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ANALYZING TÜRKİYE'S FINTECH INVESTMENT FUTURE WITH ARIMA APPROACH

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Abstract: Türkiye's fintech sector has undergone an interesting journey. Initially characterised by rapid growth and innovation, the sector has undergone a significant consolidation process in the following years. When analysing the fintech investment ecosystem in Türkiye between 2016 and 2024, it has shown remarkable flexibility and growth potential, reaching an impressive figure of $194 million by 2024, up from a modest figure of $12 million in 2016. This represents an extraordinary increase of 1.52 percent in an eight-year. Therefore, it can be assumed that the fintech ecosystem in Türkiye has moved from the growth phase to the maturity phase, the market has started to consolidate, and fewer but larger players have emerged. The aim of this paper is to analyse the future of fintech investments and, for this purpose, to identify the growth potential of the fintech sector. For this objective, the fintech data reported for the years between 2016 and 2024 in Türkiye has been estimated both before 2024 and between 2025 and 2028 using the ARIMA model. The analysis of the obtained regression estimation shows that the coefficients of AR(1) and MA(1) are negative and statistically insignificant. However, although this model provides limited benefit in predicting the future values of the fintech variable, it can be said that the overall performance of the model can be considered applicable and valid because the model is significant as a whole and there is no autocorrelation problem. As a result, fintech investment is expected to reach a new peak of $212.1 million in 2025 and maintain a strong momentum of $167.1 million in 2026. Although forecasts point to a potential market correction in 2027, this is a natural consolidation phase after years of growth, and growth of $93.1 million is expected in 2028.

Keywords: Finance, Financial Technology (Fintech), Investment, ARIMA.

JEL Code: G00, G17.

ARIMA YAKLAŞIMIYLA TÜRKİYE'NİN FİNTEK YATIRIM GELECEĞİNİN ANALİZİ

Özet: Türkiye'nin fintek sektörü ilginç bir gelişim göstermektedir. Başlangıçta hızlı büyüme ve yenilik ile karakterize olan sektör, ilerleyen yıllara doğru belirgin bir konsolidasyon sürecine girmiştir. 2016-2024 arası Türkiye fintek yatırım ortamı incelendiğinde 2016 yılında 12 milyon dolar gibi sade bir rakamdan 2024 yılına kadar 194 milyon dolar gibi etkileyici bir rakama ulaşarak kayda değer bir esneklik ve büyüme potansiyeli göstermiştir. Bu da sekiz yıllık dönemde %1.52'lik olağanüstü bir artışı temsil etmektedir. Dolayısıyla bu süreçte Türkiye'nin fintek ekosisteminin büyüme aşamasından olgunlaşma aşamasına geçtiğini, pazarın konsolide olmaya başladığını ve daha az sayıda ancak daha büyük oyuncuların ortaya çıktığı ileri sürülebilir. Bu çalışmada fintek yatırımlarının gelecek analizini gerçekleştirme ve bu amaçla fintek sektörünün büyüme potansiyelinin ortaya koyulması hedeflenmektedir. Bu amaç doğrultusunda Türkiye'de 2016-2024 arası yılları için raporlanan fintek verileri ARIMA modeli kullanılarak hem 2024 öncesi hem de 2025-2028 arası için tahmin yapılmıştır. Elde edilen regresyon tahmini incelendiğinde AR(1) ve MA(1) katsayısı negatif ve istatistiksel olarak anlamlı olmadığı ortaya koyulmuştur. Ancak fintek değişkeninin gelecekteki değerlerini tahmin etmekte bu model sınırlı fayda sağlasa da modelin bir bütün olarak anlamlı olması ve otokorelasyon sorununun olmaması modelin genel performansının uygulanabilir ve geçerli sayılacağı söylenebilir. Regresyon sonrası yapılan tahminde fintek yatırımlarının 2025 yılında 212,1 milyon dolar ile yeni bir zirveye ulaşması ve 2026 yılında 167,1 milyon dolar ile güçlü ivme sürdürmesi beklenmektedir. Tahminler 2027'de potansiyel bir pazar düzeltmesine işaret etse de bu durum yıllarca süren büyümenin ardından doğal bir konsolidasyon aşamasını temsil etmekte ve 2028'de ise 93,1 milyon dolar büyüme beklenmektedir.

Anahtar Kelimeler: Finans, Finanansal Teknoloji (Fintek), Yatırım, ARIMA.

JEL Kodu: G00, G17.

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Introduction

Nowadays, technology has an effect in every industry. While this circumstance occasionally appears on the agenda as a facilitating impact, it also creates a name for itself due to security risks. These technological changes experienced in societies are also reflected in fields such as economy and finance, fulfilling the need for financial services to be provided easily, quickly, and simply in these sectors. Companies are also increasing their investments in financial technology (fintech) by providing quality and fast services. While doing this, companies can find their place in the sector more efficiently and effectively by changing the structure of the services they provide with traditional methods. (Canbaz & Erbaş, 2021, p. 478). When it comes to efficiently providing financial services, the fintech phenomenon has a big influence on financial markets and financial organizations. The term "fintech" refers to a broad category of creative methods that arise when contemporary technology are incorporated into the financial sector, revolutionizing conventional financial services and opening the door for the creation of new business models, apps, procedures, or goods. Numerous financial services-related industries may be impacted by this idea directly or indirectly (Financial Stability Board, 2017). In other words, it is a framework that delivers creative applications and solutions that improve the user experience, optimizes financial transactions using the most recent technical advancements, and alters conventional financial systems. Businesses may now access new kinds of services, new models, new ideas, and new applications thanks to this technology (Erden & Topal, 2021, p. 70).

Fintechs may be developed in a lot of ways. These encompass domains including insurance, money management (deposits, credit service, capital growth, and portfolio management), and transaction execution (payments). Thanks to technology improvements, businesses may also offer efficient services by taking advantage of cheap search costs in financial markets, economies of scale in gathering and analyzing huge data sets, more secure and economical information transfer, and lower verification costs (Barba Navaretti et al., 2018, p. 12). However, the existence of fintech may jeopardize jobs in the financial services industry. For instance, it is anticipated that the fields of artificial intelligence and machine learning would significantly affect the financial services industry by lowering employment in this area. But it's important to note here. It is interesting to see how the potentially discussed threat between artificial intelligence (AI) and intelligence enhancement (IA) is structured. For instance, there is a claim that the process of intelligence augmentation will result in fewer job losses (Das, 2019, pp. 1002–1004).

A schematic illustrating the potential advantages and disadvantages of the fintech industry is shown in the Figure 1. Increased tax revenues, lower transaction costs, and financial inclusion and depth are some of the good effects; the influence on monetary policy, insufficient supervision, and problems with security and trust are some of the negative effects. On the one hand, fintech lowers costs and makes the financial system more accessible, but on the other, it presents new difficulties for regulators. This double effect emphasizes how crucial it is to control the broad use of applications for fintech while keeping economies and society in balance.

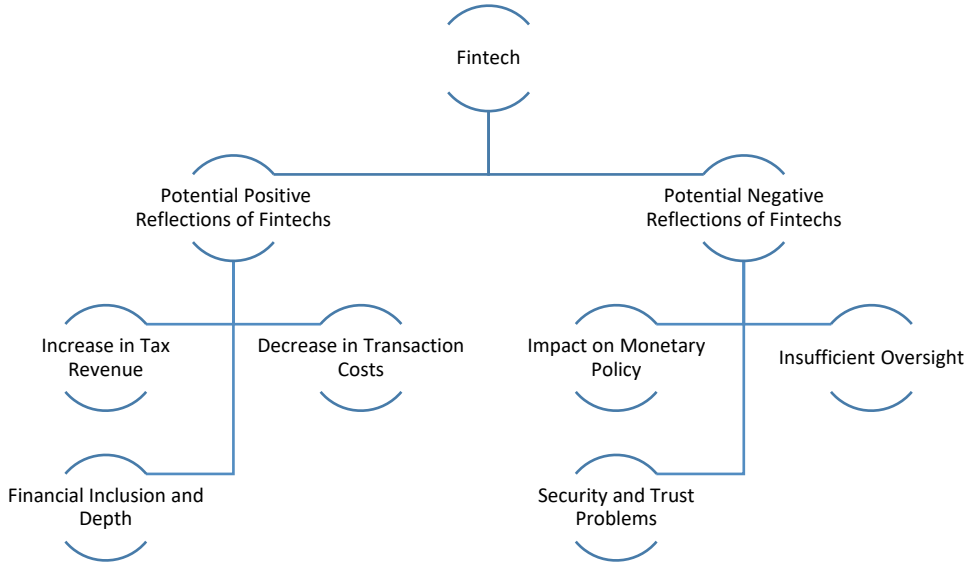
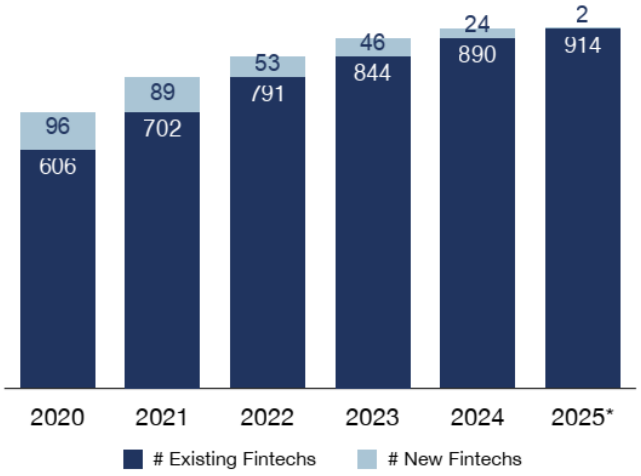


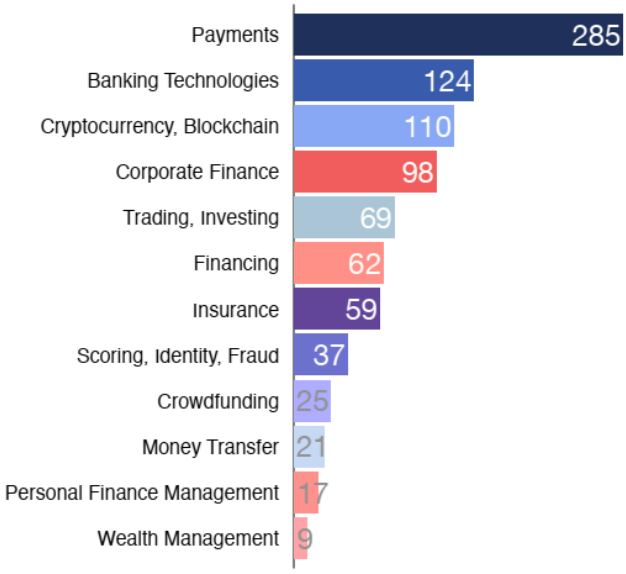
Figure 1. Positive and Negative Reflections of Fintech
Source: (Kömürcüoğlu & Akyazı, 2020)

The fintech industry in Türkiye has also seen some intriguing growth. The industry was first distinguished by its quick expansion and inventiveness, but in the years that followed, it underwent a discernible process of consolidation. The following graphs show fintech industries, fintech firms (both new and existing), and fintech investments (both in terms of deals and numbers):



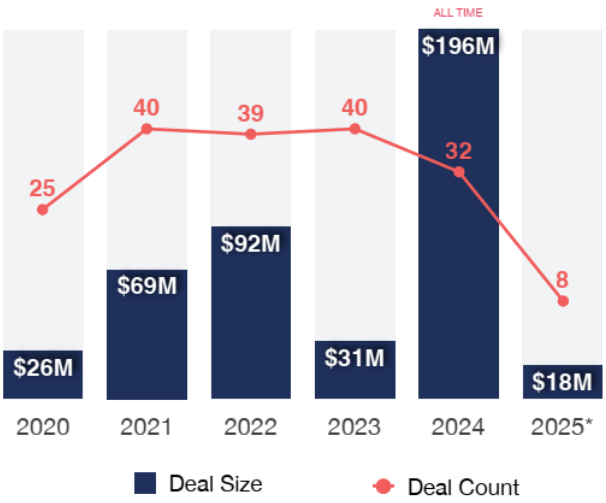
Graph 1. Fintech Companies
Source: (Türkiye Finance Office, 2025)

Graph 1 tracks fintech industry growth from 2020 to February 28, 2025, showing both existing companies (dark blue) and new entrants (light blue). The data reveals a consistent increase in total fintechs (from 606 in 2020 to 914 by early 2025), but demonstrates a dramatic slowdown in new company formation - declining steadily from 96 new fintechs in 2020 to just 2 in the first two months of 2025 - suggesting the market is maturing and consolidating after an initial period of rapid expansion.



Graph 2. Fintech Companies By Vertical
Source: (Türkiye Finance Office, 2025)

Bar chart in Graph 2 displays the distribution of fintech companies across different segments as of February 28, 2025. The data shows that the Payments sector dominates the fintech landscape with 285 companies, more than double the next largest category, Banking Technologies (124 companies). Cryptocurrency and Blockchain companies form the third largest segment with 110 companies, followed by Corporate Finance (98), Trading and Investing (69), and Financing (62). The Graph continues with Insurance (59), Scoring/Identity/Fraud (37), Crowdfunding (25), Money Transfer (21), and shows significantly fewer companies in Personal Finance Management (7) and Wealth Management (9). This distribution highlights that payment solutions remain the primary focus of fintech innovation, while areas like personal finance and wealth management have seen comparatively less development in terms of number of companies.



Graph 3. Fintech Investments
Source: (Türkiye Finance Office, 2025)

Graph 3 illustrates fintech investment trends from 2020 through February 28, 2025, tracking both total deal size (blue bars) and deal count (red line). The deal size shows significant fluctuation: starting at $26M in 2020, rising to $69M in 2021, peaking at $92M in 2022, dropping to $31M in 2023, then dramatically increasing to $196M in 2024 (marked as "all time" high), before plummeting to just $18M in early 2025. Meanwhile, the deal count shows a different pattern: beginning at 25 deals in 2020, climbing to 40 deals in 2021, slightly decreasing to 39 in 2022, recovering to 40 in 2023, then beginning a sharp decline to 32 deals in 2024, followed by a dramatic drop to only 8 deals in the first two months of 2025. The Graph reveals 2024 as a pivotal year with record-breaking total investment despite fewer deals, suggesting larger transaction sizes, while early 2025 shows both metrics declining significantly, potentially indicating a cooling investment climate in the fintech sector.

A broad conclusion drawn from Graphs 1, 2, and 3 is that the fintech ecosystem in Türkiye has moved from a development period to a maturity phase, the industry has begun to consolidate, and a smaller number of bigger firms have emerged.

In order to fill the gap in the literature on the fintech ecosystem, the growth of digital financial infrastructure, and the investment dynamics of the industry, this study applies ARIMA to anticipate fintech investments in Türkiye. In order to support entrepreneurs, investors, and corporate companies make strategic decisions, as well as to help regulatory bodies and policymakers make future-focused decisions for the growth and advancement of the industry, the analysis's findings are intended to be added to the body of knowledge on the fintech ecosystem. Indeed, there are many fintech-related fields of study and related research carried out in many nations when looking at the studies in the literature. According to Zhu (2023) and Eylasov & Çiçek (2024), for case in point, the analytical strategy employed in their ARIMA projections yielded positive outcomes. By using the ARIMA model to the reported fintech data in Türkiye for the years 2016–2024, this study, which focuses on the future analysis of fintech investments, seeks to forecast both the years prior to 2024 and 2025–2028. For this reason, it is anticipated that further research on fintech investments in Türkiye will highlight the industry's potential expansion, adding to the body of knowledge.

Literature Review

The financial technology industry uses a variety of analytical and forecasting techniques, according to recent fintech studies. These studies show that a variety of machine learning and econometric techniques may be applied as useful instruments for predicting risk and financial success in the fintech industry. When evaluating the studies conducted in the literature, Eylasov & Çiçek (2024) stated that the ARIMA-GARCH method they used to predict the returns of BTC, ETH, and BNB cryptocurrencies yielded good results. Similarly, it has been noted in the studies conducted by Zhu (2023) and Benzekri & Özütler (2021) that the ARIMA model yielded good results. Moreover, in the study conducted by Bu et al. (2023) using the MS-VAR and ARIMA models to analyze and predict fintech risks in China, it was revealed that the low to medium risk status of fintech continued for a relatively long period and that the overall risks were manageable. However, in his study where Azari (2019) analyzed Bitcoin's time series data over a 3-year period using the ARIMA model to predict its future value, it was revealed that the ARIMA model produced significant forecasting errors. The following are fintech-related studies found in the literature:

Li & Xie (2025) examined the impact of digital finance on the digital transformation of businesses in China using A-type shares traded on the stock exchange between 2015 and 2022. The results revealed that digital finance not only reduces financing barriers for businesses but also encourages them to expand their financing channels. Another finding is that increasing the financing channels a business needs facilitates digital transformation.

Privara, Mészáros, & Rahmat (2025) examined the relationship between digitalization, labor productivity, and capital efficiency in Europe and examined the impact of digital technology adoption on these parameters. Their findings indicate that digital infrastructure alone is not sufficient for the adoption of digital technologies; complementary digital skills are also necessary.

Umarbeyli & Arabacıoğlu (2025) conducted a qualitative analysis to identify the roles of financial institutions in Türkiye and highlight their importance. The findings reveal that digitalization and innovation facilitate effective and efficient service delivery for financial institutions, provide incentives in various areas (such as innovative solutions, traditional banking, payment systems, investment, and insurance), and contribute to the expansion of their customer base.

Zheng et al. (2024) investigated trends in the US stock market using artificial intelligence and deep learning methods. Through these methods, it is possible to efficiently predict changes in stock prices. The findings have revealed that the model used is consistent in predicting stock prices in the long term.

Meher et al. (2024) used data from the top three fintech businesses in India to create stock prediction models using the high-frequency random forest model in Python. The study's scope encompasses the years 2022–2023. Given that the determination coefficient for each of the chosen firms is more than 95%, the data show that the random forest prediction model has made incredibly good predictions.

Gürbüz, Kılıç, and Tatlıyer (2024) examined the impact of fintech developments on economic growth for Azerbaijan, China, Indonesia, India, Kazakhstan, Kyrgyzstan, Uzbekistan, Pakistan, Russia, Türkiye, and Tajikistan, using data from 2000 to 2020. The findings reveal that information and communication technologies and other macroeconomic factors positively affect economic growth.

Eylasov & Çiçek (2024) to predict the returns of Bitcoin (BTC), Ethereum (ETH), and Binance (BNB) cryptocurrencies, the prediction performances obtained using the LSTM (Long Short-Term Memory) deep learning approach along with ARIMA-GARCH were compared using 4763 days of data from January 1, 2011, to January 16, 2024. The obtained results show that in the BTC series, the ARIMA-GARCH method yielded better results on the training data, while the LSTM method was more effective on the test data. In the BNB series, the LSTM method has demonstrated superior performance for both the training and test data. In the ETH series, the ARIMA-GARCH method yields better results for both datasets.

Mavlutova et al. (2023) examined the impact of digital transformation, which manifests itself through the implementation of innovative technologies and solutions such as digital payments, on the sustainable development of the financial sector through literature analysis, secondary data analysis, and expert opinions. The findings reveal the latest stage of digital transformation in the European Union and the Baltic countries and the way digital technologies impact life to ensure the sustainable development of financial institutions. They demonstrate a significant increase in digital payments and a close and direct relationship between digital payments, financial inclusion, and the operational efficiency of financial institutions.

Tut (2023) investigated the impact of the Covid-19 pandemic on financial institutions and fintech adoption in Kenya. The findings reveal that the pandemic accelerated fintech adoption and increased its share in payment transactions. Fintech mitigated the negative effects of the pandemic at the beginning of 2021, but increased consumer reliance on fintech and digital systems after mid-2022.

Zhu (2023) has predicted the Bitcoin price using ARIMA, SARIMA, and linear regression through data from 2012-2021. The findings, when comparing forecast graphs, training error, and test error, showed that ARIMA and linear regression exhibited higher levels of forecasting performance than SARIMA. Due to the non-seasonal nature of Bitcoin price data, the SARIMA model is less likely to be ideal for predicting Bitcoin prices, and the ARIMA model was found to be relatively suitable among the three models.

Ruhana (2023) has predicted the impact of fintech credit data on financial performance in Indonesia from 2018 to 2023 using the ARIMA method. The findings indicate that the financial performance of fintech credit will experience an upward trend in the next 12 months, but it will still remain below the warning threshold set by the Financial Services Authority.

Bu et al. (2023) established the MS-VAR and ARIMA models using monthly data from 2010-2021 to analyze and predict fintech risks in China. The findings indicate that, over time, China's fintech has remained in a low to moderate risk state for a relatively long period, and that overall risks are manageable. In terms of external shocks, macroeconomic factors can influence financial risks, which in turn can affect the magnitude of fintech risks. Moreover, it is predicted that in the next five years, China's fintech will primarily remain in a low to medium risk state, with high-risk fluctuations occurring only in a few time periods.

Bayram, Talay, & Feridun (2022) conducted research on promoting sustainable finance through fintech in Türkiye. The study findings revealed that progress has been made in increasing financial inclusion by providing microfinance opportunities through mobile operators and online platforms, as well as contactless payment and contract systems for individuals and businesses in Türkiye who are underserved by banks.

Benzekri & Özütler (2021) predicted Bitcoin's price fluctuations and the volatility of the crypto market. Using the ARIMA model to predict Bitcoin prices for the last two quarters of 2020, the study demonstrated that it was effective in forecasting quarterly price movements and indicated that the price deviation during this period could suggest a change in the perceived investment value of Bitcoin as a digital asset to investors following the COVID-19 pandemic.

Azari (2019) predicted the future value of Bitcoin by analyzing its time series data over a 3-year period using the ARIMA model. The findings indicate that when we attempt to train the ARIMA model on a three-year period during which the bitcoin price experienced different behaviors, or when we try to use it for long-term forecasting, it results in significant prediction errors, particularly failing to capture sharp price fluctuations such as the volatility at the end of 2017.

A time series consisting of daily Bitcoin closing prices was predicted by Karasu et al. (2018) using machine learning methods, specifically linear regression and support vector machine, with data from 2012-2018. The findings suggested that the prediction model using the WMA-filtered P-SVM with a lag count of 2 was successful and would shed light on future studies.

A review of the literature to establish the study's hypothesis reveals that Li and Xie (2025) demonstrate that digital finance fosters digital transformation by expanding businesses' financing channels. Mavlutova et al. (2023) demonstrate that digital payments contribute to sustainable development in the sector by increasing financial inclusion and the efficiency of financial institutions in European and Baltic countries. Similarly, Bayram, Talay, and Feridun (2022) found that mobile and online payment systems in Türkiye have expanded financial access and supported the development of fintech-based financial services. Tut (2023) found that the rapid increase in fintech adoption in Kenya after COVID-19 has strengthened reliance on digital payment systems. Gürbüz, Kılıç, and Tatlıyer (2024) emphasize the positive effects of digital technologies on economic growth, demonstrating that a favorable macro-level environment has emerged for fintech investments. When considered together, these studies conclude that the proliferation of digital payment infrastructure and favorable regulations are key determinants of the increase in fintech investments in the coming years. Considering the studies conducted, the hypothesis of the study can be established as follows:

Hypothesis: Over the following four years (2025–2028), fintech investments in Türkiye are projected to rise as a result of the country's adoption of digital payment systems and favorable regulatory developments.

Data and Method

The study includes a future analysis of fintech investments. The aim of the study is to conduct a future analysis of fintech investments and reveal the growth potential of the fintech sector. Thus, it will provide a guiding quality for investors, entrepreneurs, and capital market regulators. For this purpose, fintech data reported for the years 2016-2024 in Türkiye was used to make predictions for both before 2024 and for the period 2025-2028 using the ARIMA model. Fintech data was obtained

from reports published by the Presidential Finance Office. The study's secondary data expresses nominal values in dollar terms. On the other hand, the fintech investment variable used is referenced from the study conducted by Bu et al. (2023).

ARIMA (Autoregressive Integrated Moving Average) method is applied for the future analysis of fintech investments. Box et al. (2015, p. 19) defined a model that reveals the probabilistic structure of a sequence of observations as a stochastic process and a time series z' = ($z1, z2, \dots, zN$) consisting of N consecutive observations as a sample realisation within an infinite population of such samples that the process can produce. In fact, the essence of statistical research is to reach the big picture by starting from a small sample. For example, forecasting is to discover the possibilities that shape the future based on past data and to make sense of uncertainty. Certain stationary stochastic processes that are important in time series modelling include autoregressive (AR), moving average (MA), and autoregressive-moving average (ARMA) processes, which are a combination of these two.

Although the ARIMA (p, d, q) model may be non-stationary, it offers a class of models that can model time series that are homogeneous and statistically stable in many dimensions. The general formula of the ARIMA model is given in Equation.1 (Box et al., 2015, p. 177):

$$\varphi(B)(1-B)^d zt = \theta_0 + \theta(B)_{a_t} \qquad (1)$$

where:

$\varphi(B)$: autoregressive (AR),

$(1-B)^d$: differentiation,

$\theta(B)$: moving average (MA),

zt: observations,

a_t: error term.

The ARIMA process is generally analysed as follows:

1) Visualisation and analysis of time series data in terms of trend, seasonality or irregularity,

2) Stationarity. ARIMA models require the data set to be stationary. That is, the mean and variance should not change over time. If the time series is non-stationary, it can be made stationary by applying differentiation (d).

3) ACF and PACF plots are used to determine the AR and MA components (p and q).

4) After determining the values of p, d and q, the Ljung-Box test is performed to check whether the error terms are random (white noise) to test the fit of the model.

5) Once the model is fitted, future observations are predicted.

6) If the predictive power of the model is not satisfactory, the model may need to be reconstructed by changing the parameters p, d, and q.

Findings of The Study

Table 1. Dickey-Fuller test for unit root

	Test Statistic	**Interpolated Dickey-Fuller**			
		1% Critical Value	**5% Critical Value**	**10% Critical Value**	**p-value**
Level	-0.795	-3.750	-3.000	-2.630	0.821
First difference	-3.885	-3.750	-3.000	-2.630	0.002

Source: Author processing

The results of the Dickey-Fuller (Dickey & Fuller, 1979) test indicate that the series is non-stationary at the level form, as the test statistic (-0.795) exceeds the critical values at the 1%, 5%, and 10% significance levels, with a p-value of 0.821, suggesting the presence of a unit root. However, upon first differencing, the test statistic (-3.885) falls below the 1% critical value, with a p-value of 0.002, indicating that the series becomes stationary. Consequently, the series is classified as integrated of order one, I(1), implying that stationarity is achieved after first differencing.

Table 2. ARIMA Regression

Sample : 2018-2024					**Number of obs** : 7		
Log Likelihood : -135.223					**Wald chi (2)** : 12.33		
					Prob > chi2 : 0.002		
	D.Fintech	**Coef.**	**OPG Std. Err.**	**z**	**P>|z|**	**[95% Conf. Interval]**	
dFintech	**_cons**	6503763	8343206	0.78	0.436	-9848619	2.29e+07
ARMA	**AR L1.**	-.735	.665	-1.11	0.269	-2.037	.568
	Ma L1	-.999	1.096	-0.91	0.362	-3.147	1.148
	/sigma	4.51e+07	.	.	.	.	.

Note: The test of the variance against zero is one sided, and the two-sided
Source: Author processing

The ARIMA regression results indicate that the model is estimated using data from 2018 to 2024, comprising seven observations. The log-likelihood is -135.223, and the Wald chi-square statistic is 12.33, with a p-value of 0.002, suggesting overall model significance.

Regarding the coefficient estimates, the constant term (_cons) in the differenced fintech variable (dFintech) is 6,503,763 with a standard error of 8,343,206, yielding a z-value of 0.78 and a p-value of 0.436, indicating a lack of statistical significance. The autoregressive (AR(1)) coefficient is -0.735 with a standard error of 0.665, resulting in a z-value of -1.11 and a p-value of 0.269, suggesting that the AR term is not statistically significant. Similarly, the moving average (MA(1)) coefficient is -0.999 with a standard error of 1.096, producing a z-value of -0.91 and a p-value of 0.362, indicating that the MA term is also not significant. The estimated standard deviation of the residuals (σ) is 4.51e+07.

Table 3. Portmanteau test for white noise

Portmanteau (Q) statistic	1.920
Prob > chi2(1)	0.166

Source: Author processing

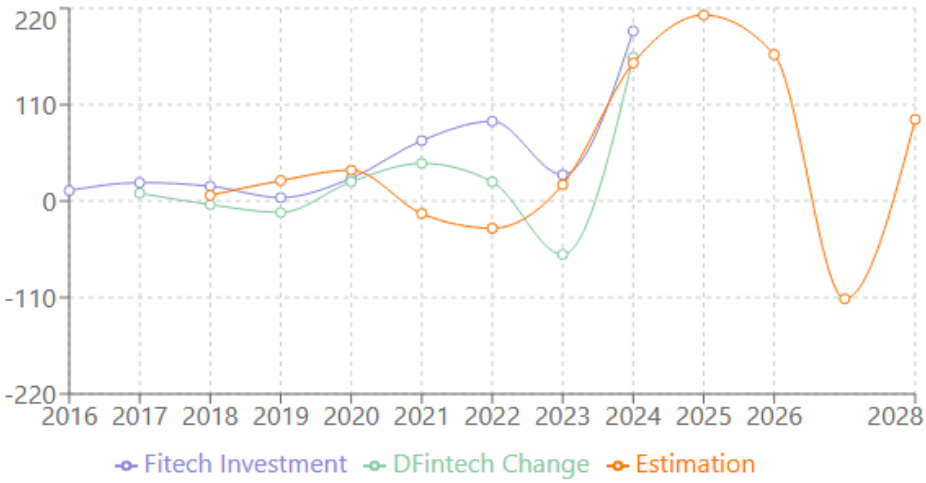
The results of the Portmanteau test (Box & Pierce, 1970) for white noise reveal a Q-statistic of 1.920, accompanied by a p-value of 0.166. Given that the p-value exceeds conventional significance levels (e.g., 0.05 or 0.10), the null hypothesis of no autocorrelation in the residuals cannot be rejected. This suggests that the residuals do not exhibit significant autocorrelation, and the model appears to adequately capture the underlying time series process.

Table 4. Fintech Investment Estimations from 2016 to 2028 by ARIMA ($ million)

Year	Fitech Investment	DFintech	Estimation	Lower	Upper
2016	12	.	.	.	.
2017	21	9	.	.	.
2018	17	-4	6.5	44.7	-31.7
2019	4	-13	23.4	87	-40.1
2020	26	22	35.3	35.7	34.7
2021	69	43	-14.3	-83.7	54.8
2022	91	22	-31	-50.3	-11.5
2023	30	-61	18.7	218.1	-180.7
2024	194	164	157.4	25	289.8
2025			212.1	.	.
2026			167.1	.	.
2027			-111.4	.	.
2028			93.1	.	.

Source: Author processing

The table includes several columns: Year, which represents the year of observation for the data; Fintech Investment ($ million), indicating the fintech investment value for each year, expressed in millions of dollars; DFintech ($ million), showing the differenced fintech values calculated by subtracting the previous year's fintech investment from the current year's, in millions of dollars; Estimation ($ million), representing the estimated fintech investment value based on the model, also expressed in millions of dollars; and Lower ($ million) and Upper ($ million), which represent the lower and upper bounds of the 95% confidence interval for the estimation, respectively, in millions of dollars. Fintech investment landscape demonstrates remarkable resilience and growth potential, expanding dramatically from a modest $12 million in 2016 to an impressive $194 million by 2024—representing a phenomenal 1,516% increase over this eight-year period. This exceptional growth trajectory, particularly the extraordinary surge between 2023 ($30 million) and 2024 ($194 million), positions Türkiye as an emerging powerhouse in the global fintech ecosystem. Future projections appear highly promising, with investments expected to reach new heights of $212.1 million in 2025 and maintain strong momentum at $167.1 million in 2026. While the forecast suggests a potential market correction in 2027, this likely represents a natural consolidation phase following years of explosive growth rather than a fundamental weakness, with recovery already anticipated by 2028 ($93.1 million).



Graph 4: Fintech Investment Trends ($ million)
Source: Author processing

Graph 4 depicts Türkiye's fintech investment journey, showing remarkable growth from modest beginnings in 2016 to a significant peak in 2024, with the purple Fintech Investment line revealing steady expansion through 2022, a temporary setback in 2023, and an impressive recovery in 2024. The green DFintech Change line highlights investment volatility with notable negative periods in 2018-2019 and 2023, contrasted by robust positive momentum in 2020-2022 and 2024. Meanwhile, the orange Estimation line projects continued growth through 2025, followed by gradual moderation in 2026, a substantial correction in 2027, and the beginning of a recovery in 2028, collectively suggesting that despite short-term fluctuations, Türkiye's fintech sector demonstrates resilience and maintains positive long-term growth potential.

Conclusion

In this study, fintech data reported in Türkiye for 2016-2024 are estimated both before 2024 and between 2025-2028 using ARIMA model. The coefficients of AR(1) and MA(1) are found to be negative and statistically insignificant when analysing the obtained regression estimation. In the post-regression forecast, fintech investments are expected to reach a new peak of $212.1 million in 2025 and maintain a strong momentum of $167.1 million in 2026. Although forecasts point to a potential market correction in 2027, this represents a natural consolidation phase after years of growth, and growth of $93.1 million is expected in 2028. When evaluating the studies in the literature, Eylasov & Çiçek (2024), Zhu (2023), and Benzekri & Özütler (2021) reported that the ARIMA model produced good results.

Although the AR(1) and MA(1) coefficients are not significant, the fact that the model as a whole is significant and free from autocorrelation problem shows the strength of the model. In the study, the hypothesis " Over the following four years (2025–2028), fintech investments in Türkiye are projected to rise as a result of the country's adoption of digital payment systems and favorable regulatory developments." cannot be rejected. This is because while a consolidation process is only predicted in the forecast interval in 2026 and 2027, fintech investments are expected to increase in 2025 and 2028. In other words, an increase is expected in 2025, a correction in 2026 and 2027, and an increase again in 2028. The literature generally emphasizes that fintech investments exhibit an upward trend. Key drivers of this trend include the proliferation of digital payment systems (Mavlutova et al., 2023; Bayram et al., 2022), increased financial inclusion, and the implementation of supportive regulations (Li & Xie, 2025). However, the literature also indirectly suggests that fintech development may exhibit seasonal variations depending on macroeconomic conditions, market confidence, and the pace of technological adoption. For example, Bayram, Talay, and Feridun (2022) noted that despite the widespread adoption of mobile payment systems in Türkiye, changes in

service delivery may lead to temporary slowdowns in fintech activity during certain periods. Similarly, Tut (2023) demonstrates a stabilization process following the rapid rise in fintech use following COVID-19 in Kenya. On the other hand, a study by Gürbüz, Kılıç, and Tatlıyer (2024) examining the effects of digital technologies on economic growth emphasizes that digitalization supports growth in the long term. Li and Xie (2025)'s findings on the digital transformation of businesses indicate that investments in financial technologies will increase sustainably in the long term. Therefore, the study's finding that fintech investments are generally on the rise, but with some periodic corrections, is fully consistent with the literature. While existing research reveals the structural factors behind this trend (digitalization, regulations, financial access), this study demonstrates that the process fluctuates over time but progresses in an upward direction over the long term.

The small sample size (N = 7) limits the reliability of the estimates. The model appears jointly significant, but individual coefficients are not statistically significant, likely due to insufficient data. Thus, future studies are recommended to use larger sample sizes. Moroever, various related factors can be included and their relationship with the areas they affect can be investigated.

Author Contribution

All processes of this study (design, data collection, analysis, writing, and editing) were performed by Bekir ZENGİN

Ethics Committee Approval

This study does not require ethics committee approval.

Conflict of Interest Statement

There is no conflict of interest with any person or institution in this study.

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