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Future of Digital Economy: How Research and Development Can Address the Digital Divide Amid Resource Constraints

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Abstract

The digital economy is unquestionably a globally recognized priority among countries, yet comprehensive scholarly discussions on the specific determinants driving its growth remain relatively limited. To fill this gap, the present study pioneers an investigation into how research and development, natural resources and economic policy uncertainty influence the digital economy in the United States of America (USA), using data from 1996Q1 to 2020Q4. Given the nonlinear and non-normal distribution of the data, the study employs a series of quantile-based approaches, particularly the wavelet quantile-on-quantile regression (WQQR). The results of the WQQR reveal that research and development, globalization, economic growth and economic policy uncertainty positively affect the digital economy, while the abundance of natural resources appears to hinder its growth. Based on these findings, policymakers in the USA should prioritize fostering innovation through R&D while addressing the challenges associated with natural resource dependence to drive the growth of the digital economy.

Keywords: Digital economy, research and development, natural resources, economic policy uncertainty

JEL Classification: O33, O30, Q32, Q33, E60

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1. Introduction

The digital economy in the USA has emerged as a transformative force, shifting traditional economic paradigms towards the integration of technology and digital services. This shift is driven by rapid technological advancements, including the expansion of the internet, artificial intelligence, cloud computing and data analytics (Fan, 2021; Zia *et al*., 2023). These innovations have facilitated increased productivity, the development of new markets and the creation of jobs in sectors such as information technology, e-commerce and digital finance. As businesses adapt to this digital shift, the economy at large experiences greater efficiency and new growth opportunities, making the USA one of the leading digital economies globally (Litvinenko, 2020). However, the transition has also introduced challenges and uncertainties that need to be addressed for sustained growth (Brynjolfsson and McAfee, 2014).

One major problem related to the digital economy is the uncertainty surrounding its development and future direction. Research and development (R&D) plays a critical role in shaping the trajectory of this economy, yet the pace of innovation is often unpredictable (Cheng *et al*., 2021; Salman and Ismael, 2023). Furthermore, news-based economic policy uncertainty (EPU) can exacerbate challenges by creating a volatile policy environment, which may hinder business investment and innovation. The issue of natural resources can further complicate this uncertainty, as the digital economy depends heavily on access to energy and raw materials, such as rare earth elements, for manufacturing electronics and components (Fan, 2021). The extraction and sustainable management of these resources are crucial for powering data centres, cloud computing and maintaining the infrastructure that underpins digital services (Ma *et al*., 2022; Zheng and Gong, 2024). Both R&D and economic policy uncertainty can influence digital markets by either promoting or stalling growth, depending on the direction and stability of policy frameworks. The uncertainty surrounding future regulations, taxation policies, natural resource availability and international trade can significantly affect the long-term strategies of digital firms (Baker *et al*., 2016).

Research and development are crucial to the advancement of the digital economy. Through continuous innovation in technology, R&D helps drive the development of digital platforms, software and infrastructure that underpin the digital economy (Litvinenko, 2020). Investments in R&D support the creation of new technologies and solutions, enabling businesses to improve their products, services and processes. For example, advancements in machine learning, artificial intelligence and blockchain technology are often the results of intensive research efforts that push the digital economy forward (Bilgili *et al*., 2023). Without a robust R&D sector, the digital economy would lack the necessary technological infrastructure and innovations required to address market demands and future challenges (Teece, 2018).

Economic policy uncertainty, particularly when related to regulations, taxation and trade policies, can have profound effects on the digital economy (Cheng and Masron, 2023). Uncertainty regarding the future direction of policies can create hesitation in business investments, reduce consumer confidence and stifle innovation. For instance, the imposition of unexpected digital taxation or stricter data privacy regulations can lead to increased operational costs for tech companies, which may, in turn, result in delays in product development or market entry (Ma *et al*., 2022). Furthermore, global economic policy uncertainty, such as trade wars or changes in intellectual property laws, can disrupt international digital trade and innovation. The interaction between economic policy uncertainty and the digital economy can thus have far-reaching implications for growth and stability (Handley and Limão, 2017).

Several studies (*e.g.*, Cheng and Masron, 2023; Jia *et al*., 2023; Litvinenko, 2020; Teece, 2018) have examined the relationship between R&D, economic policy uncertainty and the digital economy. Brynjolfsson and McAfee (2014) argued that technological advancements, driven by R&D, are at the core of the digital economy, fostering productivity and creating new economic opportunities. In contrast, Baker *et al*. (2016) highlighted how economic policy uncertainty can negatively affect business confidence and investment, particularly in emerging industries such as digital technology. Considering the above studies, it is clear that no studies explore how news-based economic policy uncertainty and research and development affect digital economy. Therefore, the present study fills this gap by asking the following research questions:

- Does research and development bolster digital economy in the USA?
- What is the impact of natural resources on digital economy in the USA?
- Does news-based economic policy uncertainty affect the digital economy in the USA?

Building on the insights, this study makes the following contributions to the existing literature. Firstly, this study pioneers investigation into how news-based economic policy uncertainty and research and development affect the digital economy; thus, we fill the gap in the literature. Secondly, this study provides valuable insights into the drivers of the digital economy within the USA. Understanding these connections is crucial for policymakers, businesses and other stakeholders as they navigate the rapidly evolving digital landscape and strive to achieve sustainable development objectives. Thirdly, the study employs the wavelet quantile-on-quantile regression to explore the association between digital economy and its determinants. This technique enables the investigation of nonlinear relationships across different quantiles of data, allowing policymakers to understand how the effects of R&D investments, natural resource availability and policy uncertainty vary over time and across different levels of the digital economy. By uncovering heterogeneous impacts that traditional models may overlook, this method provides a more comprehensive view of how these factors influence digital transformation under varying economic conditions.

The next section presents the theoretical framework and the literature review. Section 3 presents the data and methods; Section 4 depicts the findings and discussion and Section 5 presents policy recommendations based on the findings.

2. Theoretical Framework and Literature Review

2.1 Theoretical framework

Several key factors shape the digital economy. Economic growth is widely seen as a catalyst for digital transformation, as it increases demand for technological advancements and fosters innovation (Brynjolfsson and McAfee, 2014). However, some studies argue that rapid economic growth can shift focus away from long-term investments in digital infrastructure and innovation, potentially limiting the digital economy's expansion (Acemoglu *et al.*, 2006). As emphasized by Baker *et al.* (2016), economic policy uncertainty can inhibit investments in digital technologies due to increased risks and regulatory unpredictability. On the other hand, some scholars, such as Zhang *et al.* (2023) and Ali *et al.* (2023), suggest that policy uncertainty may drive innovation by creating opportunities for new digital solutions and adaptive business strategies.

Research and development (R&D) play a crucial role in advancing the digital economy by fostering technological innovations that underpin digital infrastructure and services (Alam and Hossain, 2024). However, critics argue that excessive reliance on R&D without complementary infrastructure investments can limit the impact of technological advancements (Bilgili *et al.*, 2023). The effect of total natural resources on the digital economy is debated, with some studies suggesting that resource-rich countries may underinvest in digital sectors, focusing instead on resource extraction (Balsalobre-Lorente *et al.*, 2018; Venables, 2016). Conversely, other research argues that natural resources can be utilized to fund digital innovation and infrastructure, facilitating the growth of the digital economy in resource-abundant regions (Danish and Hassan, 2023). These factors interact in several ways, shaping the trajectory of the digital economy and its role in achieving broader economic and developmental goals.

Based on the information presented above, the following hypotheses have been formulated:

H_1: Economic growth has a positive and significant impact on the digital economy, driving technological advancements and innovation.

H_2: News-based economic policy uncertainty has a significant impact on the digital economy, either inhibiting investments in digital technologies or driving innovation due to regulatory unpredictability and risk.

H_3: Research and development (R&D) has a positive and significant effect on the digital economy, fostering technological innovations that support digital infrastructure and services.

H_4: The presence of total natural resources has a significant effect on the digital economy, either hindering or facilitating its development.

2.2 Literature review

Studying the determinants of the digital economy is crucial for understanding the factors that drive technological advancements and economic transformation. As digital technologies shape global growth, identification of these key drivers – such as economic policy uncertainty, research and development and digital infrastructure – is essential for effective policymaking. Given the rapid pace of change, a review of existing research offers valuable insights for shaping strategies that promote digital inclusion, competitiveness and resilience.

Studies exploring the relationship between the digital economy and its various determinants present different yet complementary perspectives. Fan (2021) focused on China and found a direct link between economic policy uncertainty (EPU) and the digital economy, suggesting that uncertainty can drive digital innovation. This aligns with the idea that the unpredictability of policy may spur technological solutions as firms seek adaptive strategies. Cheng and Masron (2023), also examining China, highlighted market rivalry as the primary mechanism through which EPU affects corporate digital transformation, emphasizing that competition rather than uncertainty per se may be the catalyst for digital advancements. While Fan's (2021) analysis stressed the broader impact of uncertainty, Cheng and Masron's (2023) findings point to a more specific mechanism – market rivalry – that fosters digital development, thereby providing a deeper understanding of the channels through which EPU influences the digital economy.

In contrast, Zheng and Gong (2024), who examined BRICS countries from 2000 to 2021, introduced a broader context by incorporating natural resources, geopolitical risk and economic progress. Their findings reveal that while economic growth and natural resource rent positively influence the digital economy, geopolitical risk has a detrimental effect. This conclusion highlights the complexity of global dynamics where external risks, such as geopolitical conflicts, may hinder digital development, even in resource-abundant countries. This contrasts with the Chinese-focused studies, where the relationship between natural resources and the digital economy is less explicitly tied to geopolitical risks but more to domestic factors such as policy and market conditions. The negative impact of geopolitical risk, as found by Zheng and Gong (2024), emphasizes that the digital economy's growth is not only shaped by internal factors such as economic growth or resources but also by external uncertainties that may disrupt technological progress.

Song *et al*. (2024) also focused on China, investigating how digital financial development promotes a green economy. They argued that prioritizing economic transformation and R&D is crucial for maximizing the benefits of digital finance in fostering green growth. This suggests a policy recommendation for integrating digital financial strategies with green growth objectives. In a similar vein, Liu and Chen (2024) examined the asymmetric effects of natural resources, labour force and domestic investment on the digital economy across knowledge-based Asian countries. Their findings indicate that increasing the labour force, domestic investment and expansionary trade policies positively influence green development. While Liu and Chen (2024) focused on economic policies that promote green growth, Song *et al.* (2024) advocated for a more integrated approach where digital finance plays a central role in driving sustainable development. These studies complement each other by underscoring the importance of policy alignment in fostering a green digital economy, with Song *et al*. (2024) emphasizing R&D and Liu and Chen (2024) focusing on the structural economic factors.

Finally, Shaobin *et al.* (2024) and Liu and Chen (2024) highlighted the significant impact of digital governance and natural resources on digital trade and resource efficiency in China. Shaobin *et al*. (2024) found that while natural resource progress contributes to digital trade, geopolitical risks dampen this effect, suggesting that external factors must be carefully managed to avoid stymying digital trade growth. Meanwhile, Liu *et al*. (2024) argued that digital governance leads to improved natural resource use efficiency, offering a counterpoint to the geopolitical concerns raised by Shaobin *et al*. (2024). They suggested that well-structured digital governance can mitigate inefficiencies and enhance resource utilization. These findings present a nuanced view, where digital governance is seen as a tool to improve resource management, potentially offsetting the negative impacts of geopolitical risks. This highlights the dual role of digital governance in fostering both economic growth and sustainability, making it an essential component of digital economy policy.

In conclusion, while there have been some studies (*e.g.*, Ran *et al.*, 2023; Salman and Ismael, 2023; Teece, 2018; Zheng and Gong, 2024) on the determinants of the digital economy, they remain limited in number, particularly those focused on the USA. Most existing studies has been centred on China and other Asian countries. Additionally, the majority of these studies have considered only the linear attributes of time series data (*e.g.*, Litvinenko, 2020; Liu and Chen, 2024; Zheng and Gong, 2024), despite the fact that such data often exhibit nonlinear characteristics. This highlights the need for further analysis of the drivers of the digital economy, taking into account these nonlinear attributes. Moreover, previous studies have largely overlooked the significant roles of globalization and research and development in the digital economy, leaving a gap that this study aims to fill. Finally, the present study introduces a new technique that identifies causality from independent to dependent variables, considering various time scales and quantiles. By exploring new determinants of the digital economy and introducing a novel approach, this study makes a significant contribution to the literature.

3. Data and Empirical Methods

3.1 Data

Table 1 outlines the variables used in the study, along with their measurement methods and data sources. The variable digital economy (*DE*) is measured by the number of green patents related to ICTs, sourced from the OECD (2024). Economic growth (*EG*) is represented by GDP per capita (constant US$2015), with data from WDI (2024). Furthermore, news-based economic policy uncertainty (*EPU*) is captured using an index from Economic Policy Uncertainty (2024). Lastly, research and development (*RD*) is measured as the percentage of GDP spent on R&D, sourced from Global Change Data Lab (2024), while total natural resources (*TNR*) are measured as a percentage of GDP, also obtained from WB (2024). The data for this study span between 1996 and 2021. To mitigate the issue of heteroscedasticity commonly observed in time series data, all the variables were log-transformed. Given the limited timeframe of the dataset, we converted the annual data into quarterly frequency using the quadratic match sum-up approach, following the methodology adopted by Alola *et al.* (2023) and Pata *et al.* (2022).

Table 1: Variables, measurements and sources

Code	Variable	Measurement	Source
DE	Digital economy	Green patents related to ICTs	OECD (2024)
EG	Economic growth	GDP per capita constant US$2015	WB (2024)
EPU	News-based economic policy uncertainty	Index	Economic Policy Uncertainty (2024)
RD	Research and development	Research and development expenditure (% of GDP)	Global Change Data Lab (2024)
TNR	Total natural resources	% of GDP	WB (2024)

Source: Author's own elaboration

Table 2 presents the descriptive statistics. The results show that ln *EPU* has the highest mean value (4.7638), while ln *TNR* has the lowest mean (−0.0674), and the closeness between the mean and median values across the variables suggests relatively stable distributions with limited extreme variation. The standard deviation for economic growth (0.0225) is the lowest, suggesting minimal variation, while economic policy uncertainty shows the highest variability (0.3970). The skewness values show that ln *DE*, ln *EG* and ln *TNR* are negatively skewed, indicating leftward tails, while ln *EPU* has a positive skew. The kurtosis values are generally below 3, except for ln *RD*, indicating that the distributions of these variables are not highly peaked. The Jarque–Bera (J–B) test assesses normality, with significant results for ln *DE*, ln *TNR* and ln *RD* (indicating non-normal distributions), while ln *EG* and ln *EPU* show borderline significance, suggesting that these may follow a near-normal distribution.

Table 2: Descriptive statistics

	ln *DE*	**ln *EG***	**ln *EPU***	**ln *RD***	**ln *TNR***
Mean	1.9262	2.7170	4.7638	0.2491	−0.0674
Median	1.9887	2.7211	4.7837	0.2463	−0.0539
Std. dev.	0.1835	0.0225	0.3970	0.0198	0.1258
Skewness	−0.6471	−0.4965	0.4564	1.3300	−0.6141
Kurtosis	2.0565	2.5967	3.1661	4.9363	3.1042
J–B	10.688***	4.7866*	3.5875	45.105***	6.3323**
Probability	0.0047	0.0913	0.1663	0.0000	0.0421

Note: *, **, *** denote statistical significance at the 10%, 5%, 1% levels, respectively.
Source: Author's own calculations

Next, we check the correlation between the variables (see Figure 1). The matrix values represent the strength and direction of correlations. In the correlation matrix, ln *DE* is strongly positively correlated with ln *EG* at 0.92, and moderately with ln *RD* at 0.62. It shows a weak negative correlation with ln *TNR* at −0.28, suggesting that digital economy growth may slightly reduce reliance on natural resources. There is also a moderate positive correlation with ln *EPU* at 0.44.

Figure 1: Correlation matrix

Source: Author's own elaboration

3.2 Empirical method

The study employs the wavelet quantile-on-quantile regression (WQQR) suggested by Ozkan *et al.* (2024) to explore the drivers of digital economy. The wavelet quantile-on-quantile regression (WQQR) is introduced due to the limitations of the quantile-on-quantile regression (QQR) proposed by Sim and Zhou (2015). This advanced method not only detects the effect of quantiles of the independent variable (X) on the quantiles of the dependent variable (Y) but also accounts for different time scales, such as short-term, medium-term and long-term effects. The WQQR method incorporates the maximal overlapping discrete wavelet transform (MODWT), as introduced by Percival and Walden (2000), to decompose the time series data into multiple levels. This decomposition allows a more detailed analysis of the data at different frequencies and time scales, making it well-suited for capturing the dynamic relationships between variables over time.

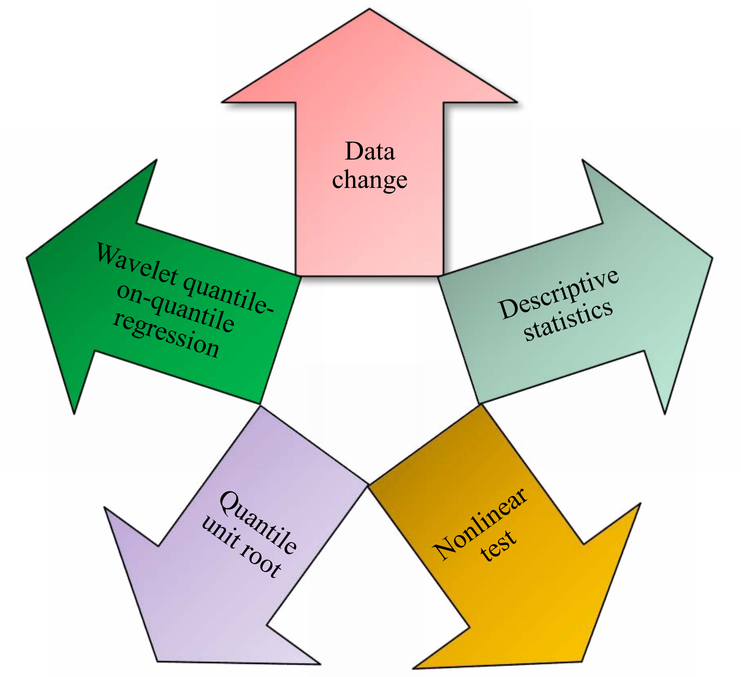
Specifically, we calculate based on the J-level maximum decomposition, following Ozkan *et al*. (2024). Three pairs of wavelets are obtained. These decompositions are categorized into short-term, medium-term and long-term effects based on the time windows of the decompositions. The first decomposition (D1: 2 to 4 quarters) represents the short-term effects, the second decomposition (D2: 4 to 8 quarters) corresponds to the medium-term effects and the third decomposition (D3: 8 to 16 quarters) reflects the long-term effects.

$$d_j[DEP_t] = \underbrace{\Big(\beta_0(\delta,\phi) + \beta_1(\delta,\phi)\big(d_j\big[IND_{(i,t)}\big] - d_j\big[IND_i^{\phi}\big]\big)\Big)}_{*} + \mathrm{e}_{\mathrm{t}}^{\delta} \tag{1}$$

where $d_j[DEP_t]$ represents the dependent variable at the time t after applying the wavelet transformation on the scale j. The wavelet transformation allows analysis of different frequency components of the time series data. $\beta_0(\delta, \varphi)$ represents the intercept term on a specific scale δ and frequency φ. $\beta_1(\delta, \varphi)$ depicts the coefficient at δ and φ, indicating the strength of the relationship between the transformed independent variable and the dependent variable at a specific wavelet scale and frequency; $d_j[IND_{i,t}]$ showcases the independent variable on the scale φ, capturing the long-term or baseline trend for the independent variable at a given frequency; e_t^{δ} stands for the error term at the time t, after applying the wavelet transformation on the scale δ. The error term captures any unmodeled effects or noise in the data.

The methodological steps of the study are depicted in Figure 2.

Figure 2: Methodological steps



Source: Author's own elaboration

4. Findings and Discussion

4.1 Nonlinearity results

In this study, we employ the Brock–Dechert–Scheinkman (BDS) test, as proposed by Brock *et al.* (1996), to examine the presence of chaos and nonlinearity in the investigated variables. The null hypothesis of the BDS test posits that the time series are independently and identically distributed (IID). The results, presented in Table 3, reject the null hypothesis, indicating that the series exhibits nonlinear characteristics. This is further corroborated by significant findings across various dimensions (M2, M3, M4, M5 and M6), suggesting that the data do not adhere to a linear model.

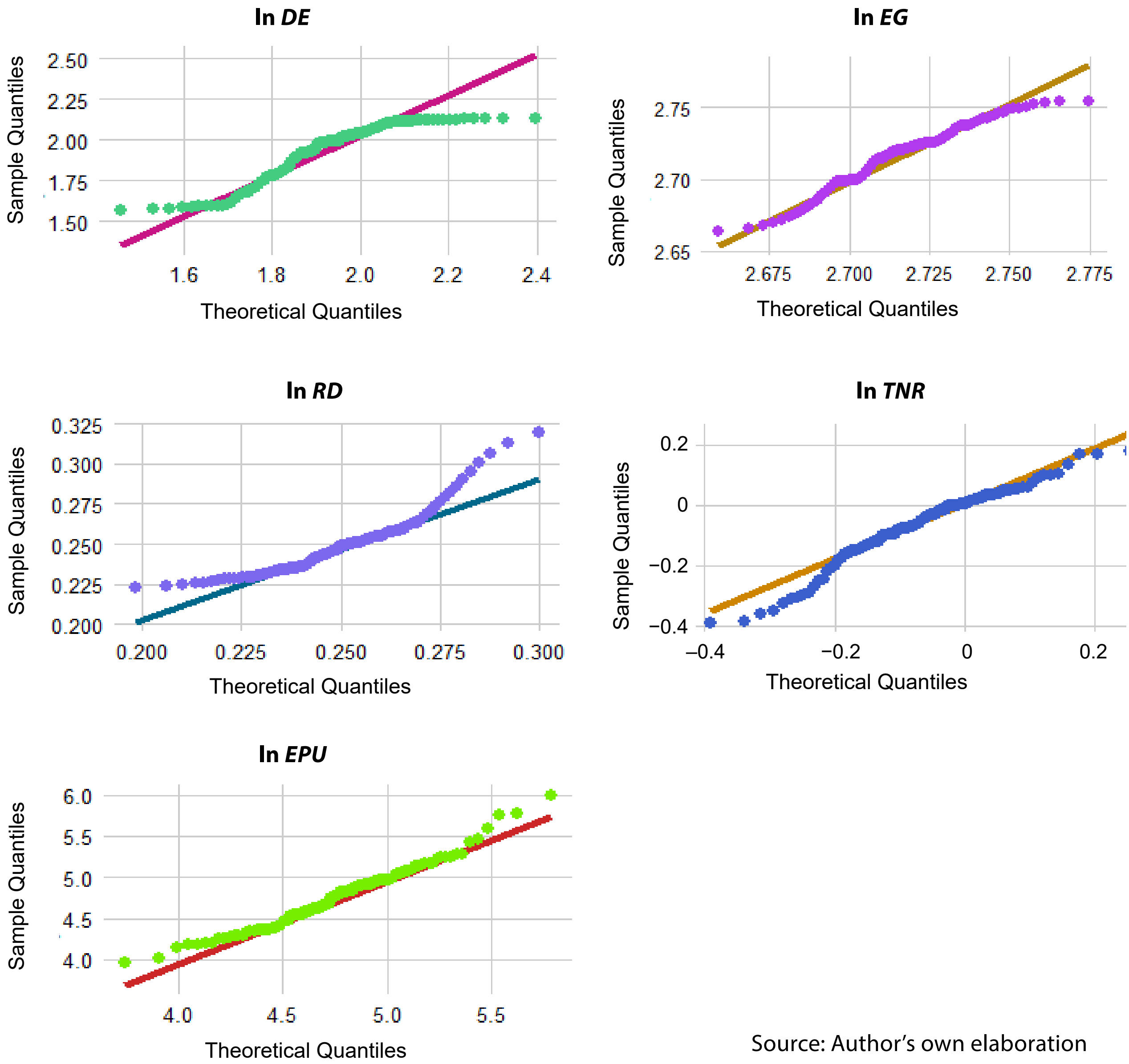
Figure 3 shows the results of the Q-Q plots for ln *DE*, ln *EG*, ln *RD*, ln *TNR* and ln *EPU*. These plots compare the sample quantiles of each variable against the theoretical quantiles of a normal distribution. The plots show a deviation from the straight line, indicating that these variables do not follow a normal distribution. These deviations imply that the variables may require further transformation or consideration of their distributional characteristics in subsequent analysis.

Table 3: Nonlinearity test results

Dimension	ln *DE*	ln *EG*	ln *EPU*	ln *RD*	ln *TNR*
M2	35.093***	32.702***	11.519***	20.235***	19.493***
M3	37.500***	34.684***	11.291***	20.717***	19.466***
M4	40.444***	37.194***	10.892***	21.647***	19.822***
M5	44.671***	40.898***	10.835***	23.332***	20.757***
M5	50.435***	46.077***	11.892***	25.789***	22.277***

Note: *** denotes statistical significance at the 1% level.
Source: Author's own calculations

Figure 3: QQ plot

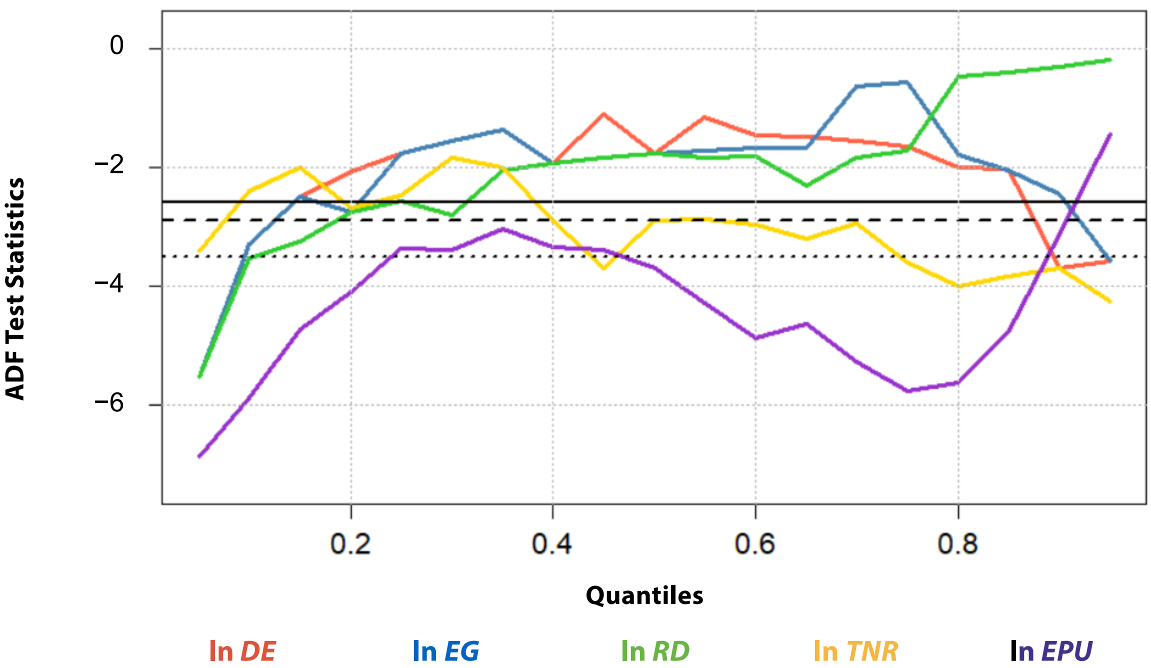


Source: Author's own elaboration

4.2 Quantile-based unit root results

Since the variables exhibit nonlinear and non-normal distributions, using linear techniques would produce misleading results. Therefore, we employ the quantile augmented Dickey–Fuller (QADF) test to verify the stationarity properties of the series across all quantiles. Figure 4 shows the results of the quantile ADF test, which is used to examine the stationarity of variables at different quantiles of their distributions rather than relying solely on the mean or median. The quantile-specific ADF results provide insights into how the stationarity of the variables varies across their distribution, offering a different perspective compared to traditional ADF tests, which typically focus only on the overall series. The results highlight that some variables may exhibit stationarity at certain quantiles but not at others, indicating that the stationarity characteristics of the series are not uniform across their distribution. Given the non-normal distribution and nonlinear nature of the variables, using a linear approach would yield misleading results. Therefore, in contrast to prior studies, we account for the data characteristics by employing a series of nonlinear methods, including wavelet quantile-on-quantile regression (WQQR).

Figure 4: QKPSS estimates for *DE*, *TNR*, *EPU*, *RD*, *GI* and *EG*



Note: The solid, dashed and dotted black lines signify the critical values of 10%, 5% and 1%.

Source: Author's own elaboration

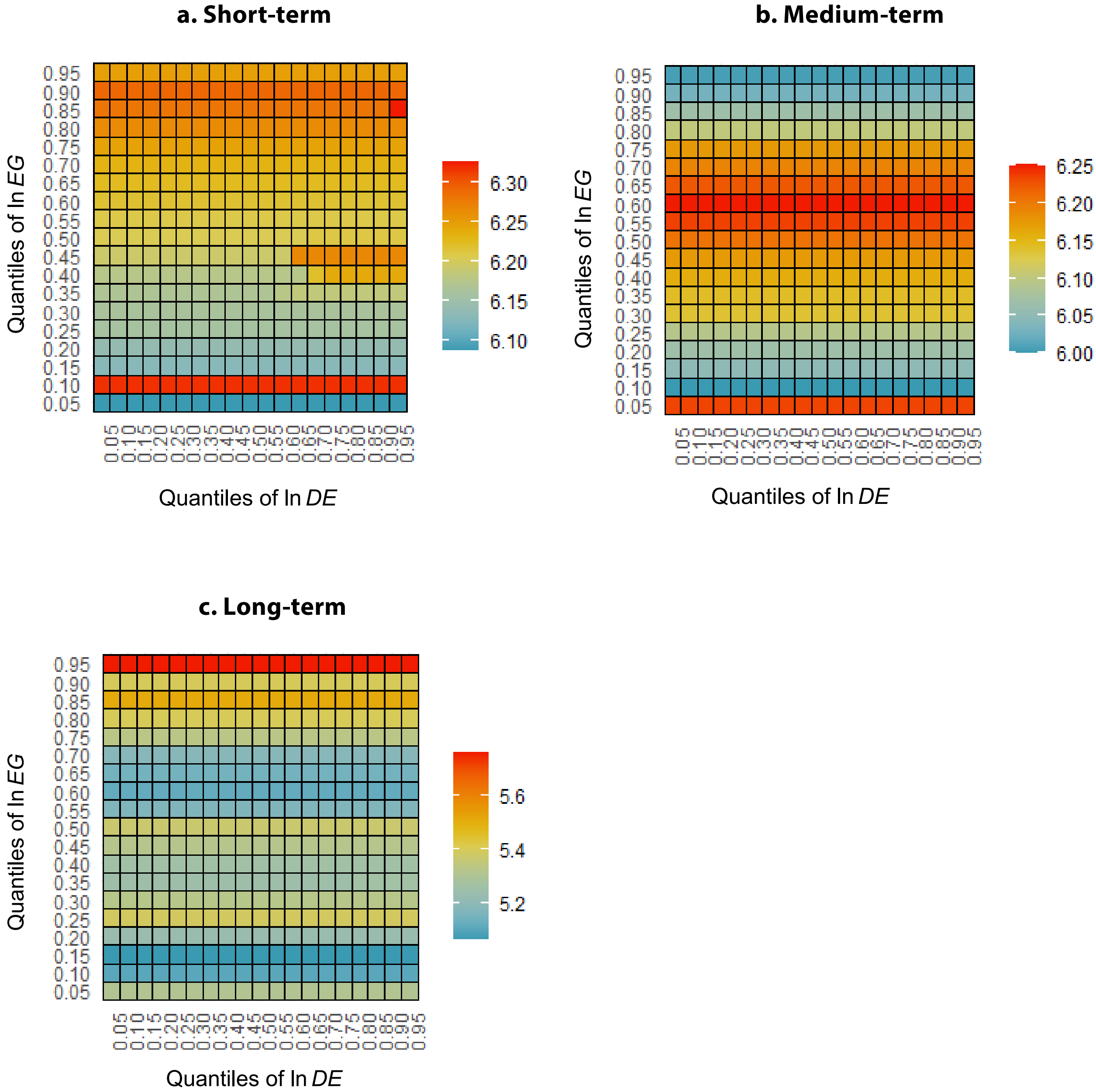
4.3 Wavelet quantile-on-quantile regression results

The study further proceeds to examine the impact of *RD*, *TNR*, *EG*, *GI* and *EPU* on *DE* using the WQQR recently suggested by Ozkan *et al*. (2024). The WQQR is a modification of the QQR. It employs wavelet transforms to decompose the time series into various time scales (*e.g.*, short-term, medium-term and long-term). This allows the investigation of interrelationships between series at different frequencies, a capability not available with the traditional QQR. Figures 5–8 display the results of the WQQR.

Figure 5(a–c) presents the impact of economic growth (*EG*) on the digital economy (*DE*) in the US context across different periods (short-term, medium-term and long-term) and various quantiles of the data. In the short-term (panel a), the relationship between economic growth and the digital economy is stronger at higher quantiles, suggesting that during periods of rapid economic growth, higher levels of economic activity are associated with a significant expansion of the digital economy. This aligns with the USA's pattern, where technological advancements often follow periods of strong economic growth. In the medium-term (panel b), the impact of economic growth on the digital economy becomes more evenly distributed across quantiles, reflecting a more stable and gradual influence of economic growth on the digital sector as both the economy and digital infrastructure mature. In the long-term (panel c), the relationship between economic growth and the digital economy weakens, particularly at the lower quantiles, indicating that the impact of economic growth on the digital economy diminishes over time. This is consistent with the US experience, where digital economy growth has slowed down as the market matures and further expansion faces diminishing returns, likely due to market saturation and technological limits.

These results support research indicating that while the digital economy experiences rapid expansion in the initial phases of economic growth, its growth rate slows down as the economy reaches maturity. For instance, Brynjolfsson and McAfee (2014) argued that initial economic growth accelerates digital transformation, but the long-term effects can become less significant as economies become more digitally integrated. Conversely, other studies, such as those by Jia *et al.* (2023), have suggested that sustained economic growth, especially in the USA, continues to drive innovation and digital sector expansion even in the long term, as the country remains a leader in technology and infrastructure development. These differing perspectives emphasize the role of contextual factors, such as the state of digital infrastructure, innovation policies and technological advancements, which can significantly influence the relationship between economic growth and the digital economy in the USA. As a global leader in digital technology, the USA exemplifies how initial rapid growth in the digital economy may level off over time, yet continued investment in innovation can mitigate some of these diminishing returns.

Figure 5: WQQR estimates between ln *DE* and ln *EG*



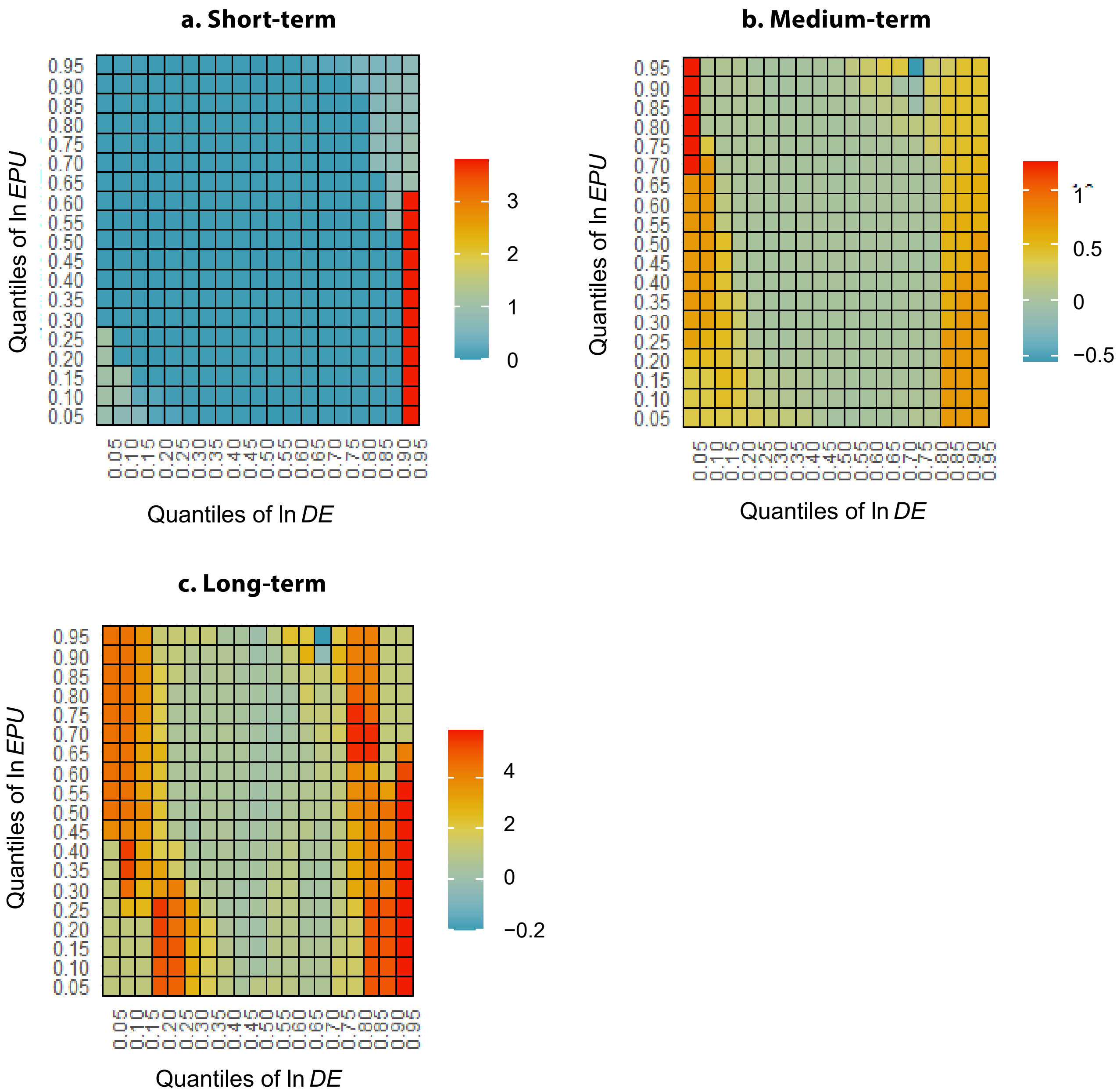
Note: The coefficient of the regression ranges from dark sea green to red.

Source: Author’s own elaboration

Figure 6 (a–c) shows the impact of economic policy uncertainty (EPU) on the digital economy (*DE*) in the USA over different periods (short-term, medium-term and long-term) and various quantiles of the data. In the short-term (panel a), the impact of economic policy uncertainty on the digital economy is negative, particularly at the higher quantiles, suggesting that increased uncertainty leads to a decline in digital economy activity at the upper levels. This might reflect how uncertainty in policy, such as changes in regulation or taxation, can create instability, leading businesses in the digital sector to delay investments or growth. In the medium-term (panel b), the relationship becomes more mixed, showing a weak effect across quantiles. At this stage, the digital economy may begin to adapt or recover from initial uncertainty, though the effects are still observable in the mid-level quantiles. In the long-term (panel c), the impact of EPU appears less severe and at the lower quantiles, a positive relationship emerges, indicating that over time, the digital economy may stabilize or even benefit from certain policy uncertainties, particularly if they lead to reforms that foster innovation.

The study observation illustrates that economic policy uncertainty has a negative short-term impact on innovation and economic activity, particularly in sectors reliant on stable policies such as the digital economy. For instance, Baker *et al.* (2016) argued that uncertainty inhibits business investment and slows economic growth, particularly in sectors such as technology and digital innovation, which are highly sensitive to policy changes. However, other studies, such as those by Cheng and Masron (2023), have disagreed with this view, suggesting that some level of uncertainty can drive innovation, as firms may take advantage of unanticipated policy shifts to innovate or adapt to new market conditions. The long-term effect, as shown in the figure, supports the idea that sustained uncertainty can push firms to innovate, especially if the uncertainty leads to more flexible, innovation-friendly policies. These contrasting views highlight the complexity of the relationship between economic policy uncertainty and the digital economy, emphasizing the importance of understanding how different levels of uncertainty affect digital sector growth at varying time horizons.

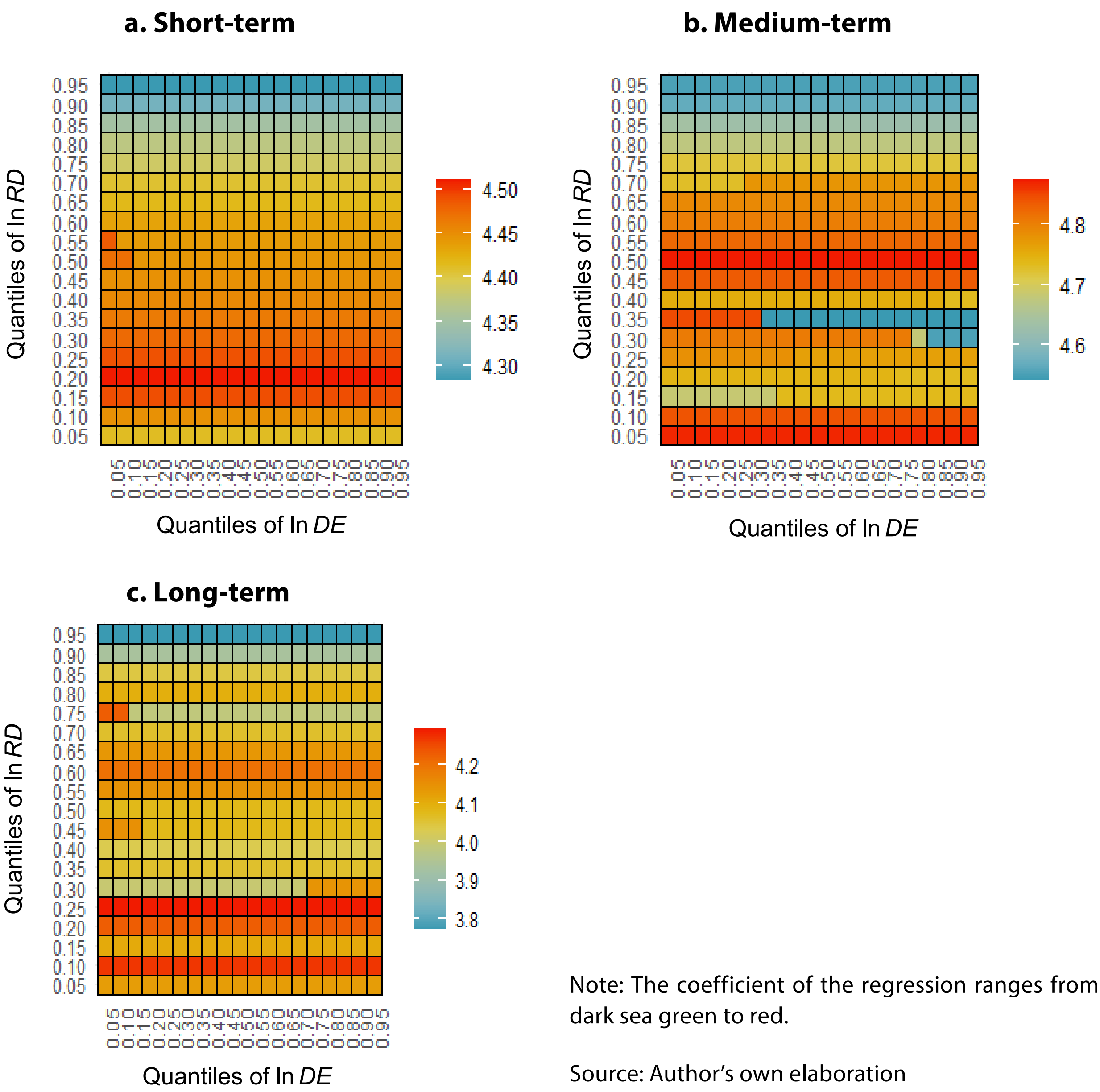
Figure 6: WQQR estimates between ln *DE* and ln *EPU*



Note: The coefficient of the regression ranges from dark sea green to red.
Source: Author's own elaboration

Figure 7 (a–c) displays the impact of research and development (R&D) on the digital economy (*DE*) in the USA, analysed across different time periods (short-term, medium-term and long-term) and various quantiles of the data. In the short-term (panel a), the relationship between R&D and the digital economy is strong, particularly at the higher quantiles, where an increase in R&D corresponds to an increase in the digital economy. This suggests that in the short term, more investment in R&D leads to significant growth in the digital sector, likely due to rapid technological innovation and early-stage adoption. In the medium-term (panel b), the impact of R&D on the digital economy remains positive but becomes more evenly distributed across quantiles, indicating a more stable, albeit less intense, relationship as the digital sector matures. In the long-term (panel c), R&D continues to have a positive effect on the digital economy, but the relationship becomes more uniform and less strong at the higher quantiles, suggesting that as the digital economy becomes saturated and more established, additional R&D investments yield diminishing returns.

Figure 7: WQQR estimates between ln *DE* and ln *RD*



Note: The coefficient of the regression ranges from dark sea green to red.

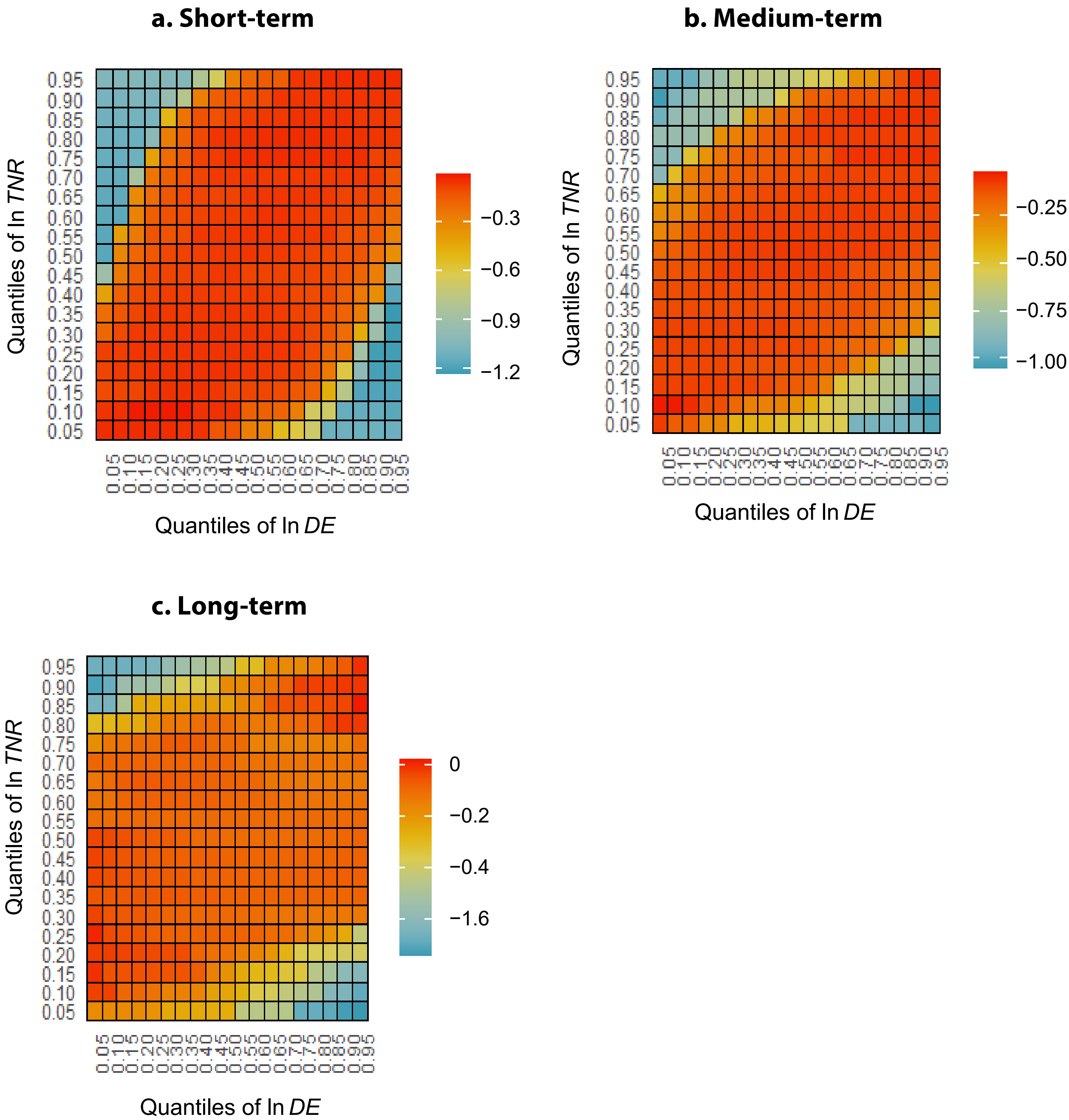
Source: Author's own elaboration

These findings align with improving the role of R&D in technological advancement and digital sector growth, especially in the short to medium term. For instance, Acemoglu *et al.* (2006) argued that investment in R&D leads to innovation, which directly fuels the growth of the digital economy by creating new technologies and improving efficiency. Similarly, Geroski (2000) noted that higher R&D spending in the early stages of technological development is crucial for fostering innovation and enabling the digital economy to thrive. However, some studies, such as Litvinenko (2020), have suggested that over time, the marginal benefits of R&D investments in the digital economy decrease as the market becomes saturated and technology reaches an advanced stage. These differing perspectives underscore the importance of balancing R&D investment and market maturity, as the impact of research and development on the digital economy can vary across different stages of growth.

Figure 8 shows the impact of natural resources (*TNR*) on the digital economy (*DE*) in the USA over different periods (short-term, medium-term and long-term) and various quantiles of the data. In the short-term (panel a), the relationship between natural resources and the digital economy is negative, especially at the higher quantiles, indicating that an increase in natural resources can lead to a decrease in the digital economy's activity. This could reflect how resource-driven industries might divert attention or investment away from the digital sector, especially in the early stages of economic growth. In the medium-term (panel b), the negative relationship persists but becomes weaker, suggesting that as the economy develops, the digital economy might start to recover from the short-term negative effects of over-reliance on natural resources. In the long-term (panel c), the relationship weakens further and becomes more neutral, indicating that the influence of natural resources on the digital economy becomes weak over time, likely because the digital economy matures and becomes less reliant on traditional resource-driven industries.

These findings align with studies suggesting that there can be a resource curse, where an over-reliance on natural resources hinders the development of other sectors, including the digital economy. For example, Badeeb *et al.* (2017) and Zou *et al.* (2024) have argued that countries rich in natural resources often experience slower economic growth because they tend to neglect other sectors, such as technology and innovation, that are crucial for sustained long-term development. Similarly, Zou *et al*. (2024) suggested that resource wealth can lead to less investment in sectors such as digital technology, hindering the growth of a diverse economy. However, other studies, such as Venables (2016), argued that the interrelationship between natural resources and digital economy growth can be more nuanced, with the possibility of positive effects if resource wealth is managed properly and reinvested into technology and infrastructure development. These conflicting views highlight the complexity of the relationship between natural resources and digital economy development, emphasizing the importance of how resources are managed and allocated to foster sustainable economic growth.

Figure 8: WQQR estimates between ln *DE* and ln *TNR*



Note: The coefficient of the regression ranges from dark sea green to red.
Source: Author's own elaboration

5. Conclusion and Policy Directions

5.1 Conclusion

The digital economy has become a cornerstone for growth and innovation, with information and communication technology (ICT) driving global economic transformations. Research and development (R&D), natural resources (TNR) and economic policy uncertainty (EPU) are three key factors that influence the digital economy's development, significantly affecting the achievement of several United Nations' Sustainable Development Goals (SDGs), including SDG 9: Industry, Innovation and Infrastructure, SDG 3: Good Health and Well-being, SDG 4: Quality Education, SDG 10: Reduced Inequalities, and SDG 12: Responsible Consumption and Production.

Thus, the present study explored the drivers of the digital economy in the USA using data from 1996Q1 to 2020Q1. To account for the nonlinear and non-normal distribution of the data, the study employed a series of quantile-based approaches. The results indicate that natural resource availability negatively affects the digital economy, while research and development, along with economic growth, positively contribute to its development. In contrast, economic policy uncertainty exhibits a mixed effect on the digital economy.

5.2 Policy remarks

To foster a thriving digital economy in the USA, policymakers must design comprehensive strategies that consider both the varying impacts of economic periods and quantile-specific effects on different segments of the economy.

In the short-term, there is a notable negative relationship between natural resources and the digital economy, especially at higher quantiles, suggesting that an over-reliance on resource-driven sectors could detract from digital sector growth. To address this, policies should focus on accelerating the transition towards a more diversified economy. This could include tax incentives for digital and technological investments, subsidies for innovation and fostering financial sector support for emerging digital technologies such as fintech, blockchain and artificial intelligence. These measures would help shift focus from traditional industries to technology-driven sectors, promoting digital sector growth even in the presence of resource-rich economies. At the same time, policies should support early-stage technological adoption across the lower quantiles of the economy, ensuring that economic diversification benefits are more widely distributed.

As the US economy transitions into the medium-term, the effects of R&D investment on the digital economy remain strong but start to become more evenly distributed across different quantiles. Here, the government should continue to prioritize public-private partnerships in R&D and incentivize private sector investments in new technologies. Additionally, stabilizing policy uncertainty becomes critical, as the digital economy is still vulnerable to policy shifts. Policymakers should design predictable regulatory frameworks that balance innovation with regulation, providing long-term stability while still allowing for the flexibility needed for rapid technological advancement. Furthermore, targeted support should be provided to small and medium-sized enterprises (SMEs) at lower quantiles, ensuring that these businesses also benefit from R&D advancements and digital technologies and that they are not left behind in the economic transformation.

In the long-term, the relationship between natural resources and the digital economy weakens, reflecting the maturing of both sectors. As economic growth shifts from resource-based to technology-driven, the USA must implement long-term strategies that foster sustainable innovation and ensure that the digital economy continues to evolve. Given that economic growth and R&D investment in the digital economy may face diminishing returns as markets mature, policies should focus on new frontiers in digital technologies, such as quantum computing and advanced artificial intelligence. Furthermore, regional policies should be designed to ensure equitable access to digital opportunities, especially in lower-income and underserved areas. Investments in digital infrastructure and education will be critical to ensure that all regions and populations can participate in the digital economy, thus fostering inclusive growth. Moreover, policymakers should remain adaptable, fine-tuning regulations to allow the digital sector to mature sustainably, with a focus on reducing market saturation and stimulating innovation even in more developed markets.

5.3 Limitations and future directions

While this study presents a novel approach to exploring the drivers of the digital economy, it is not without limitations. Firstly, the study did not account for other important drivers, such as financial development, institutional quality and trade openness. Future research should incorporate these variables to provide a more comprehensive understanding of the factors influencing the digital economy. Secondly, the study focused solely on the USA, limiting its generalizability. Therefore, future studies should expand the scope to include both developed and developing countries for broader applicability. Finally, the study employed wavelet quantile-on-quantile regression, which does not capture time-varying impacts. Future research should consider time-varying techniques to enhance policy recommendations and provide more nuanced insights.

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