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ARAŞTIRMA MAKALESİ / RESEARCH ARTICLE

AN EMPIRICAL ANALYSIS OF SPECULATIVE BEHAVIOR AND THE SPILLOVER EFFECT IN CRYPTOCURRENCY MARKETS

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Abstract

For risk management and stable pricing in the cryptocurrency market, it is necessary to determine the interdependence of speculative behaviour and crypto assets. The correlation and high volatility caused by the interdependence of financial assets in the cryptocurrency market can lead to spreading risks. The study aims to measure the speculative behaviour and spillover effect in the prices of financial assets in the cryptocurrency market. The study used the SADF test, the generalized Dickey-Fuller test (GSADF), and the frequency domain causality test of Breitung and Candelon (2006) to determine the speculative behaviour and spillover effect in the prices of financial assets in the cryptocurrency market. Empirical evidence of speculative bubble formation between January 1, 2018, and December 2021 for the cryptocurrency assets covered in the study (ADA, BNB, BTC, DOGE, ETH, XLM, and XRP) is presented. Moreover, the frequency domain causality results obtained in the study show a contagion and spillover effect between crypto assets. The results provide essential information on the development of speculative behaviour and spread risk in the formation of financial asset prices in the cryptocurrency market.

Keywords: Cryptocurrency Markets; Bubbles; Spread Risks; Right-tailed Unit Root Tests, Frequency Domain Causality

JEL Classification: D53, F38, G00

1. Introduction

Developed financial markets have positive effects on economic growth and development. One of the most studied factors among the determinants of a well-developed financial system is the interdependence among financial assets. The main reason is the integration of financial markets and assets as part of globalization. Globalization causes a shock in one country's financial system to spread rapidly to the rest of the world (Polat and Eş-Polat, 2022). A similar situation applies to the cryptocurrency market. The lack of a regulatory and supervisory mechanism in

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the cryptocurrency market and the still developing and immature technology of blockchain technology increases the volatility in the relevant market, increasing the correlation and cooperation relationship between the assets in the cryptocurrency market.

The high correlation relationship between assets in the cryptocurrency market is one factor that is also effective in financial decision-making. This is because, as Huynh (2019) states, determining the degree of interdependence between financial instruments is essential for developing portfolio management and hedging strategies. Therefore, in assessing the degree of cooperation in the cryptocurrency market, the management of financial assets is critical to the forecasting and pricing process. Another important topic is the interdependence between financial markets, the development of the movement and volatility of financial instruments, and asset prices. In particular, unstable pricing in financial markets can have substantial effects that can lead to a global financial crisis, as was the case in the 2008 global crisis. In this context, it can be assumed that one factor that triggers these strong effects on modern financial markets and instruments is the increasing correlation and volatility in the cryptocurrency market.

Research on the causes of high correlation and volatility in the cryptocurrency market is gaining momentum in two different areas (Moratis, 2021). One is that fundamental external factors such as economic, financial, and geopolitical uncertainty cause high correlation and volatility in the cryptocurrency market (Giudici and Abu-Hashish, 2019; Smales, 2019; Panagiotidis et al., 2018; Moratis, 2021). The other is intrinsic fundamentals, such as increased volatility in the cryptocurrency market and the high correlation between crypto assets (Francés et al., 2018; Ji et al., 2019). As these internal and external factors prevent investors from reducing risk, they inhibit market dynamics in cryptocurrency and all financial markets.

The primary motivation of this study is to determine the speculative behaviours and the spillover effect in the prices of seven crypto assets (ADA, BNB, BTC, DOGE, ETH, XLM, and XRP) are dominant in terms of market value in the crypto money market. Compared to other related studies examining speculative price behaviour and spillover effects in cryptocurrencies, it differs from similar studies regarding subject and method. First, the study differs from other studies in analyzing the interconnectedness and persistence of seven significant cryptocurrencies. Secondly, the study provides an essential guide, especially in shaping the markets and investor decisions, by revealing the spread of speculative price behaviours and causality effects among cryptocurrencies. Third, the fact that the selected period of the study covers the period between January 1, 2018, and December 2021 contributes to the observation of the possible effects of investors' tendency to invest in different cryptocurrencies following the rapid increase in Bitcoin prices in the last quarter of 2017. Fourth, SADF and GSADF tests, which detect price bubbles, allow better inferences than the methods in the literature, thanks to their dynamic structure, unlike indirect methods. The frequency domain causality test, another technique used, makes a significant difference in determining whether there is a connection between cryptocurrencies in the short, medium, and long term, as it allows investigation of the causality dynamics at different frequencies. Therefore, the study may provide more compelling evidence than similar studies in the literature.

This paper is organized as follows. After this introductory section, Section 2 presents an overview of previous research on the issue. Section 3 presents this study's model, dataset, and method. Section 4 introduces the empirical results of the analysis. Finally, Section 5 concludes the research undertaken in this study.

2. Literature

According to the scope of the study, the literature, bubble formation, spillover effects, and causality are examined. If the bubble concept is evaluated from an economic perspective, it is characterized as a deviation from the fundamental value of the current asset. However, it isn't straightforward to determine this fundamental value, especially in the cryptocurrency market. For this reason, bubbles in cryptocurrencies are defined as price breakouts and provide an opportunity to do more reliable valuations (Enoksen et al., 2020).

The various dynamics behind the price increase in the cryptocurrency market can be grouped under two headings in general; i) the price increase experienced as a result of the introduction of various macroeconomic dynamics that will affect the returns of traditional investment instruments, as market participants turn to digital investment instruments to compensate for their potential losses ii) price increase through speculative effects. In the literature, it is seen that the studies on the values of crypto assets primarily focus on speculative effects. It is widely believed that difficulties in determining the fundamental importance of digital currencies set the stage for speculative behaviour. Market price formation is shaped around these relationships (Kristoufek, 2013; Shahzad et al., 2022). This view is supported by the assumption that the factors that play a role in price formation in cryptocurrency markets are not based on the same dynamics as the determinants of traditional asset markets. The difference between crypto money markets from traditional financial markets is that their supply is fixed, and the investor expectations on the demand side have a critical role. Therefore, the active part of the participants in the price formations in the crypto market makes the market dynamics open to speculative behaviours. Evlimoğlu and Güder's (2021) studies support this view. The main points, how and where the determinants of potential bubbles that may occur in crypto markets and the economic bubbles experienced in the past differ, were stated in their studies. These factors are listed as the fact that the fundamental value has not been determined in the crypto markets, the supply is limited, and blockchain technology is still developing. Therefore, it is argued that the decision-making processes of market actors are determined not on a rational basis, that is, on complete information, but on asymmetric information and irrational expectations (Yanık and Aytürk, 2011). The fact that the value of crypto assets is shaped in line with the perception of market actors triggers unstable price formation, preparing the ground for speculative bubbles. Due to the price movements in cryptocurrency markets in recent years, studies focusing on bubbles in this area have come to the forefront Yermarck (2015) argues that Bitcoin, which has the most significant value in the cryptocurrency market, is a speculative asset, while Cheah and Fry (2015) argue that Bitcoin has speculative bubbles. In another study that comes to similar conclusions, cryptocurrency markets are found to be highly volatile and subject to speculative effects (Fry and Cheah, 2016). In this context, the supremum-augmented Dickey-Fuller tests (SADF) of Phillips et al. (2011) and the generalized supremum-augmented Dickey-Fuller tests (GSADF) of Philips et al. (2015) are widely used. Several studies using the method have found evidence of cryptocurrency bubble formation (Cheung et al., 2015; Su et al., 2018; Bouri et al., 2019; Waters and Bui, 2021). The empirical studies by Souza et al. (2017) using RADF, SADF, and GSADF tests prove that speculative bubbles are common in cryptocurrency. On the other hand, the study by Buğan (2021), which investigated the formation of bubbles in cryptocurrencies, found that the bubbles detected in Litecoin and Cardano were not statistically significant as a result of the GSADF test, while the existence of bubbles was accepted for Bitcoin, Ethereum, Ripple, and Chainlink. In Şahin (2020) study, the bubbles in cryptocurrencies Bitcoin, IOTA, and Ripple were tested by the GSADF test, and the bubble formation in cryptocurrencies was confirmed again. In addition, the study drew attention to the impact of news manipulation on explaining the periods when bubbles were formed.

The literature also contains studies that examine the formation of bubbles in different types of markets. Maouchi et al. (2022), using the real-time bubble detection method proposed by Phillips and Shi (2020), investigated the existence of digital financial bubbles and detected bubble formation in 3 NFT, 9 DeFi tokens, Bitcoin and Ethereum. The study's findings covering the Covid-19 period are that the bubbles in DeFi and NFTs are more giant than those in Bitcoin and Ethereum but occur less frequently. Using the PSY test (GSADF), Gharib et al. (2021) point to boom periods in the crude oil and gold markets between 2010 and 2020. In particular, the Covid-19 period has shown the contagion effect in the bubbles in the two markets. When crypto asset prices are volatile, markets give signals of uncertainty and instability. The seizure of these factors in the markets raises financial concerns for crypto assets. Therefore, it is essential to measure the interdependence and volatility spreads of cryptocurrencies in shaping the risk management mechanism within the scope of the decision processes of investors. For this reason, in addition to detecting bubbles, evaluating the contagion effect of bubbles is essential in deepening the discussion of cryptocurrencies. Uncovering the spillover and causality effects between cryptocurrencies is crucial, especially in shaping markets and investors' decisions.

Various studies have been conducted in the literature on whether there are causality and volatility spillovers between cryptocurrencies. The logistic regression results in the study by Bouri et al. (2019) show that the probability of an explosion period in cryptocurrencies is shaped by the presence of explosions in other cryptocurrencies. Huynh (2019) investigates the spillover effects between five cryptocurrencies (bitcoin, Ethereum, XRP, Litecoin, Stellar) through VAR – SVAR Granger causality and the Copulas method. The research results show that Ethereum is independently compared to other cryptocurrencies, while the validity of the spillover effect between the different cryptocurrencies is questioned. On the other hand, the Student's t-Copulas test suggests a contamination risk when cryptocurrencies contain extreme values. When examining the competition between cryptocurrencies, one study's empirical results indicate a spread from Ripple to Bitcoin (Fry and Cheah, 2016). In another study, they pointed out the presence of structural breaks in the cryptocurrency market. They concluded that systematic price fluctuations spread from currencies with low market values to those with high market values (Canh et al., 2019). Yi et al. (2018), according to the results of their studies, the existence of a spillover effect is assumed in cryptocurrencies. Global finance, uncertainty effects, and trading volume are the variables that trigger the spillover effect. Ji et al. (2019) studied the return and volatility spreads of six cryptocurrencies and found that Bitcoin and Litecoin are at the centre of returns. In addition, positive returns were shown to be weaker than negative returns.

In their study, Enoksen et al. (2020) investigated the dynamics associated with the presence of bubbles. They used the PSY (GSADF) method to detect bubbles in cryptocurrency markets, and it was found that the variables that predict bubble formation are trading volume, transactions, and volatility. Cryptocurrency bubbles show a positive relationship with EPU (economic policy uncertainty index) and a negative relationship with VIX (fear index).

Canh et al. (2019) used data from seven cryptocurrencies (Bitcoin, Litecoin, Ripple, Stellar, Monero, Dash, and Bytecoin); the Granger causality test, the LM test for ARCH, and the DCC-MGARCH method were preferred. The results of the study show that there are structural breaks and volatility spillovers in the cryptocurrency market. It is found that the spillover effect is from more minor market cap currencies to more significant coins. Empirical evidence shows that cryptocurrencies exhibit strong and positively correlated volatility spillovers. Kirikkaleli et al. (2020) present empirical evidence of bubbles in Bitcoin and Ethereum, Litecoin, and Ripple between 2016 and 2019 and accept a positive relationship between Bitcoin and three other cryptocurrencies in the short run. In their studies using the quantile Granger non-causality test, Kim et al. (2021) conclude that coins with a high market value do not exhibit a strong bidirectional relationship with other currencies. While XRP has bidirectional causality with other coins, EOS has the weakest causal relationship with all coins. On the other hand, BNC has bidirectional causality with all coins except EOS. Katsiampa et al. (2019) studied the relationship between Bitcoin-Ethereum, bitcoin-litecoin, and etherium-litecoin between August 7, 2015, and July 10, 2018, using the BEKK model. The results show that cryptocurrency price volatility relates to prior volatility and currency shocks. While there is a bidirectional spread between Bitcoin and the other two cryptocurrencies, the spread between Ethereum and Litecoin is one-way. In addition, studies examining the relationship and spillover effect between cryptocurrencies and other financial assets are also prominent. Using the VAR GARCH model, Bouri et al. (2018) found that bitcoin returns are associated with traditional assets such as stocks, commodities, currencies, and bonds. The study also found that Bitcoin is a receiver rather than a transmitter of volatility. The volatility spillover index was created using the TVP-VAR model of Cao and Xie (2022). It was found that there is an asymmetric and time-varying volatility spillover effect between cryptocurrency and the Chinese financial market. At the same time, it has been determined that the risk spread of the financial market has a feeble impact on cryptocurrency. In contrast, the risk spread of cryptocurrency on the financial market is substantial. In the study by Elsayed et al. (2020), which investigated the spillover effects between three cryptocurrencies and nine foreign currencies using the Diebold-Yılmaz method, the return spillover effect for Bitcoin and Litecoin in the first three quarters of 2017 was determined. As a result of the Bayesian chart structure model VAR (BGSVAR), it was found that the level of bitcoin to the Chinese yuan, the bitcoin and litecoin values of Ripple, and the level of litecoin are dependent on Ripple and the Chinese yuan. The result of the study is causality between cryptocurrencies; among foreign currencies, only the Chinese yuan influences cryptocurrencies.

When considered as a whole, external dynamics, such as the fact that the cryptocurrency market is an unregulated market and the technological infrastructure development process, have not yet been completed. The increase in economic and geopolitical uncertainty leads to a rise in the vulnerability of cryptocurrencies to speculative behaviours in the market and triggers the formation of a bubble. By encouraging the spread of interdependence and volatility among cryptocurrencies, these developments pave the way for market efficiency deterioration.

3. Data Set and Method

3.1. Dataset

The study empirically investigates the existence of asset price bubbles in cryptocurrency markets, asset interdependence, and the spillover effect. In this regard, the variables used in the study were ADA, BNB, BTC, DOGE, ETH, XLM, and XRP, depending on the availability of data and the volume of transactions in the cryptocurrency market. The descriptive test statistics for the above variables are shown in Table 1. Accordingly, daily data was used for the selected variables between January 1, 2018, and December 2021, obtained from the Yahoo Finance database. On December 31, 2021, the cryptocurrency market cap was approximately 92 billion USD. On the same date, the share of cryptocurrencies selected as the study's sample in the market volume was approximately 65% (https://www.coinecko.com/en/global-charts, Access Date: 15.01.2023). Another factor affecting the period selection in the study is that, following the rapid increase in Bitcoin prices in the last quarter of 2017, investors tended to invest in different cryptocurrencies.

According to the results of the descriptive statistics given in Table 1, it is seen that the cryptocurrencies with the highest standard deviation are BTC and BNB. The lowest standard deviation is seen in DOGE. On the other hand, all variables used in the study are skewed to the right. Jarque-Bera test results, which indicate whether the variables show a normal distribution or not, suggest that the variables do not comply with the normal distribution.

Table 1: Descriptive Statistics

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	J-B	Obs.
ADA	0.46	0.10	2.96	0.02	0.68	1.689	4.737	878.75(0.00)***	1461
BNB	107.67	19.69	675.68	4.52	177.68	1.723	4.491	858.83(0.00)***	1461
BTC	18375	9475	67566	3236	17760	1.303	3.153	415.30(0.00)***	1461
DOGE	0.053	0.003	0.684	0.001	0.107	2.256	7.934	2722(0.00)***	1461
ETH	937.36	346.52	4812	84.308	1196	1.646	4.490	795(0.00)***	1461
XLM	0.20	0.144	0.896	0.033	0.148	1.022	3.598	276(0.00)***	1461
XRP	0.52	0.363	3.377	0.139	0.389	2.272	11.377	5529(0.00)***	1461

Note: Values in parentheses are probability values. In addition, * indicates the significance levels of 0.10, **0.05, and *** 0.01.

3.2. Research Methodology

In the study, first, whether there are speculative bubbles in the cryptocurrency market, Phillips et al. (2011) ekus ADF (SADF) and Phillips et al. (2015) generalized Dickey-Fuller (GSADF) test. The methods in question are recursive and right-justified unit root tests that have been widely used recently due to their excellent performance in detecting speculative bubbles and their occurrence.

The Exus-ADF test (SADF), one of the most commonly used right-tailed unit root tests among these methods, was developed by Phillips et al. (2011), and the extended standard Dickey-Fuller test (ADF) was developed to detect speculative bubbles and when they occur. As Homm and Breitung (2012) found, this test performs as well as other tests using similar procedures. The SADF test is essentially based on an iterative estimation of the standard ADF test. The SADF test is obtained as the lower value corresponding to the statistical ADF sequence and is obtained by estimating the values given in Equation 1 using least squares (Philips et al., 2015).

$$x_t=\mu_x+\delta x_{t-1}+\sum_{j=1}^{j} \emptyset j_j \Delta x_{t-j}+\varepsilon_{x,},\varepsilon_{x,t}\sim NID(0,\sigma_x{}^2) \tag{1}$$

For some values of J given in equation 1, the null hypothesis H0: δ=1 and the alternative hypothesis H1: δ > 1 are formed in the right-tailed SADF unit root test so that the NID is independent and normally distributed. Iterative regressions on the sample data then increase one observation at each run. The result is repeatedly estimated using subsets.

$$sup_{r\epsilon[r_0,1]}\, ADF_r \rightarrow sup_{r\epsilon[r_0,1]} \frac{\int_0^r \tilde{W} dW}{\left(\int_0^r \tilde{W}^2\right)^{1/2}} \tag{2}$$

Equation 2 shows standard Brownian motion W and reduced Brownian motion $\tilde{W}(r) = W(r) - \frac{1}{r}\int_0^1 W$ (Philips et al., 2011: 206-207). Considering the criticism in the literature that the statistical power of the SADF test decreases in the case of multiple bubbles, Phillips et al. (2015) developed the generalized GSADF unit root test to address the shortcomings of the SADF test in this direction. Although the GSADF test has similar features to the SADF test, it differs because the standard ADF test uses an iterative soft estimate of the regression obtained from the standard ADF test in computing the test, allowing for long-term nonlinear structures and structural breaks. In this regard, the GSADF test outperforms the SADF and standard ADF unit root tests by providing more consistent and accurate results in the case of multiple bubbles (Phillips et al., 2015). Although the GSADF test is based on the recursive operation of the ADF test in subsamples, similar to the SADF test, it is referred to as the most significant ADF test because it is much broader than the SADF test.

To calculate the GSADF test statistic, we first estimate the iterative regression equation 3. Here, k is the lag length, and r1 and r2 are included in the equation to represent the start and end points of the subsample so that iterative regression estimates can be performed (Çağlı and Mandacı, 2017: 66).

$$\Delta y_t = \hat{\alpha}_{r_1,r_2} + \hat{\beta}_{r_1,r_2} y_{t-1} + \sum_{i=1} \hat{\psi}^{i}_{r_1,r_2} \Delta y_{t-i} + \hat{\varepsilon}_t \tag{3}$$

The GSADF test Equation 3 is repeatedly estimated for multiple subsamples using subsets with a future date. Unlike the SADF test, subsamples are created where the initial points of the subsamples in r1 change dynamically instead of the final moments in r2 and deviate from zero (Çağlı and Mandacı, 2008). 2017:66). From this point of view, the GADF test is calculated using the formula given in equation 4 (Philips, Shi, and Yu, 2015: 1049)

$$GSADF(r_0) = sup_{r_2 \in r_1 \in [0, r_2 - r_1] [r_0, 1]} \{ADF_{r_1}^{r_2}\} \tag{4}$$

The frequency domain causality test, another method used in the study, allows for investigating the causality relationship of the variables under study at multiple time points. Since traditional causality tests generate test statistics for a single t-period, they ignore the possibility that the causality relationship changes at different frequencies and periods (Bozoklu & Yılancı, 2013). On the other hand, traditional causality methods perform a linear causality analysis between the variables included in the study. Geweke (1982) and Hosoya (1991) proposed a causality analysis method based on spectral density decomposition at a specific frequency to address this shortcoming of traditional causality analysis. Subsequently, Breitung and Candelon (2006) developed a computational method that simplifies the complex structure of frequency-based causality analysis. This calculation method has created a procedure based on the autoregressive parameters based on the VAR model (Başarır, 2018). Due to its structure, the method also has the advantage of performing a nonlinear causality analysis between the variables included in the study. In this context, the causality analysis can be performed for different frequencies as follows:

$$M_{y \to x}(\omega) = log\left[\frac{2\pi f_x(\omega)}{|\Psi_{11}(e^{-i\omega})|^2}\right] = log\left[1 + \frac{|\Psi_{12}(e^{-i\omega})|^2}{|\Psi_{11}(e^{-i\omega})|^2}\right] \tag{5}$$

According to equation 5, in the case of $|\Psi 12(e^{-i\omega})|= 0$ above a certain w frequency, there is no causality relationship from the y variable to the x variable (Ciner, 2011:500). Breitung and Candelon (2006) change the hypothesis to equation #5, according to which if $My\rightarrow x(\omega)=0$. $|\Psi 12(e^{-i\omega})|=0$ then ,

$$\Psi(L) = \Theta(L)^{-1}G^{-1} \text{ ve } \Psi_{12}(L) = -\frac{g^{22}\Theta_{12}(L)}{|\Theta(L)|} \tag{6}$$

In equation 6, g^{22} represents the common diagonal elements of the G^{-1} matrix, $|\Theta(L)|$ represents the determinant of $\Theta(L)$. In this case, causality in the frequency domain can be tested with the following equation. (Bodart and Candelon, 2009: 143).

$$|\Theta_{12}(e^{-i\omega})| = \left|\sum_{k=1}^{p} \Theta_{12,k}\cos(k\omega) - \sum_{k=1}^{p} \Theta_{12,k}\sin(k\omega)\, i\right| = 0 \tag{7}$$

Since $\Theta_{12,}$ indicates the element of Θ_k and Θk in equation 7, the expression $|\Theta 12(e-i\omega)|=0$ can be expressed such that "y" is not the cause of "x" at "w" (Tarı et al., 2012: 10) . Breitung and Candelon (2006) model the method as a function of linear constraints, as shown in equation 8. In this case, the equation VAR can be formed with 9 for x_t.

$$\sum_{k=1}^{p} \Theta_{12,k}\cos(k\omega) = 0$$
$$\sum_{k=1}^{p} \Theta_{12,k}\sin(\mathrm{k}\omega) = 0 \tag{8}$$

$$x_t = \alpha_1 x_{t-1} + \cdots + \alpha_p x_{t-p} + \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + \varepsilon_{1t} \tag{9}$$

Since the hypothesis $My\rightarrow x(\omega)=0$ is equivalent using equations 8 and 9 with linear constraints, the H0 hypothesis can be stated in equation 10.

$$R(\omega) = \begin{bmatrix}\cos(\omega) & \cos(2\omega) & \cdots & \cos(p\omega)\\ \sin(\omega) & \sin(2\omega) & \cdots & \sin(p\omega)\end{bmatrix} \tag{10}$$

Thus, H0: $(\omega)\beta=0$ $(\beta=[\beta 1,\ldots,\beta p]')$ $R(\omega)$ is calculated using the following equation. On the other hand, it is possible to separate the causal dynamics between the variables studied in the frequency domain causality analysis temporarily and permanently. Accordingly, a short-term (temporary) causality analysis is performed when the ω-frequency value is calculated for a high frequency (ω =2.5). When the value of ω=1.5, a medium-term causality analysis is performed, while when the value of ω=0.5 (low frequency), a permanent causality analysis is possible. Therefore, causality analysis in the frequency domain allows the decomposition of causality into more than one time period.

4. Empirical Results

In this part of the study, the hypothesis formulated as H1 is first tested using the prices of 7 financial assets in the cryptocurrency market. The hypothesis states that increasing financial interconnectedness with globalization will cause a shock in the financial system to spread quickly to the rest of the world. In the case of a spillover effect, bubbles can occur when investors continue to hold assets because they believe they can sell them at a higher price than other investors, even though the financial asset's price exceeds its fundamental value. This situation, which also applies to the cryptocurrency market, leads to the unstable pricing of cryptocurrency market assets. In other words, bubbles can occur in the prices of crypto assets.

H1: External factors affecting the cryptocurrency market make for unstable pricing.

The SADF and GSADF tests were used to determine the presence of bubbles by testing the hypothesis expressed as H1 and to determine when bubbles occur. In applying the above tests, 2000 replicate Monte Carlo simulations were used for each observation. The results of the estimations are reported in Table 1.

Table 2: The SADF and GSADF Test Statistics

	SADF Test Statistic	*GSADF* Test Statistic
ADA	3.00***	12.52***
BNB	19.72***	19.81***
BTC	5.86***	8.04***
DOGE	15.99***	16.01***
ETH	5.79***	6.68***
XLM	-1.00	6.139***
XRP	-1.72	6.128***

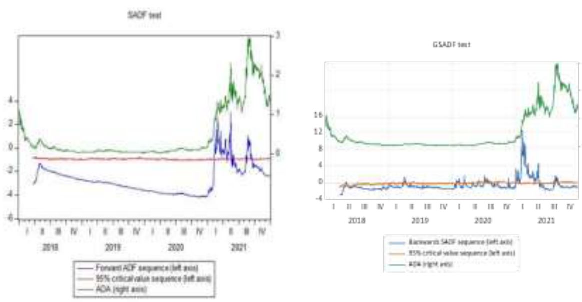
Note: Critical values for SADF statistics are 0.43, 0.69, and 1.15 for 10%, 5%, and 1% significance levels, respectively. Critical values for GSADF statistics are 1.28, 1.46, and 1.91 for 10%, 5%, and 1% significance levels, respectively. In addition, the significance levels * 0.10, ** 0.05, and *** 0.01 are given. These critical values were obtained by Monte Carlo simulation with 2,000 replicates.

Examination of the SADF and GSADF test statistics in Table 2 shows that the estimated test statistics for the cryptocurrencies ADA, BNB, BTC, DOGE, and ETH are more significant than the critical values. Therefore, a speculative bubble in these currencies was established for the analyzed periods. On the other hand, when examining the SADF and GSADF test statistics obtained for the XLM and XRP currencies from the selected assets in the cryptocurrency market, it can be seen that the estimated SADF test statistics are smaller than the critical values. In other words, the H0 hypothesis is accepted. However, the estimated GSADF test statistics are shown to be larger than the critical values, so the H0 hypothesis is rejected. Phillips et al. (2015) found that the GSADF test is more consistent and gives better results than the SADF and standard ADF tests. Based on this view, it can be said that a speculative bubble occurred for the XLM and XRP currencies during the analyzed periods.

In summary, the test results show that although the prices of all currencies exceed the fundamental value of the prices of the analyzed period, they continue to hold assets because they believe they can sell them at a higher price than other investors. In other words, it can be said that bubbles were created in the cryptocurrency market during the studied period. Thus, the obtained results confirm the hypothesis that external factors affecting the cryptocurrency market make the pricing unstable and lead to the formation of bubbles.

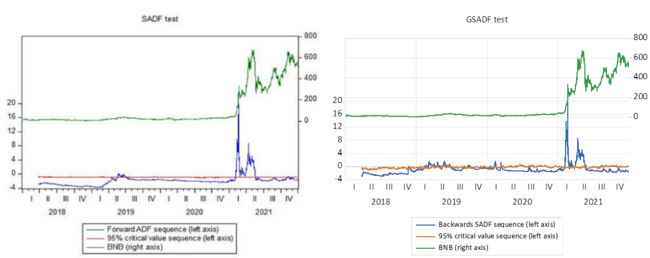
Having established the presence of bubbles in the selected cryptocurrencies, the second phase began to identify the periods in which bubbles occurred. In this way, it is possible to determine which factors cause instability in price formation and lead to the formation of bubbles.

Figure 1: ADA Cryptocurrency Test Results Charts



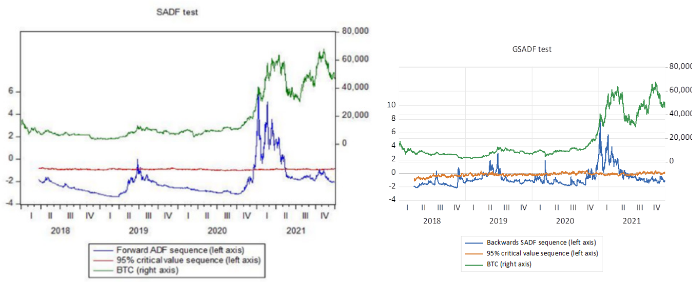
From the SADF and GSADF test charts shown in Figure 1, it can be seen that a bubble formed during the period from late January 2021 to early June 2021. During the period in question, the technological upgrade of the cryptocurrency ADA led to excessive demand for the cryptocurrency ADA by many investors, creating a bubble.

Figure 2: BNB Cryptocurrency Test Results Charts



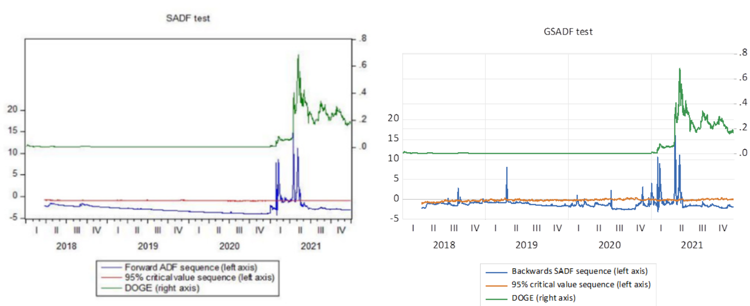
Based on the SADF and GSADF test charts of the cryptocurrency BNB shown in Figure 2, it was determined that a bubble formed from the beginning of 2021 to the end of May 2021. In the studied period, it can be said that the interventions of the cryptocurrency exchange Binance to reduce the total supply of BNB cryptocurrency and the excessive demand for BNB due to the increase in transaction costs in Ethereum drive up prices and cause the formation of a bubble.

Figure 3: BTC Cryptocurrency Test Results Charts



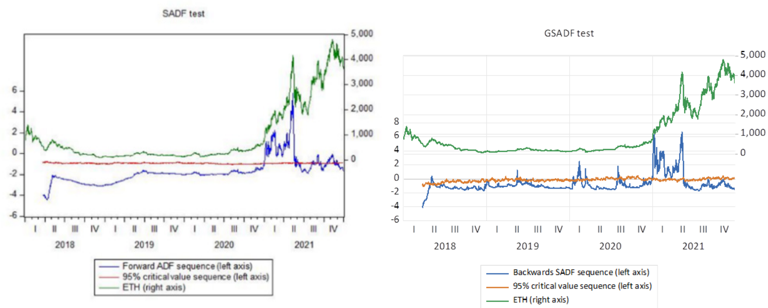
According to the SADF and GSADF charts for bitcoin in Figure 3, a bubble in the bitcoin price was observed in the last quarter of 2018, the middle of 2019, and between the last quarter of 2020 and the second quarter of 2021. During the earlier periods, the improvements in the system's functioning with the blockchain system's updates have increased the demand for bitcoin and pushed the prices. This has led to a bubble in BTC prices. On the other hand, it can be said that the big rally in BTC price was effective in the bubble formation observed between the last quarter of 2020 and the second quarter of 2021.

Figure 4: DOGE Cryptocurrency Test Results Charts



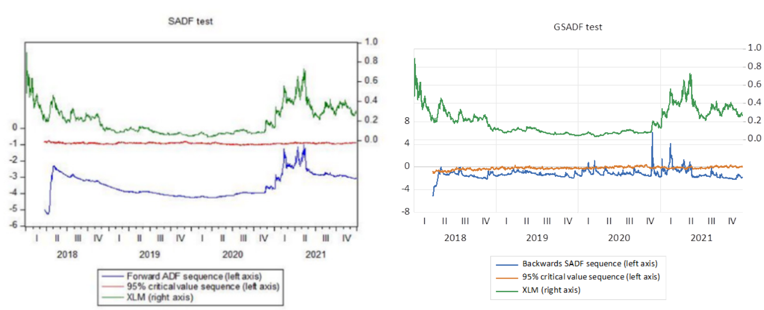
The SADF and GSADF test charts of the cryptocurrency DOGE, shown in Figure 4, indicate that there have been several bubble formations between the last quarter of 2020 and mid-2021. In the mentioned period, it can be observed that external factors are particularly effective in bubble formation in DOGE cryptocurrency prices. In particular, social media posts for the cryptocurrency DOGE created excessive demand by directing investors to this cryptocurrency during the period in question. The high demand for the stocks in question led to a large price rally. As a result, the sharp rise in prices led to a bubble.

Figure 5: ETH Cryptocurrency Test Results Charts



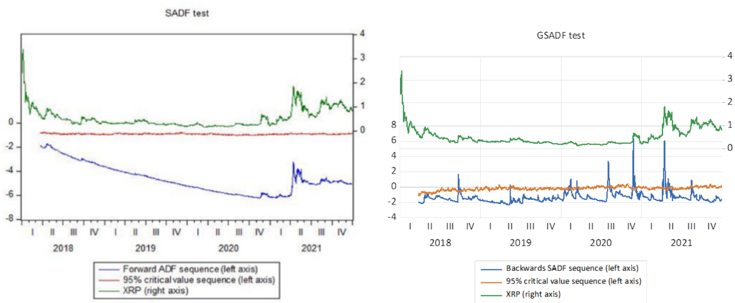
According to the SADF and GSADF charts for Ethereum in Figure 5, a price bubble can be observed from early 2021 to mid-2021. The reason for the bubble formation in the mentioned period is the announcement by the financial institutions that the Ethereum Trust will be reopened for public trading in the mentioned period. Also, in the mentioned period, the tendency of retail investors to engage in decentralized trading of virtual currencies increased the demand for Ethereum, one of the currencies with the largest market volume in the cryptocurrency markets. It contributed to the formation of speculative price bubbles.

Figure 6: XLM Cryptocurrency Test Results Charts



The SADF chart for Stellar (XLM) in Figure 6 shows no speculative price bubble during the period in question. However, the graphs of the GSADF test, which gives more accurate results than the SADF test, indicate the existence of several different bubbles during the period in question. The main reason for this difference is that while the SADF test is a powerful method for detecting bubbles, it can be weak, especially in more than one price bubble. As confirmed by the GSADF graphs, price bubbles occurred in three different periods during the relevant period: the last quarter of 2020, the first quarter of 2021, and the second quarter. It can be said that regulatory decisions made in developed countries regarding the blockchain system and cryptocurrencies were effective in forming these bubbles. In the same period, developments such as the partnership of major banks with Stellar in Europe led to an increase in demand. They became one of the factors contributing to the inflation of the Stellar price.

Figure 7: XRP Cryptocurrency Test Results Charts



The SADF chart of Ripple (XRP) in Figure 7 shows no speculative price bubble during the period. However, the charts from the GSADF test, which provides more accurate results than the SADF test, provide empirical evidence of the existence of several different bubbles during the relevant period. As shown in the GSADF charts, price bubbles are observed in the third quarter of 2018, the first and fourth quarters of 2020, and the first and third quarters of 2021. In the formation of price bubbles, banks in Japan and South Korea announced their intention to test Ripple's blockchain technology in 2018. In late 2019, Japan and South Korea will begin testing blockchain technology to reduce the time and costs of international money transfers between the two countries. In 2021, price increases in other cryptocurrencies drove up Ripple's prices and contributed to the formation of a bubble.

In this part of the study, the hypothesis formulated as H2 is tested using the prices of 7 financial assets in the cryptocurrency market.

H2: Assets in the cryptocurrency market have the power to affect each other directly

The said hypothesis, Frequency Domain Causality Test, was used to determine whether the assets in the cryptocurrency market have the power to influence each other.

The Frequency Domain Causality Test used to test the hypothesis formulated as H2, can distinguish between temporary or permanent causal dynamics between crypto assets. For this purpose, test statistics with high (ω=2.5) frequency were used when examining short-term causality, while test statistics with medium frequency (ω=1.5) were utilized for medium-term causality. Test statistics with low (ω=0.5) frequency were used to study long-term permanent causality. The test results are presented in Table 2, Table 3, and Table 4.

Table 2: Short-term (ω=2.5) Frequency Domain Causality Test Results

Causality Direction	ADA	BNB	BTC	DOGE	ETH	XLM	XRP
ADA ➟	-	6.00**	2.83	6.53**	9.81***	10.81***	6.15**
BNB ➟	17.68***	-	31.82***	51.25***	6.92**	23.20***	18.65***
BTC ➟	5.02*	10.00***	-	19.50***	17.23***	3.48	4.97*
DOGE ➟	24.88***	18.13***	2.33	-	3.64	21.18***	10.99***
ETH ➟	11.83***	1.51	20.48***	27.79***	-	16.40***	15.73***
XLM ➟	1.27	1.56	11.59***	7.21**	0.008	-	1.29
XRP ➟	0.54	1.33	7.39**	13.86***	2.02	1.68	-

Note: the significance levels * 0.10, ** 0.05, and *** 0.01 are given.

According to the results of the short-term frequency domain causality test in Table 2, a bidirectional causality relationship was found between ADA cryptocurrency and BNB, DOGE, and ETH. A bidirectional causality relationship was found between BNB cryptocurrency and ADA, BTC, and DOGE cryptocurrencies. A short-term and bidirectional causality relationship was found between the cryptocurrency BTC and the cryptocurrencies BNB, ETH, and XRP. A statistically significant and bidirectional causality relationship was found between the cryptocurrency DOGE and the cryptocurrencies ADA, BNB, XLM, and XRP. It is found that there is a transitory and bidirectional causality relationship between the cryptocurrency ETH and the cryptocurrency values ADA and BTC. Finally, a bidirectional causality relationship existed between XRP and BTC, DOGE.

On the other hand, a one-way causality relationship was found from cryptocurrency ADA to cryptocurrencies XLM and XRP. A one-way causality relationship was found between BNB and ETH. Similarly, a one-way causality relationship was found to exist from BTC to ADA. A unidirectional and statistically significant causality relationship exists between ETH to DOGE, XLM, and XRP. A unidirectional causality relationship was found to exist between XLM cryptocurrency and BTC.

Table 3: Mid-term (ω=1.5) Frequency Domain Causality Test Results

Causality Direction	ADA	BNB	BTC	DOGE	ETH	XLM	XRP
ADA ➟	-	5.80*	2.63	7.19**	9.53***	10.99***	7.02**
BNB ➟	18.74***	-	28.93***	56.03***	7.59**	23.79***	20.22***
BTC ➟	5.22*	8.62**	-	20.34***	15.99***	3.63	5.59*
DOGE ➟	26.57***	20.33***	1.65	-	3.60	21.55***	12.18***
ETH ➟	12.47***	1.36	19.46***	29.18***	-	16.91***	16.95***
XLM ➟	1.24	1.53	10.40***	7.98**	0.01	-	0.79
XRP ➟	0.40	1.29	6.37**	15.33***	2.04	1.11	-

Note: the significance levels * 0.10, ** 0.05, and *** 0.01 are given.

According to the medium-term frequency domain causality test results listed in Table 3, a bidirectional causality relationship was found between ADA cryptocurrency and BNB, DOGE, and ETH. A bidirectional causality relationship was found between BNB cryptocurrency and ADA, BTC, and DOGE cryptocurrencies. A medium-term and bidirectional causality relationship was found between the cryptocurrency BTC and the cryptocurrencies BNB, ETH, and XRP. A statistically significant and bidirectional causality relationship was found between the cryptocurrency DOGE and the cryptocurrencies ADA, BNB, XLM, and XRP. A bidirectional causality relationship existed between the cryptocurrency ETH and the cryptocurrency assets ADA and BTC. Finally, a bidirectional causality relationship existed between XRP and BTC, DOGE.

It was found that there is a one-way causality relationship between the cryptocurrency XLM and BTC. On the other hand, a one-way causality relationship existed between the cryptocurrency ADA and the cryptocurrencies XLM and XRP. It was found that there is a one-way causality from BNB to ETH, XLM and XRP. Similarly, it was found that there is a one-way causality relationship between BTC to ADA and DOGE. A unidirectional and statistically significant causality relationship exists between ETH to DOGE, XLM, and XRP.

Table 4: Long-term (ω=0.5) Frequency Domain Causality Test Results

Causality Direction	ADA	BNB	BTC	DOGE	ETH	XLM	XRP
ADA ➟	-	3.22	1.30	12.27***	5.71*	12.96***	21.42***
BNB ➟	22.03***	-	2.33	88.73***	10.14***	29.38***	41.89***
BTC ➟	10.21***	1.15	-	31.54***	3.19	7.40**	16.05***
DOGE ➟	26.43***	28.70***	4.91*	-	1.29	22.12***	25.77***
ETH ➟	14.36***	0.28	8.25**	36.93***	-	22.12***	34.05***
XLM ➟	0.93	1.21	0.32	12.98***	0.13	-	4.59
XRP ➟	1.62	0.94	0.40	22.74***	1.66	3.14	-

Note: the significance levels * 0.10, ** 0.05, and *** 0.01 are given.

According to the long-term frequency domain causality test results in Table 4, a bidirectional causality relationship was found between ADA cryptocurrency and DOGE and ETH. A bidirectional causality relationship was found between BNB cryptocurrencies and DOGE cryptocurrencies. A bidirectional causality relationship was found between BTC and DOGE. A statistically significant and bidirectional causality relationship was found between DOGE cryptocurrency and ADA, BNB, BTC, XLM, and XRP cryptocurrencies. It was found that there is an ongoing and bidirectional causality relationship between the cryptocurrency ETH, the cryptocurrency assets ADA, and BTC. It was found that there is a bidirectional causality relationship between XLM and DOGE cryptocurrencies. Finally, a bidirectional causality relationship existed between XRP and DOGE.

On the other hand, a one-way causality relationship existed between ADA cryptocurrency and XLM and XRP cryptocurrencies. It was found that there is a one-way causality from BNB cryptocurrencies to the cryptocurrencies ADA, ETH, XLM, and XRP. Similarly, it was found that there is a one-way causality relationship between BTC to ADA, XLM, and XRP. A unilateral and persistent causality relationship exists between ETH to BTC, DOGE, XLM, and XRP.

When the results of the frequency domain causality test in Table 2, Table 3, and Table 4 are evaluated together, it can be concluded that there are spillover and contagion effects between cryptocurrency markets. It can be observed that the cryptocurrency with the strongest contagion and spillover effect in the short and medium term is Binance Coin (BNB). Also, a contagion and spreading effect can be seen in Binance Coin and other cryptocurrency assets in the long term. Moreover, another conclusion is that the said effect is permanent. On the other hand, although Stellar (XLM) and Ripple (XRP) cryptocurrencies have a contagion and spread effect from other cryptocurrencies in the short, medium, and long term, the contagion and spread impact of these cryptocurrencies to other cryptocurrencies is weak. Therefore, it can be observed that the risk of Stellar (XLM) and Ripple (XRP) spreading to other cryptocurrencies is low. Another result of the frequency domain causality test is that the cryptocurrency DOGE has the highest contagion and propagation effects among other cryptocurrencies. In other words, the cryptocurrency DOGE has a very high degree of dependence on other cryptocurrencies and has the highest risk of propagation. Finally, Bitcoin (BTC) and Ethereum (ETH) have a contagion and spillover effect that causes the prices of other cryptocurrencies to change.

In contrast, the degree of influence of other cryptocurrencies is low. Bitcoin (BTC) and Ethereum (ETH) are independent cryptocurrencies with spillover effects but low impact. In conclusion, the obtained results confirm the correctness of the H2 hypothesis, which states that assets in the cryptocurrency market can directly influence each other.

5. Conclusion

The globalization process that has taken place in the financial markets in recent years has put on the agenda the need for alternative currency systems and new financial instruments. This situation has led to the emergence of cryptocurrencies, especially following the 2008 crisis. Cryptocurrencies have started to attract attention in the financial system with their advantages, such as the alternative monetary system they offer and the potential to generate high returns. Moreover, the existing regulations in the cryptocurrency market are still in their infancy, which makes the financial assets in the cryptocurrency market vulnerable to high volatility and speculative developments. In this context, the speculative behaviours observed in the cryptocurrency market may lead to price bubbles. Moreover, the correlation and high volatility caused by the interdependence of financial assets in the cryptocurrency market can lead to spreading risks. Therefore, determining the interdependence of speculative behaviour and crypto assets is necessary for risk management and stable pricing in the cryptocurrency market.

In the study, Phillips et al. (2011) (SADF) and Phillips et al. (2015) generalized the Dickey-Fuller test (GSADF) used to determine whether the external factors affecting the cryptocurrency market cause instability in price formation. In other words, it aims to determine whether the speculative behaviour of the assets in the cryptocurrency market creates a price bubble and to measure the interdependence and spillover effect of the assets in the cryptocurrency market using the frequency domain causality test. Therefore, the study estimates the speculative behaviour and spread risk in the cryptocurrency market in two dimensions. The study results show that it is statistically significant for cryptocurrencies ADA, BNB, BTC, DOGE, ETH, XLM, and XRP. Therefore, there is empirical evidence of the formation of speculative bubbles between January 1, 2018, and December 2021, which is discussed in the study. On the other hand, when examining the SADF and GSADF test statistics obtained for the XLM and XRP currencies from the selected assets in the cryptocurrency market, it was found that the SADF test is not, while the GSADF test is statistically significant. Based on the view that the GSADF test is more consistent and provides better results than the SADF test, it can be said that empirically a speculative bubble occurred within the XLM and XRP currencies for the analyzed periods.

On the other hand, the results of the frequency domain causality test in the study provide empirical evidence that there is a spillover and contagion effect between financial assets in the cryptocurrency market. In other words, price changes between selected currencies in the cryptocurrency market cause increased correlation and volatility. In particular, the degree of pegging the cryptocurrency DOGE to other cryptocurrencies was relatively high. Stellar (XLM) and Ripple (XRP) cryptocurrencies also have a high degree of pegging to other cryptocurrencies in the short, medium, and long term. However, the price changes observed in Stellar (XLM) and Ripple (XRP) cryptocurrencies do not affect other crypto assets. In other words, when a market event occurs in the Stellar (XLM) and Ripple (XRP) cryptocurrencies, it has little potential to cause an upward or downward trend in the prices of other cryptocurrencies. Therefore, sudden changes in other cryptocurrencies can be expected to simultaneously affect DOGE, Stellar (XLM), and Ripple (XRP) and increase the risk of a spread. Another important finding of the study is that Bitcoin (BTC) and Ethereum (ETH) have a contagion and spillover effect that causes the prices of other cryptocurrencies to change. In contrast, the degree of influence by other cryptocurrencies is low. Bitcoin (BTC) and Ethereum (ETH) are cryptocurrencies in their own right that pose spillover risks but are only affected by spillover and volatility risks to a small extent.

In the context of the results obtained in the study, assets in the cryptocurrency market have a spillover effect in the form of overvaluation with the impact of internal and external factors. In other words, the high interdependence of crypto assets in the crypto money market is a significant obstacle to stable price formation when supported by speculative pricing behaviour. Therefore, the study results provide a better understanding of the interconnectedness of assets in the cryptocurrency market and the transmission of contagion effects. In addition, the study's findings indicate that investors should pay attention to the moving signals in the markets. This means that any current and past change in one cryptocurrency could have a negative impact on the movement of other cryptocurrencies. Therefore, the study's findings to establish a dynamic early warning mechanism for risk management and stable pricing in the cryptocurrency market will be an essential guide.

Future studies may expand the scope of work with other currencies in the cryptocurrency market. In addition, the studies on this topic can use quantitative methods to investigate the macroeconomic and socioeconomic factors determining the cryptocurrency market's spread risk.

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ARAŞTIRMA MAKALESİ / RESEARCH ARTICLE

THE EXTENT OF HOUSEHOLD POVERTY IN AFGHANISTAN: A CASE STUDY OF MAZAR-I-SHARIF CITY, BALKH PROVINCE (2019/20 AND 2020/21)

Baqir KHAWARI *

Abstract

There is limited literature review and analysis of poverty in Afghanistan, particularly in the analysis of an urban area. Therefore, due to the limited information on the extent of poverty in Mazar-i-Sharif city especially at the micro/household level, this paper will provide such information and a more current one. To conduct the study, an actual data of 1060 households in Mazar-i-Sharif, obtained from a strictly random process, is used and applied the "Foster-Greer-Thorbecke (FGT)" measures of poverty to analyse poverty based on income and expenditure approach in two waves, before "COVID-19" (March 21, 2019-March 20, 2020) and during "COVID-19" (March 21, 2020-March 21, 2021). Also, the "Independent t-test" is applied to compare the mean of poverty indices in wave 1 compared to wave 2. It is found that, overall, the poverty rate is high in Mazar-i-Sharif, and more than two-thirds of the population severely suffers from the phenomenon, and it increased during the pandemic compared to pre-pandemic time. Also, the depth and severity of poverty are also serious issues and the indices increased in wave 2 compared to wave 1. Further, the study suggests that the government and international organizations should do urgent actions to save million lives and to overcome of this phenomenon.

Keywords: Headcount Ratio, Poverty Gap, Pandemic, Afghanistan
JEL Classification: O150, O120, I32, N15

1. Introduction

Economic development is highly desired by many developing countries, including Afghanistan. The first president of Afghanistan, Hamid Karzai, has developed the "Interim Afghanistan National Development Strategy (I-ANDS)" for 15 years to achieve Afghanistan's Millennium Development Goals (MDGs) in 2020 (ANDS, 2005). Therefore, based on the strategy, many projects have been implemented by the Afghan government and foreign direct investment (FDI) to achieve the goal, unfortunately, the country is still so far from its MDGs and severely involved with a serious and dark phenomenon, poverty. According to Mohsen et al. (2021), Afghanistan is one of the poorest countries in the world.

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The poverty rate in Afghanistan has increased over time. According to "National Risk and Vulnerability Assessment" (NRVA), in 2007/08, the poverty headcount rate was 34%, raised to 38% in 2011/12 (NRVA, 2009, 2012), and 54.5% in 2017 (CSO, 2018). However, based on "Income, Expenditure, and Labor Force Survey" (IE&LFS 2020), the poverty rate decreased from 54.5% to 47% in 2019 (NSIA, 2021), in 2020, due to the "COVID-19 pandemic", the poverty rate again dramatically increased. The World Bank estimated that approximately 15 million persons were susceptible to the COVID-19 lockdown (April-June) in Afghanistan. The analysis showed that, in urban areas, the poorest percentile of the households experienced about a 35% decrease in their consumption while the richest percentile experienced about a 19% reduction. In contrast, in rural areas, the consumption of the poorest percentile of the households was reduced by about 21%, while it was estimated to be about 24% for the richest percentile (Cancho & Pradhan, 2020). As a result, the pandemic caused the poverty rate to increase from 55% in 2017 to 72% in 2020 (United Nations, 2021).

Besides, in July 2020, the ex-president of Afghanistan, Dr. Mohd. Ashraf Ghani, announced that 90% of Afghan people are below the poverty line, $2 per person/day (AFN154), (Omid, 2020). Notably, the rate is expected to increase because of the recent political changes that have pushed the country into a predicament situation (UNDP, 2021a). On 15 August 2021, the Taliban took the power in Afghanistan, where its economy was already facing more developmental challenges such as insecurity, severe drought conditions which negatively affected agriculture production, and COVID-19, of which the third wave started in April 2021. Hence, the United Nations Development Program (UNDP) reported that about 97% of Afghans' citizens would dive below poverty line by mid-2022 (UNDP, 2021b). Also, World Food Program (WFP) announced that 95% of Afghans do not have enough food to survive (WFP, 2021). Furthermore, based on the UNDP (2021) report, the poverty gap was estimated to be 13.5% in 2019, increasing to 21% in 2020 because of the pandemic. It is predicted that the poverty gap will rise to 30% by mid-July 2022 if the poverty rate reaches 97%, considering the poverty line of AFN 2,268 or US$1. Thus, it shows that the poverty gap will be more than double in 2022 compared to 2019, and it needs urgent actions to save lives.

Besides, the poverty rate differs among the regions. For instance, according to the World Bank estimation, the headcount ratio for the southwest and central provinces was 0%-30%, for the north, west, and south provinces were 30%-40%, and for the western central, north-eastern, and eastern provinces of Afghanistan was 40%-50%. Also, it was mentioned that poverty concentration is highest in more urbanized and densely populated provinces (World Bank, 2015). So, this study focuses on one of the biggest and most populated cities, Mazar-i-Sharif. It is the provincial capital of Balkh province that was ranked as the fourth most populated province in Afghanistan with an estimated population of 1.5 million and is located in the north of Afghanistan in 2021 (NSIA, 2021). It may seem significant to analyze poverty in the capital of the province because poverty was reported to be relatively high in the province and its capital (NRVA, 2009). For instance, the poverty rate and poverty gap were estimated to be between 61%-76% and 14.8%-18.5%, respectively, in Balkh province in 2008 (NRVA, 2009).

Hall (2011) considered the per capita monthly total consumption of AFN1,289 and estimated that the poverty rate in Balkh province was 60.3%. Later, Hall (2014) conducted a research on poverty in different cities of Afghanistan and released that poverty in Mazar-i-Sharif city is serious and almost 81% of its inhabitants are under the poverty line (AFN1,710 per person/month) based on expenditure approach and 83.5% based on the income approach. To go further, "Afghanistan Research and Evaluation Unit" (AREU) reported that the poverty rate, poverty gap, and Gini coefficient for the province's consumption were estimated to be 60.3%, 17.4%, and 27%, respectively (World Bank, 2013). Temory (2017) found that the Gini coefficient for Balkh province was 0.25 or 25%. Also, the income distribution inequality in the province was found to be 20.33% between the bottom 20% and the top 20%, which shows a huge gap between the first bottom quintile and the top quintile. Generally, in rural areas poverty looks more serious than urban areas; however, Kandahar, Kabul, Balkh, Herat, and Kunduz are the provinces where urban poverty is increasing because of trends in internally displaced people and returnees from abroad. It is estimated that 80% of urban poverty is distributed in these provinces (EASO, 2020).

As shown, poverty has been a big and challenging phenomenon in Afghanistan for a long time, particularly in Balkh province and its capital. Therefore, the article will provide a more current insight regarding the issue among households in the provincial capital of Balkh province of Afghanistan in two waves, 2019/20 and 2020/21, as well as examine the influence of the pandemic on the household poverty level. Besides, the article will address the subsequent research questions:

What is the nature and extent of poverty in Mazar-i-Sharif city? How does the pandemic influence the poverty level? For the study, poverty is measured based on two approaches, income and expenditure, by employing the data which are collected from 1060 households in Mazar-i-Sharif city from May-July 2021. Further, the FGT measures of poverty and "Independent t-test" are applied to analyse poverty and test the significance of poverty indicators in the two waves.

2. Basic Concept of Poverty

The social sciences have faced difficulties in agreeing to a single definition of poverty due to its complex and multi-faceted nature (Chamhuri et al., 2012). Poverty is understood as the inability to meet a least level of living (World Bank, 1990). Gass and Adetunmbi (2000) and Raji et al. (2006) define poverty as a lack of resources that prevent individuals from achieving a basic level of social rights, such as ingress to food, water, shelter and clothing. Additionally, Tirkaso and Hess (2015) assessment poverty as an absence of sufficient income to afford the purchase of essential goods and services.

Furthermore, according to the traditional perspective, persons who do not have sufficient earnings or spending to raise them beyond a sufficient minimal level are measured as poor. Poverty line is often used to refer to this threshold. According to this perspective, poverty is primarily understood in financial terms. Another way that poverty may indeed be defined is as a lack of a particular good or service, such as housing, food, or health. These aspects of poverty are often directly measurable, for instance, by assessing education or food. The capacity of the person to operate in society is the emphasis of the widest method to well-being (and poverty). Poor individuals often lack essential skills; they may not have enough money or schooling, be in poor health, feel helpless, or lack political liberties (World Bank, 2005). For instance, tracking achievement toward the Millennium Development Goals is often done using this simple monetary approach for measuring poverty (Sanchez-Martinez & Davis, 2014). The concepts of poverty given above include a variety of conditions, including absolute poverty, relative poverty, and the idea of the poverty line, which is succinctly described as follows.

2.1. Absolute Poverty

Absolute poverty is considered to be an absence of incomes essential to meet one's basic needs, including food, water, shelter, healthcare, education, and other necessities. This type of poverty is gauged by a universal baseline that does not take into account others' incomes or access to commodities, and failure to meet the baseline indicates poverty (Eskelinen, 2011). According to the United Nations (1995), absolute poverty relies on both income and access to services and is defined by extreme deprivation of essential human necessities. This type of poverty is more concerning in circumstances where there is a risk of starvation, rather than in areas where everyone has the means to provide for themselves (Ruggeri Laderchi et al., 2003).

2.2. Relative Poverty

The level of poverty experienced by a person is dependent upon how it is evaluated in comparison to the social norms of the country and culture they live in, and this can change over time (Sanchez-Martinez & Davis, 2014). The relatively poor are individuals whose earnings are lesser than those of the rest of the population, even if they can obtain an appropriate subsistence level. In other words, relative poverty refers to those who are poorer than the rest of the community. Hence, the term "relative poverty" refers to the delivery of income and, consequently, the disparity of living circumstances within a population (Demeke et al., 2003). Measuring this kind of poverty is feasible only for developed countries (Ravallion, 1992). Thus, for least developed countries (LDCs), including Afghanistan, where the largest share of its population are living in absolute poverty (UNDP, 2021a), the emphasis on relative poverty is not of primary relevance.

2.3. Poverty Line

When measuring poverty in a certain nation and determining the most effective means of poverty reduction, one is naturally drawn to a poverty line that is deemed acceptable for that country (Hagenaars & de Vos, 1988). The beginning points for examining poverty is poverty line (PL), and it is often the most disputed. Methods to calculate the PL significantly impact poverty profiles, which are used to formulate poverty alleviation initiatives. PLs provide a variety of functions. According to Ravallion (1992), "the poverty line is the minimum level of income deemed adequate in a particular country".

Moreover, since poverty lines vary greatly across countries, the World Bank sets the international poverty line by considering the cost of living for essential food and non-food goods and services such as cloth, shelter, education, and health. Therefore, as a result, the United Nations and World Bank have chosen per individual poverty line of $1 and $2 per day/person for worldwide analyses, however for comparison of poverty inside a country, national poverty line will be more appropriate (United Nations, 2005). In July 2020, the Ministry of Economy of Afghanistan announced the national poverty line, $2 per person/day (AFN154), which contains food, cloth, shelter, healthcare, and education which follows the international poverty line. It means that if a person earns less than $2 per day, they identify as poor (Omid, 2020).

3. Measuring Poverty: Income or Expenditure Approach

The extent of poverty is largely ground on income or expenditure, which specify a person's access to goods and services. This has been a focus of a great deal of research, particularly around the United Nations' 2005 report, as it is often used to measure social and economic progress or failure. Lekobane and Seleka (2014) have argued that income and consumption are good indicators of well-being since they demonstrate a person's capability to gain the necessities of life.

According to the studies such as Beverly (1999); Mayer (1997); Mayer & Jencks (1989) and Rector et al. (1999), the income approach has been acknowledged as a viable tool for capturing the financial situation of families. It has also been seen to be advantageous when it comes to examining administration and societal well-being policies, such as food stamps, medical aid, subsidies, job assistance, and other monetary transfers (Ringen, 1988; Melkamu & Mesfin, 2016). The income method could be a good proxy for showing the ability of households to purchase basic goods and services because it measures households' resources, including individual tastes and preferences (Ali, 2019). Atkinson (1991) also stated that income is a well proxy for measuring living standards, generally difficult to quantify. Income is largely used to measure economic deprivation, and it is simpler to account accessible for much bigger samples (Meyer & Sullivan, 2003).

On the other hand, expenditure is typically a superior predictor of living standards compared to income, especially in developing nations (Boskin et al., 1998; Cutler et al., 1991; Fisher et al., 2013; Mayer & Jencks, 1993; Slesnick, 2002, 1994). Therefore, the consumption approach to measuring poverty is becoming more common (Fox et al., 2015). For instance, data from 88 developing countries showed that 36 countries used household income surveys, and 52 of them employed household expenditure surveys for measuring poverty or welfare (Ravallion, 2001). Consumption is thought to be more stable than income, especially in developing countries where income can often be subject to seasonal variation. To maintain a consistent level of utility, households will use savings or debt to balance out their spending during years of high and low income (Atkinson et al.,1994).

This was supported by McKay & Lawson (2003) and Milanovic (1999). Milanovic (1999) stated that collecting income data is more complicated than data on consumption or expenditure of households, so the output of expenditure measurement is more accurate than income in transition countries. Duclos and Araar (2006) argued that, compared to income, consumption is a much better indicator of one's accomplishments and the ability to meet fundamental requirements. Moreover, consumption can be observed, remembered, and measured in a much more accurate way than income, and there is less of an issue with underreporting. Furthermore, it is also important in understanding the necessity of consumption when it comes to determining poverty (Grosh & Glewwe, 2000).

It is shown that each approach has its advantages, and we cannot ignore them so in this article poverty indices are measured based on the two approaches to have a better analysis of poverty in Mazar-i-Sharif city, Balkh province of Afghanistan.

4. Foster-Greer-Thorbecke (FGT) Measures of Poverty

The most well-known indicators of poverty such as headcount ratio (HCR), poverty gap (PG), and poverty gap squared (PGS) indices initially defined by Foster et al. in 1984. All of the indices are often used in research (Duniya & Rekwot, 2015) to assess the incidence, depth, and severity of poverty respectively in a society (Bellù & Liberati, 2005; United Nations, 2017). The indices can be computed based on the income or expenditure approach. So, many scholars such as Dharmadasa et al. (2018); Imran et al. (2020); Le et al. (2019); Nahar et al. (2017); Olowa et al. (2013); Shroff (2009); and Adams et al. (2008) used per capita household income while Afera (2015); de Silva (2008); Etuk et al. (2015); Duniya & Rekwot (2015); Mussa (2014); Ogwumike & Akinnibosun (2013); and Oyekale et al. (2012) used per capita household expenditure to capture the FGT indicators and measure poverty. The FGT poverty index (Pα) can be broken down to show the amount of poverty experienced by various population sub-groups and how much of the overall poverty level is due to each sub-group (Borko, 2016). The formula for the FGT measure of poverty is as follows:

$$P_\alpha = \frac{1}{\mathrm{N}}\sum_{i=1}^{M}\left(\left(\frac{\mathrm{z}-y_i}{\mathrm{z}}\right)^{\alpha} * \mathrm{I}\,(\mathrm{y}_i < \mathrm{z})\right), (\alpha \geq 0)$$

The Pα measure of poverty is determined by the values of indices Pα, where N is the total population (or sample), M is the number of people living under PL, z is the PL, y_i is the per capita income or expenditure of the i^{th} household, and α is a measure of the sensitivity of the index to poverty. With values greater than 0, the measure is decreased when living standards are lower.

If α is greater than 1, the greater the poverty, the more the measure is impacted by a decrease in living standards. This is considered to be "strictly convex" in incomes, while "weakly convex" is applicable to α = 1. The indicator function I has the value of 1 if y_i is less than z and 0 if y_i is equal or greater than z. The P_α class model is described as follows:

P_0 = HCR

P_1 = PG

P_2 = PGS

The equations for the poverty indices are as follows respectively.

$$P_0 = \frac{1}{\mathrm{N}} \sum_{i=1}^{M} \left(\left(\frac{\mathrm{z} - \mathrm{y_i}}{\mathrm{z}} \right)^0 * \mathrm{I}\,(\mathrm{y}_i < \mathrm{z}) \right) = \frac{1}{N} \sum_{i=1}^{M} I\,(y_i < z) = \frac{M}{N}$$

The P_0 is the headcount ratio (poverty incidence) that measures poverty rate. If the per capita income of the household is less than \$2 [1] per day/person (AFN154), then the household is identified as poor otherwise non-poor.

$$P_1 = \frac{1}{\mathrm{N}} \sum_{i=1}^{M} \left(\left(\frac{\mathrm{z} - y_i}{\mathrm{z}} \right)^1 * \mathrm{I}\,(\mathrm{y}_i < \mathrm{z}) \right)$$

The P_1 measures the depth of poverty. It shows that how far the poor is from the poverty line.

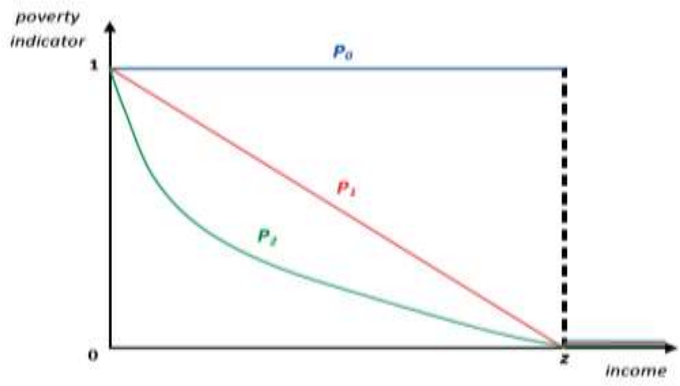
$$P_2 = \frac{1}{\mathrm{N}} \sum_{i=1}^{M} \left(\left(\frac{\mathrm{z} - y_i}{\mathrm{z}} \right)^2 * \mathrm{I}\,(\mathrm{y}_i < \mathrm{z}) \right)$$

The P_2 measures the severity of poverty. The measure puts more weight the further a poor person's observed income falls below the poverty line.

In short, the correlation among the values of the above poverty indices is shown in following figure.

1 \$1=AFN77

Figure 1: The Relationship Between P0, P1, P2



Source: United Nations (2017)

5. Sample Size

Initially, the study designed a questionnaire to collect data about household income and expenditure for the two periods, before the "COVID-19 pandemic (March 21, 2019-March 20, 2020)" and during the "COVID-19 pandemic (March 21, 2020-March 21, 2021)". The respondents were asked to give information about their income and expenditure in the two periods at the time of the survey. The study intended to survey 1100 households to raise the reliability of the result but from the original sample size, 1100 households, 40 households were not surveyed because of some problem such as unwillingness to cooperate, absence of the head of a family or a man at the house, having moved out, or being unavailable at home when the interview was conducted, so it ended up having only 1060 households.

6. Sampling Technique and Procedure

The research used a multi-stage simple random sampling approach to pick 1100 houses in the study region, which may be stated as follows:

1. Mazar-i-Sharif has 12 regions (Nahiyah). So, based on the lottery method, 4 regions, 4,7,11, and 12, were selected in the first step.

2. In the second step, since each region contains some areas (Guzars), again based on the lottery method, from each region 2 Guzars were selected randomly, which made up a total number of 8 Guzars.

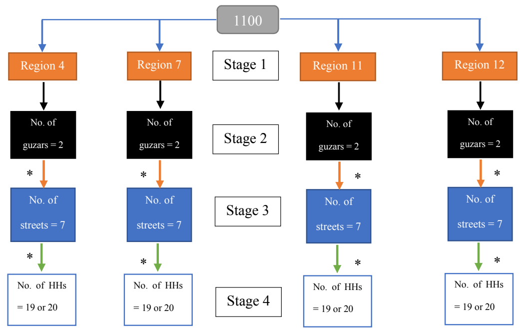
3. In the third stage, since each area consists of some streets, another simple random selection was made, and 7 streets were selected. This made up a total number of 56 streets.

4. The last stage involved a systematic random sampling of 19 or 20 households from each street,

making a total of 275 households for each region (Nahiyah).

The stages of the sampling procedure are shown in figure 2.

Figure 2: Stages of Sampling Procedure



According to a meeting that was held by the mayor of Mazar-i-Sharif, Abdul Haq Khurami, in May 2021, the four selected regions (Nahiyah) allocates more that 25% of the total population of the case study (484,492 people) to themselves. So, taking sample from these four regions could be a good representative of the total targeted population.

7. Descriptive Analysis

Table 1 displays the descriptive statistics of the demographic characteristics' of 1060 households head. The table shows that 88 per cent of the households' heads were male while around 12 per cent were female. Around (47%) of the households' heads fall above 50-year-old while the rest of the heads fall under the productive age group with 10% between the range of 18-28 years old and 44% between the range of 29-50 years old. In terms of marital status, a large percentage of the households' head (90 per cent) were married people, followed by singles (6%) and divorced (0.5%) and widows (3.4%).

Regarding the education background, most households' heads have primary and secondary education, lower and upper, with (30%) and (27.5%) respectively. 19.5 per cent with Islamic education and 15.5 per cent with university and above, while those who have zero level of education is 7.5%. Approximately 38 per cent of the households' head have elementary occupations, professional (14%), manager (1%), plant and machine operators and assemblers (around 9%). The rest of the households' head (38%) has some other occupations. Moreover, it indicates that 37 per cent and 33 per cent of the households' head were employed and self-employed, while out of the remaining 30 per cent, 6 per cent were unemployed, around 23 per cent were PAF [2], and only 1 per cent were retired heads. The majority of employed heads work in the private sector (about 78%), followed by government sectors (20%) and foreign institutions (2%).

2 The sum of the two groups persons seeking work but not immediately available and persons available to work but not seeking is called the potential additional labour force (PAF)."

Table 1: Characteristics of the Households' Head

Variables	No Remittance		Internal Remittance		International Remittance		Both		Total	
	Obs.	%	Obs.	%	Obs.	%	Obs.	%	Obs.	%
Gender										
Male	451	97.6	234	75.7	245	87.5	7	77.8	937	88.4
Female	11	2.4	75	24.3	35	12.5	2	22.2	123	11.6
Total	462	43.6	309	29.2	280	26.4	9	0.8	1060	100.0
Age										
18-28	29	6.3	31	10.0	34	12.1	0	0.0	94	8.9
29-50	238	51.5	130	42.1	98	35.0	6	66.7	472	44.5
above 50	195	42.2	148	47.9	148	52.9	3	33.3	494	46.6
Total	462	43.6	309	29.2	280	26.4	9	0.8	1060	100.00
Marital Status										
Single	25	5.4	21	6.8	18	6.4	0	0.0	64	6.0
Married	425	92.0	271	87.7	252	90.0	7	77.8	955	90.1
Divorced	0	0.0	3	1.0	2	0.7	0	0.0	5	0.5
Separated	0	0.0	0	0.0	0	0.0	0	0.0	0	0.0
Widowed	12	2.6	14	4.5	8	2.9	2	22.2	36	3.4
Total	462	43.6	309	29.2	280	26.4	9	0.8	1060	100.0
Education										
No Education at all	35	7.6	30	9.7	14	5.0	0	0.0	79	7.5
Islamic School	99	21.4	60	19.4	44	15.7	4	44.4	207	19.5
Primary School	113	24.5	93	30.1	112	40.0	2	22.2	320	30.2
Lower and Upper Secondary School	140	30.3	79	25.6	69	24.6	3	33.3	291	27.5
University and above	75	16.2	47	15.2	41	14.6	0	0.0	163	15.4
Total	462	43.6	309	29.2	280	26.4	9	0.8	1060	100
Occupation										
Elementary occupations	187	40.5	103	33.3	111	39.6	1	11.1	402	37.9
Manager	7	1.5	4	1.3	1	0.4	0	0.0	12	1.1
Professional	69	14.9	38	12.3	40	14.3	1	11.1	148	14.0
Plant and machine operators, and assemblers	50	10.8	20	6.5	16	5.7	6	66.7	92	8.7
Others	149	32.3	144	46.6	112	40.0	1	11.1	406	38.3
Total	462	43.6	309	29.2	280	26.4	9	0.8	1060	100.0
Status of Employment										
Employed	211	45.7	96	31.1	87	31.1	1	11.1	395	37.3
Self-Employed	156	33.8	97	31.4	98	35.0	1	11.1	352	33.2
Unemployed	23	5.0	16	5.2	26	9.3	0	0.0	65	6.1
Retired	4	0.9	2	0.6	1	0.4	0	0.0	7	0.7
PAF	68	14.7	98	31.7	68	24.3	7	77.8	241	22.7
Total	462	43.6	309	29.2	280	26.4	9	0.8	1060	100.0

Sector or Institution of Employment										
Government Sector	41	19.4	22	22.9	16	18.4	1	100.0	80	20.3
Private Sector	166	78.7	71	74.0	70	80.5	0	0.0	307	77.7
Foreign Institution(s)	4	1.9	3	3.1	1	1.1	0	0.0	8	2.0
Total	211	53.4	96	24.3	87	22	1	0.3	395	100.0

Table 2 indicates other related factors, which are also important as far as the characteristics of the households' heads are concerned. As can be seen from the table, 96.5 per cent of the households do not have any disabled person in their families, while 3.5 per cent represent having at least one disabled person in their family. In terms of households' structure, it is demonstrated that almost half (49%) of the sample size has more females compared to males in their families, while 25 per cent of the households have a male majority. In the rest of the households (26%), the number of males and females are equal. Interestingly, it is shown that in all categories of the households, the number of households with a female majority is greater than the other two groups. Besides, half (50%) of the sample size have more than six members in their families, around 41 per cent have a family size between the range of 4-6 people, and a low percentage of the sample size (9%) have a family size between range of 1-3 people. There is 19 per cent of the sample size have received assistance from the ex-government and NGOs since 21 March 2020, while 81 per cent receive nothing. Households who received the assistance reported that most of them (81%) received non-cash assistance than cash assistance (5%); around 14 per cent of them received both types of assistance due to COVID-19.

In addition, non-cash assistances include food and non-food goods such as clothes, coal, and wood. So, 70.7 per cent of the assistance's recipients received food while only 0.5% received non-food, and the rest (28.9%) received both types of the assistance. In terms of Zakat, 2 out of 1060 households received the Islamic assistance; however, our country is an Islamic country. Thus, the government should have a special look at these Islamic elements, which significantly affects poverty reduction in a country. Finally, it represents that around 11 per cent of the households take a loan to provide the basic needs while 81 per cent of them do not take a loan for daily needs.

Table 2: Other Important Characteristics of the Households

Variables	No Remittance		Internal Remittance		International Remittance		Both		Total	
	Obs.	%	Obs.	%	Obs.	%	Obs.	%	Obs.	%
Disability										
Yes	13	2.8	13	4.2	11	3.9	0	0.0	37	3.5
No	449	97.2	296	95.8	269	96.1	9	100.0	1023	96.5
Total	462	43.6	309	29.2	280	26.4	9	0.8	1060	100.0
HH Formation										
Male Majority	97	21.0	101	32.7	68	24.3	3	33.3	269	25.4
Female Majority	227	49.1	155	50.2	131	46.8	2	22.2	515	48.6

Female = Male	138	29.9	53	17.2	81	28.9	4	44.4	276	26.0
Total	462	43.6	309	29.2	280	26.4	9	0.8	1060	100.0
Household size										
1-3 people	22	4.8	34	11.0	37	13.2	0	0.0	93	8.8
4-6 people	178	38.5	130	42.1	120	42.9	3	33.3	431	40.7
above 6	262	56.7	145	46.9	123	43.9	6	66.7	536	50.6
Total	462	43.6	309	29.2	280	26.4	9	0.8	1060	100.0
Received Assist. Because of Covid-19										
Yes	44	9.5	70	22.7	84	30.0	6	66.7	204	19.2
No	418	90.5	239	77.3	196	70.0	3	33.3	856	80.8
Total	462	43.6	309	29.2	280	26.4	9	0.8	1060	100.0
Type of Assistances										
Cash	0	0.0	8	11.4	3	3.6	0	0.0	11	5.4
Non-Cash	41	93.2	49	70.0	69	82.1	6	100.0	165	80.9
Both	3	6.8	13	18.6	12	14.3	0	0.0	28	13.7
Total	44	21.6	70	34.3	84	41.2	6	2.9	204	100.0
Type of non-cash assistance(s)										
Food	35	79.5	50	71.4	58	69.0	1	16.7	144	70.6
Non-food	1	2.3	0	0.0	0	0.0	0	0.0	1	0.5
Both	8	18.2	18	25.7	28	33.3	5	83.3	59	28.9
Total	44	21.6	70	34.3	84	41.2	6	2.9	204	100
Received Zakat										
Yes	1	0.2	1	0.3	0	0.0	0	0.0	2	0.2
No	461	99.8	308	99.7	280	100.0	9	100.0	1058	99.8
Total	462	43.6	309	29.2	280	26.4	9	0.8	1060	100.0
Taking loan for basic needs										
Yes	38	8.2	41	13.3	35	12.5	0	0.0	114	10.8
No	424	91.8	268	86.7	245	87.5	9	100.0	946	89.2
Total	462	43.6	309	29.2	280	26.4	9	0.8	1060	100.0

8. Result and Discussion

Table 3 shows the means of poverty indices based on income and expenditure approaches for the two periods, 2019/20 and 2020/21. First, based on income approach, the result indicates that about 70% of the household are below the poverty line of $60 per month/person (AFN 4620) before the pandemic time. In contrast, the rate has increased to 77% during the pandemic time which shows a 7% increase in the headcount ratio. In terms of poverty gap, the finding demonstrates that, before the pandemic, the PG estimated to be 24% while during the pandemic time the PG increased by 4.5%. The severity of poverty is calculated 11% in the period of 2019/20 while in the next period, 2020/21, the severity of poverty increased to 13%.

On the other hand, based on expenditure approach, the table represents that the headcount ratio was about 76% in wave 1 while the rate increased to around 88% in wave 2. The poverty gap is estimated to be around 25% before the pandemic and 34% during the pandemic, which shows a 9% increase. In addition, the squared of poverty gap estimated about 11% in the first wave and 16% in the second wave which shows the inequality among the poor themselves are high as well that should be considered in policy making.w

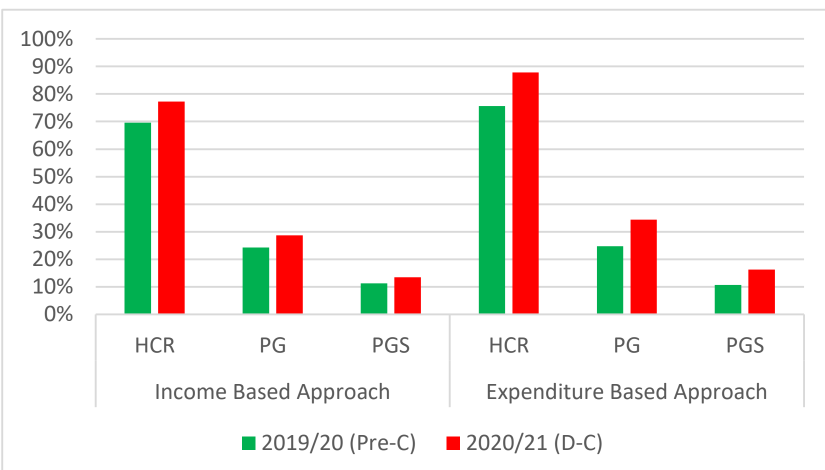
Table 3: Poverty Profile of Mazar-i-Sharif

Mean of Poverty Indices	Income Based Approach			Expenditure Based Approach		
	2019/20 (Pre-C)	2020/21 (D-C)	t-test (Pre-C vs D-C)	2019/20 (Pre-C)	2020/21 (D-C)	t-test (Pre-C vs D-C)
HCR	69.6%	77.3%	(-3.99)***	75.7%	87.8%	(-7.34)***
PG	24.2%	28.7%	(-4.42)***	24.7%	34.4%	(-10.57)***
PGS	11.2%	13.4%	(-3.41)***	10.7%	16.2%	(-9.25)***

(***), (**), and (*) represent the level of significance at 1%, 5%, and 10% respectively based on the result of Independent t-test.

Note: Pre-C = Pre-COVID-19; and D-C = During-COVID-19.

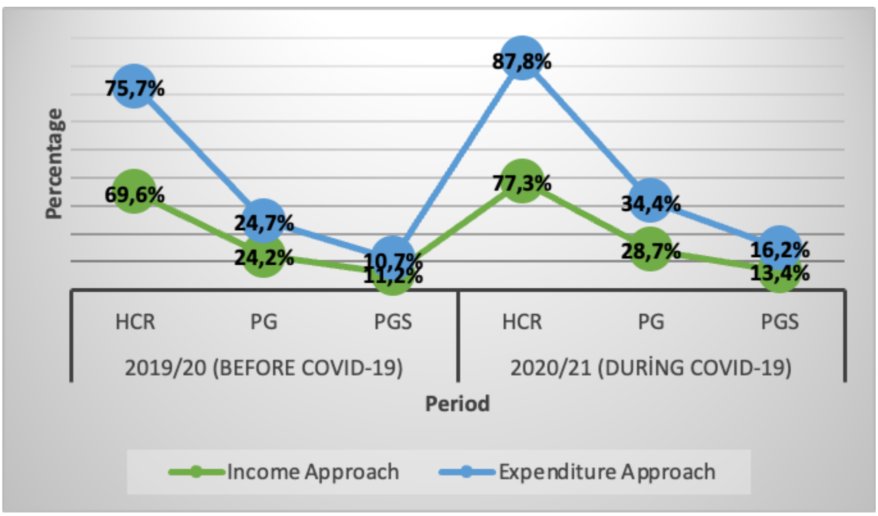
Figure 3: Household Poverty Indices in Wave 1 Compared to Wave 2 Based on Income and Expenditure Approaches



In short, the findings of the study present that, either use income or expenditure approach, poverty indices increased during the pandemic time compared to before the pandemic which is clearly shown in figure 3. It means that during the pandemic more households slip into poverty compared to pre-pandemic time; the PG and PGS indices also significantly increased in wave 2 compared to wave 1. Moreover, according to the independent t-test, all changes between wave 1 and wave 2 poverty indicators are statistically significant.

Figure 4 illustrates the differences between income and expenditure approach. It shows that in both periods, 2019/20 and 2020/21, poverty indices are estimated to be greater based on expenditure approach compared to income approach. It is because some portion of the household income might shift to saving and payment of loan that decrease the household expenditure (consumption). In addition, the figure represents that the differences between poverty indices based on expenditure approach compared to income approach is more in wave 2 than wave 1 and it is because during the pandemic households may more interested to shift higher portion of their income into saving to use it later in urgent time. Therefore, we can conclude that since households may save more during the pandemic, it is better to measures poverty indices based on income approach rather than expenditure.

Figure 4: Comparison of Income and Expenditure Approach



9. Conclusion

Poverty has been a significant obstacle for the Afghan administration for quite some time. As a result, most of the population severely suffer from this phenomenon. In this study, we measured poverty indices based on two approaches, income and expenditure, in two different periods, before COVID-19 and During COVID-19, for provincial capital of Balkh province, Mazar-i-Sharif city. Overall, the findings indicate that poverty is a serious issue in Mazar-i-Sharif city and almost two third of its population are below the poverty line in each period. In addition, it is found that either use income or expenditure approach, the poverty indices are estimated to be high during the pandemic compared to pre-pandemic time. During the pandemic not only, more households fell into poverty but also the depth and severity of poverty among poor households also relatively increased. Furthermore, the result shows that poverty indices are estimated to be greater based on expenditure approach than income, and especially during the pandemic. Hence, it is matter whether use income or expenditure approach in measuring poverty indicators, particularly during the pandemic or other economic shock.

Besides, the main reason for poverty in Afghanistan is poor governance. Because for the last two decades a significant amount of money ($77 billion) was injected in the country through Official Development Aid (ODA) and around $2 billion was inflowed between 2002-2019 through FDI to develop the economy, but still, millions of people are suffering economically. So, it shows that the Afghan government did not achieve well, particularly in terms of poverty. Thus, the current study suggests that to reduce poverty rate in the country, Afghan government should focus on how to make a good governance and reduce corruption, economic and political instability to enhance the growth.

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ARAŞTIRMA MAKALESİ / RESEARCH ARTICLE

A CROSS SECTIONAL ANALYSIS ON THE IMPACTS OF ICT ON TURKISH MANUFACTURING INDUSTRY*

Yasemin ÖZBAL**

Abstract

This paper aims to examine the impacts of information and communication technologies (ICT) on firm-level productivity in Turkish manufacturing industry. The dataset used in this paper was obtained from merging TURKSTAT's Annual Industry and Services Survey and ICT Usage in Enterprises Survey results. This study examines 2009 and 2019 data and estimates the impacts of ICT usage and ICT using labor on labor productivity to understand if the adoption of digitalization had impacts on firm-level productivity of the manufacturing industry throughout the ten years period. The results of the empirical analysis suggest a positive impact of ICT usage and ICT using labor on all technological levels of the manufacturing industry, however according to two-digit breakdown of manufacturing sectors indicate that only nine out of twenty-two sectors have statistically significant results on ICT usage.

Keywords: ICT, ERP, CRM, Software, Labor productivity, ICT labor, Manufacturing Industry, Turkey
JEL codes: D24, J24, O14

1. Introduction

Industry 4.0 or the Fourth Industrial Revolution became a topic of discussion when the German government promoted the computerization of the manufacturing industry in 2011. The "new" industrial revolution is stimulated by digital technologies, especially robots, artificial intelligence, the internet of things, 3-D printing, cloud computing, different types of software which enable companies to communicate and do business with their partners and customers, and other recent technologies. Using the methods of Information and Communication Technologies (ICT) and digital technologies, especially in the production process, lies at the heart of the Fourth Industrial Revolution.

According to a report from Boston Consulting Group (2015), the impacts of "Industry 4.0" will be significant in the next 10-15 years; the report forecasts that *"in Germany alone "Industry 4.0" will*

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contribute about one percent per year to GDP over ten years, create as many as 390,000 jobs, and add €250 billion to manufacturing investment (or 1 to 1.5 percent of manufacturers' revenues)." [1]

A business survey conducted by Pricewaterhouse Coopers (PWC) in 2016 to more than 2000 enterprises from nine major industrial sectors and 26 countries shows that the developments in digitalization will transform enterprises as well as market dynamics. According to this survey's results, the nine industries which were surveyed and that plan to invest US$907 billion per year globally in Industry 4.0 applications over the next five years were expecting annual digital revenue increases of 2.9 % on average and a minority of the enterprises surveyed expected 50 percent increases in their digital revenues.

By implementing information and communication technologies, organizations become more flexible in the production process and adapt themselves for user-end requirements. ICTs help provide connectivity and interoperability between organizations, their partners, and their customers through facilitating their storing, sharing, and processing information. (Perakovic, et. al. 2019).

Until 2000s, the studies exploring the contribution of ICT and digitalization to productivity did not find a deep impact on productivity. However, after the beginning of 2000s, the studies that are estimating the impacts of ICT on productivity growth have found stronger results (Stiroh, 2002; Brynjollfson and Hitt, 2003; Maliranta and Rouvinen 2004, etc.). Despite a wide range of studies on ICT and productivity in the U.S., Europe and emerging countries, there are only a few studies examining the impacts of ICT on output and productivity in Turkey. The main purpose of this study is to observe the Turkish firm data and the impacts of ICT on firm-level productivity in the Turkish manufacturing industry. It is important to analyze the effects of ICT utilization on firm level since the usage of ICT at the firms operating in manufacturing industry and other sectors became widespread in the past 10 years. This study will examine, how the spread of digitalization had impacts on manufacturing sectors, by different levels of technology. Although many authors have examined the ICT and productivity relationship, there is still a need to explore it by technological breakdown of the sectors considering the fact that different sectors might be affected in diverse levels.

In consideration of the fast adoption of digitalization by Turkish firms, this study's aim is to contribute the literature on the impacts of ICT to productivity analysis in Turkey from the perspective of Industry 4.0 and the digital transformation of Turkish firms. The study is organized as follows. The second section summarizes the related literature on the relationship between productivity and information and communication technologies. Third section provides quick facts and data on the ICT usage in Turkey in recent years. The fourth section is describing the data used in this study and the fifth section presents the results of the cross-section analysis using the data from TURKSTAT. The sixth section concludes the paper.

1 Boston Consulting Group, "Industry 4.0 The Future of Productivity and Growth in Manufacturing Industries", 2015

2. Literature Review

While there are several studies which emphasize the relationship between digitalization and productivity globally, especially in developed countries as United States, European Union countries and Australia, there are few studies conducted in this field in Turkey.

The origin of the impacts of "computer" or the "digital transformation" on production was initiated with Robert Solow's famous quote on New York Times Book Review in 1987: "You can see the computer age everywhere but in the productivity statistics." Solow questioned the reason behind the slowdown in productivity growth in the United States and developed countries in the 1970s and 1980s despite rapid development in the field of information technology. Since then, this idea was conceptualized as the "Solow paradox" to explain the slowdown in the productivity during a period when investment in information technologies is high.

Several studies have analyzed the empirical relationship between ICT and productivity in various performance measures, such as growth, productivity, and profitability. Earlier studies assessing the impacts and contributions of information and communication technologies to firm productivity encountered problems. Especially studies that observe American firm-level productivity data of the 1970s and 1980s had experienced negative correlations with economy wide productivity and information worker productivity (Brynjolffson 1993). Brynjolffson (1993) summarized a review on 18 articles that assess the impacts of IT on manufacturing industries, services sectors and both. He explains the shortfall of IT productivity or the disappointment in IT to the firm productivity levels because of deficiencies in measurement and methodologies used in these previous studies as well as because of mismanagement by developers and users of IT.

Later on, studies in the 2000s observed a significant contribution of IT to the productivity and output growth. The research of Brynjolfsson and Hitt (2003) which focuses on the impacts of computerization to firm-level productivity in the United States between 1987-1994, find out that for a sample of large-size firms, computerization contributed to the productivity and output growth in short term which is consistent with computer investments. Moreover, IT's contribution is even higher over longer-term periods.

A study by Barker, Fuss and Wavermann (2008) analyzed Australian firm data and other 17 OECD countries within a period covering 1980 to 2003. The results of their estimations indicate that the labor productivity increased throughout the years (from 1980 to 2003) with a contribution of ICT investment (IT usage, network penetration, etc.). Besides they also examine the potential spillover network and externality effects of ICT (ICT spillovers).

Maliranta and Rouvinen (2004) explore the use of ICT in Finnish business enterprises and observe the micro-level firm data in Finland between 1992 and 2001. According to the "lower bound estimate" of excess productivity of ICT-equipped labor, the additional productivity of ICT-equipped labor ranges from 8% to 18% where this effect is much higher in younger firms and in ICT-providing activities. Another result they found out from the estimations is that the excess productivity is somewhat higher in the services sector than the manufacturing sector where the manufacturing sector benefits from the ICT-induced efficiency through internal communication while the services sector benefits through external communication.

The studies on developing countries have mixed results. Basant et. al. (2006) study Brazilian and Indian firms by implementing a survey for a three-year period (2001-2003) and find out that in both countries, econometric evidence displays a strong relationship between ICT capital and firm productivity. Crespi & Zuniga (2012) examine the relationship between technological innovation and firm productivity in six Latin American countries (Argentina, Chile, Colombia, Costa Rica, Panama, and Uruguay) since prior studies could not establish the relationship because of survey and sampling methodologies. According to their findings, in all countries they made the research, firms that invest in knowledge and use innovation increased their labor productivity compared to other firms that did not; on the other hand, they found out that firm-level determinants of innovation investment were more heterogenous than in OECD countries.

Another study on Brazilian and Indian firms by Commander, Harrison and Menezes-Filho (2011), uses a unique data set constructed by a survey that has been implemented in both countries between April and May 2005. This study pioneers an innovative way while using the Indian firm data: It investigates the policy implementations and institutional environment on ICT capital investment and productivity. Similar to previous studies in the field; using a production function estimation, they break down the capital into two: Physical capital and ICT capital stock and also use other measures to identify the adoption of ICT with dummy variables. According to their different estimation results – in line with some evidence from studies on developed countries, there have been very high returns to ICT for both countries. Moreover, they analyze the impacts of policy and institutional environment on ICT adoption in India (since they do not have sufficient data for Brazil), and the results suggest that poorer infrastructure quality and pro-worker labor regulation are associated with lower levels of ICT capital intensity.

More recent studies in the 2010s, using a total factor productivity approach, estimate the contribution of ICT to productivity and output growth; while some of them find a smaller contribution to the TFP growth (Hawash, Lang, 2020), some of them have much more optimistic results where they find the significant contribution of ICT (Gal, et al., 2019). Hawash and Lang (2020), using panel data of 76 developing countries from 1991 to 2014, estimate the impact of ICT on total factor productivity (TFP) by three different approaches. In contrast to prior studies that were involved in the impacts of ICT on productivity, their results show that ICT has a limited impact on TFP growth. The estimation results reveal that both ICT investments and physical ICT usage of households' variables are significant and have a positive impact on TFP, however, it is a diminishing and modest impact.

Tambe and Hitt (2012), in their study, using a dataset they created themselves by matching firm-level IT employee data from a large sample of information technology workers (that they collect through an online job-search website) and with production inputs for approximately 1,800 firms across 20 years (from 1987 to 2006) in the United States. Since IT-using workers are subject to endogeneity bias, they found that the endogeneity does not substantively affect current IT estimates. The second finding in their study is that large and midsize firms are doing similar IT investments, although large firms have greater marginal products from these investments, while midsize firms benefit from these investments in the short-run. Their third finding is that the marginal product of IT using workers is higher (and accelerating) in the period 2000-2006 than in the prior years (1987-1999) in firms of all sizes, which contradicts the previous works suggest that the link between IT spending and productivity may have changed since 2000 (Jorgenson et al. 2008).

Harrigan, Reshef and Toubal (2018), using French firm data between 2009 and 2013, analyze the impacts of firm-level choices of ICT, R&D, exporting and importing on the evolution of productivity. To estimate firm-level productivity, they use a methodology allowing to measure both Hicks-neutral and skill-augmenting technology differences. They measure the adoption of ICT in the firms through the workers using ICT, whom they call "techies". According to their estimation results, both employment of "techies" and offshoring (exporting and importing) are orienting the firms to employ more skilled and unskilled workers. The results of the estimation also show that in between French firms which employ "techies" have skill-augmenting productivity which is 60 percent higher compared to the firms which do not employ "techies".

Aboal and Tacsir (2018) study Uruguayan firm data to understand the determinants of investments in ICTs and in other innovation activities at the firm level in both manufacturing and services sector. To assess the Uruguayan firm level data, they use a unified econometric framework based on a version of the CDM model (based on the "Crépon, Duguet and Mairesse" study in 1998). According to their results, "The *ICTs seem to be more important for innovation and productivity in the services sector than in the manufacturing sector. Second, investment in all other innovation activities is more important for the introduction of technological innovations in the manufacturing sector than in the services sector. Third, non-technological innovations are more important for productivity in the services sector than in the manufacturing sector.*" Their findings suggest that investment in ICT increases the probability of both technological and non-technological innovations in manufacturing. In the same direction as Alvarez (2016) and Polder et al. (2009), they find that ICT investment seems to foster innovation in the services sector.

There are few studies focusing on Turkey where the results indicate that the impacts of ICT on firms' efficiency or productivity were positive. Atasoy, Banker and Pavlou (2016) examine the longitudinal role of IT use in the firm's total number of employees. They use Information and Communication Technologies Usage in Enterprises Survey from TURKSTAT, which covers the period of 2007-2011 and establish a panel data set from it. To analyze the effects of IT use on firm-level employment, they use a "firm fixed effects model". The aim to use this model is to identify the within-firm changes in IT use and firm-level employment over time, and not by permanent unobserved differences across firms. The estimation differs by IT application types and moderated by three factors: Firm size, average wage rate, and industry technology intensity. According to their results, the use of enterprise applications affects firm-level employment over time, whereas the effects of the use of Web applications materialize in the current year. They found a positive relationship between IT use and firm-level employment on average, and the relationship varies by the category of IT applications.

The study of Kılıçaslan, Sickles, Kayış, and Üçdoğruk Gürel (2017) examines the impacts of ICT on labor productivity growth in the Turkish manufacturing sector. Using TURKSTAT's firm data from Annual Industry and Services Statistics, they develop a measure of the stock of capital, separating it as "conventional capital" and "ICT capital". They construct capital stock series by using the perpetual inventory methodology; they use the yearly amortization allowances to measure the capital stock and derivate the ICT investment from the investment, which includes office and computing equipment, communication equipment, and software investment. Two different models are estimated in the study, the first is the growth accounting approach, while the latter is using the generalized methods of moments method to estimate the impacts of ICT on labor productivity. According to their growth accounting model results, ICT capital has no special contribution compared to conventional capital in value-added growth in the Turkish manufacturing industry with some exceptions. However, according to the static and dynamic panel data models, the ICT capital's contribution to labor productivity in the manufacturing industry is around 15-20 percent larger than the conventional capital's contribution.

Most recently, Taştan and Gönel (2020) analyze the impacts of information and communication technologies on firm-level productivity in Turkey, using firm-level data sets and constructing an unbalanced panel data set covering the period 2007-2014. This study includes parameters to estimate the impacts of ICT, such as software investments, indicators for the usage of enterprise system applications (ERP, CRM, SCM), and ICT labor. According to their estimation results, there is a positive relationship between firm productivity and ICT use; the empirical results also support the complementarity hypothesis between ICT labor and software usage variables. They had similar results as existing studies for developed and developing countries that find a positive relationship between ICT usage and productivity. In addition, they also find out that, while the ICT investments and usage have positive returns in both manufacturing and services sectors, the effect is higher for the firms in the services sector.

In most recent study of Taştan (2021), he uses a descriptive model where he investigates the impacts of ICT on firm productivity. The ICT indicators are classified under three groups: Software, infrastructure and organizational structure. This study only observes 2017 data and estimates the impacts of ICT on labor productivity. According to the estimation results, in both manufacturing and services sectors, the intensity of ICT usage and the share of ICT using labor in total have a complementary relationship. Although this study does not imply there is a causality between ICT and productivity, the results indicate ICT using firms have relatively higher levels of productivity.

The related literature which analyzes the relationship between ICT and productivity in Turkey mostly focuses on aggregate productivity and the firm productivity on the manufacturing and services sector. This study will contribute the literature by examining the manufacturing industry on sectoral and technological level based on NACE Rev. 2 two-digit level and according to their technological intensity based on Eurostat classification.

3. The ICT Usage in Turkey in Recent Years

In Turkey, the ICT sector started to improve and increase at a faster pace in the mid-2000s. According to Informatics Industry Association in Turkey (TUBISAD), in the past five years, the market size of ICT in Turkey increased with an average pace of 23 percent (TUBISAD, 2013 & 2020). The information technologies (computer equipment, software, and other services) market size increased with a faster average pace of 29 percent while the communication technologies' market size increased with an average pace of 19 percent between 2017-2021.

According to TURKSTAT data, the usage of both Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM) in all sectors increased in the recent years [2]. While ERP usage in enterprises increased from 17.8 percent share in 2012 to 28 percent in 2021 in all sectors, CRM usage increased from 9.2 percent share in 2012 to 10.6 percent in 2021. Although the usage of Supply Chain Management (SCM) was only asked in 2012 and 2017, a decrease of share in the total and in the manufacturing, sector is observed, which implies that sectors are probably shifting from SCM usage to ERP and CRM. The usage of ERP and CRM increased higher in the manufacturing sector compared with the total. (See Table 1.) TURKSTAT provides the following data starting from 2012

Table 1: The Share of Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), and Supply Chain Management (SCM) Software Usage in All Sectors and Manufacturing Sector from 2012 to 2021

All sectors				Manufacturing (Section C)			
Period	**ERP**	**CRM**	**SCM**	**Period**	**ERP**	**CRM**	**SCM**
2012	17.8	9.2	17.5	**2012**	21.7	7.3	19.3
2013	18.7	8.8	-	**2013**	22.7	7.8	-
2014	14.3	7.5	-	**2014**	14.2	5.5	-
2015	20.1	9.2	-	**2015**	24.3	7.5	-
2016	-	-	-	**2016**	-	-	-
2017	13.9	18.8	9.0	**2017**	16.1	18.5	8.2
2018	-	-	-	**2018**	-	-	-
2019	20.5	18.5	-	**2019**	25.9	19.4	-
2020	-	-	-	**2020**	-	-	-
2021	28.0	10.6	-	**2021**	30.9	9.8	-

Source: Turkish Statistical Institute (TURKSTAT), Survey on Information and Communication Technology (ICT) Usage in Enterprises, 2022

Note: All values reflect economic activity (NACE Rev.2. Period is the reference period.

2 TURKSTAT's "Survey on Information and Communication Technology (ICT) Usage in Enterprises" do not include agriculture, banking, and finance sectors.

According to TURKSTAT data, the usage of internet in Turkish enterprises increased from 90.9 percent in 2010 to 94.9 percent in 2019 while the rate of firms that use platforms for web sales increased from 12.3 percent in 2010 to 77.1 percent in 2019. The latter data indicate a fast adoption of digitalization in most of the enterprises (which indicates a fast spread of e-commerce) even though Turkey might be classified as a late adopter in terms of digitalization. Due to differentiating survey questions, TURKSTAT provides the proportion of enterprises employing ICT/IT specialists by size group from 2014 to 2022. While the proportion of enterprises employing an IT/ICT specialist was 10.5 percent in 2014, it increases to 13.7 percent in 2019 and to 17.8 in 2022. The increase is much more distinguishable in large size firms (employing over 250 people), the share of enterprises employing an IT/ICT specialist increases from 53.7 percent in 2014 to 72.6 percent in 2022, while it increases from 7.1 percent to 13.8 percent for small size firms and 20.5 percent to 32.3 percent for medium size firms.

4. TURKSTAT Data and Descriptive Statistics

In this study, two datasets from the Turkish Statistical Institute (TURKSTAT) obtained from annual surveys conducted to all enterprises in Turkey are merged and combined. The first dataset is the Annual Industry and Service Statistics which is based on Turkish Revenue Administration and Social Security Institution's administrative data and Annual Industry and Service Statistics Investment Expenditure Survey results. It provides data on the turnover, the number of persons employed, the number of employees, value-added at factor cost, production value, personnel cost, total purchases of goods and services, change in stocks of goods and services. The sectors of the enterprises are classified by NACE Rev.2.

The second dataset is extracted from the Information and Communication Technologies Usage in Enterprises Survey which is in line with European Statistical Office (Eurostat) methodology. This dataset covers the enterprises and businesses from the manufacturing, construction, retail and wholesale trade and services sectors. TURKSTAT states that they use Stratified Random Sampling by taking into account the economic activities (in accordance with NACE Rev.2) and enterprise size according to the number of employees. The size-classes used are small enterprises (10–49 persons employed), medium-sized enterprises (50–249 persons employed) and large enterprises (250 or more persons employed). All censuses for enterprises with 250+ persons employed are included meanwhile they used sampling for 10-49 and 50-249 size groups. TURKSTAT states they applied weighting method to obtain parameters from the dataset resulting from sampling so as to represent the universe. [3] These parameters include design weights [4], adjustments for non-response, external distribution checks and ultimate multiplying factor. For instance, there are 6,054 observations in the 2009 dataset and 12,336 observations in the 2019 dataset.

3 Details of TURKSTAT's weighting method are provided in the "Accounting Conventions" of ICT Usage Bulletin: https://data.tuik.gov.tr/Bulten/Index?p=Girisimlerde-Bilisim-Teknolojileri-Kullanim-Arastirmasi-2022-45585

4 Since weighted data is used in the regression, heteroskedasticity test cannot be run, therefore the t statistics results are checked.

Both surveys include same enterprises' dataset; however, since ICT Usage in Enterprises Survey do not include the enterprises' value-added, turnover, total number of employee information, both survey datasets are combined by using a key code provided by TURKSTAT. Following parameters from the ICT Usage in Enterprises Survey are used in this study's analysis: Software usage, using webpage to sell online, and the share of internet using personnel or employees.

Three software are included in the ICT Usage in Enterprises Survey. Enterprise Resource Planning (ERP) helps an enterprise for purchases, sales, marketing, finance, management, human resources and organizes these activities under an integrated system and reports. ERP software supports managers to provide information much more quickly for their decision-making. Thus, it promotes the productivity and the profitability of enterprises through which increases their competitivity in their sector. ERP is used by enterprises since the 1990s. Customer Relationship Management (CRM) is saving, evaluating, reporting, and analyzing the data deduced from all the interaction of the business and its customers. There is less costing CRM software in recent years thus it is accessible for small-sized enterprises as well. Supply Chain Management (SCM) software is the software tools or modules used in executing supply chain transactions, managing supplier relationships, and controlling associated business processes in all sectors. Supply chain management maximizes the efficiency of business activities that include planning and management of the entire supply chain which helps businesses in product development, sourcing, production, and logistics by automating operations. Therefore, it increases the physical flow of business as well as informative flow.

Using a webpage to sell the products or services online is an indicator that is used to observe the impacts of digital infrastructure on the firms' profitability and efficiency. Similarly, the share of the personnel using internet is used to observe the impacts of internet/digitalization on the firms' productivity.

Other essential indicators such as internet speed which allows businesses to facilitate their business processes are also provided in the ICT Usage in Enterprises Survey after 2012. Grimes, Ren and Stevens (2012) found out from their analysis on 6,000 firms in New Zealand (from a survey conducted in 2006) that broadband adoption boosts firm productivity by 7-10%; effects are consistent across urban versus rural locations and across high versus low knowledge-intensive sectors. Although Bertschek, Cerquera and Klein (2013) found out from their analysis on German firm data (between 2001-2003) that broadband Internet has no impact on firms' labor productivity, whereas it exhibits a positive and significant impact on their innovation activity. The employment of information technologies (IT) personnel and providing education to IT personnel are also the indicators that are provided in the ICT Survey after 2012. In this study's cross-sectional analysis, the latter indicators were not available since they are provided in the surveys after 2012. An extended model for the 2019 dataset, adding these indicators, were presented in the fourth section. To understand if the adoption of digitalization had impacts on firm-level productivity throughout the ten years period, this study examines 2009 and 2019 data and estimates the impacts of ICT usage and ICT using labor on labor productivity.

Table 2: The Percentage of ICT Using Firms (2009 – 2019)

Year	ICT	All firms N	All firms (%)	Manufacturing firm N	Manufacturing firms (%)	High-tech (%)	Mid-high tech (%)	Mid-low tech (%)	Low tech (%)
2009	ERP	6.054	23%	2.267	31%	58%	44%	31%	25%
	CRM	6.054	14%	2.267	11%	18%	16%	9%	10%
	Web Page	6.054	67%	2.267	75%	88%	89%	80%	66%
	Web Order	6.054	12%	2.267	10%	10%	13%	10%	8%
2019	ERP	12.644	44%	4.386	56%	61%	68%	57%	49%
	CRM	12.644	31%	4.386	32%	40%	37%	33%	29%
	Web Page	12.644	73%	4.386	81%	92%	89%	85%	74%
	Web Order	12.644	13%	4.386	11%	11%	10%	8%	12%
	IT Specialist	12.644	39%	4.386	46%	51%	55%	46%	41%
	Internet Speed	12.644	56%	4.386	54%	62%	60%	54%	51%

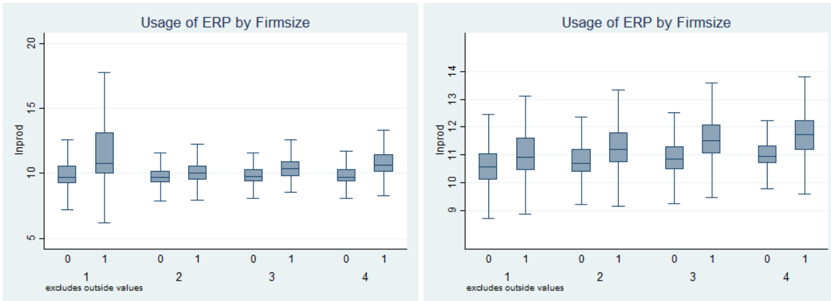
Source: Author's calculations based on TURKSTAT Annual Industry and Services Survey and ICT Usage in Enterprises Survey 2009 and 2019 datasets.

TURKSTAT's ICT Usage in Enterprises 2009 dataset covers 6,054 observations, and 2019 dataset covers 12,644 observations. From these datasets, it can be observed that the share of ERP and CRM using enterprises in total increases in 10 years from 23 percent to 44 percent and from 14 percent to 31 percent respectively. Meanwhile for the manufacturing sector it is more distinguishable; the share of ERP using firms increases from 31 percent in 2009 to 56 percent in 2019 and the share of CRM using firms increases from 11 percent in 2009 to 32 percent in 2019. (See Table 2).

According to firm size differentiation, it is observed that the logarithm of the value added at factor cost per employees (labor productivity) of the firms using ERP software is higher in all size of firms. In 2019, the gap of labor productivity increases (See Figure 1.a). Similar results are observed for the firms that are using CRM in 2009 and 2019; the labor productivity of the firms using CRM software is higher than the ones that are not using in both 2009 and 2019 (See Figure 1.b). However, in 2019, the gap between the firms using CRM software and the firms that are not using is very low.

Figure 1: The Boxplot of Labor Productivity (natural logarithm) and Usage of ERP by Firm Size (2009 and 2019)

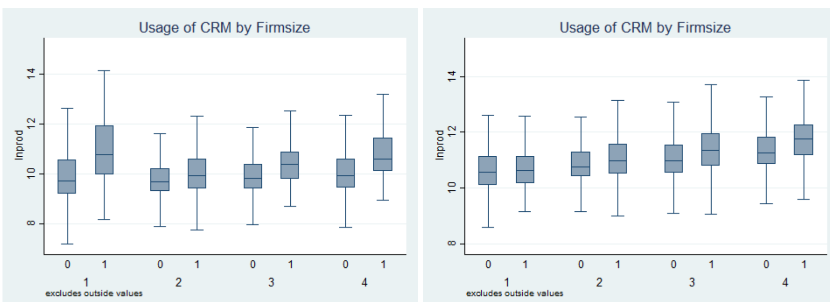
a) Usage of ERP by Firm Size



Source: Author's calculations based on TURKSTAT Annual Industry and Services Survey and ICT Usage in Enterprises Survey 2009 and 2019 datasets.

Notes: 0 and 1 represents the firm not using or using ERP software. The firm size is classified as micro sized (0-9 employees) as 1, small sized (10-49 employees) as 2, medium sized (50-249 employees) as 3 and large sized (250 and over employees) as 4.

b) Usage of CRM by Firm Size



Source: Author's calculations based on TURKSTAT Annual Industry and Services Survey and ICT Usage in Enterprises Survey 2009 and 2019 datasets.

Notes: 0 and 1 represents the firm not using or using CRM software. The firm size is classified as micro sized (0-9 employees) as 1, small sized (10-49 employees) as 2, medium sized (50-249 employees) as 3 and large sized (250 and over employees) as 4.

5. An Empirical Analysis on Firm Productivity in Turkey Using Digitalization Data

The cross-sectional regression helps to explain observations collected from many different individuals, or in our case enterprises, at a given time. Since the data from ICT Usage in Enterprises Survey includes observations from many different businesses each year and it also lacks some of the indicators every year, the cross-sectional analysis is the eligible method to observe the data in time.

Following the related literature and former studies, this study investigates if the firms that adopted a digitalization method (the software ERP, the software CRM, the webpage, the share of the personnel which uses the internet while executing their tasks) have higher productivity level. Therefore, two models to examine the relationship between ICT indicators and firm productivity in the manufacturing sectors separately are built, the latter including additional indicators.

5.1 Baseline Model

The model in this study is similar to one used by Taştan (2021), which observes the impacts of ICT usage on firm productivity. Since the dataset of ICT Usage in Enterprises Survey includes binary variables such as "using a software" (where the answer is Yes or No), and numerary variables such as "the number of personnel using internet", a linear regression model is the most applicable for this study. To observe the productivity level of the enterprises, the value added of each firm is divided by the total number of their employees. Then, the logarithm of the labor productivity and share of the internet using employees in total are taken since the range of values of the productivity level and the number of employees between the enterprises are large, and through logarithmic estimates the distribution of values is less skewed. The first model is as follows:

$$logproductivity_i = \beta_0 + \beta_1 ERP_i + \beta_2 CRM_i + \beta_3 WebPage_i + \beta_4 shareinternetemployee_i + u \quad \text{(Model 1)}$$

Where "log productivity" is the natural logarithm of labor productivity (which is measured by dividing the value added of each firm by their number of personnel) of firm "i", "ERP" and "CRM" are the software use as the indicators of ICT usage of firm "i", "Web Page" indicates the firm "i" using a webpage of their own or outsource it to sell their products online, "share internet employee" is the share of the internet using employees in total of firm "i" and u is the error term.

In the following ordinary least squares (OLS) estimation, the indicator "factor" (which is the coefficient for micro, small and medium-sized firms) is used, since TURKSTAT only gathers information from a representative number of firms from SME sized firms in the ICT Usage in Enterprises Survey. The t statistics computed from heteroskedasticity robust standard errors under the OLS for each estimation are checked and when the t statistics are higher than 0.05, the indicator is considered as statistically insignificant. The results from the estimations are grouped by the technology classification from Eurostat. Table 3 below provide the results of the OLS estimation of the baseline model for the years 2009 and 2019.

Table 3: OLS Estimation Results for Baseline Model by Technological Breakdown of Manufacturing Industry – 2009 Results

Technology level	High technology	Medium-high technology	Medium-low technology	Low technology
ERP	1.020***	0.454***	0.600***	0.287**
	(0.307)	(0.109)	(0.146)	(0.113)
CRM	0.340	-0.025	0.049	0.095
	(0.353)	(0.162)	(0.232)	(0.117)
WebPage	0.643***	0.323**	0.246**	0.219***
	(0.238)	(0.150)	(0.104)	(0.060)
shareintemployee	0.011***	0.080***	0.113***	0.111***
	(0.000)	(0.022)	(0.023)	(0.026)
Constant	9.548***	9.540***	9.629***	9.510***
	(0.184)	(0.140)	(0.078)	(0.046)
Observations	49	424	669	1,058
R-squared	0.512	0.153	0.134	0.152

Source: Author's calculations based on TURKSTAT Annual Industry and Services Survey and ICT Usage in Enterprises Survey 2009 and 2019 datasets.

Note: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3: (Continued): OLS Estimation Results for Baseline Model by Technological Breakdown of Manufacturing Industry – 2019 Results

Technology level	High technology	Medium-high technology	Medium-low technology	Low technology
ERP	0.608***	0.355***	0.429***	0.388***
	(0.174)	(0.106)	(0.091)	(0.079)
CRM	0.102	-0.045	-0.041	-0.084
	(0.192)	(0.110)	(0.086)	(0.128)
WebPage	0.399**	0.557***	0.327***	0.395***
	(0.175)	(0.084)	(0.099)	(0.079)
shareintemployee	0.607***	0.062***	0.039*	-0.052
	(0.227)	(0.004)	(0.022)	(0.056)
Constant	10.708***	10.738***	10.762***	10.605***
	(0.169)	(0.066)	(0.085)	(0.044)
Observations	302	846	1,056	2,018
R-squared	0.536	0.159	0.110	0.092

Source: Author's calculations based on TURKSTAT Annual Industry and Services Survey and ICT Usage in Enterprises Survey 2009 and 2019 datasets.

Note: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

According to estimation results for the cumulative technological breakdowns, usage of ERP software is statistically significant and has a positive sign for all technological levels of manufacturing sectors. On the other hand, usage of CRM is statistically insignificant for all technological levels. Owning a web page is also statistically significant and has a positive sign for all technological levels, however, share of internet using employees which is statistically significant becomes insignificant for low technology and medium-low technology manufacturing sectors in 2019. Therefore, more detailed sectoral estimations are conducted.

OLS estimation results of the NACE-2 two-digit sector breakdown of the manufacturing industry are in line with estimation results for the technological breakdown. The results for two sectors – production of tobacco (12) and production of petroleum products (19) were omitted due to lack of observations. Manufacturing industry sectoral breakdown's estimation results are presented in the Appendix (See Tables A.1 and A.2). For some sectors, there are interesting results:

High-technology sectors (21, 26):

According to estimation results, ERP usage and share of internet using employees are statistically significant for both high-technology sectors (pharmaceuticals – 21 and computers – 26) in 2009 and 2019. While using CRM and owning a web page are only statistically significant for computers sector (26) in 2009, they are only statistically significant for pharmaceuticals (21) in 2019.

Medium-high technology sectors (20, 27, 28, 29, 30):

For the medium-high technology sectors, the estimation results indicate that ERP usage is statistically significant for all medium-high technology sectors in 2009 except for manufacture of electrical equipment (27) in which CRM usage is statistically significant. In 2019, the ERP usage becomes statistically insignificant for all of them except it becomes significant for electrical equipment sector (27). The results are not in line with the cumulative "medium-high technology" estimation.

Medium-low technology sectors (19, 22, 23, 24, 25, 33):

While ERP usage is statistically significant for the sectors "rubber and plastic products" (22), in both 2009 and 2019, it is significant for "fabricated metal products, except machinery and equipment" (25) sector in 2019. The webpage indicator is statistically significant for "rubber and plastic products" (22) in 2019. The share of internet using employees is significant in 2009 and insignificant in 2019, which is in line with the cumulative "medium-low technology" estimation.

Low-technology sectors (10, 11, 12, 13, 14, 15, 16, 17, 18, 31, 32):

The estimation results show that the ERP usage is statistically significant and has a positive sign for the sectors food products (10), wood and of products of wood and cork, except furniture (16), and paper and paper products (17) in 2009; and ERP usage becomes statistically significant and has a positive sign for sectors textiles (13), wearing apparels (14), in 2019.

First model's estimation results indicate that both in 2009 and 2019, nine manufacturing sectors (out of 20 sectors that were eligible to conduct an estimation) that using the software ERP have a positive returns to their labor productivity. Having a webpage also have a positive returns to the labor productivity of nine sectors in 2019.

5.2. Extended Model

Extended model includes more indicators representing firm digitalization. This model was only able to be executed for the year 2019 since 2009 data do not cover the following additional indicators. The second model is as follows:

$$logproductivity = \beta_0 + \beta_1 ERP_i + \beta_2 CRM_i + \beta_3 webpage_{\ i} +$$
$$\beta_4 shareinternetemployees_i + \beta_5\, internet\ speed_i + \beta_6\, ITspecialist_i + u$$

(Model 2)

This model includes two more indicators to the first one where "internet speed" is the indicator which shows if the internet speed of firm "i" is higher than 30 megabits per second, "IT specialist" indicates if the firm "i" hires an information technology specialist or more than one employee (the exact number of employee is not provided in the Survey), and "u" is the error term. IT employee's educational training was also used in the estimation however excluded due to the correlation with the "IT specialist" indicator. The results are included in the Appendix (See Table A.3).

OLS estimation results for all manufacturing industry sectors in 2019 indicate that employing an IT/ICT specialist is statistically significant for ten out of twenty the manufacturing industry sectors (that were eligible to conduct an estimation), while the internet speed is only statistically significant for six sectors. For both high-technology manufacturing sectors employing an IT specialist and using a high speed internet connection are statistically significant and have positive signs, and surprisingly, only for some medium-low and low-technology sectors employing an IT/ICT specialist is statistically significant.

Although this study is the first which is observing the breakdown of the manufacturing industry based on NACE Rev. 2 sectors in two-digits, the results are in line with previous studies on the impacts of ICT to productivity. The results do not imply a direct relationship between ICT and firm-level productivity in whole manufacturing sector, but it is observed that using a software (especially ERP) in this case has a broad-based impact on the manufacturing sector, meanwhile the share of internet using personnel and the employment of an IT personnel has an impact on the labor productivity of some sectors.

The results of OLS estimation from baseline model indicate that the labor productivity level of high technology sectors pharmaceuticals (21) and computers (26), and medium-high technology level sector electrical equipment (27) are consistently and positively impacted by the usage of ERP software. Since these mentioned sectors were stated to have high labor productivity levels and to invest more in research and development (Doğruel and Doğruel, 2008), the estimation results are coherent with former studies. The estimation results also indicate that for sectors medium-low technology level sectors rubber and plastic products (22), and fabricated metal products, except machinery and equipment (25) and low-technology level sectors food products (10), textiles (13); and paper and paper products (17), the usage of ERP has positive impacts on the labor productivity.

Although the estimation results do not imply a direct relationship between the labor productivity and ICT indicators such as ICT usage and share of internet using employees in total, it is observed by the technological breakdown and sectoral breakdown that ERP using firms and the share internet using employees in total have positive impacts on the labor productivity of the firms with higher technology. Therefore, the estimation results of this study indicate that firms that are investing on ICT software (ERP) and ICT infrastructure (internet speed) would have higher level of labor productivity, in line with former studies on Turkey. The relationship might also be the reverse, the firms with higher level of labor productivity would invest to ICT software and ICT infrastructure to increase their output and profit. One of the issues about calculations is that the ICT capital is not observed from the datasets, and this prevents to measure its impacts on productivity.

6. Conclusion

In this study, the impacts of ICT on firm-level productivity in Turkish manufacturing industry based on NACE Rev. 2 two-digit level are analyzed with an aim to observe if ICT has differing impacts on different technological intensity levels. Our approach is similar to previous studies, especially Taştan's (2021) recent study on the firm-level evidence from Turkey, and Maliranta and Rouvinen's (2004) article about the use of ICT in Finnish business enterprises.

Unfortunately, the lack of data and observations prevents doing a more comprehensive research using other ICT indicators. An extended model using additional indicators for 2019 dataset was also carried out. The analysis shows that internet speed and IT employment are statistically significant for some of the sectors and have a positive impact on productivity. This should be assessed carefully because the lack of data (about the investments of the enterprise, the age of the enterprise, the organizational structure, etc.) prevents to do a more detailed research.

Based on the aforementioned estimation results, some policies for the enterprises and policymakers might be suggested. Given that the software usage, especially the Enterprise Resource Planning has a positive impact on labor productivity on more than half of the manufacturing industry in Turkey, training to improve the personnel that are using the software would be strongly recommended. Since the adoption of ICT-usage has a positive impact on firm productivity, central government and policymakers might implement policies that will encourage the firms to adopt more digitalization; these policies will include technology-based incentives, loans and increasing the technological infrastructure of the organized industrial zones.

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Appendix

Table A.1: OLS Estimation Results for Baseline Model by Sectoral Breakdown of Manufacturing Industry – 2009

Technology level	Low technology										
NACE Code	10	11	12	13	14	15	16	17	18	31	32
Sector	Food products	Beverages	Tobacco products	Textiles	Wearing apparel	Leather and related products	Wood and of products of wood and cork, except furniture	Paper and paper products	Printing and reproduction of recorded media	Furniture	Other manufacturing
ERP	0.939**	0.124		0.242*	0.077	-0.083	3.036***	1.955***	0.175	0.377	-0.014
	(0.399)	(0.799)		(0.143)	(0.156)	(0.158)	(0.155)	(0.547)	(0.220)	(0.244)	(0.329)
CRM	-0.335	2.690**		0.520**	0.047	0.014	-0.585***	-0.844	-0.153	-0.139	0.344
	(0.216)	(0.797)		(0.203)	(0.131)	(0.136)	(0.023)	(0.522)	(0.209)	(0.307)	(0.300)
WebPage	0.408***			0.364**	-0.025	0.148	0.257	0.446	0.359	0.029	0.725*
	(0.124)			(0.143)	(0.098)	(0.197)	(0.272)	(0.377)	(0.234)	(0.309)	(0.404)
shareintemployee	0.096***	0.781***		0.141***	0.039	0.106	-0.463	-0.680***	0.220	0.265***	-0.477*
	(0.030)	(0.082)		(0.013)	(0.035)	(0.179)	(0.988)	(0.233)	(0.355)	(0.072)	(0.241)
Constant	9.584***	10.080***		9.495***	9.554***	9.531***	9.325***	9.648***	9.448***	9.326***	9.266***
	(0.093)	(0.422)		(0.112)	(0.069)	(0.162)	(0.289)	(0.311)	(0.249)	(0.300)	(0.377)
Observations	204	7		239	256	42	37	40	101	94	36
R-squared	0.276	0.951		0.323	0.022	0.029	0.055	0.368	0.062	0.244	0.231

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations based on TURKSTAT Annual Industry and Services Survey and ICT Usage in Enterprises Survey 2009 and 2019 datasets.

Table A.1: (Continued): OLS Estimation Results for Baseline Model by Sectoral Breakdown of Manufacturing Industry – 2009

Technology level	Medium-low technology						Medium-high technology					High-technology	
NACE Code	19	22	23	24	25	33	20	27	28	29	30	21	26
Sector	Coke and refined petroleum products	Rubber and plastic products	Other non-metallic mineral products	Basic metals	Fabricated metal products, except machinery and equipment	Repair and installation of machinery and equipment	Chemicals and chemical products	Electrical equipment	Machinery and equipment n.e.c.	Motor vehicles, trailers and semi-trailers	Other transport equipment	Basic pharmaceutical products and pharmaceutical preparations	Computer, electronic and optical products
ERP		0.694***	0.612*	0.573	0.426*	0.594	1.271***	-0.220	0.311**	0.823***	1.593***	1.298***	0.761**
		(0.182)	(0.321)	(0.429)	(0.222)	(0.725)	(0.329)	(0.245)	(0.155)	(0.236)	(0.315)	(0.321)	(0.272)
CRM		0.310	0.039	0.830*	-0.034	-1.419*	-0.439	0.604**	-0.161	0.167	-0.289	-0.171	0.761**
		(0.335)	(0.460)	(0.465)	(0.259)	(0.836)	(0.320)	(0.237)	(0.198)	(0.390)	(0.340)	(0.316)	(0.276)
WebPage		0.215	-0.005	0.874**	0.409**	0.007	-0.435	1.008***	0.333*	0.592	-0.833***	0.525	0.770***
		(0.201)	(0.230)	(0.338)	(0.181)	(0.312)	(0.400)	(0.177)	(0.200)	(0.448)	(0.267)	(0.329)	(0.216)
shareintemployee		0.084***	0.080***	0.110**	0.394***	0.508***	0.092***	0.321***	0.066***	-0.173	0.248	0.427***	0.012***
		(0.020)	(0.022)	(0.052)	(0.098)	(0.041)	(0.011)	(0.038)	(0.022)	(0.639)	(0.338)	(0.087)	(0.000)
Constant		9.584***	9.754***	9.265***	9.393***	9.731***	10.353***	9.101***	9.542***	9.065***	10.186***	9.705***	9.294***
		(0.178)	(0.139)	(0.243)	(0.152)	(0.201)	(0.323)	(0.094)	(0.178)	(0.453)	(0.191)	(0.269)	(0.034)
Observations		170	174	99	189	36	74	78	151	101	20	23	26
R-squared		0.257	0.116	0.277	0.153	0.456		0.402	0.136	0.278	0.615	0.784	0.685

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Source: Author's calculations based on TURKSTAT Annual Industry and Services Survey and ICT Usage in Enterprises Survey 2009 and 2019 datasets.

Table A.2: OLS Estimation Results for Baseline Model by Sectoral Breakdown of Manufacturing Industry – 2019

Technology level	**Low technology**										
NACE Code	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**31**	**32**
Sector	**Food products**	**Beverages**	**Tobacco products**	**Textiles**	**Wearing apparel**	**Leather and related products**	**Wood and of products of wood and cork, except furniture**	**Paper and paper products**	**Printing and reproduction of recorded media**	**Furniture**	**Other manufacturing**
ERP	0.615***	0.025		0.311***	0.416**	0.155	0.240	0.848***	0.258	0.070	0.018
	(0.226)	(0.710)		(0.092)	(0.200)	(0.222)	(0.199)	(0.187)	(0.182)	(0.097)	(0.331)
CRM	-0.030	-1.056**		0.107	-0.738	0.486*	0.158	-0.366*	0.061	-0.059	0.248
	(0.159)	(0.385)		(0.112)	(0.600)	(0.259)	(0.137)	(0.202)	(0.197)	(0.096)	(0.310)
WebPage	0.397	0.837**		0.199*	0.582***	-0.088	0.427**	0.319	0.257	0.232**	0.551**
	(0.249)	(0.389)		(0.105)	(0.155)	(0.191)	(0.187)	(0.294)	(0.159)	(0.105)	(0.219)
shareintemployee	-0.111	0.281		-0.004	0.014	0.799*	0.467*	-0.282***	-0.049	-0.058	0.324
	(0.102)	(0.577)		(0.148)	(0.196)	(0.475)	(0.253)	(0.097)	(0.229)	(0.080)	(0.413)
Constant	10.511***	11.282***		11.006***	10.414***	10.740***	10.365***	10.907***	10.703***	10.682***	10.398***
	(0.068)	(0.395)		(0.093)	(0.096)	(0.088)	(0.147)	(0.274)	(0.140)	(0.091)	(0.155)
Observations	452	21		479	457	49	104	132	71	182	67
R-squared	0.078	0.639		0.112	0.146	0.257	0.146	0.261	0.081	0.058	0.286

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Source: Author's calculations based on TURKSTAT Annual Industry and Services Survey and ICT Usage in Enterprises Survey 2009 and 2019 datasets.

Table A.2 (Continued): OLS Estimation Results for Baseline Model by Sectoral Breakdown of Manufacturing Industry – 2019

Technology level	Medium-low technology						Medium-high technology					High-technology	
NACE Code	19	22	23	24	25	33	20	27	28	29	30	21	26
Sector	Coke and refined petroleum products	Rubber and plastic products	Other non-metallic mineral products	Basic metals	Fabricated metal products, except machinery and equipment	Repair and installation of machinery and equipment	Chemicals and chemical products	Electrical equipment	Machinery and equipment n.e.c.	Motor vehicles, trailers and semi-trailers	Other transport equipment	Basic pharmaceutical products and pharmaceutical preparations	Computer, electronic and optical products
ERP		0.403***	0.503*	0.374	0.344***	0.740*	0.651	0.621***	0.194	0.257	0.451	0.669***	0.451***
		(0.155)	(0.280)	(0.276)	(0.103)	(0.404)	(0.477)	(0.179)	(0.144)	(0.178)	(0.455)	(0.190)	(0.132)
CRM		-0.253	0.092	0.079	-0.022	-0.310	0.269	0.050	-0.231	0.009	0.262	0.401**	0.104
		(0.195)	(0.215)	(0.333)	(0.104)	(0.386)	(0.496)	(0.147)	(0.157)	(0.171)	(0.389)	(0.169)	(0.188)
WebPage		0.475***	0.426	0.233	0.231*	-0.161	0.866*	0.346*	0.637***	0.317***	0.424	0.556***	0.284
		(0.164)	(0.275)	(0.191)	(0.132)	(0.318)	(0.485)	(0.202)	(0.110)	(0.112)	(0.334)	(0.137)	(0.290)
shareintemployee		0.191	0.026***	0.344**	0.074	0.695*	-0.496	-0.165	0.117*	0.062***	0.787	1.109***	0.606**
		(0.544)	(0.007)	(0.136)	(0.262)	(0.387)	(0.949)	(0.256)	(0.068)	(0.003)	(0.578)	(0.126)	(0.260)
Constant		10.675***	10.543***	10.810***	10.836***	10.964***	10.783***	10.669***	10.733***	10.902***	10.461***	10.435***	10.785***
		(0.194)	(0.223)	(0.051)	(0.119)	(0.230)	(0.358)	(0.170)	(0.082)	(0.107)	(0.230)	(0.123)	(0.288)
Observations		219	238	154	356	85	89	150	255	293	59	43	259
R-squared		0.188	0.142	0.108	0.080	0.143	0.221	0.303	0.176	0.096	0.280	0.922	0.480

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Source: Author's calculations based on TURKSTAT Annual Industry and Services Survey and ICT Usage in Enterprises Survey 2009 and 2019 datasets.

Table A.3: OLS Estimation Results for Extended Model by Sectoral Breakdown of Manufacturing Industry – 2019

Technology level	Low technology										
NACE Code	10	11	12	13	14	15	16	17	18	31	32
Sector	Food products	Beverages	Tobacco products	Textiles	Wearing apparel	Leather and related products	Wood and of products of wood and cork, except furniture	Paper and paper products	Printing and reproduction of recorded media	Furniture	Other manufacturing
ERP	0.433**			0.319***	0.300	0.198	0.184	0.792***	0.248	0.058	-0.099
	(0.186)			(0.095)	(0.204)	(0.149)	(0.200)	(0.204)	(0.238)	(0.099)	(0.298)
CRM	-0.014	-0.952**		0.073	-0.802	0.464	0.107	-0.386*	0.050	-0.142	0.064
	(0.152)	(0.436)		(0.105)	(0.625)	(0.277)	(0.147)	(0.207)	(0.200)	(0.098)	(0.251)
WebPage	0.349	0.853**		0.214**	0.522***	-0.144	0.424**	0.308	0.326*	0.204*	0.664***
	(0.264)	(0.381)		(0.102)	(0.143)	(0.126)	(0.190)	(0.290)	(0.189)	(0.104)	(0.210)
IT Specialist	0.576***	-0.017		-0.056	0.278	0.538**	0.867***	0.176	-0.098	0.196	0.341
	(0.187)	(0.743)		(0.117)	(0.170)	(0.239)	(0.179)	(0.196)	(0.173)	(0.138)	(0.264)
internet speed	0.092	-0.141		0.219**	0.256	0.197*	-0.124	-0.046	0.203	0.166**	0.420**
	(0.164)	(0.332)		(0.111)	(0.171)	(0.116)	(0.178)	(0.154)	(0.217)	(0.083)	(0.171)
share int employee	-0.117	0.229		0.011	0.026	0.623	0.508*	-0.307***	-0.072	-0.060	0.117
	(0.097)	(0.646)		(0.142)	(0.193)	(0.394)	(0.291)	(0.103)	(0.244)	(0.080)	(0.293)
Constant	10.480***	11.321***		10.924***	10.339***	10.647***	10.391***	10.938***	10.601***	10.641***	10.214***
	(0.090)	(0.408)		(0.088)	(0.129)	(0.101)	(0.151)	(0.289)	(0.157)	(0.097)	(0.184)
Observations	452	21		479	457	49	104	132	71	182	67
R-squared	0.093	0.643		0.140	0.164	0.441	0.188	0.268	0.113	0.090	0.385

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Source: Author's calculations based on TURKSTAT Annual Industry and Services Survey and ICT Usage in Enterprises Survey 2009 and 2019 datasets.

Table A.3 (Continued): OLS Estimation Results for Extended Model by Sectoral Breakdown of Manufacturing Industry – 2019

Technology level	Medium-low technology						Medium-high technology					High-technology	
NACE Code	19	22	23	24	25	33	20	27	28	29	30	21	26
Sector	Coke and refined petroleum products	Rubber and plastic products	Other non-metallic mineral products	Basic metals	Fabricated metal products, except machinery and equipment	Repair and installation of machinery and equipment	Chemicals and chemical products	Electrical equipment	Machinery and equipment n.e.c.	Motor vehicles, trailers and semi-trailers	Other transport equipment	Basic pharmaceutical products and pharmaceutical preparations	Computer, electronic and optical products
ERP		0.321**	0.436	0.115	0.239**	0.659	0.989**	0.572***	0.193	0.020	0.053	0.506***	0.312**
		(0.159)	(0.297)	(0.233)	(0.100)	(0.403)	(0.411)	(0.178)	(0.152)	(0.237)	(0.625)	(0.161)	(0.128)
CRM		-0.282	0.100	-0.058	-0.034	-0.224	0.197	0.033	-0.295**	0.030	0.161	0.018	-0.016
		(0.204)	(0.215)	(0.310)	(0.105)	(0.407)	(0.393)	(0.157)	(0.146)	(0.183)	(0.386)	(0.215)	(0.157)
WebPage		0.412**	0.431	0.163	0.226*	0.007	0.471	0.343*	0.617***	0.359***	0.342	0.406***	0.188
		(0.162)	(0.274)	(0.214)	(0.129)	(0.293)	(0.393)	(0.200)	(0.115)	(0.118)	(0.340)	(0.087)	(0.298)
IT Specialist		0.398**	0.129	0.603**	0.328**	0.631	-0.733**	0.225	0.046	0.554***	0.609	0.485***	0.360***
		(0.192)	(0.234)	(0.285)	(0.130)	(0.495)	(0.297)	(0.184)	(0.140)	(0.208)	(0.518)	(0.163)	(0.127)
internet speed		-0.067	0.233	0.136	-0.112	-0.245	0.655*	-0.266*	0.256**	-0.052	0.235	0.323***	0.385**
		(0.142)	(0.194)	(0.249)	(0.110)	(0.273)	(0.366)	(0.141)	(0.113)	(0.134)	(0.342)	(0.078)	(0.168)
share int employee		0.198	0.025***	0.371***	0.072	0.562	-0.548	-0.090	0.142**	0.057***	0.670	0.825***	0.574**
		(0.548)	(0.007)	(0.138)	(0.257)	(0.379)	(0.687)	(0.266)	(0.070)	(0.002)	(0.583)	(0.176)	(0.240)
Constant		10.727***	10.440***	10.782***	10.862***	10.947***	10.843***	10.749***	10.627***	10.862***	10.376***	10.472***	10.614***
		(0.189)	(0.260)	(0.035)	(0.112)	(0.208)	(0.260)	(0.187)	(0.094)	(0.122)	(0.207)	(0.087)	(0.307)
Observations		219	238	154	356	85	89	150	255	293	59	43	259
R-squared		0.222	0.158	0.240	0.107	0.177	0.381	0.353	0.212	0.134	0.327	0.943	0.514

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Source: Author's calculations based on TURKSTAT Annual Industry and Services Survey and ICT Usage in Enterprises Survey 2009 and 2019 datasets.

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ARAŞTIRMA MAKALESİ / RESEARCH ARTICLE

THE EVOLUTION OF THE DIGITAL DIVIDE IN TURKEY

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Abstract

Disparities in information and communication technology (ICT) access and use usually correlate with demographics and socioeconomic factors. The term "digital divide" refers to demographic, economic, and social inequalities regarding access to and use of ICTs and has critical policy implications. A longitudinal analysis of the digital divide is particularly imperative to understand a country's progress toward digitalization at a high level. Bearing in mind that the full potential of digital advancements can be achieved with the widespread adoption of digital technologies, such analysis is of particular importance for emerging economies like Turkey. In this study, we aim to examine the evolution of digital gaps in Turkey to analyze the dynamics of the digital divide. By this objective, we examine the change in broadband penetration in Turkey and the evolution of digital gaps between different social groups over device access, Internet access, and Internet use between 2008-2020. The results of this study reveal significant digital inequalities between different social groups in Turkey. Although Internet access rates point to progress to some extent, the digital divide in terms of actual Internet use persists between different social groups and regions in Turkey.

Keywords: Digital Divide, Information and Communication Technology, Device Access, Internet Access, Internet Use, Digitalization, Inequality, Turkey

JEL Classification: D63, I3, J1

1. Introduction

A country's digitalization potential and capacity depend on the growth and penetration of ICTs in the region which is coupled with the concomitant rise in the even distribution of possession of the technologies within society. According to the latest data provided by the International Telecommunications Union (ITU, 2020), there are 4.6 billion Internet users worldwide, meaning that 59 percent of the population are Internet users today which was only 16 percent in 2005. The ITU estimates that 4.9 billion people, or 63 percent of the world's population, will be online in 2021. This represents a 17 percent increase over 2019, with 782 million people estimated to have

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used the Internet during that time. However, 2.9 billion people remain unconnected. Moreover, very few of those who are counted as Internet users can fully engage with all Internet services. Also, there are strong differences either by region or by different social groups.

Turkey is undergoing digital transformation and morphing into more innovative and technologically advanced organizations and systems. However, given the relationship between social connectivity and digital connectivity (Chen, 2013), the disadvantaged groups of the population would become more vulnerable to remaining socially and digitally excluded, which in turn would cause digital gaps between different social groups and regions. The digital gap, also known as the digital divide, is a new form of social inequality derived from the unequal access to and use of the modern ICT by individuals, households, businesses, and geographic areas at different socioeconomic levels. Scholars proved that ICT access and use are usually associated with socioeconomic and demographic characteristics, such as economic class, gender, race and ethnicity, age, disability, education, rural residency, occupational status, networks, and geographies, and the digital divide were found to be highly associated with these factors. Although technology becomes more integrated into everyday life and digital-intensive activities become an increasingly important component of the economies, foundational access inequalities continue to cause a gap between people who use the ICT and those who do not.

Although internet access in Turkey has been on an upward trend and smartphones are nearly ubiquitous among society, the digital divide is a critical issue in Turkey such that demographic and socioeconomic factors significantly affect Internet access and use in the country (Dalgic-Tetikol et al., 2022). The main objective of this study is to examine the evolution of digital gaps in Turkey by using longitudinal data from TurkStat's "household ICT use and access" survey for the period 2008-2020. Our hypothesis is that there are digital gaps for certain social groups in Turkey. Therefore, in this study, we aim to investigate whether and for which groups these gaps have widened, narrowed, or disappeared over the years. We look at different aspects concerning the digital divide namely, device access, Internet access, and Internet use, and present them by mostly using graphs in order to show the dynamics of the digital gaps and analyze how large the gaps are in each aspect along with different variables. The results also reveal that the digital gaps do not appear to be closing in the near future. This study thus provides the most comprehensive and detailed analysis to date examining the evolution of the digital divide in Turkey. For this reason, we believe that it provides a useful body of knowledge in the design of policies to address the digital divide in Turkey.

The particular emphasis of this article is therefore on how the digital divide in Turkey has changed over time. In accordance with the objective to study the evolution of the digital divide in Turkey, we particularly examine the change in Internet adoption in Turkey, and digital gaps between different social groups over device access, Internet access, and Internet use with respect to years. We investigate how each demographic and socioeconomic variable has progressed between 2008-2020 in terms of ICT adoption.

2. Literature Review

The widespread growth of information and communication technologies (ICT) in recent decades has created incentives for individuals to widen their participation in social, political, and economic areas of life. Notwithstanding such incentives for individuals, using ICT entails having access to technology and infrastructure, as well as learning how to deal with new ICT concepts. ICT access inequality which is referred to as the digital divide, exists among certain social groups and countries. As the Internet reaches critical importance, some social scientists are starting to investigate the demographic and socioeconomic patterns of ICT access and use. Scholars already showed that disparities in ICT access and use usually correlates with demographics and socioeconomic factors such as gender (Antonio and Tuffley, 2014; Gray et al., 2017; Korupp and Szydlik, 2005; Mumporeze and Prieler, 2017), age (Grishchenko, 2020; Peacock and Künemund, 2007; Selwyn et al., 2003), education (Bonfadelli, 2002; Chaudhuri et al., 2005; Talukdar and Gauri, 2011), income (Chaudhuri et al., 2005; Fuchs, 2009; Grishchenko, 2020; Korupp and Szydlik, 2005; Talukdar and Gauri, 2011), employment status (Robles and Torres-Albero, 2012; van Dijk and Hacker, 2003), and region of residence (Lucendo-Monedero et al., 2019; Ruiz-Rodriguez et al., 2018). On the other hand, Internet access opportunities as well as device access opportunities such that having access to various Internet-enabled devices such as computers and mobile devices, play a major role in explaining the diversity of Internet use (Lopez-Sintas et al., 2020; Reisdorf et al. 2022). In a developing country context, device access opportunities are also associated with demographics and socioeconomic factors (Lopez-Sintas et al., 2020).

There are a few studies investigating the digital divide within the Turkish context as well: Acilar (2011) discussed gender, age, education and geographic location aspects of the digital divide in Turkey based on a summary of 2010 data. Polat (2012) emphasized that digital inequalities are interwoven with other social inequalities, but existing policy initiatives fail to address the most disadvantaged groups, indicating the lack of a national strategy for digital exclusion. Köksal and Anil (2015) examined the determinants of broadband access and broadband usage in Turkey in 2012 and found that the digital divide is significantly associated with demographics and region. Dalgic-Tetikol et al. (2022) validated this result by empirically examining the digital divide from device access, Internet access, and Internet use perspectives with recent data (2020), and showed that although the majority of people have an Internet-enabled device (smartphones), age, household income and education are significant predictors of Internet access; in fact, even when access is available, large disparities exist among gender, age, income, education, and different employment groups in terms of Internet use. Also, region is another significant factor affecting both Internet access and use in Turkey. Moreover, Dalgic-Tetikol et al. (2022) and Köksal (2021) underlined the lack of coherent vision on the demand side policies in Turkey to increase Internet penetration in the country – that is, the demographic and socioeconomic factors have been disregarded while developing regulations and related policies.

It is widely acknowledged by scholars that the demographic and socioeconomic patterns of ICT access and use have critical policy implications. Thereof, several studies give particular emphasis on how differences in ICT access and use in society change over time. The literature on the digital divide is vast across individuals, regions, countries, disciplines, and services (Pérez-Amaral et al., 2021). Grishchenko (2020) underlined that the study of the digital divide requires an integrated approach to analyze its dynamics and changes. Mack et al. (2021) highlighted the importance of a longitudinal analysis of the digital divide. The summary of the literature in this section focuses on the studies which investigate the changes in ICT adoption over time.

Hoffman et al. (2000) is one of the early studies that give particular emphasis on how differences in ICT adoption are changing over time. Polykalas (2014) analyzed the historic evolution of the digital divide across the Member States of the European Union between 2004-2013. The results show that a clear improvement has been achieved in terms of rural broadband coverage, however, the EU policies have not achieved quantitative targets to mitigate the digital divide across the Member States. Ragnedda and Kreitem (2018) shed light on the digital inequalities in the particular setting of East EU by comparing and contrasting the differences and similarities between East EU countries in terms of Internet access and online engagement by analyzing the period 2008-2017. Their analysis shows that Internet penetration is rapidly rising across Europe so the number of people with no connectivity opportunities is significantly diminishing. However, despite the narrowing digital gaps, the first level digital divide has not been completely bridged. With a similar aim that of this study, Nishijima et al. (2017) sought to fill the gap in the literature on the digital divide in Latin American countries and analyze four nationally representative survey data (of years 2005, 2008, 2011, and 2013) on evolution and determinants of the digital divide between 2005 and 2013 in Brazil. The results demonstrate a diminishing trend in the digital gaps; however, digital illiteracy still possesses challenges in ICT access, especially among the elderly. Jin et al. (2018) explored the trends of the digital divide in China between 2004 and 2016, and investigate regional and stratificational digital divides in particular, including the access divide and the usage divide, and found that regional access and usage divides in China have decreased over time. Grishchenko (2020) assessed the digital inequality trends in Russia between 2008-2018, and found that sociodemographic and economic characteristics are associated with uneven distribution of ICT access and use. Specifically, the most disadvantageous groups in Russia in terms of ICT access and Internet use are the low-income, the elderly, individuals with disabilities, and those living in rural areas. The results highlight the fact that despite overall positive trend in access and use of the Internet, those social groups still remain on the unpreferred side of the divide, which exacerbates social inequality. Garín-Muñoz et al. (2019, 2022) and Pérez-Amaral et al. (2020, 2021) examined the evolution of the use of ICT in Spain and analyze the Internet adoption patterns of selected Internet services. Garín-Muñoz et al. (2019) measured the effect of individuals' socioeconomic characteristics on the adoption of Internet services such as e-commerce, e-banking, and e-government by using logistic regression techniques. Pérez-Amaral et al. (2021) measured specific digital gaps which are mainly classified according to demographic and socioeconomic variables by using survey data for the period 2007-2019. The results show that most of the gaps are narrowing. In fact, in the case of gender, the gaps end up much smaller or even reversing in signs in some cases such that in the case of VoIP and social networks women become more likely users than men. However, some gaps concerning older groups persist. Also, for low-education levels, the digital divide remains high.

Some of the contributions listed above use aggregate data, while others use cross-section, pool, or panel data. Some of them are limited to one dimension of the digital divide such as connectivity or usage or consider only one or a limited set of variables such as gender, income, race, etc. whereas, in this article, we cover a large data set such that a variety of demographic and socioeconomic variables and different aspects of the digital divide in the analysis.

3. The Data

The study draws upon annual data collected in Turkey as part of the Turkish Statistical Institution's (TurkStat) "Information and Communication Technology (ICT) Usage Survey on Households and Individuals", which is prepared and carried out in accordance with EuroStat's survey on "ICT Usage in Households and by Individuals". [1] The survey aims at collecting information about the information and communication technologies owned by households and individuals and their use every year since 2004 (except 2006). Due to missing and malformed data before 2008, this study covers the years from 2008 to 2020 and includes around 13,000-33,000 individuals of age 16-74 each year. Table 1 shows the number of individual and household participants each year with their gender distribution. The survey's questionnaire alters each year based on the evolving situation of ICT such that new variables emerge, and some variables are either renamed or omitted in some years. Therefore, the raw panel data underwent rigorous analysis, filtering, and harmonization to standardize the information collected throughout the observation period.

Table 1: Number of Observations throughout the Observation Period 2008-2020

	2008	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*	*2018*	*2019*	*2020*
Number of participants	13314	12524	13236	26355	27394	23428	20150	19623	25058	29359	28888	28675	32955
Number of households	5161	4773	5094	10235	10605	11537	9814	9827	11268	12780	12822	12947	14498
Male	6380	6025	6392	12873	13255	10778	9259	8966	11699	13924	13719	13729	16420
Female	6934	6499	6844	13482	14139	12650	10891	10657	13359	15435	15169	14946	16535

The demographic and socioeconomic variables of interest are as follows: The sampling universe is respondents of ages 16-74, who are any type of Internet user from novice to experienced. Age, income, and level of education are included as categorical variables. We categorized age into four: 16-35 (young/early working age), 36-50 (prime working age), 51-65 (mature working age), and 66-74 (elderly); monthly household income into three: less than minimum wage (low income), more than minimum wage but less than twice the minimum wage (mid-income), and more than

1 TurkStat Household Information Technologies Usage Statistics Metadata, https://data.tuik.gov.tr/Kategori/GetKategori?p=Bilim,-Teknoloji-ve-Bilgi-Toplumu-102, accessed on 20.04.2022

twice the minimum wage (high income) [2]. To identify participants' level of education, they are asked about the highest level of education attained. We categorized the education levels into three: below high school, high school, and tertiary degree. [3] We assess individuals who are employed, unemployed, student, homemaker, and retired. [4] Finally, we include 12 geographical regions of Turkey to assess if ICT access and use vary among different regions of Turkey and categorized them into three namely, west, central and east according to geographical location. [5] [6]

In the survey, participants were asked if they had Internet-enabled device(s) and an Internet connection and whether they used the Internet in the past 12 months for various types of personal use. Also, they were asked to report how often they use the Internet. The devices considered consist of desktop, laptop, tablet, smartphone, smart TV, and game consoles that enable connectivity. Internet access measure includes access to the Internet from any "Internet-enabled" device via fixed or mobile broadband or both. Internet use indicates whether the individual used the Internet in the last 12 months. We only take individual and household access and use opportunities.

4. Internet Penetration in Turkey

The Internet penetration rate corresponds to the percentage of the total population of a given country or region that uses the Internet. An Internet user is defined as anyone with the capacity to use the Internet, which requires the person to have available access to an Internet connection and the basic knowledge that is necessary to use Internet technology. Turkey has a fixed broadband penetration rate of 20.07 percent and mobile broadband penetration rate of 76.40 in 2020 (Q4) which are below OECD averages of 33.19 percent and 118.40 percent, respectively [7] Despite the upward trend in broadband adoption in Turkey, the lower rates of fixed and mobile broadband penetration rates indicate lower level of ICT utilization in Turkey compared to many other OECD countries. The evidence therefore leads us to investigate whether social categories play a role in different Internet access and use patterns with lower adoption rates. The TurkStat survey data demonstrate the upward trend in Internet penetration in Turkey between the years 2008-2020.

2 The net monthly minimum wage in Turkey in 2020 is 2,324.71 Turkish Lira.

3 The classification is based on International Standard Classification of Education (ISCED) 2011.

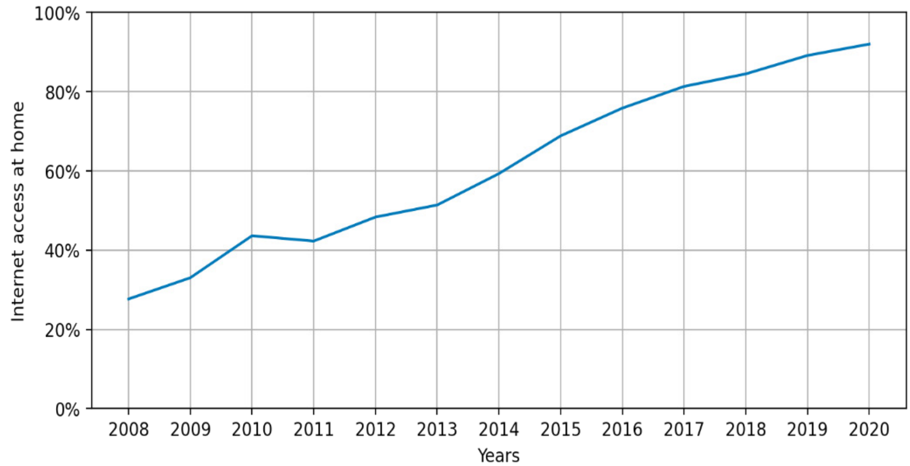
4 The classification is based on International Classification of Status in Employment (ICSE) 1993.

5 The geographical categorization of TurkStat for Turkey's regions is based on the European Nomenclature of Territorial Units for Statistics (NUTS).

6 *West:* Istanbul, West Marmara, Aegean, and East Marmara; *Central:* West Anatolia, Mediterranean, Central Anatolia, and West Blacksea; *East:* East Blacksea, Northeast Anatolia, Middle east Anatolia, and South East Anatolia

7 OECD, Broadband Portal, http://www.oecd.org/digital/broadband/broadband-statistics/

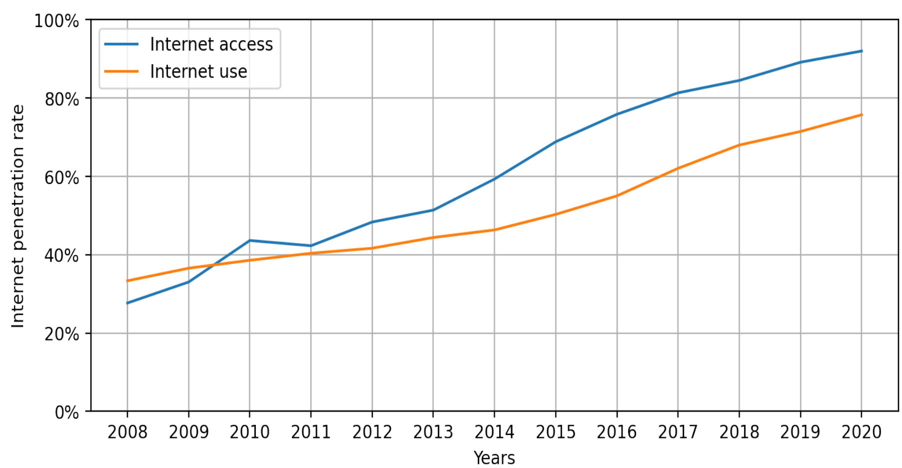
Figure 1: Share of Survey Participants with Internet Access between the Years 2008-2020



Source: Authors' elaboration based on TurkStat ICT Usage Survey

Figure 1 shows the trend of the share of TurkStat survey participants who reported having Internet access. There is a clear upward trend in the share of people with Internet access – that is, Internet penetration has increased in Turkey over years. As seen in the figure, the share was as low as below 30 percent back in 2008 but as of 2020, the share is over 90 percent. Except for the drop in 2011, the Internet penetration rate in Turkey has steadily increased. Bearing in mind that accessibility does not necessarily transform into usage, we look into the usage trends separately to see whether access and usage perform differently in certain periods.

Figure 2: Internet Access and Internet Use Trends between the Years 2008-2020



Source: Authors' elaboration based on TurkStat ICT Usage Survey

Figure 2 shows changes in the share of survey participants with Internet access and who actually use the Internet between the years 2008-2020 in separate trend curves. When we look at the Internet use curve in particular, we again see an upward trend starting from around 30 percent in 2008 up to almost 80 percent in 2020 with a constant increase. However, from the figure, we can deduce that access does not always transform into usage. Despite the continuous investments in infrastructure deployment and increasing infrastructure availability, there are other factors that limit actual usage.

5. Methodology

To analyze the evolution of the digital divide in Turkey, we measure the digital 'gaps' for each demographic and socioeconomic group. We adopt a similar method that is used in Pérez-Amaral (2021) which we believe enables us to understand whether the gaps are narrowing, widening, or remaining unchanged over time. Therefore, we used the following equation to measure the digital gaps:

$$Digital\ gap = (P_H - P_L)/P_H$$

where P is the percentage penetration of a given social group (gender, age, education, etc.).

Each group may involve two, three, four, or more categories in the sample. H and L refer to the best and poor-performing categories within the particular social group, respectively. Therefore, P_H refers to the rate of access or use of the most advantageous category in terms of Internet access such that for each social group the most advantageous categories as the following: men, 16-35 age, high education, high household income, student, west, whereas P_L refers to the less advantageous categories compared to the abovementioned categories. The equation thus refers to the difference in penetrations relative to the penetration of the highest category. As also claimed by Pérez-Amaral et al. (2021), the formula admits a straightforward interpretation since the calculations yield a value bounded between zero and one, denoting the percentage difference in the penetration for the category L of a given digital divide indicator (device access, Internet access, Internet use) relative to the penetration in the highest category H. Based on these calculations, in the following sections, we present a set of graphs illustrating the evolution of the digital gaps for each aspect of the digital divide in Turkey.

6. Results

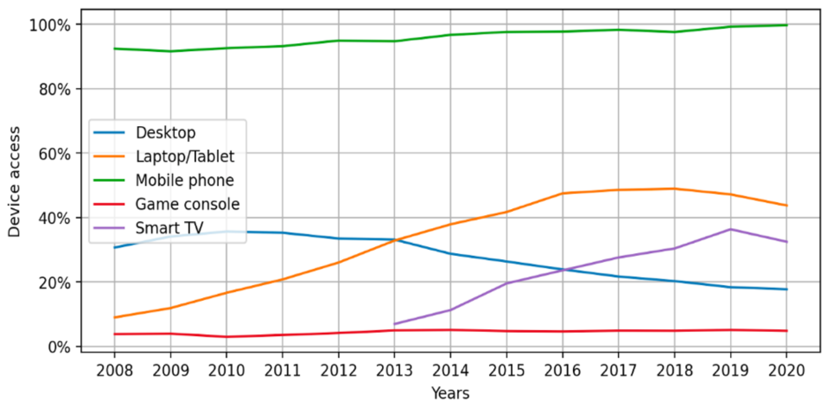
In this section, we present the results of our examination of the historic evolution of the digital divide in Turkey. The results are presented in a set of graphs that illustrate the change in various aspects of the digital divide over time and how each demographic and socioeconomic predictor of the digital divide has evolved. [8]

8 *All figures are authors' elaboration based on TurkStat's survey on ICT usage in households for years 2008-2020.*

a. The Digital Gap over Device Access

As a first step, we analyze the evolution of access to Internet-enabled devices in Turkey over the years. The TurkStat dataset contains sufficiently diversified information about Internet-enabled devices that allows for a comprehensive analysis of device ownership and device diversity among various social groups in Turkey over the years. Although access to an Internet-enabled device is necessary for connectivity, it is not sufficient by itself to connect to the Internet and maintain connectivity. Nevertheless, it is important to analyze the device ownership patterns in society to examine whether it has been a significant factor affecting connectivity. The analysis on device diversity, in particular, can give an indication of the change in Internet utilization by different social groups as one can diversify their Internet experience by using different types of devices (van Deursen and van Dijk, 2019).

Figure 3: Device Ownership with Respect to Years (Device Types)

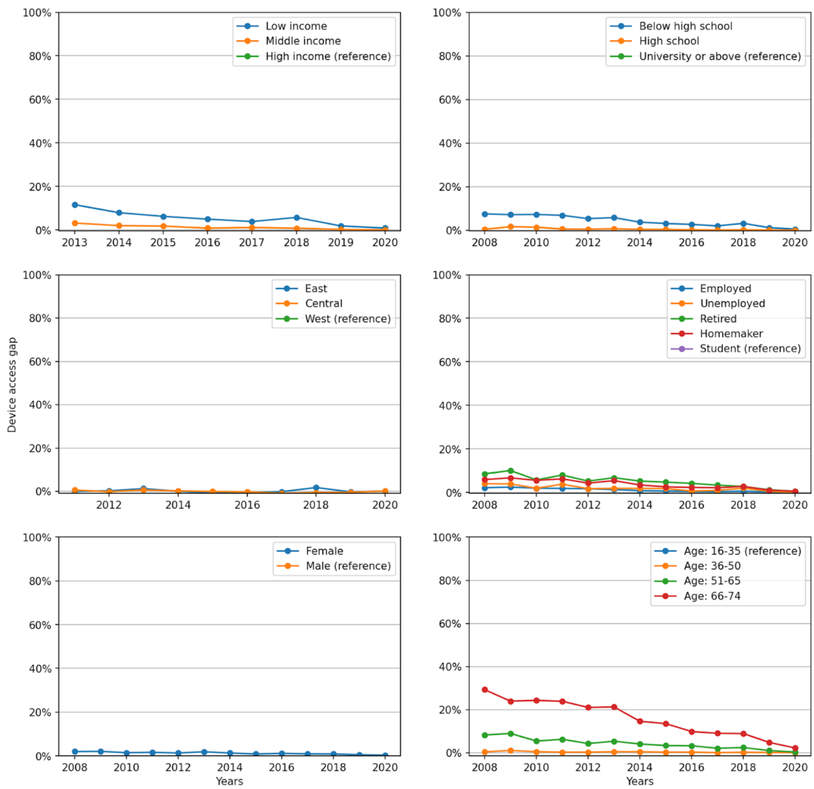


Source: Authors' elaboration based on TurkStat ICT Usage Survey

Figure 3 shows the share of the population using various Internet-enabled devices, throughout the years. This figure demonstrates that smartphones have been the most common type of device used to go online. As of 2020, almost everyone has a mobile phone that enables connectivity. Device availability at home does not necessarily enable connectivity for every household member. Many households do not have enough devices for everyone or not everyone can use all devices to access the Internet. Therefore, although device availability gives an indication of how the country performs in terms of device opportunities itself, it is particularly critical to detect which household members can actually access those devices and which cannot. Therefore, we try to uncover the digital gaps between social groups of different demographic or socioeconomic characteristics on device access.

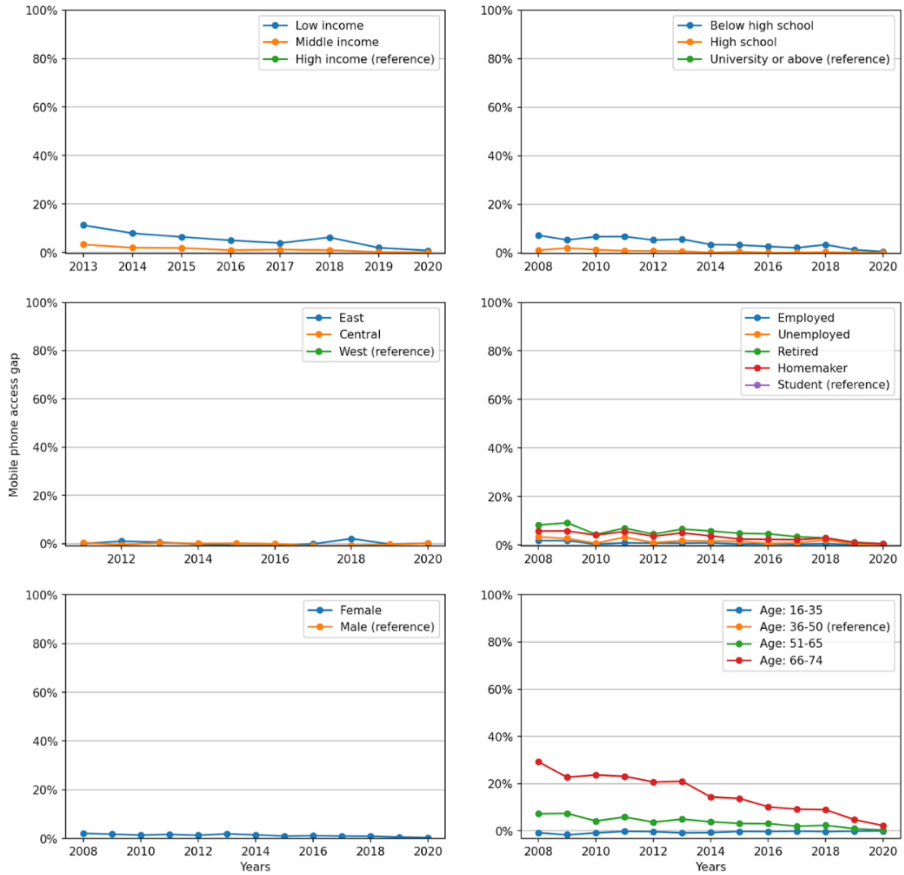
Figure 4 includes six graphs that illustrate the gap between different social groups in terms of the share of people in each group that have access to an Internet-enabled device. Each curve represents the social group and demonstrates how each category of the representative social group has progressed over time relative to the most advantageous category in that social group. Therefore, the y-axis represents the percentage gap between the categories with the best-performing category. For example, the first graph on the top left-hand side illustrates the change in the device access gap between different low – and middle-income households (represented by blue and orange lines, respectively), and high-income households.

Figure 4: The Digital Gap over Device Access



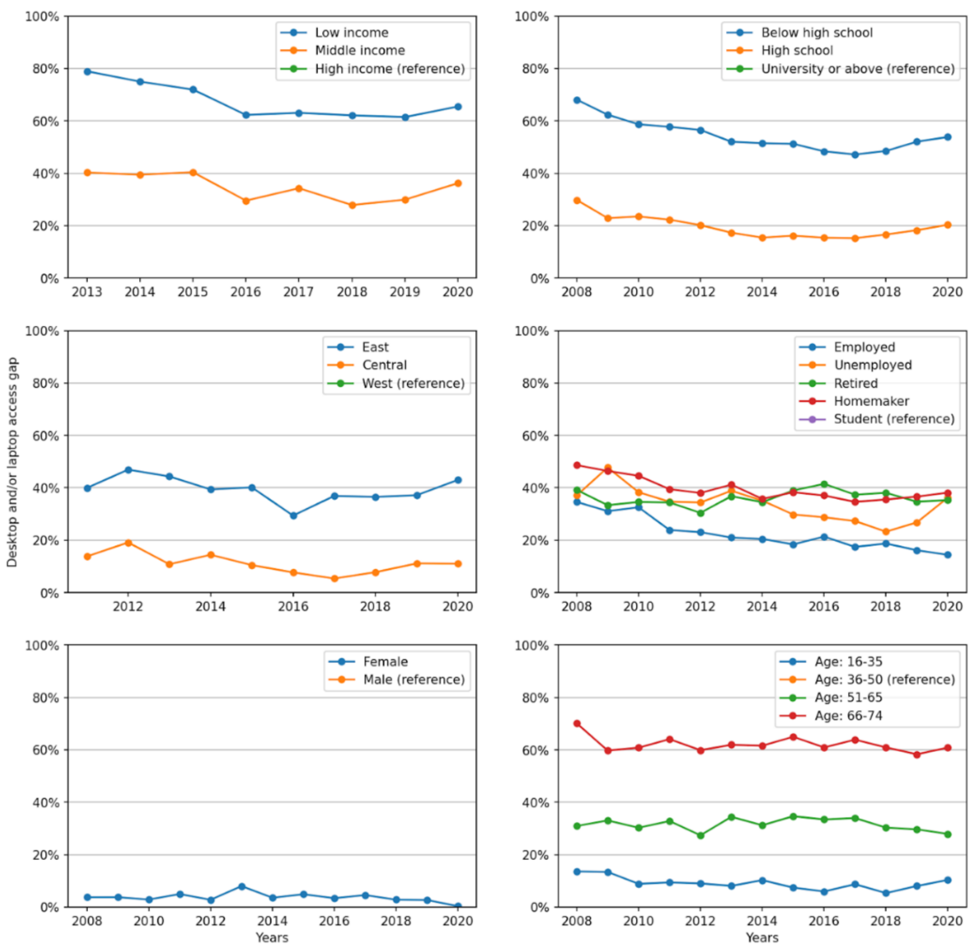
As all graphs in Figure 4 show, the digital gap over device access has been nearly closed for all social groups, which appears to be a very promising outcome of the widespread use of Internet-enabled devices. However, it is worth mentioning that the measurement of device access here includes all Internet-enabled devices, namely smartphone (or mobile phone that enables Internet connection), desktop, laptop/tablet, smarttv, and game console. From Figure 2, we deduce that today smartphone is a prevalent type of Internet-enabled device used to go online. So, we predict that the narrowed device divide between different social groups appears to be due to the widespread use of smartphones. Therefore, we specifically examine smartphone access gaps in Figure 5

Figure 5: Smartphone Access Gap



In Figure 5, we see that smartphones are available to almost everyone, hence smartphone ownership can no longer be considered an indicator for the digital divide in Turkey in terms of device access. However, although smartphones are getting more powerful and functional each year, with larger screens, faster processors, and more memory and storage coupled with unlimited data plans offered more commonly by service providers and with relatively faster networks than before, they are still limited in convenience to perform some important and relatively more sophisticated tasks such as job applications and interviews, taking online courses, writing papers for school, etc. Furthermore, previous research shows smartphones are minority groups', such as "younger, poorer and less educated users", only mean of Internet access and that their online activity over smartphones remains limited to social activities (Tsetsi and Rains, 2017). Given the evidence from the literature, we, therefore, find it important to analyze the device divide in more detail. For such an analysis, we choose to particularly consider computers (such as desktops, laptops, and tablets) because they offer a different Internet experience than that provided by smartphones, while at the same time, they can be considered a more imperative tool of today's social and professional life compared to other Internet-enabled devices like smarttvs and game consoles. Figure 5 shows the evolution of computer access gaps between different social groups.

Figure 6: Computer Access Gap



The evolution of the gaps and where the country stands with the computer access divide is apparently not the same as with the smartphone access divide which has been nearly bridged. As Figure 6 clearly illustrates that the gaps over computer access persist, indicating that the majority of the population is indeed deprived of Internet activities that can be performed effectively solely on a reliable computer as they are the primary current prerequisite for performing certain activities. On the other hand, it is worth noting that although device availability has improved, devices are of limited use without a proper connection. We, therefore, extend the analysis in the following sections to assess the evolution of Internet access and Internet use in Turkey over the years.

b. The Digital Gap over Internet Access

Based on TurkStat data, we showed that Internet penetration in Turkey has been on an upward trend (see Section 4) such that today the share of the population who reported having Internet access has exceeded 90 percent. While this points to progress, the digital divide persists among certain social groups.

Figure 7: The Digital Gap over Internet Access

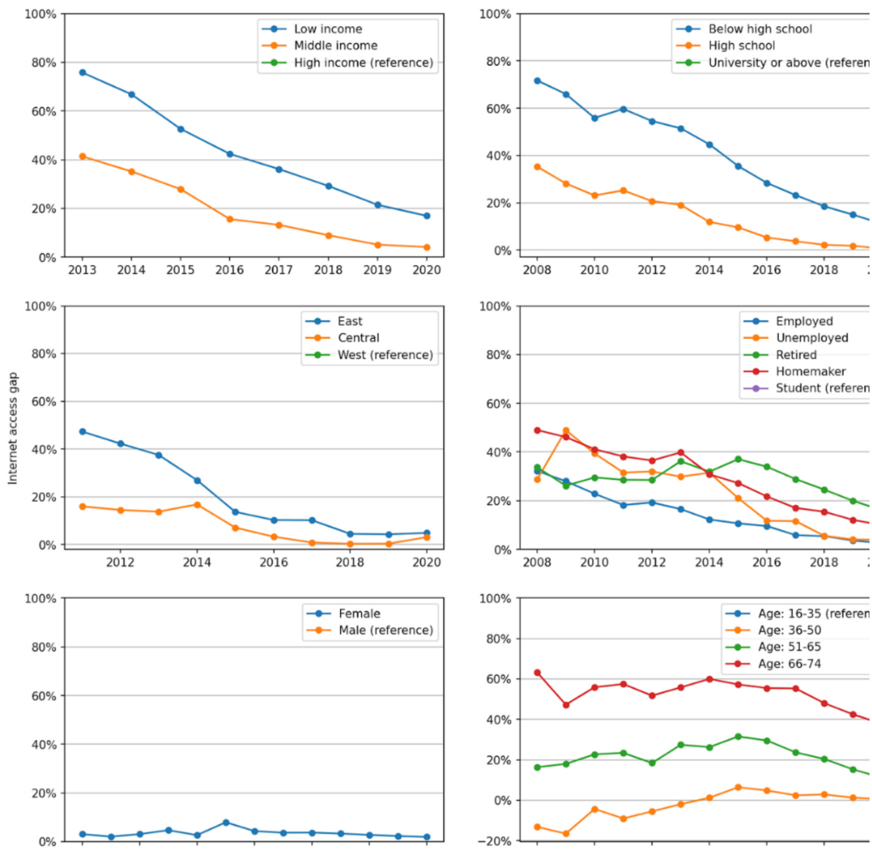


Figure 7 illustrates the gaps observed in Internet access over the years concerning demographic and socioeconomic differences. The gaps are generally decreasing over time, insomuch that the gaps between some groups are nearly closed. For example, the gap between regions is considerably small towards the end of the period (2020) compared to 10 years ago. For different income and age groups, although the gaps have been substantial among the different categories earlier, today, only the second most advantageous categories, namely middle-income and middle-education categories, could catch up with the most advantageous categories whereas low-income and low-education, are still behind of others. On the other hand, older age groups have made much slower, even stagnant, progress over the years. Despite the relative improvement in recent years, there is an almost 40 percent gap between the older and younger age groups in terms of Internet access. As for gender, there have often been small gaps between women and men, but they have always been unfavorable for women since 2008. Finally, for different employment statuses, homemakers and retired have usually been at the margins among their group, yet homemakers have made relatively better progress than the retired, who are now the least advantageous in terms of Internet access among other occupations.

c. The Digital Gap over Internet Use

Access to an Internet connection is a necessary but not a sufficient condition for Internet use. It is therefore critical to analyze how the gaps over Internet use have progressed over time, given increased and improved Internet access and Internet use in general as well as narrowing gaps over Internet access.

Figure 8: The Digital Gap over Internet Use

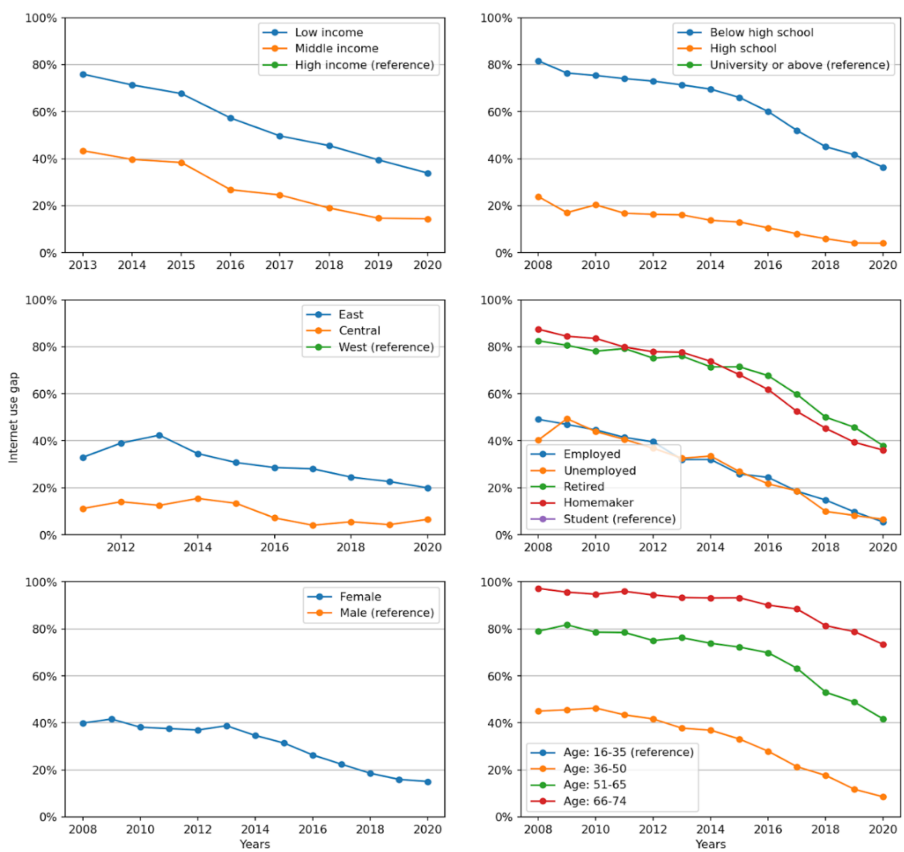


Figure 8 illustrates the evolution of digital gaps over Internet use and shows a more precise picture concerning the differences in Internet adoption in Turkey over the years. Although access divides have been mostly narrowed, high differences in usage remain for all social groups considered. Figure 8 presents a picture drastically different from Figure 7. Despite the overall increase in Internet access (Figure 1) and the decrease in access gaps for most social groups (Figure 7), in Figure 4, we see how terrible the usage gaps between certain groups still are. The increase in the number of individuals with Internet access has not been sufficient to close the digital divide. Despite a decline, especially in recent years, there is still a notable gap between the older and younger age groups. Younger adults are usually more likely than their elders to be earlier adopters of innovation and digital technologies [9], which explains the large gap of almost 100 percent in the initial year. However, the Internet adoption rate by those in the oldest age group, although it has been increasing for the last five years, is not at the desired pace to catch the younger adults up in a short time. A similar situation is also valid for education and income, particularly for those with the lowest education and income. In terms of regions, the gap between them appears to continue steadily. This might be due to region-specific factors like more rural areas where access to (high)connection is low or cultural dynamics that constrain certain social groups' linkage with the digital realm. In terms of occupational status, the gap between the students and employed and unemployed groups has been significantly narrowed. However, retired and homemakers still use the Internet much less than other employment groups. The gap indeed appears to need time to narrow if the adoption by these groups continues at similar rates. Our analysis regarding the gender gap in usage points to an interesting result. Unlike in the case of Internet access, the gender gap in terms of Internet usage, albeit has dropped compared to earlier persists – that is, female users are 20 percent less than men users despite having access opportunities alike. Moreover, the gender gap has barely improved since 2017, which is an indication of the presence of various barriers preventing a group of women from going online.

7. Conclusion

This study focuses on the digital gaps in Turkey for the period 2008-2020. For that, we investigate how the digital divide in Turkey has changed over time; particularly examine the change in digital gaps between different social groups over device access, Internet access, and Internet use. Unlike many other studies in the literature that focus solely on one variable or one aspect of the digital divide, in this article, we try to convey a detailed analysis by taking different aspects of the digital divide. This comprehensive approach fills the gap in the literature by providing an accurate body of knowledge in the design of policies to address the digital divide in Turkey.

Closing the device divide is the first integral step to closing the digital divide. There is an upward trend in device access, that is, the share of people with device access has increased over time so

9 Faverio, M. (n.d.). Share of those 65 and older who are tech users has grown in the past decade. *Pew Research Center*. Retrieved July 29, 2022, from https://www.pewresearch.org/fact-tank/2022/01/13/share-of-those-65-and-older-who-are-tech-users-has-grown-in-the-past-decade/

the vast majority of the population now has a device that can connect to the Internet. However, smartphone ownership has increased at a faster rate compared to other Internet-enabled devices. It appears that people in Turkey use smartphones as their primary means of online access. Although the increase in smartphone ownership is valuable progress towards the digital divide, reliance on smartphones for connectivity and online engagement cannot perfectly aid in mitigating the problem. On top of that despite the increased computer penetration over years, unlike smartphone access gaps, computer access gaps are still substantial. The socioeconomically disadvantaged groups have very low access rates compared to the advantaged groups. The results indicate that their Internet experience is limited to their capability to utilize what smartphones offer them.

The results reveal that Internet access gaps have been narrowing over time, and in several cases they become small. There has never been a significantly large gap between women and men. In the case of regions, income, and education, their mid categories in particular, although large at the beginning, the gaps have ended up considerably small. There is also a diminishing trend in the gaps between other social groups. Nevertheless, the elderly, retired, and low-income and low-education people are still far behind in terms of Internet access. The results point to the need for demand-side programs intended to stimulate broadband adoption widely by those groups. The policymakers' attention should not remain exclusively on the supply side. Instead, they should pay increasing attention to the demand side policies alongside supply side policies if greatly expanded adoption of broadband is the policy goal (Hauge and Prieger, 2010). Although Internet access points to progress to some extent, the digital divide in terms of actual usage persists between different social groups and regions. The lower levels of online engagement overall along with larger gaps in actual usage indicate lower and uneven digital participation in society. As shown in the Figures, not all groups are homogenous such that their digital engagement has been associated with their demographic and socioeconomic characteristics.

The Internet has become an imperative in the lives of individuals. The results in the present paper point to the need for accelerated policies targeted at inferior social groups. Given the gaps among society in terms of ICT access and use, the gaps between individuals who can access and use the technology and those who cannot, will continue widening unless the necessary actions are taken today. There are a number of ways to improve ICT access and use and provide individuals with the opportunities of a stable and open Internet. This includes strategic objectives such as expanded digital infrastructure which enhances availability and accessibility, reduced telecommunications costs, improved network efficiency, more competitive and diverse broadband markets, strengthened digital literacy through a restructured education system, empowering human capital that can use the technologies effectively and implementing policies at the local level. Each of these measures contributes to narrowing the digital gaps. The right policy should particularly target disadvantaged groups such as women, senior age, low-income, low-educated groups, homemakers, and retired people. In conclusion, reducing the digital divide in Turkey requires a combination of policies which concentrate on the underlying demographic and socioeconomic factors that contribute to the digital divide.

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ARAŞTIRMA MAKALESİ / RESEARCH ARTICLE

WHAT A HARD DECISION: CAPITAL STRUCTURE OF REITS IN ISTANBUL STOCK EXCHANGE

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Aslı AYBARS**

Abstract

By examining the factors that determine the capital structure for Turkish Real Estate Investment Trusts (REITs) in Borsa Istanbul (BIST) over the period 2014-2020, we attempt to present a contribution to the capital structure literature. In our study, we use panel data analysis that provide us proofs about the impact of financial performance, stock performance, and corporate structure on capital structure decisions of REITS. Some of the findings are remarkably similar to those of prior studies in this array of literature while our independent variables and capital structure may seem to be connected differently from the leading capital structure theories ("pecking order theory and trade-off theory"). The prominent capital structure theories of pecking order and trade-off theory likewise receive mixed support, although the link between capital structure and our independent variables appears to be skewed. As a result, the theory's assumptions indicate that capital structure changes are driven by survival.

Keywords: REIT, Debt ratio, ISE, Trade-off Theory, Pecking Order Theory, Capital Structure, Turkey
JEL Classification: C23, G17, G32

1. Introduction

One of the most important areas of the executives' attention is capital structure decisions because these decisions not only affect the firm's market value but also its survival. Capital structure can also be expressed as the financing structure that allows the companies to continue existing investments and/or make new ones.

Specifically, after the study of Modigliani & Miller published in 1958, there is a great increase in the number of empirical studies on this subject. In this prominent study, under the supposition that there is no market failure, it is contended that capital structure choices have no impact on business value. The data of 43 oil companies operating in the USA between 1947 and 1948 are

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analyzed by using cross-sectional regression analysis and it is found that changes in the capital structure have no effect on the company's profitability or value.

The Trade-off Theory argues that a company's capital structure strikes a balance between the expense of financial hardship from debt and the tax benefits of debt. Up to the optimal borrowing point, businesses gain from the tax benefits of debt, which raises the enterprise value. The risk of financial trouble and bankruptcy rises if the company continues to borrow more than is necessary, diminishing the tax benefits of the loan. (Damodaran, 2001). This explains why businesses cannot borrow continuously.

The Pecking Order Theory states that when businesses need money, they primarily rely on internal resources, which are free of any asymmetric information issues. Then, they use external sources and finally equity financing. Therefore, this theory suggests that profitable firms borrow less and this situation cannot be explained by the Trade-off Theory. As long as the firms' profitability is high, they do not need to use external resources.

The current article aims to determine which factors influence capital structure decisions by analyzing the effects of financial performance, stock performance, and corporate structure on book debt ratio. Determining the attitudes of real estate investment trusts regarding capital structure decisions will enable investors to make more effective decisions while investing in these businesses. In addition, it will shed light on the ability of real estate investment trusts, which have important effects on the economy in which they operate, to make strategic decisions in terms of the continuity of their activities. In the study, the methodology utilized rests upon panel data analysis with random effects.

This paper proceeds as follows: Firstly, literature review of theoretical and empirical studies about capital structure will be revealed. Then, data and methodology are discussed in order to present the details of the sample and the hypothesis of the study is revealed based on the corporate structure background given in previous studies. Finally, the results are presented and discussed.

2. Literature Review

The theoretical background of capital structure has been debated since the seminal paper of Modigliani & Miller (1958). Two main theoretical models, designed for the determinants of capital structure, are Pecking Order Theory and Trade-off Theory.

The Pecking Order Theory suggests that there is a hierarchy in firms' sources of financing. Initially, internal funds are used but when firms need external funding, they prefer to borrow primarily and then issue corporate bonds. As a final preference, equity is issued because investors assume that managers issue stocks as long as the stock is highly priced and prefer to borrow money as long as the stock is low-priced. Therefore, investors will not buy shares before debt capacity of a firm is exhausted and investors will force firms to follow a financial hierarchy. As a result, when there is asymmetric knowledge, issuing equity has a higher cost than borrowing.

The Trade-off Theory claims that the benefits and drawbacks of borrowing are balanced since the best debt-to-equity ratio can increase a firm's worth. The study of Kraus and Litzenberger (1973) states that financing with debt has tax saving benefits and provides a financial discipline for managers but over-indebtedness can cause bankruptcy and huge agency costs. At that point, a firm should measure the costs and benefits of financing with debt and equity to find the optimal debt ratio. If the leverage ratio of a firm is determined by balance between tax advantages of debt, weighted costs of bankruptcy and agency costs, it is said that the firm is following the static trade-off model.

The finance literature also provides several empirical studies that explain that the capital structure patterns differ from one country to another or one sector to another. The empirical studies in developed markets cannot present fully supportive results for emerging markets and also the results for different sectors are not parallel. Therefore, there are several empirical studies for different countries and sectors in the literature.

The study, conducted with the data belonging to 123 manufacturing firms in ISE, focuses on the variables that identify the capital structure of firms (Sayilgan et al., 2006). The data between 1993 and 2002 is used to perform panel data analysis in which firm size, profitability, non-debt tax shield, growth rate and fixed asset ratio are employed to analyze capital structure. The analysis reveals a positive correlation between business size and leverage ratio, whereas profitability and borrowing rate show a negative correlation.

Li et al. (2009) investigate whether the capital structure is affected by the factors of governmental ownership, foreign ownership and institutional investor ownership by using dummy variables for data of Chinese firms. The study demonstrates that governmental ownership is positively associated with access to long-term financing sources and leverage while firms that are not publicly owned have significantly less short-term liabilities and total debt than publicly owned firms. Similarly, a study that analyzes the sector balance sheets of Central Bank of the Republic of Turkey between 1996 and 2008, reports a positive relationship between growth opportunities, size, profitability, asset structure and borrowing (Sayilgan & Uysal, 2011).

In the study of Bessler, Drobetz and Kazemieh (2011), it is determined that factors such as market value-book value ratio and profitability have negative effects on corporate leverage. On the other hand, tangibility, size, expected inflation and average industry leverage ratio have positive effects on leverage ratio.

Titman and Wessels (1998) use tangibles, non-debt tax shields, growth, uniqueness of business, industry, size, volatility of income and profitability to explain leverage. As a result of this study, it is presented that long-term debt to equity and short-term debt to equity are negatively related to firm uniqueness. In addition, short-term debt has a bad impact on size and profitability.

However, long term debt and short-term debt are not significantly impacted by either volatility or asset structure.

In the study by Matias and Serrasqueiro (2017), the small and medium-sized companies operating in different regions of Portugal are examined for the period between 2007 and 2011 to identify the factors affecting capital structure. Financial leverage ratio represents the capital structure and the factors included in the study are firm size, profitability, growth and firm age. As a result of the analysis, there is a significantly positive relationship between leverage and not only firm size but also asset structure. It is found that the relationship between company age and leverage is strong and unfavorable. Contrarily, the relationship between growth and financial leverage is not statistically different. It is determined that there is a significant and negative relationship between firm age and leverage. On the other hand, there is no statistically significant relationship difference between growth and financial leverage.

Antoniou et al. (2008) focus on two different type of economies: capital market oriented (England and USA) and bank oriented (France, Germany and Japan). By using panel data analysis, the factors affecting the capital structures of companies are tried to be determined. In this study, financial leverage ratio represents the capital structure. Asset structure, firm size, profitability, growth opportunity and stock performance are used as independent variables within the scope of the analysis. As a result of the analysis, whereas firm size and asset structure are found to have significantly positive effects on leverage ratio, growth opportunity and stock performance are found to have significantly negative effects on leverage ratio.

3. Methodology

This study employs panel data analysis since this methodology combines time series and cross – sectional observations; thus, enabling data variability, enhanced informativeness, and higher degrees of freedom. Accordingly, the model applied is regarded to be superior to the models that only utilize one of those dimensions. Furthermore, panel data controls for heterogeneity, whereas time-series and cross-sectional analysis can come up with biased results in the case of heterogeneity (Baltagi, 2001). Additionally, problem of multi-collinearity is also reduced (Wooldridge, 2002).

3.1. Dataset

In this study, the data set of the analysis rests upon 27 REITs traded in BIST between the years 2014 and 2020. For the 7 years' data period, the firms have to be listed in BIST uninterruptedly; thus, the dataset is strongly balanced. The empirical study is based on data attained from Finnet 2000 Plus: Financial Markets Data Terminal and the raw sample from 2014 to 2020 includes 35 REITs traded in BIST. The REITs, which do not have data as to the financial ratios utilized in the study and are not traded uninterruptedly in BIST, are excluded from dataset in order to obtain a strongly balanced panel dataset.

3.2. Variable Selections

In the literature, leverage ratios are widely used as variables defining capital structure. As in the literature, the dependent variable is selected to be the leverage ratio defined as the ratio of financial debt, short-term debt and long-term debt, to financial debt plus equity. Moreover, there are several leverage ratios used as a measure of leverage in numerous studies such as Total debt/Total Assets, Short Term Debt/Total Assets and Long-Term Debt/Total Assets (Wald, 1999; MacKay and Phillips, 2005; Mocnik, 2001; Prasad, Dheeria and Woodruff, 2002). This study covers specifically the capital structure of REITs which is one of the most levered sectors and prefers to grow with interest bearing debt instead of equity. Since, the debt-to-capital ratio includes interest-bearing debt while it excludes all other liabilities, unlike debt ratio defined as total debt to total assets", it measures the amount of asset financed with debt (Rajan and Zingales, 1995). This measure is the most appropriate one to the objective of the analysis.

Since previous studies have identified a number of factors that influence capital structure, the following eight variables are selected as independent variables of the study.

The first variable regarded to influence the capital structure of the firm is Market-to-Book value (MTB), a measure of growth opportunities, it is considered to be negatively related to DCR (debt to capital ratio). It is known that firms with high market to book value are more profitable companies and these companies are expected to issue less debt due to their greater growth potential and therefore have lower target leverage ratios (Rajan and Zingales, 1995; Chen and Zhau, 2004).

The size (SIZE) of the firm, which is calculated by taking the natural logarithm of the firm's total assets value, is an important factor in terms of firm's performance, operating capacity, and management structure. It is considered that large-scale companies may have more opportunity to access capital markets easily and to obtain funding sources so SIZE is positively related to DCR (Rajan and Zingales, 1995). It should be mentioned that the capital structure literature has a number of empirical studies that highlight the existence of a favorable link between size and capital structure. (Marsh, 1982; Titman and Wessels, 1988; Rajan and Zingales, 1995; Bevan and Danbolt, 2002; Mocnik, 2001). In these studies, the firm size is represented with either net sales or total assets.

Another variable to affect the capital structure is Tangibility (TAN), which is calculated as the ratio of PPE (Property Plant Equipment) to total assets. PPEs can be used as collateral so it can be effective to use this resource easily when there is a need for funds. The study of Bessler, Drobetz and Kazemieh (2011) indicates that high tangibility ratio triggers high leverage ratio.

Profitability (PRO) is measured by the ratio of net profit to net sales. It is stated that companies with high profitability ratios will no longer need to use high debt in their capital structures according to Pecking Order Theory. A large part of empirical studies also demonstrates the presence of a negative relationship between leverage ratio and profitability due to the fact that companies generally prefer internal sources in funding (Rajan and Zingales, 1995; Bevan and Danbolt, 2002; Huang and Song, 2006).

Some of the previous empirical studies have shown the presence of a negative relationship between market performance (RETURN) and DCR. The study of Antoniou et al. (2008), which rests upon panel data analysis performed with the data of firms in US, UK, France, Germany, and Japan, indicates that debt ratios move in significantly negative direction while stock returns are increasing.

Another variable is selected to be firm age (AGE) and it is considered to be negatively related to DCR because increased experience makes firms more risk averse to use external sources instead of internal sources. The study conducted by Matias ve Serrasqueiro (2017) with the data of small and medium size firms between 2007 and 2011 indicates that there is a significantly negative relationship between firm age and leverage ratio.

Free Float Rate (FFR) is found to be negatively related to DCR. The study of Guner (2016), conducted with 131 publicly traded Turkish firms, implies that the firms with %50-%75 free float rate tend to have lower leverage ratios because as firms become more transparent their investors can easily follow the financing decisions of the firms. This makes firms more conservative about leverage ratios.

Lastly, firms with government share (GOV) can easily reach the funding resources so DCR of these companies is higher than those firms that do not have any government share. Li et al. (2009) identify that firms with government share have higher leverage ratios.

As stated above, panel data analysis with strongly balanced panel data is utilized in the empirical part of the study. The regression analyses aim to compare the explanatory power of 8 independent variables on the dependent variable DCR to test the effect of three main focus groups: financial performance, market performance, and corporate structure. A summary of the variables utilized together with their abbreviations can be seen in Table 1 below.

Table 1: Variables

Abbreviation	Definition	Explanation
Dependent Variables		
DCR	Debt to capital ratio	The financial debt "(short-term and long-term debt)" to equity plus financial debt
Independent Variables		
MTB	Market-to-Book	Market value of equity to book value of equity"

SIZE	Firm size	Natural logarithm of total assets
TAN	Tangibility	PPE (Property Plant Equipment) to total assets
PRO	Profitability	Net income to total assets”
RETURN	Stock Performance	Change in the year-end stock close price
AGE	Firm age	The number of years that has passed since incorporation date
FFR	Free Float Rate	Rate of public shares
GOV	Government Effect	Equal to 1 if the firm has government share, otherwise 0

3.3. The Models Utilized

The model that tests the impact of financial performance on book debt ratio is demonstrated as in the Model (1) below.

Model (1): Financial performance

$$DCR_{it} = \beta_0 + \beta_1 MTB_{it} + \beta_2 SIZE_{it} + \beta_3 TAN_{it} + \beta_4 PRO_{it} + \varepsilon_{it}$$

Additionally, the analysis in Model (2) tests whether the market performance is significant while taking capital structure decisions:

Model (2): Market performance

$$DCR_{it} = \beta_0 + \beta_1 MTB_{it} + \beta_2 SIZE_{it} + \beta_3 TAN_{it} + \beta_4 PRO_{it} + RETURN_{it} + \varepsilon_{it}$$

Finally, we want to measure the contribution of REITs’ corporate structure to capital structure as stated in Model (3).

Model (3): Corporate structure

$$DCR_{it} = \beta_0 + \beta_1 MTB_{it} + \beta_2 SIZE_{it} + \beta_3 TAN_{it} + \beta_4 PRO_{it} + \beta_5 RETURN_{it} + \beta_6 AGE_{it} + \beta_7 FFR_{it} + \beta_8 GOV_{it} + \varepsilon_{it}$$

where, subscript i represents the firms (i=1,2, …, 27); t represents time (t=1,2, …, 7) and ε_{it} is the error term.

In order to identify the most adequate estimator to our panel data analysis, we follow a series of statistical tests for three models stated in Equation (1), Equation (2), and Equation (3). At first, it has to be detected whether there is unit/time effect or the model is a classical model or not. We use Breusch Pagan LM Test, F-test, and Likelihood Ratio test and select the most adequate model according to the results consistent in all of these three tests. Then, the Hausman Specification Test helps us to determine the type of effect, either fixed or random. Finally, we check the basic assumptions of panel regression model; multi-collinearity, cross-sectional dependence, autocorrelation, and heteroscedasticity. In order to reach the robust estimators, we have to eliminate these issues if there is any of them.

The issue of multi-collinearity is checked with the help of Variance Inflation Factor (VIF) and cross-sectional dependence is tested by Pesaran's, Friedman's, and Frees' tests. Bhargava, Franzini, Narendranathan Durbin Watson (DW) and Baltagi-Wu LBI tests are utilized to detect autocorrelation. Since the results suggest that all three models have random effects, we use the tests of Levene, Brown, and Forsythe to detect the issue of heteroscedasticity.

As a result of these statistical tests, all three models are determined to be one-way models with random time effect. After determining the adequate model, basic assumptions are checked. The concerns about multicollinearity are checked tested on the level of the variance inflation factors (VIFs), which are all below 10.0 in the regression models discussed. The issue of heteroscedasticity, autocorrelation, and cross-sectional dependence are fixed with Driscoll-Kray standard errors to obtain the robust estimators (Tatoglu, 2012).

4. Results and Discussion

As can be seen in Equation (1), Equation (2), and Equation (3), three different models are created with three groups of variables to see the impact of financial performance, market performance, and corporate structure on capital structure decisions. Within this context and as stated above, 27 REIT companies traded in BIST from 2014 to 2020, whose data can be accessed, are included in this study. In addition, strongly balanced panel data is used and the above-mentioned statistical tests are run to obtain the best regression models.

According to the results of the study, the variable MTB used to evaluate the effect of growth opportunities on capital structure is found to have a significantly positive relation with DCR at %5 significant level. However, the literature indicates that the increase in growth opportunities makes firms more risk averse about debt so our results are not supportive of the previous studies (Chen & Zhao, 2006)

The size of the company is found to be positively related to DCR at 5% significance level in all three models as expected. Emerging market studies (Booth, Demirguc-Kunt and Maksimoviç (2001); Huang and Song (2006) and the study of Rajan and Zingales (1995) performed with G7 countries found a positive relationship between the leverage ratio and firm size.

The tangible assets make firms more willing to use financing resources because of their strong collateralized asset. However, our results indicate that the increase in tangibles do not trigger firms about using financing solutions. The hypothesis cannot be supported by the data of Turkish public REITs as this variable is not found to have any significant link with the selected dependent variable in all three models.

The Pecking Order Theory suggests that firms primarily choose to finance their investments from internal sources so profitable firms borrow less. Thus, firms go to the way of using debt in case that the amount of investment exceeds their profits (Myers 1984). In theory, it is stated that leverage and profitability should be in an inverse relationship. The significantly negative coefficient at 5% level in all three models supports what the theory says.

Better market performance triggers firms to use less debt because the investors observe that the firm's financial and operational situation is well enough to invest in and this causes the stock price to increase. Thus, the Pecking Order Theory supports this result.

It is expected that the older firms are less aggressive about growth opportunities so the use of debt becomes lower as the age increases. However, we obtain insignificant results about the age effect on capital structure.

As the free float rate increases, the firms tend to use more debt because the higher free float rate is a result of low operational performance and use of equity financing in previous years. This is supported by the findings of Model (3) as can be seen from the positive and significant coefficient.

Our empirical results suggest that there is a negative relationship between DCR and governmental dummy at %5 significance level so REITs with government shares tend to use less debt. There are several empirical studies that shed light to capital structure of firms from different countries so the literature presents different results for different countries. For example, the study of Deesomsak et al. (2004) indicates that the government involvement helps Canadian firms to borrow with lower rates because of the government guarantee. However, the results for Turkish public REITs are found to be the opposite during the selected observation period, like the study of Khaki and Akin (2020). The empirical results of this study state that there is negative relationship between government share and leverage for Gulf Cooperation Council (GCC) countries.

Table 2: Panel Data Analysis Results for 3 Models Designed to See the Impacts of Financial Performance, Stock Performance and Corporate Structure of ISE REITs on Book Debt Ratio

	Financial Performance	**Stock Performance**	**Corporate Structure**
Variable	**Model 1** **DCR**	**Model 2** **DCR**	**Model 3** **DCR**
MTB	8.969	9.867	9.994
	(2.962)**	(2.625)**	(2.35)**
SIZE	2.388	2.727	2.992
	(1.018)**	(0.94)**	(0.999)**
TAN	-6.580	-3.922	-4.447
	(5.258)	(5.103)	(5.011)
PRO	-49.726	-51.137	-48.4
	(18.585)**	(18.727)**	(15.6)**

RETURN		-5.412	-5.343
		(2.683)*	(2.35)**
AGE			-0.099
			(0.07)
FFR			0.17
			(0.059)**
GOV			-4.899
			(1.718)**
Constant	-47.546	-53.99	-60.531
	(20.839)**	(17.903)**	(20.566)**
R^2	0.65	0.746	0.783
Firm-years	189	189	189
legend	* p<0.10;	** p<0.05;	***p<0.01;

6. Conclusion

In this study, it is aimed to determine the debt utilization dynamics of REITs registered in BIST. Overall regression results of three models provide evidence that higher market-to-book ratio and size of the firm are associated with more book debt ratio. However, a statistically significant negative coefficient that is observed in profitability suggests that more profitability triggers less book debt ratio. These results are consistent with the expectations the study. On the other hand, tangibility is insignificant, which is contrary to what is expected because firms with more tangible assets can easily reach long-term debts. Nevertheless, the model designed to see the DCR behavior of Turkish REITs sample tells us that tangibility has a statistically insignificant effect on book debt ratio. In the third model, which is designed to measure the impact of corporate structure on book debt ratio, we have found significant results for the free float rate and government share but the result for government share is contrary to what is expected. Since the firms with government share are expected to reach external sources easily. In the regression results, the sign of the coefficient on FFR is positive and statistically significant which indicates that higher free float rate is linked with higher book debt ratio. However, the coefficient on AGE is found to be small and statistically insignificant.

In this study, the focus point is the REITs because of the importance in the Turkish economy and the different capital structure of REITs when compared to other sectors. Further studies can be performed for different periods to see the effects of different interest policies of Turkish government and inflation shocks on capital structure because REITs are sensitive to interest rate policies and inflation.

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