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Stock return predictability in the time of COVID-19

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ABSTRACT

We examine predictive ability of a relatively large number of variables from currency, bond and commodity markets for US stock returns during the COVID-19 crisis. As a novel contribution, we estimate robust Lasso predictive regressions with Cauchy errors, consistent with extreme movements and nonlinearities in the market. Both investment grade and high yield corporate bonds emerge as significant predictors of US stock returns in the period, lending support to recent policy decisions by the Federal Reserve.

1. Introduction

The COVID-19 pandemic caused unprecedented volatility in the US stock market, in addition to severe disruptions in daily life and economic activity. At the end of March of 2020, global stocks had fallen by at least 25 percent from their highs in the previous month. Additionally, the 10-year US Treasury yield was lower than 1 percent and the VIX, commonly referred to as the “fear index”, spiked to levels above those of the 2007-2008 crisis.

Recent studies examine different aspects of financial market behavior in this extraordinary period. For example, Corbert et al. (2020) and Conlon and McGee (2020) investigate whether Bitcoin acted as a safe haven during the pandemic for Chinese equity markets and S&P 500, respectively, for which neither study finds supportive evidence. Sharif et al. (2020) examine the impact of the crisis on relations between oil price, US stocks and US economic policy uncertainty. They argue that the outbreak had a greater impact on economic policy uncertainty than the stock market and that it negatively influenced oil prices. Schoenfeld (2020) finds that US corporate managers significantly underestimated the pandemic risk. Ramelli and Wanger (2020) analyze stock price reactions of US firms to the COVID-19 shock and argue that companies with any Chinese exposure experienced lower adjusted returns. Goodell (2020) discusses economic and social impact of COVID-19 by outlining past research on pandemics as related to the branches of the finance and economics.

In this letter, our goal is to add to this growing literature by examining whether stock returns exhibited predictability during the crisis. If we can identify primary predictors for equities, this information could be a part of the policy arsenal of economic decision makers to ensure stability in financial markets. The findings could also help market participants design trading strategies. Also, in reference to aforementioned study by Goodell (2020), our paper relates to the literature on impact of pandemics on financial markets linkages.

We investigate predictability for the S&P 500 index returns as well as its constituent sectors by considering a relatively large number of variables from exchange rate, bond and commodity markets. We first show that, consistent with extreme financial market movements, stock returns followed a Cauchy distribution in the period examined. Cauchy is a member of the stable family of stable distributions.

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distributions and has fatter tails than the normal distribution. Then, as the first paper in the literature, we estimate penalized (Lasso and Adaptive Lasso) predictive regressions, with Cauchy distributed errors, that can simultaneously obtain variable selection and estimation.

Our findings indicate that there was significant predictability in the stock market in the time of COVID-19, and corporate bond markets, both investment grade and high yield, were by far the most informative variables. We discuss the implications of our analysis for policy makers and market participants.

2. Data

Our data cover the period between January 2, 2020 and April 16, 2020, for a total of seventy three observations. We use exchange traded funds (ETFs) for our predictors as they can be conveniently traded on the market and in such, provide synchronous data. Specifically, our predictor variables are, with their respective ETFs in parentheses, oil price (USO), gold (GLD), British pound (FXB), euro (FXE), Japanese yen (FXY), 10 to 20-year US treasury bond index (TLH), investment grade corporate bond index (LQD), high yield corporate bond index (HYG) and the VIX expected market volatility index.

We examine predictability for the main stock index as well as industry indices, similarly using ETFs. The stock indices used are the S&P 500 (SPY), materials (XBL), energy (XLE), financial (XLF), industrial (XLI), technology (XLK), consumer staples (XLP), utilities (XLU), health care (XLV), consumer discretionary (XLY), and real estate (IYR).

We convert all variables to daily returns by taking log price differences and proceed to investigate the distributional properties of stock returns. Based on the extent of the extreme values observed in the period, we hypothesize that stock returns were not normally distributed. We propose the Cauchy distribution, a part of the stable family, as an alternative that is “fat-tailed”. We fit both distributions and report two statistics for comparison in Table 1, the Bayesian Information Criteria (BIC) and the Anderson-Darling (AD)-test. For all of the stock indices the Cauchy distribution provides a better fit, as indicated by the BIC values. Furthermore, the AD-tests consistently reject the null hypothesis that returns follow normal distribution, while the null hypothesis of Cauchy distribution cannot be rejected. Thus, in the rest of the study, we proceed with assumption that stock returns are Cauchy distributed.

3. Empirical analysis

We construct the following model to examine one-step-ahead predictability of returns:

\[ R_{i,t} = \alpha + X_{i,t-1}\beta + e_t \]

In which, \( R_{i,t} \) stands for the individual stock index return and \( X_{i,t-1} \) represents the matrix of lagged predictor variables, including \( R_{i}, t-1 \), and the error terms are Cauchy distributed.

Since we have a relatively large number of predictors, along with a smaller set of observations, we use the Lasso and its further developed version, the Adaptive Lasso, to estimate this equation. The Lasso is a penalized regression method developed by Tibshirani (1996) that can simultaneously achieve both variable selection and estimation by assigning coefficients of uninformative variables to exactly zero. In other words, intuitively, if some of our predictors are redundant, excluding them by means of a statistical variable selection method should lead to a better fitting model.

While the Lasso regression has been popular, see, Zhang et al. (2019) and Panagiotidis et al. (2018) as recent examples, it is important to note that all prior studies have assumed Gaussian errors, without testing. In other words, the present study is the first paper to consider Cauchy errors with a Lasso regression, and our analysis should be much more robust to impacts of extremes, consequently.

To briefly discuss the methodological background, all penalized regression models can be estimated by reformulating the maximization of the likelihood function to a minimization problem where the goal becomes minimizing the objective function \( Q(\beta) = -\log L(\beta) \).

\[ Q(\beta) = -\log L(\beta) + \sum_{i=1}^{K} p(\beta) \]

In which the form of \( p(\beta) \) determines the kind of the penalized regression that is used. When \( p(\beta) = |\beta| \) the regression becomes the Lasso, and the tuning parameter, \( \lambda \), determines the stiffness of the penalty. Zou (2006) develops the Adaptive version of the Lasso, which achieves optimal large sample performance by introducing weights to the penalty on each coefficient in the Lasso procedure.

The underlying intuition of the Adaptive Lasso is to use an initial MLE estimation to identify relatively more important variables and to give those more weight in the final Lasso procedure. Following Zou (2006), we use the inverse of the original maximum likelihood estimates as weights. We use a coordinate descent algorithm for the optimization, provided by the JMP software produced by SAS, and

\[ ^2 \text{To provide a perspective, tails of the normal distribution approach zero at } -3.5 \text{ and +3.5 standard deviations. In the case of the Cauchy distribution, tails still are not close to zero at } -5 \text{ and + standard deviations.} \]

\[ ^3 \text{Using ETFs is further motivated by the fact that the US Federal Reserve announced on March 23rd to set up a special entity to buy corporate bonds, investment grade and high yield, and their ETFs, in an effort to stabilize markets. In fact, both LQD and HYG are included in these programs.} \]
employ minimization of the BIC to determine the stiffness of the penalty.

Rather than making a priori decisions on the choice of method to use, we estimate the regressions for each stock index by three candidates, the standard MLE, the Lasso and the Adaptive Lasso, and then, choose the best approach for each equation by the BIC. This model comparison process is important since it is not certain that a particular method will always provide the best fit and a priori adopting a method may prove inefficient.

For example, Adaptive Lasso has the oracle property and hence, asymptotically it is should be the best model. However, in practice, it relies on initial MLE estimates to construct the weights and if those estimates are poor, Lasso could be a better option. Similarly, we argue that a variables selection approach should perform better as we have many predictors; however, the validity of this argument is not guaranteed since it could be the case that all predictors are informative, in which case the ordinary ML estimation would be the best. Our empirical process, for which the results are available upon request, leads us to choose the Adaptive Lasso in each case, save for XLP; in which, the Lasso regression provides a better fit.

We report the result of the predictive regression estimates in Table 2. We find that the corporate bond ETFs (LQD and HYG) had significant predictive ability for both the main index as well as most industry returns. The regression coefficients are rather large and the r-squared values are relatively high for predictive regressions in financial markets research. Interestingly, the market sentiment variable, VIX, does not figure as a predictor for any stock return, nor do oil or gold. Japanese yen was also a predictor for the S&P 500 index. During the crisis, in mid-March, Japanese yen values reached multi-year highs. It is plausible that yen’s predictive power emanates from its perceived safe haven status.

4. Discussion and concluding remarks

Stabilization of the stock market should be a critical part of the policies as the economy recovers from the COVID-19 crisis. Our

| Normal | Cauchy |
|--------|--------|
| BIC    | A2     | BIC   | A2    |
| SPY    | –272.54| 2.08 (0.00) | –287.43| .50 (0.35) |
| XLB    | –259.54| 1.23 (0.00) | –261.8 | .41 (0.48) |
| XLE    | –207.43| 3.00 (0.00) | –235.69| .51 (0.33) |
| XLF    | –237.14| 1.78 (0.00) | –247.65| .54 (0.31) |
| XLI    | –256.79| 2.11 (0.00) | –272.45| .49 (0.34) |
| XLK    | –250.84| 1.82 (0.00) | –262.68| .50 (0.56) |
| XLP    | –294.9 | 2.78 (0.00) | –319.13| .44 (0.43) |
| XLU    | –249.05| 2.52 (0.00) | –268.54| 1.10 (0.06) |
| XLV    | –286.86| 1.75 (0.00) | –294.26| .44 (0.43) |
| XLY    | –272.66| 2.19 (0.00) | –291.25| .42 (0.43) |
| IYR    | –243.99| 2.92 (0.00) | –271.12| .79 (0.14) |

Note: This table provides model fit statistics for Normal and Cauchy distributions to stock returns. The null hypothesis of A2 tests is returns are Normal (Cauchy) distributed and the p-values are in parentheses.

Table. 2
Predictive regression estimates.

| SPY | XLB | XLE | XLF | XLI | XLK | XLP | XLU | XLV | XLY | IYR |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| USO | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| GLD | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| FXB | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| FXY | 0.53 (0.00) | 0   | 0   | 0   | 0   | 0   | 0.27 (0.30) | 0   | 0.42 (0.16) | 0   |
| FXE | 0   | 0.83 (0.00) | –1.22 (0.58) | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| LQD | 0.92 (0.00) | 0.99 (0.00) | 0   | 0.51 (0.02) | 1.39 (0.00) | 1.13 (0.00) | 0   | 1.47 (0.00) | 0.82 (0.00) | 1.07 (0.00) | 0.93 (0.00) |
| TLH | 0   | 0   | 0   | 0   | 0   | 0   | –0.2 (0.01) | 0   | –0.24 (0.00) | 0   | –0.75 (0.00) | 0   |
| HYG | –0.89 (0.00) | –1.17 (0.00) | 0   | 0   | –1.19 (0.00) | –0.78 (0.00) | 0   | 0   | –0.73 (0.00) | 0   | –0.82 (0.17) | 0   |
| VIX | 0   | 0   | 0   | 0   | 0   | 0   | –0.06 (0.18) | 0   | 0   | 0   | 0   |
| AR1 | 0   | 0   | –0.26 (0.66) | –0.54 (0.00) | 0   | 0   | –0.28 (0.00) | 0   | 0   | 0   | 0   |
| R²  | 39% | 38% | 11% | 32% | 31% | 46% | 19% | 31% | 38% | 31% | 37% |

Note: This table provides parameter estimates for Eq. (1) by robust penalized predictive regressions. P-values for statistical significance are in parentheses.
analysis highlights that both investment grade and high yield corporate bonds were the primary risk factors across the equity market. Thus, our findings lend strong support to the unprecedented decision by the Federal Reserve to purchase both investment grade and high yield corporate bonds, and their ETFs, in addition to Treasury securities.

Furthermore, our analysis shows the importance of considering non-normal errors, especially in highly volatile periods. It is noteworthy that, in results available upon request, we also estimated our models by the Adaptive Lasso with conventional Gaussian errors and found that none of the predictors was significant. Consequently, our study would have presented completely different conclusions if we had not examined validity of the normality assumption. Therefore, an implication of our study is that estimating modern penalized regressions with fat tailed distributions could provide robust results and this approach should find more application in future financial markets research.

Author statement

I attest that I do not have any personal or financial conflicts of interest in this research.

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