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DIGITALIZATION'S DUAL IMPACT ON BANKING: EVIDENCE FROM TÜRKİYE AND THE EU

Dijitalleşmenin Bankacılık Üzerindeki İkili Etkisi: Türkiye ve AB'den Kanıtlar

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Keywords:
Finance, Banking, Financial Technologies.

JEL Codes:
G00, G21, C33.

Abstract

This study examines how digital infrastructure and internet penetration shape structural change in the banking industry in Türkiye and 24 EU member states between 2004 and 2024. We use a large panel dataset and second-generation econometric techniques, including both fixed- and random-effects models, to assess how internet usage, mobile subscriptions, and broadband access affect key banking indicators, such as employment, branch networks, ATMs (Automated Teller Machines), and POS (Point of Sale) terminals. Our findings reveal a dual nature of digitalization's impact. As more people gain internet and broadband access, a clear substitution effect reduces physical banking infrastructure (branches and ATMs) and leads to a slight drop in employment. Mobile network expansion creates new digital roles, linking it positively to employment, even as ATMs supplement branches. By offering solid, cross-national evidence that separates these conflicting effects within a single analytical framework, this study adds to the body of knowledge. Our findings provide crucial insights for policymakers and financial institutions navigating the digital transition, as they present a groundbreaking analysis that simultaneously examines substitution and complementarity dynamics using the most recent data within a 20-year panel.

Anahtar Kelimeler:
Finans, Bankacılık, Finansal Teknolojiler.

Jel Kodları:
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Öz

Bu çalışma, 2004-2024 yılları arasında dijital altyapı ve internet penetrasyonunun Türkiye ve 24 AB üyesi ülkedeki bankacılık sektöründeki yapısal değişimi nasıl şekillendirdiğini incelenmektedir. İnternet kullanımı, mobil abonelikler ve genişbant erişiminin istihdam, şube ağları, ATM'ler (Otomatik Para Çekme Makineleri) ve POS (Satış Noktası) terminalleri gibi temel bankacılık göstergelerini nasıl etkilediğini değerlendirmek için geniş bir panel veri seti ile sabit ve rassal etkiler modellerini içeren ikinci nesil ekonometrik teknikler kullanılmıştır. Bulgularımız, dijitalleşmenin çift yönlü bir etkisini ortaya koymaktadır. Daha fazla kişi internet ve genişbant erişimine kavuştukça, belirgin bir ikame etkisi fiziksel bankacılık altyapısını (şubeler ve ATM'ler) azaltmakta ve istihdamda hafif bir düşüşe yol açmaktadır. Mobil ağ genişlemesi ise, ATM'lerin şubeleri tamamlayıcı rolüne rağmen, yeni dijital roller yaratarak istihdamla olumlu bir bağlantı kurmaktadır. Bu çalışma, çelişen bu etkileri tek bir analitik çerçevede ayıran sağlam ve ülkeler arası kanıtlar sunarak literatüre katkıda bulunmaktadır. Bulgularımız, 20 yıllık bir panel içinde en güncel verilerle ikame ve tamamlayıcılık dinamiklerini eşzamanlı inceleyen çığır açıcı bir analiz sunarak, dijital geçiş sürecindeki politika yapıcılar ve finansal kurumlar için hayati önemde içgörüler sağlamaktadır.

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1. Introduction

The rapid growth of digital technologies has fundamentally transformed the global banking industry, changing how financial services are offered, accessed, and managed. The expansion of internet access, the growth in fixed broadband and mobile subscriptions, and the increased use of digital banking channels have collectively shifted the industry from traditional, branch-based banking to more flexible, technology-driven models. This change is especially significant in both developed and emerging markets, where digitalization provides opportunities to boost efficiency, reduce operational costs, and promote financial inclusion (Demirgüç-Kunt et al., 2022).

In recent years, the banking sectors in Türkiye and the European Union have undergone significant changes due to the increasing penetration of the internet and digital infrastructure. While the number of physical bank branches has decreased, the use of electronic payment methods, such as ATMs and POS terminals, has grown, reflecting the sector’s adaptation to changing customer preferences and technological progress. However, the effect of digitalization on employment in the banking sector remains debated, as automation and digital service provision may cut traditional roles but also generate new opportunities in IT (Information Technologies), data analytics, and digital product management (Bunea et al., 2016). Recent Turkish evidence supports this dual narrative. Panel data from 19 deposit banks shows digital transformation significantly enhances profitability through improved liquidity creation and operational efficiency, with causality running from digitalization to ROA (Akarçay, 2025a). Mobile banking analysis reveals active customers positively correlate with ROA and ROE, though effects vary by transaction type (credit cards, payments, investments), highlighting heterogeneous impacts across digital channels (Akarçay, 2025b).

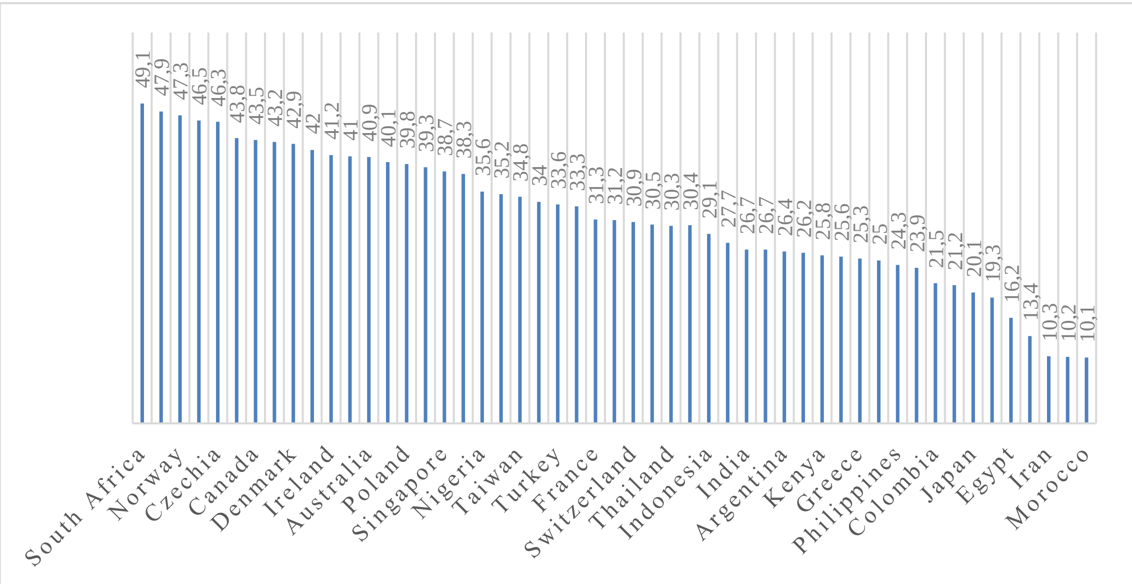

Figure 1. Use of Online Financial Services Jan’23.
Source: GWI (Q3 2022); Data Reportal / We Are Social / Meltwater - “Use of Online Financial Services” (Jan 2023).

Despite the increasing research on digital transformation in banking, there is a need for thorough, cross-country empirical evidence that captures the complex effects of internet usage and digital infrastructure on banking sector dynamics. This study fills this gap by analyzing panel data from Türkiye and 24 European Union countries from 2004 to 2024. It examines the impacts of internet usage, fixed broadband, and mobile cellular subscriptions on employment, branch networks, ATMs, and POS terminals, offering new insights into the structural and functional changes in the banking sector in the digital age. The study is organized as follows: it presents empirical literature, describes the variables, models, and econometric methods used, reports the findings, and concludes with a general evaluation of the model results.

2. Literature Review

The digital transformation of the banking sector has accelerated rapidly over the past decade, fundamentally altering the structure, operations, and competitive landscape of financial institutions worldwide (Gomber et al., 2018). The spread of internet access, mobile technologies, and broadband infrastructure has allowed banks to provide services more efficiently, cut operational costs, and serve previously underserved populations (Demirgüç-Kunt et al., 2022; European Commission, 2020). This transformation is not only technological but also strategic, requiring banks to modify their business models, invest in IT infrastructure, and promote a culture of innovation. (Arner et al., 2015; Broby, 2021). Recent empirical evidence from Türkiye confirms that digital financial inclusion has become a critical factor in banking sector transformation, with internet penetration and mobile technologies serving as primary drivers (Güz and Poyraz, 2024). Furthermore, the relationship between digitalization and banking sector performance demonstrates non-linear dynamics, suggesting that digital maturity affects corporate sustainability through complex pathways (Aksoy et al., 2025).

A growing body of research highlights the positive relationship between digitalization and banking sector performance. For example, Gomber et al. (2018) argue that digital technologies enhance efficiency, profitability, and customer experience, while also introducing new risks related to cybersecurity and regulatory compliance. The adoption of the internet and mobile banking has been shown to reduce the need for physical branches, leading to a decline in branch networks, especially in advanced economies (Keil and Ongena, 2024). However, the impact on employment is more nuanced: while some studies suggest that automation and digital channels may reduce traditional banking jobs, others find that new roles emerge in IT, data analytics, and digital service management, offsetting potential job losses (Bunea et al., 2016).

A growing body of empirical research shows that branch retrenchment is influenced by multiple interacting factors—such as technological adoption, market consolidation, and risk conditions—rather than by technology alone. Using U.S. data, Nguyen (2019) leverages post-merger consolidation as a source of plausibly exogenous variation and finds that local branch closings lead to persistent declines in small-business lending, with effects that are highly localized. Complementing this evidence in a European context, Ho and Berggren (2020) document that increasing distance to the nearest bank branch following closures depresses new firm formation across Swedish municipalities, consistent with the erosion of soft-information lending when geographic proximity weakens. Relatedly, recent Italian evidence shows that branch withdrawals are associated with lower new-firm creation, highlighting heterogeneity in real-economy effects across regions with different digital barriers and geography (Cardamone and Trivieri, 2024). Together with broader evidence linking branch decline to technology, consolidation, and fragility (Keil and Ongena, 2024), these studies temper the view that branch closures are uniformly efficiency-enhancing and underscore distributional consequences for SMEs and local communities.

In the Turkish context, banking sector dynamics reveal additional complexities. Recent evidence shows that risk-taking behavior in Turkish banks is influenced by both competitive pressures and digital transformation imperatives (Demir and Aydın, 2025). Corporate sustainability initiatives in Turkish banks during 2019-2023 demonstrate adaptive responses to digitalization, with institutions balancing physical infrastructure rationalization against digital capability building (Ünlü and Çıtak, 2025). Furthermore, the relationship between financial inclusion and monetary policy effectiveness suggests that digital channels enhance policy transmission mechanisms, though effects vary by market structure and institutional development (Yıldırım et al., 2025).

Cross-country studies reveal significant heterogeneity in the pace and effects of digital transformation. In the European Union, the Digital Single Market strategy has promoted harmonization and innovation, but disparities persist between member states, particularly in digital infrastructure and financial inclusion (Zalan and Toufaily, 2017; European Commission, 2020). Emerging markets such as Türkiye have experienced rapid growth in digital banking adoption, driven by high mobile penetration and a young, tech-savvy population. However, these markets also face challenges related to regulatory adaptation, cybersecurity, and the digital divide (Demirgüç-Kunt et al., 2022).

Recent empirical studies have employed panel data methods to analyze the effects of internet penetration, broadband subscriptions, and mobile usage on various aspects of banking sector development. The evidence consistently shows that increased internet and mobile usage are associated with reductions in branch density and growth in electronic payment infrastructure, such as ATMs and POS terminals (Katz et al., 2010; Gomber et al., 2017). Nevertheless, the relationship between digitalization and employment remains complex and context-dependent, warranting further research.

In Central and Eastern Europe, recent efforts have focused on improving POS/ATM infrastructure, expanding digital coverage, and promoting mPOS/contactless payment solutions. Research shows a clear connection between advancements in digital infrastructure and adoption metrics, the restructuring of physical banking points, and the spread of acceptance technologies in the region. For example, the CEE banking-sector digitalization index indicates that stronger broadband and mobile networks, along with higher digital adoption, correlate with better banking performance and a shift in how services are delivered. This aligns with optimizing ATM and branch networks and increasing investments in POS, mPOS, and contactless payment options (Manta et al., 2024). Europe-wide statistics also show increasing digital activity among firms and households, with the adoption of cloud and AI and the improvement of digital skills—factors that reduce the marginal cost of deploying acceptance technology and speed up contactless usage (Dedola et al., 2023). On the demand side, consumer payment surveys indicate ongoing growth in card and mobile payments at the POS and increasing access to instant payments, supporting merchant incentives to deploy mPOS/contactless terminals (ECB, 2024a). ECB payment statistics confirm this with double-digit annual growth in POS terminals and a high share of contactless-capable devices (ECB, 2024b). At the bank level, European evidence suggests that digital/IT investments improve efficiency - though possibly following inverted-U dynamics - consistent with the rationalization of cash-based infrastructure and expansion of digital acceptance channels

(Ayadi et al., 2025). These patterns align with global digital-adoption frameworks (World Bank DAI) and broader European retail payments trends that emphasize instant, contactless, and mobile modalities, reinforcing how mobile coverage and acceptance technologies facilitate the spread of mPOS/contactless payments in CEE (ECB, 2024b; García-Merino et al., 2025).

Overall, prior research indicates significant and sometimes opposing effects of digitalization on banking structure and performance. Internet- and app-based channels generally replace branches and cash-intensive transactions, while mobile penetration often supports the growth of acceptance technologies and back-office capabilities. The overall effect on employment depends on the context, influenced by the balance between automation and the creation of new digital roles. Based on this evidence, our cross-country analysis explicitly separates substitution (internet versus branches/ATMs) from complementarity (mobile with employment/POS/ATMs) from 2004 to 2024.

3. Data and Methodology

This study uses a panel dataset with annual data from 25 countries - Türkiye and 24 European Union (EU) member states - covering 2004 to 2024. It offers a comparative analysis of digitalization trends and their impacts on the banking sector. The data were collected from reputable sources such as the European Central Bank, World Bank, Eurostat, and national statistical agencies. The countries included in this study are: Türkiye, Germany, Luxembourg, Ireland, Denmark, the Netherlands, Austria, Belgium, Bulgaria, Czechia, Estonia, Finland, France, Spain, Sweden, Italy, Latvia, Lithuania, Malta, Poland, Portugal, the Slovak Republic, Slovenia, Greece, and Hungary. The variables examined are listed in Table 1. However, logarithms were applied to all variables except INTERNET. Since INTERNET reflects the Internet usage rate in percentage terms, a logarithm was not taken for INTERNET.

Table 1. Variables

Variable	Descriptions
EMP	Banking sector employment
ATM	The number of ATMs
BRANCHES	The number of bank branches
POS	The number of pos (point of sale) terminals
INTERNET	Internet usage rate (% of population)
MOBILE	Mobile cellular subscriptions (per 100 people)
FBS	Fixed broadband subscriptions
GDP	GDP (Gross Domestic Product) per capita
POPULATION	Total population

As presented in Table 1, all variables except for internet usage rate (INTERNET) are transformed into natural logarithms to facilitate interpretation and to address potential heteroscedasticity in the regression models (Levine, 2005; Demirgüç-Kunt et al., 2022). The selection of these variables is grounded in the existing literature on banking sector development and digital transformation. The inclusion of these variables allows for a comprehensive analysis of how digital infrastructure, economic development, and demographic factors jointly influence the transformation of banking sector dynamics in Central and Eastern Europe. This approach is consistent with previous empirical studies examining the interplay between digitalization and banking sector performance (Hasan et al., 2012; Levine, 2005; Levine et al., 2009; Zins and Weill, 2016; Demirgüç-Kunt et al., 2022; Manta et al., 2024). For example, EMP captures the employment level in the banking sector, serving as a proxy for sectoral growth and labor market dynamics (Levine et al., 2009). ATM and BRANCHES represent the physical infrastructure of banks, which are critical for understanding the evolution of traditional banking channels (Hasan et al., 2012). POS (Point of Sale Terminals) reflect the expansion of electronic payment infrastructure, which is a key indicator of digital payment adoption and financial inclusion (Zins and Weill, 2016; Manta et al., 2024). Similarly, the INTERNET measures the percentage of the population with internet access, indicating the level of digital connectivity and the potential for digital banking services in each (Manta et al., 2024). MOBILE (mobile cellular subscriptions per 100 people) and FBS (the logarithm of fixed broadband subscriptions) are included to capture the diffusion of digital technologies, which have been shown to drive the adoption of digital financial services and reshape banking delivery channels. GDP per capita is used as a control variable to account for differences in economic development across countries, which can influence both banking sector performance and technology adoption (Levine, 2005). POPULATION is included to control for demographic factors that may affect the scale and structure of the banking sector (Levine et al., 2009).

Table 2 presents the descriptive statistics for the variables used in the analysis. Among all variables, the INTERNET variable exhibits the highest standard deviation, indicating substantial variability in internet usage rates across countries and years. In contrast, the POPULATION variable has the lowest mean value, while the FBS variable also displays a relatively low average. The skewness and kurtosis values suggest that most variables deviate from normality, a finding further confirmed by the Jarque-Bera (JB) test results, which are statistically significant for all variables. This indicates that the assumption of normal distribution does not hold for the dataset.

Table 2. Descriptive Statistics

	ATM	Branches	EMP	FBS	GDP	Mobile	Population	POS	Internet
Mean	8.5639	3.2505	10.721	3.1466	10.233	4.7562	-0.8568	12.111	73.620
Median	8.4826	3.2277	10.628	3.3402	10.253	4.7670	-0.7193	12.075	78.300
Std. Dev.	1.5743	0.6533	1.2942	0.6746	0.6771	0.1667	1.1677	1.5475	18.260
Jarque-Bera	9.8156***	2.9862	9.2401***	4978.574***	4.7285*	129.5116***	1173.928***	3.4577*	70.358***
p-value	0.0074	0.0897*	0.0098	0.0000	0.0940	0.0000	0.0000	0.0995	0.0000

Note: *, **, *** denote normal distribution assumption is not valid at the 10%, 5%, and 1% levels, respectively.

Correlation matrices help identify models to consider in the study. As is well known, a high correlation between two independent variables can lead to multicollinearity issues in the model. Therefore, this section aims to examine the correlation matrix results. Due to the non-normal distribution of the variables, the Spearman correlation matrix was used to evaluate the relationships among the independent variables, as it provides more reliable results under such conditions.

Table 3. Spearman Rank-Order Correlation Matrix

	ATM	BRANCHES	EMP	FBS	GDP	MOBILE	POPULATION	POS	INTERNET
ATM	1.0000								
p-value	-----								
BRANCHES	0.1211**	1.0000							
p-value	0.0111	-----							
EMP	**0.9352*****	0.1312*	1.0000						
p-value	0.0000	0.0059	-----						
FBS	0.0181	-0.1981***	0.0715	1.0000					
p-value	0.7051	0.0000	0.1346	-----					
GDP	0.0364	0.0397	0.2312***	0.5921***	1.0000				
p-value	0.4464	0.4058	0.0000	0.0000	-----				
MOBILE	-0.1727***	-0.1203**	-0.1393**	0.3330***	0.2021***	1.0000			
p-value	0.0003	0.0116	0.0034	0.0000	0.0000	-----			
POPULATION	-0.1892***	0.0593	-0.1111**	0.0540	0.2111***	0.0091	1.0000		
p-value	0.0001	0.2148	0.0198	0.2583	0.0000	0.8485	-----		
POS	**0.8278*****	0.0231	**0.8414*****	0.2512***	0.1980***	-0.0842*	-0.0478	1.0000	
p-value	0.0000	0.6280	0.0000	0.0000	0.0000	0.0777	0.3170	-----	
INTERNET	-0.1638**	-0.3435***	-0.0614	**0.8525*****	0.6303***	0.3575***	0.0917*	0.1025**	1.0000
p-value	0.0006	0.0000	0.1991	0.0000	0.0000	0.0000	0.0547	0.0317	-----

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

As shown in Table 3, there is a very strong, positive, significant relationship between ATM and EMP (r=0.9352). There is also a strong, positive, significant relationship between POS and ATM (r=0.8278). A strong, positive relationship was observed between POS and EMP (r=0.8414). Additionally, this relationship is present between FBS and INTERNET (r=0.8525). Based on these findings, interrelated variables should not be included simultaneously in the model. Therefore, the models in this study were constructed accordingly.

The models are designed to explore different aspects of the banking sector's structure, including employment, branch networks, ATM deployment, and POS terminal usage. By including variables such as internet usage, mobile cellular subscriptions, fixed broadband subscriptions, GDP per capita, and population, the models aim to thoroughly evaluate the impacts of digitalization and macroeconomic factors on the banking industry. Based on the results of the Spearman correlation matrices, the following empirical models were developed to examine how internet penetration affects the structure of the banking sector. The choice of these models was based on both theoretical considerations and the observed relationships among the variables. The correlation analysis showed no significant multicollinearity issues among the independent variables, enabling reliable estimation of the models. The empirical models used in the study are as follows:

Banking Sector Employment

$$EMPit \ = f(MOBILEit, FBSit, ATMit) \qquad \text{Model (1)}$$

$$EMPit \ = f(GDPit, POPULATIONit, INTERNETit) \qquad \text{Model (2)}$$

Bank Branches

$$BRANCHESi \ = f(MOBILEit, FBSit, ATMit) \qquad \text{Model (3)}$$

$$BRANCHESi \ = f(GDPit, POPULATIONit, INTERNETit) \qquad \text{Model (4)}$$

ATMs

$$ATMit \ = f(MOBILEit, FBSit, POSit, BRANCHESit) \qquad \text{Model (5)}$$

$$ATMit \ = f(GDPit, POPULATIONit, INTERNETit, EMPit) \qquad \text{Model (6)}$$

Here, i denotes the country and t denotes the year. All variables are defined as in the data section. These models will explore how digitalization, supported by internet and mobile subscription variables, impacts various aspects of the banking sector, along with traditional banking infrastructure and macroeconomic controls. This study aims to provide evidence on the structural transformation of banking in the context of increasing digital penetration.

In panel regression analysis, firstly cross-sectional dependence in variables must be investigated so that it is possible to continue the analysis with the appropriate unit root test. In panel data analysis, cross-sectional dependence may arise due to spillover effects or common shocks across countries. Cross-sectional dependence refers to the correlation of error terms across cross-sectional units, which can undermine the reliability of classical panel estimators.

In panel regression analysis, cross-sectional dependence must first be investigated in the variables so that the analysis can be continued with an appropriate unit root test. In the case of N>T, two cross-sectional dependence tests are used: the Breusch-Pagan LM test and the Pesaran CD test. This test corrects the bias in the Breusch-Pagan LM test when the number of cross-sectional units is large. The formula is as follows:

$$LM_{BC} = \frac{1}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(\frac{T\hat{\rho}_{ij}^2 - 1}{\sqrt{2}} \right) \tag{1}$$

The Pesaran (2004) CD test examines the average pairwise correlation of residuals across cross-sectional units. The test statistics are calculated as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \tag{2}$$

where $\hat{p}_{ij}$ is the estimated correlation coefficient between the residuals of units i and j, N is the number of cross-sectional units, and T is the time dimension.

In the presence of cross-sectional dependence in variables, first-generation panel unit root tests lose their reliability, and in this case, second-generation unit root tests are used. The Pesaran CADF (Cross-sectionally Augmented Dickey-Fuller) unit root test accounts for cross-sectional dependence when testing for unit roots in panel data.

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i \overline{y}_{t-1} + \sum_{j=0}^{p-1} \delta_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{p-1} \phi_{ij} \Delta \overline{y}_{t-j} + \varepsilon_{it} \tag{3}$$

where $\overline{y}_t$ is the cross-sectional average at time t. The null hypothesis is that $\beta_i = 0$ (unit root), and the alternative is $\beta_i < 0$ (stationarity).

Model selection is a critical step in panel data analysis to determine the most appropriate estimation technique. The F test (also known as the Chow test) is commonly used to decide between pooled OLS and fixed effects models. The null hypothesis of the F test states that all individual effects are equal (i.e., no fixed effects are present). Rejection of the null hypothesis indicates that the fixed effects model is preferred over the pooled OLS model, as it accounts for unobserved heterogeneity across cross-sectional units (Baltagi, 2021).

The Hausman test (Hausman, 1978) is used to determine whether to use fixed effects or random effects models. The null hypothesis of the Hausman test is that the preferred model is random effects, which assumes that individual effects are uncorrelated with the regressors. If the null hypothesis is rejected, the fixed effects model is more appropriate, as it provides consistent estimates in the presence of correlation between individual effects and explanatory variables. The test statistic is calculated as follows:

$$H = (\hat{\beta}\mathrm{RE} - \hat{\beta}\mathrm{FE})'[\mathrm{Var}(\hat{\beta}\mathrm{FE}) - \mathrm{Var}(\hat{\beta}\mathrm{RE})] - 1\,(\hat{\beta}\mathrm{RE} - \hat{\beta}\mathrm{FE}) \quad (4)$$

where $\hat{\beta}$RE and $\hat{\beta}$FE and are the coefficient estimates from the random effects and fixed effects models, respectively. A significant test statistic suggests that the random effects estimator is inconsistent, and the fixed effects model should be used (Baltagi and Wu, 1999; Hausman, 2015). The application of these model selection tests ensures that the panel regression analysis is based on the most suitable specification, thereby improving the reliability and validity of the empirical results.

In the fixed-effects model, the heteroscedasticity issue is investigated using the modified Wald test. The Modified Wald test for groupwise heteroskedasticity is commonly employed in panel data analysis, particularly with fixed effects models, to assess whether the error variances are constant across cross-sectional units. Homoskedasticity (constant variance) is a key assumption for efficient estimation in classical regression. If heteroskedasticity is present, standard errors can be biased, leading to incorrect inferences about the significance of coefficients.

The null hypothesis (H_0) of the Modified Wald test is that the error variances are equal across all panels (i.e., homoskedasticity). The alternative hypothesis (H_1) is that the error variances differ across panels (i.e., heteroskedasticity).

The test statistic is typically calculated as:

$$W = \sum_{i=1}^{N} \frac{\left(\hat{\sigma}_i^{\,2} - \hat{\sigma}^2\right)^2}{\mathrm{Var}\left(\hat{\sigma}_i^{\,2}\right)} \quad (5)$$

where:

N is the number of cross-sectional units (panels).

$\hat{\sigma}_i^{\,2}$ is the estimated error variance for panel i

$\hat{\sigma}^2$is the pooled (overall) estimated error variance.

$\mathrm{Var}\left(\hat{\sigma}_i^{\,2}\right)$ is the estimated variance of the error variance for panel

Under the null hypothesis, the test statistic gradually approaches a chi-squared distribution with N degrees of freedom. A significant p-value (typically less than 0.05 or 0.01) leads to the rejection of the null hypothesis, indicating the presence of heteroskedasticity. In such cases, robust standard errors (like Driscoll–Kraay) are necessary to ensure valid statistical inference.

In the random-effects model, the heteroscedasticity issue is investigated using the Levene, Brown, and Forsythe test. In these tests, the null hypothesis asserts that the homoscedasticity assumption is valid. Testing for homogeneity of variances (homoskedasticity) is crucial in panel data models. For this purpose, the Levene and Brown-Forsythe tests were used. Levene’s test examines the equality of variances across groups (Levene, 1960). The test statistics:

$$W = \frac{(N-k)}{(k-1)} \cdot \frac{\sum_{i=1}^{k} n_i (Z_{i.} - Z_{..})^2}{\sum_{i=1}^{k} \sum_{j=1}^{n_i} \left(Z_{ij} - Z_{i.}\right)^2} \tag{6}$$

where $Z_{ij} = \left|Y_{ij} - \widetilde{Y_i}\right|$ and $\widetilde{Y_i}$ is the group mean or median. The Brown-Forsythe test is a variation of Levene’s test, using the group median instead of the mean:

$$Z_{ij} = \left|Y_{ij} - \mathrm{median}(Y_i)\right| \tag{7}$$

The test statistic is calculated as in Levene’s test, but with the median.

The presence of autocorrelation issues in the fixed- and random-effects models was investigated using the Modified Bhargava et al. Durbin-Watson and Baltagi-Wu LBI tests. If the value obtained from these tests is less than 2, it is concluded that the model has an autocorrelation problem. To test for serial correlation in the error terms of panel data models, the Bhargava et al. (1982). Durbin-Watson and Baltagi-Wu LBI (Baltagi and Wu, 1999) statistics were used. Bhargava et al. Durbin-Watson Statistic: Formula

$$DW = \frac{\sum_{i=1}^{N} \sum_{t=2}^{T} \left(e_{it} - e_{i,t-1}\right)^2}{\sum_{i=1}^{N} \sum_{t=1}^{T} e_{it}^2} \tag{8}$$

where e_{it} is the residual for unit i at time t. Proposed by Baltagi and Wu (1999), the Locally Best Invariant (LBI) statistic is:

$$LBI = \frac{\sum_{i=1}^{N} \sum_{t=2}^{T} \left(e_{it} - \hat{\rho} e_{i,t-1}\right)^2}{\sum_{i=1}^{N} \sum_{t=1}^{T} e_{it}^2} \tag{9}$$

where $\hat{\rho}$ is the estimated autocorrelation coefficient of the residuals.

When cross-sectional dependence, heteroskedasticity, and autocorrelation are present in panel data, conventional standard error estimators may yield biased inference. The Driscoll-Kraay estimator provides robust standard errors that are consistent in the presence of cross-sectional dependence, serial correlation, and heteroskedasticity (Driscoll and Kraay, 1998). This estimator is particularly suitable for panels with a large cross-sectional dimension and when cross-sectional dependence is detected. Therefore, Driscoll-Kraay standard errors were employed in this study to ensure the reliability and robustness of the estimated coefficients.

4. Empirical Results

In panel data analysis, it is crucial to first assess whether the variables show cross-sectional dependence. The existence or absence of this dependence dictates which unit root test to use: first-generation tests are suitable when there is no cross-sectional dependence, whereas second-generation tests yield more reliable results when such dependence exists. Therefore, before proceeding with the stationarity analysis, cross-sectional dependence among the variables was examined. Given the panel structure of this study, where the number of cross-sectional units (N=25) exceeds the time dimension (T=21), the Pesaran CD test and the Bias-corrected Scaled LM test were applied, as these tests are considered valid and robust under such conditions. The results of these tests are presented in Table 4.

Table 4. Cross-Sectional Dependence Test Results

Variables	Bias-Corrected Scaled LM	Pesaran CD
ATM	77.7301*** (0.0000)	15.7483*** (0.0000)
BRANCHES	110.4614*** (0.0000)	44.51881*** (0.0000)
EMP	84.94317*** (0.0000)	21.92247*** (0.0000)
FBS	214.8788*** (0.0000)	74.65537*** (0.0000)
GDP	135.5110*** (0,0000)	56.25822*** (0.0000)
INTERNET	204.3523*** (0.0000)	204.3523*** (0.0000)
MOBILE	95.79471*** (0.0000)	49.06721*** (0.0000)
POPULATION	25.65392*** (0.0000)	1.855686*** (0.0000)
POS	100.6855*** (0.0000)	100.6855*** (0.0000)

Notes: Probability value is given in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

As shown in Table 4, all variables exhibit cross-sectional dependence. Considering this finding, the analysis proceeds with the second-generation unit root tests that account for cross-sectional dependence, specifically the Pesaran unit root test. The relevant results are presented in Table 4.

The results of the Pesaran second-generation unit root test are presented in Table 5. The INTERNET and FBS variables were stationary at a level value. According to the findings, the null hypothesis of a unit root cannot be rejected for the level values of the variables, while the first differences of all variables are found to be stationary at the 1%, 5%, or 10% significance levels (except INTERNET and FBS).

Table 5. Pesaran Unit Root Test Results

Variables	Test Statistics	p-value
ATM	2.563	0.995
ΔATM	-1.961	0.025**
BRANCHES	-1.054	0.146
ΔBRANCHES	-3.016	0.001***
EMP	1.035	0.850
ΔEMP	-3.249	0.001***
FBS	-3.978	0.000***
GDP	3.022	0.999
ΔGDP	-3.113	0.001***
INTERNET	-2.966	0.0002***
MOBILE	0.529	0.702
ΔMOBILE	-5.359	0.0000***
POPULATION	-0.598	0.275
ΔPOPULATION	-7.074	0.0000***
POS	0.329	0.629
ΔPOS	-2.307	0.011**

Notes: *, **, *** denote significance at the 10%, 5%, and 1% levels. The Δ symbol denotes the first differences of the variable.

The study continued with the levels/differences where the variables were stationary, and the selection phase of the models to be used was started. Model selection tests were conducted, and the results are presented in Table 6.

Table 6. Model Selection Test Results

	F Test	Hausman Test	Decision
MODEL 1	3.62 (0.0000)***	8.47(0.0373)**	Fixed Effects Model
MODEL 2	3.09 (0.0000)***	11.15 (0.0109)**	Fixed Effects Model
MODEL 3	1.55 (0.0477)**	13.96 (0.0000)***	Fixed Effects Model
MODEL 4	1.79 (0.0132)**	2.73 (0.4347)	Random Effects Model
MODEL 5	1.73 (0.0183)**	8.86 (0.0646)*	Fixed Effects Model
MODEL 6	2.44 (0.0002)***	10.98 (0.0268)**	Fixed Effects Model

Not: *, **, and *** indicate rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively.

Table 6 shows that unit effects were present in all models based on the F test results. The Hausman test was used to determine whether the unit effects were random or fixed effects. The Hausman test results are also presented in Table 6. Based on these results, the random effects model was determined to be appropriate only for Model 4. For all other models, the fixed effects model was determined to be appropriate. At this stage of the study, the presence of autocorrelation and heteroscedasticity issues in the model was investigated. In the fixed-effects model, the heteroscedasticity issue was investigated using the modified Wald test. In the random-effects model, the heteroscedasticity issue was investigated using the Levene, Brown, and Forsythe test. In these tests, the null hypothesis asserts that the homoscedasticity assumption is valid. The presence of autocorrelation issues in the fixed- and random-effects models was investigated using the Modified Bhargava et al. Durbin-Watson and Baltagi-Wu LBI tests. If the value obtained from these tests is less than 2, it is concluded that the model has an autocorrelation problem.

Table 7. Results of Diagnostic Tests for Models

		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Autocorrelation Test	Modified Bhargava et al. Durbin-Watson	1.5177	1.3811	2.1125	2.0001	1.5070	1.5418
	Baltagi-Wu LBI	1.6409	1.6882	2.1730	2.0325	1.8009	1.78761
Heteroscedasticity Test		**Model 1**		**Model 3**	**Model 4**	**Model 5**	**Model 6**
Modified Wald Test		1908.90***(0.000)	4257.98***(0.000)	5066.65***(0.000)	-	2238.22***(0.000)	3053.08***(0.000)
Levene, Brown, and Forsythe’s Test	W0 (p-value)				1.7060** (0.0214)		
	W10 (p-value)	-	-	-	1.6235** (0.0334)	-	-
	W50 (p-value)				1.6521** (0.0287)		

Note: *, **, and *** indicate the presence of heteroskedasticity at the 10%, 5%, and 1% significance levels, respectively.

Table 7 shows that all models, except Model 3 and Model 4, exhibit autocorrelation issues. It also indicates that, at the 5% significance level, there is heteroscedasticity across all models. To ensure reliable results, it is important to use an estimator that addresses these problems. When models face cross-sectional dependence, autocorrelation, and heteroskedasticity, the Driscoll-Kraay estimator offers robust and consistent outputs. Therefore, this study estimated the regression models using Driscoll-Kraay standard errors to analyze how internet penetration and other financial variables affect the structure of the banking sector. The analyses were performed independently for each of the six models. Table 8 presents the estimation results for Model 1 and Model 2 using the fixed effects approach.

Table 8. Model 1 and Model 2

Dependent Variable: ΔEMP							
Variables	**Coefficient**	**Driscoll-Kray Standard Errors**	**p-value**	**Variables**	**Coefficient**	**Driscoll-Kray Standard Errors**	**p-value**
Constant	0.0775^{***}	0.0221	0.0030	**Constant**	0.0718^{***}	0.0604	0.0000
ΔMOBILE	0.1396^{***}	0.0266	0.0000	**ΔGDP**	0.1437^{**}	0.0604	0.0290
FBS	-0.0268^{***}	0.0066	0.0010	**ΔPOPULATION**	-0.0020	0.0021	0.3350
ΔATM	0.0424	0.0628	0.5090	**INTERNET**	-0.0011^{***}	0.0001	0.0000
F	**14.45^{***} (0.0010)**			**F**	**14.87^{***} (0.0000)**		

Notes: *, **, *** denote significance at the 10%, 5%, and 1% levels. The Δ symbol denotes the first differences of the variable.

Table 8 shows that 1% increase in mobile subscriptions is associated with ≈0.14% higher banking employment, while a 1% rise in fixed broadband is associated with ≈0.027% lower employment. A one percentage-point increase in internet usage is associated with ≈0.11% lower employment. ATM is not significant in these specifications.

These results suggest a mixed labor effect of digitalization — mobile expansion appears complementary to employment (new digital roles), whereas broadband and broader internet adoption are associated with modest employment reductions consistent with automation/substitution. GDP growth remains positively associated with employment, as expected.

In Table 9, Model 3 and Model 4 were estimated. Model 3 is the fixed effects model, and Model 4 is the random effects model. Table 9 shows that 1% increase in internet usage ≈0.17% decline in branch counts; a 1% increase in broadband ≈0.045% decline in branches; ATM is positively associated with branches.

Table 9. Model 3 and Model 4

Dependent Variable: ΔBRANCHES							
Variables	**Coefficient**	**Driscoll-Kray Standard Errors**	**p-value**	**Variables**	**Coefficient**	**Driscoll-Kray Standard Errors**	**p-value**
Constant	0.1045^{**}	0.0443	0.0310	**Constant**	0.0866^{***}	0.0219	0.0010
ΔMOBILE	0.1154^{*}	0.0627	0.0830	**ΔGDP**	0.1330^{***}	0.0346	0.0010
FBS	-0.0452^{***}	0.0131	0.0030	**ΔPOPULATION**	0.0011	0.0032	0.7220
ΔATM	0.1992^{**}	0.0734	0.0150	**INTERNET**	-0.0017^{***}	0.0002	0.0000
F	**26.51 (0.000*)**			**Wald**	**39.27^{***} (0.0000)**		

Notes: *, **, *** denote significance at the 10%, 5%, and 1% levels. The Δ symbol denotes the first differences of the variable.

Results point to a clear substitution effect of internet and broadband on branch density, while ATMs often remain complementary to branches and mobile expansion shows heterogeneous/weakly positive effects. These findings point to a clear substitution effect of internet and broadband on branch density, but with important nuances: ATMs often remain complementary to branches, and mobile diffusion can have mixed effects depending on market structure and distribution strategies.

In Table 10, Model 5 and Model 6 were estimated and the findings of the fixed effects model are reported. Table 10 shows that 1% percentage-point increase in internet usage is associated with ≈0.23% fewer ATMs; a 1% rise in broadband ≈0.054% fewer ATMs. BRANCHES is positively associated with ATM numbers. MOBILE, POS, and EMP are not significant here.

Table 10. Model 5 and Model 6

Dependent Variable: ΔATM							
Variables	**Coefficient**	**Driscoll-Kray Standard Errors**	**p-value**	**Variables**	**Coefficient**	**Driscoll-Kray Standard Errors**	**p-value**
Constant	0.1810^{***}	0.0556	0.0050	**Constant**	0.1755^{***}	0.0245	0.0000
ΔMOBILE	0.0781	0.0714	0.2890	**ΔGDP**	0.0788	0.0522	0.1490
FBS	-0.0539^{***}	0.0172	0.0060	**ΔPOPULATION**	-0.0025	0.0036	0.4910
ΔPOS	-0.0033	0.0038	0.4020	**INTERNET**	-0.0023^{***}	0.0003	0.0000
ΔBRANCHES	0.1518^{***}	0.0425	0.0020	**ΔEMP**	0.04985	0.1453	0.7350
F	**8.06^{***} (0.0000)**			**F**	**26.51 (0.000*)**		

Notes: *, **, *** denote significance at the 10%, 5%, and 1% levels. The Δ symbol denotes the first differences of the variable.

Findings are consistent with substitution away from cash-dispensing infrastructure as online payment channels expand, while ATMs remain linked to branch networks (co-location/complementarity). The results support a picture in which internet and broadband expansion reduce demand for physical cash points, but the persistence of positive branch–ATM complementarity implies that withdrawal infrastructure is still linked to physical presence and local service strategy.

Across Tables 8–10, the consistent pattern is that greater internet penetration and stronger fixed broadband coverage are associated with reductions in traditional physical infrastructure (branches and ATMs) and modest negative effects on employment, while mobile expansion shows more heterogeneous or positive associations with employment and (weakly) branches.

5. Conclusion

This study examines internet usage and digital infrastructure in Türkiye and 24 EU member states from 2004 to 2024 and their banking sector outcomes. We compare banking employment, branches, ATMs, and POS terminals to internet usage, mobile subscriptions, fixed broadband, GDP per capita, and population using panel regression models. This study documents how digital penetration relates to multiple facets of banking sector structure in Türkiye and the EU over 2004–2024.

This study set out to quantify the impact of the digital revolution on the banking sector's structure across Türkiye and the EU. The results paint a complex picture of transformation, characterized by both disruptive and adaptive forces. Our analysis confirms that the rise of the internet and fixed broadband infrastructure has acted as a significant substitute for traditional banking channels, leading to a measurable contraction in physical branch networks and ATM infrastructure. This trend aligns with the global shift towards online and automated services, reducing reliance on cash-based transactions and physical customer interactions.

However, contrary to a purely disruptive narrative, our findings also highlight important complementary dynamics. The positive relationship between mobile cellular subscriptions and banking employment suggests that digitalization is not merely a job-destroying force but also a job-creating one, fostering new opportunities in IT, digital product management, and data analytics. The persistent positive link between the number of branches and ATMs further indicates that, rather than a wholesale abandonment of physical infrastructure, there is a strategic consolidation and co-location of services.

The implications of these findings are multifaceted. For bank managers, the results underscore the necessity of strategic investment in digital channels while simultaneously optimizing and potentially retooling physical networks for higher-value services. For policymakers, understanding the dual nature of this impact is crucial. Strategies aimed at enhancing digital infrastructure must be coupled with policies that support workforce reskilling and mitigate the negative effects of branch closures on financial inclusion, particularly in underserved communities.

A limitation of this study is its focus on macroeconomic aggregates, which may mask important heterogeneity at the institutional or regional level. Future research could delve deeper into microdata or explore the qualitative aspects of how job roles are being transformed within banks. Nevertheless, this research provides a critical empirical foundation, demonstrating that the digital transformation of banking is not a simple story of replacement, but one of complex and simultaneous substitution and complementarity.

Declaration of Research and Publication Ethics
This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher's Contribution Rate Statement
I am a single author of this paper. My contribution is 100%.

Declaration of Researcher's Conflict of Interest)
There are no potential conflicts of interest in this study.

References

Akarçay, M. (2025a). Dijital dönüşüm ve Türk mevduat bankalarının karlılığına etkisi. *Turkish Studies - Economy, Finance, Politics*, 20(1), 1-20. https://dx.doi.org/10.7827/TurkishStudies.79429

Akarçay, M. (2025b). Mobil bankacılık hizmetlerinin Türk bankacılık sistemi karlılığına etkisi. *Ahi Evran Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, 11(1), 59-76. https://doi.org/10.31592/aeusbed.1523671

Aksoy, M., Yılmaz, M.K., Tırpan, E.C., Özşahin, M., Coşkun, E. and Uysal, Ö. (2025). Exploring the non-linear impacts of digital maturity on corporate sustainability: New evidence from Türkiye. *Ekonomi Politika ve Finans Araştırmaları Dergisi*, 10(Özel Sayı), 107-131. https://doi.org/10.30784/epfad.1486767

Arner, D.W., Barberis, J.N. and Buckley, R.P. (2015). *The evolution of fintech: A new post-crisis paradigm?* (SSRN Working Paper No. 2676553). https://doi.org/10.2139/ssrn.2676553

Ayadi, R., Chiaramonte, L., Cucinelli, D. and Migliavacca, M. (2025). Digitalization and banks’ efficiency: Evidence from a European analysis. *International Review of Financial Analysis*, 97, 103837. https://doi.org/10.1016/j.irfa.2024.103837

Baltagi, B.H. (2021). Nonstationary panels. In B.H. Baltagi (Ed.), *Econometric analysis of panel data* (pp. 337-389). Cham: Springer International Publishing.

Baltagi, B.H. and Wu, P.X. (1999). Unequally spaced panel data regressions with AR(1) disturbances. *Econometric Theory*, 15(6), 814-823. https://doi.org/10.1017/S0266466699156020

Bhargava, A., Franzini, L. and Narendranathan, W. (1982). Serial correlation and the fixed effects model. *The Review of Economic Studies*, 49(4), 533-549. https://doi.org/10.2307/2297285

Broby, D. (2021). Financial technology and the future of banking. *Financial Innovation*, 7(1), 47. https://doi.org/10.1186/s40854-021-00264-y

Bunea, S., Kogan, B. and Stolin, D. (2016). Banks vs. fintech: At last, it’s official. *The Capco Institute Journal of Financial Transformation*, 44, 14-25. Retrieved from https://www.semanticscholar.org/

Cardamone, P. and Trivieri, F. (2024). Out of sight, out of mind! Bank branch closures and new firm creation in Italy. *Regional Studies, Regional Science*, 11(1), 237-253. https://doi.org/10.1080/21681376.2024.2315187

Dedola, L., Ehrmann, M., Hoffmann, P., Lamo, A., Pardo, G.P., Slacalek, J. and Strasser, G. (2023). *Digitalisation and the economy* (ECB Discussion Paper No. 2023/2845). Retrieved from https://www.ecb.europa.eu/pub/pdf/scpdps/ecb.dp23~6b1e40acca.en.pdf

Demir, E. and Aydın, Y. (2025). Banks' risk-taking behavior in Türkiye. *Ekonomi Politika ve Finans Araştırmaları Dergisi*, 10(2), 636-654. https://doi.org/10.30784/epfad.1559922

Demirgüç-Kunt, A., Klapper, L., Singer, D. and Ansar, S. (2022). *The global Findex database 2021*. https://doi.org/10.1596/978-1-4648-1897-4

Driscoll, J.C. and Kraay, A.C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics*, 80(4), 549-560. https://doi.org/10.1162/003465398557825

ECB. (2024a). *Study on the payment attitudes of consumers in the Euro Area (SPACE 2024) – Annex B*. Retrieved from https://www.ecb.europa.eu/stats/ecb_surveys/space/html/index.en.html

ECB. (2024b). *Payment statistics: 2023 figures*. Retrieved from https://www.ecb.europa.eu

European Commission. (2020). *Digital economy and society index (DESI) 2020: Human capital*. Retrieved from https://digital-strategy.ec.europa.eu/en/library/digital-economy-and-society-index-desi-2020

García-Merino, J.D., San-Jose, L. and San-Martín, N. (2025). Determinants in adopting cashless payments in Europe: A multilevel analysis. *Financial Innovation*, 11(1), 8. https://doi.org/10.1186/s40854-024-00750-z

Gomber, P., Kauffman, R.J., Parker, C. and Weber, B.W. (2018). On the Fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. *Journal of Management Information Systems*, 35(1), 220-265. https://doi.org/10.1080/07421222.2018.1440766

Gomber, P., Koch, J.A. and Siering, M. (2017). Digital finance and FinTech: Current research and future research directions. *Journal of Business Economics,* 87(5), 537-580. https://doi.org/10.1007/s11573-017-0852-x

Güz, T. and Poyraz, G. (2024). Digital financial inclusion and its determinants: Evidence from Türkiye. *Ekonomi Politika ve Finans Araştırmaları Dergisi*, 9(4), 700-714. https://doi.org/10.30784/epfad.1553428

Hasan, I., Schmiedel, H. and Song, L. (2012). Returns from retail banking and payments. *Journal of Financial Services Research,* 41(3), 163-195. https://doi.org/10.1007/s10693-011-0114-y

Hausman, J.A. (1978). Specification tests in econometrics. *Econometrica,* 46(6), 1251-1271. https://doi.org/10.2307/1913827

Ho, C.S.T. and Berggren, B. (2020). The effect of bank branch closures on new firm formation: The Swedish case. *Annals of Regional Science*, 65(2), 261-286. https://doi.org/10.1007/s00168-020-00986-4

Katz, R.L., Vaterlaus, S., Zenhäusern, P. and Suter, S. (2010). The impact of broadband on jobs and the German economy. *Intereconomics*, 45(1), 26-34. https://doi.org/10.1007/s10272-010-0322-y

Keil, J. and Ongena, S. (2024). The demise of branch banking – Technology, consolidation, bank fragility. *Journal of Banking and Finance,* 158, 107038. https://doi.org/10.1016/j.jbankfin.2023.107038

Levene, H. (1960). Robust tests for equality of variances. In I. Olkin (Ed.), *Contributions to probability and statistics* (pp. 278-292). Stanford: Stanford University Press.

Levine, R. (2005). Finance and growth: Theory and evidence. In P. Aghion and S.N. Durlauf (Eds.), *Handbook of economic growth Vol. 1A* (pp. 865-934). https://doi.org/10.1016/S1574-0684(05)01012-9

Levine, R., Beck, T. and Demirgüç-Kunt, A. (2009). *Financial institutions and markets across countries and over time: Data and analysis* (World Bank Policy Research Working Paper No. 4943). Retrieved from https://openknowledge.worldbank.org/server/api/core/bitstreams/46a81459-f084-5d07-98ba-c1daa0cd44b5/content

Manta, A.G., Bădîrcea, R.M., Gherțescu, C. and Manta, L.F. (2024). How does the nexus between digitalization and banking performance drive digital transformation in Central and Eastern European countries? *Electronics,* 13(22), 4383. https://doi.org/10.3390/electronics13224383

Nguyen, H.L.Q. (2019). Are credit markets still local? Evidence from bank branch closings. *American Economic Journal: Applied Economics,* 11(1), 43-76. https://doi.org/10.1257/app.20170543

Pesaran, M.H. (2004). *General diagnostic tests for cross section dependence in panels* (Cambridge Working Papers in Economics No. 0435). Retrieved from https://www.econ.cam.ac.uk

Ünlü, U. and Çıtak, Ö. (2025). Corporate sustainability in Turkish banks (2019-2023). *Ekonomi Politika ve Finans Araştırmaları Dergisi,* 10(2), 758-780. https://doi.org/10.30784/epfad.1547682

Yıldırım, H., Özkan, T., Lögün, A. and Doğan, M. (2025). Financial inclusion and monetary policy effectiveness. *Ekonomi Politika ve Finans Araştırmaları Dergisi*, 10(2), 619-635. https://doi.org/10.30784/epfad.1541293

Zalan, T. and Toufaily, E. (2017). The promise of Fintech in emerging markets: Not as disruptive. *Contemporary Economics*, 11(4), 415-430. https://doi.org/10.5709/ce.1897-9254.253

Zins, A. and Weill, L. (2016). The determinants of financial inclusion in Africa. *Review of Development Finance,* 6(1), 46-57. https://doi.org/10.1016/j.rdf.2016.05.001