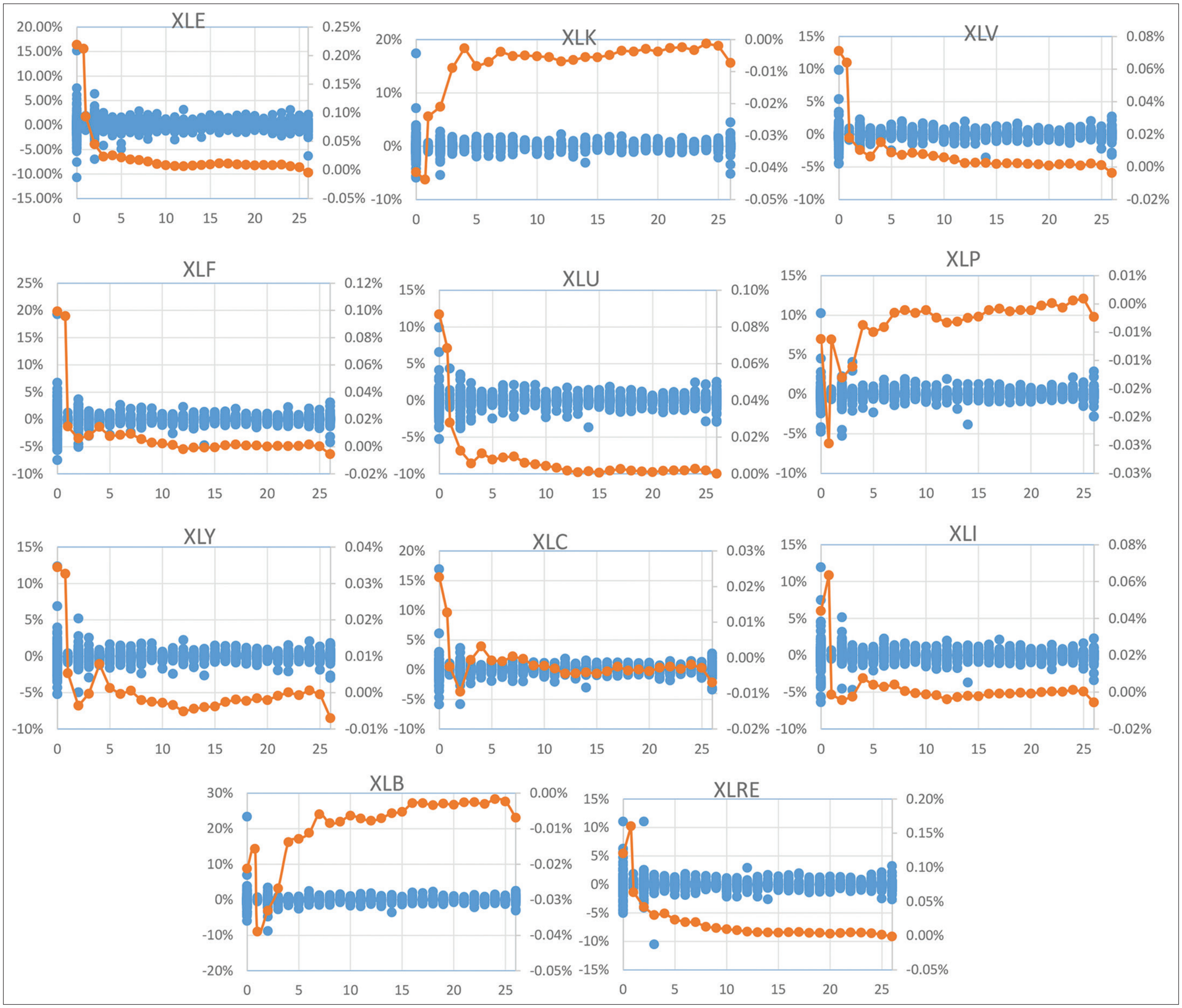
Regression results from Equation (1) are reported in Table 1. Overnight returns were significant and negative in all sectors, except for utilities. In all sectors, the returns were negative at the opening, ranging from –0.06% for real estate to –0.23% for energy. All returns were significant only in the first 30 min of trading. Further, all the negative returns observed at the open quickly turned less negative or even positive after the first 15 min for all sectors' returns except for technology and consumer discretionary. Returns turned positive for 7 sectors (energy, healthcare, utilities, consumer staples, communication services, materials, and real estate), but were significant only for 3 of those. For technology and consumer discretionary, which were less negative in after the open, returns were less negative than before, turning positive for consumer discretionary after 30 min of trade. The fluctuations observed in the first 30 min quickly dissipated for the remaining 15-min intervals of the day. Returns started to fluctuate more in the last 30 min of the day, with however no significant results. The one lag autoregressive coefficients were all significant negative for all sectors, suggesting that the previous return period has a significant impact in determining the current 15-min period return.

Table 1 shows the regression coefficients from equation (1). The dependent variable is the 15-min interval return of the 11 U.S. sectors as represent by select sector ETFs, from 12th March 2020 – 23rd February 2021. An autoregressive lag of order 1 is included to account for serial correlation in the high frequency data. Although the core trading session runs from 9.30am-4pm. we includes return from the previous close until 4.15pm Eastern time to capture overnight trades and any closing session imbalances. For brevity, only overnight, the first 4 and last 5 15-min returns are reported here, where significant results are shown in italics.

Table 1: Seasonality in high frequency returns

	XLE	XLK	XLV	XLU	XLP	XLY	XLF	XLC	XLI	XLB	XLRE	
Previous close	Open	–0.23%	–0.16%	–0.13%	–0.05%	–0.09%	–0.17%	–0.15%	–0.11%	–0.16%	–0.13%	–0.06%
Open	9.45	0.44%	–0.18%	0.07%	0.53%	0.04%	–0.18%	–0.02%	–0.03%	0.07%	0.11%	0.45%
9.45	10.00	0.15%	–0.06%	0.05%	0.02%	–0.04%	0.00%	0.05%	–0.01%	0.03%	–0.07%	0.12%
10.00	10.15	–0.03%	0.00%	–0.03%	–0.02%	0.01%	–0.02%	–0.07%	–0.02%	–0.07%	–0.07%	–0.03%
10.15	10.30	–0.06%	–0.01%	0.00%	–0.02%	–0.03%	–0.02%	–0.01%	–0.02%	–0.01%	–0.02%	0.00%
15.00	15.15	0.02%	0.02%	0.02%	0.02%	0.02%	0.03%	0.01%	0.02%	0.02%	0.01%	0.03%
15.15	15.30	0.01%	0.00%	0.01%	0.01%	0.00%	0.02%	0.00%	0.01%	0.01%	–0.01%	0.03%
15.30	15.45	0.03%	–0.02%	–0.02%	0.00%	–0.01%	–0.01%	0.01%	–0.01%	0.00%	–0.01%	0.00%
15.45	16.00	–0.06%	0.05%	0.03%	0.02%	0.03%	0.03%	0.02%	0.03%	0.02%	0.03%	–0.02%
16.00	16.15	–0.01%	–0.01%	–0.01%	0.00%	0.00%	–0.01%	0.00%	–0.01%	0.00%	–0.01%	–0.02%
AR (1)		–2.60%	–12.79%	–8.81%	–6.77%	–21.52%	–9.41%	–13.01%	–14.88%	–6.65%	–14.70%	–11.93%

Figure 2: U.S. ETF sectors returns



5.3. Intraday Seasonality in Volatility

Similar to the return regression findings, volatility in returns at the open was significant in determining the volatility for the trading day. This was observed in all the 11 U.S. sectors, ranging from a minimum of 0.011% for the materials sector to 0.052% for the energy sector. Further, except for utilities, volatility after the first 15 min decreased for all. More importantly, except for utilities and real estate, volatility again increased 30 min after the open, with a positive impact noticed for all sectors. Again, the volatility in the 9.45am-10am period was highest for energy, relative to other sectors. This is in line with the highest return observed for the same sector at the same 15-min period. Similar to the return regression results, the one period autoregressive lag was also negatively significant in the volatility regression for all sector ETFs. This suggests that a positive (negative) return in one 15-min period increasing the likelihood of having a negative (positive) return in the next 15-min period. This was observed particularly in the first 30 min of the session.

Table 2 shows the regression coefficients from equation (2). The dependent variable is the 15-min interval volatility of the 11 U.S. sectors as represent by select sector ETFs, from 12th March 2020 – 23rd February 2021. An autoregressive lag of order 1 is included to account for serial correlation in the high frequency data. Although the core trading session runs from 9.30am-4pm for stocks, we include return from the previous close until 4.15pm Eastern time to capture overnight trades and any closing session imbalances. For brevity, only the first 4 and last 5 15-min volatilities are reported here, where significant (1%, 5% and 10% levels) results are shown in italics. *Denotes significance at 10% level, **5%, 10%, and ^10% level.

5.4. Return Seasonality-Days of the Week

As observed in the heatmaps of Table 3, returns around the closing time tend to be positive and significant on specific days of the week. On Mondays, returns in all sectors (except for real estate) were positive during the 16.00–16.15 interval, with significant

Table 2: Seasonality in return volatility

		XLE	XLK	XLV	XLU	XLP	XLY	XLF	XLC	XLI	XLB	XLRE
Previous close	Open	0.052%	0.029%	0.014%	0.014%	0.011%	0.022%	0.044%	0.025%	0.027%	0.040%	0.022%
Open	9.45	0.005%	0.000%	0.001%	0.019%	–0.001%	0.001%	0.002%	0.000%	0.001%	0.003%	0.014%^
9.45	10.00	0.016%	0.004%*	0.003%	0.005%	0.004%	0.004%	0.007%	0.005%	0.006%	0.007%	0.011%
10.00	10.15	0.002%	0.001%	0.000%	0.001%	0.001%	0.001%	0.002%	0.000%	0.001%	0.000%	0.005%
10.15	10.30	0.001%	0.001%	0.000%	0.000%	0.000%	0.000%	0.001%	0.001%	0.000%	0.000%	0.000%
15.00	15.15	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15.15	15.30	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15.30	15.45	–0.001%	0.001%	0.000%	0.001%	0.000%	0.000%	0.000%	0.000%	0.000%	0.001%	0.001%
15.45	16.00	0.003%	0.004%	0.002%**	0.002%	0.002%^	0.001%	0.002%	0.002%	0.001%	0.001%	0.002%
16.00	16.15	0.000%	–0.001%	0.000%	0.000%	0.000%	0.000%	0.001%	–0.001%	0.000%	–0.004%	0.001%
AR (1)		–0.378%	–1.203%	–0.234%	–0.306%	–0.534%	–0.267%	–0.867%	–1.356%	–0.147%	–2.890%	–0.853%

Table 3: Intraday return heatmap of U.S. sector ETFs

						Mondays						
		XLE	XLK	XLV	XLU	XLP	XLY	XLF	XLC	XLI	XLB	XLRE
Previous close	Open	–0.16%	–0.31%	–0.26%	–0.13%*	–0.10%	–0.31%	–0.38%	–0.17%	–0.28%	–0.31%	–0.20%
Open	9.45	0.66%*	–0.24%	0.14%	0.69%	0.24%	–0.03%	0.33%	0.14%	0.24%	00.19%	0.50%*
9.45	10.00	0.05%	–0.22%	0.07%	0.03%	–0.04%	–0.05%	0.02%	–0.12%*	0.06%	–0.15%*	0.26%
10.00	10.15	–0.05%	–0.11%^	–0.03%	0.02%	0.01%	–0.06%	–0.04%	–0.12%*	–0.07%	–0.09%	0.00%
10.15	10.30	0.01%	0.03%	0.02%	–0.05%	0.03%	–0.01%	0.01%	0.00%	0.00%	0.03%	0.00%
15.00	15.15	0.06%	0.07%	0.05%	0.04%	0.05%	0.06%	0.03%	0.05%	0.05%	0.02%	0.07%
15.15	15.30	0.00%	0.03%	0.04%	0.05%	0.06%	0.05%	0.05%	0.03%	0.03%	0.02%	0.11%
15.30	15.45	0.06%	–0.07%	–0.03%	–0.01%	–0.04%	–0.03%	–0.02%	–0.04%	–0.02%	–0.04%	0.01%
15.45	16.00	0.05%	0.06%	0.02%	–0.02%	0.02%	0.03%	0.06%	0.04%	0.04%	0.04%	0.01%
16.00	16.15	0.12%	0.09%	0.04%	0.01%	0.10%^	0.05%	0.14%^	0.10%^	0.07%	0.13%^	–0.05%
AR(1)		–6.59%	–17.67%	–9.86%	0.35%	–23.79%	–7.83%	–11.14%	–21.04%	–5.74%*	–22.34%	–2.32%
max return		0.66%	0.09%	0.14%	0.69%	0.24%	0.06%	0.33%	0.14%	0.24%	0.13%	0.50%
min return		–0.16%	–0.31%	-0.26%	—0.13%	–0.10%	–0.31%	–0.38%	–0.17%	–0.28%	–0.31%	–0.20%
						Tuesdays						
		XLE	XLK	XLV	XLU	XLP	XLY	XLF	XLC	XLI	XLB	XLRE
Previous close	Open	–0.88%	–0.37%	–0.38%	—0.33%	–0.32%	–0.45%	–0.58%	–0.27%	–0.51%	–0.48%	–0.46%
Open	9.45	0.36%	0.11%	–0.05%	–0.06%	0.10%	0.07%	–0.28%	–0.18%	–0.07%	0.14%	–0.08%
9.45	10.00	–0.02%	–0.01%	0.08%^	0.05%	0.01%	0.07%	0.07%	0.01%	–0.02%	0.00%	0.14%*
10.00	10.15	–0.06%	–0.04%	—0.06%	–0.09%^	–0.03%	–0.05%	–0.10%	–0.02%	–0.06%	–0.12%*	–0.08%
10.15	10.30	–0.15%	–0.04%	–0.02%	–0.08%	–0.11%	–0.07%	0.00%	–0.06%	–0.06%	–0.09%	–0.04%
15.00	15.15	0.04%	0.10%	0.07%	0.04%	0.06%	0.08%	0.04%	0.08%	0.06%	0.07%	0.06%
15.15	15.30	0.08%	0.02%	0.04%	0.04%	0.02%	0.03%	0.04%	0.03%	0.04%	0.05%	0.05%
15.30	15.45	0.01%	–0.01%	–0.05%	–0.10%^	–0.04%	—0.01%	0.00%	0.00%	–0.02%	–0.02%	–0.09%
15.45	16.00	0.01%	0.13%*	0.11%	0.10%^	0.09%*	0.10%^	0.07%	0.11%*	0.09%	0.08%	0.08%
16.00	16.15	–0.01%	0.03%	–0.01%	–0.01%	0.01%	–0.01%	0.00%	0.04%	–0.01%	0.00%	0.01%
AR(1)		3.38%	–1.66%	–2.63%	4.39%	–4.45%^	6.01%*	–3.76%	–10.27%	8.82%	2.85%	4.92%^
max return		0.36%	0.13%	0.11%	0.10%	0.10%	0.10%	0.07%	0.11%	0.09%	0.14%	0.14%
min return		–0.88%	–0.37%	–0.38%	–0.33%	–0.32%	–0.45%	–0.58%	—0.27%	–0.51%	–0.48%	–0.46%
						Wednesdays						
		XLE	XLK	XLV	XLU	XLP	XLY	XLF	XLC	XLI	XLB	XLRE
Previous close	Open	–0.41%	–0.34%	–0.14%	–0.05%	–0.07%^	–0.28%	–0.22%	–0.35%	–0.22%	–0.18%	–0.12%*
Open	9.45	–0.22%	–0.25%	0.05%	–0.72%	–0.28%	–0.79%	–0.34%	–0.33%	–0.55%*	–0.18%	0.05%
9.45	10.00	0.42%	–0.07%	0.01%	0.08%	–0.02%	0.07%	0.11%^	0.04%	0.09%	0.04%	0.02%
10.00	10.15	–0.01%	0.01%	0.00%	0.04%	–0.03%	0.01%	0.04%	0.00%	0.00%	–0.07%	0.13%*
10.15	10.30	–0.04%	–0.08%	–0.02%	0.04%	–0.04%	–0.05%	–0.05%	–0.06%	–0.03%	–0.09%	0.05%
15.00	15.15	0.02%	–0.01%	–0.02%	0.01%	–0.01%	0.00%	0.00%	–0.01%	–0.02%	–0.03%	0.02%
15.15	15.30	0.09%	0.05%	0.07%	0.07%	0.04%	0.08%^	0.05%	0.07%	0.05%	0.06%	0.09%
15.30	15.45	0.02%	0.02%	0.01%	0.04%	0.01%	–0.02%	0.03%	0.01%	0.01%	–0.04%	0.01%
15.45	16.00	0.03%	0.07%	0.08%^	0.06%	0.07%^	0.06%	0.11%	0.07%	0.08%	0.08%	0.01%
16.00	16.15	0.01%	0.01%	0.01%	0.01%	0.03%	0.01%	–0.03%	–0.06%	0.01%	0.00%	0.00%
AR(1)		8.18%	–10.93%	–5.33%*	–2.91%	–13.35%	0.64%	–6.30%*	–0.12%	5.85%*	2.74%	–1.90%
max return		0.42%	0.07%	0.08%	0.08%	0.07%	0.08%	0.11%	0.07%	0.09%	0.08%	0.13%
min return		–0.41%	–0.34%	–0.14%	–0.72%	–0.28%	–0.79%	–0.34%	–0.35%	–0.55%	–0.18%	–0.12%
						Thursdays						
		XLE	XLK	XLV	XLU	XLP	XLY	XLF	XLC	XLI	XLB	XLRE
Previous close	Open	0.05%	–0.07%	–0.01%	0.06%	0.00%	0.00%	*0.21%*	0.05%	0.05%	0.03%	0.12%
Open	9.45	–0.11%	0.02%	–0.02%	–0.36%	0.31%	–0.17%	–0.25%	–0.34%	–0.16%	0.03%	–0.54%

(*Contd...*)

Table 3: (*Continued*)

Thursdays												
		XLE	**XLK**	**XLV**	**XLU**	**XLP**	**XLY**	**XLF**	**XLC**	**XLI**	**XLB**	**XLRE**
9.45	10.00	0.16%^	–0.23%	0.01%	–0.05%	–0.15%	–0.19%	–0.18%	–0.24%	0.06%	–0.13%*	0.16%*
10.00	10.15	–0.12%	0.01%	–0.06%	–0.06%	0.00%	–0.05%	–0.22%	–0.03%	–0.21%	–0.12%*	–0.23%
10.15	10.30	–0.13%	0.02%	–0.04%	–0.03%	–0.01%	–0.01%	–0.06%	0.04%	–0.04%	–0.02%	–0.10%
15.00	15.15	0.04%	0.00%	0.01%	0.02%	0.01%	0.02%	–0.01%	0.02%	0.02%	–0.01%	0.00%
15.15	15.30	–0.07%	0.01%	–0.02%	–0.06%	–0.01%	0.01%	–0.05%	–0.01%	–0.01%	–0.06%	–0.04%
15.30	15.45	0.04%	–0.05%	–0.03%	0.02%	–0.03%	–0.03%	–0.01%	–0.04%	–0.02%	0.00%	–0.02%
15.45	16.00	–0.14%	0.04%	0.02%	–0.02%	0.01%	0.02%	–0.01%	0.00%	–0.02%	0.01%	–0.08%
16.00	16.15	–0.13%	–0.01%	0.00%	0.00%	0.00%	0.00%	–0.04%	–0.01%	–0.01%	–0.05%	–0.02%
AR(1)		1.99%	–8.47%	–10.04%	–12.85%	–29.32%	–7.68%	–6.63%*	–8.84%	–13.86%	0.62%	–21.70%
max return		0.16%	0.04%	0.02%	0.06%	0.31%	0.02%	0.21%	0.05%	0.06%	0.03%	0.16%
min return		–0.14%	–0.23%	–0.06%	–0.36%	–0.15%	–0.19%	–0.25%	–0.34%	–0.21%	–0.13%	–0.54%
Fridays												
		XLE	**XLK**	**XLV**	**XLU**	**XLP**	**XLY**	**XLF**	**XLC**	**XLI**	**XLB**	**XLRE**
Previous close	Open	–0.18%	–0.01%	–0.13%	–0.02%	–0.07%	–0.16%	–0.21%	–0.14%	–0.15%	–0.15%	–0.08%
Open	9.45	0.91%	–0.37%	1.05%	1.02%	–0.22%	0.16%	0.57%	–0.27%	0.79%^	0.70%^	0.50%
9.45	10.00	0.21%	0.19%	0.03%	0.02%	–0.02%	0.14%*	0.23%	0.27%	0.00%	–0.02%	0.08%
10.00	10.15	0.05%	0.06%	0.02%	0.03%	0.04%	0.03%	0.01%	0.07%	0.01%	0.04%	0.05%
10.15	10.30	0.03%	–0.02%	0.03%	0.04%	0.03%	0.04%	0.03%	–0.04%	0.05%	0.06%	0.05%
15.00	15.15	–0.05%	–0.06%	–0.03%	–0.03%	–0.03%	–0.05%	–0.02%	–0.04%	–0.03%	–0.01%	–0.04%
15.15	15.30	–0.09%	–0.09%	–0.08%^	–0.06%	–0.06%	–0.07%	–0.09%	–0.07%	–0.09%	–0.10%^	–0.08%
15.30	15.45	0.02%	0.00%	–0.02%	0.06%	0.02%	0.01%	0.02%	0.00%	0.03%	0.00%	0.09%^
15.45	16.00	–0.26%	–0.08%	–0.09%	–0.01%	–0.06%	–0.06%	–0.10%	–0.10%^	–0.07%	–0.09%	–0.07%
16.00	16.15	–0.02%	–0.04%	–0.03%	0.01%	–0.01%	–0.01%	0.01%	–0.03%	–0.01%	–0.01%	0.00%
AR(1)		–3.75%	–5.62%*	–12.83%	–12.80%	–14.26%	–8.95%	–12.97%	–7.39%	–9.31%	–14.98%	–7.64%
max return		0.91%	0.19%	1.05%	1.02%	0.04%	0.16%	0.57%	0.27%	0.79%	0.70%	0.50%
min return		–0.26%	–0.37%	–0.13%	–0.06%	–0.22%	–0.16%	–0.21%	–0.27%	–0.15%	–0.15%	–0.08%

returns for consumer staples, financials, communication services and materials sectors. On Tuesdays and Wednesdays, returns during the 15.45–16.00 interval were positive in all sectors, and significant for health care and consumer staples. Returns at close during Thursdays and Fridays were mostly negative and insignificant. Although not shown here, normalized heatmaps were also constructed to allow for comparison across the different days of the week. Findings reveal the most significantly positive returns occurred on Mondays and Fridays 15 min following the open at 9.30 am. Most significantly negative returns occurred on Tuesdays and Wednesdays either at the open (overnight returns) or 15 min after the open.

Table 3 also supports earlier findings where overnight returns have negative impacts on the 11 sectors, returns. This was observed on all trading days, except for Thursdays where some positive returns were witnessed for 9 sectors. On Thursdays, positive overnight return was significant only in the financial sector with a contribution of 0.21%. More significant returns from the open until 10.00, and from 15.30 till 16.15 support earlier evidence that prices movements around the opening and closing time contribute more towards the return during a trading session. Most returns which occurred at the different 15-min intervals between 10.15 am and 15.30 pm were insignificant. The autoregressive lag was mostly negative and significant, particularly on Mondays and Fridays. For example, on Mondays, lagged returns ranged from –23.79% (consumer staples) to 0.35% (utilities). Except for utilities, one day lagged returns contributed negatively to the current return of the day. On Fridays, lagged returns ranged –3.75% (energy) to –14.98% (materials).

Reversals in returns were observed after the first 15 min in all sectors on Mondays and Tuesdays, with however significant positive returns observed only for utilities, real estate and energy sectors (Mondays only). However, for Wednesdays, reversals occur after 30 min post open, where 9 sectors posted positive returns at the 9.45–10.00 interval. Negligibly, positive returns were significant only for real estate. While some reversals in returns occurred on Thursdays after 15 min none were insignificant. Similar to Wednesdays, significant positive returns were observed at 9.45–10.00 am interval in the energy (0.16%), and real estate (0.16%). On Fridays, 8 of all the negative returns posted at the open were reversed in the next 15-min slot, with significant positive returns in 4 sectors (health care, utilities, industrials, and materials). During the 10.00–10.15 am time interval, all sector ETF returns were positive with however non-significant contribution to the return on the specific day of the week.

Table 2 shows the regression coefficients from equation (1), for each trading day of the week. The dependent variable is the 15-min interval return of the 11 U.S. sectors as represented by select sector ETFs, from 12th March 2020 – 23rd February 2021. An autoregressive lag of order 1 is included to account for serial correlation in the high frequency data. We include return from the previous close until 4.15pm Eastern time to capture overnight trades and any closing session imbalances. For brevity, only overnight returns, and the first 4 and last 5 15-min returns are reported here, where significant results (1%, 5%, 10%) are shown in italics. *Denotes significance at 5%, 10% level, ^ at 10% level. The heatmap color is scaled from dark blue (highest positive returns) to dark red (most negative returns) for each 15-min interval of every trading day.

5.5. Volatility Patterns-Days of the Week

To capture the volatility patterns over each trading day, coefficients of return volatilities at each 15-min interval from Monday to Friday are reported in Table 4. Overnight return volatilities are included to capture the effect of fluctuations in overnight returns at the open. Overnight returns were the most significant in contributing towards the volatility for any trading session, with highest volatility observed on Mondays, relative to the other days. The energy sector had the highest overnight volatility coefficients on all trading days, compared to all other sectors' volatilities, with the highest value of 0.074% on Mondays. Overnight volatilities from Monday to Friday support the earlier U-shaped pattern observed in the volatility of returns. As we move from Monday to Thursday, overnight volatilities, while still being significant, started to fell, before starting to recover on Fridays. While not as significant as overnight volatilities, volatilities at 9:45–10:00 am were also positive and significant in contributing towards most sectors' ETF volatilities. Autoregressive one lag period coefficients were positive significant for most sectors' return volatilities, on all trading days.

Except for Mondays, the most significantly negative volatility coefficients were observed during the first 15 min of the trading sessions, particularly on Wednesdays and Fridays. As shown in Figure 3, U-shaped volatility patterns can be observed on all trading days, with Mondays reflecting the U-shape volatility smile pattern better than in the other days. This can be explained due to the most significant overnight volatilities coefficients observed on Monday, and also due to the positive volatilities observed towards the end of the Monday sessions, with significant coefficients in consumer discretionary, financials, communication devices, materials and real estate sector ETFs. The U-shape volatility smiles for the remaining 4 days of the week were affected by the last 15 min session, where volatilities were mostly negative and insignificant. Further, volatilities at 15:45–16:00 were positive and significant for all the 11 sectors on Wednesdays and Fridays. These results suggest that the volatility smile, mostly on the remaining days can be observed until 16:00, but not further, except for Mondays. This can be explained by the fact that all the U.S. stocks of the S&P500, which are constituents of the sector ETFs trade until 16:00, after which the session is closed. The relatively low volatilities observed during the 16:00–16:15 session suggest that the closing auction imbalances do not have a significant impact relative to the volatilities observed during the day.

Figure 3 captures the intraday volatility of intraday ETFs, based on 15-min interval return of the 11 U.S. sectors as represented by select sector ETFs, from 12th March 2020 – 23rd February 2021. The scatter plot is decomposed into 5 trading days, Monday- Friday. For brevity, only overnight returns volatility, the first 4 and last 5 15-min returns volatilities are reported.

Figure 3: Volatility pattern in U.S. sector ETFs (Mondays-Fridays)

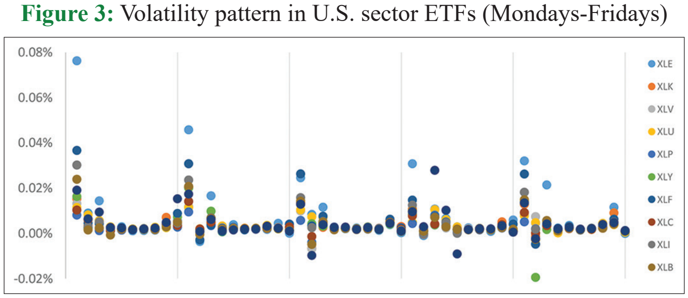


Table 4 shows the regression volatility coefficients estimated from equation (1), for each trading day of the week. The dependent variable is the 15-min interval return volatility of the 11 U.S. sectors as represented by select sector ETFs, from 12th March 2020 – 23rd February 2021. An autoregressive lag of order 1 is included to account for serial correlation in the high frequency data. We include return from the previous close until 4.15 pm Eastern time to capture overnight trades and any closing session imbalances. For brevity, only overnight returns volatility, the first 4 and last 5 15-min returns volatilities are reported here, where significant results (1%, 5%, 10%) are shown in italics. *Denotes significance at 5%, 10% level, ^ at 10% level. The heat map color is scaled from dark blue (highest positive returns) to dark red (most negative returns) for each 15-min interval of every trading day.

5.6. Predicting 15-min Returns

Based on the above findings, where 15-min ETF returns tend reverse itself, we test if it's possible to predict the next 15-min returns, based on (i) a return model which includes all 15-min returns without discriminating between the trading days, and (ii) a return model is based on each trading day. Using machine learning techniques which involve decision tree classifiers, the scores of models in their abilities to predict the next positive return is shown in Panels A and B of Figure 4 reports the scores for all the 11 ETF sectors.

All scores were higher than 0.5, which suggest that the 15-min returns can provide predictive power which are better than a random walk return. Using a model which includes 15-min return of all trading days result in decision trees scores ranging from 0.671 to 0.727 for the energy and communication sector respectively. Communication sector and healthcare also had the highest and lowest range in prediction scores of 0.138 and

Figure 4: Prediction Scores of next 15-min positive return

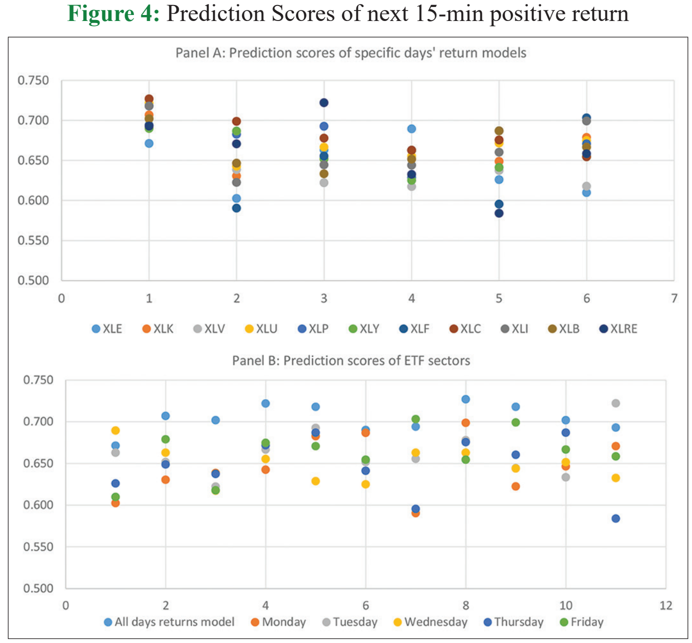


Table 4: Intraday volatility heatmap of U.S. sector ETFs returns

		XLE	XLK	XLV	XLU	XLP	XLY	XLF	XLC	XLI	XLB	XLRE
Monday												
Previous close	Open	0.074%	0.013%	0.011%	0.010%	0.006%	0.014%	0.035%	0.008%	0.028%	0.022%	0.017%
Open	9.45	0.007%	0.002%	0.000%	0.006%*	0.000%	0.000%	0.003%	0.004%	0.001%	0.000%	0.004%
9.45	10.00	0.012%*	0.000%	0.002%^	0.004%	–0.001%	0.003%*	0.002%	0.000%	0.003%	0.000%	0.007%
10.00	10.15	0.001%	–0.001%	0.000%	0.001%	0.000%	0.000%	0.000%	–0.001%	0.000%	–0.003%^	0.001%
10.15	10.30	0.001%	0.000%	0.000%	0.000%	–0.001%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15.00	15.15	–0.001%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15.15	15.30	–0.001%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15.30	15.45	–0.001%	0.000%	0.000%	0.001%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15.45	16.00	0.001%	0.005%	0.002%*	0.000%	0.002%	0.001%	0.001%	0.002%*	0.001%	0.001%	0.003%
16.00	16.15	0.004%	0.002%	0.001%	0.002%	0.001%	0.005%	0.007%*	0.002%^	0.003%	0.003%*	0.013%
AR(1)		2.984%*	9.405%	2.984%	3.265%	26.492%	1.528%	5.262%	11.561%	1.060%	13.889%	3.614%
max risk		0.074%	0.013%	0.011%	0.010%	0.006%	0.014%	0.035%	0.008%	0.028%	0.022%	0.017%
min risk		–0.001%	–0.001%	0.000%	0.000%	–0.001%	0.000%	0.000%	–0.001%	0.000%	–0.003%	0.000%
Tuesday												
		XLE	XLK	XLV	XLU	XLP	XLY	XLF	XLC	XLI	XLB	XLRE
Previous close	Open	0.044%	0.018%	0.010%	0.009%	0.007%	0.018%	0.029%	0.012%	0.022%	0.019%	0.015%
Open	9.45	–0.006%	–0.001%	0.000%	0.000%	0.000%	–0.001%	–0.005%	0.000%	–0.001%	–0.002%	–0.001%
9.45	10.00	0.015%	0.003%^	0.002%*	0.002%*	0.001%^	0.008%	0.002%	0.003%*	0.005%	0.005%*	0.004%
10.00	10.15	–0.001%	0.001%	0.001%	0.001%	0.000%	–0.001%	–0.001%	0.000%	–0.001%	0.000%	–0.001%
10.15	10.30	0.002%	0.000%	0.000%	0.000%	0.001%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15.00	15.15	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15.15	15.30	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15.30	15.45	0.000%	0.001%	0.001%	0.002%^	0.000%	0.001%	0.001%	0.000%	0.001%	0.000%	0.001%
15.45	16.00	0.002%	0.001%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
16.00	16.15	–0.002%	0.000%	0.000%	–0.001%	0.000%	–0.001%	0.002%	0.001%	–0.001%	–0.001%	–0.001%
AR(1)		16.318%	10.723%	4.540%^	15.691%	4.296%*	21.889%	28.072%	21.729%	16.566%	17.251%	17.800%
max risk		0.044%	0.018%	0.010%	0.009%	0.007%	0.018%	0.029%	0.012%	0.022%	0.019%	0.015%
min risk		–0.006%	–0.001%	0.000%	–0.001%	0.000%	–0.001%	–0.005%	0.000%	–0.001%	–0.002%	–0.001%
Wednesday												
		XLE	XLK	XLV	XLU	XLP	XLY	XLF	XLC	XLI	XLB	XLRE
Previous close	Open	0.023%	0.012%	0.008%	0.008%	0.004%	0.011%	0.024%	0.011%	0.014%	0.012%	0.011%
Open	9.45	0.006%	–0.009%^	–0.009%*	0.005%	–0.006%*	0.002%	0.001%	–0.003%	0.001%	–0.007%	–0.012%*
9.45	10.00	0.010%	0.001%	0.002%*	0.005%	0.001%*	0.001%	0.006%	0.002%	0.003%	0.003%	0.002%^
10.00	10.15	0.001%	0.000%	0.000%	0.001%	0.000%	0.000%	0.001%	0.000%	0.000%	0.000%	0.001%
10.15	10.30	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.001%
15.00	15.15	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15.15	15.30	0.001%	0.000%	0.001%	0.001%	0.001%	0.001%	0.001%	0.000%	0.000%	0.000%	0.001%
15.30	15.45	–0.001%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15.45	16.00	0.002%	0.004%	0.003%	0.004%	0.003%	0.002%*	0.004%*	0.003%	0.003%*	0.003%	0.002%*
16.00	16.15	–0.002%	0.001%	–0.001%	–0.001%	0.000%	–0.001%	0.000%	0.000%	–0.001%	–0.001%	–0.001%
AR(1)		3.401%*	17.100%	14.140%	0.570%	20.727%	4.000%	0.636%	9.544%	0.696%	9.143%	13.145%
max risk		0.023%	0.012%	0.008%	0.008%	0.004%	0.011%	0.024%	0.011%	0.014%	0.012%	0.011%
min risk		–0.002%	–0.009%	–0.009%	–0.001%	–0.006%	–0.001%	0.000%	–0.003%	–0.001%	–0.007%	–0.012%

(*Contd...*)

Table 4: (*Continued*)

Thursday											
		XLE	XLK	XLV	XLU	XLP	XLF	XLC	XLI	XLB	XLRE
Previous close	Open	0.029%	0.009%	0.003%	0.003%*	0.002%*	0.013%	0.006%	0.011%	0.008%	0.008%
Open	9.45	–0.003%	–0.002%	–0.001%	0.000%	0.001%	–0.001%	–0.001%	–0.002%	–0.001%	0.001%
9.45	10.00	0.009%	0.002%	0.002%	0.009%	0.006%	0.005%	0.002%	0.005%	0.005%	0.026%
10.00	10.15	0.005%	0.001%	0.000%	0.004%	0.001%	0.003%^	0.001%	0.003%^	0.001%	0.008%
10.15	10.30	0.001%	0.000%	0.000%	0.001%	–0.001%	–0.001%	0.000%	–0.002%	0.000%	–0.011%^
15.00	15.15	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15.15	15.30	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15.30	15.45	–0.001%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15.45	16.00	0.001%	0.003%	0.001%^	0.001%	0.001%	0.001%	0.002%	0.000%	0.001%	0.001%
16.00	16.15	0.004%	–0.001%	–0.001%	–0.001%	–0.001%	0.002%	–0.001%	–0.001%	0.000%	–0.001%
AR(1)		7.294%	8.827%	19.752%	–14.823%	39.672%	9.407%	13.089%	32.188%	12.796%	50.794%
max risk		0.029%	0.009%	0.003%	0.009%	0.006%	0.013%	0.006%	0.011%	0.008%	0.026%
min risk		–0.003%	–0.002%	–0.001%	–0.001%	–0.001%	–0.001%	–0.001%	–0.002%	–0.001%	–0.011%

Friday												
		XLE	XLK	XLV	XLU	XLP	XLY	XLF	XLC	XLI	XLB	XLRE
Previous close	Open	0.030%	0.011%	0.006%	0.006%	0.003%	0.012%	0.024%	0.007%	0.016%	0.013%	0.012%
Open	9.45	0.003%	–0.003%	0.005%	0.003%	0.000%	–0.021%	–0.007%	–0.002%	0.000%	–0.005%	—0.004%
9.45	10.00	0.019%	0.001%	0.001%	0.003%	0.002%	0.000%	0.004%^	0.001%^	0.002%^	0.004%	0.002%*
10.00	10.15	0.000%	0.000%	0.000%	–0.002%*	–0.001%	0.000%	0.000%	–0.001%	0.000%	–0.001%	0.000%
10.15	10.30	0.002%	0.001%	0.000%	0.000%	0.000%	0.000%	0.001%	0.000%	0.001%	0.000%	0.001%
15.00	15.15	–0.001%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15.15	15.30	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
15.30	15.45	0.001%	0.001%	0.000%	0.002%	0.001%	0.000%	0.001%	0.000%	0.000%	0.000%	0.002%*
15.45	16.00	0.010%	0.007%	0.003%	0.002%*	0.002%	0.002%*	0.004%*	0.003%	0.003%*	0.002%*	0.003%
16.00	16.15	–0.002%	–0.001%	–0.001%	–0.001%^	–0.001%	–0.001%	–0.001%	–0.001%	–0.001%	–0.001%	–0.001%
AR(1)		7.085%*	9.272%	19.045%	31.584%	14.560%	20.788%	11.424%	20.931%	10.664%	19.015%	7.425%
max risk		0.030%	0.011%	0.006%	0.006%	0.003%	0.012%	0.024%	0.007%	0.016%	0.013%	0.012%
min risk		–0.002%	–0.003%	–0.001%	–0.002%	–0.001%	–0.021%	–0.007%	–0.002%	–0.001%	–0.005%	–0.004%

0.021. This suggests that relying on specific days returns model for predicting the next positive return in the healthcare sectors is insignificant since all prediction scores on any day model were close to each other. Comparatively, for real estate, relying on the Tuesday return model would have yielded a much higher score of 0.722 relative to relying on Thursdays returns.

As observed in panel B, the highest scores predicting the next positive 15-min return was observed when using a model relying on all returns data, irrespective of the trading day, where 7 of the 11 sectors had their highest prediction scores. The dispersion in prediction scores shows that relying on the Monday only 15-min returns to predict the next 15-min positive return, result in the highest range of 0.108, compared to the other days of the week. This is in line with the higher U-shaped behavior observed in return on Mondays. The lowest prediction score of 0.584 was attributed to real estate, when relying on a model based solely on Thursdays' returns. Wednesdays reported the lowest range of 0.072 compared to the other days of the week. However, XLE had the highest prediction score of 0.689 when relying on Wednesdays return only.

Figure 4 captures the scores of return models in predicting the next 15-min positive returns in the 11 SPDR sector ETFs, using decision tree machine learning algorithm. Panel A displays the scores per each model, were 1, 2,3,4,5,6 on the horizontal axis represent the All-return model, Monday-returns model, Tuesday-returns model, Wednesday-returns model, Thursday-returns model and Friday-returns model. Panel B displays the scores for each ETF sector, where 1,2, 3.11 represents the eleven U.S. sector ETFs - XLE, XLK, XLV, XLU, XLP, XLY, XLF, XLC, XLI, XLB, and XLRE.

5.7. Impulse Responses-First Vaccination Rollout in U.S.

To capture the effect on the 1st U.S. vaccination rollout, we test for its impact on the ETF sector returns. Figure 5 shows that the active COVID-19 vaccination campaign in the U.S. had a positive effect with a gradual reduction in the new COVID-19 cases in the U.S. The U.S. is ranked 3rd, behind Israel and the U.K., with current average daily of administered doses far exceeding the 1.21 million required to achieve herd immunity by December 2021 (Statista, 2021). As per Figure 4, as at 21st of March 2021, a total of nearly 25% of the U.S. population (81.5 million) already received at least one dose.

Figure 5 shows the cumulative number of vaccinated people, per 1000, in the U.S. who received 1 or more doses since the first vaccination roll-out on the 14th of December 2020. These include those who received one dose of the single-shot Johnson and Johnson's Janssen COVID-19 vaccine. The secondary axis reports the number of new COVID-19 cases sourced from the Center for Disease Control and Prevention (CDC, 2021).

To capture the potential impact of the vaccination roll-out on the 11 sectors' ETF returns, we test for impulse responses of the sectors' returns to a shock in the number of new daily cases. As observed in Figure 5, although the first vaccination took place on the 14th of December 2020, the impact on the new cases was seen only around the 8th of January 2021. This can be explained by the number of days it takes for a patient to take a second doze of Pfizer-BioTech, which is the most administered COVID-19 vaccination in the U.S. to date (CDC, 2021). This is in line with Polack et al. (2020) who confirm a 95% protection against COVID-19 after a second doze. Due the 8th of January 2021 having the highest number of new COVID-19 cases and thereafter falling, we sample the data from this date and test for response of the 11 sectors' ETF returns to a shock in the number of new COVID-19 cases. Due to the number of vaccinated cases and COVID-19 cases being reported daily by 8pm ET after being verified by CDC, the impact on U.S. financial markets would be felt on the next day, due to markets being closed already. Based on a standard Vector Autoregressive (VAR) model (lags based on minimizing SIC) with stationary returns and new COVID-19 cases data (after 1st order differencing), results for impulse responses are shown in Figure 6. Except for energy, technology and financials, all sectors' returns dropped initially within the first 30 min at the open. This can be explained by the fact that new cases of COVID-19 are reported by 8pm ET, such that the effect is observed at the open on the next trading day. The effect was however short lasting with all ETF returns converging to a zero response within 1 h of the opening session.

Figure 6 displays the impulse responses of the 11 sector ETF returns to a shock in the change in the number of new COVID-19 cases. A VAR model with lag determined by minimizing SIC is used to capture the relationship between the ETF returns and change in the new COVID-19 cases. All variables are stationary based on ADF unit root test. New COVID-19 cases are sourced from the Center for Disease Control and Prevention (CDC, 2021) which reports the data daily at 8 pm ET.

Figure 5: Vaccinated people and New COVID-19 cases in U.S

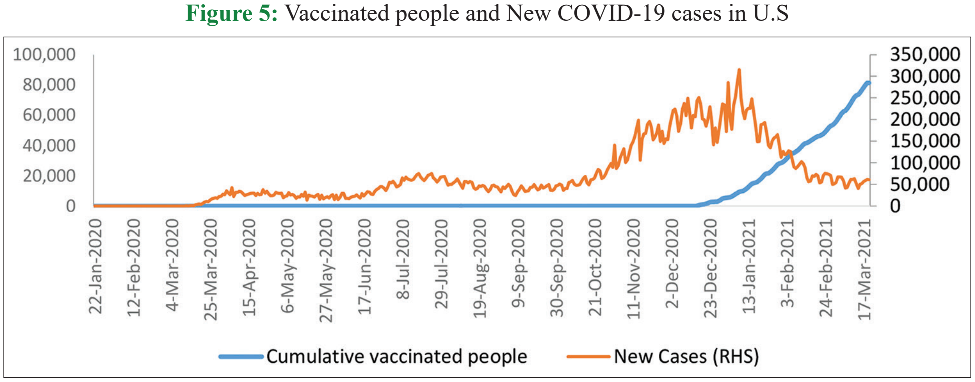
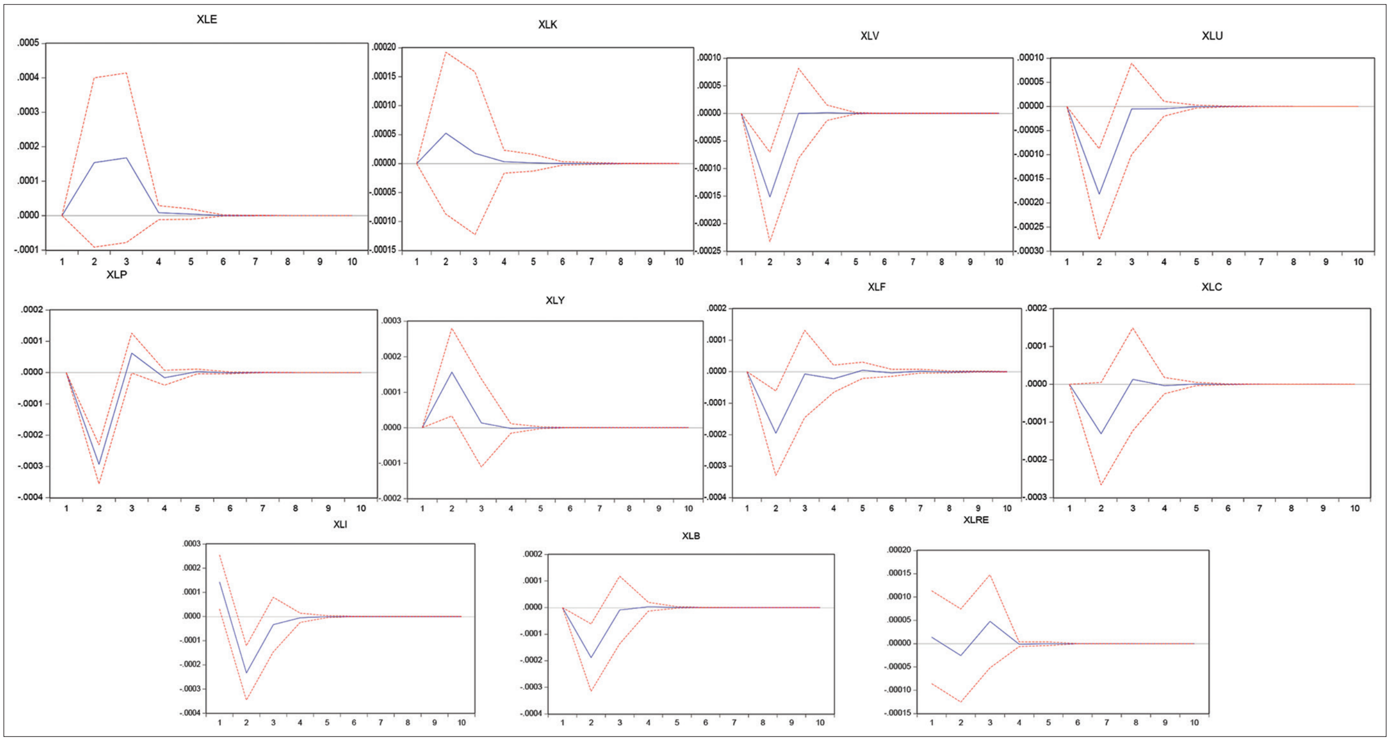


Figure 6: Impulse responses of U.S. ETF sector returns to COVID-19 vaccination rollout in the U.S



6. CONCLUSION

Substantive evidence exists regarding risk and return patterns in international equity markets. Yet, few studies have attempted to venture into similar sector analysis. We help close the gap with the first study on the 11 sector ETFs, which represent all the constituents in the S&P500, and more importantly the 11 U.S. sectors. The study covers intraday behavior in the risk and return of the 11 SPDR select sector ETFs, using 15 min data, a day-by-day decomposition to capture day-of-the-week behavior in both risk and return, and a look at the effect of the COVID-19 vaccination, which started on the 14th of December 2020, on those ETFs returns.

While all sectors' positive correlated returns at the open and close support the dissemination of information across economically linked industries, such stable relationships were not observed at the 15-min return periods after the open and close, with negative correlations observed among a few sector ETFs returns. Returns in both the first and last 15 min of the core session fluctuate more than for the rest of the day, similar to the U-smile pattern observed in equity markets. Average returns in the first 30 min of the core session tend to deviate from average returns observed at other times, with average returns in the first 15 min being highest. Average returns converge to near zero as we progress through a trading session, suggesting information accumulated throughout the day is absorbed and reflected in later prices of the day. Overnight returns were significant and negative in all sectors, except for utilities. Fluctuations observed in the first 30 min quickly dissipated for the remaining 15-min intervals of the day. The one lag autoregressive coefficients were all significantly negative for all sectors, suggesting that the previous return period has a significant impact in determining the current 15-min period return. Return volatilities at the open were significant. Volatilities in the 9.45–10 am period were highest for energy, relative to other sectors. This is in line with the highest return observed for the same sector at the same 15-min interval.

Mondays and Fridays had the most significant positive returns 15 min after the open. Similarly, the most significantly negative returns took place on Tuesdays and Wednesdays either at the open (overnight returns) or 15 min after the open. Most returns which occurred at the different 15-min intervals between 10.15 am and 15.30 pm were insignificant. Overnight returns were the most significant in contributing towards the volatility for any trading session, with highest volatility observed on Mondays, relative to the other days. The energy sector had the highest overnight volatility coefficients on all trading days, compared to all other sectors' volatilities. Overnight volatilities from Monday to Friday support the earlier U-shaped pattern observed in the volatility of returns. As we progress from Monday to Thursday, overnight volatilities, while still being significant, started to fell, before starting to recover on Fridays. Mondays' U-shape volatility smile patterns are more pronounced than in other days, due to the most significant overnight volatilities coefficients observed on Monday, and due to the positive volatilities observed towards the end of the Monday sessions. This motivates financial regulators to oversee trades in the open session at the start of the week, more diligently, as part of maintaining market stability in those sector ETF prices.

Relatively low volatilities observed during 4:00–4:15 pm sessions suggest that the closing auction imbalances do not have a significant impact relative to the volatilities observed during the day. This suggests that those 9 sector ETFs which have American options trading until 4.15pm do not significantly affect the ETF return volatilities. Due to the observation of several reversal in returns after 15-min, we test if any specific day return model would predict the next 15-min return better than a model which includes all 15-min return, without discriminating on any specific day. Using decision tree classifiers in machine learning, findings support that a Monday based return model results in the higher range compared to other days of the week models. However, the all-return model is still superior in predicting the next 15-min positive return.

Lastly, the active COVID-19 vaccination campaign in the U.S. had a positive effect with a gradual reduction in the new COVID-19 cases in the country. Except for energy, technology and financials, all sectors' returns dropped initially within the first 30 min at the open. This can be explained by the fact that new cases of COVID-19 are reported by 8pm ET, such that the effect is observed at the open on the next trading day. The effect was however short lasting with all ETF returns converging to a zero response within 1 h of the opening session. This suggests that portfolio managers who are actively managing portfolios which consist of the sector ETFs, should not be radically worried about the effects of the novel pandemic onto their portfolio risk and return, as the COVID-19 vaccination continues to decrease COVID-19 new cases, with a short-lasting effect on the return of sector ETFs.

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