Cross-Sector Comovements and Policy Impact in the COVID-19 Stock Market: A Dynamic Factor Approach *

Diana Joy Xiuyao Yang†

University of California, Irvine

This version: August 2021

Abstract

U.S. equity returns comoved remarkably during the COVID-19 pandemic. This study constructs a dynamic factor model to illuminate the sources and implications of these comovements. Estimation of the model using a Bayesian Markov Chain Monte Carlo method reveals that the comovements had a weak daily oscillation pattern. Within that pattern, monetary policy significantly impacted the equity returns of several key sectors. In addition, cross-sector equity returns were shaped by news of monetary policies, fiscal stimulus, and unemployment. News about conventional and unconventional monetary policy shocked each sector in opposite directions. Interest-rate policy surprises had a stronger positive impact on equity returns than other unconventional monetary policy shocks. News about fiscal stimulus had the most substantial impact and triggered all sectors to rebound from the bear market at the end of March 2020. Applying Natural Language Processing sentiment analysis, this study also sheds light on the positive correlation between comovements and news sentiment.

Keywords: Comovements, Monetary Policy, Dynamic Factor Model, Markov Chain Monte Carlo, Bayesian Inference, Text Mining

JEL Codes: C11, C32, E43, E44, E52, G12

*I wish to thank my dissertation committee: Dr. Gary Richardson, Dr. Ivan Jeliazkov, and Dr. Matthew Harding for their advice and encouragement.

†Email: xiuyaoy@uci.edu

1 Introduction

The turbulence in the U.S. stock market during the COVID-19 pandemic has sparked renewed interest in the long-time study of financial market comovements. Two different views on comovements of excess returns have been proposed in the literature: the traditional view attributes comovements to the expected fundamental values while an alternative view is sentiment- or friction-based. During the COVID-19 pandemic, the traditional view is inadequate to explain the comovement phenomena in the U.S. stock market. This empirical study constructs a Dynamic Factor Model (DFM) and decomposes the stock excess returns into fundamental and non-fundamental components. The model reveals that the non-fundamental components mainly drive the stock comovements during the pandemic.

Correlations in cross-sector returns are expected because macroeconomic conditions affected all sectors' expected earnings. What is puzzling is that despite the pandemic's disparate impacts on each sector, stocks from all sectors remained to comove excessively. For example, the left panel of Figure (1) shows that durable consumer goods production declined by 51% from February 2020 to April 2020, while the electric and gas output only decreased by 1.3%. The top right panel of Figure (1) shows that the hospitality industry's unemployment rates jumped from 5.7% in February 2020 to 39.3% in April 2020 due to the government's restrictions, while the finance industry only suffered an increase from 1.6% to 5.4%. Conversely, cross-sectors of the stock market moved closely together, especially during the beginning of the pandemic. (See the cross-sector excess returns in the bottom panel of Figure (1).) Additionally, at the end of March 2020, when the economy was still in recession, all sectors in the stock market comoved and rebounded together.

This study aims to explain the puzzle by measuring the latent non-fundamental forces that drove the comovements of stock returns. In this paper the non-fundamental force is market sentiment or latent sentiment, which propels the economy into periodic booms and busts.

The main results of this study is that it reveals the size and patterns of the latent sentiment. By controlling the known fundamental factors in a dynamic factor model, the unknown latent factor can be identified and measured. Using Bayesian Markov chain Monte Carlo (MCMC) approach, the study finds that, between January 1, 2020, and August 31, 2020, the latent sentiment has a weak daily oscillation pattern with an autoregressive coefficient of -0.09 in an AR(1) process. This result helps explain the stock market's extreme comovements, as well as the high volatility during the pandemic, especially in the beginning.

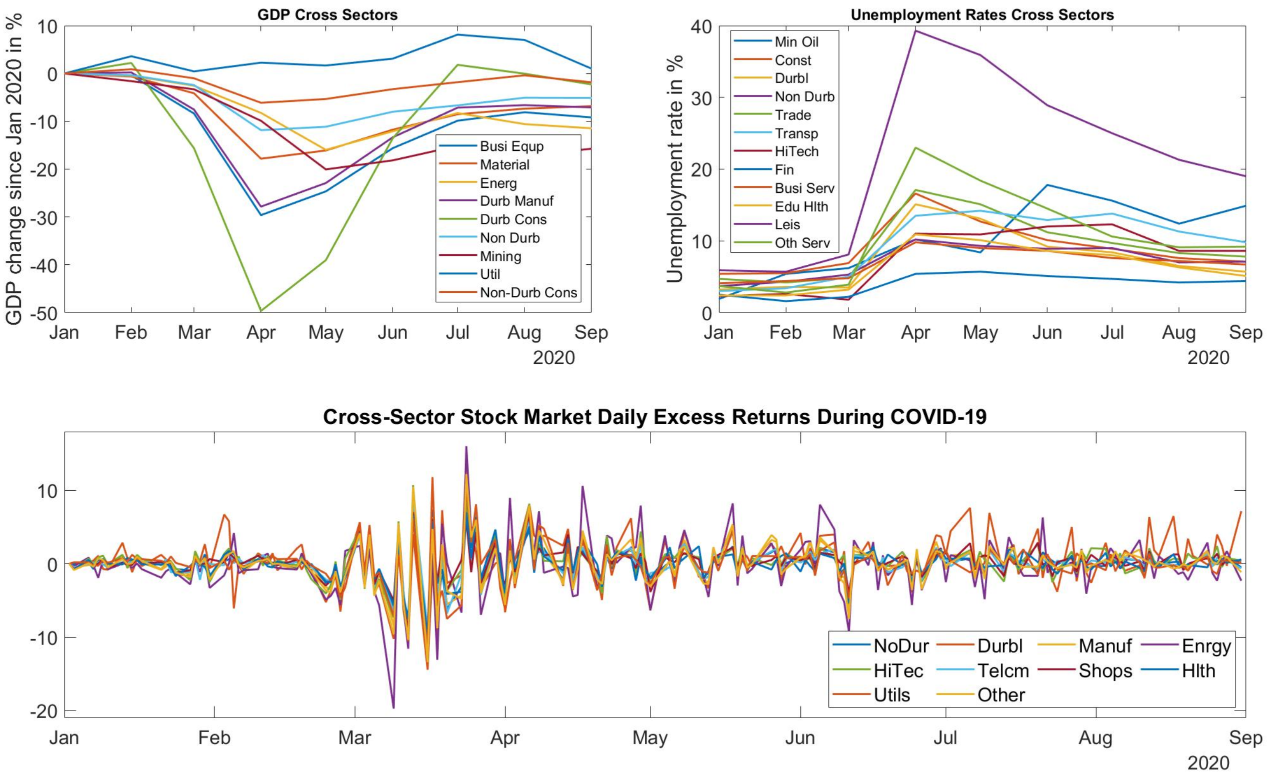


Figure 1: Cross-sector monthly unemployment, GDP, and daily excess returns from January 1, 2020 to August 31, 2020.[1]

In addition, the study identifies and measures the impact of monetary policy and various news shocks on stock returns by controlling fundamentals and the latent factor variable. In particular, the model contains 43 fundamental variables (including macroeconomics variables, financial market variables, COVID-19 related variables), four dummy variables for shocks (conventional and unconventional monetary announcements, fiscal stimulus news, and unemployment news shocks), and one latent variable. The identifying assumption is that conditioning on the above controls, the impact of monetary policy and news shocks can be isolated and measured.

The results indicate that when the Fed cut its benchmark interest rates by 100 basis points, stock prices in all sectors rose immediately. The more prominent jumps were observed in the utilities and non-durable goods sectors, which are 11.35% and 7.33%, respectively. For any given sector, the conventional and unconventional monetary policy news shocked the sector in opposite directions. Of the positive monetary news shocks, the strongest shocks were from the interest rate policy surprises, while unconventional monetary policy news had a more sluggish impact on stock returns. Conversely, fiscal stimulus news had the most substantial positive impact and triggered all sectors to rebound from the bear market at the end of March 2020.

Furthermore, this study finds evidence of the positive linkage between the latent factor and the sentiment of the Fed's communication or media news, respectively. Wall Street Journal headlines are used as a proxy of the market sentiment. This study finds a positive correlation, 0.31, at the 95% statistically significant level by exploiting the Natural Language Processing (NLP) approach — Valence Aware Dictionary for Sentiment Reasoning (VADER) algorithm. Finally, this paper explores the associations between community mobility and stock returns and finds that different mobility data categories (e.g., visiting parks or staying in residential houses) have opposite associations with stock returns.

To the best of my knowledge, this paper is the first to examine comovements combined with monetary policy effects and policy news shocks during the COVID-19 pandemic. The existing finance literature suggest that the increased comovements are due to increased shared sentiment more than increased shared economic fundamentals. For example, Shiller (1989), using a simple present value model, shows that the comovements in stock prices cannot be accounted for by those in dividends. This argument provides an alternative view to the Efficient Markets Hypothesis (EMH) (see Fama (1970)). Pindyck and Rotemberg (1993), Vijh (1994), and Barberis, Shleifer, and Wurgler (2005), among others, examine the excess comovements between industry indices in the US and find significant excess comovements.

From a methodological viewpoint, this study is closely related to the DFM estimation literature. The method was initially developed by Geweke (1977) as an extension of the time series model for analyzing cross-sectional data. The influential work by Sargent and Sims (1977) develop the dynamic index models and provide evidence that one "index" can explain a large fraction of the variance in macroeconomic variables. Stock and Watson (1989) and Sargent (1989) using maximum likelihood and the Kalman filter estimate the DFM. Stock and Watson (2002) develop a static Principal Component Analysis (PCA) estimation. The factor is essentially a weighted average with the eigenvectors of the sample variance matrix as the weights. There a few advantages of the PCA method, for example, it can deal with high dimensional data. In addition, the results of principal components are consistent and robust (see Bai and Perron (2003), Bai and Ng (2006)). Although its advantages, the PCA method remains limited. First, the principal components are computed ex-ante, treated as given in the estimation, therefore not suit for dynamics. Second, PCA method is not suitable for models have covariables. Chib and Greenberg (1996) and Chib, Nardari, and Shephard (2006) introduce blocking in the Markov Chain Monte Carlo (MCMC) method, which combines the efficient state space and the consistent nonparametric estimates approach. This blocking method allows MCMC to reduce correlations between draws efficiently by separating certain sets of parameters. Chan and Jeliazkov (2009) further improve the efficiency of the collapsed MCMC sampling by implementing a new blocking technique for the state space models. This study follows the collapsed MCMC method in Chan and Jeliazkov (2009) to investigate the puzzling comovements in the equity returns during the pandemic.

This study contributes to the emerging literature that investigates the impact of the COVID-19 pandemic on the economy. For example, Gormsen and Koijen (2020) develop a model of crisis that shows dividend futures can be a valuable tool for studying the evolving growth expectations in response to the coronavirus outbreak and subsequent policy responses. Cox, Greenwald, and Ludvigson (2020) develop a dynamic asset pricing model to investigate the causality of stock market fluctuations. Different from those studies, this study adds to this growing body of literature related to the study of monetary and fiscal policy effects by providing evidence of the policy impact on the equity returns during the COVID-19 recession. In particular, this empirical study highlights monetary policy effects and the impact of conventional, unconventional monetary and fiscal policy shocks. Therefore, it is also related to the following research. Jinjarak et al. (2020) study both fiscal and monetary policies in the Euro-zone. Levin and Sinha (2020) assess the effectiveness of monetary forward guidance. Benmelech and Tzur-Ilan (2020) and Bianchi, Ludvigson, and Ma (2020) study both fiscal and monetary policies during the COVID-19 pandemic.

The remainder of the paper proceeds as follows. In Section 2, the Dynamic Factor Model is set up. Section 3, the model is derived, and the estimation steps are described. Section 4 describes the data sets, including financial market data, macroeconomics data, COVID 19 related information, policy announcements, and restrictions related data. Section 5 presents the estimation results, and policy implications. The linkage between the latent factor and news sentiment is also studied. The final section concludes.

2 Model

To illuminate the sources of the comovements and their implications, I construct a dynamic factor model (DFM). Let $y_{i,t}$ be the dependent variable, stock market excess returns or risk premia at the end of time t for sector i, where $i \in [1, 2, ..., n]$. Let $t = 1...T$ and $y_t = [y_{1,t}, y_{2,t}, ..., y_{n,t}]'$. Let X_t represent the independent variables, which include w_{t-1}, y_{t-1}, z_{t-1} and d_t[2]. Let w_{t-1} be the COVID-19 public health variables and community movement/mobility variables. Let z_{t-1} be the observed macro variables for all sectors lagged in time, which includes monthly GDP by sector, monthly unemployment rates by sector, M1 money stock, monthly Consumer Price Index, monthly Consumer Sentiment Index, and the daily Effective Federal Funds rate. Let d_t be a vector that includes four dummy variables representing conventional and unconventional monetary announcement shocks, fiscal stimulus news shocks, and unemployment news shocks. Let f_t be the unobservable comovement, which affects the dynamics of the excess returns of the stock market.

The DF model takes the State Space representation as below,

Observation equation:

$$y_t = X_t\beta + Af_t + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \Omega) \tag{1}$$

State equation:

$$f_t = \gamma f_{t-1} + \mu_t, \qquad \mu_t \sim \mathcal{N}(0, \sigma^2) \tag{2}$$

$$\text{where } X_t = \begin{bmatrix} (1, w'_{t-1}, y'_{t-1}, z'_{t-1}, d'_t) & & & \\ & (1, w'_{t-1}, y'_{t-1}, z'_{t-1}, d'_t) & & \\ & & \ddots & \\ & & & (1, w'_{t-1}, y'_{t-1}, z'_{t-1}, d'_t) \end{bmatrix},$$

β is a vector containing the corresponding parameters ordered equation by equation, $\beta = vec\left([c : \lambda^w : \lambda^y : \lambda^z : \lambda^d]'\right)$, $vec(\cdot)$ is a vectorization operator, which stacks the columns of a matrix one underneath the other into a vector. Let c be the intercept $n \times 1$ vector and λ^w, λ^z, λ^y, and λ^d be the regression coefficients in the observation equation. The factor loading A is a $n \times 1$ vector. γ is the autoregressive correlation of the state equation. Let ε_t and μ_t denote the idiosyncratic errors that are in the zero-mean Gaussian distribution $\mathcal{N}(0, \Omega)$ and $\mathcal{N}(0, \sigma^2)$. Assume σ^2 is a scalar and Ω is a $n \times n$ diagonal covariance matrix with $(\omega_{11}, ..., \omega_{nn})$ on the diagonal and zeros on the off diagonal, which implies there is no

[2]Notation convention - we assume the values at the end of $t-1$ is equal to the values at the beginning of t and d_t is the contemporaneous shock during the day t.

concurrent correlation between $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ for all $i \neq j$[3].

Now stack equation (1) over time t, for $t = 1...T$, and we have,

$$y = \; X\beta + \mathcal{A}f + \varepsilon, \quad \varepsilon \sim \mathcal{N}(\mathbf{0}, \; I_T \otimes \Omega) \tag{3}$$

where, $\mathcal{A} = I_T \otimes A$, and

$$y = \begin{bmatrix} y_1 \\ \vdots \\ y_T \end{bmatrix}, \quad X = \begin{bmatrix} X_1 \\ \vdots \\ X_T, \end{bmatrix}, \quad f = \begin{bmatrix} f_1 \\ \vdots \\ f_T, \end{bmatrix}, \quad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_T \end{bmatrix}$$

3 Estimation

In a DFM, both parameters and latent factors are regarded as random variables whose posteriors need to be sampled from. This study follows Chan and Jeliazkov (2009) as they improve the efficiency of the Markov Chain Monte Carlo (MCMC) sampling by implementing the integrated likelihood sampling. Instead of using the Kalman filter, they propose a new blocking technique by exploiting collapsed MCMC, sampling the loading parameter marginally over the factor vector f, and then drawing the factor f from its full-conditional distribution.

As the most challenging part in this estimation consists of sampling A and f from the posterior distribution, it is worthwhile to provide details of the derivation for factor f's conditional distribution before outlining the whole sampling procedure. First, the likelihood function $\pi(y|f, \beta, A, \Omega, \gamma, \sigma^2)$ is shown, followed by the conditional density $\pi(f|\gamma, \sigma^2)$. By Bayes' theorem, the posterior probability density $\pi(f| \; y, \beta, A, \Omega, \gamma, \sigma^2)$ can be immediately derived (See Koop (2003)). For compact writing, let θ represents $\{\beta, A, \Omega, \gamma, \sigma^2\}$ including all model parameters. Also, the covariant matrix X is regard as given, in this paper I drop X from the conditioning set $\pi(f|y, X, \theta)$ to simplify the notation. By Bayes' theorem,

$$\pi(f| \; y, \theta) = \frac{\pi(y|\theta, f)\pi(f|\theta)}{\pi(y|\theta)} \tag{4}$$

the posterior probability density $\pi(f| \; y, \theta) \propto \pi(y|\theta, f)\pi(f|\theta)$.

As ε in (3) is Gaussian distribution, the conditional likelihood function is straightforward and also a Gaussian distribution,

$$\pi(y|\theta, f) \sim \mathcal{N}\left(X\beta + \mathcal{A}f, \; I_T \otimes \Omega\right) \tag{5}$$

[3]The concurrent correlation effects from cross sectors are absorbed by $y_{-i,t}$

Now, to explain the conditional density $f|\gamma, \sigma^2$, first rewrite equation (2),

$$f_t - \gamma f_{t-1} = \mu_t, \qquad \mu_t \sim \mathcal{N}(0, \sigma^2) \tag{6}$$

Subsequently, stack equation (6) over time $t = \{1, 2, 3, ..., T\}$, and rewrite as following,

$$Hf = u \tag{7}$$

where

$$H = \begin{bmatrix} 1 & & & \\ -\gamma & 1 & & \\ & \ddots & & \\ & & -\gamma & 1 \end{bmatrix}, \quad f = \begin{bmatrix} f_1 \\ \vdots \\ f_T, \end{bmatrix}, \quad S = \begin{bmatrix} \frac{\sigma^2}{1-\gamma^2} & & & \\ & \sigma^2 & & \\ & & \ddots & \\ & & & \sigma^2 \end{bmatrix}$$

,
and,

$$u = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_T \end{bmatrix} \sim \mathcal{N}(0, S), \tag{8}$$

The first top-left element in the covariance matrix S is the variance of the initial f_1, which is assumed distribute at the steady state of a first order autoregressive AR(1) process. Please refer to Chib and Greenberg (1994) for more details. The distribution is as below,

$$f_1 \sim \mathcal{N}(0, \frac{\sigma^2}{1-\gamma^2}) \tag{9}$$

Following Fahrmeir and Kaufmann (1991), the conditional density of f can be derived as,

$$f|\gamma, \sigma^2 \ \sim \mathcal{N}\Big(0, (\sigma^{-2}K)^{-1}\Big) \tag{10}$$

where the precision $\sigma^{-2}K = H'S^{-1}H$, and K $= \begin{bmatrix} 1 & -\gamma & & \\ -\gamma & 1+\gamma^2 & -\gamma & \\ & \ddots & \ddots & \ddots \\ & -\gamma & 1+\gamma^2 & -\gamma \\ & & -\gamma & 1 \end{bmatrix}$.

Now to express the conditional posterior, combine both (5) and (10),

$$[f|y, \theta] \sim \mathcal{N}(\hat{f}, P^{-1})] \tag{11}$$

where the mean and precision are given as below,

$$P = \sigma^{-2}K + \mathcal{A}'(I_T \otimes \Omega^{-1})\mathcal{A} \tag{12}$$

$$\hat{f} = P^{-1}[\mathcal{A}'(I_T \otimes \Omega^{-1})(y - X\beta)] \tag{13}$$

Following Chan and Jeliazkov (2009), this study employs their estimation method Metropolis– Hastings-within-Gibbs. The steps are as follows,

Step 1: Draw β from the conditional posterior marginalized out of f for the observation equation.

It is helpful to rewrite the model. Assume $\psi = \mathcal{A}f + \varepsilon$; subsequently, the equation (3) becomes to the following,

$$y = X\beta + \psi, \qquad \psi \sim \mathcal{N}(0, \Sigma) \tag{14}$$

where Σ is a $nT \times nT$ covariance matrix, $\Sigma = [(I_T \otimes \Omega) + (I_T \otimes A)\sigma^2 K^{-1}(I_T \otimes A)']$ obtained from equations (3) and (10).

After a few steps of derivation (Please see Appendix A for more details), the conditional posterior distribution of β is obtained:

$$[\beta|\ y, A, \Sigma, \gamma, \sigma^2] \sim \mathcal{N}(\beta, B) \tag{15}$$

where the mean β and variance B are given by,

$$B = \left(B_0^{-1} + \sum_{t=1}^{T} X_t'\Omega^{-1}X_t - \tilde{X}_t'P^{-1}\tilde{X}_t \right)^{-1} \tag{16}$$

$$\beta = B\left(B_0^{-1}\beta_0 + \sum_{t=1}^{T} X_t'\Omega^{-1}y_t - \tilde{X}_t'P^{-1}\tilde{y} \right)^{-1} \tag{17}$$

where the compact notations $P = [\sigma^{-2}K + I_T(A'\Omega^{-1}A)]$, $\tilde{X}_t = A'\Omega^{-1}X_t$ and $\tilde{y}_t = A'\Omega^{-1}y_t$.

Step 2: Draw from the joint conditional posterior of A and f for the observation equation.

To generate draws of A and f from the joint distribution $[A, f|y, \beta, \Omega, \gamma, \sigma^2]$, two substeps are required.

Step 2.1 $[a|\ y, \beta, \Omega, \gamma, \sigma^2]$, sample a first independent of f

Step 2.2 $[f|\ y, \beta, A, \Omega, \gamma, \sigma^2]$, sample f and depends on a

This study follows Chan and Jeliazkov (2009) to generate the posterior density of A marginalized over f. By Bayes' Theorem,

$$\pi(A|\ y, \beta, \gamma, \Omega, \sigma^2) = \frac{\pi(A|\ y, f, \beta, \gamma, \Omega, \sigma^2)\pi(f|\ y, \beta, \gamma, \Omega, \sigma^2)}{\pi(f|\ y, A, \beta, \gamma, \Omega, \sigma^2)} \tag{18}$$

As both loading A and factor f are unknown, there are potential sign and scale identification issues for them. However, this can be solved by restricting the first element in the loading vector to 1, that is, $A = \{1, a'\}$. More details can be found in the study of Chan and Jeliazkov (2009). As the first element in the loading vector A is fixed as 1, replacing A with a, the posterior density of a, given $(y, \beta, \gamma, \Omega, \sigma^2)$ and marginalized over f, is as follows:

$$\begin{aligned}
\pi(a|\ y, \beta, \gamma, \Omega, \sigma^2) &= \frac{\pi(a|\ y, f, \beta, \gamma, \Omega, \sigma^2)\pi(f|\ y, \beta, \gamma, \Omega, \sigma^2)}{\pi(f|\ y, a, \beta, \gamma, \Omega, \sigma^2)} && (19)\\
&\propto \frac{\pi(a|\ y, f, \beta, \gamma, \Omega, \sigma^2)}{\pi(f|\ y, a, \beta, \gamma, \Omega, \sigma^2)} && (20)
\end{aligned}$$

Notice that the loading parameter a is not involved in the term $\pi(f|\ y, \beta, \gamma, \Omega, \sigma^2)$ on the numerator, which therefore can be relegated to a constant, and can be scaled proportionately on both the denominator and numerator in calculating the acceptance ratio and eventually canceled out.

According to (20), the next step is to derive the numerator $\pi(a|\ y, f, \beta, \gamma, \Omega, \sigma^2)$. Please see more details in Appendix B. This section also skips explaining of denominator $\pi(f|\ y, a, \beta, \gamma, \Omega, \sigma^2)$ as it has been derived in the equations (11), (12) and (13).

By Metropolis-Hastings (M-H) algorithm, a proposal density is tailored closely mimicking the posterior density. In practice, it is extremely important for the candidate generating density to have fatter tails than those of the target posterior. Let a^* be the draw from the tailored proposal, a student t distribution, of which, the mean $\hat{a}$ and negative inverse of Hessian, $\hat{A}$, are obtained by Maximum Likelihood Estimation. Let df be the degree of freedom, in general, df is chosen as a small number to ensure the fat details. The jumping distribution $q(a^*|a)$ represents the distribution for the current state a to jump to the next state a^*. Rewrite the tailored proposal density as follows for notation convenience.

$$q(a^*|a) = q(a^*|\hat{a}, \hat{A}, df), \qquad q(a|a^*) = q(a|\hat{a^*}, \hat{A}^*, df) \tag{21}$$

Thus, the rate $\alpha(a, a^*)$ of accepting the next proposed draw a^* is,

$$\alpha(a, a^*) = min\left\{1, \frac{\pi(a^*|\ y, \beta, \gamma, \Omega, \sigma^2)q(a\ |\hat{a^*}, \hat{A}^*, df)}{\pi(a|\ y, \beta, \gamma, \Omega, \sigma^2)q(a^*|\hat{a}, \hat{A}, df)}\right\} \tag{22}$$

Please see more details in Appendix C.

The next step is step 2.2, which generates draws of f from $[f|\ y, a, \beta, \gamma, \Omega, \sigma^2)] \sim \mathcal{N}(\hat{f}, P^{-1})$. This study follows Chan and Jeliazkov (2009) and implement an efficient way to compute the latent factors by employing forward and back substitution techniques. Usually, the variance matrix P^{-1} is obtained by inverting the precision matrix P from (12). However, this study uses Cholesky decomposition to avoid the daunting task of inverting a matrix and only invert the Cholesky factor. Let C be the Cholesky factor, such that $C'C = P$. Multiplying $C'C$ on both sides, equation (13) becomes,

$$C'C\hat{f} = A'(I_T \otimes \Omega^{-1})(y - X\beta) \tag{23}$$

Apply the forward substitution to solve $C\hat{f}$, and use the back substitution technique with the assumption $C'm = \zeta$ and $\zeta \sim \mathcal{N}\ (0, 1)$ to solve $\hat{f}$. Draw ζ, and solve m backward, which is $m = C^{-1}\zeta$. This implies m is distributed in $\mathcal{N}\ (0, P^{-1})$, where it has the idea variance. The subsequent step is to add the mean $\hat{f}$ from (12) to the result of m. Now, a draw of $[f|y, a, \beta, \gamma, \Omega, \sigma^2] \sim \mathcal{N}\ (\hat{f}, P^{-1})$ is achieved.

Step 3: Draw from the conditional posterior of Ω for the observation equation.

Assuming Ω is a diagonal covariance matrix with $(\omega_{11}, ..., \omega_{nn})$ on the diagonal, and the conjugate inverse Gamma prior of the form, $\omega_{ii} \sim \mathcal{IG}(d_0, D_0)$, the study generates draws of each variance ω_{ii} equation-by-equation, from the conditional posterior distribution, where $ii = \{11, ..., nn\}$. The conditional posterior distribution $[\Omega|y, \beta, A, f, \gamma, \sigma^2]$ is given by,

$$\omega_{ii} \sim \mathcal{IG}(d, D) \tag{24}$$

$$d = \frac{d_0 + T}{2} \tag{25}$$

$$D = \frac{D_0 + e_i'e_i}{2} \tag{26}$$

where d_0 and D_0 are the inverse Gamma prior parameters, and e_i is the residue vector with T length from the ith observation equation.

Step 4: Draw from the conditional posterior of γ for the state equation.

To generate sample γ from the conditional posterior $[\gamma|y, f, \beta, A, \Omega, \sigma^2]$, the study adapts the usual time series Bayesian updating rules in Chib and Greenberg (1994) and Chib and Jeliazkov (2001). Draws of γ from its distribution until the factor is found in the stationary region; it is then subject to the usual M-H acceptance criterion. Specifically, let $\mathcal{F}^* = [f_1, f_2, ..., f_{T-1}]$ and $\mathcal{F}^{**} = [f_2, f_3, ..., f_T]$, and initial (γ_0, Γ_0). Draw a candidate γ^* according to the distribution below,

$$
\begin{aligned}
\gamma^* &\sim \mathcal{N}(\hat{\gamma}, \Gamma) && (27)\\
\hat{\gamma} &= \Gamma(\Gamma_0^{-1}\gamma_0 + \mathcal{F}^{*\prime}\mathcal{F}^{**}\sigma^{-2})^{-1} && (28)\\
\Gamma &= (\Gamma_0^{-1} + \mathcal{F}^{\prime *}\mathcal{F}^{*}\sigma^{-2})^{-1} && (29)
\end{aligned}
$$

Accept the proposed value γ^* with the M-H probability of move given by the ratio $\alpha(\gamma, \gamma^*)$, i.e.

$$\alpha(\gamma, \gamma^*) = min\left\{1, \frac{f_{\mathcal{N}}(f_1|(0, \frac{\sigma^2}{1-\gamma^{*2}}))}{f_{\mathcal{N}}(f_1|(0, \frac{\sigma^2}{1-\gamma^2}))}\right\} \quad (30)$$

Step 5: Draw from the conditional posterior of σ^2 for the state equation.

The way to generate draws of σ^2 from $[\sigma^2|\ y, \beta, A, f, \Omega, \gamma]$ is similar to step 3. From equations (7) and (8), the conditional distribution of σ^2 is given by an inverse Gamma distribution:

$$
\begin{aligned}
\sigma^2 &\sim \mathcal{IG}(g, G) && (31)\\
g &= \frac{g_0 + T}{2} && (32)\\
G &= \frac{G_0 + u'u}{2} && (33)
\end{aligned}
$$

where the conjugate prior of $\sigma^2 \sim \mathcal{IG}(g_0, G_0)$, $u = Hf = f_s - f_p$, $f_s = [f_1(1-\gamma)^{1/2}, f_2, ..., f_T]'$ and $f_p = [0, \gamma f_1, ..., \gamma f_{T-1}]'$.

MCMC Sampling Algorithm Summary

Step 1. Draw β from $[\beta|\ y, A, \Omega, \gamma, \sigma^2] \sim \mathcal{N}(\beta, B)$.

Step 2. Draw A and f from the joint posterior distribution $[A, f|y, \beta, \Omega, \gamma, \sigma^2]$ through the following two sub-steps.

Step 2.1 Implement MH sampling, draw a from $[a|\ y, \beta, \Omega, \gamma, \sigma^2]$ independently of f.

Step 2.2 Sample f from $[f|\ y, \beta, A, \Omega, \gamma, \sigma^2] \sim \mathcal{N}(\hat{f}, P^{-1})$.

Step 3. Draw Ω from the conditional posterior distribution $[\Omega|\ y, \beta, A, f, \gamma, \sigma^2] \sim \mathcal{IG}(d, D)$.

Step 4. Implement MH sampling, and draw γ from the conditional posterior distribution: $[\gamma|\ y, \beta, A, f, \Omega, \sigma^2]$.

Step 5. Draw σ^2 from the conditional posterior distribution $[\sigma^2|\ y, \beta, A, f, \gamma, \Omega] \sim \mathcal{IG}(g, G)$.

4 Data

There are 48 variables (including a latent variable) in the model, which are grouped into four categories. They are as follows: financial market data by sector with daily frequency; macroeconomics variables — comprising both daily and monthly frequency data; COVID-19 related data, including daily public health information and daily community mobility data; and dummy variables representing the announcements or news shocks.

First, the financial market dataset includes daily excess returns by sector and daily trading volume data, in total 11 variables. Daily excess returns are calculated by deducting the daily risk-free rates from the daily stock returns in sectors[4]. Based on the Standard Industrial Classification (SIC) codes[5], each stock in NYSE, AMEX, and NASDAQ is assigned to one of the ten sectors: consumer non-durables; consumer durables; manufacturing; energy; high-tech; telephone and television transmission; wholesale and retail; healthcare; utilities; and other[6]. This study uses the daily NASDAQ market trading volume[7] as one proxy to capture the financial market sentiment (see Baker and Wurgler (2007)). The daily trading volume reveals the underlying different opinions on the stock market between buyers and sellers. However, having the trading volume variable as the only proxy to represent market sentiment still cannot capture the majority share of variations in stock prices. The next section explains that it is still necessary to include the latent factor as it is an essential driver for the stock market returns.

[4]Daily return data are retrieved from the Fama-French database library http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[5]SIC refers to https://www.osha.gov/data/sic-manual

[6]Other sector includes mines, construction, build management, transportation, hotels, entertainment, and finance.

[7]The daily trade volume in NASDAQ is obtained from http://www.nasdaqtrader.com/

The second category is macroeconomic data, which includes 25 variables comprising daily Effective Federal Funds Rate (EFFR), monthly Gross Domestic Product (GDP) by sector, monthly unemployment rates by sector, monthly Consumer Price Index (CPI), monthly Consumer Sentiment Index, and monthly M1 money stock. All of these series are retrieved from the Federal Reserve Economic Data library (FRED)[8]. These series of data encompass daily or monthly frequency. The time-series literature comprises a few ways to handle this issue. Econometricians usually either aggregate the higher frequency data to a lower frequency or interpolate the lower frequency data to the higher frequency. However, these methods may result in the loss of helpful information while smoothing. Therefore, the estimated results can be biased. The study uses the original data only by keeping the monthly variables constant during the month, with the justification that monthly variables can be observed and updated once each month. However, it can cause a larger variance of the parameters on the monthly regressors than the daily regressors[9].

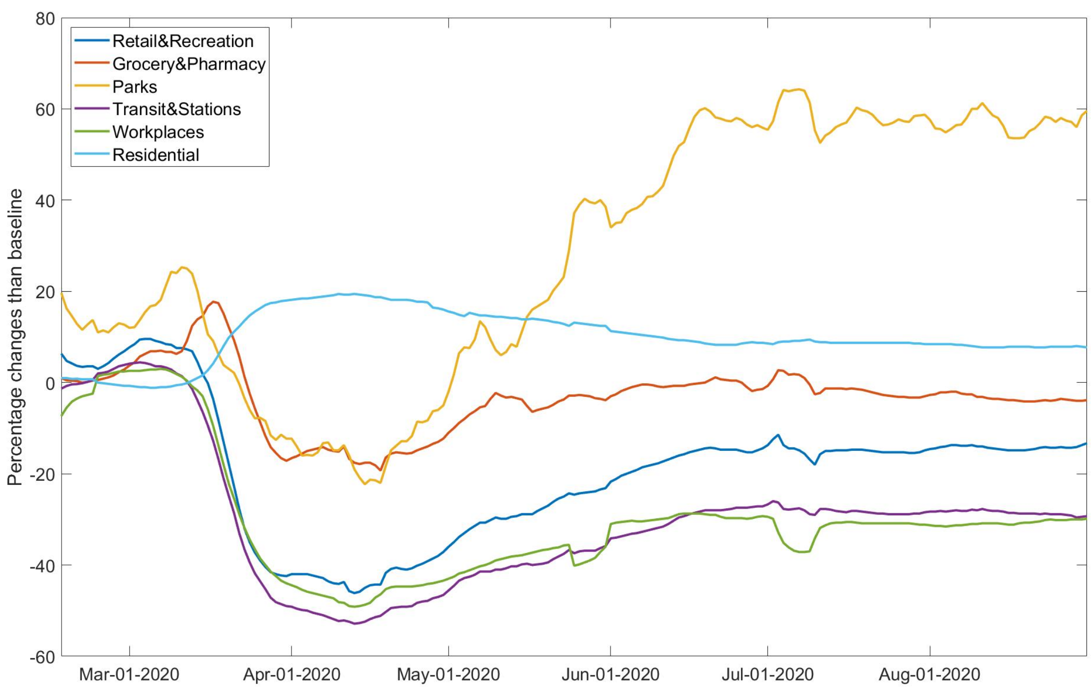


Figure 2: Google community mobility changes to baseline in 2020. Data source: https://www.google.com/covid19/mobility/

[8]https://fred.stlouisfed.org/

[9]This paper simulates 10,000 iterations with 3,000 burn-in to improve accuracy of the results

The third category dataset is COVID-19 related information, including community mobility set and public health set, a total of seven variables. The subset of the community mobility dataset for the U.S. is obtained from Google's COVID-19 Global Community mobility data center[10]. The mobility level of the community is measured by the number of visits and time spent in a particular category of location. The six categories of the locations people visit are retail and recreation, grocery and pharmacy, residential areas, transit, parks, and workplaces, as shown in Figure (2). The mobility dataset starts from January 3, 2020, before COVID-19 was widespread worldwide. The initial five weeks (from January 3 to February 6, 2020) are issued as the baseline period[11]. The baseline values in each category are the median value of the five-week baseline period, which has seven different values representing each day of a week. Google measures the mobility level in the degree of change by comparing it to the baseline values on the same day of a week. For example, Tuesday's visit to the grocery and pharmacy will only be compared to the baseline value of Tuesday visits to the grocery and pharmacy. Further, as the financial market data are only for weekdays except for holidays, the study uses the corresponding five weekdays for the mobility level and ignores the weekend data.

The COVID-19 public health status — the daily death rate variable — is collected from Our World In Data[12], which combines information from multiple sources such as the World Health Organization (WHO), Johns Hopkins University, and the European Center for Disease Prevention and Control. The study uses the daily new deaths attributed to COVID-19 smoothed per million people series in the data set. The first three deaths attributed to COVID-19 in the U.S. reported as of March 2, 2020, stand at a rounding rate of 0.001 per million[13].

This study creates four dummy variables to identify and assess the impact of shocks from monetary policy announcements, fiscal policy announcements, and government restrictions for different sectors. They represent the shocks of conventional monetary policy announcement, unconventional monetary policy announcement, fiscal news, and Unemployment rates

[10] https://www.google.com/covid19/mobility/. In their document, it also includes the data limitation.

[11] As one of the data limitations mentioned in the document of the data set, the chosen based line may not be the perfectly normal baseline days, because a short period of the year cannot represent normal for all regions in the U.S.

[12] https://ourworldindata.org/coronavirus

[13] https://www.nytimes.com/2020/04/22/us/coronavirus-first-united-states-death.html, this new information may shift the timeline of the virus's spread through the U.S. a few weeks earlier than previously believed on February 26, 2020.

news. The Conventional monetary policy includes lowering the target range for the federal funds rate and increasing the Federal Reserve's holdings of Treasury securities and agency Mortgage-Backed Securities (MBS). As the lower bound of the target range is near zero, the Federal Reserve has created several trillion dollars of loan facilities to support the economy, and this is the unconventional monetary policy. See more details in Appendix E.

Finally, all data are transformed into stationary series. See Appendix F for more details of the data and the process of transformation.

5 Estimation Results

5.1 Latent Factor and Loading Parameters

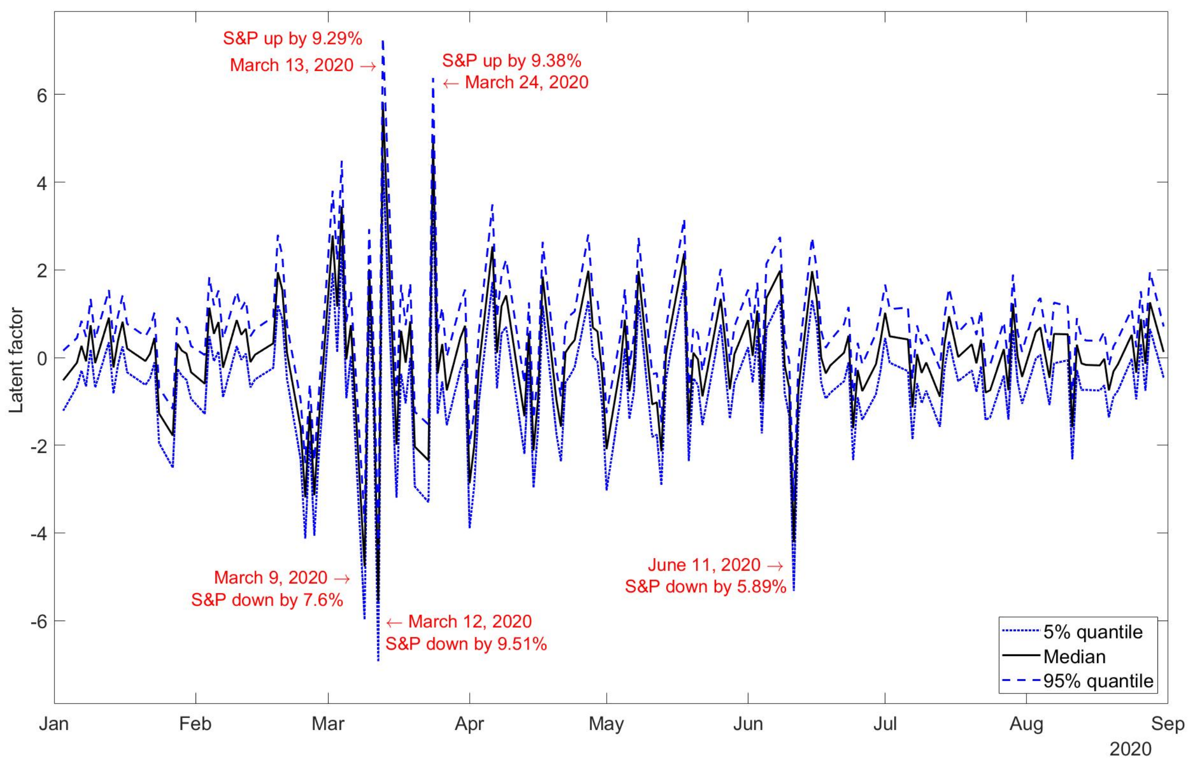


Figure 3: Latent factor estimation at 5%, 50% and 95% quantiles from January 2020 to August 2020.

The results of the estimated posterior distribution of the latent factor are presented in

Figure (3). The black line in the middle indicates the median value of the posterior distribution along with 5% and 95% quantile bands; the narrowness of the band suggests that the factor is estimated rather precisely. Figure (3) shows that there are three dives on March 9, March 12, and June 11, 2020, decreasing by 712%, 940% and 513% from the previous days, respectively. These estimation results are consistent with the fact that the Dow Jones Index dropped by -7.79%, -9.99%, and -12.93% on those three days. These three events also coincide with world events and monetary policy news. On March 11, 2020, the WHO upgraded the status of the coronavirus outbreak from an epidemic to a pandemic, and two days later, on March 13, 2020, the president of the U.S. declared a national emergency. The results of the latent factor, market sentiment, in those hectic events reflect the impact of these shocks on investors. Unprecedentedly, the stock crash in March only caused a short-lived bear market, and in April, the stock market rebounded into a bull market, indicating the extremely restless pattern of the latent sentiment. On June 11, 2020, one day after the Fed announced that interest rates would remain near zero to 2022, signaling a long road to recovery, the U.S. stock market suffered its worst one-day sell-off since March. This phenomenon can be explained by the possibility that forward guidance is also a negative signal to the market in addition to the growing fears of a second wave of COVID-19 cases. Not coincidentally, following each dive, the market shows a significant jump. The latent factor reflects this high volatility behavior with two considerable spikes shown in Figure (3). These spikes are on March 14 and March 24, 2020, with the values increasing by 204% and 312%, respectively.

On March 3 and March 15, 2020, FOMC announced lowering the benchmark rates by a half and one percentage points, respectively, and ended at zero. The estimated results of the latent sentiment on those announcement days suggest a decrease by 59% and 134%, respectively,[14] from their previous trading days. The decreasing comovements suggest that collectively with other sources of shocks, the conventional monetary policy (lowering the target rate to zero and increasing holding Treasury securities and agency MBS) is not sufficiently powerful to overcome the underlying restless latent sentiment to support the stock market. Note: These declining comovements do not represent negative effects of the monetary policy. These estimated results are the isolated comovements after controlling all macroeconomics effects, including effects of various policies and news shocks. Effects of monetary policy are explained in Section (5.2), and news impact is in Section (5.3).

[14] This number is calculated by comparing the factors between March 16, 2020, and March 13, 2020, due to weekend announcement.

5.1.1 Persistence Properties of the Dynamic Latent Sentiment

To measure the evolution of the latent factors, this study collects the autoregressive coefficients (2) at each step of the estimation procedure to obtain their distribution. The latent factors have a negative and small autocorrelation, -0.0868; the 45% and 55% quantiles of this distribution are -0.0936 and -0.0764, respectively. See Figure (4). These results can help explain the volatility of the latent sentiment and weak mean reverse pattern. For example, during the nine trading days (between March 9 and March 19, 2020), the market did not simply tumble linearly, however, on four of the nine days, the market rose by nearly 5% after the previous day crash. The estimated median of the variance of the dynamic latent factor is 2.201 (see Figure (5)).

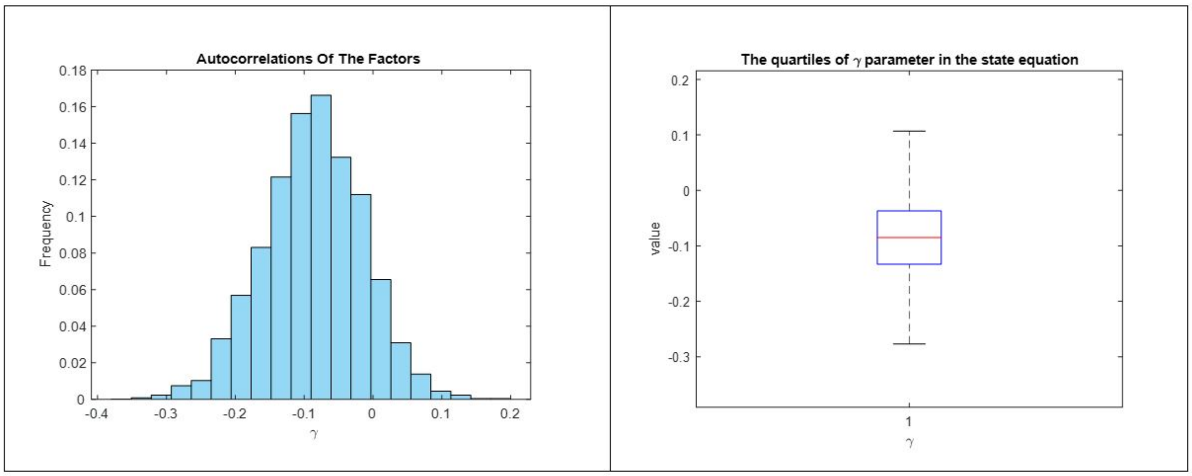


Figure 4: Persistence properties of the dynamic factors.

5.1.2 Loading Parameters

The loading parameter for each sector can be understood as a multiplier effect on the market comovements. Figure (6) displays the estimated distributions for the loading parameters. The first sector — non-durable goods — is assumed as the benchmark. The highest medium values of the loading parameters are 1.91, the energy sector; 1.67, the durable sector; and 1.64, the other sector. As the comovements permeate the whole market across sectors, it is valuable to consider the whole picture of the equity market to determine how sectors evolve during the pandemic. Figure (7) gives a three-dimensional depiction of these comovements across sector and time; the "sector" axis in this graph arrays the different sectors in the order given in Figure (6). The vertical axis is the latent factor in each sector. The colors illuminate the comovements and volatility of the market.

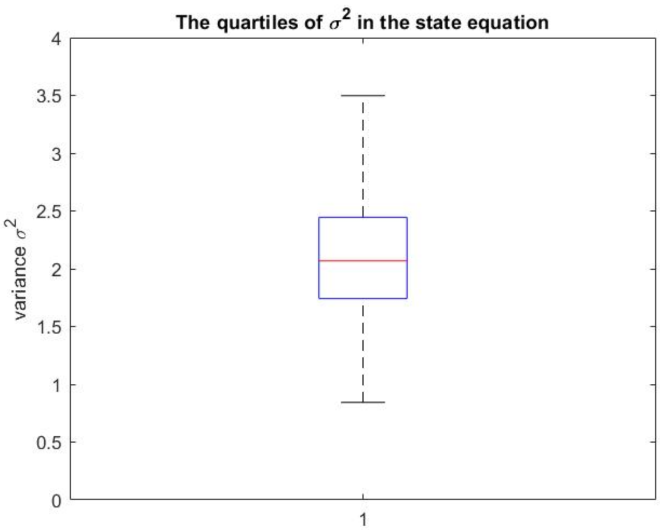


Figure 5: The boxplot of the variance of the dynamic latent factor

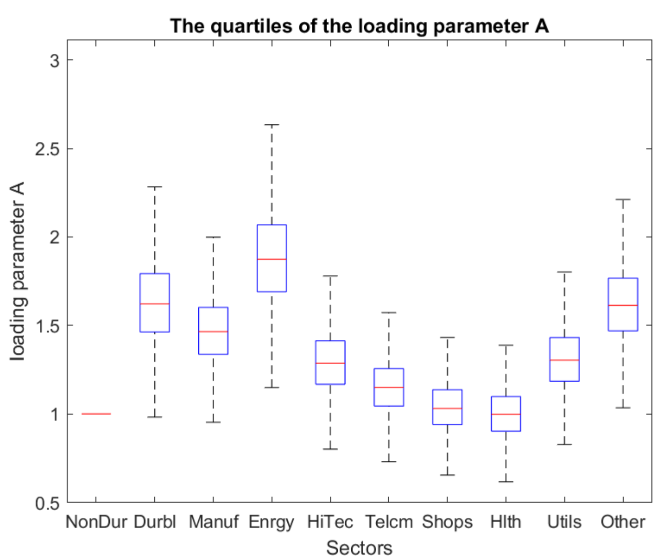


Figure 6: Coefficients in the figure correspond to the ten sectors in the loading vector A from Equation (1). NoDur, 1; Durbl, 1.67; Manuf, 1.48; Enrgy, 1.91; HiTec, 1.30; Telcm, 1.15; Shops, 1.04; Hlth,1.01; Utils, 1.33; Other,1.64.

Figure (8) displays the variances of the idiosyncratic risks in all ten sectors. After controlling the macroeconomic condition, monetary policy effects, news shocks, and their co-movements, the remaining risks are relatively small with a medium variance less than 2 for most sectors, except for the high-risk energy and durable goods sectors.

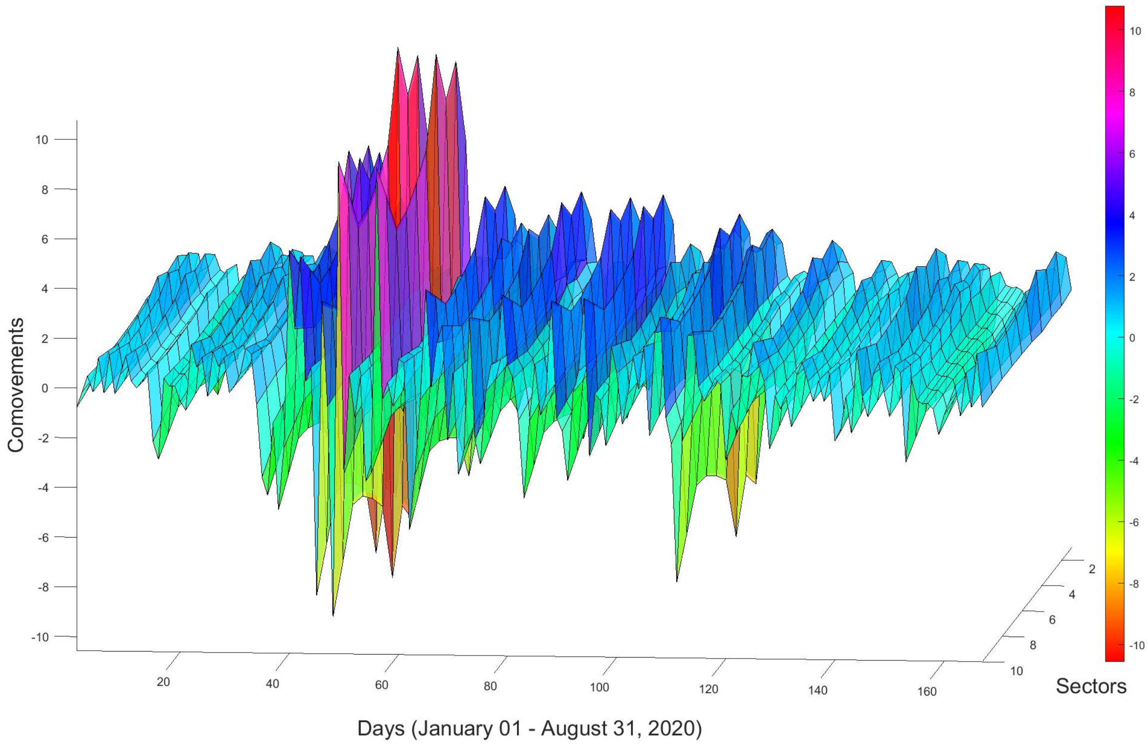


Figure 7: Comovements across sector and time. Sectors: 1-NoDur, 2-Durbl, 3-Manuf, 4-Enrgy, 5-HiTec, 6-Telcm, 7-Shops, 8-Hlth, 9-Utils, 10-Other

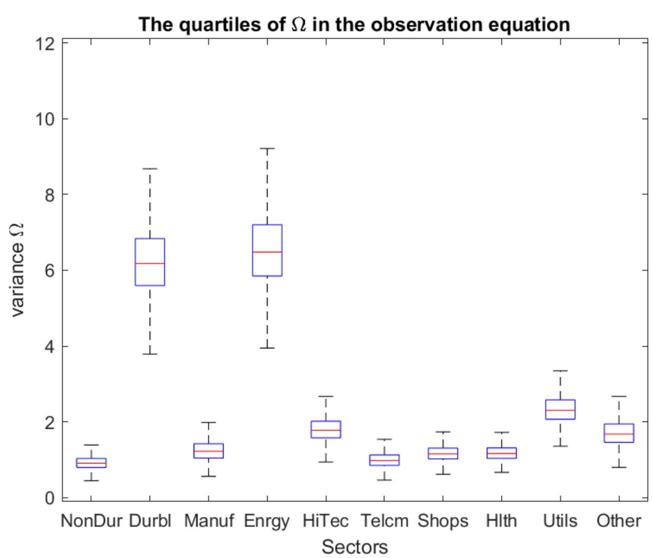


Figure 8: The boxplot of the variance of the observation equation

5.2 Monetary Policy Interest Rates Effect

First, the study briefly analyzes the effects of the monetary policy interest rates on the stock returns during the sample data between January 1 and August 31, 2020. Subsequently, in the next section, this paper examines the policy news shocks on the stock returns as part of monetary policy impact analysis. The effects of the interest rates on stock returns are reported in Table (1), and the quantile boxplot is reported in Figure (9). It shows that utilities and non-durable consumer goods sectors are the most sensitive to interest rates. The results show that if the Fed Effective Funds Rate is decreased by one percentage point, specifically, the utilities and non-durable goods stock returns increase by 11.35% and 7.328%, respectively; the overall market of ten sectors was a 4.18% increase. These estimation results are in congruence with the empirical data — between March 16, 2020 and March 17, 2020, the stock market jumped up by 11.81% in utilities and 7.40% in non-durable goods, were very close to my estimations 11.35% and 7.328%, when the Fed announced reducing interest rates by one percentage point on the evening of March 15, 2020[15]. These two sectors are defensive sectors. Whether the economy and the stock market are good or bad, people still need the necessities, such as food, water, and electricity. However, durable goods stock prices are less responsive to lower interest rates. That households reduced durable goods expenditures during the COVID-19 recession due to uncertainty about future income, made the interest rate policy accommodation less responsive in the durable goods sector.

Table 1: Estimated Coefficients on the Effective Federal Funds Rate (EFFR)

	NoDur	**Durbl**	**Manuf**	**Enrgy**	**HiTec**	**Telcm**	**Shops**	**Hlth**	**Utils**	**Other**
EFFR	-7.328	-0.849	-4.522	-2.508	-2.990	-2.451	-3.250	-4.097	-11.35	-2.501

Note: The negative signs imply that the excess returns of stocks and EFFR move in opposite directions.

5.3 Announcement Shocks

Since the first coronavirus death that shocked the U.S. media at the end of February in 2020, there was an enormous amount of news and information broadcasting every day. There was collective news including spikes of new deaths and cases, oil price tank, government's stay-at-home and closure of business orders, monetary policy announcement, fiscal stimulus, and

[15]Since March 15 is a Sunday, this paper counts the next trading day as the monetary policy day for prediction purpose.

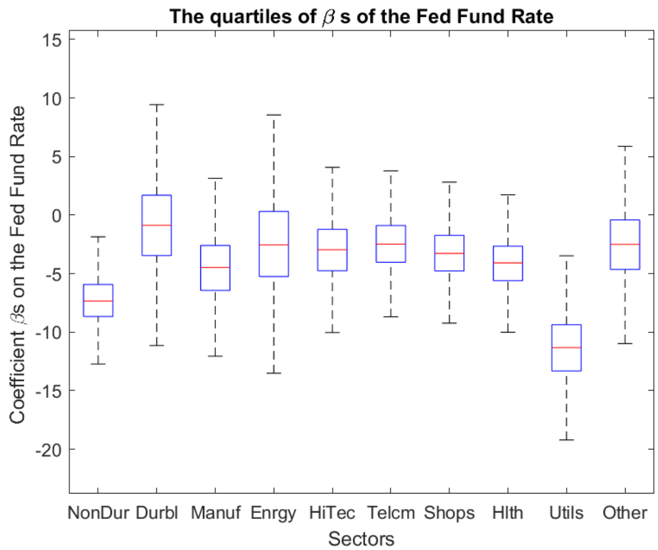


Figure 9: The Boxplot of the βs on the Fed Funds Rate variable

unemployment rate announcements. When such news is released, it has a significant effect on economic activities and the financial market. To attempt to separate the impact of an amalgam of news, the constructed four dummy variables representing four types of shocks: conventional, unconventional monetary policy announcement, fiscal stimulus announcement, and unemployment rate announcement[16].

5.3.1 Monetary Policy Announcement Shocks

Distinguishing the impact of announcements between a conventional monetary policy and an unconventional monetary policy is one of the essential results of this study. A conventional monetary policy in the U.S. refers to the Federal Reserve altering the target interest rate and opening market operations, for instance, purchasing Treasury securities and agency MBS. Conversely, an unconventional monetary policy is a situation where the Federal Reserve pursues an alternative monetary policy, such as Large Scale Asset Purchase (LASP) or forward policy guidance, when facing the Zero Lower Bound (ZLB) constraint, to influence interest rates to reach its dual mandate of full employment and stable prices. At the beginning of COVID-19, the Fed announced the conventional monetary policy of lowering the benchmark interest rate to ZLB on March 3 and March 15, 2020, respectively. Immediately after reach-

[16] Dummy variables are either one or zero. One represents an announcement for that day. It is possible that news leaks before the official day of the announcement, and it is also possible there are multiple sources of shocks on that same day, but they capture the major shocks on the financial market of that day.

Table 2: The impact of News shocks

Estimated Coefficients of The four dummy variables										
Dummy Variable	**NoDur**	**Durbl**	**Manuf**	**Enrgy**	**HiTec**	**Telcm**	**Shops**	**Hlth**	**Utils**	**Other**
Conventional MP News	1.711	-1.544	1.300	1.095	-0.856	0.786	-0.598	-0.464	1.440	-0.461
Unconventional MP News	-0.006	0.783	-0.086	0.222	0.688	0.030	0.231	0.288	-0.371	0.447
Fiscal News	4.265	4.448	6.267	6.883	3.986	4.592	1.256	4.213	5.980	6.147
Unemployment News	0.475	-0.043	0.383	0.228	-0.666	0.157	-0.351	-0.127	0.010	0.189

ing the constrain, on March 17, 2020, the Federal Reserve Board announced establishment of a Commercial Paper Funding Facility (CPFF) to support the flow of credit to households and businesses. Subsequently, there were 15 announcements regarding unconventional monetary policies establishing nine new lending facilities from the middle of March to May 2020 (See the event details in Appendix E). These interventions can also be reviewed as signals that the Fed acknowledges the economy is suddenly heading toward the brink of recession and "they will do whatever they can" to help support the economy.

Table (2) reports the estimated impact of four different news, including conventional and unconventional monetary policy announcement, fiscal stimulus and unemployment news. Coefficients are in units of percentage. For instance, the top left number 1.711 implies that, on average, the conventional monetary policy announcement shock caused excess return on the non-durable goods sector by 1.711% at the end of that announcement day. One caveat is that it is "average" effects, because the FOMC cut half percent on March 3; on March 15, 2020, a full one percent is cut and reached ZLB. I also present the corresponding coefficients' distribution in Figure (10) and Figure (11) for the non-durable and utility sectors[17]. As shown in the quantile box plots, the coefficients' inter-quantile ranges are all centered and the variances are quite small, which imply the results are significant.

In addition to Table (2), Figure (12) helps us visually explain the differences between the two types of monetary policy announcement impact. The bars labeled blue in Figure (12) indicate the impact of the announcements regarding conventional monetary policy shocks, while the bars labeled in red are the impact of the unconventional monetary policy shocks.

The positive impact of the announcements of conventional monetary policy is 1.711% in

[17]Graphs for other sectors are also available upon request. Notched boxplot version is also available implying results significance.

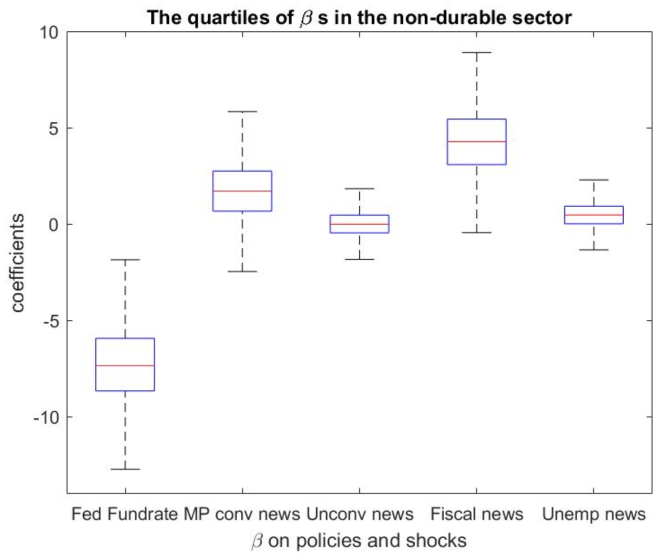


Figure 10: Boxplot for the impact of news shocks in non-durable sector

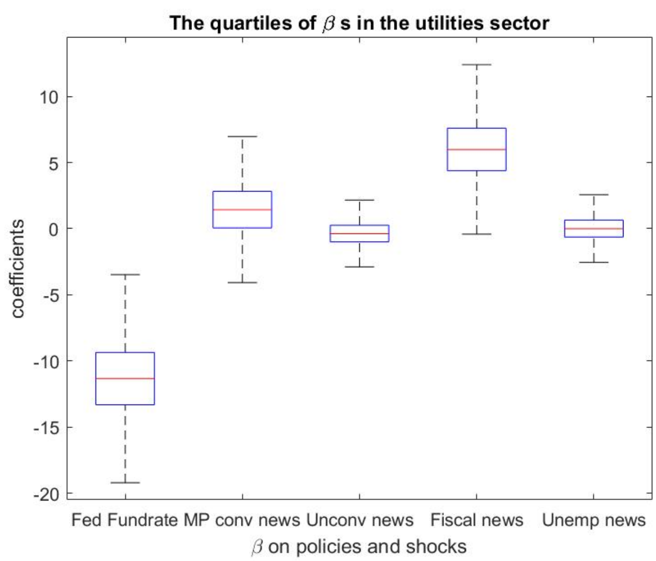


Figure 11: Boxplot for the impact of news shocks in utilities sector

non-durable consumer goods, 1.440% in utilities, 1.300% in manufacturing, 1.095% in energy and 0.786% in communication sectors. These results are expected and similar to the interest rate effects because defensive sectors in the stock market are sensitive to the interest rate. Further, another reason that could contribute to the announcement impact is the striking phenomenon of consumers' panic-buying to stock-up essentials during the beginning of the COVID-19 pandemic. For example, when the WHO advised that the best defense against

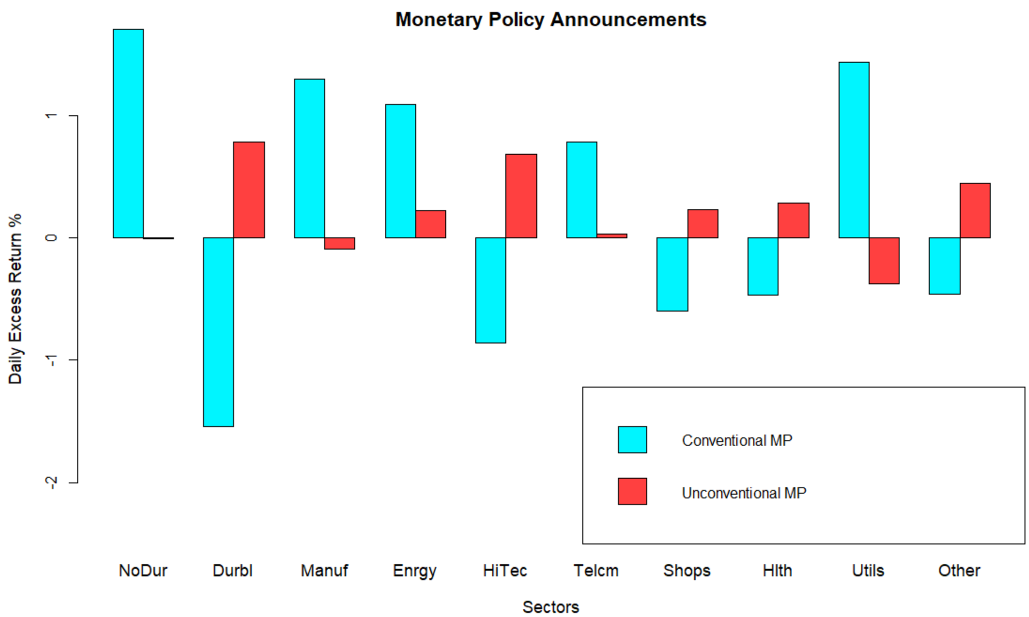


Figure 12: The impact of conventional and unconventional monetary policy shocks on stock market cross ten sectors.

Coronavirus was hand soap, sanitizer, and wearing masks, many consumers immediately began to purchase large quantities of these items. This led to a surge in demand, prompting producers to increase their production. Therefore, with the announced cutting interest rate, the non-durable goods sector responded to it positively. However, durable goods and high-tech sectors responded to the announcement shock negatively on a relatively larger scale. The GDP for durable consumer goods decreased by more than 26% between March and April 2020. As mentioned in Section 5.2, the second conventional monetary policy of cutting interest rates announced on Sunday morning (March 15, 2020) could be a negative signal that the Fed Reserve acknowledges that a recession is coming in the near future. Therefore, it is reasonable to believe that lowering the interest rates did not positively impact durable goods and other sectors.

The red bars shown in Figure (12) present the impact of the unconventional monetary policy shocks on the stock market. There were overall 16 FOMC announcements, which have created nine new lending facilities from the middle of March till that of May 2020. For the same sector, the estimated effects for the unconventional monetary policy shocks have opposite directions to the impact of the conventional monetary policy shocks[18]. As indicated

[18]Except for the health sector, both are negative. However, unconventional policy shock is close to zero.

in Table (2), the magnitude of the impact is smaller for both positive or negative. For energy, shops, health, and other sectors, there is essentially no impact. Durable goods and high-tech sectors display 0.783% and 0.688% sluggish increases on risk premia from unconventional monetary policy shocks, while those announced shocks negatively impact the rest sectors. It seems reasonable to interpret the mixed signs of the coefficients demonstrating enormous uncertainties and volatility on the stock market cross sectors during the first two months of the COVID-19 crisis.

Table 3: Estimated coefficients of three dummy variables

Dummy Variable	**NoDur**	**Durbl**	**Manuf**	**Enrgy**	**HiTec**	**Telcm**	**Shops**	**Hlth**	**Utils**	**Other**
Monetary Policy News	0.262	0.402	0.119	0.334	0.453	0.140	0.123	0.152	-0.125	0.294
Fiscal News	4.481	4.254	6.387	7.074	3.751	4.714	1.200	4.133	6.242	6.003
Unemployment News	0.413	-0.003	0.320	0.180	-0.619	0.124	-0.325	-0.104	-0.074	0.224

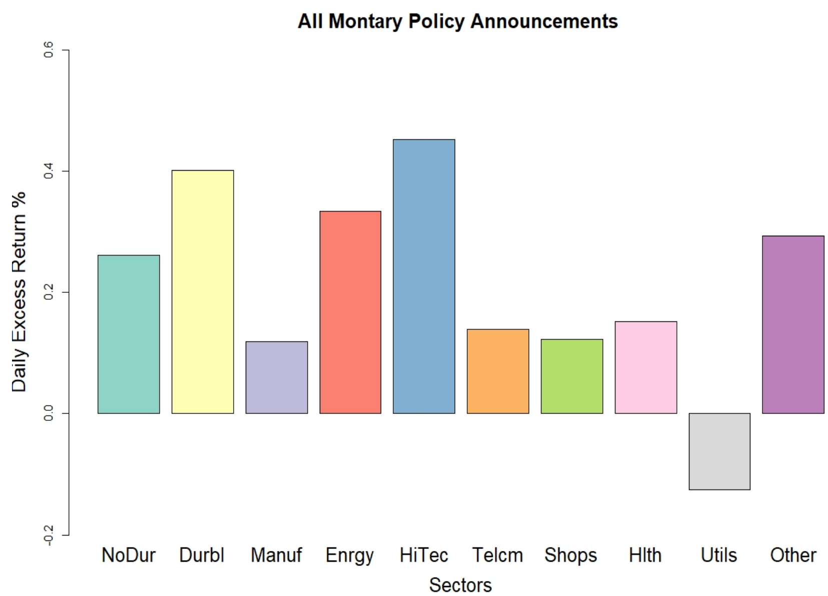
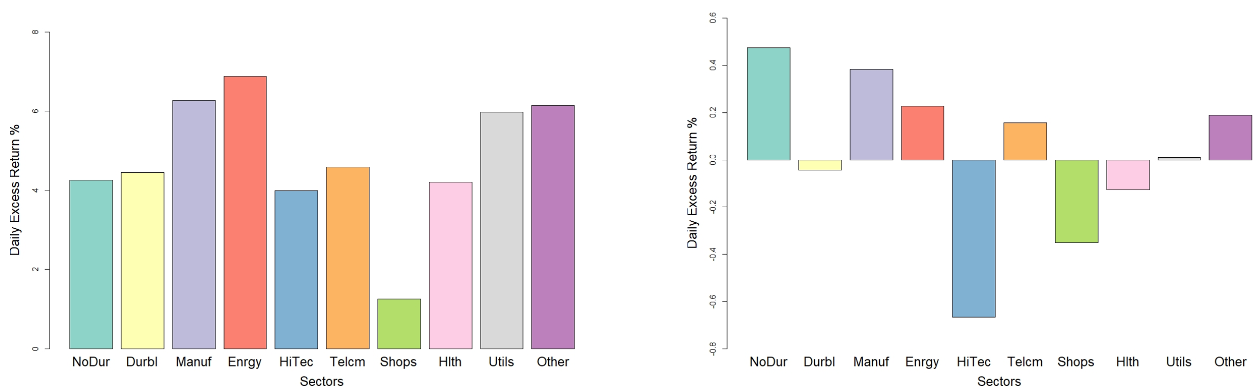


Figure 13: The impact of both conventional and unconventional monetary policy announcements cross sector (with a total of three dummy variables).

Few announcements that are difficult to classify as conventional or unconventional only. For example, on March 23, 2020, the Federal Reserve issued the FOMC statement that announced to continue purchasing Treasury securities and agency MBS can be regarded as an open market operation or a forward guidance policy. In addition, on that same day, the Fed also created three new facilities-the Primary Market Corporate Credit Facility (PMCCF), the Secondary Market Corporate Credit Facility (SMCCF), and the Term Asset-Backed Securities Loan Facility (TALF). Overall, as the main "surprise" is establishing new facilities, this study classifies it as an unconventional monetary policy shock focused. Owing to these reasons, the study attempts to investigate the overall effects of the shocks of the monetary policy regardless of whether they are conventional and unconventional by re-estimating the model (1) with three dummy variables in total: monetary policy, fiscal stimulus, and unemployment shocks. See the results[19] in Table (3) and Figure (13). As Figure (13) shows, the overall monetary policy announcement shocks on stocks are positive (except the utilities sector) during the sample period.



(a) Fiscal Policy Announcements

(b) Unemployment Announcements

Figure 14: Left panel: The impact of the $2.2 trillion fiscal stimulus announcement. Right panel: The impact of unemployment rate news from the Department of Labor.

5.3.2 Fiscal Stimulus Announcement Shocks

Conversely, the announcement of fiscal stimulus has a strong positive impact on all ten stock market sectors. See the third row in Table (2) and left panel in Figure (14). There is distinct focus between fiscal policy and monetary policy. Fiscal stimulus is regarded as spending power that can directly help a business that suffers from the COVID-19 pandemic or people who need financial support. Monetary policy, however, has lending powers that can

[19] As the number of total independent variables reduced by one, all coefficients estimation results changed, but the changes for non-dummy variable coefficients are trivial. Therefore, I only report the coefficients for the three dummy variables.

make secured loans to institutions, companies, or individuals to help the economy. Another reason that can also explain the significant positive effect of the fiscal stimulus package is timing. Before the fiscal stimulus package, the market of March 23 was at the lowest point, where the S&P 500 has dropped by 31.32 % since the beginning of 2020. Concerning the $2.2 trillion fiscal stimulus package passed by the Senate on the night of March 25, 2020 [20], the stock market responded to the news immediately and pivoted to a new direction with a remarkable rebound from the bottom and manifested a strong positive impact on all ten sectors.

5.3.3 Unemployment Rate News Shocks

The Bureau of Labor Statistics (BLS) releases the employment situation summary on the first Friday of every month[21]. Historically, if this release comes in significantly different from consensus estimates, it can lead to fluctuations in the stock market to fluctuate. The impact of the unemployment rate news is reported in the last row in Table (2) and right panel of Figure (14), where there are mixed positive and negative results across sectors. There are five sectors, (e.g., durable goods and manufacturing) that have positive impacts after the unemployment rates are announced. The remaining sectors (e.g., high-tech and shops) have negative impacts due to the release. The nature of the shocks could explain these findings. When presented with surprising news, optimist and pessimist investors have different expectations and may have different market behaviors. In February 2020, the U.S. unemployment rate of 3.5% was at the lowest in 50 years. When the coronavirus started to spread quickly in the U.S., the unemployment rate in April 2020 surged from 10.3% to 14.7%, the largest over-the-month increase for all data available in history. The leisure and hospitality industries' unemployment rates were the worst and reached 39.3% in April 2020. When these rates of unemployment were issued, the stock market tumbled immediately. The durable goods and energy sector slumped by 6.36% and 6.33%, respectively, on that Friday. However, as the stock market constantly involves investors' different attitudes, a shock to the opposite directions can also happen. For example, on June 5, 2020, although the unemployment rates of the leisure and hospitality industry in May were still 35.9%, it was much better than the

[20] Even the final stimulus package was officially signed off on the late night of March 25, 2020, some newspapers had leaking the news and announced "The Senate appeared close to reaching a deal on a massive stimulus bill" since March 24, 2020. For example, https://www.cbsnews.com/news/senate-coronavirus-economic-stimulus-package-bill-2020-03-24/

[21] Job report is released at 8:30 a.m. EST on the first Friday of every month https://www.bls.gov/schedule/news_release/empsit.htm

market's expectation. The Dow Jones jumped up by 6.8%, and S&P 500 rose by 4.9% immediately. This hectic financial behavior during the COVID-19 pandemic also substantiates that the latent factor is a vital variable in the model and play a crucial role in explaining the hectic movements of the stock prices during the COVID-19 stock market.

5.4 Latent Factor and Sentiment Indicators

We do not know what the latent factor exactly includes, by definition, but we can explore it by associating it with something we can measure. This section aims to use the sentiment analysis technique to explore the linkage between the latent factor and the market sentiment, which is extracted from the multi-dimensional aspects of information released. This paper examines Federal Open Market Committee (FOMC) communications and Wall Street Journal daily news. Notably, the study does not claim any causality due to data limitation but focuses on the correlations between the estimated latent factor and market sentiment.

5.4.1 Text Mining Techniques

There is an emerging interest in text mining or Natural Language Processing (NLP) in big data, and many soft computing methods and techniques have been developed. Although text mining is widely applied in computer science, it is still relatively new in economics and finance. This section applies two different techniques, sentiment lexicon and rule-based model (in addition to sentiment lexicon). They both show that the latent factor and the sentiment of the communications or news headlines are positively correlated.

The first technique is a sentiment lexicon term-frequency tool that identifies the sentiment polarity of words and texts. Although many algorithms are built to construct a sentiment lexicon with sentiment-aware word embedding, most of them focus on product reviews, movie reviews, and emotional states. Loughran and McDonald (2011) have shown that dictionaries developed in other fields can be possibly ineffective for economics and finance texts and may result in misclassification errors. Given the formal characteristics of the Fed's communication, this study chooses to use Loughran and McDonald Sentiment Word Lists[22] and build the Dictionary Sentiment Score (DSS). This method is a common way of measuring market sentiment in the finance literature, where word lists are chosen to reflect the positive and negative tone and applied to text. See the literature Tetlock (2007),

[22] https://sraf.nd.edu/textual-analysis/resources/

Tetlock et al. (2008), Loughran and McDonald (2011), and Loughran and McDonald (2014).

The dictionary sentiment score is defined as,

$$DSS = \frac{(N_{pos,t} - N_{neg,t})}{N_{tot,t}} 100\% \tag{34}$$

where $N_{pos,t}$ is the number of positive tone words in the context released at time t, $N_{neg,t}$ is the number of negative tone words released at time t, and $N_{tot,t}$ is the total number of words of the context released at time t. The formula gives a percentage measure, which can be greater than zero, classified as a positive sentiment, less than zero, classified as a negative sentiment, or equal to (round to) zero, classified as a neutral tone.

The second technique used in this study is called Valence Aware Dictionary for Sentiment Reasoning (VADER), which combines both lexicon sentiment analysis and embodies grammatical and syntactical conventions that express and emphasize sentiment intensity. VADER is an NLP algorithm created in 2014 and is a fully open source under the MIT License[23]. This algorithm is sensitive to both polarity (positive/negative) and the intensity of emotions. It is attuned to several domain contexts, such as NY Times editorials, movie reviews, product reviews, and performs exceptionally well in social media texts.

5.4.2 Event Study of FOMC Communication and Latent Factor

The Federal Open Market Committee (FOMC) holds eight regularly scheduled meetings during one calendar year. During the sample period between January 2020 and August 2020, the FOMC holds seven meetings and six press conferences, including two unscheduled meetings and one canceled scheduled meeting. FOMC meetings' statements and the press conference's scripts that are always released on the same day as the events happen, therefore can be used for sentiment analysis. The FOMC meetings' minutes are not included because minutes usually are released three weeks later after the date of the policy decision.

First, the study applies the DSS method to the text of FOMC statements and the press conference transcripts downloaded from the Fed Reserve's website[24]. This method demonstrates success in extracting sentiment from the text, and the results are presented in Figure

[23]Hutto, C.J. Gilbert, E.E. (2014). VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text. Eighth International Conference on Weblogs and Social Media (ICWSM-14). Ann Arbor, MI, June 2014.

[24]www.federalreserve.gov

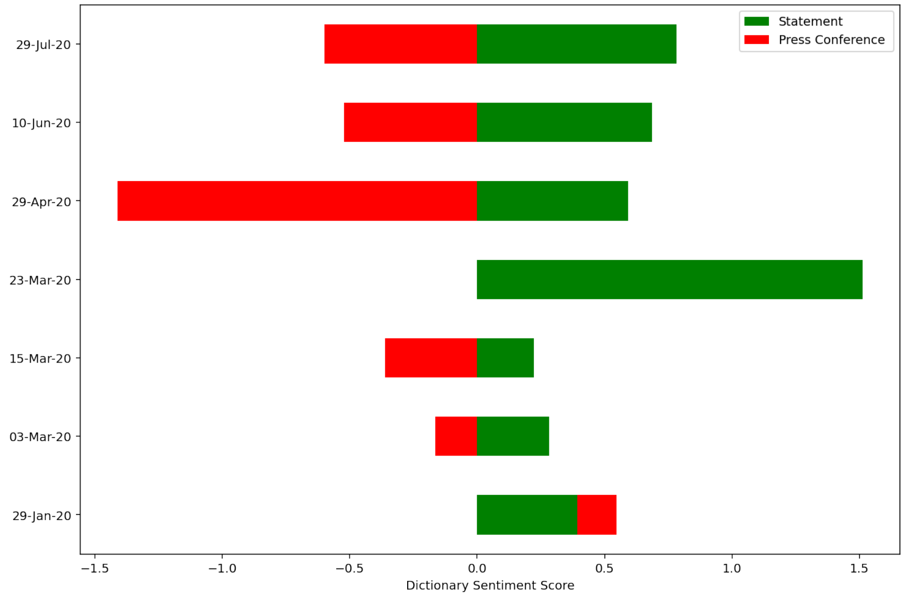


Figure 15: DSS Analysis of the Fed Communications

(15). Overall, FOMC statements are concise communications (total of 760 words on average from the sample), which have high quality in the sense that Committees use words precisely, and the formats of the statements are also very consistent; all DSS appear positive. The FOMC press conference gives a market update and answers reporters' questions after a Fed's monetary policy meeting. The transcripts have a longer length (a total of 8190 words on average), and all the DSS appear as negative tones since the COVID-19 breakout. For example, consider the following scripts excerpt from the March 15, 2020 conference:

"Against this favorable backdrop, the virus presents significant economic challenges. Like others, we expect that the illness and the measures now being put in place to stem its spread will have a significant effect on economic activity in the near term. Those in the travel, tourism, and hospitality industries are already seeing a sharp drop in business. In addition, the effects of the outbreak are restraining economic activity in many foreign economies, which is causing difficulties for U.S. industries that rely on global supply chains. The weakness abroad will also weigh on our exports for a time. Moreover, the energy sector has recently come under stress because of the large drop in global oil prices. Inflation, which has continued to run below our symmetric 2 percent objective, will likely be held down this year by the effects of the outbreak."

This excerpt has a total of 139 words including one positive tone word, ['favorable'], and 10 negative tone words, ['against', 'challenges', 'drop', 'difficulties', 'weakness', 'under', 'stress', 'drop', 'below', 'down']. The entire press conference scripts on March 15, 2020, has a -0.36% DSS ratio, which has a total word count of 7471 with 140 positive tone words, and 167 negative tone words. See Figure (15).

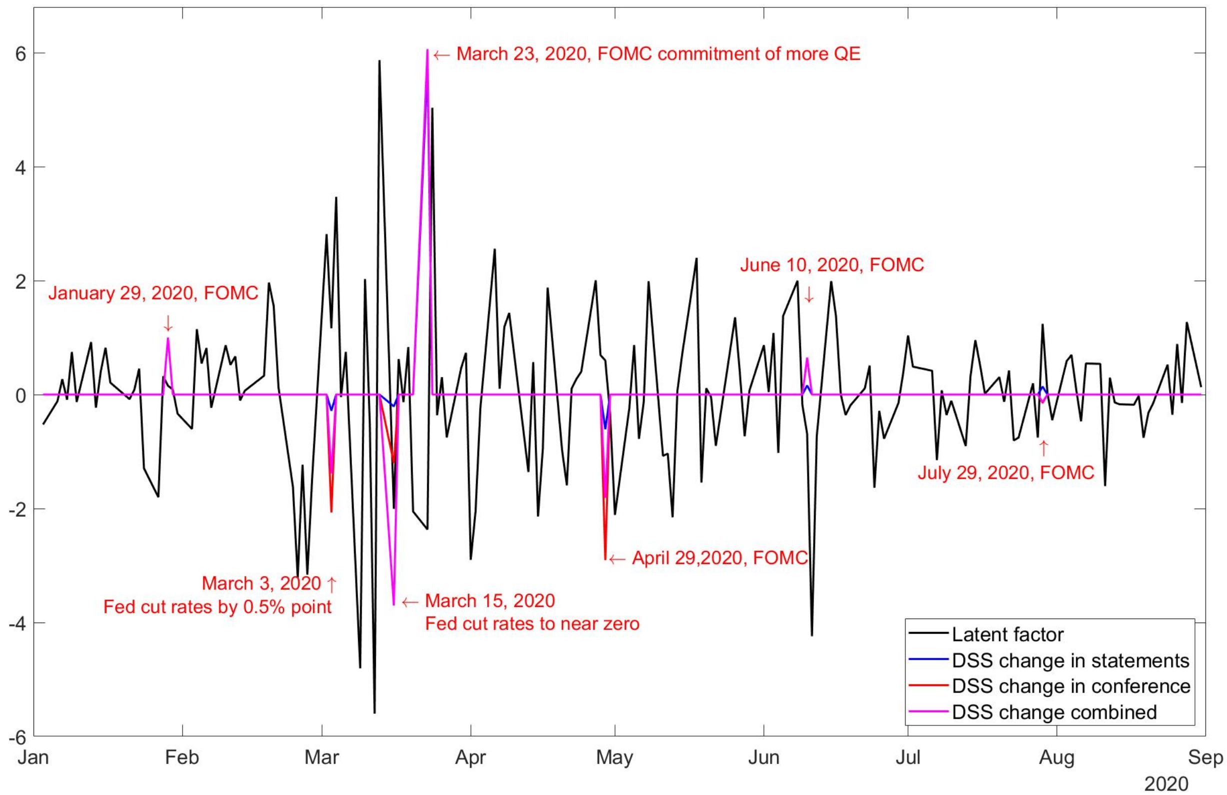


Figure 16: Latent factor value and change in DSS of the Fed Communications

Next, the study combines the contents from both statements and press conferences' scripts and study the links between FOMC communications and the latent factor. Figure (16) visually shows the change in sentiment scores during the seven FOMC meetings. The most significant positive change of the sentiment was on March 23, 2020, and only an FOMC statement was released. The DSS is six times the last communication from FOMC, and the stock market pivoted to a new direction on March 23, 2020, and ended the bear market. This event is shown as a significant spike in Figure (16), where the study plots both changes in DSS and the values of the latent factor together. The most significant negative change in the DSS ratio was on March 15, 2020, when the FOMC announced reducing interest rates by one percentage point. In the previous section, Figure (3) shows the latent movement in the stock market plunged by 134% on the following trading day. Overall, it is evident that the latent movement and the changes in the sentiment of the Fed communications are positively associated.[25]

5.4.3 Wall Street Journal Headlines And Latent Factor

FOMC communication textual data is scarce during the sample period. However, there are incredibly abundant information and news from the internet and social media. The shortfall of this type of data is that they are noisy[26], and some might not be trustworthy. The study scrapes the daily headline news from Wall Street Journal (WSJ) as a proxy of diversified aspects of market news[27]. For example, here are some examples of WSJ headlines on March 15, 2020, and a full-day sample is presented in Appendix (G).

"U.S.
Top Health Official Urges Americans to Stay Home Amid Coronavirus
U.S. Economy
Fed Slashes Rates to Fight Coronavirus Slowdown Coronavirus Social-Distancing Forces Painful Choices on Small Businesses
Schools
New York City Schools to Close Over Coronavirus
Economy
Fed Takes Emergency Actions as Virus Pushes Economy Toward Recession
Election 2020
Democratic Debate Between Sanders and Biden: The Moments That Mattered"

The bubble chart Figure (17) and (18) visually show sentiment scores using DSS or VADER algorithm. The bubbles' diameters and the shade of the colors reflect the changes in sentiment intensity of the WSJ headlines from January 1, 2020, to August 31, 2020. Figure (17) is the result from the DSS method showing a vague V-shaped trajectory. The sentiment scores from the VADER algorithm are plotted in Figure (18), where negative sentiments dominate throughout the sample period because this method estimates both sentiment valence (intensity) and sentiment polarity. Two regressions, regressing the daily changes in the latent factor on the changes of the DSS ratios and the changes of VADER scores, are constructed separately. The first regression obtains a positive coefficient of 0.184, the second

[25]Due to the limitation of data, I do not draw any statistical inference.

[26]In the sample period, in addition to the COVID-19 pandemic, we also have news about the 2020 U.S. presidential election, which can also impact the stock market.

[27]WSJ archive website: https://www.wsj.com/news/archive/years

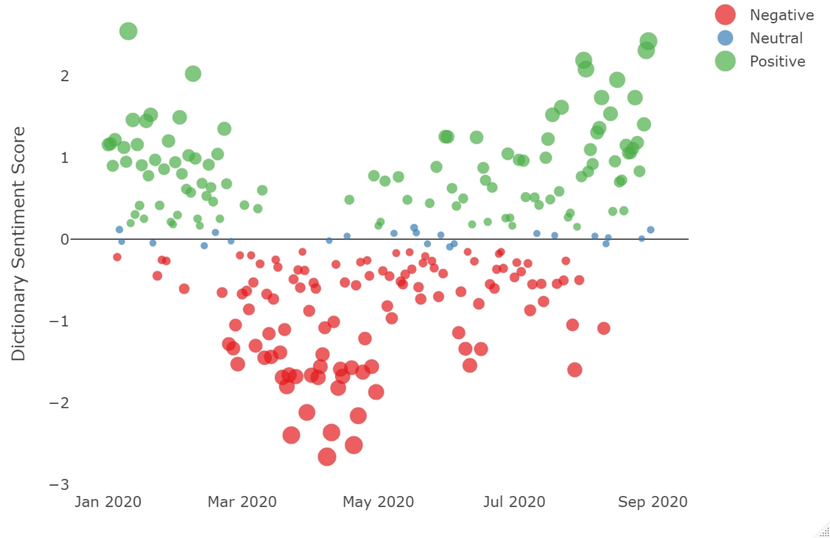


Figure 17: DSS for the WSJ headlines

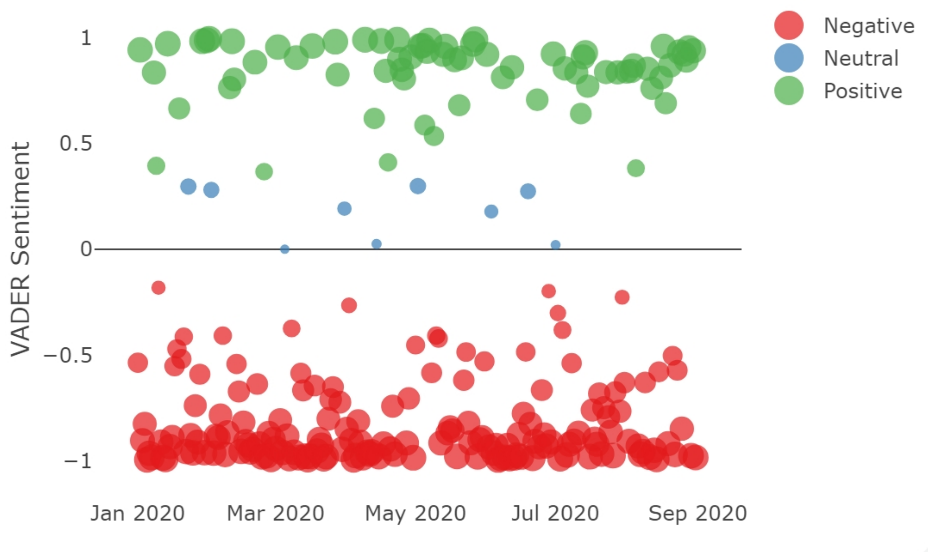


Figure 18: VADER for the WSJ headlines

also obtains a positive coefficient, 0.315, and both are at the 95% statistic significant level. From both NLP techniques, results show that the positive correlations between the latent comovement of the stock market and sentiment extracted from the WSJ headlines. The results validate the contribution of having the latent factor in the model; without latent factors, shown in Section 3, it becomes an omitted variable problem. As initially mentioned, this does not mean that the WSJ headlines trigger the stock market's movements, nor does the market causes some of the headlines reported. Owing to both the stock market and the WSJ headlines data in low daily frequency, high-frequency data are required to research their causality and bring more insights.

5.5 Government Restrictions

The COVID-19 impacts the economy through both direct and indirect channels. The direct channel is that it impacted laborers' health and their ability to work, especially during the first half year of 2020. There are also various indirect channels, one of which is through the government's restrictions, such as stay-home orders or the closure of non-essential business. Community mobility data can capture this kind of information. People's voluntary activities, such as grocery shopping or visiting a park, reflect their psychological state during the pandemic. Therefore, it is reasonable to assume that financial market returns are associated with mobility levels because they are associated with economic activities and people's psychological states.

Table 4: Estimated Coefficients On Mobility In Six Categories

	Retail Rec	**Grocery**	**Parks**	**Transit**	**Workplaces**	**Residential**
NonDur	-0.42%	-0.07%	0.05%	0.47%	0.20%	0.81%
Durbl	-0.67%	0.03%	0.08%	0.82%	0.26%	1.46%
Manuf	-0.47%	0.00%	0.06%	0.46%	0.26%	0.91%
Enrgy	-0.53%	0.01%	0.09%	0.49%	0.49%	1.63%
HiTec	-0.49%	0.00%	0.04%	0.39%	0.15%	0.29%
Telcm	-0.26%	-0.02%	0.01%	0.35%	0.10%	0.60%
Shops	-0.38%	0.07%	0.01%	0.44%	0.06%	0.53%
Hlth	-0.45%	-0.03%	0.04%	0.47%	0.10%	0.46%
Utils	-0.57%	-0.02%	0.06%	0.60%	0.18%	0.80%
Other	-0.49%	0.00%	0.07%	0.50%	0.30%	1.04%

Table (4) reports the estimated coefficients on the six categories of mobility level for each sector. All numbers are in percentage point shown in Table (4) and Figure (19). The retail and recreation category coefficients are all negative, the grocery and pharmacy coefficients are close to zero, and the rest are all positive. I also include non-durable and utility sectors' boxplots, see Figure (20) and Figure (21). Graphs for other sectors are also available upon request.

The community mobility level in the residential category has been increasing since March

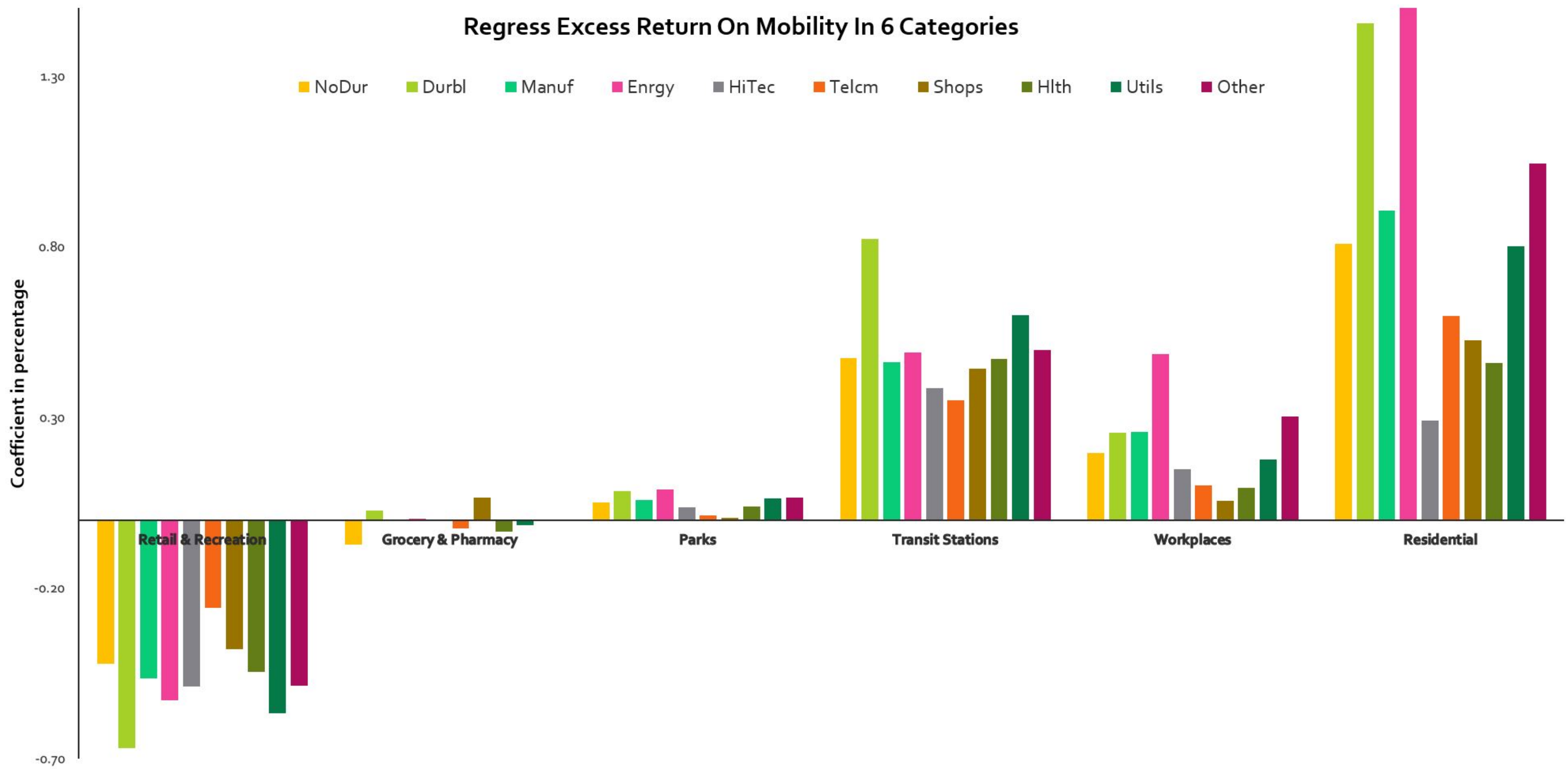


Figure 19: Regression coefficients of the six Mobility variables

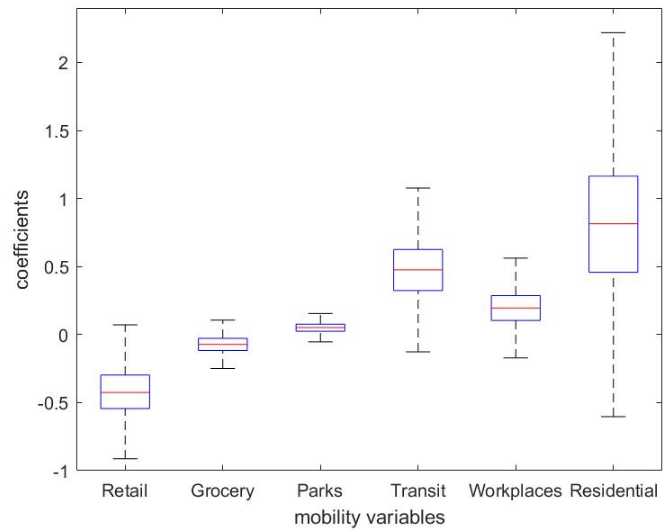


Figure 20: Boxplot for mobility coefficients in non-durable sector

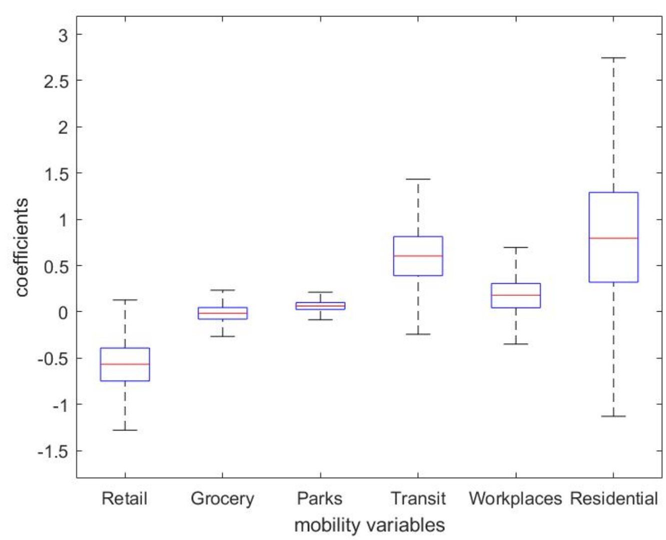


Figure 21: Boxplot for mobility coefficients in utility sector

2020 due to the stay-at-home order, and the average level for all states in the U.S. has reached 20% more time relative to the baseline. Since May 2020, some states have eased up and released lockdown orders. As of August 31, 2020, the level of staying-at-home is still 10% more than the baseline. The correlations between stay-home levels and stock returns are positive for all sectors, with the highest correlations, 0.0163, in the energy sector, and 0.0146 in the durable goods sector. These results imply, respectively, that a one percent increase in the stay-home level is correlated with a 1.63% and 1.46% rise in the energy and durable goods sector.

Visits to workplaces and transit are remarkably similar because the local government highly regulates them both. In the middle of March 2020, the government ordered the closure of non-essential businesses to help prevent the spread of COVID-19. Both visits have declined by 50% compared to the baseline at the end of March 2020 and the beginning of April 2020. Since May 2020, some state governments have slowly relaxed COVID-19 restrictions on businesses to help the economy recover. Positive associations are shown in Table (4) and Figure (19) between visits to work or transit and returns on the stock market. The positive association mirrors the correlation between public health status and the public economy. The coefficients of the visit to the workplace are much smaller than those of visits to transit. One possible reason is that many jobs and economic activities can be conducted at home. Therefore, the association between visiting the workplace and the economy is smaller.

Visits to parks have been dropped by 20% and picked up since the beginning of May. Moreover, in August, it has reached 60% more than the baseline before COVID times. The coefficients on park visits are also positive in a smaller magnitude in all sectors. Positive associations are due to visits that are voluntary activities; the more visits, the less people are worried, and the more optimism there is about economic recovery. Therefore, more visits to parks are correlated with increases in the stock market returns.

In the middle of March 2020, visits to the retail and recreation stores immediately declined when the closures of non-essential businesses and social distancing protocols went into effect. In the middle of April 2020, visits to retail shops decreased by 50% from the baseline level, while the stock market rebounded. At the end of August 2020, visits to retail stores and recreation are only at 87% of the baseline, while the stock market recovered and was in a rally. Hence, the correlation between visits in the retail and recreation stores and stock market returns are all negative across sectors.

Visits to grocery and pharmacy stores are considered essential trips. Since June 2020, the visits are back to the baseline level. Without the coronavirus pandemic, the number of visits should not be associated with asset returns. As shown in Table (4), manufacturing, high-tech, and other sectors have zero coefficients. However, at the beginning of COVID-19, grocery and drug store visits dramatically increased due to consumers' panic-buying behavior. Stock prices plummeted simultaneously, causing the non-durable goods sector stock to show a negative association, -0.07%, while revenue grew in the shops sector, showing a positive association, +0.07%, between stock returns in the shops sector and visits to grocery and pharmacy stores.

6 Conclusions

This study examines the cross-sector comovements that occurred in the U.S. stock market during the COVID-19 pandemic. The findings confirm that the latent sentiment is the driving force behind financial market behaviors. In addition, the latent sentiment had a weak daily oscillation pattern with a -0.09 autoregressive coefficient in an AR(1) process. This pattern explains the stock market's extreme comovements and high volatility.

Moreover, this study estimates the impact of the monetary policy interest rate on each stock market sector. The results indicate that when the Fed Effective Funds Rate was reduced by one percentage point, utilities and non-durable goods stock returns substantially jumped by 11.35% and 7.328%, respectively. In addition, this study explores the impact of news shocks, including monetary policy news, fiscal stimulus news, and unemployment news, on cross-sector equity returns. For any given sector, the conventional and unconventional monetary policy news shocked the sector in opposite directions. Of the positive monetary news shocks, the strongest shocks were from the interest rate policy surprises, while unconventional monetary policy news had a more sluggish impact on stock returns. Conversely, fiscal stimulus news had the most substantial positive impact and triggered all sectors to rebound from the bear market at the end of March 2020.

Furthermore, by applying Natural Language Processing (NLP) sentiment analysis, this study sheds light on the positive correlation between comovements and news sentiment. Using the Wall Street Journal headlines as proxies of the market sentiment, the study finds a positive correlation, 0.31, at the 95% statistically significant level, between the comovements and market news sentiment.

Finally, in estimating the associations between the cross-sector asset returns and the government's social distancing policy, this study finds that the stay-at-home orders and restrictions on transit have positive associations with asset returns. Conversely, increases in retail and recreation activities have negative associations with asset returns in general. Owing to the government's policies and restrictions enacted to protect public health by slowing the spread of COVID-19, some economic activities have been curtailed in the short term. However, in the long term, these government restrictions help the public's welfare and the economy. Future studies to explore the different impacts between government restrictions and voluntary social distancing could provide fruitful results.

References

Bai, J. and S. Ng (2006). "Confidence Intervals for Diffusion Index Forecasts and Inference for Factor-Augmented Regressions". In: *Econometrica* 74.4, pp. 1133–1150.

Bai, J. and P. Perron (2003). "Computation and analysis of multiple structural change models". In: *Journal of Applied Econometrics* 18.1, pp. 1–22.

Baker, M. and J. Wurgler (2007). "Investor Sentiment in the Stock Market". In: *Journal of Economic Perspectives* 21.2, pp. 129–152.

Barberis, N., A. Shleifer, and J. Wurgler (2005). "Comovement". In: *Journal of Financial Economics* 75.2, pp. 283–317.

Benmelech, E. and N. Tzur-Ilan (July 2020). *The Determinants of Fiscal and Monetary Policies During the Covid-19 Crisis*. NBER Working Papers 27461. National Bureau of Economic Research, Inc.

Bianchi, F., S. C. Ludvigson, and S. Ma (June 2020). *Belief Distortions and Macroeconomic Fluctuations*. NBER Working Papers 27406. National Bureau of Economic Research, Inc.

Chan, J. and I. Jeliazkov (2009). "Efficient Simulation and Integrated Likelihood Estimation in State Space Models". In: *International Journal of Mathematical Modelling and Numerical Optimisation* 1, pp. 101–120.

Chib, S. and I. Jeliazkov (2001). "Marginal Likelihood From the Metropolis-Hastings Output". In: *Journal of the American Statistical Association* 96, pp. 270–281.

Chib, S. and E. Greenberg (1994). "Bayes Inference In Regression Models With ARMA (p, q) Errors". In: *Journal of Econometrics* 64, pp. 183–206.

— (1996). "Markov Chain Monte Carlo Simulation Methods in Econometrics". In: *Econometric Theory* 12.3, pp. 409–431.

Chib, S., F. Nardari, and N. Shephard (2006). "Analysis of high dimensional multivariate stochastic volatility models". In: *Journal of Econometrics* 134.2, pp. 341–371.

Cox, J., D. L. Greenwald, and S. C. Ludvigson (2020). *What Explains the COVID-19 Stock Market?* Working Paper 27784. National Bureau of Economic Research.

Fahrmeir, L. and H. Kaufmann (1991). "On kalman filtering, posterior mode estimation and fisher scoring in dynamic exponential family regression". In: *Metrika: International Journal for Theoretical and Applied Statistics* 38.1, pp. 37–60.

Fama, E. (1970). "Efficient Capital Markets: A Review of Theory and Empirical Work". In: *Journal of Finance* 25, pp. 383–417.

Geweke, J (1977). "The dynamic factor analysis of economic time series". In: *Latent Variables in Socio-Economic Models*.

Gormsen, N. J. and R. S. J. Koijen (2020). *Coronavirus: Impact on Stock Prices and Growth Expectations*. Working Paper 27387. National Bureau of Economic Research.

Jinjarak, Y. et al. (2020). *Accounting for Global COVID-19 Diffusion Patterns, January-April 2020*. Working Paper 27185. National Bureau of Economic Research.

Koop, G. (2003). *Bayesian econometrics*. John Wiley and Sons Inc.

Levin, A. T. and A. Sinha (Aug. 2020). *Limitations on the Effectiveness of Monetary Policy Forward Guidance in the Context of the COVID-19 Pandemic*. NBER Working Papers 27748. National Bureau of Economic Research, Inc.

Loughran, T. and B. McDonald (2011). "When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks". In: *Journal of Finance* 66.1, pp. 35–65.

Pindyck, R. and J. Rotemberg (1993). "The Comovement of Stock Prices". In: *The Quarterly Journal of Economics* 108.4, pp. 1073–1104.

Sargent, T. (1989). "Two Models of Measurements and the Investment Accelerator". In: *Journal of Political Economy* 97.2, pp. 251–87.

Sargent, T. and C. Sims (1977). *Business cycle modeling without pretending to have too much a priori economic theory*. Working Papers 55. Federal Reserve Bank of Minneapolis.

Shiller, R. J. (1989). "Comovements in Stock Prices and Comovements in Dividends". In: *The Journal of Finance* 44.3, pp. 719–729.

Stock, J. H. and M. W. Watson (1989). "New Indexes of Coincident and Leading Economic Indicators". In: *NBER Macroeconomics Annual 1989, Volume 4*. National Bureau of Economic Research, Inc, pp. 351–409.

— (2002). "Forecasting Using Principal Components from a Large Number of Predictors". In: *Journal of the American Statistical Association* 97.460, pp. 1167–1179.

Vijh, A. M. (1994). "The Spinoff and Merger Ex-date Effects". In: *Journal of Finance* 49.2, pp. 581–609.

Appendices

A Appendix: The conditional posterior of β

This part is to explain the detail steps of how to obtain (16) and (17) in the estimation step 1. Starting from the equation (14) below,

$$y = X\beta + \psi, \qquad \psi \sim \mathcal{N}(0, \Sigma)$$

where,

$$\Sigma = [(I_T \otimes \Omega) + (I_T \otimes A)\sigma^2 K^{-1}(I_T \otimes A)'] \tag{35}$$

As shown in Koop (2003), given Σ and assuming a natural conjugate prior $\pi(\beta) \sim \mathcal{N}(\beta_0, B_0)$, the posterior distribution of β are given by the following expressions,

$$[\beta|\ y, A, \Sigma, \gamma, \sigma^2] \sim \mathcal{N}(\beta, B) \tag{36}$$

where,

$$B = \left(B_0^{-1} + X'\Sigma^{-1}X\right)^{-1} \tag{37}$$

$$\beta = B\left(B_0^{-1}\beta_0 + X'\Sigma^{-1}y\right) \tag{38}$$

The existence of the inverse matrix Σ^{-1} is the most tricky step in solving the mean and variance in the posterior distribution. I follow the steps from Chan and Jeliazkov (2009) employing Woodbury Matrix Identity formula as shown below,

$$(E + FGH)^{-1} = E^{-1} - E^{-1}F(G^{-1} + HE^{-1}F)^{-1}HE^{-1} \tag{39}$$

It is straight forward to obtain,

$$\begin{aligned}
\Sigma^{-1} &= [(I_T \otimes \Omega) + (I_T \otimes A)\sigma^2 K^{-1}(I_T \otimes A)']^{-1} \\
&= (I_T \otimes \Omega^{-1}) - (I_T \otimes \Omega^{-1})(I_T \otimes A)\Big[\sigma^{-2}K + (I_T \otimes A)'(I_T \otimes \Omega^{-1}(I_T \otimes A)\Big]^{-1} \\
&\quad (I_T \otimes A)'(I_T \otimes \Omega^{-1}) \\
&= (I_T \otimes \Omega^{-1}) - (I_T \otimes \Omega^{-1}A)\Big[\sigma^{-2}K + I_T(A'\Omega^{-1}A)\Big]^{-1} \\
&\quad (I_T \otimes A'\Omega^{-1})
\end{aligned} \tag{40}$$

Using the compact notation $P = [\sigma^{-2}K + I_T(A'\Omega^{-1}A)]$ and combining (37), (38) and (40), the mean and variance for the posterior can be obtained as following,

$$B = \left(B_0^{-1} + X' \Big[(I_T \otimes \Omega^{-1}) - (I_T \otimes \Omega^{-1} A) P^{-1} (I_T \otimes A'\Omega^{-1}) \Big] X \right)^{-1} \tag{41}$$

$$\beta = B \Big(B_0^{-1}\beta_0 + X' \Big[(I_T \otimes \Omega^{-1}) - (I_T \otimes \Omega^{-1} A) P^{-1} (I_T \otimes A'\Omega^{-1}) \Big] y \Big) \tag{42}$$

Simplify above and obtain,

$$B = \left(B_0^{-1} + \sum_{t=1}^{T} X_t' \Omega^{-1} X_t - \tilde{X}_t' P^{-1} \tilde{X}_t \right)^{-1} \tag{16}$$

$$\beta = B \left(B_0^{-1}\beta_0 + \sum_{t=1}^{T} X_t' \Omega^{-1} y_t - \tilde{X}_t' P^{-1} \tilde{y} \right)^{-1} \tag{17}$$

where $\tilde{X}_t = A'\Omega^{-1} X_t$ and $\tilde{y}_t = A'\Omega^{-1} y_t$.

B Appendix: Details of step 2.1 sample $[a|\ y, \beta, \Omega, \gamma, \sigma^2]$

This part is to explain the steps of how to obtain draw a from $[a|\ y, \beta, \Omega, \gamma, \sigma^2]$ in details.

I follow Chan and Jeliazkov (2009) to generate the posterior density of A marginalized over f. By Bayes' Theorem,

$$\pi(A|\ y, \beta, \gamma, \Omega, \sigma^2) = \frac{\pi(A|\ y, f, \beta, \gamma, \Omega, \sigma^2)\pi(f|\ y, \beta, \gamma, \Omega, \sigma^2)}{\pi(f|\ y, A, \beta, \gamma, \Omega, \sigma^2)} \tag{43}$$

Since both loading A and factor f are unknown, there is potential sign and scale identification issues for them, however, this can be solved by restricting the first element in the loading vector to 1, i.e. $A = \{1, a'\}$. More details can be found in Chan and Jeliazkov (2009). As the first element in the loading vector A is fixed as 1, replacing A with a, the posterior density of a, given $(y, \beta, \gamma, \Omega, \sigma^2)$ and marginalized over f, is as follows,

$$\begin{aligned} \pi(a|\ y, \beta, \gamma, \Omega, \sigma^2) &= \frac{\pi(a|\ y, f, \beta, \gamma, \Omega, \sigma^2)\pi(f|\ y, \beta, \gamma, \Omega, \sigma^2)}{\pi(f|\ y, a, \beta, \gamma, \Omega, \sigma^2)} && (44) \\ &\propto \frac{\pi(a|\ y, f, \beta, \gamma, \Omega, \sigma^2)}{\pi(f|\ y, a, \beta, \gamma, \Omega, \sigma^2)} && (45) \end{aligned}$$

Notice the loading parameter a is not involved in the term $\pi(f|\ y, \beta, \gamma, \Omega, \sigma^2)$ on the numerator, which therefore can be relegated to a constant, and can be scaled proportionately on both denominator and numerator in calculating the acceptance ratio and eventually cancelled out.

According to (45), the next step is to derive the numerator $\pi(a|\ y, f, \beta, \gamma, \Omega, \sigma^2)$.

The equation (3) can be rewritten as,

$$y = X\beta + \mathcal{F}A + \varepsilon, \quad \varepsilon \sim \mathcal{N}(\mathbf{0},\ I_T \otimes \Omega) \tag{46}$$

where $\mathcal{F} = diag(f_1, f_2, ..., f_T)$.

Assume a conjugate prior of $a \sim \mathcal{N}(a_0, A_0)$, then the conditional posterior of a also follows Gaussian distribution,

$$\begin{aligned} [a|\ y, f, \beta, \gamma, \Omega, \sigma^2] &\sim \mathcal{N}(\bar{a}, V_a) && (47) \\ \bar{a} &= V_a[A_0^{-1}a_0 + \mathcal{F}'(I_T \otimes \Omega)^{-1}(y - X\beta)] && (48) \\ V_a &= [A_0 + \mathcal{F}'(I_T \otimes \Omega)^{-1}\mathcal{F}]^{-1} && (49) \end{aligned}$$

I skip explaining of denominator $\pi(f|\ y, a, \beta, \gamma, \Omega, \sigma^2)$ as it has been derived in the equations (11), (12) and (13).

By M-H sampling, a proposal density is tailored closely mimicking the posterior density. In practice, it is very important for the candidate generating density to have fatter tails than those of the target posterior. Let a^* be the draw from the tailored proposal, a student t distribution, of which, the mean $\hat{a}$ and negative inverse of Hessian, $\hat{A}$, are obtained by Maximum Likelihood Estimation. Let df be the degree of freedom, in general, df is chosen as a small number to ensure the fat details. The jumping distribution $q(a^*|a)$ represents the distribution for the current state a to jump to the next state a^*. Rewrite the tailored proposal density as below for notation convenience.

$$q(a^*|a) = q(a^*|\hat{a}, \hat{A}, df), \qquad q(a|a^*) = q(a|\hat{a^*}, \hat{A}^*, df) \tag{50}$$

Thus, the rate $\alpha(a, a^*)$ of accepting the next proposed draw a^* is,

$$\alpha(a, a^*) = min\left\{1, \frac{\pi(a^*|\ y, \beta, \gamma, \Omega, \sigma^2)q(a\ |\hat{a^*}, \hat{A}^*, df)}{\pi(a|\ y, \beta, \gamma, \Omega, \sigma^2)q(a^*|\hat{a}, \hat{A}, df)}\right\} \tag{51}$$

C Appendix: The acceptance ratio of α

Metropolis-Hastings algorithm can take many different forms. The algorithm in this paper is a special case, which is often referred to M-H within Gibbs. This appendix briefly explains the M-H sampler in the algorithm step 2(1) and how the acceptance rate (51) is derived.

Let a^* be the tailored proposed value, a draw from a student t distribution, of which the mean $\hat{a}$, and the variance as the negative inverse of the Hessian, $\hat{A}$ obtained by using maximum likelihood. The notation $q(a^*|a)$, is the proposed density, representing if the current state is a, then the proposed density $q(a^*|a)$ generates a^* in the next state. Thus, in the M-H algorithm the probability accepting the proposed draw a^* is,

$$\alpha(a, a^*) = min \left\{ 1, \frac{\pi(a^*|\ y, \beta, \gamma, \Omega, \sigma^2) q(a|\hat{a^*}, \hat{A}^*, df)}{\pi(a|\ y, \beta, \gamma, \Omega, \sigma^2) q(a^*|\hat{a}, \hat{A}, df)} \right\} \tag{52}$$

Recall the posterior density of a marginalized over f is $\pi(a|\ y, \beta, \gamma, \Omega, \sigma^2) \propto \frac{\pi(a|\ y, f, \beta, \gamma, \Omega, \sigma^2)}{\pi(f|\ y, a, \beta, \gamma, \Omega, \sigma^2)}$, hence, the probability of accepting the proposed draw a^* becomes,

$$\alpha(a, a^*) = min \left\{ 1, \frac{\frac{\pi(a^*|\ y, f, \beta, \gamma, \Omega, \sigma^2)}{\pi(f|\ y, a^*, \beta, \gamma, \Omega, \sigma^2)} q(a|a^*)}{\frac{\pi(a|\ y, f, \beta, \gamma, \Omega, \sigma^2)}{\pi(f|\ y, a, \beta, \gamma, \Omega, \sigma^2)} q(a^*|a)} \right\} \tag{53}$$

D Appendix: MCMC Sampling Algorithm Detailed Summary

Step 1. Draw β from $[\beta|\ y, A, \Omega, \gamma, \sigma^2] \sim \mathcal{N}(\beta, B)$, as specified by (15), (16) and (17).

Step 2. Draw A and f from the joint posterior distribution $[A, f|y, \beta, \Omega, \gamma, \sigma^2]$ by the following two sub-steps,

Step 2.1 Sample a first from $[a|\ y, \beta, \Omega, \gamma, \sigma^2]$ independently of f. Implement M-H sampling by drawing the proposed candidate a^* from the student $\mathcal{T}(\hat{a}, \hat{A}, df)$ with an accepting rate at α from (51),

$$\alpha(a, a^*) = min \left\{ 1, \frac{\pi(a^*|\ y, \beta, \gamma, \Omega, \sigma^2) q(a|\hat{a^*}, \hat{A}^*, df)}{\pi(a|\ y, \beta, \gamma, \Omega, \sigma^2) q(a^*|\hat{a}, \hat{A}, df)} \right\}$$

Step 2.2 Sample f from $[f|\ y, \beta, A, \Omega, \gamma, \sigma^2] \sim \mathcal{N}(\hat{f}, P^{-1})$ as specified by (12) and (13). I also make use to Cholesky decomposition and back substitution according to (23).

Step 3. Draw Ω from the conditional posterior distribution $[\Omega|\ y, \beta, A, f, \gamma, \sigma^2] \sim \mathcal{IG}(d, D)$ as specified by (47), (25) and (26).

Step 4. Draw γ from the conditional posterior distribution $[\gamma|\ y, \beta, A, f, \Omega, \sigma^2]$ as specified by (27) (28) and (29), with an accepting rate at $\alpha(\gamma, \gamma^*)$ from (4),

$$\alpha(\gamma, \gamma^*) = min \left\{ 1, \frac{f_{\mathcal{N}}(f_1|(0, \frac{\sigma^2}{1-\gamma^{*2}}))}{f_{\mathcal{N}}(f_1|(0, \frac{\sigma^2}{1-\gamma^2}))} \right\}$$

Step 5. Draw σ^2 from the conditional posterior distribution $[\sigma^2|\ y, \beta, A, f, \gamma, \Omega] \sim \mathcal{IG}(g, G)$ as specified by (31), (32) and (33).

E Appendix: Monetary Policy Announcement Shocks

Table 5: Federal Reserve Announcements

Type	Date	Time	Event	Main Information
Conventional	2020-03-03	10:00 AM	Lower benchmark rate	Lower the target range for the federal funds rate by 1/2 percentage point, to 1 to 1.25 percent.
Conventional	2020-03-15	5:00 PM	-Lower benchmark rate	Lower the target range for the federal funds rate by 1 percentage point, to 0 to 0.25 percent. reduced the interest rate on discount window loans by 1.5 percentage points, bringing it to 0.25 percent.
Unconventional	2020-03-17	10:45 AM	Establishment CPFF	The Federal Reserve Board announced today that it will establish a Commercial Paper Funding Facility (CPFF) to support the flow of credit to households and businesses.
Unconventional	2020-03-17	6:00 PM	Establishment PDCF	The Federal Reserve Board on Tuesday announced that it will establish a Primary Dealer Credit Facility (PDCF).
Unconventional	2020-03-18	11:30 PM	Establishment MMLF	The Federal Reserve Board establishes a Money Market Mutual Fund Liquidity Facility (MMLF) which will make loans available to eligible financial institutions secured by high-quality assets by the financial institution from money market mutual funds purchased.
Unconventional	2020-03-19	9:00 AM	U.S. Dollar liquidity arrangements with other Central Banks	The Federal Reserve announces the establishment of temporary U.S. dollar liquidity arrangements with other central banks. These new facilities will support the provision of U.S. dollar liquidity in amounts up to $60 billion each for the Reserve Bank of Australia, the Banco Central do Brasil, the Bank of Korea, the Banco de Mexico, the Monetary Authority of Singapore, and the Sveriges Riksbank and $30 billion each for the Danmarks National bank, the Norges Bank, and the Reserve Bank of New Zealand. These U.S. dollar liquidity arrangements will be in place for at least six months.
Unconventional	2020-03-20	10:00 AM	Extended U.S. Dollar liquidity arrangements with other Central Banks	The Bank of Canada, the Bank of England, the Bank of Japan, the European Central Bank, the Federal Reserve, and the Swiss National Bank are today announcing a coordinated action to further enhance the provision of liquidity via the standing U.S. dollar liquidity swap line arrangements. These central banks have agreed to increase the frequency of 7-day maturity operations from weekly to daily. These daily operations will commence on Monday, March 23, 2020, and will continue at least through the end of April. The central banks also will continue to hold weekly 84-day maturity operations.
Conventional	2020-03-23	8:00 AM	FOMC statement	The Federal Reserve will continue to purchase Treasury securities and agency MBS to support smooth market functioning and effective transmission of monetary policy to broader financial conditions.

Continued on next page

Table 5 continued from previous page

Type	Date	Time	Event	Main Information
Unconventional	2020-03-23	8:00 AM	Establishment of PMCCF, SMCCF, and TALF, expand MMLF, CPLF	-Supporting the flow of credit to employers, consumers, and businesses by establishing new programs that, taken together, will provide up to $300 billion in new financing. The Department of the Treasury, using the Exchange Stabilization Fund (ESF), will provide $30 billion in equity to these facilities. -Establishment of two facilities to support credit to large employers – the Primary Market Corporate Credit Facility (PMCCF) for new bond and loan issuance and the Secondary Market Corporate Credit Facility (SMCCF) to provide liquidity for outstanding corporate bonds. -Establishment of a third facility, the Term Asset-Backed Securities Loan Facility (TALF), to support the flow of credit to consumers and businesses. The TALF will enable the issuance of asset-backed securities (ABS) backed by student loans, auto loans, credit card loans, loans guaranteed by the Small Business Administration (SBA), and certain other assets. -Facilitating the flow of credit to municipalities by expanding the Money Market Mutual Fund Liquidity Facility (MMLF) to include a wider range of securities, including municipal variable rate demand notes (VRDNs) and bank certificates of deposit. -Facilitating the flow of credit to municipalities by expanding the Commercial Paper Funding Facility (CPFF) to include high-quality, tax-exempt commercial paper as eligible securities. In addition, the pricing of the facility has been reduced.
Unconventional	2020-03-31	8:30 AM	Establishment FIMA Repo Facility	Establishment of a temporary repurchase agreement facility for foreign and international monetary authorities (FIMA Repo Facility) to help support the smooth functioning of financial markets, including the U.S. Treasury market, and thus maintain the supply of credit to U.S. households and businesses.
Unconventional	2020-04-6	2:00 PM	Establish a facility to provide term financing backed by PPP loans	Federal Reserve will establish a facility to facilitate lending to small businesses via the Small Business Administration's Paycheck Protection Program (PPP) by providing term financing backed by PPP loans. Agencies announce changes to the community bank leverage ratio.
Unconventional	2020-04-9	8:30 AM	Provide up to $2.3T in loans. Bolster SBA's PPPLF. Establish MSLP. Expand the PMCCF, SMCCF, and TALF.	Took additional actions to provide up to $2.3 trillion in loans to support the economy. This funding will assist households and employers of all sizes and bolster the ability of state and local governments to deliver critical services during the coronavirus pandemic. Establishment of the MSLP. Expand the PMCCF, SMCCF, and TALF.
Unconventional	2020-04-23	5:45 PM	Expansion of the PPPLF	the Federal Reserve announces it is working to expand access to its Paycheck Protection Program Liquidity Facility (PPPLF) for additional SBA-qualified lenders as soon as possible.

Continued on next page

Table 5 continued from previous page

Type	Date	Time	Event	Main Information
Unconventional	2020-04-27	4:30 PM	Expansion of the MLF	the Federal Reserve Board announces an expansion of the scope and duration of the Municipal Liquidity Facility. The facility, which was announced on April 9 as part of an initiative to provide up to $2.3 trillion in loans to support U.S. households, businesses, and communities, will offer up to $500 billion in lending to states and municipalities to help manage cash flow stresses caused by the coronavirus pandemic.
Unconventional	2020-04-29	2:00 PM	FOMC statement	The Fed decided to maintain the target range for the federal funds rate at 0 to 1/4 percent (Forward Guidance). Support the flow of credit to households and businesses, the Federal Reserve will continue to purchase Treasury securities and agency residential and commercial mortgage-backed securities in the amounts needed to support smooth market functioning, thereby fostering effective transmission of monetary policy to broader financial conditions. In addition, the Open Market Desk will continue to offer large-scale overnight and term repurchase agreement operations. The Committee will closely monitor market conditions and is prepared to adjust its plans as appropriate.
Unconventional	2020-04-30	10:00 AM	Expand the Main Street Lending Program	the Federal Reserve Board announces it is expanding the scope and eligibility for the Main Street Lending Program.
Unconventional	2020-04-30	5:15 PM	Expand PPPLF	the Federal Reserve expands access to its Paycheck Protection Program Liquidity Facility (PPPLF) to additional lenders, and expands the collateral that can be pledged.
Unconventional	2020-05-11	10:30 AM	Update MLF	The Municipal Liquidity Facility (MLF) , which was established under Section 13(3) of the Federal Reserve Act, with approval of the Treasury Secretary, will offer up to $500 billion in lending to states and municipalities to help manage cash flow stresses caused by the coronavirus pandemic.
Unconventional	2020-05-12	1:15 PM	Update TALF	Federal Reserve publishes updates to the term sheet for the Term Asset-Backed Securities Loan Facility (TALF) and announces information to be disclosed monthly for the TALF and the Paycheck Protection Program Liquidity Facility.

Note: If policy announced after the trading hours, the dummy variable will reflect on the next trading day.

F Appendix: Data Transformation Summary

The column trans-code denotes the following data transformation for a series x: (1) No transformation; (2) Change: Δx_t; (3) Growth rate: $\Delta log(x_t)$; (4) Indexing: $\frac{x_t}{benchmark}$; (5) Normalizing: $\frac{x_t - min}{max - min}$.
An asterisk is tagged these variables to indicate that they been adjusted from the source.

Table 6: Data Transformation

ID	Trans-Code	Name/FRED	Description	Frequency
1	1	NoDur	Stock Returns by Secotor	Daily
2	1	Durbl	Stock Returns by Secotor	Daily
3	1	Manuf	Stock Returns by Secotor	Daily
4	1	Enrgy	Stock Returns by Secotor	Daily
5	1	HiTec	Stock Returns by Secotor	Daily
6	1	Telcm	Stock Returns by Secotor	Daily
7	1	Shops	Stock Returns by Secotor	Daily
8	1	Hlth	Stock Returns by Secotor	Daily
9	1	Utils	Stock Returns by Secotor	Daily
10	1	Other	Stock Returns by Secotor	Daily
11	3	IPBUSEQ	Industrial Production: Equipment: Business Equipment	Monthly
12	3	IPZ53010S	Industrial Production: Materials Excluding Energy Materials	Monthly
13	3	IPB53300S	Industrial Production: Energy Materials	Monthly
14	3	IPDMAN	Industrial Production: Durable Manufacturing (NAICS)	Monthly
15	3	IPDCONGD	Industrial Production: Durable Consumer Goods	Monthly
16	3	IPNMAN	Industrial Production: Non-Durable Manufacturing (NAICS)	Monthly
17	3	IPMINE	Industrial Production: Mining, Quarrying, and Oil and Gas Extraction: Mining (NAICS = 21)	Monthly
18	3	IPUTIL	Industrial Production: Utilities: Electric and Gas Utilities (NAICS = 2211,2)	Monthly
19	3	IPNCONGD	Industrial Production: Non-Durable Consumer Goods	Monthly
20	3	LNU04032230	Unemployment Rate - Mining, Quarrying, and Oil and Gas Extraction, Nonagricultural	Monthly
21	3	LNU04032231	Unemployment Rate - Construction Industry	Monthly
22	3	LNU04032233	Unemployment Rate - Durable Goods Industry	Monthly
23	3	LNU04032234	Unemployment Rate - Non Durable Goods Industry	Monthly
24	3	LNU04032235	Unemployment Rate - Wholesale and Retail Trade	Monthly
25	3	LNU04032236	Unemployment Rate - Transportation and Utilities Industry	Monthly
26	3	LNU04032237	Unemployment Rate - Information Industry	Monthly
27	3	LNU04032238	Unemployment Rate - Financial Activities Industry	Monthly
28	3	LNU04032239	Unemployment Rate - Professional and Business Services	Monthly
29	3	LNU04032240	Unemployment Rate - Education and Health Services	Monthly

Continued on next page

Table 6 continued from previous page

ID	Trans-Code	Name/FRED	Description	Frequency
30	3	LNU04032241	Unemployment Rate - Leisure and Hospitality	Monthly
31	3	LNU04032242	Unemployment Rate - Other Services Industry	Monthly
32	3	M1SL	M1 Money Stock	Monthly
33	3	CPIAUCSL	Consumer Price Index for All Urban Consumers	Monthly
34	4	UMCSENT	University of Michigan: Consumer Sentiment, Index 2020 : M1 = 1	Monthly
35	5	Death Rate	COVID-19 Death Rate Smoothed	Daily
36	3	Trade Volume	NASDAQ Stock Market Trade Volume	Daily
37	1*	Retail, Recreation	Google Community Mobility	Daily
38	1*	Grocery, Pharmacy	Google Community Mobility	Daily
39	1*	Parks	Google Community Mobility	Daily
40	1*	Transit Stations	Google Community Mobility	Daily
41	1*	Workplaces	Google Community Mobility	Daily
42	1*	Residential	Google Community Mobility	Daily
43	2	DFF	Effective Federal Funds Rate	Daily
44	1	MPC	MP Conventional Announcement Dummy Variable	Daily
45	1	MPUNC	MP Unconventional Announcement Dummy Variable	Daily
46	1	FISC	Fiscal announcement Dummy Variable	Daily
47	1	UNEMP	Unemployment Announcement Dummy Variable	Daily

H

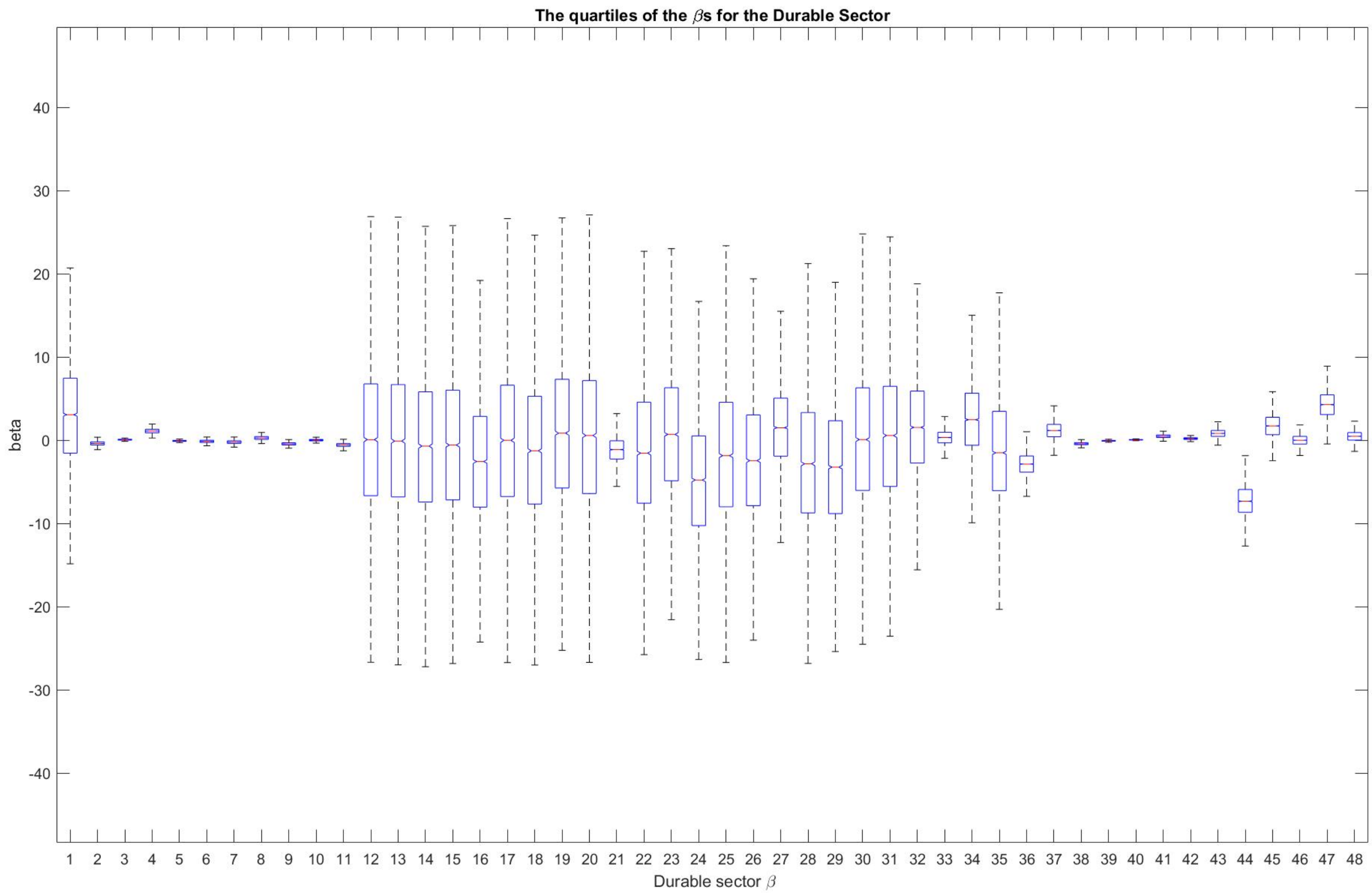


Figure 22: Notched Boxplot For Coefficients In The Durable Sector

Note: the order numbers of the coefficients are the same order numbers as in (6) but adding one, because the first coefficient is for the intercept. Graphs for other sectors are also available upon request.

G Appendix: Sample of Wall Street Journal headlines on March 15, 2020

This is a one-day sample to show that the sentiment analysis captures collective news shocks during the sample period (January 1, 2020 - August 31, 2020). The news headlines include all aspects of the society, i.e., health, education, economy, business, election, world news shocks, etc.

Election 2020
Inside and Outside the Democratic Debate, a World Transformed

Election 2020
Biden, Sanders Split on Policy, Unite Against Trump

World
Coronavirus Measures Put New Limits on Daily Life

Business
United Starts Union Talks as Cuts Deepen

New York
De Blasio to Ban Dining at New York City Restaurants, Bars, Cafes

Election 2020
Democratic Debate Between Sanders and Biden: The Moments That Mattered

Business
Wynn, MGM to Temporarily Close Las Vegas Strip Casinos Over Coronavirus

Journal Reports: Wealth Management
Travel vs. Environmentalism? Millennials Try to Do Both

Europe
European Nations Impose Stricter Novel Coronavirus Measures

U.S.
Top Health Official Urges Americans to Stay Home Amid Coronavirus

U.S. Economy
Fed Slashes Rates to Fight Coronavirus Slowdown

Health Policy
Census Worker Tests Positive for Novel Coronavirus

Markets
Biggest U.S. Banks Halt Buybacks to Free Up Capital for Coronavirus

U.S.
Fliers Back From Abroad Face Long, Crowded Lines at Airports

U.S.
Trump Says He Is Considering Pardoning Michael Flynn

Review Outlook
Virus Relief but New Business Burdens

Review Outlook
The Federal Reserve Returns to 2008

Review Outlook
Mississippi's Biggest Loser

State Street
Coronavirus Roils New York Election Plans
Commentary Don't Credit the Minimum Wage for Growing Paychecks

Commentary
Let the Fed Administer an Antiviral Shot

Bookshelf
'Experimentation Works' and 'The Power of Experiments' Review: Test, Test and Test Again

Notable Quotable
Notable Quotable: ISIS on the Coronavirus

Inside View
Crisis Means a New Business Era

The Americas
Economic Flu Stalks Latin America

Economy
Economy Week Ahead: Focus on Fallout From the Coronavirus

Election 2020
Joe Biden Nods to Liberals With College Tuition, Bankruptcy Proposals

Schools
New York City Schools to Close Over Coronavirus

Economy
Fed Takes Emergency Actions as Virus Pushes Economy Toward Recession

U.S.
Despite Coronavirus, Some Religious Services Continue

Business
Coronavirus Prompts Abercrombie, Nike, Others to Close Shops

Middle East
Blue and White Leader Gantz to Get First Shot at Forming Israeli Government

Europe
Germany Accuses U.S. of Trying to Lure a Drug Maker Working on Coronavirus Vaccine

The A-Hed
Brine With a Dash of Beet Juice—A Pungent Cocktail for Icy Roads

New York
Gov. Cuomo Wants to Close New York City's Public-School System

Business
Grocers Fail to Keep Up With Demand as Pandemic Spreads

Business
For Airlines, a Week That Went From Bad to Worse

TikTok to Stop Using China-Based Moderators to Monitor Overseas Content

World
As Virus Spreads, Governments Rush to Secure Ventilators

New York
Homemade Hand Sanitizer Hits New York Store Shelves

Business
Sports, Retailers, Airlines, Autos: The Damage Across Business

Politics
Adam Schiff Says Former Aide Tests Positive for Virus

Media Marketing
Domestic Box Office Suffers Worst Weekend in Nearly 20 Years

Letters
On the Readmission of Criminal Immigrants

Letters
Schumer's Intimidating Supreme Court Rant

Letters
Fed Actions Should Truly Promote Liquidity

Letters
Graduate-School Regression Had Other Compensations

Letters
The Fed Liquidity Stimulus Must Be Enough to Succeed

Business
Coronavirus Social-Distancing Forces Painful Choices on Small Businesses