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# The fourth industrial revolution and environmental efficiency: The role of fintech industry

Sulaman Muhammad<sup>a</sup>, Yanchun Pan<sup>a,\*</sup>, Cosimo Magazzino<sup>b</sup>, Yusen Luo<sup>c</sup>, Muhammad Wagas<sup>d</sup>

<sup>a</sup> College of Management, Shenzhen University, Guangdong, 518060, PR China

<sup>b</sup> Department of Political Sciences, Roma Tre University, Italy

<sup>c</sup> School of Management, Jiangsu University, Zhenjiang, 212013, PR China

<sup>d</sup> China Special Economic Zone Research Center, Shenzhen University Guangdong, 518060, PR China

## A R T L C L E I N F O

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# ABSTRACT

In the recent years, fintech industry of the fourth industrial revolution has grown multifold, which raised the concerns of scholars over the excessive usage of electricity. This paper places contribution to the existing literature by analyzing the impact of fintech industry on environmental efficiency across selected EU countries. We also utilized indicators like high-tech industry and e-commerce along with fintech industry to better understand the relationship between fourth industrial revolution and environmental efficiency. This study used Data Envelopment Analysis (DEA) to evaluate environmental efficiency using two different techniques i.e., Slack-Base Measure (SBM) and Epsilon-Based Measure (EBM). Method of Moments Quantile (MMQ) regression is employed as a basic regression technique, while instrumental variables Generalized method of Moments (IV-GMM) is used for robust analysis. The results show that, the overall environmental efficiency of EU countries have improved over the years. As the indicators of the fourth industrial revolution, fintech industry and ecommerce exert a positive effect and improve environmental efficiency; however, high-tech industry reduces environmental efficiency. The results further show that, economic growth and green finance investment promote environmental efficiency, while industrialization and R&D deteriorates it. The results can be of special interest for the policy makers of technological world.

#### 1. Introduction

Technological innovation in the past 30 years triggered the fourth industrial revolution, which is also known as 4IR or Industry 4.0. Technologies like machine learning, artificial intelligence (AI), blockchain, robotics, and the Internet of Things (IoT) revolutionize the daily life of people through products like 3D printers, electric cars, digital finance, and online shopping (Shahbaz et al., 2020). Industry 4.0 is expected to immensely transform our economic and financial systems in a digital and technological way (Machkour and Abriane, 2020). The fourth industrial revolution and the environment are interrelated megatrends, which can work as a double edge sword. The adaptation of technological innovation in the economic system and financial services can help to improve environmental quality (Herweijer et al., 2018). However, on the other hand, it can also damage environmental quality by increasing the demand for electricity and producing an excessive amount of electronic waste (Tao et al., 2022).

Fintech (financial technology) revolution is in full swing globally, which aims to use technology to improve financial activities and compete with traditional financial culture. Fintech is defined as, technological-based financial innovation which led to new business models, applications, processes, or products that could significantly enhance financial services (FSB, 2017). The synchronization of technology with a financial system made financial services such as investment, borrowing, stocks, payments, etc., more accessible to the general public. Fintech industry revolutionizes online shopping, payment system, insurance, crypto trading, and the credit market with blockchain digital ledger (Thakor, 2020). In 2018, a total investment of 112 billion (\$) was recorded in the fintech industry (Zveryakov et al., 2019).

Fintech industry is growing multifold across Europe in the past few years, where the total investment in the fintech industry reached 58 billion USD in 2019 (CB Insights, 2021). The financial sector is regarded as the major beneficiary of technological innovation (Chang et al., 2020). Technological advancement in the financial system can

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<sup>\*</sup> Corresponding author. E-mail address: panyc@szu.edu.cn (Y. Pan).

significantly enhance financial services; however, it might pose a threat to the natural environment. As numerous researchers have highlighted that Fintech industry significantly increases the demand for electricity and energy resources (Sadorsky, 2010; Zhang, 2011). Financial innovation can escalate the demand for energy by facilitating access to cars and appliances, increasing wealth effect through the stock market, and promoting new and existing business; hence increasing energy demand, boosting foreign investment, and creating a bulk of e-waste (Croutzet and Dabbous, 2021). However, Fintech can also help to promote environmental quality and reduce energy demand through renewable energy initiatives, financing electric cars, promoting carbon-neutral business models, and investing in energy-saving ventures (Kim and Park, 2016).

In the previous literature, researchers studied the link between financial development and environmental pollution (Assi et al., 2021; Ibrahim and Vo, 2021; Xu et al., 2021; Zhao et al., 2021); however, the nexus between fintech industry and environment is still a very young topic and not much research has been done in this regard (Tao et al., 2022). studied the relationship between fintech industry and the low-carbon economy globally at the city level only for the year 2018. Where, the fintech data used by the authors was a city-wise index of fintech ecosystem. Croutzet and Dabbous (2021) explored the impact of fintech on renewable energy use across OECD countries (Muganyi et al., 2021). analyzed the relationship between sulfur dioxide and fintech industry at the city level across a single country, China. Elheddad et al. (2021) studied the relationship between fintech industry and carbon emissions across OECD countries; where, the authors used electronic finance as a proxy for fintech industry and the fourth industrial revolution. This present study is different from previous studies, as in this study we used the fintech variable as the total investment in fintech industry in a particular country for a specific year, rather than using e-investment, fintech city index or financial development. Furthermore, in this study, we used environmental efficiency instead of  $CO_2$  emissions or any other pollutant.

The objectives of this study are as below. First, to probe the relationship between the fourth industrial revolution and the environment by investigating the nexus between fintech industry and environmental efficiency across EU countries. We also utilized variables like high-tech enterprises and e-commerce as control variables to better understand the relationship between the fourth industrial revolution and environmental efficiency. Second, to computer the environmental efficiency of selected countries using input/output DEA analysis.

The rest of the paper is arranged in following manner. Section 2 displays the literature review, section 3 introduces methodology and data, empirical results are displayed in section 4, a discussion of results is presented in section 6, and section 5 proposes conclusions along with the policy implications.

## 2. Literature review

The term "Fintech" was initially introduced in the early 1990's by John Reed, a former chairman of Citicorp (Puschmann et al., 2020). In the early days, the term fintech was used only for Insurtech (insurance technology) related services; however, later on, it evolved and now is used for all financial technology related products and services.

The relationship between fintech industry and environmental pollution can be explained through four different theories (see Fig. 1)



Fig. 1. Influencing mechanism between fintech industry and environmental pollution. (Author's own illustration based on the theoretician mechanisms proposed by Sadorsky, 2011; Coban and Topcu, 2013).

i.e., direct effect, wealth effect, business effect, and substitution effect (Sadorsky, 2011; Coban and Topcu, 2013). According to the direct effect, fintech industry facilitates access to durable electric products such as phones, laptops, tablets, and other electronic business items, which can escalate the demand for electricity and energy consumption and therefore deteriorate environmental quality. Furthermore, it directly facilitates the cryptocurrency sector which use blockchain and is considered one of the most electricity-intensive sectors in the fintech industry. De Vries (2018) estimated that the whole crypto network consumes the same amount of electricity as countries like Austria, Hong Kong, and Ireland. Cryptocurrency is considered a serious threat to the natural environment; where according to the most extreme prediction, Bitcoins alone can push the global temperature above 2 °C (Mora et al., 2018). In addition, this will also generate a huge amount of e-waste once these electric items reach the end of their useful life and therefore will exert a negative effect on the natural environment and create environmental pollution (Gangwar et al., 2019). According to the wealth effect, fintech industry can increase the wealth of individuals by boosting economic activities and providing earning opportunities for individuals in areas like cryptocurrency and NFTs (non-fungible tokens). This, in return, will increase the demand for electricity and energy usage, and therefore damage the environmental quality. Business effect theorized that fintech industry promotes and facilitates new business models in the field of financial technology which can grow business volume, spending, and jobs; thus, increasing the demand for energy consumption. Fintech has witnessed a sharp growth in new startups where the total investment grew sixfold since 2013 (Zveryakov et al., 2019). According to the substitution effect, fintech industry facilitates access to green technologies and energy savings initiatives which can help to reduce the demand for energy consumption and therefore reduce environmental pollution (Tao et al., 2022). Electric cars such as Tesla and Rivian are gaining popularity, which reduces the dependence on traditional fuel oil and reduces energy consumption (Herweijer et al., 2018).

In the existing literature, there is no unanimous conclusion among researchers regarding the effect of fintech on environmental pollution, as very few studies have explored this relationship (Tao et al., 2022). studied the impact of fintech industry on global greenhouse gas (GHG) emissions using Generalized Method of Moments (GMM) and Two-Stage Least Squares (2SLS) regression estimations. The authors also account for Gross Capital Formation (GCF) and total exports. Their results indicated that fintech industry can significantly reduce GHG emissions and improve environmental quality. Muganyi et al. (2021) explored the impact of fintech industry, industrialization, trade, and green finance on environmental pollution by employing semi-parametric difference-in-difference estimation. Empirical findings show that fintech industry and green finance are essential for improving environmental quality and mitigating pollution. Elheddad et al. (2021) studied the relationship between carbon emissions and fintech industry across OECD countries by employing Fixed Effects (FE), Random Effects (RE), and Quantile Regression (QR) estimation. The results indicate that fintech reduces carbon emissions across OECD countries.

Some studies, on the other hand, used financial development to explore the nexus. Liu and Song (2020) investigated the impact of financial development on CO<sub>2</sub> across China using spatial-temporal techniques. Applied results evidenced how financial development increases carbon emissions in China. L. Wang et al. (2020) explored the nexus between financial development and carbon emissions across G-7 countries using the Auto-Regressive Distributed Lags (ARDL) technique. The authors found that financial development along with globalization and natural resource consumption increase carbon emissions across G-7 countries. Zaidi et al. (2019) studied the relationship between financial development and carbon emissions across the APEC countries using VECM and causality tests. Empirical results clarified that financial development along with economic growth cause carbon emissions across APEC countries. R. Wang et al. (2020) studied the impact of financial development on carbon emissions across N-11 countries by employing the panel CCEMG and AMG estimator. The results confirmed that financial development promotes carbon emissions in the sample.

The next strand of research focuses on green finance, R&D, and environmental pollution. The relationship between green finance and pollution can be explained through three theories, i.e., resource allocation effect, capital support effect, and technological innovation effect (He et al., 2019; Liu et al., 2019). According to the resource allocation effect, green finance enhances the efficiency of capital utilization and diverts financial resources from the pollution-intensive sector to the high-efficiency and low-polluting sector. This helps to reduce pollution and achieve high-efficiency output. The capital support effect states that green finance provides capital to less pollution-intensive sectors of industry to achieve higher output with maximum efficiency and gain a competitive edge against pollution-intensive sectors, leading to improve environmental quality. Technological innovation effect state that green finance provides credit support for technological innovation and adaption of green and advanced technologies, which helps to mitigate pollution and improve environmental quality. Zhou et al. (2020) examined the impact of green finance on environmental pollution across China by employing Generalized Least Squares (GLS) estimations. The results evidenced that green finance reduces environmental pollution across Chinese provinces. Ren et al. (2020) explored the nexus between green finance and carbon emissions across China using a VECM, concluding that green finance promotes non-renewable energy use and therefore reduces environmental pollution. Saeed Meo and Karim (2022) examined the impact of green finance on carbon emissions across developed countries using quantile-quantile regression. Their results indicated that green finance promotes environmental quality and reduces carbon emissions.

## 3. Methodology and data

#### 3.1. Environmental efficiency

This study employed the Data Envelopment Analysis (DEA) to measure environmental efficiency (EE) using two different techniques i. e., Slack-Base Measure (SBM) and Epsilon-Based Measure (EBM) to measure environmental efficiency. We employed the modified undesirable models of SBM and EBM to measure environmental efficiency using input-output DEA analysis.

#### 3.1.1. SBM analysis

SBM model was proposed by Tone (2001), which utilized the slack variable to measure the efficiency. SBM model provides more reliable result as compared to other models such as BCC and CCR, as it provides a true reflection of the efficiency evaluation without deviation (Luo et al., 2021). The original SBM model has the shortcoming as it does not differentiate between good and bad outputs. Therefore, Tone (2003) developed a modified SBM model, which includes undesirable outputs. We used the SBM undesirable model to compute the EE of European Union (EU) countries.

Equation (1) represents the SBM model with undesirable outputs. *X* represents input while  $y^D$  and  $y^{UD}$  represent desirable and undesirable outputs, respectively.  $\omega_i$ ,  $\alpha_j$ , and  $\beta_k$  indicates variable's intensity.

$$\theta_{0}^{*} = \min \frac{1 - \frac{1}{i} \sum_{i=1}^{l} \frac{x_{i}^{*}}{x_{i0}}}{1 + \frac{1}{j+k} \left( \sum_{j=1}^{j} \frac{x_{j}^{p}}{y_{j0}^{p}} + \sum_{k=1}^{k} \frac{x_{k}^{UD}}{y_{k0}^{D}} \right)}$$
(1)

s.t.  $x_{i0} = \omega_{i0}X + s_i^x$  $y_{j0}^U = \alpha_{j0}Y - s_j^D$  $y_{k0}^{UD} = \beta_{k0}Y + s_k^{UD}$ 

$$s_i^x \ge 0, s_i^D \ge 0, s_k^{UD} \ge 0, \omega_i \ge 0, \alpha_j \ge 0, \beta_k \ge 0$$

where,  $s_i^x$  indicates input surplus,  $s_j^D$  represents the shortcoming of desirable output and  $s_k^{UD}$  is the surplus of undesirable output.  $\theta$  represents the efficiency and its value ranges from 0 to 1.

#### 3.1.2. EBM analysis

This study also employed EBM-DEA analysis for measuring environmental efficiency to overcome the shortcoming of the SBM model. The non-redial SBM are based on efficiencies of slack variables and avoid radial assumptions, seek to maximize the input and output inefficiencies by identifying the points farthest from the frontier, indicating that the original ratio information for the efficiency front projection value is lost. This might provide inconsistent results. Therefore, to overcome these problems we employed the modified version of the EBM model with undesirable outputs, presented by Tone and Tsutsui (2010). The EBM model for measuring environmental efficiency is written below:

$$\delta^* = \min \frac{\gamma - \varepsilon x \sum_{i=1}^{m} \frac{\omega_i^{-s} s_i^{-b}}{xik}}{\psi + \varepsilon y \sum_{r=1}^{s} \frac{\omega_r^{+s} s_r^{+b}}{yrk} + \varepsilon y \sum_{p=1}^{q} \frac{\omega_p^{-b} s_p^{-b}}{b_{pk}}}$$
(2)

s.t. 
$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \gamma x_{ik}i = 1, 2..., m$$
  
 $\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^{+g} = \psi y_{rk}r = 1, 2..., s$   
 $\sum_{j=1}^{q} b_{pj}\lambda_j + s_p^{-b}\lambda = \psi b_{pk}p..., q$   
 $\lambda_j \ge 0, s_i^- \ge 0, s_r^{+g} \ge 0, s_p^{-b} \ge 0$ 

where, *m* represents the total number of inputs, while *s* and *q* indicate the total number of desirable and undesirable outputs.  $s_i^-, s_r^{+g}$  and  $s_p^{-b}$  indicate the slack of input *i*, desirable output *r*, and undesirable output *p*, respectively; while  $\omega_r^{+g}$  and  $\omega_p^{-b}$  denoted the weight of desirable and undesirable outputs.  $\delta$  represents the efficiency and its value ranges from 0 to 1.

#### 3.2. The econometric model

To analyze the link between fintech and environmental efficiency this study follows Tao et al. (2022) and Croutzet and Dabbous (2021), adding various explanatory variables such as green finance, high-tech enterprises, and R&D to better understand the relationship. Equation (3) represents the econometric model for this study:

$$EE = f$$
 (FIN, PGDP, GF, R&D, HTE, FDI, IND, EC) (3)

where *EE* represents the environmental efficiency, *FIN* and *PGDP* indicate fintech industry and GDP per capita, respectively. *GF* and R&D denote green finance and research and development. While, *HTE*, *FDI*, *IND*, and *EC* represent high-tech enterprises, foreign direct investment, industrialization and e-commerce, respectively. Equation (4) below shows the logarithmic form of eq. (1).

Table 1			
Descriptive statistics	of input and	output	variables.

Tabla 1

$$\begin{split} lnEE_{it} = \alpha_{it} + \beta_{1}lnFIN_{it} + \beta_{2}lnPGDP_{it} + \beta_{3}lnGF_{it} + \beta_{4}lnR\&D_{it} + \beta_{5}lnHTE_{it} + \\ \beta_{6}lnFDI_{it} + \beta_{7}lnIND_{it} + \beta_{8}lnEC_{it} + \Phi_{it} \end{split}$$

where, *t* and *i* denotes year (*t*) for country (*i*).  $\alpha$  and  $\beta$  are the coefficients, and  $\Phi$  represents the error term.

This study utilizes the Method of Moments Quantile (MMQ) regression to study the relationship between energy efficiency and its determinants. MMQ regression is the modified version of traditional QR developed by Machado and Santos Silva (2019), which provides coefficient values at different quantile distributions. MMQ provides more efficient results by not only taking care of heterogeneity and endogeneity, but also considering the asymmetric and non-linear association between dependent and independent variables. The location-scale variant of the conditional quantile  $Q_y(\tau|X)$  equation is expressed as below.

$$y_{it} = \alpha_i + x'_{it}\beta + (\delta_i + Z'_{it}\gamma)U_{it}$$
(6)

where, the probability  $P \{\delta_i + Z'_{itl'} > 0\} = 1$ ,  $(\alpha, \beta', \delta, \gamma')'$  are the parameters to be calculated. The individual *i* fixed effects are labeled as  $(\alpha_i, \delta_i)$ , i = 1, ...n. Vector *k*, the known element of *X*, is denoted by *Z*, which are differentiable conversions with element *l* presented as:

$$Z_l = z_i(X) \ l = 1...,k$$
<sup>(7)</sup>

 $X_{it}$  and  $U_{it}$  are independent and identical for individual (*i*) at time (*t*), where  $U_{it}$  is orthogonal to  $X_{it}$ . Transforming eq. (6):

$$Q_{y}(\tau|X) = (\alpha_{i} + \delta_{i}(\tau)) + X'_{it}\beta + Z'_{it}\gamma q(\tau)$$
(8)

 $X_{it}$  denotes the vector of independent variables i.e., *FIN*, *PGDP*, *GF*, *R&D*, *HTE*, *FDI*, *IND* and *EC*. While,  $Q_y(\tau|X)$  is the quantile distribution of dependent variable  $Y_{it}$ , which in this study is the environmental efficiency (*EE*). *i* and  $\tau$  are denoted by scaler coefficients identified as  $\alpha_i(\tau) = \alpha_i + \delta_i q(\tau)$ .  $q(\tau)$  is the demonstration of sample quantile  $\tau^{\text{th}}$ , which can be computed through the function below.

$$min_{q}\sum_{i}\sum_{t}\rho_{\tau}\left(R_{it}-\left(\delta_{i}+Z_{it}^{'}\gamma\right)q\right)$$
(9)

In eq. (8),  $\rho_{\tau}(A) = (\tau - 1) AI \{A \le 0\} TAI \{A > 0\}$  represents the function of checking.

## 3.3. Data

We used the data of 23 EU countries from 2013 to 2019 based on data availability. Shorter time series and only 23 EU countries were selected based on the limited data availability, particularly for the fintech industry as this is relatively a new industry and no historic data is available. The values of environmental efficiency are calculated though DEA-SBM and DEA-EBM analysis using three input variables, energy consumption, capital stock and labor; and two output variables gross domestic product (desirable output) and carbon emissions (undesirable output). The summary statistics of variables for input and output are presented in Table 1. Fintech data is retrieved from the database created by Cornelli et al. (2020), which has been widely utilized in the literature by numerous researchers in the field of environment and finance, such as (Carbó-Valverde et al., 2021; Kowalewski and Pisany, 2021; Papadimitri et al., 2021). The value of fintech is measured in US \$ indicating total fintech credit of a country for a particular year. The definition, measuring unit and descriptive statistics of variables used in

I/O	Variables	Unit	Mean	St. dev	Min	Max
Input	Energy consumption	Kiloton of oil equivalent	43550.69 5021034	52181.07 6337096	2247.937 191989 1	208057.4 $2.10e\pm07$
	Labor	Number of persons	1.02e+07	1.21e+07	675958	4.36e+07
Output	GDP Carbon emissions	USD Kiloton	8.16e+11 136643	1.03e+12 173742.2	2.21e+10 7120	3.96e+12 777630

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## Table 2

Statistical summary of explanatory variables.

Variables	Unit	Mean	St. dev	Min	Max
Fintech industry	million USD	429.304	1533.08	0.01	11476.03
GDP per capita	USD	39381.77	21512.49	7143.462	92556.32
Green finance	Million Euros	76.430	107.475	0.10	528.5
Research and development	% of GDP	1.8985	0.837	0.44	3.39
High-tech industry	No. of high-tech enterprises	50535.71	54180.37	3117	229452
Foreign direct investment	% of GDP	3.861	10.852	-37.712	81.301
Industrialization	% of GDP	24.075	5.012	17.188	38.429
E-commerce	% of population	55.857	18.901	12	87



a) DEA-SBM analysis

b) DEA-EBM analysis

Fig. 2. Environmental efficiency of EU countries.

econometric analysis are presented in Table 2. Data is retrieved from Eurostat (2021) and World Bank (2021).

## 4. Results

## 4.1. Environmental efficiency

This study utilized DEA-SBM and DEA-EBM technique with undesirable output to evaluate the environment of EU countries. The environmental efficiency (EE) of SBM and EBM analysis for each country is shown below in Fig. 2. The results of both SBM and EBM analyses indicate that the EE of EU improved over the year. However, Belgium, Bulgaria, Italy, and Slovenia are the only countries whose EE deteriorated. While, the environmental efficiency of Estonia, France, Germany, Lithuania, Latvia, Switzerland, and UK remain consistently positive over the years. The results of SBM and EBM analysis show a consistent result.

Fig. 3 shows the comparison of environmental efficiency and  $CO_2$  over the years. The values of SBM and EBM gradually increased simultaneously over the years, which shows a linear upward trend, this indicates the improvement of environmental efficiency of EU countries in these years. Instead, the total carbon emissions of EU countries show a steady decrease over the years. This is because of the pollution reduction policies adopted by EU countries such as carbon trading, the transition toward renewable energy, and strict environmental regulations on the industrial sector.

## 4.2. Preliminary tests

The results of panel cross-sectional dependence test are provided in Table 3. These tests have the null hypothesis of cross-sectional independence, which means the absence of cross-sectional dependence. The

results in Table 3 exhibit that there is no cross-sectional dependence among variables at a panel level.

Testing for unit root is a standard econometric practice before executing the main regression analysis. This study employed two unitroot tests, Fisher-ADF (Maddala and Wu, 1999) and LLC (Levin et al., 2002) tests. Both tests have the null hypothesis that unit root exists and data is non-stationary. Table 4 presents the results of both Fisher-ADF (augmented dickey fuller) and LLC tests. which exhibit that the null hypothesis of both tests is rejected for all variables at first difference with 1% and 5% significance level. This demonstrates that all variables sequences are stationary.

In the next step of preliminary diagnostics tests, we employed the Kao cointegration test to verify the long run association among the variables(Kao, 1999). This test is based on five parameters, which includes modified DF (Dickey-Fuller), DF, Augmented DF (ADF), unadjusted modified DF, and unadjusted DF. The results of cointegration test are presented in Table 5, which shows that the null hypothesis is rejected. Hence, this confirms that cointegration exists among the variables.

## 4.3. Panel data analysis

Before employing the MMQ, we checked the normality of the data using the Shapiro-Wilk and Shapiro-Francia tests, to confirm whether MMQ estimation is the best fit for this data or not (Shapiro and Francia, 1972). Shapiro-Wilk and Shapiro-Francia tests have the null hypothesis of normality. According to the results of normality tests in Table 6, the null hypothesis is rejected. This indicates that the data is not normally distributed.

The results of the MMQ regression for SBM-environmental efficiency are presented in Table 7. The results indicate that different variables



Fig. 3. Comparison of EE and carbon emissions of EU region.

#### Table 3

Panel cross-sectional dependence tests.

Cross-sectional dependence test	Statistics	P-value
Pesaran test	0.442	0.658
Frees test	2.625	0.3583
Friedman test	8.844	0.9904

 $H_0 =$ Cross-sectional independence.

exert a heterogeneous effect on environmental efficiency. Fintech industry significantly increases environmental efficiency and reduces pollution across all levels of quantiles. The coefficient value of fintech industry increases with higher quantiles and the significance level also improves. This indicates that fintech industry improves environmental efficiency as the industry gets mature and penetrates the market. GDP per capita also has a positive effect and increases environmental efficiency almost across all quantiles at a 1% significance level. The coefficient of green finance also has a positive effect, indicating that an increase in green finance investment promotes environmental efficiency

#### Table 4

Results of panel stationarity tests.

1	,				
Variables	Fisher-ADF		LLC		
	Level	First difference	Level	First difference	
lnSBM	34.608	111.242***	-7.137***	-60.535***	
<i>ln</i> EBM	24.776	74.096**	-2.238*	-70.229***	
<i>ln</i> FIN	281.949***	357.471***	-15.787***	-22.350***	
<i>ln</i> PGDP	55.548	106.650***	-10.270***	-15.893***	
<i>ln</i> GF	43.777	361.980***	1.768	-69.369***	
lnR&D	27.142	130.692***	17.793	-2.748**	
<i>ln</i> HTE	160.636***	328.145***	-0.734	$-15.642^{***}$	
<i>ln</i> FDI	193.722***	338.083***	-6.219***	-24.169***	
<i>ln</i> IND	29.450	91.057***	-16.261***	-18.431***	
<i>ln</i> EC	90.976***	294.192***	-5.727***	-65.851***	

 $H_o = Unit$  root exist in the data.

 $H_1 =$ Unit root does not exist in the data.

\*\*' \*\*\* null hypothesis rejection at 5% and 1% significance level.

#### Table 5

Results of the cointegration test.

Parameters	of Kao test	Statistics	P-value
Kao test	Modified Dickey-Fuller t	3.757***	0.000
	Dickey-Fuller t	6.204***	0.000
	Augmented Dickey-Fuller t	6.133***	0.000
	Unadjusted modified Dickey-Fuller t	-3.137***	0.000
	Unadjusted Dickey-Fuller t	0.137	0.445

 $H_o$  = Cointegration does not exists among the variables. \*\*\* null hypothesis rejection at 1% significance level.

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Table 6	
Tests for normal	distribution

Variables	Shapiro-Wilk	test	Shapiro-Francia test		
	Statistics	P-value	Statistics	P-value	
<i>ln</i> SBM	3.863	0.001	3.290	0.007	
<i>ln</i> EBM	8.680	0.000	5.873	0.000	
<i>ln</i> FIN	8.957	0.000	9.563	0.000	
<i>ln</i> PGDP	5.502	0.000	5.537	0.000	
<i>ln</i> GF	4.288	0.000	4.701	0.000	
lnR&D	6.830	0.000	6.971	0.000	
<i>ln</i> HTE	6.603	0.000	6.600	0.000	
<i>ln</i> FDI	104.915	0.000	116.526	0.000	
<i>ln</i> IND	4.711	0.000	4.573	0.000	
<i>ln</i> EC	12.071	0.000	13.033	0.000	

 $H_0 = Data$  is normally distributed.

\*\*' \*\*\* null hypothesis rejection at 5% and 1% significance level.

and reduces environmental pollution. The coefficient value of green finance is insignificant at the 85th and 95th quantiles. In addition, R&D has a negative impact and reduces EE across early quantiles at a 5% significance. However, the coefficient value of R&D is insignificant after 45th quantile. The high-tech industry has a negative effect and reduces EE across all quantiles at a 5% significance level. Regarding FDI, the results show that FDI has a negative effect and reduces EE. The coefficient value of FDI is insignificant at the early level of quantiles, however at later quantiles the significance level increase. The industrialization has a negative effect and reduces EE at a 10% significance. However, the coefficient value of industrialization is insignificant at higher quantiles. Regarding e-commerce, the results show that the coefficient value of *EC* is insignificant across all quantile levels.

The MMQ regression results for EBM-environmental efficiency is presented in Table 8. According to the results, fintech industry has a significantly positive effect and increases environment efficiency almost across all quantiles at a 5% and 10% significance level; except for the first quantile, where the coefficient of FIN is insignificant. GDP per capita has a positive significant impact and improves environmental efficiency almost across all quantiles at a 5% and 1% significance level. However, the coefficient value of PGDP is not significant at the 85th and 95th quantiles. Green finance also exerts a positive effect and increases EE at a 1%, 5% and 10% significance level. However, the coefficient value of *GF* is not significant at the 85th and 95th quantiles. *R&D* has a negative effect and reduces environmental efficiency at a 5% and 10% significance level. The coefficient value of *R&D* is not significant after the 55th quantile. Regarding the high-tech industry, the results show that the high-tech industry has a negative effect and reduces environmental efficiency across all quantiles at a 1% and 5% significance level. Foreign direct investment exerts a negative effect and reduces EE at higher quantile levels. However, the value of FDI is not significant at lower quantiles. The results of industrialization and e-commerce indicate that the coefficient values of IND and EC are insignificant and do not exert any effect on environmental efficiency.

#### 4.4. Robustness checks

We further perform a two-step Instrumental Variable (IV) GMM regression as a robust estimation to confirm the validity and consistency of the previous results (see Table 9). IV-GMM provide efficient results in the presence of unknown heteroskedasticity and is robust to auto correlation (Baum et al., 2003). In addition, IV-GMM address the issue of variable omission bias and provide consistent results. In this study, for IV-GMM analysis we used instrumental variables by taking the lag of all right-hand side variables, following the study of (Arellano and Bond, 1991). The results indicate that fintech industry increases EE at a 5% significance for both SBM and EBM. GDP per capita also has a positive effect and improves environmental efficiency at a 10% for SBM and 5% for EBM. The coefficient value of R&D is negative but insignificant;

	05th	15th	25th	35th	45th	55th	65th	75th	85th	95th
<i>ln</i> FIN	0.036*	0.037**	0.037**	0.038**	0.040**	0.041**	0.041**	0.042**	0.043**	0.044**
	(-0.019)	(-0.018)	(-0.017)	(-0.016)	(-0.015)	(-0.015)	(-0.016)	(-0.016)	(-0.018)	(-0.02)
<i>ln</i> PGDP	0.847***	0.785***	0.726***	0.646***	0.511***	0.426***	0.345***	0.270***	0.165	0.099
	(-0.167)	(-0.14)	(-0.137)	(-0.132)	(-0.127)	(-0.127)	(-0.129)	(-0.133)	(-0.143)	(-0.159)
<i>ln</i> GF	0.099**	0.093**	0.088**	0.080**	0.067**	0.059**	0.052**	0.041*	0.035	0.029
	(-0.030)	(-0.028)	(-0.026)	(-0.025)	(-0.023)	(-0.023)	(-0.024)	(-0.025)	(-0.028)	(-0.030)
lnR&D	-0.764**	-0.683**	-0.605**	-0.499**	-0.320**	-0.208	-0.101	-0.001	0.138	0.224
	(-0.176)	(-0.136)	(-0.136)	(-0.135)	(-0.132)	(-0.131)	(-0.131)	(-0.134)	(-0.143)	(-0.161)
<i>ln</i> HTE	-0.231**	-0.230**	-0.299**	-0.288**	$-0.225^{**}$	$-0.223^{**}$	$-0.222^{**}$	-0.220**	-0.218**	-0.217***
	(-0.047)	(-0.044)	(-0.042)	(-0.039)	(-0.037)	(-0.037)	(-0.038)	(-0.040)	(-0.044)	(-0.048)
<i>ln</i> FDI	-0.047	-0.052	-0.057	-0.063*	-0.074*	-0.081*	-0.087*	-0.093*	$-0.102^{**}$	-0.107**
	(-0.042)	(-0.039)	(-0.037)	(-0.035)	(-0.033)	(-0.033)	(-0.034)	(-0.036)	(-0.039)	(-0.042)
<i>ln</i> IND	-0.446*	-0.437*	-0.428*	-0.416*	-0.395	-0.382	-0.369	-0.357	-0.341	-0.331
	(-0.26)	(-0.243)	(-0.23)	(-0.215)	(-0.202)	(-0.202)	(-0.209)	(-0.221)	(-0.244)	(-0,262)
<i>ln</i> EC	0.208	0.199	0.19	0.179	0.159	0.147	0.135	0.124	0.109	0.099
	(-0.19)	(-0.178)	(-0.168)	(-0.157)	(-0.148)	(-0.148)	(-0.153)	(-0.162)	(-0.178)	(-0.191)
Cons.	-6.757**	-6.068**	-5.404**	-4.502**	-2.976**	-2.028	-1.111	-0.267	0.918	1.658
	(-1.977)	(-1.681)	(-1.629)	(-1.569)	(-1.508)	(-1.505)	(-1.527)	(-1.583)	(-1.711)	(-1.891)
The Std. I	Dev. is reported in	n parentheses. **	*, **, and * indic	ate the statistical	significance at th	ie 1%, 5%, and 1	0% levels, respec	tively.		

Table 8MMQ regressions for EBM-EE.

	05th	15th	25th	35th	45th	55th	65th	75th	85th	95th
<i>ln</i> FIN	0.0391	0.0349*	0.033*	0.031**	0.030**	0.028**	0.027**	0.025**	0.024**	0.023*
	(-0.027)	(-0.019)	(-0.016)	(-0.014)	(-0.013)	(-0.011)	(-0.011)	(-0.011)	(-0.011)	(-0.012)
<i>ln</i> PGDP	0.729***	0.559***	0.500***	0.421***	0.361***	0.294***	0.244***	0.194**	0.136	0.087
	(-0.204)	(-0.153)	(-0.135)	(-0.116)	(-0.104)	(-0.092)	(-0.087)	(-0.086)	(-0.089)	(-0.096)
lnGF	0.132***	0.101***	0.089**	0.074**	0.063**	0.050**	0.041**	0.032*	0.021	0.012
	(-0.041)	(-0.030)	(-0.027)	(-0.023)	(-0.020)	(-0.018)	(-0.017)	(-0.017)	(-0.018)	(-0.019)
lnR&D	-0.765**	-0.531**	-0.448**	-0.340**	-0.256**	-0.164*	-0.094	-0.025	0.055	0.122
	(-0.197)	(-0.152)	(-0.133)	(-0.115)	(-0.105)	(-0.092)	(-0.088)	(-0.086)	(-0.086)	(-0.094)
<i>ln</i> HTE	-0.152**	-0.148**	-0.146**	-0.144 **	-0.142**	-0.140**	-0.139**	-0.137**	-0.136**	-0.134***
	(-0.061)	(-0.045)	(-0.04)	(-0.033)	(-0.029)	(-0.026)	(-0.025)	(-0.025)	(-0.026)	(-0.028)
<i>ln</i> FDI	-0.045	-0.046	-0.046	-0.047	-0.047*	-0.047*	-0.048*	-0.048*	-0.048*	-0.049**
	(-0.052)	(-0.038)	(-0.034)	(-0.028	(-0.025)	(-0.022)	(-0.021)	(-0.021)	(-0.022)	(-0.024)
<i>ln</i> IND	-0.175	-0.185	-0.188	-0.193	-0.196	-0.2	-0.203	-0.206	-0.209	-0.212
	(-0.331)	(-0.244)	(-0.215)	(-0.182)	(-0.16)	(-0.144)	(-0.137)	(-0.137)	(-0.144)	(-0.156)
<i>ln</i> EC	0.207	0.166	0.151	0.132	0.117	0.101	0.085	0.076	0.062	0.050
	(-0.248)	-0.183	(-0.162)	(-0.137)	(-0.121)	(-0.108)	(-0.103)	(-0.103)	(-0.108)	(-0.117)
Cons.	-7.196**	-5.069**	-4.320**	-3.336**	-2.575**	-1.743	-1.106	-0.484	0.246	0.851
	(-2.493)	(-1.879)	(-1.65)	(-1.416)	(-1.27)	(-1.13)	(-1.075)	(-1.065)	(-1.09)	(-1.184)

The Std. Dev. is reported in parentheses. \*\*\*, \*\*, and \* indicate the statistical significance at the 1%, 5%, and 10% levels, respectively.

therefore R&D has no significant impact on environmental efficiency. The high-tech industry exerts a negative effect and reduces EE for both EE-SBM and EE-EBM at a 5% significance level. FDI and industrialization have no significant effect on EE-SBM and EE-EBM. Lastly, the result of e-commerce shows that EC exerts a significantly positive effect and

#### Table 9

IV-GMM robust estimation.

Variables	SBM		EBM	
	Coef.	P-value	Coef.	P-value
<i>ln</i> FIN	0.002**	0.018	0.001**	0.044
<i>ln</i> PGDP	0.009*	0.050	0.003**	0.007
lnGF	0.005*	0.072	0.004*	0.089
lnR&D	-0.007	0.518	-0.006	0.500
<i>ln</i> HTE	-0.011**	0.019	-0.007**	0.019
<i>ln</i> FDI	-0.009	0.281	-0.007	0.211
<i>ln</i> IND	-0.005	0.758	-0.002	0.895
lnEC	0.028**	0.014	0.027***	0.000
AR (1) value	-2.16**	0.031	-1.90*	0.057
AR (2) value	-0.68	0.499	-0.92	0.360
Hansen test	8.90	0.781	11.05	0.606

The Std. Dev. is reported in parentheses. \*\*\*, \*\*, and \* indicate the statistical significance at the 1%, 5%, and 10% levels, respectively.

Instruments validity test: Hansen test. H<sub>o</sub>: Instruments are valid and not overidentified. increases EE-SBM and EE-EBM at a 5% and 1% significance level respectively.

The validity of the IVs used for GMM analysis is confirmed through Hansen's test. The null hypothesis of this test states that the IVs are appropriate and not over-identified. The results of Hansen's test confirm the validity of IVs. In addition, Arellano-Bond tests, AR(1) and AR(2) checked the autocorrelation at first and second-order difference. The null hypothesis of no auto-correlation for AR(2) is not rejected according to the results, thus confirming that the estimators are consistent.

### 5. Discussion

The results show that fintech industry has a positive impact and increases environmental efficiency across EU countries. This rejects the hypothesis of direct effect, wealth effect, and business effect, while accepting the hypothesis of sustainable effect. This means that fintech industry facilitates and promotes the adaptation and utilization of green technologies and energy-saving initiatives, which helps to reduce pollution and improve EE. In addition, the inclusion of fintech in the banking and finance sector significantly reduces the dependence on traditional energy-intensive banking IT sector and helps to improve environmental efficiency. Fintech like Amazon Web Services (AWS) and Microsoft Azure can significantly relieve the burden on the traditional IT sector through cloud computing and therefore emit fewer emissions. Reports have shown that AWS is 3.6 times more energy efficient than traditional data centres (DANIEL BIZO, 2019). While and Azure is up to 93% more energy efficient and 98% more carbon efficient than traditional data centres (Microsoft Corporation, 2018). In addition, both AWS and Azure are on the path to shift to 100% renewable energy by 2025. According to Daniel Bizo, 2019b, moving to the AWS system can significantly reduce the carbon footprints of the IT sector up to 88%, as it is 3 times more energy-efficient than traditional IT system. European environmental regulation authority endorsed and, in many ways, worked as a catalyst by enhancing the competition, lowering prices for consumers, and facilitating the innovation of fintech in green sectors (Novikov, 2021). All these factors help fintech industry to achieve a sustainable growth by increasing economic activities, improving environmental efficiency, and reducing pollution.

Economic growth per capita also has a positive effect and increases environmental efficiency across EU countries. EU countries are highly developed countries with higher income per capita and the governments of those countries focus more on environmental issues along with economic development. These countries have reached a certain level of development where an increase in PGDP helps to reduce environmental pollution and improve environmental efficiency through green and advanced technologies in the industrial and manufacturing sector, stringent environmental regulations, environmental awareness among the general public, and advanced energy structure. Our results support the findings of Nepal et al. (2021) and Koengkan and Fuinhas (2021), who also testified the positive impact of economic growth on the environmental quality.

Green finance exerts a positive impact and improves environmental efficiency across EU countries. Green finance in EU countries indicates the total expenditure for environmental protection. EU governments invest this amount in the up-gradation of pollution-intensive equipment in the industrial sector and replace it with more efficient and green machinery. Furthermore, green finance also covers the cost of transition toward renewable energy by installing new renewable energy projects in the country. Forest management and green vegetation are also financed through green investment. All these factors help to reduce pollution and improve the environmental efficiency of these EU countries. Our findings are in line with the studies of A. Zhang et al. (2022).

R&D decreases environmental efficiency at lower quantiles, while its impact is insignificant at higher quantiles. This indicates that the R&D expenditure in EU countries is utilized for research and development mostly in sectors other than the environment. Regarding high-tech enterprises, the results show that it exerts a negative effect and reduces EE across EU countries. High-tech enterprises mostly operate their business through cloud computing backed by highly energy-intensive data centres. The ICT sector produces 2% of global missions, mainly due to its energy-intensive data centres, which is roughly the same as the global carbon emissions produced by the aviation industry (Jones, 2018). The data centres run by these big-tech companies are highly energy and electricity-intensive and their annual consumption increase alarming rate as the number of high-tech companies and data centres also increase (Jones, 2018). The majority of the electricity consumed by these data centres of high-tech companies is generated through non-renewable energy sources, which results in the deterioration of environmental efficiency.

Inward FDI in EU countries reduces environmental efficiency across higher quantiles, while its impact is insignificant across lower quantiles and IV-GMM regression. This indicates that the majority of the inward FDI goes into pollution-intensive and dirty sectors of industry, which increase pollution and reduce environmental efficiency. The relationship between industrialization and environmental efficiency is insignificant.

Regarding e-commerce and environmental efficiency, the results show that e-commerce has no significant impact on environmental efficiency across different quantiles of MMQ; however, it exerts a positive effect and increases environmental efficiency across IV-GMM. The positive effect of e-commerce on environmental pollution can be explained through the argument that e-commerce reduces the physical commute of consumers and therefore reduce the fuel consumption and transportation emission of each consumer, as a single delivery truck can deliver items to all consumers in a district. Furthermore, in the case of online shopping; large inventories are usually stored in a single warehouse at a convenient location. Which, results in less energy consumption as compare to offline shopping. A study, from MIT shows that traditional shopping has two time the carbon footprint as compare to online shopping (Weideli, 2019).

#### 6. Conclusions and policy implications

This study provides new insight into the relationship between the fourth industrial revolution and the environment by investigating the nexus between fintech industry and environmental efficiency across 23 EU countries from 2013 to 2019. The countries and time series period are selected according to the data availability, especially the data of fintech industry. Method of moments quantile regression (MMQ) regression is employed as a basic estimation technique, while IV-GMM (instrumental variables - generalized method of moments) is employed as a robust estimator. This study also utilized variables like high-tech enterprises and e-commerce as control variables to better understand the relationship between the fourth industrial revolution and environmental efficiency.

The results show that the overall EE of EU improved over the years. This is because of the pollution reduction policies adopted by EU countries such as carbon trading, the transition toward renewable energy, and strict environmental regulations on the industrial sector. The empirical results of econometric analysis show that fintech industry improves the environmental efficiency of EU countries. Fintech industry facilitates the adaptation of green technologies and energy-saving initiatives, which helps to improve environmental efficiency. Furthermore, the inclusion of fintech in the banking and finance sector significantly reduces the dependence on traditional energy-intensive banking IT sector and helps to improve environmental efficiency. Per capita GDP also has a positive effect and increases environmental efficiency. EU countries have reached a certain level of development where an increase in GDP helps to reduce environmental pollution and improve EE through advanced technologies in the industrial sector, stringent environmental laws, and advanced energy structure. Green finance exerts a positive impact and increases environmental efficiency. Green finance in EU countries is utilized for the up-gradation of pollution-intensive equipment in the industrial sector and replace it with more efficient and green machinery. In addition, green finance also covers the cost of installing new renewable energy projects forest management, and green vegetation to reduce environmental pollution. R&D decreases environmental efficiency across EU countries. This essentially means that the R&D expenditure spent in EU countries is utilized for research and development mostly in sectors other than the environment. High-tech enterprises reduce environmental efficiency across EU countries. The reason for this might be the energy and electricity-intensive data centres used by these enterprises for their business operations. FDI reduces the environmental efficiency of EU countries. This depicts that the inward FDI coming into the EU countries mostly goes into pollution-intensive and dirty sectors of industry which pollute the environment. Moreover, the results show that e-commerce improves the environmental efficiency of EU countries. E-commerce reduces the physical interaction between the customer and market, which results in less transportation and therefore less environmental pollution.

On the basis of empirical results, this study proposed the following policy recommendation.

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- Fintech plays a significant role in improving environmental efficiency; therefore, governments should promote and formulate special policies for the promotion of fintech, particularly in the banking sector. In addition, EU governments should invest the funding of "green finance" for the promotion and facilitation of fintech industry.
- 2) Financial regulators should facilitate fintech industry by formulating policies for cryptocurrency, NFTs, and others fintech to integrate them with the mainstream banking sector.
- 3) FDI and high-tech enterprises deteriorate environmental efficiency across the EU region; therefore, governments should impose strong environmental regulations on foreign firms and high-tech enterprises through a market-incentive approach, integrating command-andcontrol mechanism and voluntary environmental information disclosure to counter the negative effect of FDI and high-tech enterprises on environmental efficiency.

Future work is proposed as follow. First, we focused on 23 EU countries with the time period from 2013 to 2019 due to the unavailability of data. In the future, we intend to cover more countries with longer time series and divide them into several groups to better understand the relationship. Second, this study used three variables as a proxy for the fourth industrial revolution i.e., fintech industry, high-tech enterprises, and e-commerce. Thus, we expect to utilize more diverse variables to represent the fourth industrial revolution. In future we intend to utilize more robust indicators of the fintech industry to get a better understanding of the relationship between environment and fintech.

#### CRediT authorship contribution statement

Sulaman Muhammad: Conceptualization, Data curation, Formal analysis, Writing – review & editing. Yanchun Pan: Conceptualization, Supervision, Funding acquisition. Cosimo Magazzino: Writing – review & editing. Yusen Luo: Writing – review & editing, Formal analysis. Muhammad Waqas: Writing – review & editing, Data curation.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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