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# **Leveraging IoT for Industrial Energy Productivity: Evidence from European Firms**

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## **Abstract**

This article analyzes if the Internet of Things (IoT) can contribute to increasing energy productivity across firms that adopt this technology. The empirical analysis is based on a sample of more than 8,000 firms from various sectors across 26 European countries, surveyed by the European Investment Bank across the years 2022 and 2023. Methodologically, we combine two-way fixed-effects models (TWFE), differences-in-differences and matching methods. Our results indicate significant effects of IoT on energy productivity, although these effects seem to be concentrated among manufacturing/construction sectors and medium/big firms only. Our findings suggest that digital technologies such as IoT can potentially play a key role in energy transitions toward more sustainable economies.

**Keywords:** Internet of Things; Digitization; Energy productivity; Energy efficiency

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## 1. Introduction

The increasing urgency derived from climate change, and the growing complexity of energy systems, has intensified the demand for innovative strategies and new technological tools to reduce energy consumption without compromising growth and welfare. In particular, the industrial sector accounts for nearly 25% of final energy use in the European Union (EU), making it a key sector for achieving climate targets and enhancing resources' efficient uses (European Environment Agency, 2022).

In this context, the Internet of Things (IoT) has emerged as a transformative force in the industrial landscape. IoT is defined as a network of physical devices embedded with sensors, software, and connectivity tools that enable real-time data collection and exchange. IoT technologies have the potential to radically improve how energy is consumed, managed, and optimized across supply chains and production processes (Li et al., 2017).

The rise of the so-called "Industry 4.0" has further accelerated the integration of digital tools in industrial operations, as IoT systems are not only technically feasible but strategically attractive. Through these tools, firms can simulate potential operations, implement predictive maintenance, and make data-driven decisions to enhance energy efficiency (Lee, Bagheri, & Kao, 2015; Tao et al., 2018). This is particularly relevant in energy-intensive sectors, in which even marginal improvements can yield substantial economic and environmental gains.

This article investigates whether the adoption of IoT technologies leads to significant improvements in firm-level energy productivity among European firms. Our analysis is based on a novel dataset from a survey conducted by the European Investment Bank (EIB), which has not been accessed before. The panel covers various sectors across 26 European countries<sup>1</sup> for the 2022-2023 period.

This question is motivated by the growing interest among scholars and policymakers in understanding how digital transformation intersects with energy efficiency and sustainable industrial growth (Beier, Niehoff, & Xue, 2018; Ardito et al., 2019). Despite the increasing deployment of IoT across sectors, rigorous empirical evaluations of its impact on energy productivity remain very limited.

From an academic perspective, this topic contributes to a growing literature that explores the relationship between technological adoption and firm-level performance. While several studies have documented the efficiency gains of IoT in specific domains such as logistics, inventory control, and predictive maintenance (Zhou, Chong, & Ngai, 2015), fewer analyses examine how these benefits translate

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<sup>1</sup> Sectors included are manufacturing (NACE C), construction (NACE F), services (NACE G/I), others (NACE D/E/H/J). Countries of the firms included are Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovenia, Slovakia, Spain, and Sweden.

into energy-use improvements; the heterogeneity of IoT's effects (across sectors, firm sizes, and technological complementarities) remain an open area of research.

From the policy perspective, it is necessary to understand the real-world impact of emerging technologies on energy consumption, as EU's promotion of its twin transition towards digitalization and decarbonization suggests. In particular, in a context in which the digital revolution is proving to be intensive in energy consumption (for example, due to high scale datacenters and AI training models), the research question addressed in this paper is critical to understand how digitization can be an ally of the green agenda.

Our findings can contribute to the design of industrial innovation programs, green digital subsidies, and more efficient regulations (Porter & Heppelmann, 2014). If IoT adoption proves to have a significant positive effect on energy productivity, it could serve as a critical tool for achieving climate targets while maintaining industrial competitiveness.

This study builds on existing conceptual and empirical work to articulate and test the following hypotheses:

- H1: Firms that adopt IoT technologies exhibit higher energy productivity than non-adopters, on average.
- H2: The positive effect of IoT adoption on energy productivity is stronger in manufacturing sectors and among medium-to-large firms.
- H3: The effect of IoT adoption on energy productivity remains significant when controlling for green investment, firm age, firm size, and energy prices.

To test these hypotheses, we build an unbalanced panel of more than 8,000 European firms, with variables related to IoT adoption, production characteristics, and energy inputs. Our methodological approach combines fixed effects regression models, difference-in-differences estimations and matching to account for both observable and unobservable heterogeneity elements to isolate the causal impact of IoT on energy productivity.

Our findings show that IoT adoption is positively and significantly associated with higher energy productivity at the firm level. The impact of IoT is more pronounced in manufacturing and medium-to-large firms, which shows that scale and sectoral characteristics mediate on the impact of digital adoption.

The results in this paper represent an important contribution to the literature on IoT adoption, as it is the first paper, to the best of our knowledge, that empirically shows its potential for improving energy efficiency. Most of the literature does not empirically test this potential impact with the granularity and robustness that our database allows.

The rest of this paper is structured as follows. Section 2 reviews the relevant literature on IoT, industrial productivity, and energy efficiency. Section 3 presents the data and descriptive statistics. Section 4 outlines the empirical strategy and estimation techniques. Section 5 addresses some robustness checks. Section 6 concludes with a summary of the main findings and highlights future research avenues.

## **2. Literature review**

The integration of IoT in industrial contexts has garnered substantial academic attention over the past decade, particularly regarding its capacity to enhance operational efficiency and promote more sustainable production strategies. Within the industrial landscape, IoT is often deployed through Cyber-Physical Systems (CPS), digital twins<sup>2</sup>, and smart monitoring tools, all of which aim to improve resource allocation, streamline processes, and optimize decision-making (Lee, Bagheri, & Kao, 2015).

We group the literature on the relationship between IoT adoption and energy efficiency around three axes: production techniques, industrial sustainability, and empirical evidence around these areas. Even if this literature is relatively scarce, there is a consensus on the potential that IoT has to significantly enhance industrial productivity and energy efficiency.

From a production standpoint, IoT is key for the so-called “smart manufacturing systems”. Lee, Bagheri, and Kao (2015) present a conceptual framework in which IoT, as part of cyber-physical systems, enables factories to transition toward Industry 4.0 architectures. This transformation allows firms to harness big data analytics, edge computing, and automation to improve productivity and responsiveness. Tao et al. (2018) explore the use of digital twins to simulate and optimize energy use in manufacturing systems. Their findings suggest that digital twins supported by IoT can lead to enhanced energy productivity through more informed decision-making processes.

Porter and Heppelmann (2014) offer a strategic perspective, asserting that smart, connected products can reconfigure the nature of competition. According to this, firms that adopt IoT technologies are better positioned to create a supply, reduce operational costs, and implement adaptive production systems. These outcomes are particularly relevant for energy consumption, which depends not only on technical improvements but also on organizational capabilities and strategic alignment.

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<sup>2</sup> Virtual representations of physical assets

Derived from these new production techniques, and the subsequent strategies, literature explores how IoT adoption can contribute to a more sustainable industrial landscape. Beier, Niehoff, and Xue (2018) argue that the Industrial Internet of Things (IIoT) facilitate more efficient manufacturing processes through predictive maintenance, reduced resource wastage, and circular production models. This is particularly impactful in energy-intensive industries, in which real-time automated processes can lead to significant energy savings.

Complementing this view, Buchanan, Russo, and Anderson (2015) examine the psychological and behavioral aspects of energy consumption, highlighting how IoT-enabled feedback systems can influence users' energy-saving behaviors. They contend that while the presence of feedback mechanisms is necessary, its format and frequency are key for determining their effectiveness.

Finally, from the empirical point of view, research supports the notion that IoT drives energy efficiency gains. Li et al. (2017), in a comprehensive survey of enabling IoT technologies, reports widespread applications of IoT in energy management systems, logistics, and machine maintenance, all of which can contribute to enhanced energy productivity. Similarly, Zhou, Chong, and Ngai (2015) emphasize that IoT-based supply chain management reduces energy expenditure through better demand forecasting and real-time tracking.

The link between digital transformation and environmental impact is explored by Ardito et al. (2019). According to their findings, firms are more likely to engage in green innovation and experience improvements in energy intensity. Similar results can be found in Miorandi et al. (2012). This article provides evidence of IoT's transformative potential across sectors, which suggests that efficiency gains are particularly pronounced when IoT is combined with complementary organizational practices and digital skills.

Literature converges on the notion that IoT applications have the potential to significantly enhance industrial energy productivity through multiple channels, including real-time energy monitoring, predictive maintenance, enhanced supply chain visibility, and strategic flexibility.

The impact of IoT is mediated by firm characteristics, sectoral context, and the presence of complementary assets such as data analytics capabilities and organizational readiness. These findings provide a robust theoretical foundation, paired with some empirical incipient findings, for investigating the causal impact of IoT adoption on firm-level energy productivity in the specific context of European industrial firms, a topic that has not been sufficiently explored in the literature.

### 3. Database and descriptive analysis

As mentioned in the Introduction, we exploit a unique, unused dataset from a EIB survey. The sample consists of a panel of firms from various sectors across 26 European countries<sup>3</sup> for the 2022-2023 period. It provides unique firm-level information about investment decisions and investment finance choices, both from the general and specific digital perspectives.

The dependent variable for the analysis is the logarithm of energy productivity, that is defined as the ratio of sales by energy consumption spending. This is the total amount received in respect of sales of goods and services, divided by how much each company spent on energy in the same period. All monetary variables are expressed in euros.

The IoT variable is built as a binary indicator, taking value of 1 if the firm has adopted this technology, and 0 in other cases. The questionnaire defines IoT as *“Electronic devices that communicate with each other without human assistance for example smart heating/cooling systems, wireless inventory or delivery trackers, wearable devices with sensors”*. This will be the treatment variable to be empirically tested.

As for the control variables, it is important to consider that the firm-level fixed effects are already controlling for most structural firm characteristics that are expected to explain energy productivity disparities. For example, fixed effects will account for differences in the economic sector (relevant because the different industries may vary significantly in terms of their energy consumption, as pointed by Atalla and Bean, 2017; and Sineviciene et al, 2017). Location effects are also captured by the fixed effects. In addition, any other firm-level unobservable factors that can be expected to vary little over time (such as knowledge stock, absorptive capacity, managerial talent, or intangible capital) should be largely captured by the firm’s fixed effects, particularly considering the short timeframe considered.

We also include firms’ age as a proxy for their technological experience. Older firms are supposedly better equipped to assess the risks and benefits of the introduction of new technologies such as IoT, but younger ones are supposed to be more flexible to organizational changes which may also have an impact on firm performance metrics. This is why it is hard to hypothesize its potential impact beforehand.

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<sup>3</sup> Sectors included are manufacturing (NACE C), construction (NACE F), services (NACE G/I), others (NACE D/E/H/J). Countries of the firms included are Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovenia, Slovakia, Spain, and Sweden.

Investment in capital has also been identified as a potential driver of energy productivity (Atalla and Bean, 2017; Sineviciene et al, 2017). Firms with high investment intensity should replace their capital stock faster, therefore being expected to have on average newer energy-productive capital (Atalla and Bean, 2017). We control this factor through the investment intensity variable, defined as total investment per full-time employee.

The quality of capital is another potential driver of energy productivity, according to Uwasu et al (2012). We control for this element through two different binary variables. First, green investment, defined as a dummy variable that takes the value 1 if the firm is investing or has made investments to tackle the impacts of weather events and to help reduce carbon emissions (0 in other cases). And second, investment in energy efficiency measures that may not necessarily be related to IoT (including heating, cooling improvements or energy management).

Total Factor Productivity (TFP) also plays a role in the determination of energy productivity, according to Uwasu et al. (2012). We calculated the TFP for each firm following the procedure proposed by Wooldridge (2009) to estimate firm-level production functions using materials to control for unobservable shocks.

Finally, we also included the price of electricity as a control. The variable is defined as a non-household price for medium-sized consumers with an annual consumption between 500 MWh and 2000 MWh. Eurostat reports data by semester, so annual averages were calculated. As argued by Atalla and Bean (2017), energy prices are usually an important component of production costs, with higher prices being expected to lead to lower energy consumption and to shift the development and investment towards less energy intensive capital.

Table 1 presents descriptive statistics for the variables to be used in empirical analysis. As can be appreciated, 39.3% of the firms in the sample declare to use IoT, reflecting an important number of treated observations for empirical analysis.

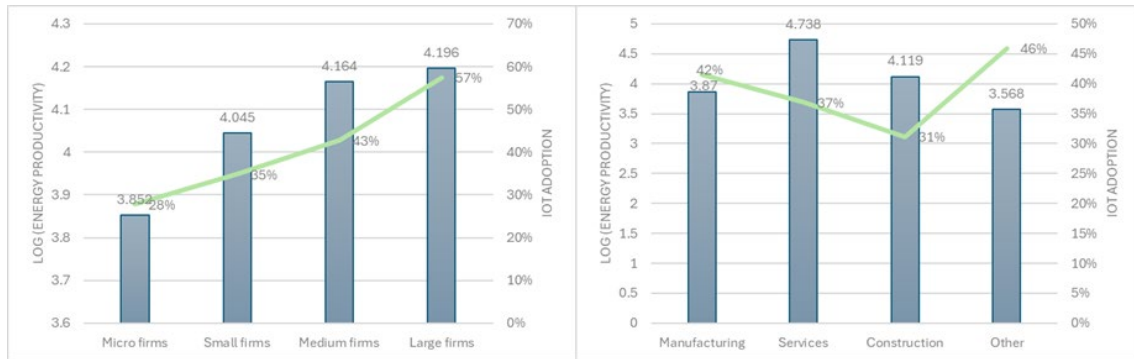
**Table 1. Descriptive statistics**

Variable	Mean	Std. Dv.
Log(Energy Productivity)	4.066	1.834
IoT	0.393	0.488
Investment intensity	91,349.580	11,500,000.000
TFP	4,089.180	20,043.730
Green investment	0.462	0.499
Firm age	4.527	0.786
Energy efficiency investment	0.590	0.492
Energy Price	0.185	0.054
Foreign firm	0.181	0.385

*Source: authors' analysis*

Data shows that there are important disparities in firm productivity and IoT adoption by firm groups (Figure 1). In particular, the larger the firm group, the higher energy productivity and the average adoption of IoT, as expected. By economic sector, Services is the most productive category, although it is not among the top IoT adopters. This evidence suggests the importance of identifying nuances in the effects by firm group, as we do next.

**Figure 1. Log(Energy productivity) and IoT adoption by firm size and sector**



Source: EIB

Preliminary results do not suggest that IoT has contributed to higher energy productivity. This seems clear from a simple t-test analysis, from which the mean value of energy productivity is similar for both IoT adopters and non-adopters (Table 2).

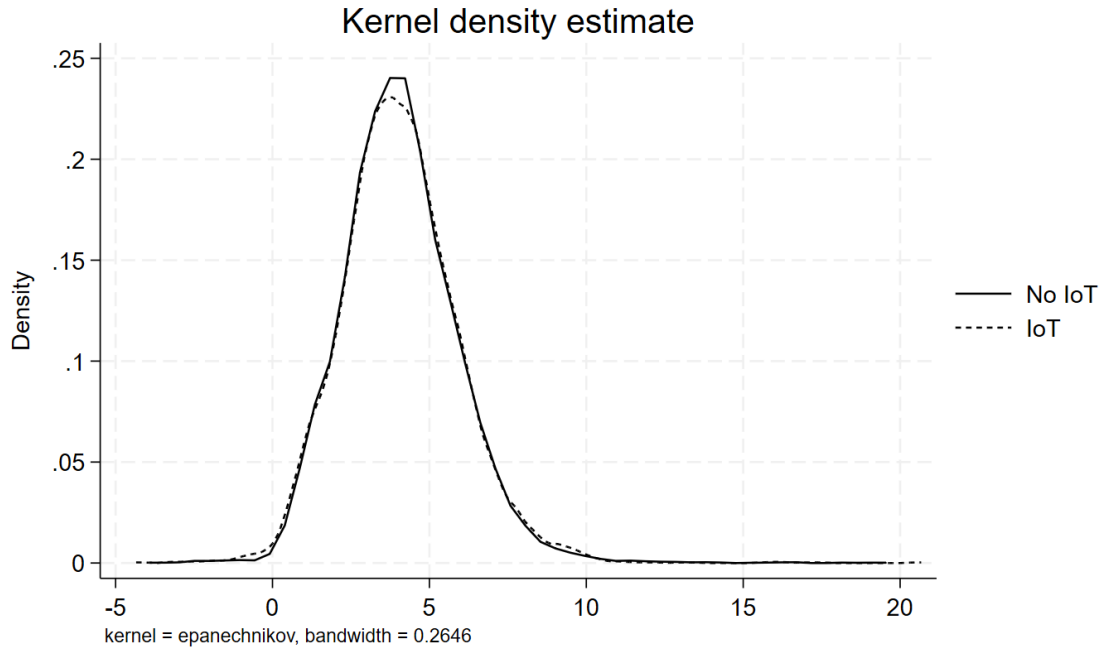
**Table 2. Log(Energy Productivity) – by IoT condition**

Group	Observations	Mean	Std. Dv.
No IoT	5,647	4.067480	0.024189
IoT	3,673	4.062883	0.030841
Combined	9,320	4.065669	0.019039
Difference		-0.004597	0.038964

Source: authors' analysis

Similarly, the kernel density function of energy productivity series by IoT adopters vs. non-adopters shows almost identical distributions, which suggests no difference in the behavior of the dependent variable for both groups (Figure 2).

**Figure 2. Kernel density of Log(Energy Productivity) – by IoT condition**



Source: authors' analysis

Consequently, preliminary evidence seems to contradict the main hypothesis of this paper; it remains unclear whether there is a statistically significant treatment effect, once the appropriate regression methodologies are used, as we do in Section 4.

#### 4. Estimation results

The main estimation is the following:

$$\text{Log}(\text{Energy productivity}_{it}) = \alpha_i + \delta_t + \beta \text{IoT}_{it} + \gamma X_{it} + \varepsilon_{it}, (1)$$

where  $i$  and  $t$  denote respectively firm and time. The dependent variable, labeled as “Energy productivity”, is measured as total sales per energy expenditure.  $\alpha_i$  consists of a firm-level fixed effect,  $\delta_t$  is a time indicator to absorb exogenous technological improvement,  $\beta$  reflects the use of IoT in the firm,  $X$  represents a vector of controls accounting for energy productivity drivers, and  $\varepsilon$  represents a well-behaved error term. All estimates include firm and year fixed effects, as well as robust standard errors clustered by firm. In addition to the above-mentioned controls, we add binary variables to account for firm size: small (10-49 employees), medium (50-249 employees) and big firms (more than 250 employees), being the micro firms (5-9 employees) the baseline scenario.

First, we start with simple two-way fixed-effects estimations. Results presented in Table 3 indicate that IoT only presents a significant coefficient (at a 10% level) when most of the control variables are introduced, as done in columns (vi) and (vii). This suggests the existence of a weak evidence linking IoT with energy productivity.

**Table 3. TWFE estimations of Energy Productivity drivers**

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
IoT	0.062367 [0.125910]	0.127195 [0.150273]	0.143991 [0.146447]	0.145924 [0.150166]	0.157546 [0.151462]	0.280088* [0.167243]	0.308544* [0.167239]
Inv. intensity	0.000000 [0.000001]	0.000002 [0.000002]	0.000002 [0.000002]	0.000002 [0.000002]	0.000002 [0.000002]	0.000001 [0.000002]	0.000002 [0.000002]
TFP		0.000009 [0.000101]	0.000016 [0.000092]	0.000016 [0.000097]	-0.000002 [0.000097]	0.000050 [0.000114]	0.000047 [0.000116]
Small firm			-0.442490 [0.716121]	-0.455265 [0.715578]	-0.498859 [0.721462]	-1.542242 [1.043618]	-1.580512 [1.032758]
Medium firm			-0.654257 [0.679476]	-0.675983 [0.681984]	-0.717846 [0.689962]	-1.666271* [0.988873]	-1.647236* [0.960441]
Big firm			-0.358310 [0.836463]	-0.275400 [0.886694]	-0.364271 [0.884818]	-0.746878 [1.155746]	-0.612016 [1.111220]
Green investment				0.238881* [0.142447]	0.187195 [0.142557]	0.227390* [0.130918]	0.205032 [0.138438]
Firm age					0.245655* [0.149057]	0.376321** [0.178697]	0.395808** [0.175303]
Energy efficiency inv.						0.137761 [0.252415]	0.171919 [0.261591]
Energy price							2.735220 [1.906361]
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
R-squared	0.002	0.011	0.020	0.025	0.031	0.100	0.110
Observations	9,119	5,271	5,271	5,160	5,159	4,484	4,484
Number of id	8,415	5,003	5,003	4,902	4,902	4,268	4,268

Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Robust standard errors (clustered by firm) in brackets

Source: authors' analysis

The estimations presented in Table 3 exhibit important limitations that make the conventional TWFE procedure problematic for this kind of analysis; the estimates presented above do not represent an accurate research design to evaluate causal effects. As explained by Callaway and Sant'Anna (2021), the canonical differences-in-differences format to estimate causal effects consists in two time periods and two groups: in the first period no one is treated, and in the second period some firms are treated (the treated group), and some others are not (the control group).

If we assume that, in the absence of treatment, the average outcomes for treated and control groups would have followed a parallel path, then it is possible to estimate the average treatment effect for the treated group (ATT). This can be done by comparing the average change in experienced outcomes by the treated group to the average change in outcomes experienced by the control one.

Only under the canonical conditions described above, the TWFE can be considered an accurate estimator of the ATT. However, the estimations presented in Table 3 do not represent that canonical format required for an accurate causal estimation. First, there is only a minority of firms with a proper panel structure, as most of them have been surveyed in a single year (either 2022 or 2023). For example, in the estimation presented in column (i), there is a total of 8,415 groups (unique firms) and only 9,119 overall observations. This means that just a small fraction of the sample is repeated in the panel and exhibit *within* variability. On the contrary, for those firms surveyed in a single year, all the variability in the dependent variable will be absorbed by the firm fixed effects.

Second, there are several firms already treated in period 1: all the firms adopting IoT in the first year of the panel, 2022. This is considered a forbidden comparison for firms adopting IoT in the second period as already treated observations are not a valid control group. Additionally, there are also leavers. These are firms that were treated in period 1 but are untreated in period 2. As pointed out by several authors, the standard TWFE estimator represents a weighted sum of the average treatment effects, where weights can be negative, affecting the estimated regression coefficient (Goodman-Bacon, 2021; De Chaisemartin and d'Haultfoeuille, 2020).

In our sample, the TWFE estimation consists in a sum of 698 average treatment effects on the treated (ATTs), of which 475 receive a positive weight and 223 receive a negative weight. Clearly, this evidence invalidates the suitability of conducting conventional TWFE analysis. This means that an alternative procedure has to be used in order to account for these inconsistencies.

We will rely on one of the novel differences-in-differences methodologies specifically designed to overcome these limitations. The De Chaisemartin and d'Haultfoeuille (2020) estimator will be used, as it explicitly considers the case of both joiners and leavers, and it uses as weights the share of each cohort in their respective group, therefore under this estimation design all weights are positive.

The estimator assumes the existence of stable groups across consecutive periods. This means that if there is a group of firms that switch to the treatment condition (not adopting IoT in the first period, and adopting it in the second one), then there should be another one that is untreated in both periods (not IoT adopter in both years). Similarly, if there are firms that leave the treatment condition (adopting IoT in the first period, but not in the second one), then there should be another group of treated observations in both periods (always adopting IoT).

Considering that we have all the required cases (Table 4), then this methodology is especially accurate for our empirical analysis.

**Table 4. Treated and Untreated observations by period**

	Treated (2023)	Untreated (2023)
Treated (2022)	166	78
Untreated (2022)	106	349

De Chaisemartin and d'Haultfoeuille (2020) define their estimator as follows:

$$\begin{aligned}
DID_{+,t} &= \sum_{g:D_{g,t}=1, D_{g,t-1}=0} \frac{N_{g,t}}{N_{1,0,t}} (Y_{g,t} - Y_{g,t-1}) - \sum_{g:D_{g,t}=D_{g,t-1}=0} \frac{N_{g,t}}{N_{0,0,t}} (Y_{g,t} - Y_{g,t-1}) \\
DID_{-,t} &= \sum_{g:D_{g,t}=D_{g,t-1}=1} \frac{N_{g,t}}{N_{1,1,t}} (Y_{g,t} - Y_{g,t-1}) - \sum_{g:D_{g,t}=0, D_{g,t-1}=1} \frac{N_{g,t}}{N_{0,1,t}} (Y_{g,t} - Y_{g,t-1})
\end{aligned}$$

Where  $DID_{+,t}$  consists in the effect for those firms switching-in, while  $DID_{-,t}$  represents the effect for those firms switching-out, or leaving the treatment.

Finally, the treatment effect is calculated from both  $DID_{+,t}$  and  $DID_{-,t}$  expressions, as follows:

$$DID_M = \sum \left( \frac{N_{1,0}}{N_S} DID_{+,t} + \frac{N_{0,1}}{N_S} DID_{-,t} \right)$$

Our specific case, with only two periods, the De Chaisemartin and d'Haultfoeuille (2020) is even simpler than under its generic form, as it becomes unnecessary to account for staggered adoption and heterogeneous effects across time.

After non panel and forbidden comparisons are removed, the remaining sample is restricted to approximately 600 observations. This means that we will have to conduct a robustness check using an alternative estimation procedure for treatment effects that does not get rid of so many observations available in the sample.

As shown in Table 5, under the proper differences-in-differences framework, the effect of IoT on energy productivity is positive and significant at a 5% level across all estimates. We start by not including any controls, as shown in column (i). Control variables do not seem to be relevant in a short panel like ours, possibly because most drivers of energy productivity disparities are structural or vary little over in the period considered.

Even though, we include those controls that were found to be significant in some of the estimates presented in Table 3. In particular, we add in green investment in column (ii), firm age in column (iii), and firm size in column (iv). Finally, all these controls are introduced together in column (v).

Overall, results provide evidence of a positive impact of IoT on energy productivity, with a coefficient ranging from 0.286 to 0.309. The inclusion of controls seems to increase the relevance of IoT as a driver of energy productivity (as was seen before

in Table 3), which suggests that the estimations without the controls should be considered as lower bound.

**Table 5. ATT of IoT on Energy Productivity – Diff in Diff estimator**

	(i)	(ii)	(iii)	(iv)	(v)
ATT (IoT)	0.286217** [0.143682]	0.295183** [0.142028]	0.292826** [0.144043]	0.296056** [0.144375]	0.308569** [0.142650]
Control for Green Investment	NO	YES	NO	NO	YES
Control for Firm Age	NO	NO	YES	NO	YES
Controls for Firm Size	NO	NO	NO	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
N	535	542	534	535	541
Switch x Periods	123	125	123	123	125

*Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Robust standard errors (clustered by firm) in brackets*

*Source: authors' analysis*

The evidence presented points show that IoT diffusion enhances operational efficiency and promotes more sustainable production strategies, through better resource allocation, streamline processes, and optimizing decision-making. This is aligned with some of the theoretical arguments reviewed in the literature, such as those exposed by Lee, Bagheri, and Kao (2015), Tao et al. (2018), and Heppelmann (2014), among others.

We conduct alternative estimations intending to find out heterogeneities in the impact according to certain firm characteristics. We split the sample according to the specific firm groups in Table 6. We consider both firms' sectors (manufacturing and construction on the one hand, and services on the other) and by firms' size (micro and small on the one hand, and medium and big ones on the other).

We split the sample into two groups. Estimations are conducted without including any controls, as these are actually the most conservative estimates, as has been already mentioned

**Table 6. ATT of IoT on Energy Productivity – Diff in Diff estimator by firm characteristic**

	By sector		By size	
	<u>Manufacturing and construction</u>	<u>Services</u>	<u>Micro and small</u>	<u>Medium and big</u>
ATT (IoT)	0.569983*** [0.203570]	0.010224 [0.198299]	0.124125 [0.184135]	0.447866* [0.240295]
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	266	267	338	191
Switch x Periods	50	74	74	49

*Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Robust standard errors (clustered by firm) in brackets*

*Source: authors' analysis*

Results in Table 6 show that manufacturing and construction firms improve energy productivity after adopting IoT, as they reflect a larger coefficient with respect to the overall sample, at a 1% significance level. The coefficient for services firms is not significant.

The relevance of IoT for the manufacturing sector has been already identified in the literature, as shown by Lee, Bagheri, and Kao (2015), Tao et al. (2018), Beier, Niehoff, and Xue (2018). This can be explained for a number of reasons. First, industrial firms are typically more energy-intensive than service firms (with the exception of transportation).

Second, within factory contexts there are typically more IoT use cases that can be exploited, such as predictive maintenance, process optimization, real-time monitoring and fleet management. On the other hand, processes tend to be simpler in most service-related firms, which may not yield important efficiency gains. In other words, in service-related firms the impact can be considered incremental or minor.

We also split the sample by size. Medium and big firms experience efficiency gains derived from IoT diffusion, while the smaller ones are not capable of doing so. This can be explained as efficiency gains are expected to take place when IoT is combined with complementary organizational practices and digital skills (Miorandi et al., 2012), these being scarcer in smaller firms. Smaller firms typically lag behind in terms of knowledge stock, that is usually considered a determinant of absorptive capacity, which may influence firm capabilities to make the most of new technologies (Benhabib and Spiegel, 1994; Cohen and Levinthal, 1990). Past research has also found that bigger companies can deal better with sunk costs, present more capacity for risk diversification, and have lower financial constraints (Acs and Audretsch, 1988; or Cohen and Klepper, 1996).

However, despite expecting a larger effect on bigger firms, it is still critical to identify ways for smaller ones to make a productive use of IoT. This is especially relevant as micro and small firms are the vast majority of registered businesses in most of the countries surveyed.

## **5. Robustness checks – Matching**

Differences-in-differences estimations are the most accurate to estimate the causal estimations of treatment effects for the research purpose of this article. However, given the limitations that this approach has, we test the robustness of our findings using the matching approach. Matching is designed to estimate treatment effects without requiring a panel structure of the data; we can keep most of the available sample, while estimating an ATT that can be compared with differences-in-differences.

Matching “mimics” randomization, which means developing a counterfactual or control group that is as similar to the treatment one as possible. Non-treated observations that can be considered similar to the treated ones are selected based on the characteristics not affected by the IoT adopting condition; each treated observation is matched with an observationally similar untreated one. The average difference in outcomes across the two groups is compared to getting the treatment effect.

To find out the relevant variables for identifying firms to match, we conduct a series of probit estimations using IoT as dependent variable (results presented in Table A1 in the Appendix). All tested drivers of IoT adoption are significant in at least one of the estimations presented in the Appendix. We include them all for the building process of the propensity scores and distance calculations. Literature shows that with large samples it is beneficial to include all variables that can be potentially related to the outcome (Garrido et al, 2014).

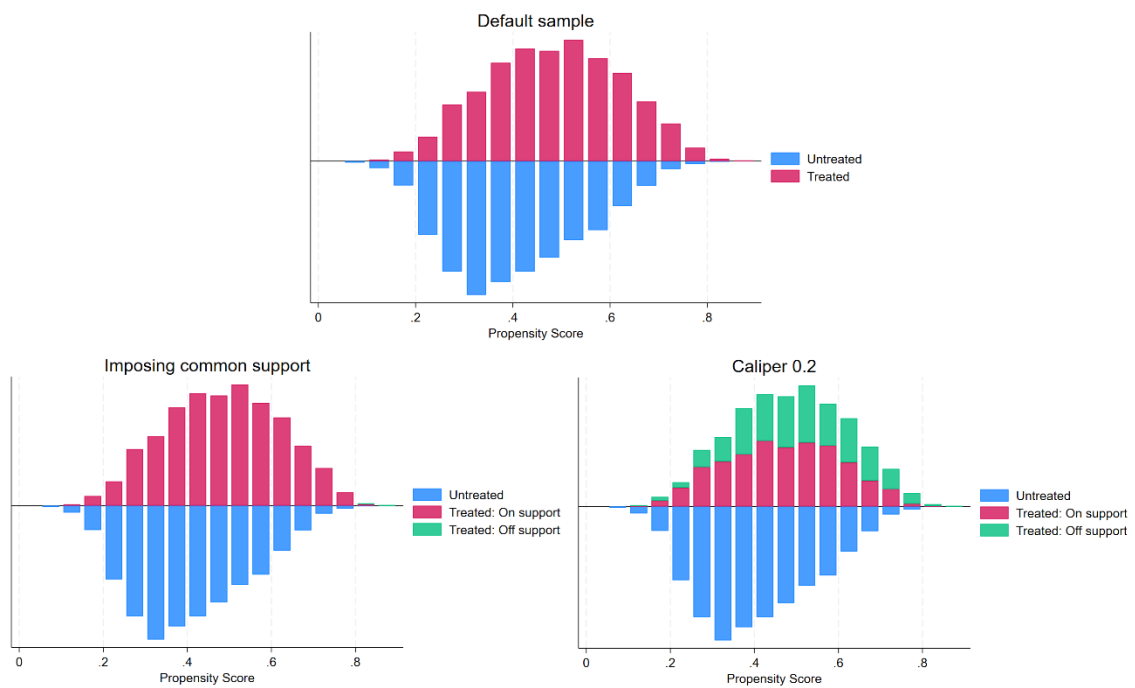
As the comparison must be made through a common support area, a large and roughly equal number of treated and non-treated observations is desirable. This is the case in our sample.

There is no loss of treated observations due to absence of matching under the default sample, while under the common support imposition the losses are minimal, as shown in Figure 3. When introducing a caliper of 0.2 as suggested by some literature (Austin, 2011), the number of treated observations being off increases considerably. All these possibilities are tested through different matching estimations.

The analysis is conducted first through the nearest-neighbor matching. This is considered the most common form of matching, according to Greifer (2025). It requires the specification of a distance measure to identify which are the control units closest to the treated ones. Closest neighbor matching (one to one) prioritizes

closest matches first. We test both the propensity score difference (consisting in the criteria of the difference between the propensity scores of each treated and control units), as well as the Mahalanobis distance approach, that can be convenient in our case for a number of reasons.

**Figure 3. Samples for Matching**



*Source: authors’ analysis*

Mahalanobis distance match pairs of treated and control firms based on the multivariate distance across all covariates, not just a single summary measure as the propensity score. This ensures that matched pairs are similar across the full set of observed characteristics, which can yield better covariate balance than propensity score matching, where units with similar propensity scores may still differ substantially on individual covariates (Greifer, 2025; King and Nielsen, 2019). This procedure also standardizes variables and accounts for correlations among them, making it particularly suitable when covariates are measured on different scales or are correlated, as happens in our sample. This approach is also particularly effective with small to moderate numbers of covariates, as in our case.

The estimates presented in Table 7 suggest no significant effect through the propensity score distance method as presented in column (i), although when using Mahalanobis distance in column (ii), it yields a positive and significant result, pointing to a relevant effect of IoT on energy productivity. Additional variations in terms of common support imposition or by using heteroskedasticity-consistent

analytical standard errors proposed by Abadie and Imbens (2006) contribute to validating the results.

Results are also robust when introducing a caliper. The selection of the caliper is important, as a very narrow one excludes units, while on the other hand, a wider one can allow poor matches. Some studies have suggested that the optimum Caliper is 0.2 (Austin, 2011), which we use in column (iii).

**Table 7. ATT of IoT on Energy Productivity – One to one matching**

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
ATT (IoT)	0.031169 [0.074251]	0.178855** [0.073702]	0.159384* [0.083712]	0.178973** [0.073728]	0.178855*** [0.069249]	0.178973*** [0.069172]
Common support	NO	NO	NO	YES	NO	YES
Abadie and Imbens (2006) standard errors	NO	NO	NO	NO	YES	YES
Distance method	PSM	Mahalanobis	Mahalanobis	Mahalanobis	Mahalanobis	Mahalanobis
Untreated obs.	2,503	2,503	2,503	2,503	2,503	2,503
Treated obs.	1,977	1,977	1,094	1,975	1,977	1,975
Off support	0	0	883	2	0	2
Caliper	-	-	0.2	-	-	-

*Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .*

*Source: authors' analysis*

A disadvantage of the nearest neighbor procedure is that it can be vulnerable to poor matches if the nearest neighbor is distant. Also, some of the untreated ones are discarded (nearly 500 in our case), which reduces sample size and statistical power. To curb this issue, we conduct further estimates through other matching methodologies.

We test three alternative matching methods. First, k-neighbors matching balances some of the bias by using more than one control per treated unit. It is expected to be efficient with large control pools. However, as the number of controls increases, the quality of the matches may be reduced. A broader one-to-many match will increase sample size and efficiency but can also result in greater bias from matches that are not as close as the initial match (Garrido et al, 2014). We will check both 3 and 5 neighbor estimates.

Second, kernel matching has the advantage of maximizing sample retention. Under this approach, each treated observation is given a weight of one. A weighted composite of comparison observations is used to create a match for each treated observation, where comparison ones are weighted by their distance in score from treated individuals within a range. Only observations outside the range of common support are discarded. According to Garrido et al (2014), kernel matching maximizes precision by retaining sample size, without worsening bias (by giving greater weight to better matches).

Finally, we also test radius matching, as it retains all controls within a specific caliper. This method seems to work well with large control groups, as in our sample.

Results are presented in Table 8. We also provide results when imposing a caliper of 0.2. In all cases we rely on Mahalanobis distances, that seemed to work better in the context of our sample.

**Table 8. ATT of IoT on Energy Productivity – Alternative matching methods**

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
ATT (IoT)	0.129398** [0.064859]	0.079173 [0.061906]	0.150092** [0.063636]	0.142137** [0.057163]	0.171644** [0.078595]	0.001519 [0.038375]	0.138976* [0.075880]
Untreated obs.	2503	2503	2503	2503	2503	2503	2503
Treated obs.	1977	1977	1094	1094	980	1977	1094
Off support	0	0	883	883	997	0	883
Method	3-neighbor	5-neighbor	3-neighbor	5-neighbor	Kernel	Radius	Radius
Caliper	-	-	0.2	0.2	-	-	0.2

*Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . All estimates conducted using Mahalanobis distances.*

*Source: authors' analysis*

Results confirm a positive and significant effect from IoT to energy productivity in almost all cases. The exceptions are the 5-neighbor estimation presented in column (ii), for which the quality is a little poor under so many controls, and in the radius matching presented in column (vi). However, when imposing a caliper, the results become positive and significant, under both methodologies.

Under the most conservative and statistically significant estimates, IoT adoption will increase energy productivity by 12.9%. This is a more moderate figure than the one obtained under the differences-in-differences estimator with a reduced sample.

## 6. Conclusions and guidelines for future research

The aim of this article is to analyze the role of IoT adoption as a tool to enhance energy productivity across firms. Drawing on a unique and previously unused dataset from a survey conducted by the EIB, this study analyzes firm-level data spanning multiple sectors across 26 European countries during the 2022–2023 period. Our results indicate significant effects of IoT on energy productivity, although the impact seems to be concentrated among manufacturing/construction sectors and medium/big firms only.

These results suggest that digital technologies such as IoT can play a key role in energy transitions toward more sustainable economies. This is particularly relevant in a context in which the digital revolution is proving to be intensive in energy consumption, largely due to high scale datacenters and AI models. The evidence

presented in this paper shreds some light in how digitization can be an ally of the green agenda.

There are, however, plenty of unanswered questions and limitations that should be considered by future research on this topic. First, it remains necessary to understand why smaller and service-related firms seem to struggle to extract the efficiencies generated by IoT. In particular, the key role of digitization for the green agenda cannot be limited to medium and big firms, if it aims to be successful. Second, our sample presented important limitations, as only a small part of the surveyed firms was available as a panel, which limits the identification of the treatment effects.

From a policy perspective, the evidence found in this article supports the initiatives that have been promoting most European countries in linking the digital and the green agendas. A critical policy area to be addressed remains the case of smaller firms, that typically lag behind in digital adoption, and also in their capacity to extract efficiency gains from technology. Targeted plans aimed at helping micro and small firms to adopt cutting-edge technologies is critical. Otherwise, the future impact of IoT will be constrained only to a small group of larger companies.

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## Appendix

**Table A1. Probit model of drivers of IoT adoption**

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Inv. intensity	0.000000** [0.000000]	0.000000** [0.000000]	0.000000 [0.000000]	0.000000 [0.000000]	0.000000 [0.000000]	0.000000 [0.000000]	0.000000 [0.000000]
Foreign firm		0.081137*** [0.013246]	0.030773 [0.020614]	0.026976 [0.023647]	0.028034 [0.023898]	-0.017100 [0.038612]	0.026988 [0.038426]
TFP			0.000003*** [0.000001]	0.000004*** [0.000001]	0.000004*** [0.000001]	0.000002*** [0.000001]	0.000002** [0.000001]
Green investment				0.341613*** [0.019498]	0.340854*** [0.019858]	0.291444*** [0.031490]	0.192496*** [0.031458]
Firm age					0.008674 [0.012846]	-0.034404*** [0.013126]	-0.042435* [0.021771]
Small firm						0.141292*** [0.028876]	0.069356 [0.047094]
Medium firm						0.291942*** [0.029680]	0.205595*** [0.048416]
Big firm						0.602882*** [0.034513]	0.536382*** [0.056540]
Energy efficiency inv.							0.248155*** [0.032206]
Sector dummies	YES	YES	YES	YES	YES	YES	YES
Country dummies	YES	YES	YES	YES	YES	YES	YES
Observations	74,229	74,229	25,734	19,916	19,913	19,913	7,639

Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Robust standard errors in brackets.

Source: authors' analysis