Department of
Economics and Finance

THE COVID-19 PANDEMIC AND THE DEGREE OF PERSISTENCE OF US STOCK PRICES AND BOND YIELDS

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Abstract

describes the data and presents the empirical results. Section 5 offers some concluding remarks.

2. Literature Review

Stock prices are some of the most frequently analysed economic series (see Granger, 1992). A variety of approaches have been followed in the literature. For instance, Wang et al. (2010) applied an interacting stochastic systems framework and built a model based on the random continuum percolation to investigate in investor behaviour. Hedayati et al. (2016) used instead artificial neural networks (ANNs) to forecast the daily NASDAQ; specifically, they trained feedforward ANNs through back-propagation algorithms.

Atsalakis and Valavanis (2009) modelled stock prices by means of a neuro-fuzzy system including an Adaptive Neuro Fuzzy Inference System (ANFIS) controller; they showed that this method provides better forecasts than rival ones and represents a challenge for the weak form of the Efficient Market Hypothesis (EMH). Schotman et al. (2008) studied the implications of asset return predictability for long-term portfolio choices when return-forecasting variables are fractionally integrated; they estimated orders of integration of approximately 0.8 for key predictors, such as the dividend-price ratio and interest rates, and thus a higher long-term risk for stocks and bonds compared to the estimates obtained from a stationary VAR.

Most recently, a few studies have examined specifically the impact of the Covid-19 pandemic on financial markets. For instance, Salisu and Vo (2020) evaluated the importance of health-news trends to forecast stock returns for a list of countries with high incidence of Covid-19; their results showed that a model incorporating a health-news index outperforms the benchmark historical average model; in addition, including macroeconomic factors and financial news improves the forecasting performance of the health news-based model. (2020) studied instead the effects of Covid-19 on Crude Oil price and three US stock indices: DJI, S&P 500, and NASDAQ Composite; their approach to forecasting commodity and stock prices integrates the stationary wavelet transform (SWT) and bidirectional long short-term memory (BDLSTM) networks.

Other studies focus on asset price volatility. As highlighted by Dräger et al. (2020), the degree of long memory in stock market volatility can be interpreted as a measure of uncertainty: high degrees of long memory imply a low degree of uncertainty. Caporale et al. (2018) studied the degree of persistence of market fear as measured by the VIX index from 2004 to 2016 and found that its properties vary over time: in normal periods it exhibits anti-persistence, whereas during recession persistence increases. Hiremath and Bandi (2010) obtained evidence of long memory in volatility in the case of the Indian stock market using the fractionally integrated generalized autoregressive conditional heteroscedasticity (FIGARCH) model, which is shown to capture more accurately the persistence in volatility than the conventional ARCH-GARCH models. The same conclusions have been also reached by Christensen and Nielsen (2007) and Kasman and Torun (2007) for other markets. Martens et al. (2004) used instead a nonlinear Autoregressive Fractionally Integrated Moving Average (ARFIMA) model to analyse volatility in the S&P500 stock index.

3. Methodology

Our modelling approach is based on the concept of fractional integration and is more general than the standard framework that only allows for integer degrees of differentiation. Specifically, a time series x_t is said to be integrated of order d or I(d) if it can be represented as:

$$(1 - B)^d x_t = u_t, \quad t = 1, 2, \ldots, \tag{1}$$

where B is the backshift operator, and u_t exhibits short-memory, is integrated of order 0 (I(0)) and follows a white noise or weakly autocorrelated (e.g., ARMA) process. If $d > 0$ in (1) then x_t is said to be a long-memory process since the autocorrelations decay hyperbolically, and the higher the value of d is, the slower is the rate of decay.

In our empirical analysis we also allow for a linear time trend and consider the following general specification:

$$y_t \qquad t \quad x_t\,, \qquad t \quad 1, 2, ..., \qquad (2)$$

where y_t stands for the series of interest, x_t is the error term, and parameters to be estimated, respectively a constant and the coefficient on the linear time trend. The estimation is based on the Whittle function in the frequency domain and follows a testing procedure developed by Robinson (1994) which is most appropriate in the case of nonstationary series such as those analysed in this paper.

4. Data and Empirical Results

We examine four seasonally unadjusted US stock market indices (NYSE, NASDAQ 100, S&P500, and Dow Jones) as well as US 10-year and 1-year Treasury bond yields and their spread (measured in percentage points); the series are monthly and the sample period goes from January 1966 to January 2021, therefore the total number of observations in each case is 661. The chosen time span includes the last 8 NBER-dated recessions (NBER, 2021). The data source is Thomson Reuters Eikon.

Our objective is to analyse the possible impact of the Covid-19 pandemic on the parameter d, which is a measure of persistence, for both stock prices and bond yields; therefore, as a first step we estimate the model up to December 2019 (namely, immediately before the start of the pandemic), and then use recursive methods to investigate the evolution of d from January 2020 onwards (namely, during the pandemic). Table 1 displays the estimates of d and the corresponding 95% confidence bands in the case of stock prices for the sample period ending in December 2019; we consider three possible specifications: i) no deterministic terms, ii) an intercept only, and iii) an intercept and a linear time trend. We also assume that the error term, i.e., u_t in (1), is a white noise

differently depending on their maturity. Figure 2 displays the recursive estimates of d (again for the case of Bloomfield errors) over the pandemic period. It can be seen that, unlike the case of stock prices, the degree of persistence of bond yields appears to have been affected by the Covid-19 pandemic. In particular, the estimated parameter d increases from around 1 to values significantly above 1 in the case of 10-year bond yields; by contrast, the estimated values of d are still significantly below 1 for 1-year bond yields (which implies mean reversion), and the increase in this parameter occurs a few months later. Finally, all values are significantly above 1

On the whole, our findings point to a greater degree of market efficiency in the case of stock prices, which appear to be unpredictable since they exhibit a unit root and thus follow a random walk - unlike bond yields, for which there is evidence of some predictability. Volatility persistence is a further important issue to be investigated in future work given the high degree of uncertainty generated by the Covid-19 pandemic (see Baker et al., 2020).

Wang, J., Wang, Q., Shao, J. (2010). Fluctuations of stock price model by statistical physics systems. Mathematical and Computer Modelling, Volume 51, Issues 5 6, Pages 431-440. https://doi.org/10.1016/j.mcm.2009.12.003.

Table 1: Estimates of d: Stock indices. Sample period: January 1966-December 2019

Series	No terms	An intercept

Table 2: Estimates of d: Bond yields. Sample period: January 1966-December 2019

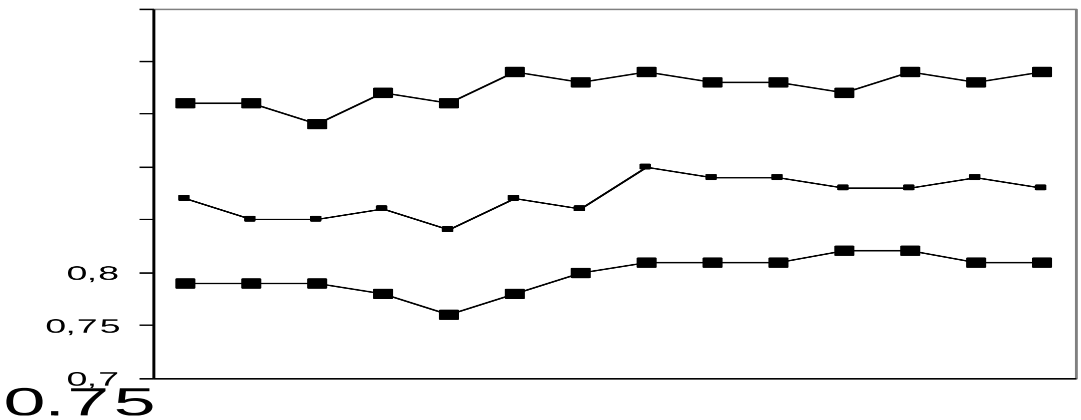
Series	No terms	An intercept	An intercept and a linear time trend
i) White noise			
TY - 10	1.04 (0.99, 1.10)	**1.19 (1.13, 1.26)**	1.19 (1.13, 1.26)
TY 1	1.01 (0.96, 1.08)	**1.14 (1.06, 1.24)**	1.14 (1.06, 1.24)
Spread	**1.22 (1.16, 1.29)**	1.22 (1.16, 1.29)	1.22 (1.16, 1.29)
ii) Autocorrelation (Bloomfield)			
TY - 10	1.01 (0.94, 1.09)	**1.02 (0.95, 1.10)**	1.02 (0.95, 1.10)
TY 1	0.98 (0.90, 1.07)	**0.87 (0.79, 0.96)**	0.86 (0.78, 0.96)
Spread	**1.09 (1.02, 1.19)**	1.09 (1.02, 1.19)	1.09 (1.02, 1.19)

iii) Seasonal monthly AR

Figure 2: Recursive estimates of d from January 2020 to February 2021. Bond yields

i) TY-10

ii) TY-1



iii) Spread