ECONOMICS – WORKING PAPERS 2024/04

The impact of the digital and green transitions on investment inefficiency

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European Investment Bank

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Published by the European Investment Bank.

Printed on FSC® Paper.

pdf: QH-01-24-012-EN-N ISBN 978-92-861-5824-7 ISSN: 2599-736X doi: 10.2867/1050208

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The impact of the digital and green transitions on investment inefficiency[1]

Francesco Cimini[#] and Fotios Kalantzis[Δ]

Abstract – *This study examines the impact of green and digital investments on the investment inefficiency level of European firms. We define investment inefficiency as the deviation from the optimal investment level, which depends on both the net present value (NPV) of the projects and the marginal benefit and cost of investment. Leveraging matched data from the European Investment Survey (EIBIS) and ORBIS, which results in a sample of 4,892 firm-year observations from 27 European countries surveyed over the period 2021-2023, we employed a panel data regression model to estimate the effect of green and digital investments on investment inefficiency. Our analysis shows that both types of investments reduce investment inefficiency, particularly for under-investing firms. We also find evidence of a statistically significant interaction effect between green and digital investments for over-investing firms, suggesting that digital technologies can enhance the efficiency gains from green investments. Our results have important implications for policy makers and business managers who aim to foster the twin digital and green transition in Europe and improve their investment efficiency and competitiveness.*

J.E.L. Classification Numbers: M41, G31, Q53, O33

Keywords: European Investment Bank Investment Survey, Investment Inefficiency, Green investment, Digital investment, Twin transition.

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[1] We are very grateful to Sofia Dominguez and Christoph Weiss (EIB) for the useful comments and suggestions. The views expressed in this paper do not necessarily reflect those of the European Investment Bank. The usual disclaimers apply.

1 – Introduction

Digitalisation and the green transition are two of the most important trends characterising the European economy nowadays. In 2022, 53% of European firms invested in measures aimed at adapting to weather events and reducing GHG emissions; at the same time, 46% of them invested in digitalisation, a trend which was reinforced by the COVID-19 pandemic (European Investment Bank, 2022). These transformations are likely to further reinforce under the impulse of strong policy support in the European Union. Specifically, with the aim of achieving the goals set forth in the European Green Deal, the European Commission aims at mobilising around €1tn over the 2021-2030 period to finance green investments; at the same time, around a third of the €750bn Next Generation EU Funds will be devoted to digitalisation. Furthermore, the development of Industry 4.0-related technologies has gained considerable momentum since the introduction of the European Industry Initiative in 2016 (Teixeira and Tavares-Lehmann, 2022).

The literature points to the existence of important mutual implications between investments in green and digital technologies (see Ortega-Gras et al., 2021; Husain et al., 2022; Fouquet and Hippe, 2022) and goes so far as to analyse them jointly as the "twin transition". Whether, however, digitalisation can enhance the green transition or slow it down is still controversial (Bianchini et al., 2023). Some scholars tend to adopt an optimistic stance, arguing that digitalisation has a positive impact on the transition (Haller et al., 2023; Lesecq et al., 2022). In their view, digitalisation results in a larger availability of data about production processes, thereby allowing to optimise them, monitor their environmental impact, and reduce industrial waste (Muench et al., 2022). Other scholars are instead more pessimistic. Andersen et al. (2021) suggest that the digitalisation of the economy may encourage the adoption of environmentally unsustainable practices. Also, in advanced countries, data centres consume significant amounts of energy (Strubell, 2019). Needhidasan et al. (2014) outline the issue of disposing technological devices, which contain many elements that cannot be recycled. Finally, Fouquet and Hippe (2022) suggest that communication transitions tend to be faster than energy transitions, which may result in a high-carbon structural transition of the economy.

This paper attempts to analyse the relationship between the twin digital and green transition and investments inefficiency levels on a sample of European firms. The concept of investment efficiency is a direct by-product of an intense scholarly effort which, starting from Franco Modigliani and Merton Miller's 1958 seminal paper on the irrelevance of firm's capital structure, attempted to construct a theory of optimal corporate investment. In particular, according to Modigliani and Miller (1958), in a world without market frictions firms should invest in all projects showing a positive net present value (NPV). Hayashi (1982) built on this theory by adding that firms should keep investing until the marginal benefit of investment equals the marginal cost. Recognising that market frictions do exist, however, the literature has also examined the sources of potential investment inefficiencies. Specifically, agency problems and information asymmetries are understood as the main sources of deviation from optimal investment level (Myers and Majluf, 1984; Khediri, 2021). Hubbard (1998) points to financing constraints as a source of frictions, while Jensen and Meckling (1976) outline the role of agency problems as a source of inefficiencies. In particular, firms may under-invest or over-invest. In a scenario with no market frictions, efficient investment amounts to selecting all projects with a positive NPV; thus, over-investment amounts to selecting projects with a negative NPV, while under-investment amounts to forgoing some projects that nonetheless have a positive NPV (Biddle et al., 2009).

In the first place, our study attempts to assess whether corporate digital and green investments can, separately, affect a firm's investment efficiency level; then, it focuses on firms embarking on the twin transition, that is to say, on an investment strategy comprising green and digital investments at the same time. The existing literature documents a negative relationship between green investments and investment inefficiency, on one side, and between digitalisation and investment efficiency on the other. Arguably, however, it does not address thoroughly the interaction between investment inefficiency and a “twin” investment strategy involving both digitalisation and climate-related investments. Should these latter engage in a mutually reinforcing relationship, there might be positive spillovers on the overall investment strategy, resulting in a lower level of investment inefficiency; conversely, a mutually destructive relationship between the two may lead to a suboptimal investment plan, signalled by a higher investment inefficiency. In order to assess the effect of a combination of green and digital investments, this paper combines the *ORBIS* dataset with European Investment Bank Investment Survey (*EIBIS*) dataset, which provides insight into the investment behaviour of a large set of European companies.

Our analysis yields three key results. First, we show that green investments, aimed at mitigating climate change or at enhancing firms’ resilience to climate change-related adverse events, reduce investment inefficiency, and that this effect is largely driven by under-investing firms. We also show that investments in digital technologies reduce firms’ investment inefficiency level. These results are robust to alternative tests. Finally, we find evidence that a moderating effect of digital investments on green investments exists for firms that over-invest, whereby digital investments enhance the positive effect of green investments on investment efficiency.

The rest of the paper is organised as follows. Section 2 reviews the existing literature and presents the testing hypotheses. Section 3 presents the data and the methodology. Section 4 and 5 present and discuss the results, while section 6 concludes.

2 – Literature review and testing hypotheses

The purpose of this paper is to explore the relationship between investment inefficiency, green investments and investments in digital technologies, with a particular focus on whether digital investments can modify the effect, if any, of green investments on investment inefficiency. Several papers have addressed separately the effects of green investments on investment inefficiency and of digital investments on investment inefficiency. However, to the best of our knowledge, no study to date has dealt expressly with whether a joint effect of digital and green investments on investment efficiency is verified. To shed some further light on the topic, we start by reviewing the literature. The three research streams - green and digital investments on investment efficiency, as well as the twin transition - are analysed separately.

2.1 – Green investments and investment inefficiency

Climate change poses a severe threat to the stability of the biosphere and prompt action is needed in order to slow it down and reverse its pace (IPCC, 2014). To this purpose, many firms have already adopted measures to limit their climate footprint (European Investment Bank, 2022). Whereas few research papers have investigated whether these efforts can impact a firm’s investment efficiency level, several studies have addressed the relationship between corporate social responsibility and investment inefficiency (see, for instance, Lee, 2020; Khediri, 2021; Benlemlih and Bitar, 2015; Samet and Jarboui, 2017; Cook et al., 2018; Erawati et al., 2021). Since green investments are a type of Corporate Social Responsibility (CSR) engagement, it is worth addressing the main results of these papers.

Two conflicting views exist on the effects of corporate CSR engagement. According to the first stream of thought, which can be traced back to Friedman (1970), managers adopting CSR initiatives are arbitrarily channelling funds towards negative-NPV projects in what constitutes an agency problem. Krüger (2015) builds on this view and argues that CSR practices create conflicts between stakeholders. Some early empirical results (see Aupperle et al., 1985) support this argument, showing that CSR investments have a depressing effect on firm performance. Instead, according to the *Stakeholder Theory* (Freeman et al., 2010), CSR can enhance firm value. Following this view, Porter and Kramer (2006) argue that, if carefully embedded in corporate strategy, CSR engagement can foster firms' competitiveness.

The scholarly debate on the effects of CSR is far from resolved and, since Friedman and Freeman's attempts, it has extended to various aspects of business performance, including investment inefficiency. Using a sample of Western European firms observed from 2004 to 2011, Khediri (2021) documents a negative correlation between CSR engagement and investment inefficiency. The correlation is stronger for those CSR practices that address primary stakeholders. He argues that the reduction of information asymmetries is the main channel through which this effect materialises. Lee (2020) shows that CSR "significantly mitigates investment inefficiency among Taiwanese firms". Using a sample of Indonesian companies, Erawati et al. (2021) find that higher CSR involvement mitigates the suboptimal investment behaviour which typically characterises family businesses. Cook et al. (2018) use a large dataset of publicly traded companies and find that firms with high CSR engagement invest more efficiently. Likewise, Samet and Jarboui (2017) use a panel of around 400 European listed companies and find that better CSR performance helps bring corporate investment levels closer to the optimum. They also point to the reduction of information asymmetries as the main driver of this effect. Finally, in an influential paper involving US firms, Benlemlih and Bitar (2015) use a sample of 21,030 firm-year observations and find a strong negative correlation between firms' CSR involvement and investment inefficiency, and that once again such effect is more pronounced when considering CSR practices that address firms' main stakeholders.

Conversely, the correlation between green investments and investment inefficiency has received less scholarly attention. Kim and Kim (2023) find that investment inefficiency correlates positively with firm-level greenhouse gas emissions in a sample of Korean firms. Using a panel of Chinese listed companies, Zeng et al. (2019) also find that environmental commitment has a strong negative effect on investment inefficiency, which however needs some time to manifest itself.

Notwithstanding the scarcity of empirical results, we are then able to predict that higher environmental commitment lowers firms' investment inefficiency, and we postulate the following hypothesis:

H1: *Climate action reduces the investment inefficiency level of EU firms.*

2.2 – Digitalisation and investment efficiency

Corporate digitalisation can be understood as the progressive incorporation of digital technologies into an organisation's processes. Nowadays, many firms rely on digital technologies for conducting their business operations; not coincidentally, digitalisation as a research topic in the field of social sciences has been drawing significant interest over the last years.

Digitalisation is generally thought of as improving firm performance (Jung and Gómez-Bengoechea, 2022). Thanks to digitalisation, firms can analyse large amounts of data and identify new business opportunities (Benitez et al., 2022). Also, digitalisation can potentially lower communication costs (Jorgenson, 2001), both between the firm and external stakeholders (Yu et al., 2010) and at an internal firm level (Zhai et al., 2022). Finally, according to Ribeiro-Navarrete et al. (2021), digitalisation, when applied to production processes, has the power to generate competitive advantages.

Empirically, many studies confirm the existence of a positive effect of digitalisation on company performance (Jung and Gomez-Bengoechea, 2022). These studies outline that such effect materialises through the channels that were just outlined. However, not all studies agree with these general findings. For instance, Aral and Weill (2007) find that digitalisation does not significantly affect performance, while Cappa et al. (2021) find a negative relationship. Instead, the relationship between a firm's digitalisation effort and investment inefficiency has drawn less academic attention. Huo and Wang (2022) analyse a panel of Chinese listed companies observed from 2007 to 2019 and find that the development of the digital economy has a negative effect on firm-level investment inefficiency by reducing over-investment. Xu et al. (2023) also use a panel of Chinese listed companies to examine the effect of firm-level inefficient investment on digital transformation; they find that corporate investment inefficiency is detrimental to firm-level digitalisation, and that such negative relationship is exacerbated by the presence of financing constraints.

Based on the findings of these studies, we can predict that higher levels of corporate investment in digital technologies will be associated with lower levels of investment inefficiency. Thus, we postulate the following:

> ***H2:*** *Digital investments reduce the investment inefficiency level of EU firms.*

2.3 – Digitalisation, green investments and investment efficiency

At a theoretical level, digitalisation has the potential to affect firms' green transition to a significant extent (Mondejar et al., 2021). Muench et al. (2022) attempt to classify the various channels by which digitalisation impacts the transition, showing that the interplay between the two revolves essentially around the opportunity offered by digital technologies to analyse large amounts of data. By acquiring valuable and detailed information, firms may monitor their activities and reduce production waste; they could also identify new and more efficient production processes employing forecasting techniques. Additionally, virtualising commercial practices reduces the need for people to relocate, which lowers emissions and increases efficiency. Other channels may exist in some specific industries. For instance, in the transport sector, the availability of data can help optimise traffic flows, thus reducing emissions and reducing inefficiency (Muench et al., 2022). That digitalisation affects the green transition in firms is also supported by theoretical evidence. Using a panel of Chinese listed companies observed from 2007 to 2020, Liu et al. (2023) find that digitalisation improves corporate green innovation. Li et al. (2023) also use a panel of Chinese companies to show that digitalisation fosters green innovation at multiple levels.

To the best of our knowledge, the relationship between digitalisation, green investments and investment efficiency has never been addressed directly by the academic literature. This paper, among other things, hypothesises the following:

> ***H3***: *Green investments reduce investment inefficiency more effectively for firms that also invest in digital technologies.*

3 – Data and Methodology

3.1 – Sample Selection

To examine empirically the relationship between green investments, investments in digital technologies and investment inefficiency, we use data from two sources: the 2024 edition of the annual European Investment Bank Group Survey on Investment and Investment Finance (*EIBIS*) and the Bureau van Dijk *ORBIS* database. *EIBIS* is an EU-wide survey that gathers information on firms' investment activities and financing requirements since 2016. It uses a stratified sampling methodology and is designed to be representative at the EU, country, sectoral and firm size levels. The Bureau van Dijk's *ORBIS* database provides the balance sheets and income statements of the surveyed firms. The main advantage of the dataset is that it provides unique information on firms' investments to tackle climate change-related risks and digital adoption, as well as other variables that describe their profiles and financial positions.

To construct our sample, we consider *EIBIS* firms with non-missing financial information observed from 2021 to 2023 in the 27 EU Member states. EIBIS does not include financial firms. This is convenient, in that their investment behavior is affected by government regulation; thus, including them would weaken the validity of our results. Not coincidentally, several papers (such as Biddle et al., 2009, Chen et al., 2017 and Benlemlih and Bitar, 2015) exclude financial firms from their analyses. Our final sample includes 4,892 firm-year observations derived from 3,628 different firms. Table 1 presents the sample distribution by year, country and sector. The sectorial classification is based on four broad categories: manufacturing, infrastructure, services and construction[2].

Most of the observations were taken in 2021 and 2022, with 2023 accounting for as little as 10% of the overall sample. The reason is that only a fractional portion of the firms that were surveyed in 2023 had published their annual reports at the time the survey was taken. The sectorial distribution is more balanced, although manufacturing is slightly overrepresented as it accounts for almost 34% of observations, while construction is underrepresented (19%). Finally, we consider the regional breakdown[3]. Firms in Central and Eastern Europe are overrepresented with 42% of observations, while firms in Southern Europe account for around 29% of the observations each.

3.2 – Explanatory variables

3.2.1 - The GREEN *variable*

We selected two variables from the *EIBIS* questionnaire to quantify firms' investment level in green and digital technologies. First, we focus on green investments. Variable *GREEN* is a dummy variable that equals one if a firm reported investing in measures to tackle the impact of weather events or to reduce carbon emissions in a given year. These measures may include both adaptation and mitigation actions.

Table 1 also presents the distribution of *GREEN* by year, sector and country group. Over the three years, an increasing number of firms reported investing or having invested in mitigation or adaptation. Such increase was particularly pronounced between 2021 and 2022, arguably a positive rebounding after the economic shock caused by the COVID-19 pandemic. When considering the regional distribution, the highest average value for *GREEN* (around 50%) is observed in Western and Northern Europe, while the lowest value (around 31%) is observed in Central and Eastern Europe. Manufacturing and transportation have the highest average value for this variable.

3.2.2 - The DIGITAL *variable*

Variable *DIGITAL* instead is a dummy equal to one if the firm in a given year implemented multiple digital technologies. A first striking difference with *GREEN* is that average values tend to be higher with *DIGITAL*. In economic terms, this means that firms are on average more prone to invest in digital technologies than to invest in technologies aimed at reducing emissions or making the firm more resilient to climate-change-related events.

Table 1 also shows the distribution of *DIGITAL* by year, sector and country group. Once again, we observe a strong positive rebounding between 2021 and 2022, although figures decline between 2022 and 2023. Manufacturing and transportation still retain the two top positions, while construction is again the one with lowest values. The regional distribution is fairly balanced, with Western and Northern Europe still displaying the highest value.

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[2] Based on the *NACE* classification of economic activities, (a) "Manufacturing" includes firms in group C, namely manufacturing companies; (b) "Construction" includes firms in group F (construction companies); (c) "Services" includes firms in group G (wholesale and retail trade) and I (accommodation and food services activities) while (d) "Infrastructure" includes firms in group E (utilities), H (transportation and storage) and J (information and communication).

[3] Western and Northern Europe includes the following countries: Austria, France, Germany, Luxembourg, Netherlands, Sweden, Finland, Ireland, Denmark, Belgium; Southern Europe includes Cyprus, Italy, Malta, Spain, Greece, Portugal; Eastern Europe includes Bulgaria, Romania, Slovenia, Czech Republic, Slovakia, Poland, Latvia, Lithuania, Estonia, Hungary, Croatia.

3.3 – The dependent variable: investment inefficiency

Investment inefficiency can be thought of as the extent to which firms fail to undertake all projects with positive net present value. Obtaining a measure of a firm's level of investment inefficiency is difficult, however, because the full array of projects that are available to a firm cannot be observed. In order to quantify the investment inefficiency level associated with a company i in year t, we follow prior research (e.g., Benlemlih and Bitar, 2015; Biddle et al., 2009; Gomariz and Ballesta, 2014; Mazboudi and Hasan, 2018) to estimate the firm-specific model of investment (measured by capital expenditures over one-year lagged total assets) as a function of growth opportunities (measured by annual sales growth), and then use residuals as a firm-specific proxy for deviation from expected investment, representing the level of investment inefficiency. Specifically, this paper uses the residuals from the following equation as the investment inefficiency variable:

$$INV_{i,t} = \mu_0 + \mu_1 SALESGROWTH_{i,t-1} + \gamma_{i,t} \tag{1}$$

where $INV_{i,t}$ is the yearly variation in fixed assets plus depreciation, all scaled by lagged total assets of firm i in year t, while $SALESGROWTH_{i,t-1}$ is the rate of change in sales of firm i from $t-2$ to $t-1$. Because measurement errors in most datasets affect more than 1% of observations in each tail (Hampel et al., 1986), we winsorise these variables – $INV_{i,t}$ and $SALESGROWTH_{i,t}$ – at the 10% level. The equation is then estimated cross-sectionally for each year and sector for all industry-years with at least 15 observations. The sectorial classification is based on NACE two-digit codes. The residuals $\gamma_{i,t}$ from the regression model reflect the deviation from the expected investment level, and they are used as a firm-specific proxy for investment inefficiency. The positive residual indicates over-investment, while the negative residual indicates under-investment (Jensen, 1986; Biddle et al., 2009). Since both under-investment and over-investment are considered inefficient investments, we take the absolute value of the residuals and use it as a firm-specific proxy for investment inefficiency.

Similar to the variables *GREEN* and *DIGITAL*, we look once again at the distribution by year, sector and region (see Table 1). Although the absolute level of inefficiency has little economic significance, relative values of inefficiency can provide useful insight. Investment inefficiency has remained stable over the years; also, the level of investment inefficiency in Central and Eastern European countries is significantly higher than that of other regions. Likewise, the construction sector shows a higher level of investment inefficiency than the other sectors, which are fairly aligned.

3.4 – Other explanatory variables

To control for country-, sector- and year- specific effects, we include three categorical variables, namely, *COUNTRY*, *SECTOR* and *WAVE*. *COUNTRY* includes all the 27 EU Member states, while *SECTOR* is based on a broad classification which categorises firms as belonging to either, manufacturing, services, construction and infrastructure.

Moreover, in order to identify the effect of green investments and investments in digital on investment inefficiency, and following a large body of previous research (among others, Benlemlih and Bitar, 2015; Lee, 2020; Khediri, 2021; Jensen, 1986), we include several control variables. These variables may have an impact on a firm's investment inefficiency level, and including them reduces the risk of omitted variable bias.

Managers may be inclined to exercise caution if the firm is experiencing lower profitability. They may become particularly careful if the firm is incurring losses. For this reason, following Benlemlih and Bitar (2015), we include variables *PROF* and *LOSS*. The former is defined as EBITA/Total assets as it appears in the financial statement of the year prior to the survey, while the latter is a dummy equal to one if the firm experienced a loss during the financial year prior to the survey. We then predict that the sign of the relationship between *LOSS* and investment inefficiency be negative and, similarly, we predict a positive correlation between *INVEFF* and *PROF*.

AGE is the natural logarithm of the difference between survey year and the year in which company *i* was founded. According to Benlemlih and Bitar (2015), older companies may have more financial experience, which reduces their investment inefficiency. On the other hand, however, they may also have more financial resources, which may be used in unproductive ways (Lee, 2020). For this reason, we do not predict the sign of the coefficient associated with this variable.

Following Benlemlih and Bitar (2015) we also include *LEV*, a proxy for firm's leverage, computed as the ratio between the sum of loans and long-term debts over total assets. According to Jensen (1986), a higher leverage ratio generates agency problems when obtaining additional funds, which raises investment inefficiency; at the same time, however, debt holders play a monitoring role on the firm, reducing investment inefficiency (Lee, 2020; Benlemlih and Bitar, 2015; Jensen, 1986). Thus, this paper does not predict the sign of the relationship between a firm's financial leverage level and its level of investment inefficiency.

Following Chen et al. (2011) and Benlemlih and Bitar (2015), we include *TANG*, a proxy for the collateral value of assets, computed as the ratio between fixed assets and total assets. The higher the collateral value of assets, the easier it is for managers to raise funds, which may lead to investment inefficiency (Lee, 2020). Therefore, this paper predicts a positive relationship between the level of collateral value of assets and investment inefficiency.

As a measure of financial slack, we include *CASH*, a variable defined as cash reserves to total assets for firm *i* in year *t*. Higher cash reserves may lead to greater agency problems and thus to higher investment inefficiency (Benlemlih and Bitar, 2015; Khediri, 2021). At the same time, however, managers are more likely to engage in projects with positive NPV if there is more cash available, which increases investment efficiency (Lee, 2020). For these reasons, once again, we do not predict the sign of the correlation between cash level and the level of investment inefficiency.

Table 1 – *Descriptive Statistics*

	#Obs	Frequency	GREEN	Sd(GREEN)	DIGITAL	Sd(DIGITAL)	INV	Sd(INV)	SALESGROWTH	Sd(SALESGROWTH)	INVEFF	Sd(INVEFF)
Whole sample	4.748	100%	37,64%	0,4845	32,58%	0,4687	5,22%	0,0569	4,32%	0,1740	4,3535	3,2951
2021	2.515	53,0%	32,76%	0,4694	29,03%	0,4540	5,00%	0,0556	-2,46%	0,1547	4,2847	3,2912
2022	1.768	37,2%	42,59%	0,4946	37,67%	0,4847	5,48%	0,0579	11,68%	0,1636	4,4304	3,3192
2023	465	9,8%	45,16%	0,4982	32,47%	0,4688	5,41%	0,0591	12,88%	0,1590	4,4329	3,2223
Manufacturing	1.633	34,4%	45,01%	0,4977	39,01%	0,4879	5,51%	0,0543	3,95%	0,1732	4,1877	3,2345
Construction	890	18,7%	23,82%	0,4262	15,17%	0,3589	4,86%	0,0587	4,67%	0,1994	4,7408	3,3901
Services	1.040	21,9%	32,69%	0,4693	31,25%	0,4637	3,63%	0,0472	4,64%	0,1720	3,3500	3,0465
Transportation	1.185	25,0%	42,19%	0,4941	37,97%	0,4855	6,50%	0,0629	4,29%	0,1555	5,1716	3,2607
Central and Eastern Europe	2.012	42,4%	31,41%	0,4643	29,22%	0,4549	5,66%	0,0594	4,91%	0,1794	4,5669	3,4303
Southern Europe	1.358	28,6%	34,76%	0,4764	32,84%	0,4698	4,64%	0,0542	3,37%	0,1816	4,2106	3,2050
Western and Northern Europe	1.378	29,0%	49,56%	0,5002	37,23%	0,4836	5,15%	0,0552	4,39%	0,1571	4,1826	3,1633

	LOSS	Sd(LOSS)	PROF	Sd(PROF)	AGE	Sd(AGE)	LEV	Sd(LEV)	TANG	Sd(TANG)	CASH	Sd(CASH)
Whole sample	13,06%	0,3370	12,43%	0,2084	29,7917	20,0809	18,33%	0,2712	38,58%	0,2550	14,36%	0,1620
2021	15,63%	0,3632	11,58%	0,2192	30,5189	20,4812	18,41%	0,2010	39,40%	0,2547	14,32%	0,1632
2022	10,24%	0,3032	13,25%	0,2038	29,0470	19,8760	18,45%	0,3409	38,14%	0,2544	14,11%	0,1577
2023	9,89%	0,2989	13,94%	0,1578	28,6903	18,4929	17,50%	0,3014	35,81%	0,2563	15,54%	0,1707
Manufacturing	13,53%	0,3422	12,78%	0,1858	33,9106	22,8938	18,66%	0,1824	40,09%	0,2043	12,06%	0,1411
Construction	8,31%	0,2763	12,45%	0,1596	24,5214	14,2242	14,40%	0,1770	28,22%	0,2198	18,15%	0,1748
Services	13,65%	0,3435	11,55%	0,2689	29,3615	18,6803	19,45%	0,2701	31,09%	0,2513	13,40%	0,1594
Transportation	15,44%	0,3615	12,71%	0,2095	28,4515	19,7456	19,87%	0,3999	50,86%	0,2881	15,52%	0,1746
Central and Eastern Europe	12,13%	0,3265	13,63%	0,1670	24,1879	14,8037	16,95%	0,3375	42,48%	0,2608	13,69%	0,1638
Southern Europe	14,58%	0,3530	8,12%	0,1919	33,0655	18,9571	23,77%	0,2193	37,20%	0,2450	13,65%	0,1508
Western and Northern Europe	12,92%	0,3355	14,94%	0,2646	34,7475	25,1968	15,00%	0,1884	34,26%	0,2476	16,03%	0,1687

Table 1 presents the dataset. In the first section (upper-left corner), observations are classified based on wave, sector and region. All other sections present mean and standard deviations for the variables that are used in the model, be they the variables of the investment efficiency equation (*INV* and *SALESGROWTH*) or the variables of the main models (*INVEFF, GREEN, DIGITAL, LOSS, PROF, AGE, LEV, TANG, CASH*). For each variable, means and standard deviations by wave, sector and region are also shown.

3.5 – Models

To test our hypotheses, and following the approach taken by Kim and Kim (2023), we run three separate regressions aimed at testing, respectively, the impact of green investments on investment inefficiency, the impact of investments in digital on investment inefficiency, and the moderating effect of investments in digital on the relationship, if any, between green investments and investment inefficiency. The first regression is the following:

$$INVEFF_{i,t} = \beta_0 + \beta_1 GREEN_{i,t-1} + \beta_2 LOSS_{i,t} + \beta_3 PROF_{i,t} + \beta_4 AGE_{i,t} + \beta_5 LEV_{i,t} + \beta_6 TANG_{i,t} + \beta_7 CASH_{i,t} + \sum \beta_j\, COUNTRY + \sum \beta_k\, SECTOR + \sum \beta_w\, WAVE + \varepsilon_{i,t} \quad (2)$$

Where $INVEFF_{i,t}$ is investment inefficiency; β_0 is a constant; $GREEN_{i,t-1}$ is our explanatory variable for this model, namely green investments; $LOSS_{i,t}$ is a dummy equal to one if the firm experienced a loss in the financial year prior to the survey; $PROF_{i,t}$ is the company's profitability level defined as EBITA/Total assets as of the financial statement prior to the survey; $AGE_{i,t}$ is the age of the company; $LEV_{i,t}$ is the leverage ratio, defined as loans and long-term debt over total assets; $TANG_{i,t}$ is a proxy for the collateral value of assets and $CASH_{i,t}$ is a proxy for financial slack. Finally, $\sum\beta_j COUNTRY$, $\sum\beta_k SECTOR$ and $\sum\beta_w WAVE$ are the country, sector and time fixed effects. The former, $\sum\beta_j COUNTRY$, is a set of dummy variables mapping the 27 different EU Member states; $\sum\beta_k SECTOR$ maps instead the four sectors firms may belong to – manufacturing, transportation, services and transportation. Similarly, $\sum\beta_w WAVE$ maps the waves. Finally, $\varepsilon_{i,t}$ is the error term. The equation is estimated using the random effect generalised least squares method. The use of this methodology instead of the fixed effects approach is warranted whenever many entities are observed during a short period of time and in presence of a large number of time-invariant variables. In these cases, the fixed-effects method would lead to multicollinearity issues and inconsistency of the estimators (Baltagi, 2005; Pathan, 2009). Indeed, in our sample the *N* is very large compared to the number of survey waves; moreover, fixed effects estimation would inevitably lead to the exclusion of all country and sector fixed effects as they are time-invariant.

To mitigate the risk of omitted variable bias, we set temporal precedence and regress $INVEFF_{i,t}$ on the one-year lag of variable $GREEN_{i,t}$. Since the control variables are mainly taken from financial statements, they refer to the financial year prior to the survey, thus both $GREEN_{i,t-1}$ and the control variables refer to the same period. Because we predict that green investments reduce a company's investment inefficiency, we expect β_1 to be negative and significant.

As far as our second hypothesis is concerned, we run a slightly modified version of the previous model, where *GREEN* is replaced by *DIGITAL* as the main explanatory variable. This latter is a dummy equal to one if, as of the survey year, the company incorporates multiple digital technologies in its business. The model will be as follows:

$$INVEFF_{i,t} = \beta_0 + \beta_1 DIGITAL_{i,t-1} + \beta_2 LOSS_{i,t} + \beta_3 PROF_{i,t} + \beta_4 AGE_{i,t} + \beta_5 LEV_{i,t} + \beta_6 TANG_{i,t} + \beta_7 CASH_{i,t} + \sum \beta_j\, COUNTRY + \sum \beta_k\, SECTOR + \sum \beta_w\, WAVE + \varepsilon_{i,t} \quad (3)$$

Once again, we set temporal precedence and regress $INVEFF_{i,t}$ on the one-year lag of $DIGITAL_{i,t}$. This latter is, again, temporally aligned with the control variables. Since our second hypothesis predicts that investments in digital technologies reduce investment inefficiency, we expect once again β_1 to be negative and significant.

Finally, to test our third hypothesis, we run a new version of the model that combines the previous two. In this final version, we add an interaction term between the one-year lags of $GREEN_{i,t}$ and $DIGITAL_{i,t}$, which aims at capturing the moderating effect of digital investments on the relationship, if any, between green investments and investment inefficiency. The mediator role of $DIGITAL_{i,t}$ is tested based on the intuition proposed by Baron and Kenny (1986) and frequently used in the subsequent literature (see Hicks and Tingley, 2011; Samet and Jarboui, 2017; Cook et al., 2018), whereby a moderating effect is verified to be in place if the coefficient associated with the interaction term is statistically significant. Notably, in line with Baron and Kenny (1986), whether the coefficients associated with the individual dummies *GREEN* and *DIGITAL* are statistically significant is, instead, not relevant to testing the moderator hypothesis. We thus run the following model:

$$INVEFF_{i,t} = \beta_0 + \beta_1 GREEN_{i,t-1} + \beta_2 DIGITAL_{i,t-1} + \beta_3 GREEN_{i,t-1} \times DIGITAL_{i,t-1} + \beta_4 LOSS_{i,t} + \beta_5 PROF_{i,t} + \beta_6 AGE_{i,t} + \beta_7 LEV_{i,t} + \beta_8 TANG_{i,t} + \beta_9 CASH_{i,t} + \sum \beta_j \, COUNTRY + \sum \beta_k \, SECTOR + \sum \beta_w \, WAVE + \varepsilon_{i,t} \tag{4}$$

Because of hypothesis 3, which postulates a moderating effect of digital investments, whereby these latter enhance the negative effect of green investments on investment inefficiency, we expect β_3 to be negative and significant. Given the above, we also disregard β_1 and β_2.

4 – Results

Table 2 presents the results of the three models outlined in the previous section, namely, the regression of *INVEFF* on *GREEN*, on *DIGITAL* as well as on *GREEN×DIGITAL*. We run the three models both without and with controls. Moreover, not only do we run them on the whole sample; we also run separate regressions using firms that over-invest exclusively (that is, firms with positive values of the residuals from the investment inefficiency equation) and using firms that under-invest exclusively (namely, firms with negative values of residuals). The two subsets, namely firms that over-invest and that under-invest, are not equal in size: most firms (3,024 observations, around 64% of the sample) under-invest, while only 1,724 over-invest (around 36%).

Generally speaking, we find that green investments are negatively associated with investment inefficiency in a statistically significant way. Indeed, the coefficient associated with *GREEN* is negative and statistically significant when adding controls, both when considering the overall sample as well as when considering under-investment only. Statistical significance, however, is not verified in the over-investment case. This confirms our hypothesis 1, namely, that green investments reduce the level of investment inefficiency. These results are in line with the empirical findings that we addressed in the literature review section (see Kim and Kim, 2023; Zeng et al., 2019).

We also find that investments in digital technologies are negatively associated with investment inefficiency and that such relationship is strongly statistically significant: the coefficient that we obtain from running regression *2* has a very low *p-value* both without and with controls. The same results emerge when considering the over-investment and under-investment subsets of our sample, as the coefficients associated with *DIGITAL* are negative and statistically significant at the 1% level when adding controls. This shows that our hypothesis 2 is also confirmed, which is to say, digital investments reduce the level of investment inefficiency. These findings are also in line with those of other authors, namely Huo and Wang (2022) and Xu et al. (2023).

Table 2 – *Main model results*

	GREEN (Lag)						DIGITAL (Lag)						GREEN (Lag) × DIGITAL (Lag)					
	Whole sample		Over-investment		Under-investment		Whole sample		Over-investment		Under-investment		Whole sample		Over-investment		Under-investment	
GREEN (Lag)	**-0.098**	**-0.180***	**-0.337**	**-0.248**	**-0.135***	**-0.174****							0.098	0.016	0.117	0.196	-0.120	-0.176**
	(0.101)	**(0.103)**	**(0.215)**	**(0.217)**	**(0.074)**	**(0.074)**							(0.127)	(0.125)	(0.266)	(0.266)	(0.091)	(0.088)
DIGITAL (Lag)							**-0.341*****	**-0.266****	**-0.952*****	**-0.578*****	**-0.149***	**-0.209*****	-0.157	-0.052	-0.534*	-0.117	-0.135	-0.218**
							(0.104)	**(0.103)**	**(0.222)**	**(0.217)**	**(0.077)**	**(0.075)**	(0.135)	(0.133)	(0.295)	(0.282)	(0.097)	(0.095)
GREEN (Lag) × DIGITAL (Lag)													**-0.446****	**-0.500****	**-0.943****	**-1.070****	**0.009**	**0.066**
													(0.213)	**(0.207)**	**(0.443)**	**(0.426)**	**(0.155)**	**(0.149)**
2022		0.130		0.119		0.201***		0.134		0.116		0.207***		0.130		0.141		0.204***
		(0.096)		(0.219)		(0.066)		(0.095)		(0.219)		(0.066)		(0.096)		(0.219)		(0.066)
2023		0.033		-0.345		0.402***		0.020		-0.370		0.391***		0.032		-0.374		0.406***
		(0.160)		(0.327)		(0.133)		(0.159)		(0.326)		(0.133)		(0.159)		(0.325)		(0.133)
Construction		0.620***		1.825***		0.045		0.590***		1.711***		0.031		0.577***		1.714***		0.015
		(0.142)		(0.315)		(0.091)		(0.142)		(0.318)		(0.092)		(0.142)		(0.320)		(0.092)
Services		-0.731***		-0.360		-0.765***		-0.728***		-0.340		-0.762***		-0.748***		-0.374		-0.774***
		(0.131)		(0.305)		(0.084)		(0.131)		(0.303)		(0.084)		(0.131)		(0.302)		(0.084)
Transportation		0.692***		0.065		1.006***		0.697***		0.033		1.022***		0.682***		0.002		1.019***
		(0.136)		(0.274)		(0.108)		(0.136)		(0.274)		(0.108)		(0.136)		(0.275)		(0.108)
LOSS		-0.214		-0.325		0.117		-0.227		-0.359		0.105		-0.229*		-0.382		0.108
		(0.138)		(0.351)		(0.092)		(0.138)		(0.352)		(0.092)		(0.138)		(0.352)		(0.092)
PROF		0.856**		2.512**		-0.487***		0.837**		2.541**		-0.515***		0.842**		2.531**		-0.503***
		(0.352)		(1.010)		(0.154)		(0.357)		(1.021)		(0.156)		(0.352)		(1.024)		(0.156)
AGE		-0.510***		-0.861***		-0.165***		-0.513***		-0.859***		-0.167***		-0.500***		-0.829***		-0.159***
		(0.082)		(0.172)		(0.060)		(0.082)		(0.169)		(0.060)		(0.082)		(0.172)		(0.060)
LEV		0.382		1.833***		0.014		0.380		1.811***		0.016		0.381		1.794***		0.007
		(0.321)		(0.625)		(0.181)		(0.322)		(0.623)		(0.183)		(0.321)		(0.621)		(0.181)
TANG		2.280***		4.724***		-0.341**		2.239***		4.639***		-0.376**		2.284***		4.697***		-0.346**
		(0.236)		(0.572)		(0.163)		(0.235)		(0.568)		(0.163)		(0.236)		(0.570)		(0.163)
CASH		0.038		0.473		0.248		0.018		0.408		0.241		0.007		0.349		0.230
		(0.296)		(0.876)		(0.212)		(0.295)		(0.873)		(0.211)		(0.295)		(0.875)		(0.211)
Constant	4.381***	4.631***	6.111***	5.753***	3.425***	3.446***	4.452***	4.666***	6.301***	5.889***	3.424***	3.459***	4.422***	4.646***	6.264***	5.791***	3.458***	3.503***
	(0.061)	(0.447)	(0.137)	(0.932)	(0.044)	(0.305)	(0.060)	(0.448)	(0.132)	(0.928)	(0.043)	(0.309)	(0.070)	(0.450)	(0.162)	(0.933)	(0.050)	(0.309)
Observations	4,748	4,748	1,724	1,724	3,024	3,024	4,748	4,748	1,724	1,724	3,024	3,024	4,748	4,748	1,724	1,724	3,024	3,024
Number of firms	3,540	3,540	1,472	1,472	2,427	2,427	3,540	3,540	1,472	1,472	2,427	2,427	3,540	3,540	1,472	1,472	2,427	2,427
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 2 presents the results obtained when running the main models, consisting of regressions of *INVEFF* on *GREEN* and *DIGITAL* as well as on their interaction. The coefficients reported in the table are accompanied by either three, two, one or zero stars, representing, respectively, a statistical significance level of 1%, 5%, 10% and higher than 10%. Below each coefficient the corresponding standard error is also present. Each of the three sections, referred to regressions of *INVEFF* on *GREEN*, *DIGITAL* and *GREEN×DIGITAL*, is further divided into three parts: regressions run using the whole sample; regression run over the sample of firms that over-invest only; regressions run over the sample of firms that under-invest only. For each of these parts, both the univariate and the multivariate analyses are shown. In particular, *LOSS*, *PROF*, *AGE*, *LEV*, *TANG* and *CASH* are the control variables. Year and sector fixed effects results are also shown in the table, while country fixed effects, although present, are not displayed.

Turning to the moderating role of digital investments on the relationship between green investments and investment inefficiency, we find that such effect is present when considering the whole set of firms as well as over-investing firms. Recalling that a moderating effect exists when the coefficient of the interaction term is statistically different from zero (Baron and Kenny, 1986), we note that the coefficients in these two cases are negative and statistically significant at the 5% level. Conversely, the coefficients are not statistically significant in the under-investment case. This constitutes evidence that a moderator role of digital investments exists whereby these latter enhance the positive effect of green investments on investment efficiency; our third hypothesis is then also verified.

Next, we consider control variables. A number of studies such as Cook et al. (2018) and Lee (2020) document a negative relationship between variable *LOSS* and investment inefficiency, perhaps reflecting the fact that managers may exercise extra care when choosing investments when their firm is under-performing. In our study, the coefficient associated with *LOSS* is generally not statistically significant. However, notably, PROF correlates positively and significantly with investment inefficiency, arguably reflecting that managers may be more inclined to dissipate financial resources when their firm is performing well, which confirm our predictions. Notwithstanding this, the sign of the coefficient reverses when we consider firms that under-invest, where indeed we observe a negative and statistically significant correlation. In line with the majority of studies (see Samet and Jarboui, 2017; Cook et al., 2018; Lee, 2020), *AGE* correlates negatively with investment inefficiency in a statistically significant way, indicating that older firms can deploy superior investment capabilities due to higher managerial experience. We also find strong evidence that higher financial leverage correlates positively with investment inefficiency for firms that over-invest, perhaps because highly leveraged firms have extra cash which enhances their agency problems, as suggested by Lee (2020). However, when considering the overall sample as well as firms that under-invest, we find no such statistical correlation, which perhaps reflects the contrasting effects about *LEV* that were outlined in section 3.4. When considering the overall sample, *TANG* correlates positively with investment inefficiency in a statistically significant way, and this effect is mainly driven by the sub-sample of over-investing firms. This is in line with the Lee's (2020) predictions and with our hypothesis. We also find that higher *CASH* has no statistically significant correlation with investment inefficiency.

Finally, we address briefly fixed effects. Wave 2022 is associated with a higher inefficiency level than wave 2021 for under-investing firms; inefficiency is even higher when considering wave 2023. Moreover, firms in the construction and transportation industry have a higher inefficiency level than manufacturing firms.

5 – Robustness checks

5.1 – First alternative specification of the investment efficiency equation

In line with previous research (see Biddle et al., 2009), we run additional tests to check the validity of our results. As a first robustness check, we design a different investment efficiency equation which attempts to fix an issue that emerges when using the standard equation described in the previous pages and used in many studies. Indeed, when running equation (1) cross-sectionally by each year and each industry, some of the estimated coefficients associated with *SALESGROWTH* turn out to be negative. In other words, when using equation (1), some of the values of the *INVEFF* variable, which constitute one of the pillars of the research design, result from equations which model a negative relationship between firms' growth opportunities and investment growth. This is clearly counterintuitive; to fix this issue, we run a modified version of regression (1) which is not estimated cross-sectionally by year and industry, but rather across the whole sample of observations, and which includes country, year and industry fixed effects:

$$INV_{i,t} = \mu_0 + \mu_1 SALESGROWTH_{i,t-1} + \sum \beta_j COUNTRY + \sum \beta_k SECTOR + \sum \beta_h WAVE + \gamma_{i,t} \quad (5)$$

Again, we re-run the equations. Results are displayed in Table 3. Because we are no longer dropping observations when their industry-year is too small, we observe a slight increase in sample size. The first set of regressions, without the interaction term, yields similar results to those of the main model. When adding controls, the coefficients associated with the lagged *GREEN* variable are negative and statistically significant both when using the whole sample and when considering firms that under-invest only. Notably, in this latter case, the coefficient is statistically significant at the 1% level. When adding controls, coefficients associated with the lagged *DIGITAL* variable are also negative and statistically significant when considering the whole sample as well as firms that under-invest, while they are not statistically significant when considering over-investing firms. As usual, we then consider the regressions with the interaction term. Notably, the coefficient associated with the interaction is negative and statistically significant at the 1% level when running the regressions on the whole sample of firms, while it is negative and significant at the 5% level when considering firms that under-invest and at the 10% level when considering firms that over-invest. As a whole, these results provide strong support for our three hypotheses.

5.2 – Second alternative specification of the investment efficiency equation II

As a second robustness check, we attempt to modify the investment inefficiency equation by accounting for the fact that firms' investment behaviour may change in case of negative revenue growth. We then introduce in equation (1) variable *NEG*, a dummy equal to one if the firm experienced negative sales growth during the financial year prior to the survey, and zero otherwise (see Chen et al., 2011; Gomariz and Ballesta, 2014; Samet and Jarboui, 2017). The modified investment inefficiency equation looks as follows:

$$INV_{i,t} = \mu_0 + \mu_1 SALESGROWTH_{i,t-1} + \mu_2 NEG_{i,t-1} + \gamma_{i,t} \quad (6)$$

After running again the main models, we confirm the previous results (see Table 4). When considering the first set of regressions, we observe that green investments affect negatively the newly defined proxies for investment inefficiency. Coefficients are statistically significant at the 10% level when considering the overall sample, while they are statistically significant at the 5% level in the under-investment case.

Table 3 - *Regression results (one single investment efficiency regression)*

	GREEN (Lag)						DIGITAL (Lag)						GREEN (Lag) × DIGITAL (Lag)					
	Whole sample		Over-investment		Under-investment		Whole sample		Over-investment		Under-investment		Whole sample		Over-investment		Under-investment	
GREEN (Lag)	-0.157	-0.255**	-0.257	-0.198	-0.192***	-0.251***							0.088	-0.005	0.080	0.093	-0.097	-0.145*
	(0.100)	(0.100)	(0.215)	(0.214)	(0.067)	(0.065)							(0.127)	(0.123)	(0.265)	(0.260)	(0.082)	(0.078)
DIGITAL (Lag)							-0.278***	-0.214**	-0.674***	-0.343	-0.094	-0.148**	-0.016	0.077	-0.327	-0.016	0.033	-0.016
							(0.103)	(0.101)	(0.224)	(0.216)	(0.072)	(0.066)	(0.134)	(0.129)	(0.298)	(0.283)	(0.090)	(0.080)
GREEN (Lag) × DIGITAL (Lag)													-0.616***	-0.673***	-0.805*	-0.772*	-0.250*	-0.267**
													(0.210)	(0.202)	(0.448)	(0.432)	(0.140)	(0.130)
Controls and fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
	Controls and fixed effects not shown. See Tables at the end																	
Constant	4.456***	4.998***	6.174***	5.530***	3.480***	4.137***	4.487***	4.994***	6.292***	5.586***	3.444***	4.111***	4.460***	4.976***	6.265***	5.531***	3.472***	4.142***
	(0.060)	(0.432)	(0.135)	(0.927)	(0.042)	(0.296)	(0.060)	(0.433)	(0.131)	(0.926)	(0.040)	(0.297)	(0.069)	(0.435)	(0.159)	(0.932)	(0.047)	(0.297)
Observations	4,892	4,892	1,766	1,766	3,126	3,126	4,892	4,892	1,766	1,766	3,126	3,126	4,892	4,892	1,766	1,766	3,126	3,126
Number of firms	3,628	3,628	1,510	1,510	2,493	2,493	3,628	3,628	1,510	1,510	2,493	2,493	3,628	3,628	1,510	1,510	2,493	2,493

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3 presents the results of the first robustness test, consisting of regressions of *INVEFF* on *GREEN* and *DIGITAL* as well as on their interaction. In this second set of regressions, the tests use a modified investment efficiency equation which is not estimated cross-sectionally by year and industry, but rather across the whole sample of observations, and which includes country, year and industry fixed effects. The coefficients reported in the table are accompanied by either three, two, one or zero stars, representing, respectively, a statistical significance level of 1%, 5%, 10% and higher than 10%. Below each coefficient the corresponding standard error is also present. Each of the three sections, referred to regressions of *INVEFF* on *GREEN*, *DIGITAL* and *GREEN×DIGITAL*, is further divided into three parts: regressions run using the whole sample; regression run over the sample of firms that over-invest only; regressions run over the sample of firms that under-invest only. For each of these parts, both the univariate and the multivariate analyses are shown. Controls as well as country, year and sector fixed effects, although present, are not shown in the table. The complete table can be found in the appendix.

Table 4 - *Regression results (investment efficiency equation with NEG dummy)*

	GREEN (Lag)						DIGITAL (Lag)						GREEN (Lag) × DIGITAL (Lag)					
	Whole sample		Over-investment		Under-investment		Whole sample		Over-investment		Under-investment		Whole sample		Over-investment		Under-investment	
GREEN (Lag)	-0.112	-0.186*	-0.326	-0.249	-0.145*	-0.175**							0.068	-0.008	0.019	0.085	-0.111	-0.158*
	(0.101)	(0.102)	(0.214)	(0.214)	(0.074)	(0.074)							(0.127)	(0.124)	(0.264)	(0.262)	(0.091)	(0.088)
DIGITAL (Lag)							-0.367***	-0.287***	-0.862***	-0.484**	-0.220***	-0.280***	-0.203	-0.096	-0.548*	-0.131	-0.197**	-0.278***
							(0.103)	(0.103)	(0.219)	(0.212)	(0.078)	(0.076)	(0.134)	(0.132)	(0.292)	(0.278)	(0.097)	(0.095)
GREEN (Lag) × DIGITAL (Lag)													-0.389*	-0.442**	-0.695	-0.813*	-0.015	0.035
													(0.211)	(0.205)	(0.442)	(0.424)	(0.156)	(0.150)
Controls and fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
	Controls and fixed effects not shown. See Tables at the end																	
Constant	4.365***	4.670***	6.003***	5.959***	3.439***	3.529***	4.439***	4.710***	6.165***	6.067***	3.456***	3.560***	4.418***	4.697***	6.159***	5.996***	3.487***	3.601***
	(0.060)	(0.443)	(0.135)	(0.934)	(0.044)	(0.297)	(0.060)	(0.445)	(0.131)	(0.934)	(0.043)	(0.301)	(0.070)	(0.446)	(0.161)	(0.939)	(0.050)	(0.301)
Observations	4,748	4,748	1,747	1,747	3,001	3,001	4,748	4,748	1,747	1,747	3,001	3,001	4,748	4,748	1,747	1,747	3,001	3,001
Number of firms	3,540	3,540	1,485	1,485	2,412	2,412	3,540	3,540	1,485	1,485	2,412	2,412	3,540	3,540	1,485	1,485	2,412	2,412

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4 presents the results of the first robustness test, consisting of regressions of *INVEFF* on *GREEN* and *DIGITAL* as well as on their interaction. In this second set of regressions, the tests use a modified investment efficiency equation which includes *NEG*, a dummy variable equal to one if the firm experienced negative revenue growth during the financial year prior to the survey. The coefficients reported in the table are accompanied by either three, two, one or zero stars, representing, respectively, a statistical significance level of 1%, 5%, 10% and higher than 10%. Below each coefficient the corresponding standard error is also present. Each of the three sections, referred to regressions of *INVEFF* on *GREEN*, *DIGITAL* and *GREEN×DIGITAL*, is further divided into three parts: regressions run using the whole sample; regression run over the sample of firms that over-invest only; regressions run over the sample of firms that under-invest only. For each of these parts, both the univariate and the multivariate analyses are shown. Controls as well as country, year and sector fixed effects, although present, are not shown in the table. The complete table can be found in the appendix.

Digital investments also seem to mitigate investment inefficiency in this last robustness check: when adding controls, the depressing effect on investment inefficiency is verified at the 5% level in the over-investment case and at the 1% level in the whole sample and under-investment case. Finally, we turn to the models with the interaction term. Again, we observe that a moderating effect exists when running the regressions on the whole sample of firms, in that the coefficient is negative and statistically significant at the 5% level when adding controls. This effect is mostly driven by over-investing firms. No such effect is verified for firms that under-invest, instead. When considered in their entirety, these results confirm hypotheses one, two as well as three. Finally, it should be noted that because we are no longer dropping observations when industry-year groups are too small, we observe a slight increase in sample size from previous tests.

6 – Conclusions

In this study, we investigate the influence of investments in green, digital and both areas simultaneously on corporate investment efficiency. To the best of our knowledge, no study to date has directly addressed the effect of simultaneous corporate investment in green and digital on investment efficiency. We report the following findings: (a) corporate green investments aimed at either mitigating a company's environmental footprint or adapting to adverse weather events due to climate change reduce a firm's investment inefficiency level mainly by reducing under-investment; (b) corporate investments in digital technologies also reduce a firm's investment inefficiency level; the results are particularly robust for under-investing firms; (c) a moderating effect of corporate digital investments on corporate green investments, whereby digital technologies enhance the positive effect of green investments on investment efficiency, is also verified; (d) for firms that under-invest, wave 2022 is associated with a higher inefficiency level than wave 2021; inefficiency is even higher when considering wave 2023; (e) firms in the construction and transportation industry are generally associated with a higher inefficiency level than manufacturing firms (namely, the base case); (f) higher company age is strongly and significantly associated with higher efficiency levels for firms that over-invest as well as for firms that under-invest; (g) there is evidence that higher leverage increases inefficiency on over-investing firms; (h) overall, there is evidence that higher collateral value of assets increases investment inefficiency; (i) finally, across all tests the number of firms that under-invest is significantly larger than that of firms that over-invest.

Our results provide useful information at multiple levels. At a corporate level, they encourage the adoption of green and digital technologies and, upon further scrutiny, they may also encourage their contemporaneous implementation. At a policy level, they show that public authorities should actively support firms' efforts to mitigate their environmental footprint and to enhance their digital infrastructure. Arguably, the enhanced level of investment efficiency generated by these types of investments is desirable for two reasons: first, more effective investment plans are directly associated with a better allocation of factors of production to their most valuable uses, resulting in higher economic efficiency and higher values of aggregate welfare; second, higher aggregate investment efficiency can be understood as a lower statistical dispersion of investment levels, which may allow for a deeper understanding of the comovement between aggregate investments and other macroeconomic variables. This in turn would help policymakers design more effective monetary policy, thereby further enhancing overall economic efficiency. Aside from investment efficiency considerations, investments in green and digitals should arguably be supported for a variety of additional reasons, perhaps the most important being the necessity to face up to climate change and its adverse economic and social implications.

Despite these contributions, our study has some limitations. By imposing temporal precedence between the explanatory and explained variables we showed that the latter may be a product of the former; however, the causal mechanism linking investments in green and digital on one side and investment efficiency on the other deservers further scrutiny. Similarly, a potential explanation for why digital investments may enhance the effect of green investments has been proposed, but not tested. Third, the survey was conducted on advanced economies, characterised by high levels of capital accumulation. It remains to be tested whether these effects materialise in emerging economies as well. Finally, and most importantly, our dataset did not include any continuous variable measuring the amount of financial resources invested in either green or digital technologies; indeed, *GREEN* and *DIGITAL* were dummies. Further research involving continuous variables may confirm or disprove our results, although we believe there is enough evidence by now to predict that investments in green and digital technologies reduce corporate investment inefficiency. Notwithstanding these limitations, we believe that our results are noteworthy, and we hope they will be useful for researchers as well as policymakers.

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Tables

Tables A1 and A2 shown below are a more detailed version of in-text tables 3 and 4, respectively.

Table A1 - *Regression results (one single investment efficiency regression)* – Complete table

	GREEN (Lag)						**DIGITAL (Lag)**						**GREEN (Lag) × DIGITAL (Lag)**					
	Whole sample		Over-investment		Under-investment		Whole sample		Over-investment		Under-investment		Whole sample		Over-investment		Under-investment	
GREEN (Lag)	**-0.157**	**-0.255****	**-0.257**	**-0.198**	**-0.192*****	**-0.251*****							0.088	-0.005	0.080	0.093	-0.097	-0.145*
	(0.100)	**(0.100)**	**(0.215)**	**(0.214)**	**(0.067)**	**(0.065)**							(0.127)	(0.123)	(0.265)	(0.260)	(0.082)	(0.078)
DIGITAL (Lag)							**-0.278*****	**-0.214****	**-0.674*****	**-0.343**	**-0.094**	**-0.148****	-0.016	0.077	-0.327	-0.016	0.033	-0.016
							(0.103)	**(0.101)**	**(0.224)**	**(0.216)**	**(0.072)**	**(0.066)**	(0.134)	(0.129)	(0.298)	(0.283)	(0.090)	(0.080)
GREEN (Lag) × DIGITAL (Lag)													**-0.616*****	**-0.673*****	**-0.805***	**-0.772***	**-0.250***	**-0.267****
													(0.210)	**(0.202)**	**(0.448)**	**(0.432)**	**(0.140)**	**(0.130)**
2022		0.183**		0.276		0.212***		0.188**		0.271		0.217***		0.183**		0.283		0.210***
		(0.093)		(0.219)		(0.056)		(0.093)		(0.219)		(0.056)		(0.093)		(0.220)		(0.056)
2023		0.240		0.320		0.329***		0.219		0.299		0.308***		0.237		0.299		0.330***
		(0.152)		(0.331)		(0.096)		(0.152)		(0.331)		(0.096)		(0.151)		(0.331)		(0.096)
Construction		0.426***		1.398***		-0.097		0.416***		1.346***		-0.093		0.396***		1.344***		-0.118
		(0.139)		(0.310)		(0.086)		(0.139)		(0.312)		(0.086)		(0.139)		(0.312)		(0.086)
Services		-0.739***		-0.360		-0.933***		-0.725***		-0.346		-0.915***		-0.755***		-0.368		-0.942***
		(0.130)		(0.306)		(0.072)		(0.130)		(0.305)		(0.072)		(0.130)		(0.305)		(0.072)
Transportation		0.754***		-0.045		1.109***		0.760***		-0.064		1.121***		0.739***		-0.084		1.108***
		(0.132)		(0.276)		(0.097)		(0.132)		(0.275)		(0.098)		(0.132)		(0.276)		(0.097)
LOSS		-0.105		-0.059		0.104		-0.116		-0.080		0.092		-0.118		-0.092		0.097
		(0.133)		(0.343)		(0.084)		(0.134)		(0.345)		(0.083)		(0.133)		(0.345)		(0.084)
PROF		0.848***		1.889**		-0.403***		0.831***		1.911**		-0.433***		0.835***		1.898**		-0.413***
		(0.277)		(0.836)		(0.138)		(0.278)		(0.837)		(0.139)		(0.275)		(0.840)		(0.139)
AGE		-0.548***		-0.960***		-0.157***		-0.558***		-0.965***		-0.164***		-0.538***		-0.943***		-0.152***
		(0.082)		(0.177)		(0.055)		(0.082)		(0.175)		(0.055)		(0.082)		(0.177)		(0.055)
LEV		0.399		1.347*		0.005		0.403		1.338*		0.013		0.403		1.334*		0.007
		(0.352)		(0.736)		(0.223)		(0.355)		(0.734)		(0.228)		(0.353)		(0.732)		(0.225)
TANG		2.257***		5.240***		-0.575***		2.202***		5.179***		-0.623***		2.263***		5.220***		-0.565***
		(0.229)		(0.573)		(0.143)		(0.229)		(0.572)		(0.144)		(0.229)		(0.573)		(0.143)
CASH		0.130		1.440*		0.082		0.122		1.383		0.093		0.106		1.354		0.074
		(0.283)		(0.858)		(0.184)		(0.283)		(0.857)		(0.185)		(0.282)		(0.858)		(0.184)
Constant	4.456***	4.998***	6.174***	5.530***	3.480***	4.137***	4.487***	4.994***	6.292***	5.586***	3.444***	4.111***	4.460***	4.976***	6.265***	5.531***	3.472***	4.142***
	(0.060)	(0.432)	(0.135)	(0.927)	(0.042)	(0.296)	(0.060)	(0.433)	(0.131)	(0.926)	(0.040)	(0.297)	(0.069)	(0.435)	(0.159)	(0.932)	(0.047)	(0.297)
Observations	4,892	4,892	1,766	1,766	3,126	3,126	4,892	4,892	1,766	1,766	3,126	3,126	4,892	4,892	1,766	1,766	3,126	3,126
Number of firms	3,628	3,628	1,510	1,510	2,493	2,493	3,628	3,628	1,510	1,510	2,493	2,493	3,628	3,628	1,510	1,510	2,493	2,493
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A1 presents the results of the first robustness test, consisting of regressions of *INVEFF* on *GREEN* and *DIGITAL* as well as on their interaction. In this second set of regressions, the tests use a modified investment efficiency equation which is not estimated cross-sectionally by year and industry, but rather across the whole sample of observations, and which includes country, year and industry fixed effects. The coefficients reported in the table are accompanied by either three, two, one or zero stars, representing, respectively, a statistical significance level of 1%, 5%, 10% and higher than 10%. Below each coefficient the corresponding standard error is also present. Each of the three sections, referred to regressions of *INVEFF* on *GREEN*, *DIGITAL* and *GREEN×DIGITAL*, is further divided into three parts: regressions run using the whole sample; regression run over the sample of firms that over-invest only; regressions run over the sample of firms that under-invest only. For each of these parts, both the univariate and the multivariate analyses are shown. In particular, *LOSS*, *PROF*, *AGE*, *LEV*, *TANG* and *CASH* are the control variables. Year and sector fixed effects are shown, with wave "2021" and sector "Manufacturing" representing the base cases. Country fixed effects are also present, but they are not shown.

Table A2 - *Regression results (investment efficiency equation with NEG dummy)* – Complete table

	GREEN (Lag)						DIGITAL (Lag)						GREEN (Lag) × DIGITAL (Lag)					
	Whole sample		Over-investment		Under-investment		Whole sample		Over-investment		Under-investment		Whole sample		Over-investment		Under-investment	
GREEN (Lag)	-0.112	-0.186*	-0.326	-0.249	-0.145*	-0.175**							0.068	-0.008	0.019	0.085	-0.111	-0.158*
	(0.101)	(0.102)	(0.214)	(0.214)	(0.074)	(0.074)							(0.127)	(0.124)	(0.264)	(0.262)	(0.091)	(0.088)
DIGITAL (Lag)							-0.367***	-0.287***	-0.862***	-0.484**	-0.220***	-0.280***	-0.203	-0.096	-0.548*	-0.131	-0.197**	-0.278***
							(0.103)	(0.103)	(0.219)	(0.212)	(0.078)	(0.076)	(0.134)	(0.132)	(0.292)	(0.278)	(0.097)	(0.095)
GREEN (Lag) × DIGITAL (Lag)													-0.389*	-0.442**	-0.695	-0.813*	-0.015	0.035
													(0.211)	(0.205)	(0.442)	(0.424)	(0.156)	(0.150)
2022		0.148		0.135		0.235***		0.152		0.131		0.241***		0.148		0.145		0.238***
		(0.096)		(0.216)		(0.067)		(0.096)		(0.215)		(0.067)		(0.096)		(0.216)		(0.068)
2023		0.016		-0.502		0.438***		0.003		-0.532*		0.431***		0.016		-0.534*		0.445***
		(0.159)		(0.324)		(0.137)		(0.159)		(0.323)		(0.136)		(0.159)		(0.322)		(0.136)
Construction		0.640***		1.838***		0.043		0.606***		1.749***		0.017		0.592***		1.743***		0.001
		(0.141)		(0.311)		(0.091)		(0.142)		(0.315)		(0.092)		(0.142)		(0.316)		(0.092)
Services		-0.696***		-0.322		-0.754***		-0.693***		-0.310		-0.752***		-0.713***		-0.340		-0.764***
		(0.130)		(0.299)		(0.085)		(0.130)		(0.298)		(0.085)		(0.130)		(0.297)		(0.085)
Transportation		0.688***		0.056		0.993***		0.694***		0.025		1.015***		0.680***		0.001		1.010***
		(0.135)		(0.271)		(0.109)		(0.135)		(0.271)		(0.109)		(0.135)		(0.272)		(0.109)
LOSS		-0.201		-0.367		0.157*		-0.215		-0.389		0.140		-0.218		-0.410		0.143
		(0.137)		(0.349)		(0.093)		(0.137)		(0.350)		(0.092)		(0.137)		(0.351)		(0.092)
PROF		0.870**		2.847***		-0.482***		0.850**		2.873***		-0.516***		0.856**		2.865***		-0.504***
		(0.350)		(1.071)		(0.148)		(0.355)		(1.082)		(0.150)		(0.351)		(1.087)		(0.150)
AGE		-0.529***		-0.939***		-0.181***		-0.531***		-0.942***		-0.180***		-0.518***		-0.912***		-0.172***
		(0.082)		(0.168)		(0.061)		(0.081)		(0.165)		(0.061)		(0.082)		(0.168)		(0.061)
LEV		0.369		1.181*		0.032		0.366		1.170*		0.031		0.366		1.162*		0.023
		(0.370)		(0.659)		(0.268)		(0.371)		(0.657)		(0.271)		(0.370)		(0.655)		(0.268)
TANG		2.288***		4.866***		-0.322*		2.246***		4.779***		-0.355**		2.290***		4.845***		-0.326*
		(0.237)		(0.562)		(0.167)		(0.236)		(0.560)		(0.166)		(0.237)		(0.562)		(0.167)
CASH		0.140		0.702		0.282		0.118		0.636		0.267		0.109		0.604		0.256
		(0.299)		(0.877)		(0.220)		(0.298)		(0.876)		(0.219)		(0.298)		(0.877)		(0.218)
Constant	4.365***	4.670***	6.003***	5.959***	3.439***	3.529***	4.439***	4.710***	6.165***	6.067***	3.456***	3.560***	4.418***	4.697***	6.159***	5.996***	3.487***	3.601***
	(0.060)	(0.443)	(0.135)	(0.934)	(0.044)	(0.297)	(0.060)	(0.445)	(0.131)	(0.934)	(0.043)	(0.301)	(0.070)	(0.446)	(0.161)	(0.939)	(0.050)	(0.301)
Observations	4,748	4,748	1,747	1,747	3,001	3,001	4,748	4,748	1,747	1,747	3,001	3,001	4,748	4,748	1,747	1,747	3,001	3,001
Number of firms	3,540	3,540	1,485	1,485	2,412	2,412	3,540	3,540	1,485	1,485	2,412	2,412	3,540	3,540	1,485	1,485	2,412	2,412
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A2 presents the results of the first robustness test, consisting of regressions of *INVEFF* on *GREEN* and *DIGITAL* as well as on their interaction. In this second set of regressions, the tests use a modified investment efficiency equation which includes *NEG*, a dummy variable equal to one if the firm experienced negative revenue growth during the financial year prior to the survey. The coefficients reported in the table are accompanied by either three, two, one or zero stars, representing, respectively, a statistical significance level of 1%, 5%, 10% and higher than 10%. Below each coefficient the corresponding standard error is also present. Each of the three sections, referred to regressions of *INVEFF* on *GREEN*, *DIGITAL* and *GREEN×DIGITAL*, is further divided into three parts: regressions run using the whole sample; regression run over the sample of firms that over-invest only; regressions run over the sample of firms that under-invest only. For each of these parts, both the univariate and the multivariate analyses are shown. In particular, *LOSS*, *PROF*, *AGE*, *LEV*, *TANG* and *CASH* are the control variables. Year and sector fixed effects are shown, with wave "2021" and sector "Manufacturing" representing the base cases. Country fixed effects are also present, but they are not shown.

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October 2024

European
Investment Bank

pdf: ISBN 978-92-861-5824-7

2024-0244