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How Does Digital Banking-Driven Financial Inclusion Affect Income Inequality in Türkiye?

Türkiye'de Dijital Bankacılık Kanalıyla Finansal Içerilme Gelir Eşitsizliğini Nasıl Etkiler?

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ABSTRACT
This study empirically investigates the impact financial inclusion through digital banking channels has on income inequality in Türkiye using quarterly data for the 2011:Q1-2021:Q4 period. The study uses the Gini index to measure the dependent variable of income inequality and employs two variables as proxies for digital banking. The first variable is the share of the investment volume in the total financial transaction volume made by retail customers through Internet banking. The second variable is a factor constructed based on the transaction volume per unit of main items under financial transactions. The study relies on time series approaches to test whether digital banking-driven financial inclusion has a significant impact on income inequality in Türkiye. As for the empirical evidence, the study employs the dynamic ordinary least squares method to obtain long-run coefficients, a vector autoregressive model to obtain short-run dynamics through impulse response functions with bias-corrected bootstrap confidence intervals that account for the bias and skewness of the small sample, and a causality analysis. The findings show that digital financial inclusion has a widening impact on income inequality. Regarding the dynamic interactions, the Gini coefficient has been discovered to increase in response to digital banking innovations. The findings also reveal digital banking to have a forecasting ability on income inequality in Türkiye regarding the sample period.

Keywords: Digitalization, Banking, Financial inclusion, Income inequality, Economic development
Jel Classification: C32, G21, O11

ÖZ
Bu çalışma Türkiye'de dijital bankacılık kanalıyla yaygınlaşan finansal içerilmenin gelir eşitsizliği üzerine etkisini 2011:Ç1 ve 2021:Ç4 dönemine ait çeyreklik veri seti ile ampirik olarak incelemiştir. Gelir eşitsizliğini ölçmek için kullandığımız Gini katsayısı bağımlı değişken olarak belirlenmiştir. Dijital bankacılığı ölçmek için iki tane vekil değişken kullanılmıştır. Birinci vekil değişken Internet bankacılığı kanalıyla bireysel müşteriler tarafından yapılan yatırım işlemlerine ait işlem hacminin

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toplam finansal işlemler hacmi içindeki payı olarak belirlenmiştir. İkinci vekil değişken ise yine bireysel yatırımcılar tarafından Internet bankacılığı kanalıyla yapılan ve finansal işlemler altındaki kalemlerin birim başına düşen işlem hacimlerinden elde edilen faktör olarak belirlenmiştir. Türkiye'de dijital bankacılık yoluyla artan finansal içerilmenin gelir eşitsizliği üzerinde anlamlı bir etkisinin olup olmadığını test etmek için zaman serileri yaklaşımları kullanılmıştır. Ampirik bulgular için dinamik olağan en küçük kareler yöntemi, küçük örneklemler için yanlılığı ve çarpıklığı dikkate alan güven aralıklarına sahip etki-tepki fonksiyonlarını ede etmek için vektör otoregresif modeli ve nedensellik testi kullanılmıştır. Analiz sonuçlarına göre dijital finansal içerilme zengin ve yoksul hane halkları arasındaki gelir eşitsizliğini arttırıcı etki göstermiştir. Dinamik etkileşimler dikkate alındığında ise dijital bankacılık kullanımının yaygınlaşmasına tepki olarak Gini katsayısının arttığı ortaya çıkmıştır. Ayrıca, Türkiye için söz konusu analiz döneminde dijital bankacılıktan gelir eşitsizliğine doğru tek yönlü bir nedensellik ortaya koyulmuştur.

Anahtar Kelimeler: Dijitalleşme, Bankacılık, Finansal içerilme, Gelir eşitsizliği, İktisadi gelişme
Jel Sınıflaması: C32, G21, O11

1. Introduction

The Group of Twenty (G20) have highlighted the importance of digital financial inclusion in helping to improve the economic and financial opportunities of economic agents (Global Partnership for Financial Inclusion [GPFI], 2016). The G20 promotes a digital approach to financial inclusion as the first principle in their G20 High-Level Principles for Digital Financial Inclusion. Digital financial inclusion could allow low-income level groups to access and use financial services by reducing market imperfections such as the asymmetric information and transaction costs that prevent them from benefiting from financial services (Demir, Pesqué-Cela, Altunbas, and Murinde, 2022). Therefore, digitalization can be an important factor that leads to financial inclusion.

The theme of income inequality is one of the main central concerns in economic theory and policy because it affects political and social stability and efficiency regarding economic activity. Income inequality is also a good indicator of the state of a country's socioeconomic environment. Therefore, testing whether digital financial inclusion impacts income inequality is an important policy issue.

However, mixed evidence is found regarding the actual impact of digital financial inclusion on income inequality. On one hand, digital technology improves economic activity and productivity by reducing transaction costs. This mechanism improves labor market conditions and income levels, thus narrowing income inequality. On the other hand, digital technology may widen income inequality by favoring skilled workers and their income (Yin and Choi, 2022).

Digitalization has led to an evolution in the financial sector's service delivery. The main financial intermediaries offer several helpful options and digital services to customers at different income levels through Internet banking and mobile banking. This paper investigates whether digital financial inclusion through banking channels impacts income inequality in Türkiye.

This paper makes the following contributions. First, to the best of my knowledge, this is the first paper to analyze the impact of digital financial inclusion through digital banking on income inequality in Türkiye. Second, regarding the proxy for digital financial inclusion, this paper is the first to use retail financial transactions to construct a factor representing digital banking. In particular, the study uses micro variables to conduct a macro analysis. Third, papers investigating the impact of financial inclusion on income inequality generally consider a group of countries in their research. The relevant literature lacks a single-country analysis on this topic. The current paper also fills this gap by considering only the case of Türkiye.

The findings suggest that digital financial inclusion widens income inequality. This result may imply that retail customers who make financial transactions through digital banking are generally in the high-income level group.

The rest of the paper is organized as follows. Section 2 presents background information about the technological developments in communication and digital banking in Türkiye. Section 3 reviews the existing literature. Section 4 describes the data and empirical methodology. Section 5 discusses empirical results. Section 6 concludes.

2. Recent Developments in Communication Technology and Digital Banking in Türkiye

Developments in communication technology have created a more digitalized environment. In line with this evolution, connectivity has expanded, and information processing speed has improved. According to statistics released by the International Telecommunication Union (ITU), which is the official source for global information and communications technology (ICT), the number of Internet users worldwide was around 4.9 billion (63% of the total population) in 2021. In the same year, around 70 million people were using the Internet in Türkiye (81% of the total population), with 86% of the male population and 76% of the female population using the Internet. More individuals between the ages of 15-24 years old were connected than those between 25-74. This former group shows 96% of youths and roughly 78% of the latter group to be using the Internet in Türkiye. According to ITU statistics regarding the skills individuals in Türkiye require to perform activities, 28% reported requiring basic skills, 22% reported requiring standard skills, and 3% reported requiring advanced skills.

Regarding infrastructure and access in 2021, 88% of households had Internet access at home, and 53% additionally had a computer. In rural areas, 27% of households had Internet access at home in rural areas, while this is 55% for urban areas. Twice as many people use the Internet in urban areas compared to rural areas in Türkiye. Moreover, 93% of the population had a mobile phone in 2021. The population covered by at least a 4G mobile network was around 97% in that same year.

With the advent of new technologies, new forms of finance-related products have also been introduced. The services banks provide have increased in variety and led customers with different income levels to use digital channels more frequently. The banking sector in Türkiye has adopted digitalization and innovated more to acquire new customers. Along with the growth in Internet access, the number of customers banking through digital channels has also increased in recent years. While the number of active retail digital banking customers was around 33.4 million in 2017, this number had increased to 74.5 million by the end of 2021, according to the Digital, Internet, and Mobile Banking Statistics released by the Banks Association of Türkiye (TBB, 2022b). The sex-based breakdown shows females to comprise a third of the total number of active retail digital banking customers at 24.5 million, with the total number of males being 50 million. As the number of customers increases, banking transactions have also increased in volume. The volume of financial transactions made through Internet banking was around 1.326 billion TL and 2.995 billion TL in 2017 and 2021, respectively. Statistics show the volume of financial transactions in mobile banking to have been 5.833 billion TL in 2021.

Regarding the volume of investment transactions, Internet banking customers had a volume of 258 billion TL in 2017 and 673 billion TL in 2021, with this volume that went through mobile banking being around 2.031 billion TL in 2021. Compared to Internet banking, the volume of transactions made through mobile banking was higher.

3. Literature Review

This paper involves the literature that has empirically investigated how digitalization affects inequality. Therefore, this section of the study reviews the related empirical literature upon which the study's main hypothesis relies.

Richmond and Triplett (2018) used a sample of 109 countries between 2001-2014 to examine the empirical link between ICT and income inequality. They used two versions of the Gini index of inequality (i.e., post-tax and pre-tax). To measure the different types of ICT, they used the number of Internet users per 100 inhabitants, the number of residential and fixed subscriptions from organizations per 100 inhabitants at downstream speeds equal to or greater than 256 kbit/s, and the number of mobile cellular subscriptions per 100 inhabitants. Their findings suggested the impact of ICT on income inequality to vary according to the ICT type and Gini index measure. They observed greater Internet usage and more mobile phone subscriptions to have a reducing impact on income inequality. On the other hand, they also noted an increase in fixed broadband subscriptions to widen the income disparity between low-income and high-income level groups.

Asongu and Nwachukhwu (2018) examined the relationship between mobile banking (use of mobile phones to pay bills and send/receive money) and inclusive development (poverty and inequality) by estimating ordinary least squares (OLS) regressions for a cross-section of 93 developing countries for 2011. They decomposed whole data into seven sub-panels based on regions (Latin America, Asia and Pacific, Central and Eastern Europe, and the Middle East and North Africa) and income levels (upper middle income, lower middle income, and low income). Their findings suggested that the increased use of mobile phones to pay bills is negatively correlated with poverty in lower- and upper-middle-income and

Latin American countries. Moreover, they found that using mobile phones to send/receive money is negatively associated with lower- and upper-middle-income and Central and Eastern European countries and inequality in upper-middle-income and Central and Eastern European and Latin American countries.

Tchamyou, Erreygers, and Cassimon (2019) studied the role of ICT on income inequality through financial development in a sample of 48 African countries between 1996-2014. They employed the generalized method of moments (GMM) for the empirical evidence and used mobile phone subscriptions, Internet subscriptions, and fixed broadband (all per 100 people) to measure ICT. They used the Gini coefficient (traditional measure), the Palma ratio, and the Atkinson index to measure income inequality. Regarding financial development, they considered the dimensions of depth in terms of money supply and liquid liabilities, efficiency at the banking and financial system levels, and size. The estimation results suggested that financial depth and financial size reduce income inequality contingent on ICT. Moreover, the authors provided evidence of the significant role formal (as opposed to informal) financial sector development and formalization have through which ICT can mitigate inequality.

Asongu and Odhiambo (2019a) examined the association between mobile banking technology and income inequality using interactive quantile regressions with a sample of 93 developing countries in 2011. They used bill payments and money transfers to capture the effects of mobile banking dynamics on inequality in mobile banking. Their findings showed an increase in the use of mobile banking to pay bills to be negatively associated with inequality.

Asongu and Odhiambo (2019b) also analyzed the association between ICT and income inequality in 48 African countries by estimating GMM with annual data from 2004-2014. The authors used three variables to measure inequality: the Gini coefficient, the Atkinson index, and the Palma ratio. As for the ICT indicators, they used mobile phone penetration, Internet penetration, and fixed broadband subscriptions. They found ICT to have a reducing impact on income inequality.

Canh, Schinckus, Thanh, and Ling (2020) studied the impacts of technological developments on inequality for an initial sample of 87 economies and two subsamples (41 high-income and 46 low- and middle-income countries) for the period of 2002-2014. The authors followed the GMM as the econometric approach. Regarding technology, the authors considered Internet, mobile phone, and fixed phone usage and found income inequality to narrow following the growth of Internet and mobile phone usage for the full sample. The impact of technology on reducing income inequality was also present in the two subsamples based on income levels.

Daud, Ahmad, and Ngah (2021) evaluated the impact of digital technology on the relationship between financialization and income inequality for a panel of 54 countries covering the period of 2010-2015. They used the Gini index to measure income inequality and the number of secure Internet servers per 1 million people as the proxy for digital technology. The authors followed the system GMM as the estimation technique. Based on their estimation results, digital technology was found to be in favor of people with high incomes. Put differently, their study showed digital technology to widen income inequality.

Demir et al. (2022) investigated the relationship between financial technologies (FinTech), financial inclusion, and income inequality. They assessed whether FinTech affects inequality through financial inclusion for a panel of 140 countries for 2011, 2014, and 2017 by estimating a quantile regression analysis. They considered the Gini coefficient of disposable income for measuring income inequality and employed the use of mobile phones to pay bills as a proxy for FinTech. Financial inclusion was captured by three different types of formal financial services, including the proportion of adults owning a bank account, the share of the adult population with savings in a formal financial institution, and the share of the same population with loans from a formal financial institution. Their estimation results suggested financial inclusion to play a key role as a transmission channel through FinTech and to affect income inequality. While financial inclusion reduces income inequality in all quintiles, its impact was seen to be larger in the upper quintiles.

Yin and Choi (2022) examined the impact of digitalization on income inequality for a panel of 19 G20 countries from 2002-2018. The authors used the Gini index to measure income inequality and employed Internet use, mobile subscription, and broadband subscription for measuring digitalization. They also included gross domestic product (GDP) per capita, trade openness, foreign direct investment (FDI), and political stability as control variables. Their findings suggested that digitalization reduces income inequality. They also found the interaction between digitalization and trade openness to narrow the income gap between the low-income and high-income level groups in the full sample. However, they provided heterogenous evidence based on the countries' income level group. While the interaction between digitalization and trade openness widens income inequality in high-income countries, it reduces income inequality in middle-income countries.

Based on the literature review above, the main hypothesis to be tested in this paper is that digital financial inclusion has an impact on income inequality.

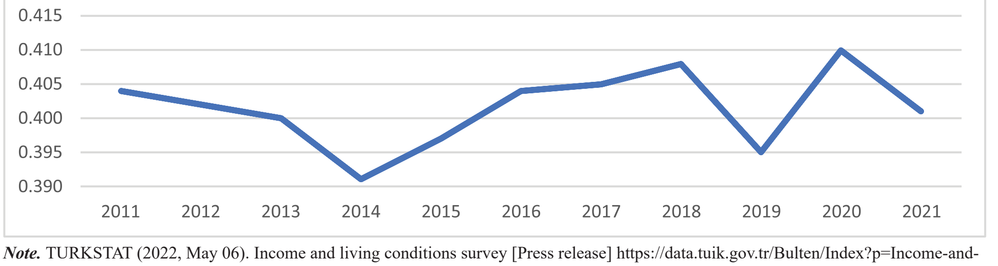
4. Data and Methodology

This section introduces the data and the econometric approach this paper uses to test the main hypothesis. The first part presents the sample and variables, while the second part explains the estimation techniques.

4.1. Data, Variables, and Sample

This paper investigates how financial inclusion through digital banking influences income inequality in Türkiye using a set of quarterly data for the 2011:Q1-2021:Q4 period for the empirical analysis. As the independent variable, the study uses the Gini index to measure income inequality. The Gini index takes a value between 0 and 100 (World Bank, n.d.). While a value of 0 indicates perfect income equality, a value of 100 implies perfect inequality. However, the Gini index is in annual frequency. Therefore, the study has interpolated and converted the frequency of the Gini coefficient from annual to quarterly data for the purposes of estimation. Figure 1 depicts the time series behavior for the estimates of the Gini coefficient in Türkiye. According to the Income and Living Conditions Survey (Turkish Statistical Institute-TURKSTAT, 2022) results, the estimated Gini coefficient was 0.401 in 2021 and less than 0.41, which was the highest value recorded in 2020. Based on the Gini time series, the estimated coefficient was also observed to have been 0.391 in 2014, which was the lowest value over the last decade.

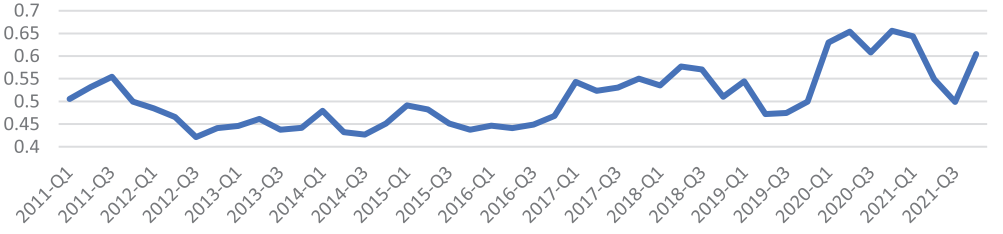
Figure 1. Time Series for the Estimates of the Gini Coefficient



Note. TURKSTAT (2022, May 06). Income and living conditions survey [Press release] https://data.tuik.gov.tr/Bulten/Index?p=Income-and-Living-Conditions-Survey-2021-45581&dil=2

The main independent variable of interest is the banking channel through which retail customers conduct their banking needs, with the study considering two types (i.e., digital and physical/traditional). The study also considers two alternative variables for measuring digital banking. The first proxy is the percentage of the volume of investment transactions to all financial transactions that retail customers make through Internet banking. Figure 2 displays the time series of this percentage over time. Over the sample horizon, investment transactions make up between 40%-65%. These statistics imply that the volume percentages of investment transactions make up a significant part of all financial transactions.

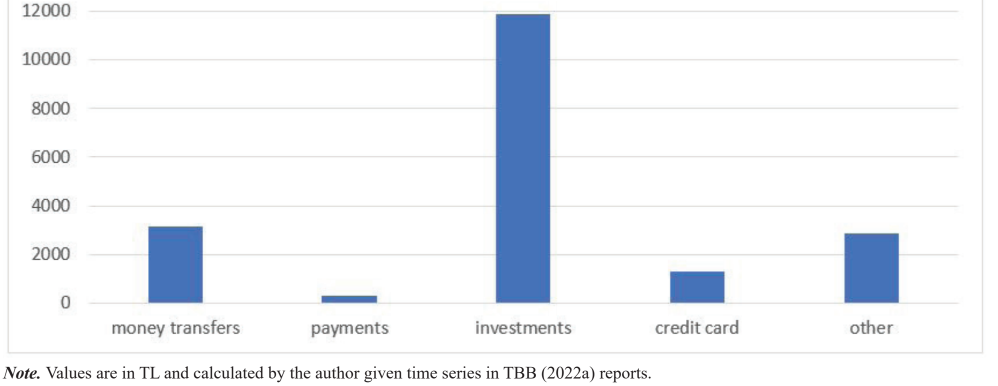
Figure 2. Time Series of Investment Transaction Volume as a Percentage of the Total Financial Transaction Volume



Note. Values are calculated by the author given time series in TBB (2022a) reports.

The second proxy is a factor extracted from volumes per financial transaction by item. For this purpose, I consider the numbers and volumes of main items under financial transactions, including "money transfers," "payments," "investments," "credit cards," and "other." Then, for each main item, I divided the total volume by the number of corresponding transactions to obtain transaction volume per unit transaction. Figure 3 displays the average volume per unit financial transaction by item. Regarding the volume per unit transaction, the investment item always has the highest value compared with the other items. It ranges between 5,760 TL and 22,853 TL over the sample horizon. On average, the transaction volume per unit investment transaction is around 12,000 TL for the sample period. The financial transaction item with the lowest transaction volume per unit is payments, whose volume lies between 121 TL and 811 TL, with an average of 300 TL.

Figure 3. Transaction Volume per Unit Transaction by Item



Note. Values are in TL and calculated by the author given time series in TBB (2022a) reports.

The study then conducts a set of tests as a prerequisite for the factor analysis to work. Sampling adequacy was achieved with the Kaiser-Meyer-Olkin (KMO) = 0.85, as well as the presence of a substantial correlation ($p \leq 5\%$ for Bartlett's test). Factor analysis suggests that all items can be represented by the single factor of digital banking, as that factor can explain 84% of the total variance. The other factor of physical (traditional) banking was also constructed as a proxy using the time series of the number of bank branches and personnel. The KMO = 0.847 and Bartlett's test result with $p \leq 5\%$ suggest the study should conduct a factor analysis. As a result, one factor (i.e., physical banking) was obtained that represents these time series.

Consistent with the literature, the study also uses a set of control variables. This set includes consumption, government, trade openness, and inflation. Data were collected from different sources to create the variables used in this study. The main sources are as follows: the Banks Association of Türkiye (TBB), TURKSTAT, Interbank Card Center (BKM), and the Electronic Data Delivery System by the Central Bank of the Republic of Türkiye (EVDS-CBRT). Detailed information about the variables, their definitions, how they are constructed, and their source are displayed in the Appendix's Table A1, and summary statistics of the variables in Table A2.

4.2. Methodology

This study uses the approaches mainly reserved for time series analyses. The following subsections introduce the econometric techniques that were utilized for the paper's empirical investigation.

4.2.1. Dynamic OLS

This study conducted the regression analysis using the dynamic ordinary least squares (DOLS) approach to obtain the coefficients. Saikkonen (1991) and Stock and Watson (1993) constructed an asymptotically efficient and unbiased estimator with a time domain correction. This approach augments the cointegrating regression with leads and lags for the independent variables. Therefore, this estimator is robust against potential endogeneity and serial correlation. Moreover, this method can be applied to small sample sizes, as is the case here.

The DOLS equation is as follows:

$$Y_t = c_0 + \sum_{r=-k}^{r=k} \alpha_i \Delta X_{t+r} + L_i + \varepsilon_t \tag{1}$$

where i is the number of independent variables. is the coefficient for the lead and lag differences of the independent variables ΔX. The number of leads and lags are shown by k, which is determined by minimizing the information criterion. The long-run coefficients are represented by L_i.

4.2.2. Vector Autoregression (VAR)

This study estimates vector autoregression (VAR) models to investigate the dynamic interactions between variables and uses impulse response functions to interpret the estimation results obtained through VAR. To achieve the impact of the shocks, the structural VAR for the vector of endogenous variables y_t can be written as $A(L)y_t = \varepsilon_t$, where $A(L)$ is a matrix of the lagged polynomial and ε_t is a column vector of orthogonalized structural shocks. Assume u_t to be the reduced form innovations of the linear combination of the structural shocks, which is equivalent to $B\varepsilon_t = u_t$, where $B = \mathrm{A}^{-1}(L)$ is an n x n matrix. An impulse response function will then plot $\frac{\partial y_{t+j}}{\partial \varepsilon_t}$ for all $j = 0, \ldots, h$, where h is the horizon of the plot.

The study follows Kilian (1998) for constructing the confidence intervals in the impulse response functions. This approach suggests a bias-corrected bootstrap confidence interval for the impulse response estimates over a small sample. Kilian (1998) proposed a double-bootstrap algorithm that explicitly corrects for the bias and skewness in the impulse response estimator that arises due to insufficient observation. The algorithm consists of the following steps:

1. Determine lag order and estimate a VAR model to obtain coefficients,
2. Run a residual bootstrap to obtain bootstrap coefficient estimates. These are then used to compute a bias correction of the original estimates,
3. Bias correct the VAR coefficients using the bias-corrected coefficients,
4. Construct the orthogonalized impulse responses using the bias-corrected bootstrap coefficients,
5. Derive the empirical quintiles of the bias-corrected bootstrap impulse responses.

4.2.3. Toda-Yamamoto (T-Y) Granger non-Causality

This paper conducts the Toda-Yamamoto (T-Y; 1995) Granger non-causality test to investigate the causal relationships among the variables of interest in the analysis. This approach is superior to the traditional Granger non-causality test for the following reasons. First, the T-Y test allows one to test the general restrictions on parameters irrespective of the order of integration of the time series and cointegration among variables in the process. Second, the T-Y approach avoids problems stemming from size distortions due to rank deficiency. The application consists of the following steps:

1. Determine the maximum order of integration $d_{\max}$,

2. Determine the optimal lag length k,
3. Estimate a VAR model in levels with an order of $(k + d_{max})$,
4. Ignore the coefficient matrices of the last d_{max} lagged vectors in the model and test for causality using the modified Wald restriction test, whose statistic follows an asymptotic chi-square distribution with degrees of freedom.

To apply the T-Y (1995) Granger non-causality test, the following VAR models are tested in levels:

$$y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i y_{t-i} + \sum_{i=k+1}^{d_{max}} \alpha_i y_{t-i} + \sum_{i=1}^{k} \omega_i x_{t-i} + \sum_{i=k+1}^{d_{max}} \omega_i x_{t-i} + u_{1t} \quad (2)$$

$$x_t = c_0 + \sum_{i=1}^{k} \beta_i x_{t-i} + \sum_{i=k+1}^{d_{max}} \beta_i x_{t-i} + \sum_{i=1}^{k} \phi_i y_{t-i} + \sum_{i=k+1}^{d_{max}} \phi_i y_{t-i} + u_{2t} \quad (3)$$

For Eq. 2, the null hypothesis against an alternative is shown as follows:

$$H_0: \omega_i = 0, \forall_i = 1,2,..k,$$

$$H_1: \omega_i \neq 0$$

A rejection of the null hypothesis implies a Granger causality from x to y. A similar argument is valid for Eq. (3), where is said to Granger cause x if $\phi_i \neq 0$.

5. Empirical Evidence

Checking whether a time series contains a unit root is essential in a time series analysis. Therefore, the study conducts traditional unit root tests that have a null hypothesis of a unit root (i.e., Augmented Dickey-Fuller [ADF; 1979] and Phillips-Perron [PP; 1988] unit root tests). Table 1 presents the results of the unit root tests. The associated *p*-values of the test statistics indicate all variables to be integrated of order 1, or I (1), at 5%.

Next, the study regresses the Gini index over the independent variables to get coefficients and analyzes how these independent variables affect the dependent variable. To do so, the equations are estimated using DOLS. Table 2 reports the estimation results from the regressions, in which Gini is the dependent variable. Columns 1-4 consider proxies for digital banking, whereas Columns 5 and 6 use a proxy for physical banking.

Table 1: Results from the Unit Root Tests

Test	Variables	Level		First Difference	
		t-statistic	*p*	t-statistic	*p*
ADF	Gini	-2.72*	0.07	-4.65***	0.00
	Digital Banking 1	-1.97	0.29	-5.44***	0.00
	Digital Banking 2 (Factor)	1.15	0.99	-8.04***	0.00
	Physical Banking	1.3	0.62	-3.12**	0.03
	Consumption	-2.03	0.27	-8.82***	0.00
	Government	-2.52	0.11	-8.3***	0.00
	Trade Openness	0.9	0.99	-8.47***	0.00
	Inflation	-0.47	0.88	-3.39***	0.01
PP	Gini	-2.15	0.22	-4.67***	0.00
	Digital Banking 1	-1.97	0.29	-6.32***	0.00
	Digital Banking 2 (Factor)	4.03	0.99	-8.69***	0.00
	Physical Banking	-1.52	0.51	-3.08**	0.03
	Consumption	-1.91	0.32	-9.08***	0.00
	Government	-2.42	0.14	-8.36***	0.00
	Trade Openness	0.77	0.99	-8.46***	0.00
	Inflation	-0.29	0.92	-3.51***	0.01

Note. MacKinnon (1996) one-sided p-values. *, **, and *** show significance at 10%, 5%, and 1%, respectively.

The study uses Digital Banking 1 (Investment) and Digital Banking 2 (Factor) to measure digital banking. Columns 1 and 3 show the estimation results when only Gini is regressed over the digital banking proxies. Columns 2 and 4 control for additional variables and regress Gini on digital banking proxies and a series of control variables, including consumption, government, trade openness, and inflation. Similar regressions are conducted in Columns 5 and 6 except now considering physical banking.

Table 2: Estimation Results of DOLS Regression

Regressors	Digital Banking 1: Investment		Digital Banking 2: Factor		Physical Banking: Factor	
	1	2	3	4	5	6
Banking	0.04***	0.05**	0.002*	0.005*	-0.002**	-0.003***
	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
Consumption		3.5**		8.11**		-1.07
		(1.44)		(2.96)		(1.55)
Government		0.53***		0.65***		0.25*
		(0.18)		(0.21)		(0.13)
Trade Openness		-0.08**		-0.04		-0.08***
		(0.03)		(0.03)		(0.02)
Inflation		0.04**		0.05**		0.01
		(0.02)		(0.02)		(0.01)

Constant	0.38***	-3.1**	0.4***	-7.63**	0.4***	1.4
	(0.00)	(1.43)	(0.00)	(2.9)	(0.00)	(1.55)
Obs.	41	41	41	41	41	41
Adjusted R^2	0.38	0.67	0.12	0.62	0.27	0.77

Note. Standard errors are reported in parentheses. *, **, and *** show significance at 10%, 5%, and 1%, respectively.

In Table 2, Column 1 shows the coefficient regarding digital banking to be positive and statistically significant. This finding suggests adopting digital banking to have a widening impact on income inequality. Regressing Gini over all variables shows statistically significant coefficients for all variables (see Column 2). All coefficients have positive signs except trade openness. The coefficient of positive consumption suggests the expenditures of the high-income level group to be higher than those of the low-income level group. This result suggests a widening of income inequality. Government redistribution is observed to positively affect income inequality. This result implies the benefit the high-income population receives from the government to be higher than that of the low-income population.

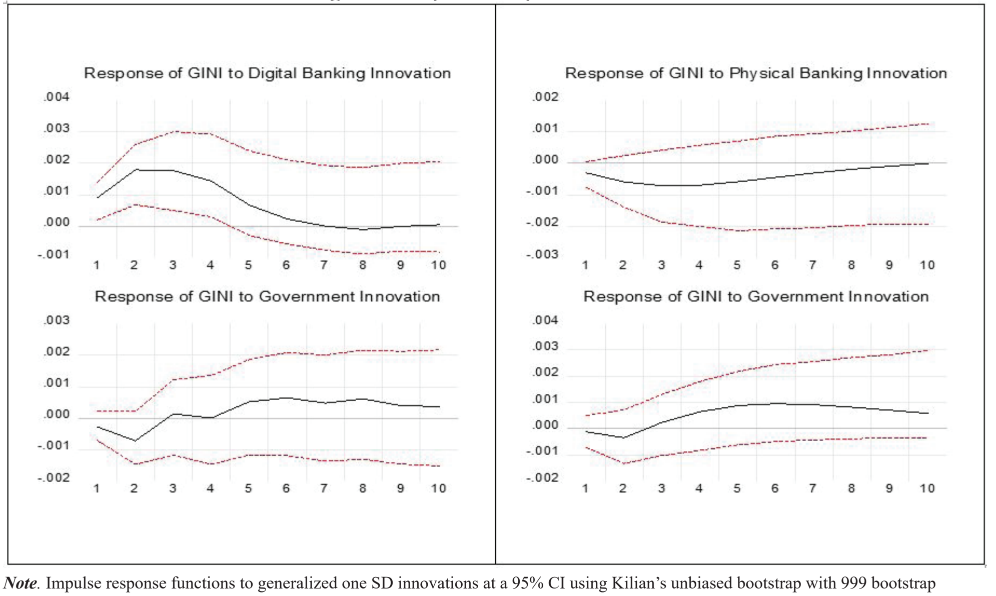
Put differently, the redistributive effect of government fails to reach the low-income-level group in society. A negative coefficient was also found for trade openness, indicating a negative relationship between economic openness and income inequality. Namely, increasing trade has a reducing impact on income inequality between the low-income and high-income level groups. In a developing economy where low-skilled labor is abundant, an increase in trade openness increases the wages of low-skilled labor while decreasing that of high-skilled labor. This effect reduces income inequality. The estimated coefficient for inflation is found to be positive and statistically significant. This result implies a positive relationship between income inequality and inflation. An increase in inflation in an economy negatively affect people's purchasing power. As people's real income decreases, poverty increases. This effect is pronounced in low-income-level groups.

The coefficients displayed in Columns 5 and 6 from Table 2 were obtained through a regression where a proxy was used for traditional banking instead of digital banking. Similar to the previous exercises, these cases first regressed income inequality over physical banking only, then regressed income inequality over physical banking alongside a set of control variables. The estimated coefficients for traditional banking have negative signs in both regressions, indicating that physical banking reduces income inequality.

The estimation results from the regressions suggest that digital banking increases income inequality, whereas traditional banking reduces it. One possible explanation for this result is that most retail customers who access the Internet are in the upper-income level group. They are likely to receive more economic and financial opportunities from digital banking compared to the low-income level group.

The study also estimated the appropriate VAR models to obtain the short-run dynamics among the variables. Figure 4 depicts the impulse response functions. In the VAR model using digital banking, Gini increases in response to a shock regarding digital banking innovation. The response is statistically significant for four periods. Gini's response is not statistically significant when a shock occurs regarding redistributive policies. The second specification uses physical banking, and statistically insignificant impulse responses were observed from Gini to shocks regarding both physical banking and government.

Figure 4. Impulse Response Functions



Note. Impulse response functions to generalized one SD innovations at a 95% CI using Kilian's unbiased bootstrap with 999 bootstrap repetitions and 499 double bootstrap repetitions.

Table 3 presents the Granger non-causality test results. Panel A tests the null hypothesis of causality based on the estimation of the VAR model by including digital banking, whereas Panel B tests the same but using physical banking. The VAR-based T-Y approach implies innovation in digital banking to affect income inequality, whereas physical banking does not help explain income inequality. Regarding the causality from redistributive policies to income inequality, evidence has been obtained that both types of banking Granger cause the Gini coefficient in this study's sample.

Table 3: Results from the T-Y Granger Non-Causality Test

Panel A			
Null hypothesis	**Wald chi-square Statistic**	**Prob.**	**Reject**
Digital Banking does not Granger cause Gini	7.48	0.05	**Y**
Government does not Granger cause Gini	8.91	0.03	**Y**
Gini does not Granger cause Digital Banking	5.68	0.12	N
Government does not Granger cause Digital Banking	3.5	0.32	N
Gini does not Granger cause Government	5.8	0.12	N
Digital Banking does not Granger cause Government	0.5	0.91	N

Panel B			
Null hypothesis	**Wald chi-square Statistic**	**Prob.**	**Reject**
Physical Banking does not Granger cause Gini	2.54	0.28	N
Government does not Granger cause Gini	6.45	0.04	**Y**
Gini does not Granger cause Physical Banking	1.27	0.53	N
Government does not Granger cause Physical Banking	0.63	0.72	N
Gini does not Granger cause Government	7.8	0.02	**Y**
Physical Banking does not Granger cause Government	0.45	0.8	N

Note. Y = Yes, N = No

6. Conclusion

The theory suggests that optimal source allocation cannot be achieved under asymmetric information. Additionally, the existence of transaction costs prevents full participation in the market. Under such market failures, exclusion manifests itself. These market imperfections are harmful, especially for low-income households, as they are likely to be excluded from financial markets. FinTech may appeal to more segments and help individuals with low-income be included in the financial system. In other words, FinTech is a key enabler of financial inclusion. Digital financial inclusion is also believed to have an income inequality-reducing effect.

This paper empirically examines the impact of accessing and using digital banking channels regarding income inequality in Türkiye over the 2011-2021 period using quarterly data. This study considers the Gini coefficient to measure income inequality and the financial transactions retail customers make through Internet banking to measure digital banking. This study employs a time series analysis to test how financial inclusion through digital banking affects income inequality. The study estimated the DOLS and VAR models, interpreted the results based on impulse responses with bias-corrected confidence intervals, and conducted VAR-based Granger non-causality tests.

Overall, the findings confirm that digital financial inclusion impacts income inequality. Digital financial inclusion has also been found to widen income inequality between low- and high-income groups, which is in line with the finding of Daud et al. (2021). Evidence has also been provided that shows the government's redistributive policies to favor groups with high-income levels. Moreover, inflation widens income inequality. As for causality, the null hypothesis has been rejected, with digital banking being concluded to Granger cause income inequality. When replacing digital banking with physical banking, the estimation results suggest physical banking to have a narrowing effect on income inequality.

More than offering digital access opportunities may be required to observe the actual impact of digital financial inclusion. To address the advantages of digitalization on low-income groups, authorities should consider several dimensions and offer policies accordingly. First, gender-based exclusion should be mitigated. Particular attention should be given to policies supporting the inclusion of females. Second, customers' digital skills also matter. Therefore, the authorities should adopt policies to improve the skills of existing and potential customers who need to learn digital skills. Third, infrastructure in rural areas should be improved. Although 88% of households have Internet at home, this share is very low for households living in rural areas where the low-income level group is most likely to live. Therefore, infrastructure, especially in rural areas, should also be improved to expand Internet access.

Appendix

Table A1: Variables and their Definitions, Construction, and Source

Variables	Definition	Construction	Data Source
Gini	Income inequality	Estimate of Gini coefficient	TURKSTAT
Digital Banking 1	Access and use of formal digital banking services through the Internet	The volume of investment transactions as a percentage of the total volume of retail financial transactions made through the Internet.	TBB
Digital Banking 2		Factor extracted from volumes per retail financial investment transactions, including money transfers, payments, investments, credit cards, and other transactions made through the Internet.	TBB
Physical Banking	Access and use of formal traditional banking services	Factor extracted from the number of bank branches and the number of personnel they hire	BKM
Consumption	Expenditure incurred by the household on goods and services	Consumption expenditure as a share of GDP	TURKSTAT, EVDS-CBRT
Government	Government spending on goods and services for the direct satisfaction of members of society	Government final consumption expenditure as a share of GDP	TURKSTAT, EVDS-CBRT
Trade Openness	International trade	Sum of exports and imports as a share of GDP	TURKSTAT
Inflation	Rate of rising prices	Year-over-year change in the price index	

Table A2: Descriptive Statistics (2011:Q1-2021:Q4)

Variables	Mean	SD	Max	Min
Gini	0.402182	0.003835	0.41	0.391
Digital Banking 1	0.507135	0.066163	0.656603	0.420588
Digital Banking 2	-6.06E-17	1	2.39639	-1.38001
Physical Banking	2.27E-07	1	1.48635	-1.84775
Consumption	0.980495	0.001256	0.982674	0.977913
Government	0.143238	0.009025	0.172255	0.1152
Trade Openness	0.470262	0.058512	0.674338	0.390232
Inflation	0.143711	0.129454	0.606099	0.020065

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