What matters to firm energy efficiency in developed economies: ICT investment or ICT expenditure? ---- an exploratory study of the UK

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Data availability statement

The data that support the findings of this study are available through an application to the UK Data Service Secure Lab, or an application to the Office for National Statistics Secure Research Service. Restrictions apply to the availability of these data, which were used under license for this study. Data are available [DOI: 10.5255/UKDA-SN-7451-16] with the permission of the Data Service.

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Highlights

- This study estimates firm energy efficiency with stochastic frontier analysis.
- ICT investment is positively associated with firm energy efficiency.
- ICT expenditure is also positively associated with firm energy efficiency.
- Firm location, firm size, and energy regulation affect firm energy efficiency.

Abstract

Energy use for business operations accounts for a considerable amount of emissions. Improving firm energy efficiency is crucial to achieving the goal of emissions reduction. Meanwhile, information and communication technology (ICT) has altered how firms operate. There is a trend that firms in developed economies tend to subscribe to ICT services rather than owning ICT assets. In other words, ICT expenditure is becoming more popular than ICT investment. However, few researchers have studied the relationship between firm ICT behaviours and energy efficiency, and none has compared the effect of ICT expenditure with that of ICT investment on energy efficiency.

This study uses stochastic frontier analysis (SFA) to compare ICT investment and ICT expenditure and explores their impacts on firm energy efficiency. The study analyses panel data for over 1,000 firms in 33 industries for the years 2008-2015 from the UK Annual Business Survey. The results indicate that both firm ICT expenditure and firm ICT investment are significantly positively correlated with firm energy efficiency. Foreign firms and London firms are less energy efficient. Non-profit firms, firms paying the Climate Change Levy, and firms with high advertising costs are more energy efficient. Firm size has a mixed effect on energy efficiency.

Keywords

ICT investment; ICT expenditure; Energy efficiency; Stochastic frontier analysis

1. Introduction

Climate change, which is mainly caused by burning fossil fuels for energy use, has been worrying human beings for decades. While reducing energy use can mitigate climate change, most economic activities require energy as a necessary input, making it challenging to reduce energy consumption since it restrains economic growth. Improving energy efficiency can be a solution, and it is essential to explore energy efficiency on economic foundations because sustainability and economic development are both important. A number of studies have explored economy- or regional-level energy efficiency; however, very few have explored firm-level energy efficiency. Studying *firm-level* energy efficiency may bring more profound policy implications. As a microscopic economic entity, a firm has more independence in decision-making and reflects a wider range of varieties. This paper will fill gap in the literature with a firm-level analysis.

Information and communication technology (ICT) is becoming increasingly prevalent in businesses and has the potential to improve energy efficiency. Nevertheless, there is a lack of empirical evidence on ICT *expenditure* and energy efficiency (Section 2.1). Instead, most studies focus on ICT development at the economy level or ICT investment at the industry level. There are two ways ICT enters firm operations: a) one-off ICT investment; b) ongoing ICT expenditure, see Figure 2. ICT investment includes the purchase of new hardware or software; it usually becomes fixed capital that can be used again in the long term (OECD, 2023). It can facilitate manufacturing firms' production, or upgrade service firms' office equipment. ICT expenditure refers to annual repair and maintenance expenses after an ICT investment (Colombo, 2022; World Bank, 2023). These expenses result from regular management of ICT assets, e.g., database updates, network hardware repair, system upgrades, etc. ICT expenditure also includes software licenses and cloud-based services, which are two of the most popular ICT behaviours in firms (Slingerland, 2023; Wehner, 2020).

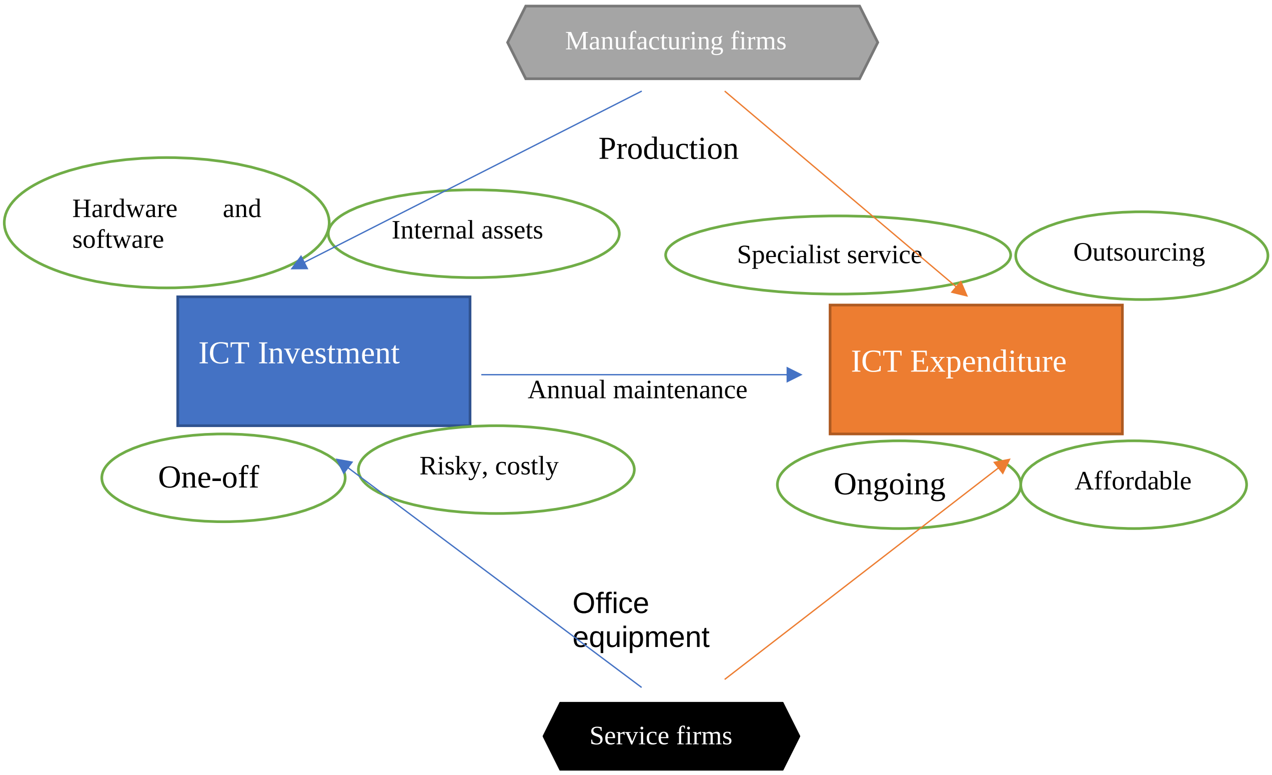

Figure 1 Comparison of firm ICT investment and firm ICT expenditure

There is a trend that firms are switching from owning ICT assets to outsourcing ICT services, especially in developed economies (Consultancy.uk, 2021; GlobalData, 2022; OECD, 2023; UK Parliament, 2017). In other words, there is a shift from firm ICT investment to firm ICT expenditure. Figure 2 shows the average firm ICT expenditure and firm ICT investment in the UK from 2008 to 2020. We can see that ICT expenditure has been growing by around 18% whilst ICT investment remains at a similar level. The following sections will show that ICT expenditure and ICT investment may have different impacts on energy efficiency (Section 2.1).

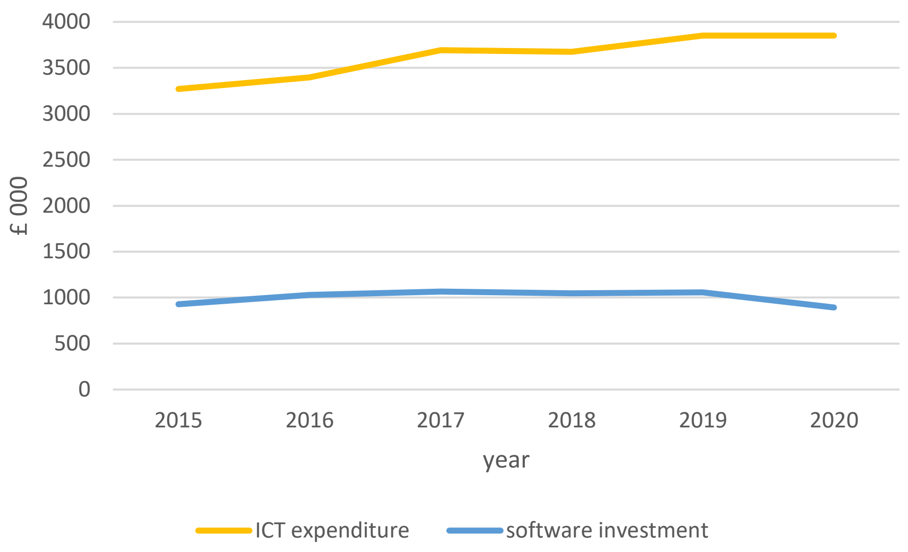

Figure 2 Average UK firm ICT expenditure and software investment between 2015 and 2020

Source: Office for National Statistics (2022)

ICT expenditure and ICT investment are both interrelated and different, but very few, if any, studies have compared the two terms (Section 2.1). The main interrelation is that an ICT investment can trigger ICT expenditure on future repair and maintenance services. The main difference is that ICT expenditure is an operating expense on the income statement, while ICT investment becomes an asset on the balance sheet. Due to this different nature, ICT investment and ICT expenditure have different implications for firms (Figure 1). Compared to ICT investment that results in internal assets, ICT expenditure reflects a wide range of outsourced ICT services (Ruivo et al., 2015). ICT expenditure is more affordable, especially for small and medium-sized enterprises (SMEs). It can be risky and costly to obtain new software and hardware with ICT investment, but ICT expenditure allows SMEs to maintain or upgrade existing ICT facilities without a bulky investment. With the above differences, it is likely that ICT expenditure and ICT investment will have different impacts on a firm's energy efficiency. However, the comparison between ICT expenditure and ICT investment is yet to be done in the literature, with a particular lack of firm-level studies.

This paper will fill the gap in the literature and explore the impact of ICT investment and the impact of ICT expenditure on energy efficiency with evidence at firm level. The paper will examine energy efficiency in terms of technical energy efficiency. Section 2 is the literature review, Section 3 explains the methodology, Section 4 summarizes the data, Section 5 illustrates the results, Section 6 is further analysis and robustness check, and finally, Section 7 concludes the findings.

2. Literature review and hypotheses

Despite decades of research on ICT and energy use on economic foundations, very few, if any, studies have attempted to analyse the impact of ICT *expenditure* on energy use or compare its impact with that of ICT investment. There is a particular lack of evidence at the firm level. This section will build hypotheses, then present a literature review on ICT and energy use, and finally, discuss energy efficiency measurements.

2.1 ICT expenditure, ICT investment and energy efficiency ---- hypotheses

There has been evidence suggesting that ICT investment, ICT capital services, ICT development, ICT patent stock and digital economy are positively related to energy efficiency, but there is no evidence suggesting the relationship between ICT expenditure and energy efficiency. Khayyat et al. (2014) and Khayyat et al. (2016) both used a cost minimization function; this is a simulation modelling method to test the extent to which energy can substitute other inputs. They found that ICT investment substitutes energy as an input in Korean and Japan industries. Schulte et al. (2016) applied a cost-share theorem to panel data of 27 industries for 10 OECD countries; they found that ICT capital services is negatively related to the demand for non-electric energy but is not associated with electric energy demand. Zhao et al. (2022) measured energy efficiency as GDP per unit of energy use and found that ICT development upsurge energy efficiency in the long run in eight emerging Asian economies from 1991 to 2019. There is also a group of studies on China that suggests digital economy improves energy efficiency. Yan et al. (2018) used a DEA-based model to study 50 economies and found that the stock of ICT patents significantly improves energy efficiency. There is also a number of studies showing that digital economy improves energy efficiency in various Chinese regions (Wang & Shao, 2023; Xin et al., 2024; Zhang et al., 2021; Zhang et al., 2022). These studies use a DEA method and measure digital economy by ICT infrastructure, ICT services or ICT businesses. For example, Wang and Shao (2023) measured a digital economy as Internet broadband usage, mobile phone subscription, number of employees in the ICT sector, science and technology expenditure, digital financial inclusion, etc. They studied 282 prefecture-level Chinese cities from 2012 to 2018 and find that the digital economy has significantly improved energy efficiency. Section 2.2 will provide a more comprehensive literature review.

The idea that ICT investment improves firm energy efficiency stems from two intuitions. First, ICT investment improves firm performance with less-than-proportionate increase in energy use. A vast amount of literature has confirmed that ICT investment improves firm productivity or firm operational efficiency. For instance, Kılıçaslan et al. (2017) found that ICT investment positively influenced firm productivity in 22,000+ Turkish manufacturing firms in the period 2003 to 2012. Arendt and Grabowski (2017) surveyed 1,000 Polish companies and finds that ICT investment improves innovation capacity and firm productivity. The positive impact of ICT investment on firm performance is worldwide, including Nigeria (Adebambo & Toyin, 2011), Malaysia (Fernando et al., 2022), Turkey (Kılıçaslan et al., 2017), Italy (Atzeni & Carboni, 2006), Poland ((Arendt & Grabowski, 2017), Eastern Europe (Skorupinska & Torrent-Sellens, 2017), etc. In addition, researchers have found that ICT investment improves firm operational efficiency. For example, Mouelhi (2009) analysed 1,824 manufacturing firms in Tunisia and found that firms that have a relatively intensive use of ICT are an average 5% more efficient than those that do not. If we assume ICT investment improves firm *operational efficiency* with less-than-proportionate increase in energy use, then ICT investment will also improve firm *energy efficiency*.

Second, ICT investment is a form of innovation and knowledge acquisition that can induce energy efficiency (Popp, 2019; Popp et al., 2010). Technological change, such as ICT, facilitates the acquisition of knowledge that then enhances productivity, such as energy efficiency. A group of researchers have found that energy efficiency is linked with knowledge spillover (Costantini et al., 2017; Liu et al., 2024; Nemet, 2012; Popp, 2002; Popp & Newell, 2012; Sun et al., 2021). For instance, Popp (2002) used patent citations in the US from 1970 to 1994 to measure usefulness of existing scientific knowledge base, and found knowledge stock has a significantly positive impact on energy efficiency innovations. Sun et al. (2021) analysed patent data from 24 innovating countries between 1994 and 2013 to examine how domestic and foreign innovation influenced a given country's energy efficiency measured by SFA. They found that knowledge spillover from technological innovation of one country improves the energy efficiency performance of its neighbouring countries. Adekoya et al. (2023) studied 59 Belt and Road Initiative (BRI) countries between 2000 and 2019, which have collaborative relationships with China. They found that China's technological spillover promotes energy efficiency in other BRI countries.

Empirical evidence has indicated that ICT improves energy efficiency and reduces carbon emissions through knowledge spillover and technological innovation. Al-Qubaisi et al. (2018) conducted a survey to approximately 500 employees in an oil and gas company in the UAE and found that ICT improves firm energy efficiency through knowledge management. Su et al. (2023) studied 269 Chinese cities from 2010 to 2020 and found that ICT development influences regional carbon emissions through technological innovation and knowledge spillover. Shahnazi and Dehghan Shabani (2019) studied 28 Iranian provinces during the years 2001 to 2015 and found that ICT capital stock of one province has a spillover effect on the carbon emissions of other provinces. Gu and Surendra (2004) analysed survey data of 6000+ Canadian businesses in 1999 and found that firms that invest in ICT tend to adopt more organizational practices to improve efficiency and productivity than firms that do not invest in ICT.

Similarly, we can expect ICT expenditure to improve energy efficiency for the same two reasons as ICT investment: a) improving firm efficiency with less-than-proportionate increase in energy use; b) inducing energy efficiency technologies with innovation and knowledge acquisition. Empirical evidence has also shown that ICT expenditure improves firm performance. For example, Adebambo and Toyin (2011) analysed 100 median and large manufacturing companies in Nigeria and found that ICT expenditure reduces operating costs in logistics. Skorupinska and Torrent-Sellens (2017) found that ICT expenditure improves labour productivity in Eastern European manufacturing companies. Fernando et al. (2022) surveyed 123 manufacturing firms in Malaysia and find that using blockchain technology for carbon trading improves their energy efficiency.

Despite the above two reasons, there are more reasons why further research needs to be done to investigate ICT *expenditure* and firm energy efficiency. ICT is a form of intangible assets that require special caution to its functionality and value to a firm, as a great deal of information is hidden as to how intangibles spark new ideas and smart implementation (Lev & Gu, 2016: Chapter 8). ICT expenditure differs from ICT investment in two ways; this may give rise to firm energy efficiency performance differently. First, ICT expenditure represents repair and maintenance services in the deployment phase of ICT after its initial installation. As many countries, especially developed countries, are in the deployment phase, ICT expenditure may be of more importance in improving firm efficiency. Second, ICT expenditure has a service nature, representing collaboration between ICT firms and non-ICT firms. Collaboration also leads to knowledge spillover that could result in energy efficiency improvement. The following will expand on these two arguments.

A few studies have compared ICT expenditure with ICT investment on economic foundations and found large differences between the two terms. The literature has emphasized the importance of ICT services, e.g., software subscriptions and cloud services, on economic development and productivity growth. These ICT services support the infrastructure from ICT investment, including hardware and software. Nevertheless, the volume of ICT services is often underestimated because it does not appear as ICT investment but as ICT expenditure. Byrne and Corrado (2017) extended a multi-sector growth model by including purchased ICT services, e.g., cloud and data analytic services, into the measurement of ICT. They found that, in the last decade, ICT can be a driver of growth when ICT investment remains low; this partly attributed to the diffusion of ICT technology via purchases of cloud and related ICT services. Van Ark (2016) found that there is a shift from ICT investment to ICT services in Germany, the US, and the UK. He used a lifecycle model of innovation to explain that this is a shift from the "installation phase" obtaining new ICT assets into "deployment phase" in which services are essential to support these ICT assets. Jackson et al. (2012) conducted 34 semi-structured interviews with regional ICT providers, managers, technicians, and users in rural Namibia. They found that after investment in ICT infrastructure, ICT repair and maintenance services are essential to sustain and adapt ICT systems over time in the global south. Koman et al. (2022) interviewed 15 ICT firms in Slovenia and found that with the transition to cloud computing, the business model of the ICT sector shifts from offering products and services to “everything as a service” through a subscription. Ruivo et al. (2015) presented a framework on the development of ICT services nearshore in Portugal. In their framework, outsourcing has evolved to “as a service”, in which ICT services are accessed via software and platforms to improve functionality.

Based on the above proposed differences between ICT investment and ICT expenditure, this paper proposes two theories on ICT and firm energy efficiency, which then form two hypotheses. First, diffusion of technology follows an S-shape (David, 1969; Griliches, 1957), so does ICT investment. ICT investment experiences an increasing return then a diminishing return (Grant & Yeo, 2018). ICT investment and ICT expenditure also have different utilities for firms in the installation phase and in the deployment phase (Van Ark, 2016). Therefore, this paper proposes a theoretical framework ---- the impact of ICT on energy efficiency by two development phases: a) installation phase; b) deployment phase (Figure 1). The return of ICT on energy efficiency increases dramatically during the installation phase when firms acquire ICT assets through ICT investment. After firms are equipped with sufficient ICT assets, they enter the deployment phase in which the return of ICT on energy efficiency decreases. In the deployment phase, ICT expenditure is essential to realize the full potential of ICT investment in energy efficiency gain. If firms only increase ICT investment, the return on energy efficiency is moderate. However, if firms increase ICT expenditure in addition to ICT investment, the return on energy efficiency will be much higher. It is difficult to distinguish whether firms are in the installation phase or the deployment phase, but firms in *developing* countries are more likely to be in the installation phase, and firms in *developed* countries are likely to be in the deployment phase.

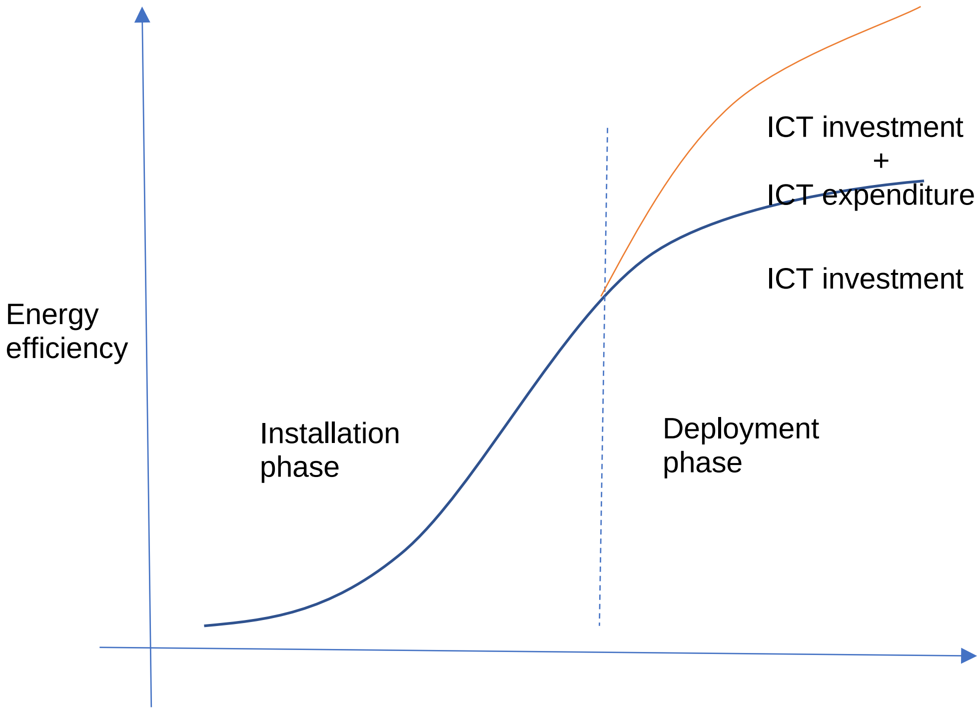

Figure 1 Diminishing impact of ICT investment on energy efficiency by development phase

Source: Grant and Yeo (2018); Van Ark (2016)

Second, in a developed economy, ICT expenditure is likely to influence firm energy efficiency because it represents another form of innovation and knowledge spillover from the ICT industry. In a developed economy, the ICT market is more mature, and ICT expenditure represents more outsourced ICT services; these form close and long-term collaboration between non-ICT firms and ICT firms. Strong collaboration is positively related to knowledge spillover and therefore energy efficiency (Kang et al., 2022; Liu et al., 2023), probably because the value creation from ICT is highly dependent upon firms' external connections with its trading partners and the macro environment (Kumbhakar & Lovell, 2003; Melville et al., 2004). ICT expenditure is a better representative of these external connections between ICT firms and non-ICT firms, especially in a developed economy, which may promote firm energy efficiency through innovation and knowledge spillover. Researchers have found that, in addition to internal ICT assets, ICT services and external connections also improve firm innovation and efficiency performance. Parida and Örtqvist (2015) surveyed 100+ technology-based small Swedish firms and measured ICT capability by ICT internal use, ICT collaboration and ICT communication. They found that ICT capability improves firm innovation performance, and the effect is even higher if firms have the ability to use external relationships. Gu and Surendra (2004) analysed 6,000+ Canadian businesses and found that both ICT investment and ICT use (defined by the share of workers using computer) are correlated with organizational innovations in production and efficiency practices. Arvantis et al. (2011) classified ICT as internal information system, e-sales, and e-procurement. They surveyed 304 Greek firms and found that internal information systems have a strong positive impact on product and process innovation, and e-sales have a positive impact on process innovation.

Based on the above two theories, this study proposes the following hypotheses:

Hypothesis 1: ICT *investment* is positively associated with firm energy efficiency in developed economies.

Hypothesis 2: ICT *expenditure* is positively associated with firm energy efficiency in developed economies.

2.2 Literature review of ICT and energy use on economic foundations

Table summarises the results of an illustrative selection of studies on ICT and energy use on economic foundations. These studies were selected by searching keywords "energy" with "ICT" or "digital" in Google Scholar and identifying the econometric studies. The results are mixed; this is due to different scopes, different measurements of energy use, and different definitions of ICT. Due to the lack of firm-level data, econometric studies that explore the relationship between ICT and energy use are either at the economy level, regional level, or industry level. However, these levels of studies are not sufficient to ascertain the relationship between ICT and energy use, because there is high heterogeneity between industries, between regions, and between countries. It is more robust to compare firms that are in the same industry and in the same country. What is more, a firm-level analysis may shed light on how the impacts of ICT on energy use vary between industries, and what kind of industries have the potential to increase energy efficiency via ICT.

Table 1 Empirical analyses of ICT and energy use on economic foundations

References	**Definitions of ICT**	**Models and methods**	**Research scope and findings**
Asongu et al. (2018)	Mobile phone and Internet penetration rates	Two-step Generalized Methods of Moments (GMM)	Studying 44 sub-Saharan African countries from 2000 to 2012, they found that ICT has a positive net effect on carbon emissions.
Higon et al. (2017)	Fixed telephone subscription, mobile phone subscription, personal computer ownership, Internet usage, broadband subscription	Model: environmental Kuznets curve model with a quadratic form of ICT Methods: pooled OLS, the Driscoll-Kraay Fixed Effects, and the instrumental variable fixed effect	Studying 142 countries between 1995 and 2010, they found that ICT and carbon emissions have an inverted U-shaped relationship, and developing countries have a lower turning point.

Ishida (2015)	ICT investment	Model: production function, energy demand function Methods: stationary tests, autoregressive distributed lag (ARDL) bounds co-integration test	Studying times series data of Japan between 1980-2010 he found that there is a long-run stable relationship between ICT investment and energy consumption; however, the impact of ICT investment is statistically insignificant.
Khayyat et al. (2016)	ICT capital investment	Model: dynamic factor demand model, normalized restricted cost function Method: full-information maximum likelihood	Studying 30 Japanese industries and 30 South Korean industries over the periods 1973-2006 and 1980-2009 respectively, they found that both ICT and non-ICT capital are substitutes for labour and energy use; this indicates that ICT has a negative impact on energy use.
Lee and Brahmasrene (2014)	Fixed telephone usage, mobile phone subscription, Internet usage, broadband subscription	Panel unit root test, panel co-integration tests, co-integration regression estimation	Studying 9 Southeast Asian countries between 1991 and 2009, they found that ICT, carbon emissions and GDP have long-run equilibrium, and ICT has significant positive effects on both GDP and carbon emissions.
Lu (2018)	Internet usage	Panel unit root test, panel co-integration tests	Studying 12 Asian countries from 1993-2013, he found that ICT, energy consumption, GDP and carbon emissions has long-run equilibrium, and ICT has a significant negative effect on carbon emissions.
Majeed (2018)	Online services, Internet usage, fixed and broadband subscriptions, e-government, and telecommunication infrastructure	Ordinary Least Squares (OLS), Pooled OLS, Two Stage Least Squares and GMM	Studying 132 countries over the years 1980-2016, they found that ICT helps to reduce carbon emissions.
Mirza et al. (2020)	Mobile and fixed broadband internet penetration rates	Two-step GMM	Studying 81 developing countries for the period 2010–2014, they found that ICT complements carbon intensity, which suggests a negative impact on carbon emissions.
Salahuddin and Alam (2016)	Internet usage, mobile phone subscription	Panel unit root test, panel co-integration tests, Pooled Mean Group Regression technique, and Dumitrescu–Hurlin causality test	Studying 26 OECD countries for the period 1990-2012, they found that ICT has a positive effect on electricity consumption.
Saidi et al. (2018)	Internet usage	Production function approach	Studying 13 Middle East and North Africa countries from 1990 to 2012,

			they found that energy consumption and ICT both have a bidirectional relationship with GDP.
Schulte et al. (2016)	ICT capital services	translog variable cost function	Studying a panel dataset covering 13 years, 10 OECD countries, and 27 industries, they found that ICT capital services is negatively related to the demand for non-electric energy but is not associated with a significant change in the demand for electric energy.
Shabani and Shahnazi (2019)	Fixed telephone subscription, mobile phone subscription, and broadband subscription; and ICT capital stock per capita	Dynamic ordinary least squares, panel error correction model, Granger causality test	Studying Iran over the period 2002-2013, they found that ICT has positive effect on carbon emissions in the industrial sector, but negative effect in the transportation and service sectors. Furthermore, ICT is the cause of energy consumption and carbon emissions.
Usman et al. (2021)	Mobile cellular subscriptions	ARDL, Generalized least Square (GLS), stationary tests	Studying 4 South Asian economies from 1990 to 2018, they found that only India has achieved energy efficiency as a result of increased use of ICT.
Wang and Han (2016)	ICT investment divided by gross domestic product (GDP)	Model: STIRPAT Methods: stationary tests, co-integration tests, Driscoll–Kraay (DK) estimation, panel error correction model	Studying 30 Chinese provinces between 2003 and 2012, they found that ICT investment significantly reduced energy intensity in the long run but not in the short run.
Wang and Lee (2022)	Fixed telephone subscription, mobile phone subscription, international Internet bandwidth, household computer ownership, household Internet usage	Finite mixture model with the Expectation-Maximization algorithm	Studying 34 OECD and 39 non-OECD countries over the period of year 2007-2017, they found that ICT has both positive and negative impacts on energy demand.
Wang and Shao (2023)	Digital economy, measured by Internet broadband usage, mobile phone subscription, number of employees in ICT sector, science and technology expenditure, digital financial inclusion, etc.	GMM model, GTFEE measured by data envelopment analysis (DEA)	Studying 282 prefecture-level Chinese cities from 2012 to 2018, they found that a digital economy has significantly improved energy efficiency. With the improvement of economic development level, the role of digital economy in promoting energy efficiency gradually increases.

Xin et al. (2022)	Digital economy, measured by digital finance, digital industry employees, total telecommunication services, Internet penetration, and mobile phone penetration.	GMM model, GTFEE measured by DEA	Studying 284 prefecture-level Chinese cities from 2008 to 2018, they found that a digital economy promotes energy efficiency by reducing unnecessary energy consumption through the R&D innovation effect. The energy efficiency is mainly reflected in the improvement of pure technical energy efficiency.
Yan et al. (2018)	ICT patent stock	DEA	Studying 50 economies over the period 2005 to 2013, they found that the stock of ICT patents significantly improves economy-level energy efficiency.
Zhang and Liu (2015)	Gross output of electronic and information manufacturing industry	Model: Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) Method: fixed effect regression	Studying 29 Chinese provinces between 2000 and 2010, they found that gross output of ICT manufacturing industry has a significant negative impact on carbon emissions in eastern and central China, the more developed area, but no significant effect in western China.
Zhang et al. (2021)	Digital economy, measured by telecommunication services, software business revenue, mobile phone penetration, Internet penetration, e-commerce sales, etc.	Green total factor energy efficiency (GTFEE) measured by DEA	Studying 30 Chinese provinces from 2006 to 2018, they found a positive correlation between a digital economy and energy efficiency in Eastern and Central China.
Zhang et al. (2022)	Digital economy, measured by Internet penetration, mobile phone penetration, e-commerce sales, software business revenue, electronic information industry income, etc.	STIRPAT model, energy efficiency measured by DEA	Studying 30 Chinese provinces from 2012 to 2019, they found that the development of a digital economy in China intensifies carbon emissions, and energy efficiency serves as a vital partial mediator between the two.
Zhao et al. (2022)	Broadband subscription, mobile cellular subscription	Energy efficiency is measured as GDP per unit of energy use	Studying 8 emerging Asian economies from 1991 to 2019, they found that ICT diffusion upsurge energy efficiency in the long run.

Table shows that most studies focus on ICT and energy *demand*, or ICT and *carbon emissions*, and only a few have explored energy *efficiency*. Energy demand and carbon emissions are absolute values, while energy efficiency is a relative value of energy demand to economic output. Studying energy demand and ICT, or carbon emissions and ICT may have econometric challenges such as endogeneity. Economic output can be an endogenous factor, because energy demand and carbon emissions are associated with economic output (Mutumba et al., 2021), and ICT is also associated with economic output (Vu et al., 2020). Studying energy efficiency can be an alternative option to avoid the endogeneity issue. Studying energy efficiency will provide policy implications on whether ICT improves *relative* productivity in energy use, because higher energy efficiency indicates that energy demand increases less than disproportionately with economic growth.

A few studies suggest that ICT is positively related to energy efficiency (Wang & Shao, 2023; Xin et al., 2024; Yan et al., 2018; Zhang et al., 2021; Zhang et al., 2022; Zhao et al., 2022), which will be discussed in Section 2.1. However, these studies have certain limitations. The studies use data envelopment analysis (DEA) or energy/output ratio, which have disadvantages compared to stochastic frontier analysis (SFA) (Section 2.3). These studies focus on either Chinese regions or Asian economies, which are limited in scope. There may be a wide discrepancy between developing countries and developed countries in how ICT interacts with renewable energy, economic complexity, human capital and financial development (Huang et al., 2022). It is necessary to explore ICT and energy efficiency in a developed economy. In addition, these studies are at an economy- or regional-level, which has heterogeneity issues. This paper will address these literature gaps by analysing firm energy efficiency in the UK.

Most studies define ICT as ICT development, digital economy, ICT capital stock, or ICT patent stock, but ignore the growing popularity of ICT expenditure. ICT development measures the development level of the ICT infrastructure in an economy, such as broadband speed and Internet usage. ICT investment is the purchase of new ICT assets that can happen in a firm, an industry, or an economy. ICT capital stock is the static value of currently owned ICT assets in a firm, an industry, or an economy. However, there is a lack of discussion on ICT expenditure, i.e., the ongoing management cost of ICT assets. The impact of ICT expenditure should not be neglected for its growing popularity and importance (Section 1). This paper will fill in this literature gap by analysing both ICT expenditure and ICT investment.

2.3 Energy efficiency measurements

To study the relationship between energy efficiency and a form of technology, i.e., ICT, this paper argues that SFA is the appropriate measurement for energy efficiency among all four common methods, namely: a) output/energy index; b) cost share theorem (CST); c) data envelopment analysis (DEA); and d) stochastic frontier analysis (SFA). The following will explain the reasons.

As shown in Table , there are four common methods to measure energy efficiency with economic values. The simplest method is output/energy index that divides revenue by energy cost (Lawrence et al., 2018; Martin et al., 2012; Montalbano & Nenci, 2019). However, this method does not consider different mixes of output other inputs and thus violates micro-economic theories that output is produced with a set of inputs including capital and labour. CST divides energy costs by total variable cost based on the theory that the partial output elasticity of energy input is equal to the share of energy costs in total costs (Martin et al., 2012; Montalbano & Nenci, 2019; Roy & Yasar, 2015). CST considers mixes of other inputs; however, it has two weak assumptions. First, it assumes no constraints on input combinations, but energy input often has a limited extent to substitute other inputs. Second, it assumes no correlation between any input and technology (total factor productivity), but our research aim is to test the interdependence between energy input and ICT investment, so CST may not be optimal. Both weaknesses mean CST is not suitable for research into energy efficiency and ICT expenditure/investment, because firstly energy input often has a limited extent to substitute other inputs, so Assumption 1 does not hold; second, the research aims test the interdependence between energy input and a type of technology called ICT, so Assumption 2 is invalid.

Table 2 Comparison of measurements of energy efficiency on economic foundations

Methods	**Advantages**	**Disadvantages**	**Examples in Literature**
Output/energy index	Quick, easy	Does not consider different mixes of output and other inputs	Lawrence et al. (2018) ; Martin et al. (2012); Montalbano and Nenci (2019)
Cost share theorem (CST)	Relatively quick, easy; considers mixes of inputs	Assumes no constraints on input combinations and no interdependence between inputs and technology	Martin et al. (2012); Montalbano and Nenci (2019); Roy and Yasar (2015)
Data envelopment analysis (DEA)	Requires no specification of functional form required	Does not consider statistical noises	Haider and Mishra (2019); Yan et al. (2018); Zhang et al. (2016)
Stochastic frontier analysis (SFA)	Considers statistical noises and different mixes of other inputs and output	Requires specification of functional form	Boyd (2008); Hu (2014); Lundgren et al. (2016); Lutz et al. (2017); Shui et al. (2015)

In contrast, SFA and DEA are principally based on the theory of productive inefficiency in the context of the micro-economic theory of production framework (Filippini & Hunt, 2015). SFA is a parametric econometric method that transforms production function into a regression to obtain the efficiency score of each unit. Since SFA treats energy as one input in the production function, SFA considers mixes of inputs. Furthermore, SFA is superior to CST for my study, because first, it runs the regression with historical observations of input combinations, rather than assuming no constraints on input combinations; second, it recognizes the contribution of technology to efficiency, rather than assuming no correlation between energy input and technology. More details are offered in the Methodology Section. DEA is a "nonparametric approach that estimates efficiency by solving mathematical programming models" (Zhang et al., 2016). DEA is similar to SFA because DEA also considers mixes of inputs and compares an individual firm's energy use to the best practice in the industry (technology frontier). However, DEA does not consider statistical noises such as measurement error. SFA also partially addresses unobserved heterogeneity and allows statistical testing. Both of these two advantages make SFA more favourable than DEA in energy efficiency analysis, because energy services are very heterogeneous and the chance of omitted variable bias and unobserved heterogeneity is high (Filippini & Hunt, 2015).

2.4 Energy efficiency via SFA

There have been two decades of research into energy efficiency with SFA, but very few researchers, if any, have explored the effect of ICT on energy efficiency, especially at the firm level. The following will discuss details.

As shown in Table 3, Feijoo et al. (2002) is one of the first to pioneer SFA in measuring firm-level energy efficiency. They used energy input as an independent variable and output as dependent variable; they then measured the distance between an individual firm's energy use to the best practice of energy use given the same output in the industry. They analysed cross-sectional data for 9,984 Spanish firms in 66 Spanish industries and found that firms can reduce the total Spanish industrial energy consumption by up to 23.4% and industrial carbon emissions by up to 29.4%; man-made fibres, wood processing, mechanical engineering services and furniture industries have a much higher possibility of reduction than other industries; firms need a more intensive use of capital and a less intensive use of labour to achieve such reductions. However, this method treats energy as an independent variable, and cannot clearly separate the energy efficiency effect from the effects of other input variables on productivity.

Table 3 Studies of firm-level energy efficiency with stochastic frontier analysis

References	Models	Data	Findings
Feijoo et al. (2002)	Technical energy efficiency where energy	Cross-sectional data for 9,984 firms that were classified into	By improving energy efficiency, firms can reduce the total Spanish industrial energy consumption by up to 23.4% and industrial carbon emissions by up to 29.4%. To achieve

	input is an independent variable and output is dependent variable	66 Spanish industry sectors and measured separately	energy reduction for most sectors, firms need a more intensive use of capital and a less intensive use of labour.
Boyd (2008)	Technical energy efficiency via energy input distance function model	Plant-level data of US wet corn milling industry with 37 observations over a period of 2 years	The difference between median and best practice energy use is 12%, and firms at the median level (25th percentile) of energy efficiency have to reduce energy by 5% (12%) to qualify for Energy Star.
Lundgren et al. (2016)	Same as Boyd (2008)	4,297 firms across 14 Swedish manufacturing sectors over 9 years	There is potential to improve energy efficiency for fuel and electricity use in all sectors, with the mean scores ranging from 70.0% (Stone/Mineral industry) to 98.2% (Rubber/Plastic industry), and the median scores ranging from 75.4% (Electronics industry) to 98.8% (Rubber/Plastic industry). EU ETS had a modest or no effect on energy efficiency.
Boyd and Lee (2019)	Same as Boyd (2008)	6 repeated cross-sections for five US metal-based durable manufacturing industries over 6 years	Mean energy efficiency estimates range from a low of 33% (fuel energy in the Computer and Electronic Products industry) to 86% (electricity energy in the Fabricated Metal Products industry). Assuming that all plants in the least efficient quartile of the efficiency distribution achieve a median level of performance, the decline in total energy use will be 21%.
Lutz et al. (2017)	Same as Boyd (2008)	27,977 German manufacturing firms in separated 15 industries over 10 years	Energy efficiency scores are relatively high in all industries, with the average ranging from 0.803 to 0.903 and the median ranging from 0.835 to 0.999. They also find that exporting, higher R&D investment and higher environmental protection investment made firms more energy efficient, while EU ETS regulated firms are less efficient.
Haider and Mishra (2021)	Technical energy efficiency with Bayesian SFA via energy input distance function model	82 Indian iron and steel firms over 15 years	Most of the firms can reduce their energy consumption by half. R&D expenditure, patenting activity and disembodied technology flow led to higher energy efficiency. In addition, Bayesian SFA outperformed classical SFA
Hu (2014)	Similar to method used by Boyd (2008)	150 Chinese energy firms for the period 2000-2005	The average technical efficiency of the sample plants rose from 93.5% of the frontier to 96.8%, and in terms of allocative efficiency, the magnitude of overuse of inputs was around 85% over the years, whereas that of underuse varied

			largely, from about 100% to 35%.
Macharia et al. (2022)	Similar to method used by Boyd (2008)	~1200 observations of Kenyan manufacturing firms for 2007, 2013 and 2018	The average energy efficiency ranges from 63%-69%. Exporting status, research and development, top managers' experience and female ownership enhance energy efficiency. Labour productivity negatively influences energy efficiency; the effect of firm age and size is ambiguous.

Different from Feijoo et al. (2002) who use energy input as an independent variable, Boyd (2008) use energy input as a dependent variable, which more explicitly and directly measures energy efficiency. Boyd (2008) is one of the first to derive an energy input distance function model with SFA, which has been widely used in academia since then; this study also adopts Boyd's (2008) model, see Section 3. Boyd (2008) analysed plant-level data of the US wet corn milling industry with 37 observations over a period of 2 years. He found that the difference between median and best practice energy use is 12%, and firms at the median level/25th percentile of energy efficiency had to reduce energy by 5%/12% to qualify for the energy efficiency standard in Energy Star. Boyd's method is later widely applied to measuring energy efficiency at the economy level, regional level (Hadian et al., 2022), and firm level (Boyd & Lee, 2019; Haider & Mishra, 2021; Hu, 2014, Lundgren et al., 2016; Lutz et al., 2017). Haider and Mishra (2021) further applied Bayes' Theorem in Boyd's (2008) method, and used Bayesian SFA to analyse 82 Indian iron and steel firms over 15 years. Haider and Mishra (2021) found that most of the firms can reduce their energy consumption by half; R&D expenditure, patenting activity and disembodied technology flow leads to higher energy efficiency. Hu (2014) assessed 150 Chinese energy firms for the period 2000-2005 with SFA and found that average technical efficiency of the sample plants rose from 93.5% of the frontier to 96.8%. Macharia et al. (2022) analysed around 1,200 observations of Kenyan manufacturing firms for years 2007, 2013 and 2018, and found that the average energy efficiency ranged from 63%-69%. They also found that exporting status, research and development, top managers' experience and female ownership enhance energy efficiency, but labour productivity negatively influences energy efficiency.

3. Methodology

This paper estimates energy efficiency with the so-called energy input distance function, see Equation (3), in which firm i's energy input e_i is compared to the best practice in industry e^* after controlling for the output y_i, capital input k_i and labour input l_i (Kumbhakar & Lovell, 2003: Chapter 4).

To illustrate, suppose we have two inputs----energy and another input----to produce one output (Figure 4). If we fix the output amount and study the input combinations of energy and the other input in all firms in the same industry, then the most efficient firms will form a concave line l called the frontier line (Coelli et al., 2005: chapter 2). Efficient firms such as Firm *A* and Firm *B* lie on the frontier line but could have different minimum combinations of inputs (Timmer, 1971). Both Firm *A* and Firm *B* have a technical energy efficiency of 100%. Inefficient firms such as *C* and *D* that lie above the frontier line *l*. Firm *C*'s technical energy efficiency is *OA/OC*, which measures the minimum energy use compared to its own energy use. To achieve the maximum technical energy efficiency, Firm *C* should move to the frontier, point *A*. Similarly, Firm *D*'s technical energy efficiency is *OB/OD*, and achieves the maximum technical energy efficiency by moving to point *B*.

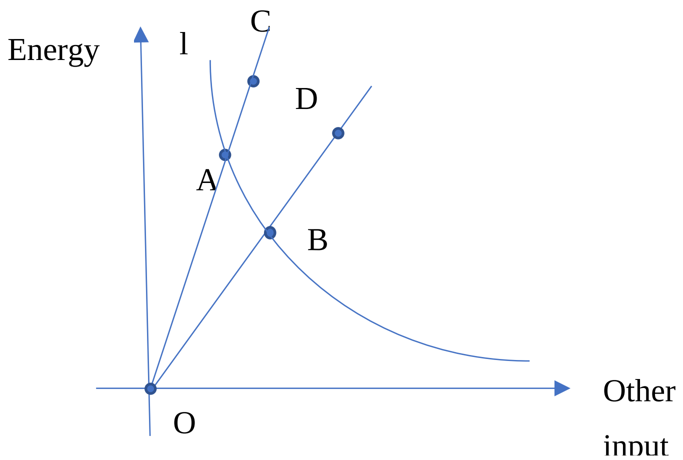

Figure 4 Technical energy efficiency

In SFA, energy efficiency is defined as the minimum possible energy input to produce a given output for a given combination of other inputs (Lin & Long, 2015; Zhou et al., 2012), including capital and labour:

$$min(energy \mid given\ output, capital, labor) \tag{1}$$

where energy, capital, and labour are inputs. Equation (1) measures technical energy efficiency.

Technical efficiency measures how much energy in terms of *quantity* firms can reduce compared to the best practice on the technology frontier (Fried et al., 2008; Zhou et al., 2012). The distance between the individual firm's energy use quantity to the frontier is that firm's technical energy efficiency (Haider & Mishra, 2021). The technical energy efficiency for firm *i* is shown in Equation (2).

$$\mathrm{D}(\mathrm{y_i}, \mathrm{k_i}, \mathrm{l_i}) = \sup(\lambda > 0\colon (\mathrm{y_i}, \mathrm{l_i}, \mathrm{k_i}, \mathrm{e_i}/\lambda) \in \mathrm{T}) \tag{2}$$

where *k* is capital, *l* is labour, *e* is energy, and *y* output. D(.) is a function of *y*, *k*, *l*, and *e* that measures technical energy efficiency. λ is a parameter larger than *0*. *T* is the technology level for firm *i*'s industry.

Following Haider and Mishra (2021), let us denote the distance between firm i's and the minimum-level energy expenditure as $D(y_i, k_i, l_i, e_i)$, then the distance is e^*/e_i, as shown in Equation (3).

$$\mathrm{D}(\mathrm{y_i}, \mathrm{k_i}, \mathrm{l_i}, \mathrm{e_i}) = \mathrm{e}^*/\mathrm{e_i} \tag{3}$$

If we specify a functional form of optimal energy input (e*) form as $f(y_i, k_i, l_i)$, then firm i's energy efficiency becomes:

$$\mathrm{D}(\mathrm{y_i}, \mathrm{k_i}, \mathrm{l_i}, \mathrm{e_i}) = \mathrm{e}^*/\mathrm{e_i} = \mathrm{f}(\mathrm{y_i}, \mathrm{k_i}, \mathrm{l_i})/\mathrm{e_i} \tag{4}$$

Our ultimate goal is to obtain the value of $D(y_i, k_i, l_i, e_i)$ for firm i, which represents the distance of firm i from the energy efficiency frontier in that sector. To achieve the goal, first, we take logarithm of Equation (5):

$$\ln[\mathrm{D}(\mathrm{y_i}, \mathrm{k_i}, \mathrm{l_i}, \mathrm{e_i})] = -\ln\mathrm{e_i} + \ln[\mathrm{f}(\mathrm{y_i}, \mathrm{k_i}, \mathrm{l_i})] \tag{5}$$

Rearrange Equation (5):

$$\ln\mathrm{e_i} = \ln[\mathrm{f}(\mathrm{y_i}, \mathrm{k_i}, \mathrm{l_i})] - \ln[\mathrm{D}(\mathrm{y_i}, \mathrm{k_i}, \mathrm{l_i}, \mathrm{e_i})] \tag{6}$$

In Equation (6), $f(y_i, k_i, l_i)$ can be estimated by a Cobb Douglas production function (Coelli et al., 2005: Chapter 8 & 9), see Equation (7):

$$\ln\mathrm{e_i} = \beta_0 + \beta_1\ln\mathrm{y_i} + \beta_2\ln\mathrm{k_i} + \beta_3\ln\mathrm{l_i} - \ln[\mathrm{D}(\mathrm{y_i}, \mathrm{k_i}, \mathrm{l_i}, \mathrm{e_i})] \tag{7}$$

where $\beta_0, \beta_1, \beta_2$ …are parameters to be estimated.

In Equation (7), $ln[D(y_i, k_i, l_i, e_i, m_i)]$ represents the 'inefficiency' of firm *i* and enters into the error term of the regression, let us rewrite it as u_i; next, we introduce v_i to represent stochastic noise from the regression following Aigner et al. (1977) and Battese and Coelli (1995). I therefore rewrite Equation (7) as:

$$\mathrm{lne_i} = \beta_0 + \beta_1 \mathrm{lny_i} + \beta_2 \mathrm{lnk_i} + \beta_3 \mathrm{lnl_i} + \mathrm{v_i} - \mathrm{u_i} \qquad \textbf{(8)}$$

where $v_i - u_i$ are the error terms for the regression.

SFA therefore separates the error term into two parts, v_i and u_i. The exponential form of u_i is firm efficiency score, ranging from 0 to 1.

$$\mathrm{e^{u_i}} \in [0,1] \qquad \textbf{(9)}$$

In Equation (8), v_i is white noise and measures stochastic noises such as measurement error in the regression, v_i following a distribution in Equation (10):

$$\mathrm{v_i} \sim (0, \delta_\mathrm{v}^2) \qquad \textbf{(10)}$$

In Equation (8), u_i measures the inefficiency level of firm *i* and our ultimate goal to obtain the value of u_i. u_i is the logarithm of the distance between a firm's energy consumption to the minimum consumption for firms in that sector – as the $ln[D(y_i, k_i, l_i, e_i)]$ in Equation (7). The most efficient firm has an energy efficiency value of 1, then every other firm's efficiency is between 0 and 1. We can assume u_i follows a truncated and one-sided normal distribution (Stevenson, 1980):

$$u_i \sim (\mu, \delta_u^2), 0 < \mu \leq 1 \qquad \textbf{(11)}$$

3.1 Model specification

This research adopts SFA to estimate technical energy efficiency. Relative energy efficiency is estimated for each firm by their industry; this compares a firm's own energy use to that of the most energy efficient firm in the same industry at a specific time (Zhou et al., 2012). R is the main software for the analysis. There are two parts of the analysis: Equation (12) estimates firm energy efficiency, while Equation (13) analyses firm energy efficiency and firm ICT behaviours.

For firm *i* in year *t*,

$$\mathrm{lne_{it}} = \beta_0 + \beta_1 \mathrm{lny_{it}} + \beta_2 \mathrm{lnk_{it}} + \beta_3 \mathrm{lnl_{it}} + \mathrm{v_{it}} - \mathrm{u_{it}} \quad \textbf{(12)}$$

$$\begin{aligned}\mathrm{u_{it}} = \alpha_0 + \alpha_1 \ln\left(\sum_{n=t-3}^{t-1} \frac{\mathrm{ICTi_{in}}}{3}\right) + \alpha_2 \ln\left(\sum_{n=t-3}^{t-1} \frac{\mathrm{ICTe_{in}}}{3}\right) + \alpha_3 \mathrm{lnAD_{it}} \\ + \alpha_4 \mathrm{lnWATER_{it}} + \alpha_5 \mathrm{SIZE_i} + \alpha_6 \mathrm{BRITISH_i} + \alpha_7 \mathrm{LONDON_i} \\ + \alpha_8 \mathrm{PRIVATE_i} + \alpha_9 \mathrm{CCL_{it}} + \alpha_{10} \mathrm{INDUSTRY} + \alpha_{11} \mathrm{YEAR}\end{aligned} \quad \textbf{(13)}$$

Statistical distribution of inefficiency term:

$$\mathrm{u_{it}} \sim \mathrm{N}\left(\mu, \delta_\mu^2\right), \mu > 0 \quad \textbf{(14)}$$

Statistical distribution of error term:

$$\mathrm{v_{it}} \sim \mathrm{N}(0, \delta_v^2) \quad \textbf{(15)}$$

Where *ln* denotes natural logarithm, $\beta_0, \beta_1, \beta_2$ …are parameters to be estimated, $v_{it} - u_{it}$ are the error terms for the regression, α_1, α_2, α_3, …are also parameters to be estimated, *SIZE* is the quintile of total stock value with a value of 1 to 5, *INDUSTRY* and *YEAR* are dummy variables measuring industry effects and year effects respectively. See Table 4 for details of other abbreviations.

In Equation (12), this study uses a Cobb-Douglas production function to estimate energy inefficiency, following (Coelli et al., 2005: Chapter 8 & 9). The Cobb-Douglas function is preferred over a translog function in this study, because the latter has multicollinearity issues due to high correlations between the inputs and the cross-products of inputs, see Table 5. The production function generates an error term that is then separated into two parts, v_i and u_i . v_i represents stochastic noise such as measurement error following Aigner et al. (1977) and Battese and Coelli (1995), see Equation (13).

u_{it} measures the inefficiency level of firm *i* at year *t*; and our goal is to obtain u_{it}. The reason this study measures time-varying effect is that a firm at different years is likely to have different energy efficiencies. u_{it} is the natural logarithm of the distance between a firm's energy consumption and the minimum consumption for firms in that sector. The most efficient firm at the most efficient year has a *u* value of 1, then every other firm's efficiency is between 0 and 1. As in Equation (14), this study assumes u_{it} follows a truncated and one-sided normal distribution (Stevenson, 1980). v_{it} is stochastic noise following a normal distribution with mean value of 1, see Equation (15).

Following the one-stage approach by Battese and Coelli (1995), this study runs simultaneous maximum likelihood regressions (MLE) to explain energy inefficiency u_{it}, see Equation (13). The reason this study regresses inefficiency rather than efficiency is that efficiency scores are exponential values of the inefficiency error term, so inefficiency has a higher variation and provides more accurate results.

To analyse energy efficiency and firm ICT behaviours, Equation (13) regresses energy inefficiency on ICT investment (*ICTi*) and ICT expenditure (*ICTe*). Both ICT investment and ICT expenditure are measured as the moving average of the previous three years' values. For example, the moving average ICT investment at year 2015 will be the average of year 2012, year 2013 and year 2014 ($ICTi_{2012}$, $ICTi_{2013}$, $ICTi_{2014}$). As ICT investment and ICT expenditure can be contingent behaviours that happen occasionally over the years, a moving average can smooth out such contingency and produce a flowing value of the past. To check for robustness, this study also uses current-year value of ICT investment and current-year ICT expenditure in another specification. In addition, this study measures ICT investment as a continuous variable but not as a dummy variable, because over 80% of the observations in the sample have non-zero moving average values of ICT investment.

In addition to dummy variables controlling for industry and year effects, Equation (13) also tests the effects of other control variables on energy efficiency. The following explains the reasons for choosing these variables.

Advertising expenditure (*AD*) can be associated with firm energy efficiency because efficient firms may be more inclined to advertise heavily to attract customers and improve corporate image. In other words, advertising expenditure serves as a signal of firm efficiency, which in turn boost firm performance (Bagwell, 2007: Chapter 6; Nelson, 1974). There is empirical evidence that advertising is positively associated with firm performance (Chen & Waters, 2017; Rahman et al., 2018), and also positively associated with firm sustainability performance and corporate social responsibility (CSR) (Chiu & Lin, 2023; Weinmayer et al., 2023). It is likely that energy efficiency firms tend to spend more on adverting to signal their sustainability contributions to society.

Water expenditure (*WATER*) is controlled because it can be used as classification firms' business activities. Firms with very different water expenditure probably differ in their product offering or input mixes. For example, firms in the textile industry consume large amounts of water, but the consumption also varies widely depending on the type of product produced (woven, knit, etc.), and the specific processes and equipment (Raja et al., 2019). Water expenditure can be a proxy of the variation in business activities, since high water expenditure is usually observed in certain business activities such as beverage production, paper production or rice farming.

Firm size (*SIZE*) may influence firm energy efficiency because it determines a variety of micro-economic and macro-economic factors, such as firm's capability in investing in innovation and technology, and the environmental regulations and policies with which a firm has to comply (Costa-Campi et al., 2015; Zhang et al., 2016).

Domestic ownership (*BRITISH*) is controlled for two reasons: a) domestic firms may face different sustainability duties; b) domestic firms can have a different level of green technology diffusion. A large number of studies have confirmed the impact of domestic ownership or foreign ownership on firm energy efficiency. There are at least two reasons for this correlation. First, environmental regulations differ across countries, and firms in countries with stricter regulations tend to be more energy efficient (Balaguer et al., 2023; Kim et al., 2016). Or rather, multinational companies choose to move their pollution intensive businesses to countries with loose environmental regulations, i.e., the so-called pollution heaven (Ben-David et al., 2020; Mabey & McNally, 1999). The UK has comparatively stricter environmental regulations than many other countries, so domestic firms are expected to have higher energy efficiency. Second, firms from developed countries may spread more advanced green technology to developing countries (Bu et al., 2019; Herrerias et al., 2013; Jiang et al., 2015). Vice versa, firms from developing countries may still need to improve their energy efficiency technology when they move to developed countries such as the UK.

London location (*LONDON*) is treated as a dummy variable because London stands out from other UK areas for its high economic productivity, abundant business opportunities and high concentration of resources (Clawson, 2019; Marsh & Arnett, 2014; Overman, 2017). These London features mean that a firm located in London can have a different energy efficiency score due to the differences in its cost of inputs and volume of demand, compared to a firm located elsewhere (Krugell & Rankin, 2012). For instance, the cost of employing labour in London is 20% higher than the rest of the UK (ONS, 2024). Another important fact is that London has huge clusters of innovative professional business service firms (Girardi & Marsden, 2017). The agglomeration economy in London emerges because knowledge-intensive and service-oriented businesses benefit from localized collective learning, and the proximity and accessibility to clients (Keeble & Nachum, 2002). The nature of the business models in London may be different; this focuses more on seeking collaborators, hiring high-skilled labour and broadening consumer markets. This could affect firms' decision-making processes in enhancing energy efficiency. London firms may be less incentivized to improve energy efficiency because it is a relatively trivial contributor in comparison to many other factors towards business success.

Legal status (*PRIVATE*) is also considered because non-profit organizations (NPOs) and government organizations may be more environmentally aware because they are less profit driven and more protective of their public image (Jackson et al., 2018; Kong & Farrell, 2010). Researchers have shown that NPOs are playing an important role in boosting the impact of business on the United Nations' sustainable development goals (Diaz-Perdomo et al., 2021; Harangozo & Zilahy, 2015; Sebestova et al., 2021). Hence, non-profit and government organizations are expected to be more energy efficient as they have higher incentives for improving energy efficiency performance.

Climate change levy (*CCL*) is a tax levied on businesses since 2001 for the use of electricity, gas, and solid fuels such as coal and lignite (Pearce, 2006; UK Government, 2024). Certain businesses are exempt from CCL, including businesses that use small amounts of energy and charities engaged in non-commercial activities. Certain fuels are exempt from CCL, for example, if the electricity was generated from renewable sources before 2015, or if the fuels will not be used in the UK. A discount of 77-92% can be applied to an energy intensive business if it has entered into a delegated climate change agreement. CCL is treated as a dummy variable in this study taking the value of either 0 or 1, as over half the firms in the sample do not pay CCL and those that do pay CCL do not pay substantially different amounts within the same industry. CCL is found to reduce energy intensity and increase energy efficiency with empirical evidence at both the micro and macro level (Barker et al., 2007; Martin et al., 2009).

4. Data

The data for this study come from the Annual Business Survey (ABS) provided by the UK Data Service (ONS, 2022). ABS is the largest business survey conducted by the UK Office for National Statistics (ONS) in terms of the combined number of respondents. It surveys all largest businesses with a progressively reducing fraction of smaller business and provides high-level indicators of economic activities. ABS does not have sufficient information on ICT variables from 2015, so this study only analyses years before 2015. ABS is a series of repeated cross-sectional yearly surveys. This study obtains a panel dataset by matching individual firms from the yearly surveys. Only a small proportion of firms have been repeatedly surveyed, so the more years being matched, the fewer firms being observed. To balance the trade-off between number of years and number of firms, this study selects eight years of data (2008-2015).

To investigate the effects of ICT investment and ICT expenditure on firm energy efficiency, this study analyses a sample of 9,836 observations in 33 industries over 8 years (2008-2015). This study considers all the available industries in the dataset (Appendix 1) but excludes healthcare and education industries, because maximizing annual turnover is usually not the main goal in these two industries. All monetary values are adjusted by consumer price inflation (CPI) (ONS, 2023). Following the definition of long-term internal assets (Section 2.1), ICT investment is measured as the investment in hardware and software as part of a firm’s capital acquisitions. ICT investment includes software developed by a firm’s own staff or externally, e.g., network ware, large databases, specialist packages, word processing packages, and spreadsheet packages. Following the servicing and collaborating nature of ICT expenditure, ICT expenditure is measured by the sum of cost of computer and related services purchased, and cost of telecommunication services purchased. It is the ongoing management cost of ICT hardware and software that includes ICT repair and maintenance services. Table 4 shows the definitions and summary statistics of all variables.

Table 4 Variable definitions and summary statistics

Meanings	Variables	Abbr.	1st Qu.	Mean	3rd Qu.	s.d.
					Unit: £,000	
Costs of energy used in the running of the business	Energy input	e	458	4,699	2,599	31,301
Total turnover excluding value added tax (VAT)	Output	y	53,301	445,820	275,788	2,407,758
Total employment costs	Labour input	l	9,839	37,590	33,626	79,444
Total stock at the end of the year	Capital input	k	2,017	32,554	20,723	128,527
Cost of computer and related services, and telecommunication services purchased	ICT expenditure	ICTe	165	1,838	1,038	8,932
Software and hardware capital expenditure acquisitions	ICT investment	ICTi	1	603	264	2,750
Cost of advertising and marketing services purchased	Advertisement expenditure	AD	36	3,668	1,181	17,861
Cost of water used in the running of the business	Water expenditure	WATER	12	224	127	866
Dummy variables					Unit: fraction	
"1" indicates the firm is ultimately owned by a British firm. "0" indicates the opposite.	British ownership	BRITISH	-	52.60%	-	49.90%
"1" indicates the firm is registered in London. "0" indicates the opposite.	London firm	LONDON	-	89.00%	-	9.20%
"1" indicates the firm is NOT a non-profit or government organization. "0" indicates the opposite.	non-profit firm	PRIVATE	-	0.90%	-	31.20%
"1" indicates the firm pays climate change levy. "0" indicates the opposite.	Paying levy	CCL	-	86.60%	-	34.00%
Total number of observations			9,836			

To choose between Cobb-Douglas and translog production function for estimating energy efficiency, we check the correlation coefficients of second-order variables (Table 5). Table 5 shows a high correlation between some second-order variables that may cause multicollinearity problems, so the Cobb-Douglas function is preferred. However, results with some second-order variables are presented for robustness check (Table 8).

Table 5 Correlation matrix of variables in production function

	lnk	lny	$(lnl)^2$	$(lnk)^2$	$(lny)^2$	$lnl \times lny$	$lnk \times lny$	$lnk \times lnl$
lnl	0.40	0.66	0.98	0.39	0.66	0.91	0.50	0.65
lnk		0.61	0.41	0.73	0.61	0.54	0.97	0.92
lny			0.66	0.64	0.997	0.89	0.74	0.67
$(lnl)^2$				0.40	0.66	0.89	0.51	0.64
$(lnk)^2$					0.64	0.55	0.70	0.66
$(lny)^2$						0.89	0.74	0.67
$lnl \times lny$							0.67	0.73
$lnk \times lny$								0.94

To avoid multicollinearity, Table 6 checks the correlations between the explanatory variables of energy efficiency. No strong correlation has been found.

Table 6 Correlation matrix of variables explaining energy efficiency

	$ICTi$	$WATER$	CCL	$BRITISH$	$LONDON$	$PRIVATE$	AD
$ICTe$	0.30	0.26	-0.04	-0.02	-0.06	0.03	0.41
$ICTi$		0.21	-0.01	0.02	-0.05	-0.03	0.17
$WATER$			0.14	0.02	-0.01	-0.08	0.21
CCL				0.01	-0.03	0.00	0.00
$BRITISH$					-0.02	0.00	0.03
$LONDON$						-0.01	0.02
$PRIVATE$							0.02

Finally, to test the statistical difference between the ICT investment variable and ICT expenditure variable, this study has carried out three statistical tests. The test results conclude that ICT investment and ICT expenditure have different mean values, different variances, and are not significantly correlated (Table 7). With the statistical differences, the ICT investment variable and ICT expenditure variable can be used in the same regression model.

Table 7 Comparison between ICT investment and ICT expenditure

Null hypothesis	Test method	P value	Decision
Equal mean	Welch two sample t test	<0.001	Reject null
Equal variance	F test	<0.001	Reject null

Correlated	Pearson product-moment correlation test	<0.001	Reject null

5. Results

Table 8 shows two simultaneous steps in SFA: energy efficiency estimation and regression of energy inefficiency on explanatory variables. To estimate energy efficiency, this study regresses energy expenditure on a natural logarithm of annual turnover, labour expenditure and total stock value, see Equation (12). In the second step, the energy inefficiency error term is regressed on explanatory variables, see Equation (13). The explanatory variables include ICT investment and ICT expenditure, as well as other control variables. The control variables include 32 industry dummies that classify 33 industries, defined by a 2-digit standard industrial classification (SIC) code. Appendix 1 presents the names of these industries. Table 8 reports the parameters and significance levels of all variables. As the Table analyses the determinants of energy *inefficiency*, the coefficient signs of explanatory variables shall be interpreted in the opposite way to those for energy *efficiency*.

For cross-validation, three variations of models are shown in Table 8. Model 1 and Model 3 both use the Cobb-Douglas production function. Model 2 also uses the cross-products variables in the translog production function, such as $lnk \times lnl$, but does not use any quadratic form variables, such as $(lnk)^2$. This is because the quadratic variables are omitted for high multicollinearity when running the analysis. Model 1 and Model 3 analyse the moving average of ICT expenditure and ICT investment from the past three years. Model 3 analyses ICT expenditure and ICT investment at the current year. In addition, three goodness of fit tests are presented: sigma squared, gamma and log likelihood. Sigma squared (σ^2) is the sum of error term variance and inefficiency term variance, see Equation (**16**). Gamma (γ) is the ratio of inefficiency over the sum of error term, see Equation (**17**). Log likelihood is the likelihood that a stochastic frontier analysis model *with* an inefficiency term is better than a model *without* an inefficiency term.

$$\sigma^2 = \sigma_u^2 + \sigma_v^2 \tag{16}$$

$$\gamma = \frac{\sigma_u^2}{\sigma^2} \tag{17}$$

Where σ_u is the standard deviation of inefficiency term, σ_v is the standard deviation of stochastic noise.

Table 8 Stochastic frontier analysis of firm energy efficiency

	Model 1		Model 2		Model 3	
Energy efficiency estimation						
Intercept	1.3	***	8.2	***	1.3	***
lnk	0.017	***	-0.2	***	0.017	***
lny	0.5	***	-0.1		0.5	***
lnl	0.1	***	-0.6	***	0.1	***
$lnk \times lnl$			0.0008			
$lny \times lnl$			0.1	***		
$lny \times lnk$			0.014	***		
Explanatory variables						
Intercept	-3119.1	***	-8495.9	***	-1998.1	***
$ICTe$ $(3\ year\ moving\ average)$	-3.3	***	-8.2	***		
$ICTi$ $(3\ year\ moving\ average)$	-1.1	***	-3.6	***		
$ICTe$ $(current\ year)$					-0.6	**
$ICTi$ $(current\ year)$					-2.4	***
$BRITISH$	-25.5	***	-46.4	***	-16	***
$LONDON$	15.8	**	33.5	*	6.1	
$PRIVATE$	326.4	***	1900.6	***	120.8	***
CCL	-73.5	***	-144.5	***	-46.0	***
$WATER$	-21.8	***	-78.2	***	-11.2	***
AD	-1.5	***	-4.8	***	-0.7	***
$SIZE$ $(2nd\ quintile\ dummy)$	-61.9	***	-212.8	***	-34.9	***
$SIZE$ $(3rd\ quintile\ dummy)$	-1.5		-19.6	**	4.2	
$SIZE$ $(4th\ quintile\ dummy)$	17.6	*	68	***	0.1	
$SIZE$ $(5th\ quintile\ dummy)$	-6.5		-41.9	***	-8.8	
$INDUSTRY\ dummies$ $(2\ digit\ SIC\ code)$	YES		YES		YES	
$YEAR\ dummies$	YES		YES		YES	
Goodness of fit						
σ^2	1075.7	***	4105.2	***	553.3	***
γ	0.99	***	0.99	***	0.99	***
log likelihood	-16849.2	***	-16538.9	***	-16944.7	***

*Note: *, ** and *** represents 95%, 99% and 99.9% level of confidence respectively.*

Table 8 reveals the relationships between energy expenditure and annual turnover, labour expenditure, and total stock value. When applying a Cobb-Douglas model, energy expenditure is significantly positively related to all three variables, i.e., annual turnover, labour expenditure and total stock value. However, when introducing cross-products in the production function, energy expenditure is negatively related to the three variables but positively related to the cross-products. The change of signs could be a result of multicollinearity. Further research needs to be undertaken to verify the relationships between energy input, other inputs, and output. So far, the results in the Cobb-Douglas model suggest that energy input may be complemented by other inputs and the output. An increase in human resources, capital investment or economic output may increase energy demand. Nevertheless, further investigation is needed, as price effects have not been considered and the Cobb-Douglas model has limitations, such as the assumption of a constant elasticity of substitution of one.

Table 8 tests the relationship between firm ICT behaviours and energy efficiency. We can see that both firm ICT investment and ICT expenditure have a significantly positive relationship with firm energy efficiency. Model 1 indicates that a 1% increase in firms' past three years' ICT expenditure (ICT investment) is associated with 3.3% (1.1%) increase in energy efficiency. Model 3 suggests that 1% increase in firms' current-year ICT expenditure (ICT investment) is associated with 0.6% (2.4%) increase in energy efficiency. This largely confirms Hypothesis 1 and Hypothesis 2 that firm ICT investment and ICT expenditure are both positively associated with firm energy efficiency. The conclusion remains the same when estimating with cross-products in the production function (Model 2).

Table 8 shows the effects of control variables on energy efficiency. According to Model 1, British firms have 26% higher energy efficiency than foreign firms, London firms are 16% less energy efficient than firms located outside London, NPOs and government organizations are over three times more energy efficient than other firms, companies that are paying climate change levy are 74% more efficient than companies that are not. Companies with high advertising costs and high water expenditure are also more energy efficient. According to Model 1, a 1% increase in advertising costs is associated with 1.5% increase in energy efficiency, and a 1% increase in water expenditure is associated with a 22% increase in energy efficiency. Annual turnover may have a mixed effect on firm energy efficiency with the size quintile dummies taking both positive and negative values. Model 2 and Model 3 show similar coefficient signs of the control variables as Model 1, although the coefficient magnitudes differ. Overall, the highest impact on firm energy efficiency may come from a firm's legal status (NPO or not), followed by climate change levy, firm ownership location (domestic or foreign), firm water expenditure, and firm registration location (London or non-London).

Finally, in all three models, gamma values are close to 1, and log likelihood hypothesis tests are rejected at 0.1% significance level. The goodness of fitness statistics show that the inefficiency effects are highly significant, indicating good fit of the models.

6. Robustness check

The above analysis uses 2-digit SIC codes to classify industries. This section does a robustness check by classifying industries on a more disaggregated level, using 5-digit SIC codes instead of 2-digit SIC codes (Table 9). A total of 74 industry dummy variables are used to include 75 industries. The results are very similar to the above main analysis, including coefficient signs and coefficient magnitudes, confirming robustness of the analysis.

Table 9 Stochastic frontier analysis with 5 digit SIC code classification

	Model 4	
Energy efficiency estimation		
Intercept	0.04	
lnk	0.017	***
lny	0.7	***
lnl	0.1	***
Explanatory variables		
Intercept	-1101	***
$ICTe$ $(3\ year\ moving\ average)$	-1.8	***
$ICTi$ $(3\ year\ moving\ average)$	-1.5	***
$BRITISH$	-93	***
$LONDON$	22.1	**
$PRIVATE$	261	***
CCL	-218.8	***
$WATER$	-17.4	***
AD	-3.1	***
$SIZE$ $(2nd\ quintile\ dummy)$	-2.3	
$SIZE$ $(3rd\ quintile\ dummy)$	-20.2	*
$SIZE$ $(4th\ quintile\ dummy)$	38.1	**
$SIZE$ $(5th\ quintile\ dummy)$	-9	
$INDUSTRY\ dummies$ $(\mathbf{5\ digit\ SIC\ codes})$	YES	
$YEAR\ dummies$	YES	
Goodness of fit		
σ^2	1428.9	***
γ	0.99	***
log likelihood	-7356.8	***

*Note: *, ** and *** represents 95%, 99% and 99.9% level confidence respectively.*

7. Discussion and conclusions

This study is one of the first to compare the effect of ICT expenditure with the effect of ICT investment on energy efficiency via a relatively advanced econometric method, called the stochastic frontier analysis (SFA). First, the study proposes a comprehensive theoretical framework that outlines the differences between ICT expenditure and ICT investment (Figure 1). In short, ICT expenditure is a recurring expense to hire specialized ICT firms to provide ICT services; whereas ICT investment is procurement of internal assets to obtain essential ICT hardware and software. In a developed economy, ICT expenditure represents closer and longer-term collaboration with ICT specialists to obtain a wide range of services. Theoretically, both ICT investment and ICT expenditure improve firm energy efficiency by enhancing firm performance with less-than-proportionate energy input, and by enhancing innovation and knowledge spillover. This study proposes two hypotheses then confirms them with empirical analyses:

Hypothesis 1: ICT *investment* is positively associated with firm energy efficiency in developed economies.

Hypothesis 2: ICT *expenditure* is positively associated with firm energy efficiency in developed economies.

To test the hypotheses, the study analyses ~1,000 UK firms between 2008 and 2015. The study estimates firm energy efficiency by industry and regresses energy inefficiency on ICT expenditure/investment in a one-stage approach following Battese and Coelli (1995). The study investigates firm technical energy efficiency with an energy input distance function in SFA, which measures how much energy expenditure a firm can reduce given a technology frontier. In other words, this paper measures relative energy efficiency by comparing a firm's energy expenditure with the best practice in the industry. Energy expenditure is regressed on labour expenditure, capital stock, and annual turnover. The error term of the regression comprises not only stochastic noise but also an energy inefficiency term. The energy inefficiency term is simultaneously regressed on explanatory variables including ICT-related variables and some control variables.

The results are in line with the hypotheses that are based on the literature. The study has found that both firm ICT investment and ICT expenditure are positively correlated with firm energy efficiency, especially in industries that have lower profitability, higher capital intensity and lower labour intensity. There are two explanations for the findings. First, ICT investment is the purchase of hardware of software that establishes or upgrades internal infrastructure, whilst ICT expenditure is the ongoing management cost of ICT assets, which is usually outsourced services from specialists (Byrne & Corrado, 2017; Koman et al., 2022; Ruivo et al., 2015; Van Ark, 2016). Once firms enter an ICT deployment phase after initial ICT instalment, both ICT investment and ICT expenditure are important in improving firm energy efficiency. The former establishes or upgrades internal ICT systems, and the latter maintains internal ICT assets and builds external connections with the ICT assets (Byrne & Corrado, 2017; Grant & Yeo, 2018; Jackson et al. 2012; Van Ark, 2016). Second, both ICT investment and ICT expenditure are associated with firm innovation and knowledge spillover effects, which may improve energy efficiency. ICT investment provides knowledge spillover from the ICT industry (Al-Qubaisi et al., 2018; Gu & Surendra, 2004; Shahnazi & Dehghan Shabani, 2019; Su et al., 2023), while ICT expenditure reflects collaboration between ICT firms and non-ICT firms, especially in developed economies (Kang et al., 2022; Kumbhakar & Lovell, 2003; Liu et al., 2023; Melville et al., 2004). Knowledge spillover and innovation are related to energy efficiency (Costantini et al., 2017; Liu et al., 2024; Nemet, 2012; Popp, 2002; Popp & Newell, 2012; Sun et al., 2021.

The study offers empirical insights for policymakers on how to improve energy efficiency, especially for those in developed economies. There are two ways firms may improve their energy efficiency. First, firms may invest in ICT capital to upgrade or purchase new facilities. Second, if firms have easy access to high-quality ICT services through close collaboration with ICT specialists, they also have a significant opportunity to increase their energy efficiency. It is crucial to encourage the development of the ICT industry and the spillover of this industry to improve overall energy efficiency of the economy and to tackle climate change. The positive spillovers from ICT firms to non-ICT firms may improve the energy efficiency of the economy. Meanwhile, the empirical evidence shows that it is ICT expenditure not ICT investment that affects energy efficiency. It is important to promote a long-term cooperation between ICT firms and other firms, which has much higher impact on energy efficiency than the one-off ICT investment.

The research also reveals the effects of other variables on firm energy efficiency, including location, firm size, regulation, and awareness of public image. First, firm location affects energy efficiency. British firms have higher energy efficiency, probably because national energy policies encourage domestic firms to implement energy saving measures. London firms are less energy efficient; this may be explained by the fact that London firms are less incentivized to reduce energy use, a relatively low-cost input compared to other inputs such as high labour cost. Second, firm size affects energy efficiency. Annual turnover has a mixed effect on firm energy efficiency. This may be explained by economies of scale and diseconomies of scale. When a firm grows bigger, its energy efficiency increases until it reaches the optimum size; when the firm continues growing above its optimum size, its energy efficiency will decline. Third, companies that are paying a climate change levy are more efficient. This indicates the effectiveness of imposing environmental regulations. Fourth, awareness of public image affects firm energy efficiency. NPOs and government organizations are more energy efficient, and companies with high advertising costs are more energy efficient, which may be due to higher awareness of public image.

There are at least four limitations of this study. First, due to data availability, this study cannot identify the specific accounting items that compose ICT expenditure or ICT investment. The current research only identifies the phenomenon, but the underlying mechanism still needs to be tested, ideally with qualitative methods. Second, this study cannot ascertain the causality between ICT and firm energy efficiency due to the restriction in re-identifying firms under the confidential data agreement. It is likely that firms with higher energy efficiency have more resources to invest in ICT or purchase ICT services, which results in higher ICT investment or higher ICT expenditure. Third, the data analysis is carried out in an Intranet environment where there are only basic programming tools and packages, so some advanced econometric methods cannot be used easily, such as Greene's true fixed effect (Greene, 2005). Fourth, the data in the study is before year 2015, which may not fully reflect the most recent ICT innovations.

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Appendix 1 SIC names

Table 1a shows the names of all the standard industrial classification (SIC) codes used, defined by the ONS (2022).

Table 1a Names of SIC codes in this study

SIC codes	SIC names
10	Manufacture of food products
11	Manufacture of beverages.
13	Manufacture of textiles
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media.
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products.
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing
33	Repair and installation of machinery and equipment
35	Electricity, gas, steam and air conditioning supply
36	Water collection, treatment and supply
41	Construction of buildings.
42	Civil engineering
43	Specialised construction activities
46	Wholesale, except motor vehicles and motorcycles’
55	Accommodation
56	Food and beverage service activities

61	Telecommunications
91	Libraries, archives, museums and other cultural activities.