Financial Technologies (Fintech) Revolution and Covid-19. Time Trends and Persistence

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Abstract: The financial and banking sector has experienced a great revolution in recent years with the appearance of FinTech, applying the concept of digital transformation to the financial services industry. The focus of this research paper is to analyze the stochastic properties of the banking revolution and financial technologies (FinTech) before and after COVID-19 episode. This study adds a new dimension to the literature because it is the first research paper that uses advances methodologies based on fractional integration and artificial intelligence to understand the behavior of the FinTech industry. The results exhibit a high degree of persistence in both cases. However, it is observed in the behavior of the subsamples that before the pandemic, the so-called "FinTech revolution" period, we find a behavior of mean reversion in the event of an external shock. After the pandemic episode, the series behaves like non mean reversion, where shocks are expected to be permanent, causing a change in trend. This last result is in line with the one obtained using machine learning techniques predicting the behavior of the new trend in the next 365 days.

Keywords: FinTech; banking revolution; mean reversion; persistence; fractional integration; machine learning.
JEL Classification: C22; C45; G20; O30.

1. INTRODUCTION

Since 1850s, financial services and banking industry has been using technology to carry out its activity. The sector, in the past two decades, has experienced far-reaching technological and regulatory changes due to deregulation and liberalization, advances in information and communication technologies, novel solutions for transactions and saving, changes in cybersecurity and digitalization.

The term FinTech appears to describe breakthroughs in technology that provide financial solutions to individuals and firms, applying the concept of digital transformation to the financial services industry (see Puschmann, 2017). These technology firms have the power to transform the provision of financial services, drive the creation of novel business models, applications, processes, and products, as well as lead to consumer gains (see Arner, Barberis, & Buckley, 2015; Feyen, Frost, Gambacorta, Natarajan, & Saal, 2021; Sironi, 2016), offering services that have been only offered by traditional financial institutions.

Following the argument of Imerman and Fabozzi (2020), Global Financial Crisis (GFC) was the limelight that really thrust FinTech innovations.

According to Guiso et al. (2004), Gennaioli et al. (2015), A.V. Thakor (2020), among others, the decisions to adopt new products and services from a traditional or digital institution depends on the perception of trust.

Following to Venture Scanner[1], from 2010 through the end 2019 that was the period referred to “Fintech Revolution”, more than $165.5 billion was poured into these companies. Hu et al (2019) stated that the worldwide Fintech investment surged roughly 12 times between 2010 and 2016, from USD 12.2 billion to USD 153.1 billion.

On 11 March 2020, the World Health Organization (WHO) officially declared the coronavirus (COVID-19) outbreak as a global pandemic. This fact caused strong doubts surrounding it extent and its implications on the global economy.

Financial services and banking industry, among all economic actors, were forced to take up an enormous challenge. Maintain their activity and minimize the economic and financial impact of the crisis on their results.

According to Imerman and Fabozzi (2020), the COVID-19 pandemic is the breakpoint where the FinTech innovations are widely adopted and those that do not provide a solution to consumers and businesses disappear.

Shahzad et al. (2022) provided several reasons about the Fintech adoption during the COVID-19. They found significant and positive impact on perceived ease of use, trust, and use innovativeness towards attitude and behavioral intention to use online loan aggregator platforms.

This paper offers several contributions to the scanty literature on time trends and persistence in the banking revolution and financial technologies (FinTech). To the best of our knowledge, this paper is the first study to examine persis-

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[1] https://www.venturescanner.com/tag/fintech/

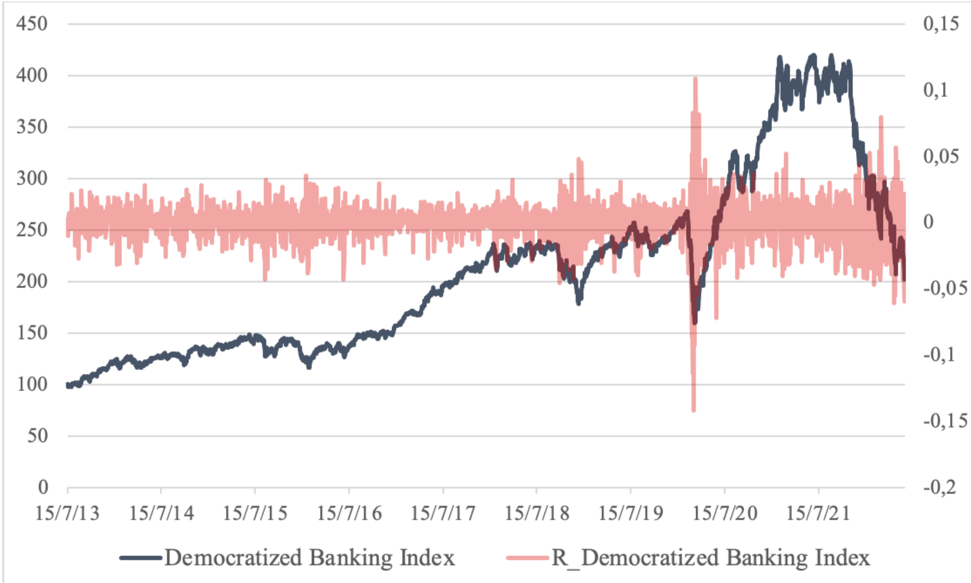

Fig. (1). Fintech sector evolution.

tence in the digital transformation of the financial services industry considering COVID-19 as a structural break. Specifically, this study makes twofold contribution. First it applies long memory techniques to provide evidence on the stochastic properties (more specifically, mean reversion and persistence) of the FinTech market. This is an advantage because is more general than standard approaches based on I(0)/I(1) dichotomy since it allows for fractional values of the integration. Second, we examine the effects of structural break originated by the coronavirus pandemic using an Artificial Neural Network model based on a Multilayer Perceptron (MLP) neural network for time series prediction.

The structure of this paper is as follows. Section 2 describes the data used for our study. Section 3 explains the methodologies used to carry out the research. The results are discussed in Section 4. Finally, the conclusions are found in Section 5.

2. DATA

The database analyzed in this research paper was obtained from S&P Kensho New Economy Indices and the variable used to carry out this study is S&P Kensho Democratized Banking Index[2] that is an aggregate price index focused on innovations within financial services, including direct lending, crowdfunding, automated wealth management, usage / on-demand insurance services, and digital currencies and related capabilities.

We use daily frequency data from July 15, 2013 to June 16, 2022 and it is represented in the Fig. (**1**). As we can see in the figure and in accordance with the literature cited above, two periods can be differentiated: pre and post pandemic. From 2013 through the end 2019 was the period referred to "Fintech Revolution" where the key forces based on technology innovation, process disruption and services transformation occur (see Gomber et al., 2018). The Economist (2015) stated that the disruption of geeks in T-shirts and venture capital put financial services as payments, wealth management, peer-to-peer lending, crowdfunding, etc. in its sights. So, a new generation of startups and a source of income valued at $4.7 trillions originated this revolution in the financial sector.

The confinement due to COVID-19 favored accessible online services without having to leave home and in the post-COVID era, 2021, the trend of online financial services and products returned to similar or lower levels than before COVID-19 due to various factors such as the closure of businesses, reduction of investments, increased the debt of the firms and the adaption of traditional banking to the needs of the post-COVID customers.

3. METHODOLOGY AND RESULTS

3.1. Unit Root Methods

Augmented Dickey Fuller (ADF) test, based on Fuller (1976) and Dickey and Fuller (1979), has been used to know the stationarity of the data analyzed in the paper. Other methods have also been examined such as the non-parametric one based on the spectral density at the zero-frequency of Phillips (1987) and Phillips and Perron (1988), along with Kwiatkowski et al. (KPSS, 1992), Elliot et al. (ERS, 1996) and Ng and Perron (2001).

3.2. ARFIMA (p, d, q) Model

To carry out this research, we also employ fractionally integrated methods, which are more flexible that the unit root tests above mentioned. The idea that is behind is that the number of differences to be adopted in the series to render it stationary I(0) may be a fractional value between 0 or 1, or even above 1.

[2] https://www.spglobal.com/spdji/es/indices/equity/sp-kensho-democratized-banking-index/#overview

Table 1. Results of Long Memory Tests.

Data analyzed	Sample size (days)	Model Selected	d	Std. Error	Interval	I(d)
Original Time Series						
Democratized Banking Index	2249	ARFIMA (2, d, 1)	1.00	0.035	[0.94, 1.05]	I(1)
Before COVID-19 (“FinTech Revolution period”)						
Democratized Banking Index	1677	ARFIMA (2, d, 2)	0.96	0.111	[0.77, 1.14]	I(1)
After COVID-19						
Democratized Banking Index	572	ARFIMA (2, d, 2)	1.00	0.034	[0.94, 1.05]	I(1)

Using a mathematical notation, a time series x_t, t = 1,2,,… follows an integrated of order d process (and denoted as $x_t \approx I(d)$) if:

$$(1-L)^d x_t = u_t, \qquad t = 1, 2, \quad (1)$$

where d refers to any real value, L indicates to the lag-operator ($Lx_t = x_{t-1}$) and u_t is a covariance stationary process I(0) where the behavior of the spectral density function is characterized by being positive and finite at all its frequencies.

It is said that x_t is ARFIMA (p, d, q) when u_t is ARMA (p, q). So, depending on the value of the parameter d in Equation (1) the reading of the results can be: x_t is anti-persistent if $d < 0$ (see Dittmann and Granger, 2002); when $d = 0$ we say that the process is short memory I(0); with a high degree of association over a long time we say that the process displays the property of long memory if $d > 0$; $d < 1$ means that the shock is transitory and the series reverts to the mean; finally, when $d \geq 1$ we expect that the shocks will be permanent.

We follow the methodology based on the likelihood function and proposed by Sowel (1992) instead of other parametric or even semiparametric approaches (see, Geweke and Porter-Hudak, 1983; Phillips, 1999, 2007; Sowell, 1992; Robinson, 1994, 1995a,b; Shimotsu and Phillips, 2005, 2006, etc.) and to select the most appropriate ARFIMA model we use the Akaike information criterion (AIC) (Akaike, 1973) and the Bayesian information criterion (BIC) (Akaike, 1979).

4. RESULTS

We have first conducted standard unit root test (see Dickey and Fuller 1979; Elliot, Rothenberg, and Stock 1996; Phillips and Perron 1988; Kwiatkowski et al. 1992). The results suggest that the original time series and the periods before and after COVID-19 are non-stationary I(1). However, following authors such as Diebold and Rudebusch (1991), Hassler and Wolters (1994), Lee and Schmidt (1996) and others, it is now a well stylized fact that all unit root methods have very low power if the true data generating process displays long memory or if it is fractionally integrated. Thus, in what follows, fractional orders of differentiation are allowed.

From Table **1** we observe that the estimates of parameter d in all cases is 1 or is very close to 1, observing in the three cases a high degree of persistence, ranging from 0.96 (before COVID-19 that is the period considered FinTech Revolution) to 1.00 (for the original and after COVID-19 time series).

The time series that includes the entire period analyzed and the subsample analyzed that begins since the pandemic was declared show the same behavior, where the parameter d is equal to 1.00, which means no mean reversion. Therefore, shocks are expected to be permanent, causing a change in trend and thus, extraordinary measures will be required to reverse the situation and recover the original trend. According to Bacq et al. 2020, Ratten, 2020 and Shareef et al. 2021, entrepreneurship activities experienced a change in trend during and after COVID-19. For the case of FinTech revolution period we observe that the time series has a different behavior (mean reversion) although according to the confidence interval, we cannot reject the hypothesis of I(1).

Finally, due to the high degree of persistence of time series and its degree of integration, we can use advanced computational intelligence techniques based on machine learning to understand the behavior and the evolution of these financial services in the future. For this purpose, we have used the Multilayer Perceptron (MLP) neural network to predict the time-series. The motivation is that the underlying model (non-parametric model) is required to get the results. It also presents interesting features such as its non-linearity. The MLP Neural Network method is based on the back-propagation rule where the errors are propagated throughout the network and allow for the adaptation of the hidden processing elements. It has a massive level of interconnectivity that means that any element of a given layer feeds all the elements of the next layer. It is trained using error correction learning (Güler and Ubeyli, 2005; Martínez et al. 2019; Mapuwei, Bodhlyera, and Mwambi 2020).

The forecasting accuracy using the ANN model is measured by Root Mean Square Error (RSME) and is very close to zero (0.028) what allows us to forecast the digital transformation in financial services industry (Fig. **2**).

As can be seen, the start of the pandemic caused a strong acceptance of the different financial products offered by FinTechs, leading to strong growth.

Since the end of the third quarter of 2021, we see how these products cease to have an interest due to various factors such as the closure of businesses, reduction of investments, increased the debt of the firms and the adaption of traditional banking to the needs of the post-COVID customers.

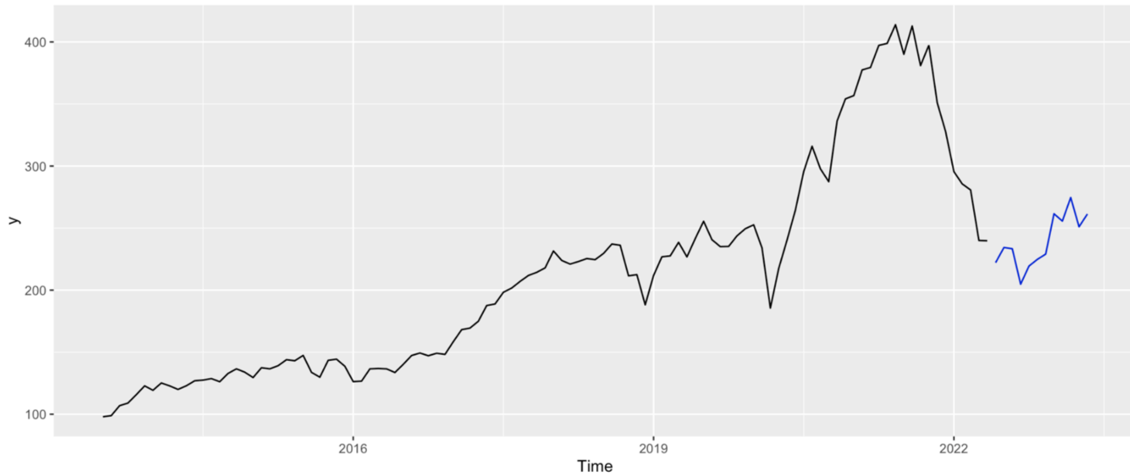

Fig. (2). Forecasting using machine learning model.

Therefore, we expect the index to go from being worth 201.94 dollars to being worth 251.82 dollars in the next 12 months, that is, 24.70% more.

5. CONCLUDING REMARKS

From 2010 to 2019, the "Fintech Revolution" was experienced. This period used technology to respond to the needs of individuals and companies in the financial services industry.

Consumer confidence and the sanitary restrictions imposed by the different governments around the world during the COVID-19 crisis, was the key to the greater growth of these new services. Access to technology and digital media during these restrictions allowed the use of FinTech to carry out financial operations.

For this reason, this research article analyzes the behavior of FinTech sector before and after COVID-19 using methodologies based on fractional integration and machine learning. To do so, we use methodologies based on fractional integration and machine learning to get the statistics properties of the S&P Kensho Democratized Banking Index.

First we see that the results obtained are very persistent and show a different behavior before and after the pandemic period. We get that until March 2020, FinTech industry presented a behavior of mean reversion, with shocks disappearing in the very long run. After the pandemic began and in line with the research papers of Bacq et al (2020), Ratten (2020) and Shareef et al. (2021), we find that the shocks have a permanent component causing changes in the trend and therefore extraordinary measures will be required to reverse the situation and recover the original trend.

On the other hand, using a machine learning technique based on Multilayer Perceptron (MLP) neural network to verify the previous results, we observe the change in trend after COVID-19 caused by various factors such as the closure of businesses, reduction of investments, increased the debt of the firms and the adaption of traditional banking to the needs of the post-COVID customers. This change in trend is also being aggravated because different governments are highlighting the need for a more active regulatory intervention in this market, to face the growing risks of consumer protection, and avoid a crisis in traditional banking. This is affecting the use of these applications.

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Received: April 13, 2023 Revised: April 17, 2023 Accepted: July 12, 2023