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FINTECH PENETRATION AND UNEMPLOYMENT IN NIGERIA: A TODA-YAMAMOTO CAUSALITY ANALYSIS OF THE DIGITAL-LABOUR MARKET CHANNEL

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ABSTRACT

Does the spread of mobile phones and the internet help explain movements in Nigeria's unemployment rate? This paper answers the question with Granger causality tests of the kind proposed by Toda and Yamamoto, which remain valid whatever the integration and cointegration properties of the data. The system covers 1996-2023 (the longest period for which all of the required series are continuous) and contains the ILO modelled unemployment rate, a principal-component index of mobile and internet penetration, output growth, consumer price inflation and remittance receipts; a first-order vector autoregression is augmented with one extra lag to reflect the highest order of integration detected. Causality is insignificant in both directions ($p = 0.945$ from the fintech index to unemployment and $p = 0.378$ in reverse). Impulse responses show only a negligible, slowly accumulating fall in unemployment after a fintech shock, and the index accounts for less than one per cent of the forecast error variance of unemployment even at an eight-year horizon. The unaugmented levels system has a near-unit root, which is informative about the trending index and is also the reason the augmented procedure is preferred. The findings are interpreted through creative destruction, skill-biased technical change and the conditional view of digital financial inclusion, and are compared with mostly positive cross-country evidence linking ICT to youth employment. Expanding mobile and internet infrastructure alone is unlikely to shift national unemployment. Connectivity, while necessary is not sufficient, and requires complementary policies on digital skills, start-up finance, and fintech support.

Keywords: Fintech, Unemployment, Digital Penetration, Toda-Yamamoto, Granger Causality

1 INTRODUCTION

Nigeria's unemployment rate, as modelled by the International Labour Organization, drifted from below 4 per cent through most of the 2000s to a peak above 5.7 per cent in 2020, before falling back toward 3 per cent by 2023 (World Bank, 2026), a period that coincides almost exactly with the country's most rapid expansion in mobile and internet infrastructure. This coincidence invites a natural question with real policy stakes: has Nigeria's digital connectivity boom, widely credited with expanding financial access and enabling new categories of online and platform-based work, had any measurable causal relationship with the national unemployment rate, in either direction?

An earlier paper in this series asked whether the same digital expansion deepened bank credit and, using ARDL bounds testing on a cointegrated system, found that it did not. Unemployment calls for a different tool. There is no reason to assume in advance that the unemployment rate and the fintech index share an order of integration or a long-run equilibrium. The policy question is whether one variable helps predict the other rather than what the long-run elasticity is. The Toda and Yamamoto (1995) procedure suits this setting, because its Wald tests for Granger non-causality are valid whether the series are stationary, integrated or cointegrated; impulse responses and forecast error variance decompositions are added to describe the dynamics.

The question matters for reasons beyond Nigeria. Digital infrastructure has been promoted across Sub-Saharan Africa as a tool for both financial inclusion and job creation, and a World Bank study of the continent finds that mobile internet availability raises enterprise productivity and jobs: where quality 3G or 4G internet had been available for at least three years, labour force participation rose by 3 percentage points in Nigeria and 8 percentage points in Tanzania (Begazo, Dutz & Blimpo, 2023). Earlier African evidence on mobile phones was similarly optimistic: Klonner and Nolen (2010) used the staggered rollout of mobile phone coverage in rural South Africa to show that employment rose by 15 percentage points when a locality received network coverage, with most of the gain coming from women, while Aker and Mbiti (2010) reviewed evidence that mobile phones reduced search costs, improved market efficiency and created new jobs in mobile-related services.

At the same time, a parallel literature warns that the automation of routine tasks, including routine financial-service tasks such as cash handling, loan processing and customer verification, can displace labour as well as create it. Autor, Levy and Murnane (2003) show that computerisation substitutes for workers performing routine tasks while complementing those performing non-routine analytical and interactive tasks, and Acemoglu and Restrepo (2019) argue that the net employment effect of automation depends on whether the displacement of labour from existing tasks is offset by the creation of new tasks. The history of the automated teller machine illustrates the ambiguity: in the United States the number of bank tellers did not fall after ATMs spread, because cheaper branches led banks to open more of them and tellers shifted towards relationship tasks (Bessen, 2015). Which effect, job creation or displacement, dominates in Nigeria's aggregate labour-market data, if either does, is an empirical question this study is positioned to answer directly.

2 LITERATURE REVIEW

2.1 Conceptual Review

2.1.1 Fintech Penetration

The fintech regressor is a single principal component of mobile cellular subscriptions and internet use, which move almost in lockstep ($r = 0.97$) and cannot be entered separately without severe collinearity; its value is zero in 1996 and reaches its maximum of 100 in 2023, a path traced out as telecommunications liberalisation gave way to mobile banking and fintech start-ups. Mobile connectivity matters for labour markets as well as for finance. In Kenya, households with access to M-Pesa absorbed income shocks without cutting consumption (Jack & Suri, 2014), and mobile money allowed an estimated 185,000 women to leave farming for business or retail work (Suri & Jack, 2016), effects that could support self-employment even where formal lending is unaffected, as the an earlier paper on bank credit found (citation will be required).

2.1.2 Unemployment

The dependent variable in this study is the modelled International Labour Organization estimate of Nigeria's total unemployment rate, expressed as a percentage of the total labour force. This measure provides a methodologically consistent, internationally comparable series across the full sample period, in contrast to Nigeria's own National Bureau of Statistics definition, which changed substantially in 2021, complicating direct time-series comparison across the full study window.

2.1.3 Macroeconomic Controls

Three macroeconomic controls enter the system. Faster output growth raises the derived demand for labour; inflation adds cost uncertainty that can delay hiring; and remittance receipts can either reduce recipients' need to look for work or finance small enterprises that create it.

2.2 Empirical Review

2.2.1 Digital Finance and Unemployment in Nigeria

Evidence that links digital technology to Nigerian labour-market outcomes is still thin. The most direct evidence comes from the World Bank's analysis of mobile internet rollout, which finds that the arrival of quality 3G or 4G coverage raised labour force participation by 3 percentage points in Nigeria, with the largest gains among the poorest and least educated households (Begazo, Dutz & Blimpo, 2023). That finding concerns participation in local areas newly reached by mobile broadband, however, and does not by itself imply a reduction in the national unemployment rate, since higher participation can raise measured unemployment if new entrants do not immediately find work.

Other works point to channels that could weaken or offset the employment gains. Credit markets and labour markets are linked, and the earlier ARDL analysis of bank lending detected no long-run effect of the fintech index on private-sector credit; if fintech penetration does not deepen private credit, any credit-mediated employment channel would be correspondingly muted (citation will be required). Task-based models of technological change also predict displacement of workers performing routine tasks (Autor, Levy & Murnane, 2003; Acemoglu & Restrepo, 2019), which in the financial sector includes many of the activities that mobile and internet banking automate.

2.2.2 ICT and Employment Across Sub-Saharan Africa

A broader continental literature on information and communication technology and employment offers a mostly positive, but heterogeneous, picture. Hjort and Poulsen (2019) show that the gradual arrival of submarine internet cables, which brought fast internet to coastal Africa, increased employment rates in the connected locations, with the largest gains in skilled occupations. Using system GMM for 48 Sub-Saharan African countries over 1991-2018, Metu, Ajudua, Eboh, Ukeje and Madichie (2020) found that mobile phone subscriptions, broadband and Wi-Fi subscriptions and internet bandwidth all had significant negative effects on youth unemployment. For South Africa, Matjokana and David (2024) used mobile telephony, fixed-line telephony and internet penetration jointly as a proxy for the Fourth Industrial Revolution over 1980-2019, a construction conceptually close to the composite Fintech Penetration Index used in the present study, and found a positive relationship between ICT development and employment in both the short and long run. These are, however, studies of different outcomes, samples and estimators, and they do not establish that an aggregate digital-technology index must be related to the national unemployment rate.

Country-level case studies show how sensitive the relationship is to the specific technology. In Rwanda, Caldarola, Grazzi, Occelli and Sanfilippo (2023) combined network coverage maps with census and labour force survey data for 2002-2019 and found that mobile internet coverage increased employment opportunities and shifted the composition of the labour market. In Uganda, by contrast, Balgobin and Dubus (2022) found no evidence that mobile internet use improved employment or job quality, while basic mobile phone use was positively associated with both, suggesting that the mode of digital technology use, rather than access per se, may be what matters. At a more structural level, Wamboye, Tochkov and Sergi (2015) found that fixed-line and mobile telephone access raised labour productivity growth in Sub-Saharan Africa only after penetration reached a critical mass, estimated at roughly 20 to 30 per cent for telephones and about 5 per cent for internet use, a threshold that Nigeria's own penetration crossed well within the sample window used here.

Taken together, the literature does not point unambiguously toward either a job-creating or a job-displacing effect of digital finance and ICT more broadly in Nigeria or Sub-Saharan Africa, with results appearing sensitive to the specific digital indicator used, the unemployment measure chosen (aggregate versus youth-specific), the sector or enterprise type studied, the sample period and the econometric method. This heterogeneity is itself a motivation for applying a causality-testing framework capable of handling the full range of integration properties found in the data, instead of presupposing a direction and estimating only its size.

2.3 Theoretical Framework

2.3.1 Technological Unemployment and Creative Destruction

Schumpeter's (1942) theory of creative destruction holds that new technologies simultaneously destroy existing jobs and create new ones, with the net short-run employment effect depending on the relative speed of destruction and creation. Applied here, the theory implies that fintech penetration could plausibly show either a positive or a negative association with unemployment, or, as this study finds, no measurable net association at the aggregate level if the two effects are of similar magnitude and timing.

2.3.2 Digital Financial Inclusion Theory

Ozili's (2018) Digital Financial Inclusion Theory, applied in the companion study to financial deepening, is equally relevant to the labour market: it holds that the realised benefit of digital financial infrastructure depends on the

surrounding regulatory and economic environment, implying that digital penetration alone, absent complementary conditions such as digital skills or access to capital for digitally-enabled entrepreneurship, may not translate into measurable employment gains.

2.3.3 Skill-Biased Technological Change

Skill-biased technological change theory holds that new technologies tend to raise the relative demand for skilled labour capable of working with them, while offering less benefit, or even displacing, workers without the requisite digital skills (Acemoglu, 2002). In the Nigerian context, where digital literacy is unevenly distributed, this theory offers one explanation for why aggregate fintech penetration might show no net relationship with aggregate unemployment, even if the composition of employment, between digitally skilled and unskilled workers, shifts in ways this aggregate study cannot detect.

3 METHODOLOGY

3.1 Data Sources

The labour-market outcome is the ILO's modelled total unemployment rate, which, like the other variables, is drawn from the July 2026 release of the World Bank's development database (World Bank, 2026) for 1996-2023. The controls are remittance inflows scaled by GDP, the growth of real output and the yearly change in the consumer price index, and the fintech index is the mobile-internet principal component described in Section 2.1.

3.2 Model Specification

Following Toda and Yamamoto (1995), the Granger causality procedure first requires the maximum order of integration, d_{max}, among the series under study. A conventional vector autoregression of order p is then augmented by d_{max} additional lags, and the model is estimated in levels without differencing or imposing cointegration restrictions:

$$Y_t = \alpha + \sum_{i=1}^{p+d} \Phi_i Y_{t-i} + \varepsilon_t \qquad 1$$

Where Y_t is the vector $[UNEMP, FTI, GDPG, INFL, REM]'$ at time t, p is the lag order selected by conventional information criteria, d is the maximum order of integration found among the five series, and Φ_i are the coefficient matrices. Granger non-causality from one variable to another is tested by a standard Wald test restricting only the coefficients on the first p lags, not the additional d augmenting lags, of the candidate causal variable to zero; this restriction has a standard asymptotic chi-squared distribution regardless of whether the series are stationary, integrated or cointegrated, which is the central practical advantage of the Toda-Yamamoto approach over both plain Granger causality testing and an ARDL or vector error-correction framework.

3.3 Description of Model Variables

Within the system, UNEMP denotes the unemployment rate, FTI the fintech index, GDPG real output growth, INFL consumer price inflation and REM remittance receipts relative to GDP.

3.4 Analytical Procedures

The Augmented Dickey-Fuller (Dickey & Fuller, 1979) and Kwiatkowski-Phillips-Schmidt-Shin (Kwiatkowski, Phillips, Schmidt & Shin, 1992) tests establish each series' order of integration and the resulting d_{max}. Conventional lag-order selection criteria (Akaike, 1974; Schwarz, 1978; Hannan & Quinn, 1979) determine p for the standard vector autoregression. The augmented model of order $p + d_{max}$ is then estimated, and pairwise Wald tests are conducted for Granger (1969) non-causality between all variable pairs, restricting only the first p lags so that the test statistic retains its asymptotic chi-square distribution (Dolado & Lütkepohl, 1996), with particular attention to the fintech-unemployment relationship in both directions. A standard vector autoregression of order p is also estimated, without the Toda-Yamamoto augmentation, purely to generate impulse response functions and forecast error variance decompositions (Sims, 1980; Lütkepohl, 2005), which describe the dynamic relationship implied by the model independently of the formal causality test; the stability of this underlying vector autoregression is also reported as a diagnostic in its own right.

4 RESULTS AND DISCUSSION

4.1 Descriptive Statistics

Table 1: Descriptive statistics, 1996-2023 (N = 28)

Variable	Mean	Median	Std. Dev.	Minimum	Maximum
UNEMP (%)	4.08	3.86	0.61	3.07	5.71
FTI (index, 0-100)	40.05	37.19	35.53	0.00	100.00
GDPG (%)	4.50	4.67	3.94	-6.37	15.33
INFL (%)	13.20	12.38	5.41	5.39	29.27
REM (% GDP)	3.72	3.83	2.20	0.16	8.33

Table 1 shows that unemployment averaged 4.08 per cent between 1996 and 2023 and was comparatively stable, ranging narrowly from 3.07 to 5.71 per cent (standard deviation 0.61). The Fintech Penetration Index moved from near zero to 100.00 over the same period (mean 40.05, standard deviation 35.53), while GDP growth averaged 4.50 per cent, inflation 13.20 per cent, and remittances 3.72 per cent of GDP; all three macroeconomic series are considerably more volatile than unemployment itself.

4.2 Unit Root Tests and Maximum Order of Integration

Table 2: Augmented Dickey-Fuller unit root test

Variable	Level (t-stat)	1st Diff. (t-stat)	Order of Integration
UNEMP	-2.014 (c) / -3.474 (ct)	-2.801*	I(0) trend-stationary / I(1)
FTI	0.912 (c) / -3.056 (ct)	-3.756***	I(1)
GDPG	-1.106	-4.457***	I(1)
INFL	-0.517	-1.392 (borderline)	I(1), low power
REM	-2.275	-4.975***	I(1)

Significance: *** 1 per cent, * 10 per cent. 'c' marks a test equation with an intercept and 'ct' one with an intercept and linear trend. With no I(2) series, the Toda-Yamamoto augmentation uses $d_{max} = 1$.

Table 2 shows that none of the series is integrated of order two, so the maximum order of integration in the system is one. Unemployment is borderline, appearing trend-stationary under the specification with a trend but requiring first-differencing under the intercept-only specification, while the fintech index, GDP growth, inflation and remittances are each I(1). With $d_{max} = 1$, the Toda-Yamamoto procedure can be applied without pretesting unemployment's exact order of integration.

4.3 Vector Autoregression Order Selection

Table 3: VAR lag order selection

Lag	AIC	BIC	HQIC
1	5.930	7.392*	6.335*
2	5.999	8.680	6.743
3	2.953*	6.854	4.035

* indicates the minimising lag for each criterion. The Bayesian and Hannan-Quinn criteria, more conservative in small samples, both select lag 1; lag 3 is not used given the resulting loss of degrees of freedom in a 28-observation annual sample. p = 1 is adopted, giving an augmented Toda-Yamamoto estimation order of $p + d_{max} = 2$.

Table 3 shows that the Akaike criterion favours a lag length of 3, while the more conservative Bayesian and Hannan-Quinn criteria both select a lag length of 1. Because the annual sample has only 28 observations, lag 1 is adopted to

preserve degrees of freedom, giving an augmented VAR estimation order of $p + d_{max} = 2$ for the Toda-Yamamoto causality tests that follow.

4.4 Toda-Yamamoto Granger Causality Tests

Table 4: Pairwise Granger non-causality Wald tests (selected pairs)

Null hypothesis	Chi-sq	df	p-value	Decision
FTI does not Granger-cause UNEMP	0.005	1	0.945	Fail to reject
UNEMP does not Granger-cause FTI	0.826	1	0.378	Fail to reject
GDPG does not Granger-cause UNEMP	0.009	1	0.927	Fail to reject
INFL does not Granger-cause UNEMP	0.171	1	0.685	Fail to reject
REM does not Granger-cause UNEMP	0.329	1	0.575	Fail to reject
GDPG does not Granger-cause FTI	3.093	1	0.099	Reject at 10%
REM does not Granger-cause FTI	2.923	1	0.108	Fail to reject at 10%
INFL does not Granger-cause GDPG	5.232	1	0.037	Reject at 5%

Table 4 shows that none of the five variables, the fintech index included, Granger-causes unemployment. The system does reveal two other links: output growth helps predict the fintech index at the 10 per cent level, plausibly because households buy more handsets and data in good years, and inflation helps predict output growth at the 5 per cent level.

4.5 Vector Autoregression Stability Diagnostic

The underlying level vector autoregression of order one is found to be dynamically unstable: one characteristic root has a modulus of 0.976, just inside the boundary required for stability. This is not treated as an estimation error but as the expected signature of including the Fintech Penetration Index, confirmed I(1) in Table 2, in a model estimated in levels; a near-unit root in one equation is the standard symptom of a non-stationary regressor in a levels vector autoregression. This instability is precisely why the formal causality conclusions in Section 4.4 rely on the Toda-Yamamoto augmented Wald tests, which remain asymptotically valid under exactly this condition, rather than on a plain Granger test conducted on an unstable system; it also means the impulse responses reported below should be read as indicative of short-to-medium-run dynamics rather than as describing shocks that fully dissipate within the sample's effective horizon.

4.6 Impulse Response Functions

Table 5: Response of UNEMP to a one-standard-deviation shock in FTI

Horizon (years)	0	1	2	3	4	6	8
Response (pp)	0.000	-0.002	-0.005	-0.007	-0.008	-0.009	-0.009

Table 5 shows that unemployment barely moves after a one-standard-deviation innovation to the fintech index: the response edges down to about -0.009 percentage points by year eight and then levels off. Set against mean unemployment of 4.08 per cent, this is negligible, and it agrees with the insignificant causality tests in Table 4. Its sign hints at slight net job creation, but the effect is far too small, and the system too near instability, for that reading to carry weight.

4.7 Forecast Error Variance Decomposition

Table 6 shows that unemployment's own past values dominate its forecast error variance throughout the eight-year horizon, falling only gradually from 100 per cent to 90.5 per cent. Fintech penetration never explains more than 0.7 per cent of that variance, consistently the smallest contributor among the four explanatory variables; GDP growth and remittances, by contrast, grow to explain 3.9 and 4.4 per cent respectively by year eight. This decomposition reinforces the causality and impulse response findings: whatever influence fintech penetration has on Nigeria's aggregate labour market, it is quantitatively minor relative to conventional macroeconomic channels.

Table 6: Share of UNEMP forecast error variance explained, by horizon

Horizon (years)	UNEMP	FTI	GDPG	INFL	REM
1	100.0%	0.0%	0.0%	0.0%	0.0%
2	97.8%	0.3%	0.6%	0.7%	0.6%
3	95.7%	0.5%	1.6%	0.7%	1.6%
5	92.5%	0.7%	2.9%	0.5%	3.4%
8	90.5%	0.7%	3.9%	0.5%	4.4%

5 DISCUSSION

Fintech penetration therefore neither Granger-causes nor is Granger-caused by aggregate unemployment. Read together with the earlier finding that the same index bears no long-run relation to bank credit, the result suggests that Nigeria's rapid digital build-out has not yet left a measurable mark on either credit depth or national unemployment, even though local evidence shows that mobile broadband raised labour force participation where it arrived (Begazo, Dutz & Blimpo, 2023).

The result also differs from the cross-country finding that ICT development reduces youth unemployment in Sub-Saharan Africa (Metu et al., 2020). Three explanations seem plausible and are offered without over-claiming. First, the present study examines total, not youth-specific, unemployment, and the labour-market effects of digital technology plausibly concentrate among younger, more digitally engaged workers, consistent with skill-biased technological change theory. Second, the present study tests Granger causality in a single-country time series rather than estimating a pooled cross-country effect, which is a materially different and generally more conservative standard of evidence. Third, the composite Fintech Penetration Index used here captures infrastructure penetration rather than digital-economy activity or fintech-sector investment specifically, and these are conceptually distinct constructs that need not move together.

The weak link found here is also consistent with the possibility of offsetting effects. Task-based models predict that automation displaces some workers while creating new tasks for others (Autor, Levy & Murnane, 2003; Acemoglu & Restrepo, 2019), and the experience of automated teller machines shows that the net effect on even a directly affected occupation can be close to zero (Bessen, 2015). Under Schumpeter's (1942) creative destruction framework, a genuine job-creation effect and a genuine job-displacement effect operating simultaneously, and of broadly offsetting magnitude, would be observationally similar to the null result obtained here. Distinguishing between a true absence of effect and two offsetting effects is not possible within an aggregate causality framework, and is flagged as a priority for future sectoral or micro-level research.

The continental ICT-employment literature reviewed in Section 2.2.2 offers a further, complementary reconciliation. Wamboye, Tochkov and Sergi (2015) find that telecommunications raise productivity growth only once a critical mass of penetration is reached; if Nigeria's digital expansion had stalled below such a threshold, a null result might simply reflect incomplete diffusion. The Fintech Penetration Index constructed for this study, however, rises from zero to its sample maximum over the sample window, which makes an incomplete-diffusion explanation less persuasive for Nigeria than for a country still in the early stages of mobile or internet rollout. The Ugandan finding that mobile internet specifically, as opposed to basic mobile phone use, shows no positive employment association (Balgobin & Dubus, 2022) offers a closer parallel, since the Fintech Penetration Index blends this more advanced, internet-dependent layer of digital activity with basic mobile telephony, and the net null result could mask offsetting effects between the two.

6 CONCLUSION AND POLICY RECOMMENDATIONS

This study tested whether Nigeria's fintech penetration, proxied by a composite index of mobile and internet connectivity, has had any causal relationship with the national unemployment rate between 1996 and 2023. Using a Toda-Yamamoto augmented vector autoregression, chosen specifically because it remains valid regardless of the series' integration properties, no significant Granger-causal relationship is found in either direction, and impulse response and variance decomposition analysis confirm that any dynamic relationship that does exist is economically negligible relative to conventional macroeconomic drivers of unemployment.

Policy implications follow directly. Expanding mobile and internet infrastructure is unlikely, on its own, to shift the national unemployment rate; connectivity looks necessary but far from sufficient, as Ozili's (2018) conditional account

of digital financial inclusion would predict. Employment-oriented digital policy therefore needs to address the complementary constraints: digital skills, start-up finance for digitally enabled businesses, and support for fintech employers. For research, the gap between this null aggregate result and the positive youth-unemployment evidence for the region suggests disaggregating by age group and type of employment.

Limitations and Directions for Future Research

The results carry three caveats. To begin with, the underlying levels vector autoregression is dynamically unstable, a diagnostic finding discussed in Section 4.5 that is itself informative but that also means the impulse responses should be read with appropriate caution regarding their long-run behaviour beyond the reported horizon. Second, the aggregate national unemployment rate may mask substantial heterogeneity by age, education and region; the strong youth-specific result reported elsewhere in the literature suggests that a disaggregated study using age-specific or state-level Nigerian labour-force data, where available, could reach materially different conclusions. Third, the composite Fintech Penetration Index captures infrastructure penetration rather than the scale of fintech-sector employment or investment directly; a future study incorporating fintech-sector-specific employment or investment data, as it becomes available for Nigeria, would more directly test the job-creation channel that this study's infrastructure-based proxy can only partially capture.

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