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Doing good in good times only? Uncertainty as contingency factor of warm-glow investment

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ABSTRACT

Recent studies in investor behavior have put forth a so-called warm-glow theory, suggesting that investors appear to have developed a preference for socially responsible investments. The theory explains why investors appear willing to pay a premium for responsible assets. According to recent reports, however, Covid-19, supply chain uncertainties, and the recent surge in inflation have led to a resurgence of investment in what could be considered non-responsible assets. Investor sentiment thus appears to have changed. Our research question in this paper is whether market uncertainty acts as a contingency variable of warm-glow preferences, such that in times of crisis, investors lose the taste for responsible assets, in favor of the preservation of their consumption and wealth. Exploring a global sample of 882 financial sector firms over two decades, we use panel regressions to link both operating and stock performance to environmental, social, and governance (ESG) ratings. We break down our sample into periods of low and high uncertainty. Our results indicate that uncertainty may moderate investors' warm-glow preferences, as hypothesized. Thus, our study adds uncertainty as an important contextual contingency to discussions on socially responsible investing: investors may be willing to do good in good times only.

1. Introduction

The period during and after the Covid-19 crisis has been characterized by unprecedented levels of uncertainty in the financial markets, as witnessed by the record lows measured in both consumer and business sentiment indices. The Russian invasion of Ukraine has further deteriorated sentiment in Europe and the US, as energy and food prices have risen sharply. At the same time, and countering previous trends, there has been a sudden relative rise in carbon-intensive investments. According to the United Nations Conference on Trade and Development (UNCTAD), there is thus a negative trend in responsible investments that "reflects a shift in investor sentiment due to the food, fuel, and finance crises around the world, the Ukraine war, rising inflation and interest rates, and fears of a coming recession […]" (UNCTAD, 2022). This suggests that perceived uncertainty, a commonly used contingency factor in international management research (see e.g., Sund, 2013; Sund et al., 2016; Sund et al., 2022), might lead to a weaker preference of investors toward socially responsible investments, which is an important observation to those researching the nascent "warm-glow" theory, whereby investors experience a warm-glow feeling from socially responsible investments.

The growing interest of investors in sustainable finance over the past two decades demonstrates that wealth gain alone does not

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explain investor preferences. Investors in equity markets have seemingly developed a taste for sustainable and responsible investments. For example, Porzio et al. (2023) show that Italian investors prefer to purchase stocks of companies that are engaged in corporate social responsibility (CSR) activities. Andersen and Dreyer (2023) present similar evidence for the Scandinavian market, and Dreyer and Smith (2024) for the US market. Moreover, the presence of green innovation in a firm seems to increase the number of equity analysts following that firm, especially in bank-oriented markets (Fiorillo et al., 2022), which could be considered a further sign of investors' preferences for sustainability and CSR activities. Consequently, investors treat such investments as consumption goods (Fama and French, 2007) and are willing to pay a premium price for these (Renneboog et al., 2008; Ibikunle and Steffen, 2017). This explains why investors appear willing to accept lower risk-adjusted returns when investing in sustainable stocks (Pástor et al., 2021; Dreyer and Smith, 2024; Dreyer et al., 2023b). The opposite logic can be applied to carbon-intensive assets. Dreyer et al. (2023b) and Dreyer and Smith (2024) term these preferences for socially responsible investments as "warm glow", referencing the concept of warm-glow altruism originally theorized by Andreoni (1990). Evidence of a warm-glow effect has recently been found in both the stock market (Dreyer et al., 2023b) and bond market (Baldi and Pandimiglio, 2022). Thus, investors not only invest to ensure future consumption, but also to generate a current warm-glow feeling.

In this paper, and in view of recent anecdotal reports, we argue that in times of higher uncertainty, such as crisis periods, investors become more concerned about their level of intertemporal consumption and wealth, leaving the warm-glow feeling aside until better economic times. In times of high uncertainty, there is a domination of what some call "the spirit of capitalism" (Zou, 1994; Zhang, 2006), over the warm-glow effect, with investors indifferent between sustainable and conventional investments. Thus, we hypothesize that in crisis periods, when uncertainty is exceptionally high, investors reduce the allocation of their wealth placed in sustainable assets. If this were the case, the prices of sustainable assets should fall, increasing their expected risk-adjusted returns to the same level as their conventional peers. Sustainable investments thus would no longer underperform conventional ones. We explore empirically this relationship between uncertainty and warm-glow investment for the international financial sector. The financial sector can be seen as a good laboratory for our type of exercise for two reasons. First, it is a highly internationalized sector, with firms locating their activities and investments worldwide. Second, the sector is critical for the financing of green transition projects, and is thus under considerable pressure from governments, investors, and stakeholders to contribute to climate goals (Rahi et al., 2021).

Methodologically, we quasi-replicate Nollet et al. (2016) and regress both the yearly operating performance and excess stock returns of listed companies in the finance and insurances sector on ESG (environmental, social, and governance) measures, as these have become the go-to metrics of investors (Sund, 2023). We use both aggregated and disaggregated ESG measures for individual companies. We also control for international macroeconomic variations. In all, our sample comprises 882 financial sector companies, listed on Asian, European, and US stock markets from 2002 to 2020. Conducting a structural break analysis, we look for evidence of periods of breaks in the warm-glow preferences of investors, consistent with times of crisis and high uncertainty.

We find a consistently negative influence of ESG scores on excess stock returns, except for the environmental pillar from 2002 to 2007. This consistent negative relationship is what is predicted by the warm-glow theory of asset pricing (Dreyer et al., 2023b; Dreyer and Smith, 2024; Pástor et al., 2021); whereby many shareholders prefer companies with higher ESG scores and are ready to pay a higher price for stocks that have this label. The expected returns for companies perceived to be responsible are thus lower. Strikingly, our results for crisis periods indicate that financial sector investors appear to lose this ESG appetite (i.e., warm-glow feeling) in times of high economic uncertainty. This implies that in these times investors seem to revert to a behavior focused more squarely on maximizing risk-adjusted returns.

To extend our analysis, we further examine operating performance. This allows us to test whether the observed behavioral effect in stock performance has a parallel in firms' operating performance, and to check the robustness of our results against those of the literature that we quasi-replicate methodologically. There is recent evidence that if consumer choices are no longer based only on economic factors but also on ethical considerations (see e.g., Civero et al., 2021; Risitano et al., 2022), they should be willing to pay a premium for sustainable goods and services, which could possibly increase such firms' operating performance. We find that scoring highly on the environment or governance pillars is associated with a lower operating performance. The opposite is true for the social pillar score. We find no statistically significant relationship between aggregate ESG score and operating performance in any period. Moreover, when we split our sample in time and test these relationships for the high-uncertainty period of the financial crisis, we find no evidence that ESG scores influence firms' operating performance, irrespective of how we define the crisis period. This result is in line with Tatomir et al. (2022); (2023), who show that excess stock returns and operating performance can be decoupled, as only the former variable is affected by the warm-glow effect. Our results provide some initial evidence that market uncertainty indeed may act as a contingency variable of warm-glow preferences.

2. Warm-glow theory and uncertainty

2.1. Literature and theory

There is a rich literature on how investors price assets. For example, the seminal works of Rubinstein (1976), Lucas (1978), and Breeden (1979) defend the notion that households invest to smooth their consumption over time. Other authors, however, follow Marshall (1920) and defend that, not just consumption, but also wealth *per se* affects household utility, even if it might never be used to finance future consumption. Some scholars incorporate elements of psychology, such as the consequences of the asymmetric emotions that investors experience following wealth gains or losses, as indicated by prospect theory (Barberis et al., 2001; Kahneman and Tversky, 1979). Irrespective of how one incorporates wealth into investor preferences, there seems to be agreement in the literature that fluctuations of wealth affect an investor's utility.

Investors might also be concerned about status (Postlewaite, 1998) and thus may invest according to habit-formation preferences, deriving utility from increases in the level of consumption over time (Abel, 1990, Campbell and Cochrane, 1999). Habit formation could also be external, where the wealth preferences of investors depend on those of others (Zou, 1994; Zhang, 2006). Rather than the level of wealth, one could instead consider its growth (savings) as the key variable that affects investor utility (Dreyer et al., 2013, 2020).

Finally, following Fama and French (2007), who recognize that an investor's utility might depend on the type of assets they purchase, Dreyer et al. (2023b) find that saving-based preferences are dependent on the perceived greenness of the investor's portfolio. The theoretical explanation given in that work is that investors are willing to pay more (i.e., they will earn less) for green assets as these have an additional utility effect beyond just increasing wealth; whereby they also generate a so-called warm-glow feeling. Others have theorized similar effects of sustainability preferences on stock returns, but without econometric testing. For example, Luo and Subrahmanyam (2019) and Pástor et al. (2021) developed models that also theoretically defend that sustainable assets should underperform their peers, in line with the warm-glow theory.

2.2. Further empirical findings

Empirically investigating the links between ESG scores, as a proxy for sustainable or responsible companies, and both stock and operating performance has become popular in recent years, leading to a flood of empirical papers, many of which, however, are thin on theoretical explanations. There is thus no unique view on how sustainable or socially responsible investments (SRIs) should perform, relative to the market benchmark. Among those defending their underperformance, White (1995) shows, using the Domini Social Index to proxy returns on SRIs, that green funds in the US, but not in Germany, are associated with a negative Jensen's alpha. Brammer et al. (2006) find that environmental and community responsibility-based scores in the UK are negatively correlated with returns, but the contrary is found for employment indicators. Renneboog et al. (2008) advocate for SRI underperformance, pointing to a price for ethics when considering the returns of mutual funds in Europe, the US, and Asia. Ghoul et al. (2018) show for 30 different countries that environmental stocks underperform in the manufacturing sector. Finally, Hubel and Scholz (2020) found that SRI stocks underperformed in Europe between 2003 and 2016.

Many authors question this underperformance, finding either an equal performance (e.g., Hamilton et al., 1993) or overperformance (e.g., Derwall et al., 2005). Although initially accepting the argument of the underperformance of SRI funds for Australia between 1992 and 1996, Bauer et al. (2006) defend that this underperformance is no longer significant in more recent periods (i.e., closer to their study in 2006). For Canada and the UK, Bauer et al. (2007) and Gregory and Whittaker (2007) defend that SRIs and conventional funds perform equally. For the period 2015–2019, Naffa and Fain (2022) show that SRIs performed on a par with conventional mutual funds composed of world stocks. Cai and He (2014) claim that environmental funds overperform in the long term against their peers. More recently, Khan (2019), Alda (2020), and Consolandi et al. (2020) also defend that SRI funds overperform. While Khan (2019) used a sample of world stocks from 2009 to 2017, Alda (2020) considered UK pension funds from 2016 to 2018, and Consolandi et al. (2020) US stocks from 2008 to 2019.[1]

The lack of consistency in the results can partly be explained by differences in the methodologies and lack of consistency in the very definition of social responsibility and ESG-related measures (Dreyer et al., 2023a). However, a further problem with comparing all these findings is that they cover very different time periods, with at least some of these incorporating periods of high uncertainty and economic crisis. The effect of high uncertainty on responsible stock returns has, to some extent, been identified in existing studies. Nofsinger and Varma (2014) claim that socially responsible portfolios outperform conventional ones in times of market distress, while the opposite occurs in normal economic periods. They claim this is because socially responsible portfolios can help mitigate risks (Ferriani and Natoli, 2021; Broadstock et al., 2021; Shanaev and Ghimire, 2022). In line with this finding, Umar et al. (2022) argue the case for an increase in the returns associated with renewable energy following the Russian–Ukrainian conflict. The same observation can be made for clean energy investments and green bonds following the outbreak of the COVID-19 pandemic (Yousaf et al., 2022).

For the US stock market, Climent and Soriano (2011) found that SRI funds underperformed relative to non-SRI funds between 1987 and 2009. Contrary to the overall results, the authors show that the opposite could be verified between 2001 and 2009 (a shorter period but one that includes the global financial crisis of the time), where funds overall performed in line with each other independently from their SRI scores. The same type of analysis was performed by Ibikunle and Steffen (2017), but for European funds between 1991 and 2014. The authors found negative abnormal returns for green funds when compared to conventional ones, even though in the last periods of their sample this underperformance overall disappeared (2011–2014), exactly during the Euro crisis. We would thus argue that it is possible to reconcile the literature by showing the importance of dividing samples into time periods that account for market uncertainty.

2.3. Hypothesis development

Following the warm-glow theory (as theorized in Dreyer et al., 2023b), suppose the lifetime utility function of the investor can be described as follows:

[1] One could also link overperformance in the EU to default risk. For example, Meles et al. (2023) show that in European countries, green innovation mitigates a company's risk of default.

$$E\sum_{t=0}^{\infty} e^{-\theta\Delta t} U(C_t, \lambda_{g,t}, W_t)\Delta t \tag{1}$$

$$U(C_t, \lambda_{gt}, W_t) = \frac{\left(C_t^{\alpha}\lambda_{g,t}^{b}W_t^{d}\right)^{1-\gamma}}{1-\gamma} \tag{2}$$

where C_t is the level of household consumption in period t, λ_{gt} is the share of wealth invested in sustainable assets, W_t is the level of household wealth, α is the taste for consumption, b is the taste for sustainable wealth, d is the taste for total wealth, and γ is a coefficient that combined with the others will allow measurement of the relative risk aversion according to Khilstrom and Mirman (1974), (1981). The consumption capital asset pricing model (CCAPM) can be recovered by setting $b = d = 0$. Now, if $b > 0$ and $d = 0$, there is a proportional warm-glow effect. When $b > 0$ and $d > 0$, it leads to a total warm-glow effect. If $b = 0$ and $d > 0$, we observe the spirit of capitalism (Zou, 1994; Zhang, 2006), where the level of the investor wealth alongside their consumption is what really matters, irrespective of the type of asset the investor purchases.

Suppose the investor has this type of warm-glow preference and is faced with a period of moderate uncertainty. In this case, potential losses in their wealth should make them question their present and future consumption. In such periods, the marginal utilities of their intertemporal consumption as well as of their wealth should relatively increase compared to the marginal utility of socially responsible investments. This should lead the investor to exchange responsible assets for both consumption and conventional assets. In other words, during a period of moderate uncertainty, the investor's appetite for responsible assets decreases, consequently reducing the relative prices of responsible assets and increasing their expected returns. Suppose now uncertainty rises extremely because of an extreme event, such as a strong recession, economic crisis, pandemic, or war. We could imagine a scenario in which the investor is so fearful they may lose entirely their appetite for SRIs. Thus, they may no longer differentiate between responsible and conventional assets.

To summarize, we theorize that in periods of high uncertainty, the warm-glow feeling from SRIs disappears, with investors now more concerned about losses and the consequent effects on their intertemporal consumption and the level of their total wealth. As a result, they reduce the responsible assets in their portfolios, neutralizing the price premium that would otherwise result from the warm-glow effect. Thus, we expect that (a) *in normal periods, the expected risk-adjusted returns of responsible assets should be lower than the level of conventional assets; and (b) in periods of high uncertainty, the expected risk-adjusted returns of responsible assets should increase relative to the level of conventional assets*. In other words, in these periods, the traditional spirit of capitalism dominates over the warm-glow effect in asset pricing.

3. Methodology

Methodologically, we quasi-replicate Nollet et al. (2016). Given the global integration of the financial industry and markets, we would expect to verify our hypothesis worldwide. Thus, we selected an international sample of stocks in the sector for our analysis, covering the regions of Asia, Europe, and the US. More specifically, our data comprised companies listed in the US, China, Japan, and South Korea. For Europe, we followed Auer and Schumacher (2016) by selecting financial sector stocks in Austria, Belgium, Germany, Spain, Finland, France, Greece, Ireland, Italy, Netherlands, Portugal, Switzerland, Denmark, UK, Norway, and Sweden. A few important Asian markets could not be added to the sample because we found no comparable data on business confidence for these.

3.1. Data

For the US, we collected stock prices from the NYSE and NASDAQ. For Asian and European countries, we similarly collected prices from their main stock exchanges. Company individual data, such as return on assets (ROA), leverage, revenues, and ESG scores were extracted from Refinitiv Eikon and DataStream. We collected yearly data from 2002 to 2020, with the starting data dictated by the data availability. Our sample comprised 882 listed stocks within the financial sector. We used the industry definition in Refinitiv DataStream of "Banking and Investment, Financial Technology, and Insurance" to concentrate our data sample into a broad approach for the banking industry. This definition can be further broken down into three subcategories, namely, "Banking & Investment Services", "Financial Technology & Infrastructure", and "Insurance." An overview of the definition of each of the variables can be found in Appendix 1, as well as descriptive statistics for our data (Table A1), correlation, and VIF analysis (Tables A2 and A3), and the sample breakdown into subindustries and regions (Tables A4 and A5).

To measure operating performance, we used return on assets (ROA) following Nollet et al. (2016). According to the definition in Refinitiv DataStream, ROA is the ratio between the sum of net income and interest expenses, and the year's average of the total assets. To proxy financial performance, we calculated excess stock returns, defined as the difference between the annual stock returns of each stock and the risk-free rate. We converted all returns to USD. The risk-free rates were extracted from Kenneth R. French's Data Library.

3.2. Selecting high-uncertainty periods

To define appropriate high-uncertainty periods, we decided to use the Business Confidence Index (BCI) of the different sampled countries between 2002 and 2020, as published by the OECD. Considering the global nature of the financial industry, our sample, and investors, we calculated an average of this index for each year to proxy business confidence overall. Fig. 1 illustrates the resulting

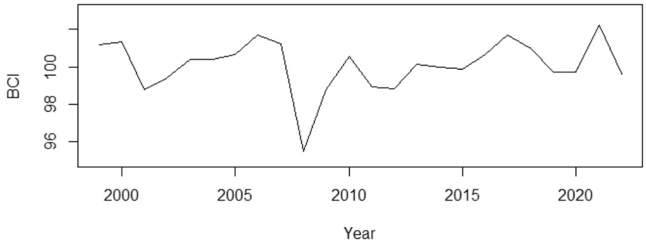

Fig. 1. Business confidence index (BCI). Source: Elaborated by the author using data from the Business Confidence Index of the sampled countries, 2002–2020, OECD.

average over the sample period.

To identify periods of high uncertainty, we looked for structural breaks in this data. We followed the methodology of Bai and Perron (1998) and Lindskov et al. (2023) by fitting a constant to the mean of the BCI for the entire sample period and then applied the CUSUM (cumulative sum control chart) fluctuation test to search for structural changes. Thus, we can write the structural break model and the null hypothesis of "no break" as:

$$\overline{\boldsymbol{Index_t}} = \boldsymbol{\beta_t x_t^{'}} + \boldsymbol{\varepsilon_t} \quad (\mathrm{t} = 2002, \ldots, 2020)$$

$$\boldsymbol{H_0} : \boldsymbol{\beta_t} = \boldsymbol{\beta_0} \tag{3}$$

where $\overline{\boldsymbol{Index_t}}$ is the mean of the BCI for the sample period, β_t is a vector of the coefficients, x_t is a vector indicating each year from 2002 to 2020, β_0 is a constant, and ε_t is the residual. The alternative hypothesis is of the existence of a structural break. We reject the null hypothesis if we find evidence that the β coefficient varies over time. In this case, we followed by searching for the date of the breaks[2] according to the method of Bai and Perron (1998), (2003).

3.3. Panel regressions

We followed Nollet et al. (2016) by regressing ROAs and excess stock returns on variables that are specific to each company, including their ESG scores. We proxied international macroeconomic information through year dummies. Thus, we can write our regression according to the following equation:

$$y_{i,t} = \alpha_0 + \beta_1 ESGF_{i,t} + \beta_2 FIRM^{'}_{i,t} + \beta_3 MACRO^{'}_{i,t} + \varepsilon_{i,t}, \tag{4}$$

where, $y_{i,t}$ is the performance (ROA or Excess Stock Returns) of firm i in year t; $ESGF_{i,t}$ is the ESG factor (either composite, environmental, social, or governance pillar score)[3]; and the vector $FIRM^{'}_{i,t}$ is composed of the firm specific variables, such as $Leverage_{i,t}$ (debt to equity), which measures financial risk, and $Sales_{i,t}$, that account for the company's size. One could question the use of the variable *Sales* as a proxy for size. Specifically, total assets and market capitalization are also typically used to measure bank size. We decided to use sales for different reasons: 1) our methodology quasi-replicates Nollet et al. (2016), who also used sales; 2) our sample includes fintech and insurances companies; and 3) sales may be the most appropriate way to measure bank size in practice. This was concluded by Schildbach (2017), who found that sales appear to be more reliable in terms of stability than the other measures (market cap and total assets). Since the MACRO vector is supposed to proxy international macroeconomic information that only changes in time, but is fixed cross-sectionally, we decided to employ year dummies to account for these.[4] Finally, $\varepsilon_{i,t}$ are idiosyncratic errors.

4. Findings

4.1. Uncertainty periods

We found breaks from 2007 to 2008 and from 2009 to 2010, suggesting that the correct definition for the financial crisis uncertainty period would be from 2008 to 2009. At the end of 2007, the US market experienced a bust in housing prices that had consequences worldwide in all industrialized financial markets. These markets recovered in 2010, exactly matching the second break point.

[2] We use the OLS method according to Bai and Perron (1998), (2003) to specify the number of breaks and their dates as a result of the minimization of the BIC criterion (see Lindskov et al., 2023 for more details).

[3] To avoid multicollinearity issues, we avoid combining ESG pillar scores, and pillar scores with ESG composite scores in the same estimation (see Tatomir et al., 2022).

[4] Macroeconomic conditions might fluctuate in times of uncertainty, so that investor preferences might change accordingly. Since in the specific setting of our research the macroeconomic variables are the same for all individuals (stocks) and consequently change equally for all of them every year, they should be perfectly collinear with time dummies. Thus, time dummies are used to proxy any macroeconomic effect in all our estimations.

Table 1
Regression results for excess stock returns in the total period.

	Dependent variable: Excess Stock Returns 2002–2020			
Model (ESGF)	A (ESG)	B (EPS)	C (SPS)	D (GPS)
ESGF	-0.1265***	-0.0814***	-0.0579**	-0.0946***
	(0.0308)	(0.0171)	(0.0227)	(0.0285)
Leverage	0.0009	0.0009*	0.0009	0.0008
	(0.0005)	(0.0005)	(0.0006)	(0.0006)
Relative sales	-0.0919	-0.1137	-0.2503***	-0.2230***
	(0.0962)	(0.0939)	(0.0901)	(0.0823)
Constant	-22.1457***	-23.7342***	-23.9928***	-21.5464***
	(2.7995)	(2.7093)	(2.7296)	(2.9011)
R^2	0.1742	0.1738	0.1724	0.1741
Adj. R^2	0.1716	0.1712	0.1698	0.1714
N (obs.)	6616	6616	6616	6616
n (Firms)	882	882	882	882

Source: Author's own calculations using Refinitiv DataStream Data from 2002 to 2020. ESG for the composite ESG score, EPS for the environmental pillar score, SPS for the social pillar score, and GPS for the governance pillar score.
* $p<0.1$,
** $p<0.05$,
*** $p<0.01$. [a] Standard error terms appear in parentheses; [b] All regressions include Year fixed effects.

Table 2
Regression results for excess stock returns in the pre-uncertainty period.

	Dependent variable: Excess Stock Returns 2002–2007			
Model (ESGF)	A (ESG)	B (EPS)	C (SPS)	D (GPS)
ESGF	-0.0010	0.1543*,**	-0.0053	-0.0415
	(0.0625)	(0.0480)	(0.0552)	(0.0424)
Leverage	0.0029	0.0018	0.0029	0.0030
	(0.0021)	(0.0022)	(0.0021)	(0.0020)
Relative sales	-0.4933***	-0.7750***	-0.4861***	-0.4477***
	(0.1640)	(0.1577)	(0.1548)	(0.1579)
Constant	-25.6499***	-29.4323***	-25.5435***	-23.9300***
	(3.6387)	(3.3390)	(3.5621)	(3.5839)
R^2	0.361	0.3666	0.361	0.3616
Adj. R^2	0.355	0.3607	0.355	0.3557
N (obs.)	871	871	871	871
n (Firms)	196	196	196	196

Source: Author's own calculations using Refinitiv DataStream Data from 2002 to 2020. ESG for the composite ESG score, EPS for the environmental pillar score, SPS for the social pillar score, and GPS for the governance pillar score.
* $p<0.1$,
** $p<0.05$,
*** $p<0.01$. [a] Standard error terms appear in parentheses; [b] All regressions include Year fixed effects.

One could question the application of a structural break analysis for a sample period with so few years. In such a small sample, we would likely need the index to display an extreme change so that a break could reach statistical significance. Moreover, just one year after the breakpoint of 2010, the markets were hit by the Euro sovereign debt crisis. This prolonged the volatility of the financial markets up to 2012 when Mario Draghi calmed European markets with his "whatever it takes" speech. The continuing volatility was, however, not strong enough to point to more breaks in our sample. Thus, to ensure the consistency and robustness of our findings, we decided to define two different uncertainty periods: one from 2008 to 2009 and an extra longer one from 2008 to 2012, which included the Euro crisis.[5]

4.2. Estimations

We omitted the coefficients associated with the year dummies in all the tables. However, these are available upon request. In all regressions, we controlled for possible residual heteroscedasticity and autocorrelation by adjusting standard errors according to the so-called Heteroscedasticity and Autocorrelation Consistent (HAC) estimator (Newey and West, 1987). We divided the analysis of our results both according to the dependent variable (Excess Stock Returns or ROA) and according to non-crisis (normal) and crisis periods. The reader should note that for simplicity we included the analysis of the total period as part of our non-crisis analysis.

[5] This approach is also used by Dreyer and Schmid (2020).

Table 3
Regression results for excess stock returns in post-uncertainty periods.

	Dependent variable: Excess Stock Returns 2010–2020			
Model (ESGF)	A (ESG)	B (EPS)	C (SPS)	D (GPS)
ESGF	-0.1470***	-0.1079***	-0.0651**	-0.1066***
	(0.0359)	(0.0190)	(0.0260)	(0.0347)
Leverage	0.0009*	0.0010*	0.0009	0.0009
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Relative sales	0.0571	0.0967	-0.1593	-0.1255
	(0.1194)	(0.1181)	(0.1134)	(0.1006)
Constant	14.9827***	13.5121***	11.9572***	14.3522***
	(2.5305)	(2.2502)	(2.3194)	(2.6556)
R2	0.1131	0.1136	0.1107	0.1127
Adj. R2	0.1109	0.1114	0.1085	0.1105
N (obs.)	5257	5257	5257	5257
n (firms)	882	882	882	882
	Dependent variable: Excess Stock Returns 2013–2020			
Model (ESGF)	A (ESG)	B (EPS)	C (SPS)	D (GPS)
ESGF	-0.1689***	-0.1033***	-0.0611**	-0.1449***
	(0.0410)	(0.0200)	(0.0281)	(0.0408)
Leverage	0.0011***	0.0012***	0.0011***	0.0011***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Relative sales	0.0864	0.0584	-0.2022	-0.0869
	(0.1298)	(0.1287)	(0.1244)	(0.1054)
Constant	42.1074***	39.6585***	38.1389***	42.4567***
	(2.9632)	(2.5897)	(2.7017)	(3.1284)
R2	0.1049	0.1041	0.1015	0.1057
Adj. R2	0.1029	0.1021	0.0995	0.1037
N (obs.)	4437	4437	4437	4437
n (firms)	881	881	881	881

Source: Author's own calculations using Refinitiv DataStream Data from 2002 to 2020. ESG for the composite ESG score, EPS for the environmental pillar score, SPS for the social pillar score, and GPS for the governance pillar score.
* $p<0.1$,
** $p<0.05$,
*** $p<0.01$. [a] Standard error terms appear in parentheses; [b] All regressions include Year fixed effects.

4.2.1. *Excess stock returns*

4.2.1.1. Full period 2002–2020 and normal periods. We start with the analysis of the full sample period 2002–2020. Table 1 presents the estimation results for our regressions. Irrespective of the ESG score used, the associated coefficient is negative and statistically significant. The aggregate ESG, the environment pillar, and the governance pillar each have coefficients that are significant at the 1 % level. The social pillar is also significant, but at the 5 % level. The leverage variable is not statistically significant in any of the regressions, while relative sales are significant in two of the models at the 1 % level, with the expected negative sign. This implies that the bigger the firm, the lower its expected returns (i.e., indicating a size effect).

Table 2 shows the results for the normal period (pre-crisis) 2002–2007. Here, we notice that ESG ratings have no correlation with stock returns, except for the environment pillar, which is positive and significant at the 1 % level. Leverage is not significant, while the effect of relative sales is negative and significant at the 1 % level in all cases. The lack of significance for the ESG variable specifically in the pre-crisis period is in line with Dreyer et al. (2023b), who found that the warm-glow effect is not statistically significant if one considers exclusively the period that precedes the financial crisis of 2007.

Table 3 offers the statistical results for the two different post-uncertainty periods, i.e., 2010–2020 and 2013–2020. In line with the warm-glow theory, we find again negative returns associated with ESG performance. The coefficients associated with ESG factors are significant at the 1 % level for the aggregated ESG score, for the environmental pillar, and for the governance pillar. The social pillar is significant at the 5 % level. During these post-crisis periods, we find no evidence of significance of relative sales. The significance of leverage depends on the period analyzed: For 2013–2020, it is positive and significant in all estimations at the 1 % level, while for the longer period 2010–2020, it is only significant at the 10 % level and in two of the regressions.

Table 4 offers the statistical results for the joint normal periods of (2002–2007 and 2010–2020) and (2002–2007 and 2013–2020), respectively. ESG scores have coefficients that are consistently negative and significant at the 1 % level, except for the social pillar score, which has significance at the 5 % level.

4.2.1.2. Uncertainty periods. Table 5 indicates that, irrespective of how we define our uncertainty period, the results are consistent with our uncertainty hypothesis. The coefficients associated with the ESG variables lack statistical significance during this period. This indicates that during uncertainty periods, investors do not pay a premium for ESG stocks. Thus, uncertainty might lead to a lower appetite of investors for ESG stocks. Moreover, in crisis periods, we do not observe a company size effect either, as in none of the regressions relative sales is significant. Leverage is associated with lower returns in crisis periods as its coefficient is negative and significant at the 5 % level in the regressions for 2008–2009 and at the 1 % level in the regressions for 2008–2012.

Table 4
Regression results for excess stock returns in normal periods.

	Dependent variable: Excess Stock Returns 2002–2007 and 2010–2020			
Model (ESGF)	A (ESG)	B (EPS)	C (SPS)	D (GPS)
ESGF	-0.1248***	-0.0820***	-0.0543**	-0.0954***
	(0.0326)	(0.0178)	(0.0237)	(0.0304)
Leverage	0.0010**	0.0010**	0.0010*	0.0009*
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Relative sales	-0.0750	-0.0877	-0.2371**	-0.2021**
	(0.1010)	(0.0990)	(0.0945)	(0.0859)
Constant	-22.3170***	-23.8628***	-24.2097***	-21.6411***
	(2.8574)	(2.7582)	(2.7754)	(2.9738)
R2	0.1403	0.14	0.1385	0.1403
Adj. R2	0.1376	0.1373	0.1358	0.1376
N (obs.)	6128	6128	6128	6128
n (Firms)	882	882	882	882
	Dependent variable: Excess Stock Returns 2002–2007 and 2013–2020			
Model (ESGF)	A (ESG)	B (EPS)	C (SPS)	D (GPS)
ESGF	-0.1400***	-0.0743***	-0.0496**	-0.1253***
	(0.0365)	(0.0186)	(0.0253)	(0.0348)
Leverage	0.0012***	0.0012***	0.0012***	0.0011***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Relative sales	-0.0752	-0.1460	-0.2806***	-0.1870**
	(0.1086)	(0.1058)	(0.1011)	(0.0904)
Constant	-21.8573***	-23.9586***	-24.2634***	-20.3609***
	(3.0483)	(2.9120)	(2.9480)	(3.2004)
R2	0.1359	0.1347	0.1335	0.1369
Adj. R2	0.1333	0.1321	0.1309	0.1343
N (obs.)	5308	5308	5308	5308
n (Firms)	882	882	882	882

Source: Author's own calculations using Refinitiv DataStream Data from 2002 to 2020. ESG for the composite ESG score, EPS for the environmental pillar score, SPS for the social pillar score, and GPS for the governance pillar score.
* $p<0.1$,
** $p<0.05$,
*** $p<0.01$. a Standard error terms appear in parentheses; b All regressions include Year fixed effects.

4.2.2. Operating performance (ROA)

4.2.2.1. Full period 2002–2020 and normal periods. We start again with an analysis of the full sample period 2002–2020. Table 6 presents the estimation results from our regressions. Over the entire period, ESG scores present no consistent relationship with ROA. Depending on the regression, they can be negative and significant, positive and significant, or not significant. While the aggregate ESG score is not significant, the environment and governance pillars are negative and significant at the 1 % level, and the social pillar is positive and significant at the 5 % level. As was the case with the excess stock returns, leverage is not statistically significant in any of the regressions. The variable relative sales is negative and significant at the 1 % level in all models, corresponding to a negative effect of company size on ROA.

Table 7 presents the statistical results for the normal period 2002–2007 (i.e., pre-uncertainty). There is no clear direction of the effects of ESG ratings on ROA. When using the aggregate ESG score or the social pillar scores, no significance is found. When looking at the environmental and governance pillars, a negative relationship is observed at the 5 % significance level. Leverage and relative sales have negative signs and are significant at the 1 % level.

Table 8 presents the statistical results for the normal periods (i.e., post-uncertainty) 2010–2020 and 2013–2020. We find again no clear indication of the direction of the relationship between ROA and ESG scores. They range from not being significant as in the case of the aggregate ESG to being significant and positive at the 5 % and 1 % levels in the case of the social scores, and to being significant and negative at the 1 % and 5 % levels in the case of environmental scores, or at the 5 % level in the case of governance scores. During post-uncertainty periods, we find no evidence of significance for leverage, and significance at the 1 % level for the negative sign associated with relative sales (i.e., a size effect).

Table 9 confirms this lack of consistency in how ESG scores are associated with ROAs. The aggregate ESG score is not significant, while the social scores are positive and significant at the 5 % and 1 % level depending on the period analyzed. Finally, the environmental scores are negative and significant at the 1 % and 5 % levels, depending on the time sample, while the governance scores are negative and significant at the 1 % level. Leverage has no statistical significance independent from the regression analyzed. Relative sales are negatively associated with ROAs at the 1 % significance level in all regressions, in line with what we would expect as a result of the size effect.

4.2.2.2. Uncertainty periods. Table 10 indicates that none of the ESG scores show significance during uncertainty periods, irrespective of the model used or the definition of the crisis period. Here, we observe a negative and significant effect at the 10 % level of leverage on ROAs, implying that in crisis periods ROA decreases with leverage. The same negative relationship is found for relative sales (i.e., a

Table 5
Regression results for excess stock returns in uncertainty periods.

	Dependent variable: Excess Stock Returns 2008–2009			
Model (ESGF)	A (ESG)	B (EPS)	C (SPS)	D (GPS)
ESGF	-0.0999	-0.0330	-0.0697	-0.0627
	(0.0875)	(0.0692)	(0.0786)	(0.0685)
Leverage	-0.0075**	-0.0079**	-0.0078**	-0.0079**
	(0.0036)	(0.0037)	(0.0035)	(0.0035)
Relative sales	-0.2421	-0.3742	-0.3116	-0.3552
	(0.3340)	(0.3347)	(0.3281)	(0.3017)
Constant	-35.3694***	-37.6374***	-36.3792***	-36.0698***
	(3.7638)	(3.1968)	(3.5711)	(3.5806)
R2	0.3848	0.3837	0.3843	0.3844
Adj. R2	0.3797	0.3786	0.3792	0.3793
N (obs.)	488	488	488	488
n (firms)	253	253	253	253
	Dependent variable: Excess Stock Returns 2008–2012			
Model (ESGF)	A (ESG)	B (EPS)	C (SPS)	D (GPS)
ESGF	-0.0424	-0.0815	-0.0639	0.0332
	(0.0661)	(0.0519)	(0.0618)	(0.0422)
Leverage	-0.0084***	-0.0079***	-0.0083***	-0.0088***
	(0.0030)	(0.0031)	(0.0030)	(0.0029)
Relative sales	-0.1577	0.0068	-0.1043	-0.3289
	(0.2462)	(0.2490)	(0.2309)	(0.2167)
Constant	-37.7457***	-36.5177***	-37.0318***	-40.5926**
	(2.9740)	(2.5900)	(2.9130)	(2.6527)
R2	0.3136	0.3153	0.3142	0.3136
Adj. R2	0.3099	0.3116	0.3105	0.3099
N (obs.)	1308	1308	1308	1308
n (firms)	284	284	284	284

Source: Author's own calculations using Refinitiv DataStream Data from 2002 to 2020. ESG for the composite ESG score, EPS for the environmental pillar score, SPS for the social pillar score, and GPS for the governance pillar score.

* $p<0.1$,

** $p<0.05$,

*** $p<0.01$. [a] Standard error terms appear in parentheses; [b] All regressions include Year fixed effects.

Table 6
Regression results for ROA in the total period.

	Dependent variable: Return on Assets (ROA) 2002–2020			
Model (ESGF)	A (ESG)	B (EPS)	C (SPS)	D (GPS)
ESGF	-0.0030	-0.0085***	0.0090**	-0.0114***
	(0.0048)	(0.0026)	(0.0043)	(0.0041)
Leverage	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Relative sales	-0.1684***	-0.1462***	-0.1977***	-0.1549***
	(0.0130)	(0.0120)	(0.0128)	(0.0109)
Constant	3.2090***	3.3003***	2.9276***	3.5896***
	(0.5655)	(0.5474)	(0.5603)	(0.5808)
R2	0.0155	0.0164	0.0162	0.0168
Adj. R2	0.0124	0.0133	0.0130	0.0137
N (obs.)	6616	6616	6616	6616
n (firms)	882	882	882	882

Source: Author's own calculations using Refinitiv DataStream Data from 2002 to 2020. ESG for the composite ESG score, EPS for the environmental pillar score, SPS for the social pillar score, and GPS for the governance pillar score.

* $p<0.1$,

** $p<0.05$,

*** $p<0.01$. a Standard error terms appear in parentheses; b All regressions include Year fixed effects.

size effect), but with significance at the 1 % level.

4.3. Robustness

To check the robustness of our estimates, we decided to rerun all the estimations, but in different ways. First, it could be that within the broad definition of the banking sector we used, certain industry subcategories could lead to different results. Thus, we decided to break down the general industry category of Refinitiv DataStream "Bank and Financial Services" into Refinitiv DataStream high-level subcategories: "Banking & Investment Services", "Financial Technology & Infrastructure", and "Insurance", and include fixed effects

Table 7
Regression results for ROA in the pre-uncertainty period.

	Dependent variable: Return on Assets (ROA) 2002–2007			
Model (ESGF)	A (ESG)	B (EPS)	C (SPS)	D (GPS)
ESGF	-0.0179	-0.0145**	-0.0017	-0.0221**
	(0.0112)	(0.0069)	(0.0088)	(0.0089)
Leverage	-0.0014***	-0.0013***	-0.0014***	-0.0014***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Relative sales	-0.1326***	-0.1325***	-0.1561***	-0.1338***
	(0.0202)	(0.0238)	(0.0215)	(0.0199)
Constant	4.0855***	3.9395***	3.6282***	4.5165***
	(0.8024)	(0.6641)	(0.7286)	(0.8473)
R2	0.0658	0.0655	0.0636	0.0708
Adj. R2	0.0571	0.0569	0.0549	0.0622
N (obs.)	871	871	871	871
n (firms)	196	196	196	196

Source: Author's own calculations using Refinitiv DataStream Data from 2002 to 2020. ESG for the composite ESG score, EPS for the environmental pillar score, SPS for the social pillar score, and GPS for the governance pillar score.
* $p<0.1$,
** $p<0.05$,
*** $p<0.01$. a Standard error terms appear in parentheses; b All regressions include Year fixed effects.

Table 8
Regression results for ROAs in post-uncertainty periods.

	Dependent variable: Return on Assets (ROA) 2010–2020			
Model (ESGF)	A (ESG)	B (EPS)	C (SPS)	D (GPS)
ESGF	-0.00003	-0.0077***	0.0122**	-0.0098**
	(0.0055)	(0.0029)	(0.0050)	(0.0048)
Leverage	-0.00005	-0.00004	-0.00005	-0.00005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Relative sales	-0.1721***	-0.1410***	-0.2060***	-0.1525***
	(0.0165)	(0.0143)	(0.0159)	
Constant	3.0491***	3.3257***’	2.6110***	3.4843***
	(0.4205)	(0.3749)	(0.4189)	(0.4197)
R^2	0.0108	0.0115	0.0119	0.0117
Adj. R^2	0.0083	0.0091	0.0095	0.0093
N (obs.)	5257	5257	5257	5257
n (firms)	882	882	882	882
	Dependent variable: Return on Assets (ROA) 2013–2020			
Model (ESGF)	A (ESG)	B (EPS)	C (SPS)	D (GPS)
ESGF	0.0020	-0.0065**	0.0169***	-0.0112**
	(0.0065)	(0.0033)	(0.0058)	(0.0056)
Leverage	-0.00003	-0.00002	-0.00003	-0.00003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Relative sales	-0.1779***	-0.1452***	-0.2201***	-0.1502***
	(0.0189)	(0.0161)	(0.0186)	(0.0146)
Constant	3.0520***	3.3514***	2.5403***	3.6205***
	(0.3969)	(0.3353)	(0.3719)	(0.4135)
R^2	0.0089	0.0094	0.0109	0.01
Adj. R^2	0.0066	0.0071	0.0087	0.0078
N (obs.)	4437	4437	4437	4437
n (firms)	881	881	881	881

Source: Author's own calculations using Refinitiv DataStream Data from 2002 to 2020. ESG for the composite ESG score, EPS for the environmental pillar score, SPS for the social pillar score, and GPS for the governance pillar score.
* $p<0.1$,
** $p<0.05$,
*** $p<0.01$. [a] Standard error terms appear in parentheses; [b] All regressions include Year fixed effects.

for these in our regressions. Appendix 2, Table A6 contains these results. In an additional test of robustness, the subsamples were further divided into 12 subindustries (Banks, Consumer Lending, Corporate Financial Services, Investment Banking & Brokerage Services, Investment Management & Fund Operators, Diversified Investment Services, Financial & Commodity Market Operators & Service Providers, Multiline Insurance & Brokers, Property & Casualty Insurance, Life & Health Insurance, Reinsurance, Financial Technology, and Blockchain & Cryptocurrency). Appendix 2, Table A7 provides a summary of these last estimations. Except for a few differences concerning the effects of the ESG variables on ROA, results are generally stable for most estimations. This is especially true for regressions of excess stock returns.

We decided to further test for robustness using individual regressions for each of the three subcategories Banking & Investment

Table 9
Regression results for ROAs in normal periods.

	Dependent variable: Return on Assets (ROA) 2002–2007 and 2010–2020			
Model (ESGF)	A (ESG)	B (EPS)	C (SPS)	D (GPS)
ESGF	-0.0027	-0.0085***	0.0097**	-0.0118***
	(0.0050)	(0.0027)	(0.0045)	(0.0043)
Leverage	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Relative sales	-0.1698***	-0.1467***	-0.2001***	-0.1552***
	(0.0138)	(0.0126)	(0.0135)	(0.0114)
Constant	3.1988***	3.2971***	2.9092***	3.6034**
	(0.5680)	(0.5480)	(0.5619)	(0.5851)
R2	0.0147	0.0156	0.0154	0.0161
Adj. R2	0.0117	0.0125	0.0124	0.0130
N (obs.)	6128	6128	6128	6128
n (firms)	882	882	882	882
	Dependent variable: Return on Assets (ROA) 2002–2007 and 2013–2020			
Model (ESGF)	A (ESG)	B (EPS)	C (SPS)	D (GPS)
ESGF	-0.0015	-0.0076**	0.0131***	-0.0133***
	(0.0057)	(0.0030)	(0.0051)	(0.0048)
Leverage	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Relative sales	-0.1737***	-0.1510***	-0.2094***	-0.1544***
	(0.0152)	(0.0138)	(0.0151)	(0.0123)
Constant	3.1671***	3.2773***	2.8263***	3.6640***
	(0.5766)	(0.5506)	(0.5679)	(0.5971)
R2	0.0131	0.0138	0.0144	0.0148
Adj. R2	0.0102	0.0108	0.0114	0.0118
N (obs.)	5308	5308	5308	5308
n (firms)	882	882	882	882

Source: Author's own calculations using Refinitiv DataStream Data from 2002 to 2020. ESG for the composite ESG score, EPS for the environmental pillar score, SPS for the social pillar score, and GPS for the governance pillar score.
* $p<0.1$,
** $p<0.05$,
*** $p<0.01$. a Standard error terms appear in parentheses; b All regressions include Year fixed effects.

Services, Financial Technology & Infrastructure, and Insurance. However, the subcategory "Financial Technology" comprised only 19 companies in total. Thus, we decided to concentrate our analysis on the other two subcategories. See Appendix 2, Tables A8 and A9 for a summary of results for the individual subindustries. In these cases, we find important differences in the results. While the "core" banking subcategory "Banking & Investment Services" displays stable results compared to all our findings, this is not the case for "Insurance" companies. Apparently, both the warm-glow effect and its relationship with uncertainty that we defend in this article are less present for this sub-sample. Detailed regression results for the tables in Appendix 2 are available upon request.

5. Discussion

Our findings are in line with the warm-glow theory of asset pricing (Dreyer et al., 2023b; Dreyer and Smith, 2024; Pástor et al., 2021). Table 11 provides a summary of these findings. Investors prefer stocks that carry the label of being responsible, in this case proxied by higher ESG scores. Thus, the expected returns for these stocks will be lower. When considering the period of high uncertainty in the two decades we examined, our results indicate that investors in stocks that belong to the financial sector tend to lose this responsibility appetite (i.e., the desire for the warm-glow feeling). This is consistent with our stated hypothesis that in times of uncertainty investors seem to revert to investment strategies that are more concentrated on simply maximizing their risk-adjusted returns.

Analysis of the ROAs tells another story. It shows that environmental and governance performances are negatively related with ROA. For the social pillar, we verify the opposite: the higher the social pillar score, the higher the ROA. There is no indication of a relationship between the aggregate ESG and ROA, irrespective of the sample period. Breaking the sample into subindustries further muddies the picture (see Appendix 2). This was to be expected since different companies in different subindustries face different problems of optimization and resource orchestration (Sund et al., 2018). As pointed out by Tatomir et al. (2022) and, (2023), excess stock returns and operating performance can be decoupled, as only the former variable is affected by the warm-glow effect.

Our findings may be consistent with, on the one hand, existing studies that find a neutral effect on excess stock returns (e.g., Hamilton et al., 1993; Bauer et al., 2006; Bauer et al., 2007; Gregory and Whittaker, 2007; Naffa and Fain, 2022), and on the other hand, those that report a negative effect (e.g., White, 1995; Brammer et al., 2006; Renneboog et al., 2008; Ghoul et al., 2018; Hubel and Scholz, 2020). Our theory of uncertainty as a contingency factor on the green preferences of investors allows us to offer a possible explanation that reconciles these seemingly opposing strands of research results. This can be confirmed by those few studies that directly or indirectly incorporate uncertainty in the analysis of company performance (Nofsinger and Varma, 2014; Ferriani and Natoli, 2021; Broadstock et al., 2021; Shanaev and Ghimire, 2022; Umar et al., 2022; Yousaf et al., 2022; Climent and Soriano, 2011;

Table 10
Regression results for ROAs in uncertainty periods.

	Dependent variable: Return on Assets (ROA) 2008–2009			
Model (ESGF)	A (ESG)	B (EPS)	C (SPS)	D (GPS)
ESGF	0.0021	-0.0010	0.0068	-0.0034
	(0.0161)	(0.0084)	(0.0142)	(0.0132)
Leverage	-0.0017**	-0.0016***	-0.0017***	-0.0016***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Relative sales	-0.1557***	-0.1478***	-0.1668***	-0.1445***
	(0.0407)	(0.0389)	(0.0397)	(0.0379)
Constant	3.0316***	3.1322***	2.8761***	3.2408***
	(0.9869)	(0.7232)	(0.8723)	(0.9857)
R2	0.031	0.0309	0.0313	0.0311
Adj. R2	0.0229	0.0229	0.0233	0.0230
N (obs.)	488	488	488	488
n (firms)	253	253	253	253
	Dependent variable: Return on Assets (ROA) 2008–2012			
Model (ESGF)	A (ESG)	B (EPS)	C (SPS)	D (GPS)
ESGF	-0.0047	-0.0093	-0.0038	-0.0030
	(0.0093)	(0.0063)	(0.0083)	(0.0077)
Leverage	-0.0011*	-0.0010*	-0.0011*	-0.0011*
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Relative sales	-0.1477***	-0.1285***	-0.1499***	-0.1531***
	(0.0274)	(0.0272)	(0.0231)	(0.0263)
Constant	3.1152***	3.2603***	3.0831***	3.0853***
	(0.6641)	(0.5616)	(0.6270)	(0.6817)
R2	0.0293	0.0305	0.0293	0.0292
Adj. R2	0.0241	0.0253	0.0240	0.024
N (obs.)	1308	1308	1308	1308
n (firms)	284	284	284	284

Source: Author's own calculations using Refinitiv DataStream Data from 2002 to 2020. ESG for the composite ESG score, EPS for the environmental pillar score, SPS for the social pillar score, and GPS for the governance pillar score.
* $p<0.1$,
** $p<0.05$,
*** $p<0.01$. a Standard error terms appear in parentheses; b All regressions include Year fixed effects.

Table 11
Summary of our findings.

	ESG		EPS		SPS		GPS	
Sample Period	RET	ROA	RET	ROA	RET	ROA	RET	ROA
2002–2020	-	N	-	-	-	+	-	-
2002–2007	N	N	+	-	N	N	N	-
2010–2020	-	N	-	-	-	+	-	-
2013–2020	-	N	-	-	-	+	-	-
2002–2007, 2010–2020	-	N	-	-	-	+	-	-
2002–2007, 2013–2020	-	N	-	-	-	+	-	-
2008–2009	N	N	N	N	N	N	N	N
2008–2012	N	N	N	N	N	N	N	N

"N" for neutral, "-" for negative, and "+" for positive relationships; RET for excess stock returns; ROA for operating performance (return on assets); ESG for the composite ESG score; EPS for the environmental pillar score; SPS for the social pillar score; and GPS for the governance pillar score. *Source: This summary of results is based on the author's own regression results (in total, 64 regressions) using Refinitiv DataStream Data from 2002 to 2020.*

Ibikunle and Steffen, 2017). We speculate that differences in sample periods, and on a more fine-grained level, individual subindustry differences in periods of high and low uncertainty, could lead different researchers to different conclusions. Adding uncertainty as a key contingency variable in the study of warm-glow investing, and more generally of responsible investment, therefore appears a must. The above also helps explain the differences we find between core banking and insurance. Future research could extend our analysis by defining different periods of uncertainty for different industries; in other words, by measuring uncertainty in a more fine-grained way. Moreover, once data become fully available, it would be interesting to look at the very recent period of high uncertainty that followed the Covid 19 crisis, supply chain woes, and Russian invasion of Ukraine.

6. Conclusion

According to the warm-glow theory of asset pricing, investors have a preference for and are ready to pay a premium to invest in sustainable assets. In our study, we explored whether uncertainty could affect this preference. We found that in periods of high uncertainty, warm-glow investors may move their wealth from responsible assets to more conventional assets, motivated by a fear of loss of wealth and future consumption. That is, the marginal utilities of consumption and wealth increase. We thus theorize that in times of high uncertainty, this should lead investors to be more indifferent to the choice between sustainable and conventional assets. To test our assumptions, we collected data on stocks of the global financial sector from 2002 to 2020, examining both excess stock returns and operating ROA (where the former is expected to be influenced by the warm-glow effect) and ESG scores.

Our results confirm our suspicions: ESG scores are systematically negatively associated with stock returns only in periods characterized by normal levels of uncertainty. Thus, in periods of normal uncertainty, the warm-glow feeling of investors leads them to pay a premium for sustainable stocks, which lowers the expected returns. An analogous reasoning is applied to non-sustainable stocks. In periods of high uncertainty however, the warm-glow feeling disappears and sustainable stocks can be expected to pay relatively higher returns. This is consistent with the findings of Umar et al. (2022) and Yousaf et al. (2022) that showed that sustainable investments can be considered a safe haven in times of crisis.

In terms of the policy implications, our results suggest that governments should be careful when it comes to subsidizing the sustainable transition. In normal times, investors are already willing to pay a premium for sustainability. This should act as a natural market catalyst for this transition (see e.g., Dreyer & Smith 2023) as it lowers the cost of capital for these companies. During high-uncertainty periods, the returns for sustainable stocks grow compared to common stocks. Any lack of a warm-glow effect is thus substituted by the higher expected returns of sustainable stocks, making these "automatically" more attractive to investors.

Data availability

Data will be made available on request.

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Appendix 1. Definition of Variables and Data Sample

Return on Assets (ROA)

For return on assets, we used the definition in Refinitiv DataStream as follows:

- Banks: Net Income – Bottom Line + ((Interest Expense on Debt-Interest Capitalized) × (1-Tax Rate))) / Average of Last Year's (Total Assets - Customer Liabilities on Acceptances) and Current Year's (Total Assets - Customer Liabilities on Acceptances) × 100. Customer Liabilities on Acceptances are only subtracted when included in the Total Assets
- Insurance Companies: (Net Income – Bottom Line + ((Interest Expense on Debt-Interest Capitalized) × (1-Tax Rate))) + Policyholders' Surplus) / Average of Last Year's and Current Year's Total Assets × 100
- Other Financial Companies: (Net Income – Bottom Line + ((Interest Expense on Debt-Interest Capitalized) × (1-Tax Rate))) / Average of Last Year's (Total Assets - Custody Securities) and Current Year's (Total Assets - Custody Securities) × 100

Excess Stock Returns

We calculated stock returns in USD from the Refinitiv DataStream adjusted closing prices. Then, excess stock returns were calculated using the difference between stock returns and the risk-free rate.

Risk-Free Rate

We used annual risk-free rates according to the annual T-Bill rates reported by Kenneth R. French Data Library.

ESG Scores

We used all ESG scores according to Refinitiv DataStream ESG research. They represent an overall company score based on self-reported data on environmental, social, and corporate governance pillars.

- Environmental Pillar Score: A weighted average relative rating of a company based on the reported environmental information and the resulting three environmental category scores: resource use, emissions, and innovation.
- Social Pillar Score: A weighted average relative rating of a company based on the reported social information and the resulting five social category scores: workforce, human rights, community, product, and responsibility.
- Governance Pillar Score: A weighted average relative rating of a company based on the reported governance information and the resulting three governance category scores: management, shareholders, and CSR strategy.

Relative Sales

We calculated net sales or revenues from Refinitiv DataStream. They represent gross sales and other operating revenues less discounts, returns, and allowances. To fit our regressions, we then calculated this variable in relative terms using yearly sample averages so that the time series became stationary.

Leverage

We collected leverage data from Refinitiv DataStream. Its definition is ((Long Term Debt + Short Term Debt & Current Portion of Long Term Debt) / Common Equity × 100)).

Table A1
Descriptive statistics

	N	Mean	St. Dev.	Min	Max	Median
EPS	6616	33.413	29.524	0.000	98.980	23.65
SPS	6616	41.427	21.383	0.620	97.580	38.52
GPS	6616	50.068	22.495	0.290	97.370	50.85
ESG	6616	42.075	19.154	1.520	94.320	39.825
ROA (%)	6616	2.718	6.566	-84.310	128.440	1.26
Leverage (%)	6616	213.663	1147.216	-15,948.530	85,785.870	83.7
Rel. Sales	6616	2.130	4.209	-3.322	32.892	0.3964
Ex. Ret. (%)	6616	4.833	41.953	-102.223	1416.24	1.7016

Source: Author's own calculations using Refinitiv DataStream Data from 2002 to 2020. Note: In our sample of 6616 points, only 18 points of relative sales are negative and 40 have negative equity, and consequently a negative leverage. We decided to leave these in the sample.

Table A2
Pearson's correlation matrix

	ROA	Ex. Ret.	ESG	EPS	SPS	GPS	Rel. Sales	Leverage
ROA	1.000							
Ex. Ret	0.107	1.000						
ESG	-0.064	-0.065	1.000					
EPS	-0.082	-0.034	0.740	1.000				
SPS	-0.031	-0.044	0.884	0.683	1.000			
GPS	-0.071	-0.061	0.787	0.395	0.445	1.000		
Rel. Sales	-0.107	-0.022	0.491	0.531	0.451	0.317	1.000	
Leverage	-0.020	0.025	0.030	0.063	0.031	0.005	0.046	1.000

Source: Author's own calculations using Refinitiv DataStream Data from 2002 to 2020.

Table A3
Variance inflation factors (VIFs)

Dependent variable: ROA							
	Regressions						
	1	2	3	4	5	6	7
ESG	118.884						1.318
EPS	5.863	2.149		1.397			
SPS	38.649	2.040	1.441		1.257		
GPS	27.715	1.287	1.275			1.112	
Leverage	1.005	1.005	1.003	1.004	1.002	1.002	1.002
Rel. Sales	1.441	1.440	1.286	1.395	1.258	1.115	1.320
Dependent variable: Excess Stock Returns							
	1	2	3	4	5	6	7
ESG	118.884						1.318
EPS	5.863	2.149		1.397			
SPS	38.649	2.040	1.441		1.257		
GPS	27.715	1.287	1.275			1.112	
Leverage	1.005	1.005	1.003	1.004	1.002	1.002	1.002
Rel. Sales	1.441	1.440	1.286	1.395	1.258	1.115	1.320

Source: Author's own calculations using Refinitiv DataStream Data from 2002 to 2020.

Table A4
Number of firms by region, subindustry, and in total

	ASIA	EUROPE	US	TOTAL
Banking and Investment Services	118	191	397	706
Financial Technology and Infrastructure	2	7	10	19
Insurance	22	46	89	157
TOTAL	142	244	496	882

Source: Author's own calculations using Refinitiv DataStream Data from 2002 to 2020.

Table A5
Number of observations by region, subindustry, and in total

	ASIA	EUROPE	US	TOTAL
Banking and Investment Services	978	1536	2338	4852
Financial Technology and Infrastructure	5	18	58	81
Insurance	193	560	930	1683
TOTAL	1176	2114	3326	6616

Source: Author's own calculations using Refinitiv DataStream Data from 2002 to 2020.

Appendix 2. Summary of Robustness Tests

Table A6
Summary of results: Using fixed effects to differentiate between three subindustries[6]

	ESG		EPS		SPS		GPS	
Sample Period	RET	ROA	RET	ROA	RET	ROA	RET	ROA
2002–2020	-	N	-	-	-	+	-	-
2002–2007	N	N	+	(N)	N	N	N	-
2010–2020	-	N	-	-	-	+	-	-
2013–2020	-	N	-	-	-	+	-	-
2002–2007, 2010–2020	-	N	-	-	-	+	-	-
2002–2007, 2013–2020	-	N	-	-	-	+	-	-
2008–2009	N	N	N	N	N	N	N	N
2008–2012	N	N	N	N	N	N	N	N

"N" for neutral, "-" for negative and "+" for positive relationships; RET for excess stock returns; ROA for operating performance (return on assets); ESG for the composite ESG score; EPS for the environmental pillar score; SPS for the social pillar score; and GPS for the governance pillar score. *Source: This summary of results is based on the author's own regression calculations (total 64 regressions).*

[6] Banking & Investment Services, Financial Technology & Infrastructure and Insurance.

Table A7
Summary of results: Using fixed effects to differentiate between 12 subindustries[7]

	ESG		EPS		SPS		GPS	
Sample Period	RET	ROA	RET	ROA	RET	ROA	RET	ROA
2002–2020	-	(-)	-	-	-	(-)	-	-
2002–2007	N	(-)	+	-	N	(-)	N	-
2010–2020	-	(-)	-	-	-	(N)	-	(N)
2013–2020	-	(-)	-	-	-	(N)	-	-
2002–2007, 2010–2020	-	(-)	-	-	-	(-)	-	-
2002–2007, 2013–2020	-	(-)	-	-	-	(-)	-	-
2008–2009	N	N	N	N	N	N	N	N
2008–2012	N	N	N	(-)	N	(-)	N	N

"N" for neutral, "-" for negative and "+" for positive relationships; RET for excess stock returns; ROA for operating performance (return on assets); ESG for the composite ESG score; EPS for the environmental pillar score; SPS for the social pillar score; and GPS for the governance pillar score. In parentheses, those relationships that changed, underscored those results that the change implied also a change of sign. *Source: This summary of results is based on the author's own regression results (total 64 regressions) using Refinitiv DataStream Data from 2002 to 2020.*

[7] Banks, Consumer Lending, Corporate Financial Services, Investment Banking & Brokerage Services, Investment Management & Fund Operators, Diversified Investment Services, Financial & Commodity Market Operators & Service Providers, Multiline Insurance & Brokers, Property & Casualty Insurance, Life & Health Insurance, Reinsurance, Financial Technology, and Blockchain & Cryptocurrency.

Table A8
Summary of individual regressions for banking and investment services

	ESG		EPS		SPS		GPS	
Sample Period	RET	ROA	RET	ROA	RET	ROA	RET	ROA
2002–2020	-	(-)	-	-	-	(N)	-	-
2002–2007	N	N	+	(N)	N	N	N	-
2010–2020	-	N	-	-	-	+	-	-
2013–2020	-	N	-	-	-	+	-	-
2002–2007, 2010–2020	-	(-)	-	-	-	(N)	-	-
2002–2007, 2013–2020	-	N	-	-	-	+	-	-
2008–2009	N	N	N	N	N	N	N	N
2008–2012	N	N	(-)	(-)	N	N	N	N

"N" for neutral, "-" for negative and "+" for positive relationships; RET for excess stock returns; ROA for operating performance (return on assets); ESG for the composite ESG score; EPS for the environmental pillar score; SPS for the social pillar score; and GPS for the governance pillar score. In parentheses, those relationships that changed, underscored those results that the change implied also a change of sign. *Source: This summary of results is based on the author's own regression results (total 64 regressions) using Refinitiv DataStream Data from 2002 to 2020.*

Table A9
Summary of individual regressions for insurance firms

	ESG		EPS		SPS		GPS	
Sample Period	RET	ROA	RET	ROA	RET	ROA	RET	ROA
2002–2020	(N)	N	(N)	-	(N)	(-)	(N)	(N)
2002–2007	N	N	+	(N)	N	(-)	N	(N)
2010–2020	(N)	N	-	-	(N)	(-)	(N)	(N)
2013–2020	(N)	N	-	-	(N)	(-)	(N)	(N)
2002–2007, 2010–2020	(N)	(-)	(N)	-	(N)	(-)	(N)	(N)
2002–2007, 2013–2020	(N)	(-)	(N)	-	(N)	(-)	(N)	(N)
2008–2009	N	(+)	N	N	N	N	N	(+)
2008–2012	N	N	N	N	N	N	N	N

"N" for neutral, "-" for negative and "+" for positive relationships; RET for excess stock returns; ROA for operating performance (return on assets); ESG for the composite ESG score; EPS for the environmental pillar score; SPS for the social pillar score; and GPS for the governance pillar score. In parentheses, those relationships that changed, underscored those results that the change implied also a change of sign. *Source: This summary of results is based on the author's own regression results (total 64 regressions) using Refinitiv DataStream Data from 2002 to 2020.*

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