Capital-market effects of ESG scores: Evidence from a quasi-natural experiment

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Abstract

We investigate the capital-market effects of the release of environmental, social, and governance (ESG) scores on the Bloomberg Professional Terminal. To estimate causal effects for a group of treated companies (i.e., stocks with newly available ESG scores), we exploit the unanticipated publication of Sustainalytics ESG scores vis à vis a matched control group in a difference-in-difference setting. We find a significant increase in market liquidity and abnormal returns in the treated group. The most substantial effects prevail in regions with lower ESG awareness and for companies with above-median ESG scores.

Keywords:
ESG information, capital-market effects, stock market reaction, event study, difference-in-differences

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I. Introduction

The accessibility and development of one component of non-financial disclosure, i.e., scores for environmental, social, and governance (ESG) aspects, has fuelled the debate of whether such ESG scores contribute to capital-market efficiency. While evidence exists that mutual funds faced significantly higher inflows after having received a high Morningstar sustainability rating (Ammann et al., 2019; Hartzmark and Sussman, 2019), the capital-market effects of an unexpected publication of ESG scores have not been investigated on the company-level. Since trading behavior depends on the level of information companies disclose (Christensen et al., 2016), the release of ESG scores may impact liquidity and return patterns if ESG scores include relevant information (Diebecker and Sommer, 2017). Therefore, we conduct a quasi-natural experiment around the release of Sustainalytics ESG scores on Bloomberg Professional Service Terminals to investigate the capital-market effects of ESG scores based on an international panel of publicly-listed companies. Treated companies, which received Sustainalytics ESG scores published by Bloomberg, exhibit higher market liquidity and abnormal returns than propensity score-matched companies directly following the event. Thus, this paper supports the hypothesis that the availability of ESG scores reduces information asymmetry and has pricing implications on capital markets.

A large body of literature uses measures of market liquidity to assess the level of adverse selection and information asymmetry in financial markets (e.g., Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985; Easley and O'Hara, 1987). Market participants rely on the level of information that companies disclose, as they are uninformed regarding inside corporate information (e.g., Kyle, 1985; Venkatesh and Chiang, 1986). Higher transparency in companies' reporting thus leads to lower levels of information asymmetry (Christensen et al., 2016). The fact that uninformed investors avoid trading as long as they perceive high adverse selection due to information asymmetry results in the link between information and stock liquidity (Chae, 2005). Furthermore, market makers charge trading costs to protect themselves against adverse selection in the presence of information asymmetry (e.g. Llorente et al., 2002).

ESG scores as an indicator for non-financial disclosure have been identified to be valuable for investors since information asymmetry between management and investors, to some extent, relates to such non-financial indicators (Diebecker and Sommer, 2017). Hence, ESG scores potentially reduce costs for market participants stemming from adverse selection. A reduction of such costs improves liquidity (Glosten and Milgrom, 1985; Diamond and Verrecchia, 1991; Verrecchia, 2001). Furthermore, first evidence (Riedl and Smeets, 2017; Hartzmark and Sussman, 2019) shows that some investors integrate sustainable motivations and labels into their asset management approach. Our study takes advantage of the fact that Sustainalytics ESG scores have not been available before their release on Bloomberg to the Bloomberg subscribers in general, but only to a small group of informed market participants that had already purchased these scores directly from Sustainalytics.[1] Thus, if ESG scores contain value-relevant information, oth-

[1] In contrast to financial credit ratings (e.g., from S&P, Moody's and Fitch), ESG scores are proprietary data of sustainability rating agencies and have to be acquired by market participants.

erwise not noticed by market participants, the event is expected to reduce adverse selection in capital markets.

In this study, we exploit the unanticipated release of Sustainalytics ESG scores on Bloomberg Professional Service[2] to identify causal evidence for capital-market effects (liquidity and return) based on a global sample. The event around the release mitigates many concerns that typically arise in studies investigating the link between sustainable performance and financial market reactions. In detail, our findings are unlikely to be endogenous since the release of the Sustainalytics ESG scores provides us a unique event setting ruling out reverse causality. Further, we aim to capture omitted variables by the application of a propensity score matching. Moreover, our setting offers additional unique advantages: First, Bloomberg has the highest market share (33.4%) among financial data providers and reaches financial professionals on 325,000 licensed terminals. Compared to its competitors, Bloomberg's services are mainly specialized in buy-side, sales and trading, and asset management applications. Therefore, the Sustainalytics ESG score release on Bloomberg reached a broad and relevant community of market participants. Second, Sustainalytics ESG scores obtain high recognition. Several well-known index families (e.g., S&P Dow Jones Sustainability Index Series, Morningstar Global Sustainability Index Series, STOXX Global ESG Indices) base their sustainability assessments on Sustainalytics ESG research. Moreover, Sustainalytics

[2]On May 27th, 2014, Bloomberg published a new data point, the Sustainalytics ESG scores, in the conventional Bloomberg terminal (see press release online as of May 27th, 2014, 09:18 Eastern Time: `https://www.globenewswire.com/news-release/2014/05/27/639569/10083237/en/Sustainalytics-ESG-Research-Now-Available-on-Bloomberg.html`)

provides ESG scores for a global universe of companies. This variation across countries allows us to analyze the influence of ESG scores separately for different regions of integrated markets.

In a first step, we investigate the capital-market effects of ESG scores to assess the impact of the scores' release on information asymmetry. We measure information asymmetry based on three individual proxies for stock market liquidity: bid-ask spreads, stock price volatility, and relative turnover. We estimate the differential effects of the Sustainalytics ESG score release on liquidity measures in a difference-in-differences setting with daily observations over six-months around the event. The treated group in our analysis consists of all companies that received a Sustainalytics ESG score on Bloomberg as of May 27th, 2014. The control group contains propensity score-matched companies without Sustainalytics ESG scores on Bloomberg.

We find a substantial improvement in market liquidity after the release of the Sustainalytics ESG scores on Bloomberg. For instance, the bid-ask spread improved by 5% for the treated sample relative to the control group in the entire sample. Following Christensen et al. (2016), we can translate this improvement into average trading cost savings of approximately US$ 22 million per year and sample company, which implies a combined yearly benefit of the Sustainalytics ESG score release of 0.17% of the market capitalization. This magnitude is economically significant. In sum, our results suggest that access to Sustainalytics ESG scores leads to substantial economic benefits in capital markets. This pattern is particularly pronounced for companies with above-median Sustainalytics ESG scores and in the samples of North American and Japanese companies. In contrast, European companies show no significant change in liquidity. To gauge the validity of our identification strategy, we tested the parallel-trends assumption. Moreover, a placebo event test to accurately assess the role of Sustainalytics' ESG score release showed that liquidity and broader capital-market implications responded relatively sharply around the event date.

In a second step, we examine broader capital-market implications of the Sustainalytics ESG score release that might be related to an alignment of investor beliefs on financial returns. Under the efficient market hypothesis, information asymmetry between informed (i.e., access to ESG scores) and uninformed market participants results in equilibrium with trading frictions if ESG scores contain value-relevant information. Economic theory links higher trading costs, induced by adverse selection between buyers and sellers of shares, to firms' cost of capital (Diamond and Verrecchia, 1991; Leuz and Verrecchia, 2000). However, the direct link between information asymmetry and stock market returns from an investor's perspective is ambiguous. Following the logic of Miller (1977), the Sustainalytics ESG score event on Bloomberg should result in higher expected future returns due to a reduced dispersion among investor beliefs for the treated stocks. This stream of argumentation is based on the fact that the Sustainalytics ESG scores release revealed new value-relevant information to market participants. In this case, we would observe an upward adjustment of financial market equilibrium prices of treated companies (Norden and Weber, 2004). On the other hand, dispersion in investor beliefs is a proxy for uncertainty and could, therefore, result in higher future returns to compensate investors for higher risks (Gibson et al., 2019). This would imply that the publication of the ESG scores and the consequential positive contribution to an alignment of investor beliefs would result in a negative effect on future expected returns.

Therefore, we analyze whether the release of Sustainalytics ESG scores per se and also their level, particularly, have price implications. We conduct an event study around the Sustainalytics ESG score release and show that cumulative abnormal returns (in terms of alphas of the Fama and French (2015) market model) of treated companies are 0.786% higher in the first month (23 trading days) following the event than for control firms. This differential cumulative abnormal return relates to an abnormal increase in market capitalization of US$ 92 million for an average-sized treated company.

The group of market participants who had already purchased the Sustainalytics ESG scores before the Bloomberg release did certainly not adjust their beliefs to adverse selection costs of treated stocks since the event constituted no information update. In general, the level of the reduction in adverse selection after the release of the Sustainalytics ESG scores is heterogeneous among different types of agents. It differs according to investors' preferences and awareness. One explicit source of heterogeneity in the beliefs arises since Bloomberg has already published Bloomberg ESG disclosure scores before the release of the Sustainalytics ESG scores on May 27th, 2014. Bloomberg ESG disclosure scores focus on the ESG disclosure quality but are inappropriate to measure corporate social performance. Therefore, they fundamentally differ from Sustainalytics ESG scores.

Hence, the release of the Sustainalytics ESG scores conditional on the knowledge of the Bloomberg ESG disclosure scores may lead to differing updates in beliefs and expectations. We test to what extent Sustainalytics ESG scores shifted the beliefs of market participants by measuring the market impact for subsets of companies, e.g., for companies with a positive ESG surprise meaning that Bloomberg ESG disclosure score of a company was below the sample median, while the Sustainalytics ESG score of the respective company is above the sample median. The results suggest that the increase in liquidity is highest for companies with a high ESG surprise.

The contribution of this paper is threefold: First, we provide causal evidence that the publication of ESG scores has significant economic capital-market effects, both based on liquidity measures and stock price performance, in an international cross-section of companies. The majority of prior evidence showing such benefits focus on the link between ESG scores and firm performance (e.g., Edmans, 2011; Lins et al., 2017). Another stream of studies examines the link between ESG scores and information asymmetry (Cho et al., 2013; Cui et al., 2018). Evidence from these studies often cast doubt on the fact that the reduction of the information asymmetry and stock price performance is stemming from the ESG scores, since their identification strategy allows only to provide correlations instead of causality. Reverse causality may–in contrast to our study–bias the estimates in this literature since the level of disclosure may impact both high liquidity and high ESG scores. Cui et al. (2018) base their analysis on two different methodologies to rule out endogeneity (i.e., 2SLS and dynamic panel system generalized method of moment). To our knowledge, no other study has made use of a quasi-experimental setting to study the effect of the release of ESG information on capital markets. Our study therefore differentiates from Cui et al. (2018) insofar as our starting position, based on the event under analysis, enables us to make concluding remarks on causality without specifically controlling for endogeneity.

At the same time, also the extensive research on the link between ESG scores and stock performance has not been able to provide causal evidence on the direction of the relationship. Investors' appetite for high ESG stocks may yield a demand-driven price impact that has so far not been disentangled from other factors, such as fundamentals, which are potentially linked to ESG criteria and additionally drive stock returns. With our study we can draw some inference on the demand-driven price effect directly following the event.

Third, our study considers the reaction of a large cross-section of market participants and investment types. Our results generalize those of earlier studies (Krueger, 2015; Blitz and Fabozzi, 2017; Ammann et al., 2019; Hartzmark and Sussman, 2019; Ceccarelli et al., 2019), as we do not restrict our analysis to a specific set of investors (e.g., sustainable investors) nor to a certain type of equity (e.g., conventional vs sustainable investments). Furthermore, although the general regulatory environment did not force investors (particularly institutional investors) to account for ESG scores in their investment decision in 2014, we additionally control for the level of the institutional ownership of each stock to capture effects as documented in Dyck et al. (2019).

The remainder of this paper is organized as follows. Section II describes the sample selection and our data set. Section III discusses the impact of ESG scores on measures of liquidity. Section IV presents an event study to investigate abnormal returns around the Sustainalytics ESG score release on Bloomberg. Section V outlines a comparison to the Bloomberg disclosure scores, which were available already prior to our event. Section VI concludes with a critical discussion of the results and potential implications.

II. Data and methodology

A. Event and sample selection

As of May 27th, 2014, Bloomberg released the Sustainalytics ESG scores for 1,525 companies as a piece of new information within the Bloomberg interface accessible for all Bloomberg subscribers. Bloomberg subscribers without access to Sustainalytics' ESG scores before the release therefore gained additional company-specific information through the scores. We consider the Sustainalytics ESG score release as an unexpected event since neither Bloomberg nor Sustainalytics advertised the update beforehand. Thus, the release presents an ideal laboratory to understand the contribution of ESG scores to the company transparency (e.g., a reduction of information asymmetry) in terms of ESG scores' potential impact on liquidity and price building mechanisms on capital markets.

Sustainalytics is a relevant market participant with a track record of 25 years, the scores are well-known and constitute a significant development in the quality of the ESG data published. Sustainalytics' rating process includes more than 220 indicators in 450 fields covering more than 11,000 companies. [3]

We refer to the companies with newly available Sustainalytics ESG scores as the treated sample in our analysis. To control for a possible selection bias of companies with available Sustainalytics ESG scores, we apply a propensity score matching (PSM) approach to define a control sample. The sample of control companies acts as counterfactual without available Sustainalytics ESG scores on Bloomberg. For every treated company, the respective control company approximates the development of a treated company in the hypothetical case of non-treatment. We employ an exact matching for companies according to their industry group and their country of the primary exchange. We then estimate propensity scores using the following variables: firm size (total assets and net sales or revenues), performance (EBIT and operating income) and leverage (total debt over common equity).[4] Using the Eikon Screener tool, we select control companies from a sample of more than 35,000 available stocks with a market cap of more than USD 100k. As of our event date, we use data from Datastream to define the set of companies which match our treated sample best. After the matching, we compose a panel data set with daily observations for the period from May 27th, 2013 to August 27th, 2014. We retrieved Sustainalytics ESG scores from Bloomberg (only for the treated companies), daily price data (total return index,

[3] For more information refer to `https://www.sustainalytics.com/esg-data/`.

[4] In detail, we use the natural logarithm of the variables due to their skewed distributions in the matching. Moreover, we excluded companies with negative leverage. We also applied the matching without these filters. In this case, the matching is less accurate, but the final results are similar.

bid and ask prices) from Datastream, daily turnover data from Eikon, monthly accounting and fundamental data from Worldscope, and monthly institutional ownership data from Eikon. Furthermore, we account for daily returns of the five risk factors (Fama and French, 2015) in our return analysis.[5] The appendix of this paper contains a complete list of variables and data sources (see Table A.14).

After applying the PSM and excluding any company that has no matching partner and pairs of companies without available price information as of May 27th, 2014, our final sample comprises 1219 treated and 1219 control companies (see Table 1). The cross-section of companies includes 498 companies from the US and Canada, 319 companies from Europe, 289 companies from Japan, and 113 from the Asia-Pacific region. The companies are distributed over eleven industries with 34% of the companies operating in either the sector "Industrials" or "Consumer Discretionary." The industry "Telecommunications" contributes the lowest proportion of companies to the sample (2.5%).

[5] We thank Kenneth R. French for providing the data on https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 1: Descriptive statistics of PSM variables: region and industry.

	category	treated	control
Region			
1	US and Canada	498	498
2	Europe	319	319
3	Japan	289	289
4	Asia-Pacific, Australia, and New Zealand	113	113
Industry			
1	Basic Materials	98	98
2	Consumer Discretionary	207	207
3	Consumer Staples	87	87
4	Energy	83	83
5	Financials	184	184
6	Health Care	92	92
7	Industrials	213	213
8	Real Estate	76	76
9	Technology	79	79
10	Telecommunications	31	31
11	Utilities	69	69
Total		1219	1219

Notes: This table reports the number of stocks classified into four regions (i.e., the region of the exchange) and eleven industry sectors.

To capture the accidental missing of single values in ask and bid prices and the turnover values, we replaced them by the average of the leading and lagging numbers. In case of multiple subsequent missing values, no replacement was applied. Furthermore, institutional ownership values of more than 100% were replaced by a value of 100%. After excluding trading holidays, we winsorized spreads, returns (based on the total return index), ROA, leverage and turnover at the 1% and the 99% level on each trading day, separately for the treated and the control group. In general, the PSM yielded similar samples of treated and control companies (see Table 2). Some differences between the treated and control sample exist in company size which is consistent with the bias that ESG rating agencies are more likely to provide ESG scores for larger companies.

Table 2: Descriptive statistics of PSM variables.

	sample	mean	median	sd	min	max	p5	p95	skewness	kurtosis
ln(EBIT(in mn USD))	treated	13.6	13.5	1.18	10.2	17.5	12.0	15.8	0.45	3.18
	control	12.0	12.0	1.04	7.71	16.6	10.3	13.7	0.43	5.18
ln(OperatingIncome)	treated	13.5	13.4	1.21	6.55	17.4	11.9	15.7	0.15	4.06
	control	11.9	11.9	1.08	7.08	16.6	10.2	13.6	0.0086	5.51
ln(NetSalesorRevenue)	treated	15.7	15.6	1.32	5.51	19.7	13.7	17.9	−0.29	5.49
	control	14.4	14.5	1.15	8.47	19.1	12.4	16.2	−0.37	5.16
ln(TotalDebtCommonEquity)	treated	4.03	4.16	1.43	−4.61	8.83	1.65	5.96	−1.49	8.37
	control	3.87	4.15	1.51	−4.61	7.67	1.12	5.85	−1.45	6.95
ln(TotalAssets)	treated	16.8	16.5	1.43	13.4	21.8	14.9	19.7	0.87	3.83
	control	15.3	15.1	1.15	13.1	20.9	13.8	17.7	1.01	4.30

Notes: This table reports descriptive statistics of the variables used in the PSM for the final sample of 1,219 treated companies and their 1,219 matching partners. All companies of the treated sample observed a Sustainalytics ESG score on Bloomberg, while the control companies did not obtain such an ESG score on Bloomberg.

III. The liquidity-effect of the Sustainalytics ESG score release

A. Dependent variables to measure information asymmetry

We base our analysis on three proxies of information asymmetry widely acknowledged in theoretical and empirical literature (Leuz and Verrecchia, 2000; Glosten and Milgrom, 1985; Christensen et al., 2016). The first variable to capture a change in the stock liquidity is the bid-ask spread (SPREAD). The bid-ask spread can be considered as an explicit measure of information asymmetry (Leuz and Verrecchia, 2000). The underlying assumption is that a portion of the differential between the average price that investors ask for a stock and the price that investors bid for the same stock on average is driven by information asymmetry in the market. This effect is particularly influenced by market makers deliberately widening spreads to cover perceived information asymmetries (Glosten and Milgrom, 1985). Transactions between equally informed investors are expected to result in a smaller divergence between bid and ask price and therefore a lower bid-ask spread. The adverse information cost component inherent bid-ask spreads has been found to be affected by the release of new information, such as earnings announcements (Diamond, 1985; Kim and Verrecchia, 1994).

We calculate the bid-ask spread for stock i on day t following Affleck-Graves et al. (2000) as the ratio of the difference between the ask and the bid price to the midpoint:

$$SPREAD_{i,t} = (Ask_{i,t} - Bid_{i,t})/Midpoint_{i,t} \tag{1}$$

As a second measure of information asymmetry, we analyze stock price volatility. We define volatility as standard deviation of price returns in the past 60 days (VOLATILITY). Prior studies (e.g., Lang and Lundholm, 1993; Leuz and Verrecchia, 2000) have used stock price volatility as a proxy for information asymmetry. Low levels of stock price volatility suggest less information asymmetries since a smooth development of stock prices indicate the absence of information asymmetries between managers and shareholders, or among investors. Nevertheless, many factors unrelated to information asymmetry may influence stock price volatility. For instance, Bushee and Noe (2000) show an effect of disclosure on volatility that depends on the type of (institutional) investors attracted to the company. Thus, as a measure of information asymmetry, volatility is likely to be the least reliable among the three proxies.

Our third measure is the relative trading volume calculated as total trading volume of stock i on day t divided by the number of shares outstanding on day t (REL_TURNOVER). Turnover reflects the willingness of investors to sell, respectively buy stocks and is expected to be inversely related to information asymmetry. However, trading volume can at the same time be driven by other factors, such as portfolio strategies, risk preferences, and uncertainty, and hence not exclusively capture adverse selection among shareholders (Barinov, 2014; Leuz and Verrecchia, 2000). Therefore, as with stock price volatility, turnover is expected to provide less specific insight on information asymmetry than the bid-ask spread.

B. Estimating the differential effect of the Sustainalytics ESG score release

Our identification strategy to analyze the impact of the Sustainalytics ESG scores release on liquidity is a difference-in-differences (DiD) setting. The DiD variable represents the interaction term of the treatment dummy (indicating whether a company's Sustainalytics ESG score was published on Bloomberg as of May 27th, 2014) and the after-treatment dummy (differentiating the period before and after treatment). To measure abnormal liquidity after the event day, we follow Leuz and Verrecchia (2000); Christensen et al. (2016); Cho et al. (2013) and explain the variation in daily measures of liquidity as a function of the DiD variable and common control variables leverage (*ln*(LEVERAGE)), market capitalization (*ln*(MARKETVALUE)), profitability (ROA), institutional ownership (INST_OWN) and the inverse of the price (*ln*(1/PRICE)). Table 3 contains summary statistics for these variables. We specify the main model as follows:

$$Liquidity_{i,t} = \beta_0 \cdot DiD_{i,t} + \sum_{j=1}^{5} \beta_j \cdot ln(Control_{j,i,t}) + \alpha_i + \eta_t + \varepsilon_{i,t} \tag{2}$$

where company and day fixed-effects are denoted by α_i and η_t and standard errors are clustered at company level (as supposed by Petersen, 2009). We include daily time fixed-effects to control for the volatile nature of bid-ask spreads and shocks affecting all companies on a specific day t and company fixed-effects to control for characteristics of the treated companies that might not be perfectly captured by the control sample. Since we include company and day fixed-effects, we omit the treatment and the after-treatment dummies due to multicollinearity.

We base our DiD analysis on the assumption that companies cannot choose to be rated by Sustainalytics and hence, do not specifically opt for having their ESG rating published on Bloomberg, i.e., companies cannot self-select into treatment. We assume that the mean liquidity measures of the treatment and the control group follow a parallel trend, which is supported by Figures A.3, A.4 & A.5 in the Appendix.

Table 3: Sample overview and descriptive statistics.

	sample	mean	median	sd	min	max	p5	p95	skewness	kurtosis
Dependent Variables										
ln(SPREAD)	treated	−2.69	−2.63	1.21	−5.73	0.00	−4.58	−0.75	0.05	2.19
	control	−1.93	−1.82	1.31	−4.87	1.08	−4.10	0.20	0.01	2.34
ln(VOLATILITY)	treated	0.27	0.29	0.29	−0.67	0.99	−0.24	0.71	−0.21	2.65
	control	0.43	0.45	0.31	−0.74	1.58	−0.12	0.89	−0.36	3.42
ln(REL_TURNOVER)	treated	−1.63	−1.65	0.69	−3.25	0.14	−2.79	−0.35	0.19	2.92
	control	−2.07	−1.91	1.19	−6.55	0.15	−4.35	−0.38	−1.11	5.16
Control Variables										
ROA	treated	5.83	4.96	5.68	−11.03	24.93	−0.45	16.60	0.71	5.02
	control	4.26	3.95	4.63	−10.73	21.14	−2.71	11.45	0.40	6.03
ln(LEVERAGE)	treated	4.01	4.14	1.45	−4.61	6.82	1.39	6.01	−1.70	9.19
	control	3.88	4.17	1.52	−4.61	6.57	1.01	5.80	−1.57	6.92
ln(MARKETVALUE)	treated	23.30	23.16	1.02	21.09	27.01	21.83	25.23	0.61	3.09
	control	21.46	21.50	1.02	17.56	25.90	19.74	23.02	0.14	4.35
INST_OWN	treated	66.78	67.61	22.30	0.42	100.00	31.29	100.00	−0.25	2.16
	control	70.90	73.35	23.55	0.06	100.00	31.57	100.00	−0.54	2.58
ln(1/PRICE)	treated	−3.42	−3.53	1.19	−12.16	0.78	−5.02	−1.32	−0.21	6.44
	control	−3.00	−3.11	1.43	−9.32	4.07	−4.96	−0.40	0.21	5.57
SUST_SCORE	treated	53.25	54.17	29.09	0.00	100.00	5.75	96.55	−0.13	1.83

Notes: This table reports the descriptive statistics of the final sample after the PSM (1,219 treated companies and their 1,219 matching partners) as of the event day (May 27th, 2014.)

C. Empirical results

This section studies whether stock liquidity of treated companies measured by *ln*(SPREAD), *ln*(VOLATILITY) and *ln*(REL_TURNOVER) increases after the event date. The results of the difference-in-differences regression model presented in Table 4 show that the release of the Sustainalytics ESG scores on Bloomberg caused a reduction of information asymmetry for treated companies compared to our control sample based on bid-ask spreads and stock price volatility based on daily observations in a period of six months around the event. The coefficients -0.051 for *ln*(SPREAD) and -0.040 for *ln*(VOLATILITY) of the variable of interest (DiD) in the entire sample (see Column "all" of Table 4) are significantly lower than zero at the 1% significance level. This indicates that in the three months following the event, an average treated sample company exhibits a 5.1% lower measure for liquidity than an average control company, and thus represents the treatment effect. Taking into account the mean log_SPREAD of 2.69 (see Table 3), the treatment effect results in a decrease of the bid-ask spread of 6.5% ($e^{-2.69-0.051} = 0.06451$).

We translate the percentage effects into value-weighted average savings in annual trading costs per company to gauge the economic magnitude of the results. These values represent a lower bound on the capital-market effects since the economic effects of liquidity improvements go beyond trading costs. We use the estimated coefficient of the bid-ask spread to determine the annual trading cost savings as the product of the estimated trading cost reductions with the relative yearly dollar trading volume per company (Christensen et al., 2016). The 5.1%

differential increase in liquidity for an average treated sample company relative to the control group translates into average trading cost savings of approximately US$ 22 million per year and sample company, which implies a combined yearly benefit of the Sustainalytics ESG score release of 0.17% of the market capitalization. These numbers are economically significant, in particular when considering the recurring nature of the savings.

Table 4: Difference-in-Differences model in the overall sample.

	all	above median	below median
Dependent variable: ln(SPREAD$_{it}$)			
DiD	−0.051***	−0.077***	−0.027
	(−2.98)	(−3.10)	(−1.12)
Daily FE	Yes	Yes	Yes
Institution FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
#Obs.	275,447	138,793	136,654
F-statistic	7.987	6.939	2.803
p-value	0.000	0.000	0.010
Dependent variable: ln(VOLATILITY$_{it}$)			
DiD	−0.040***	−0.046***	−0.032***
	(−6.52)	(−5.44)	(−3.74)
Daily FE	Yes	Yes	Yes
Institution FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
#Obs.	282,606	142,067	140,539
F-statistic	11.098	7.804	4.073
p-value	0.000	0.000	0.000
Dependent variable: ln(REL_TURNOVER$_{it}$)			
DiD	−0.015	−0.011	−0.018
	(−1.45)	(−0.78)	(−1.19)
Daily FE	Yes	Yes	Yes
Institution FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
#Obs.	281,171	141,623	139,548
F-statistic	1.576	2.281	1.657
p-value	0.150	0.034	0.128

Notes: This table reports the estimates of the DiD coefficients in the regression analysis following Equation 2 for three measures of liquidity (spread, volatility, and rel_turnover). The first column (all) contains the results estimated based on the entire sample. The last two columns contain the results for two subsamples, one including all companies with Sustainalytics ESG scores above the sample median and one including all companies with scores below the sample median. We ran these regressions for a period of three months before and three months after the event (February 27th, 2014 to August 27th, 2014) based on daily observations. We included company and day fixed-effects, and clustered standard errors at the company level. The coefficients of the control variables are unreported in this table. t-values are in parentheses. $^{*}p < .1$, $^{**}p < .05$, $^{***}\ p < .01$.

We further investigate whether measures of liquidity of treated companies are sensitive to the level of the Sustainalytics ESG scores. Therefore, we split our sample in two groups, companies with Sustainalytics ESG score above (below) the sample median and run the regression analysis for both groups separately. We distribute the control companies in the same group as the respective treated company. The results of the *ln*(SPREAD) panel clearly indicates that liquidity increases to a higher extent if companies have better (above median) ESG scores. While treated companies with above median ESG scores exhibit a significant change in bid-ask spreads, the liquidity of companies with below median ESG scores has not significantly increased compared to the respective control companies. Since previous studies suggested that companies with high ESG scores are less crash prone, due to fewer hidden bad news (Kim et al., 2014; Utz, 2018) and less affected by litigation (Koh et al., 2014; Fauser and Utz, 2020), our results complete, whiche findings by showing lower actual adverse selection costs for companies with high ESG scores.

The results for stock price volatility, which is also considered to be an indicator for investor uncertainty, reveals a strongly significant effect irrespective of the level of the ESG score. The coefficient and the t-value for the below median-sample is lower than the quantities of the above group, however, not significantly different (unreported results). Thus, the release of the Sustainalytics ESG scores significantly reduced the stock price volatility of all treated companies to a higher extent than matched control companies. With regards to the REL_TURNOVER, we do not find significant differences between control and treatment around the event date. The effect on relative turnover remains insignificant in either of the two separate ESG score groups.

To summarize, we present evidence that the release of the Sustainalytics ESG scores results in an improvement of treated companies' liquidity measured as spread and volatility. At the same time, relative turnover exhibits no significant changes. While this result is somewhat counter-intuitive, it could point to the fact that ESG scores reduce information asymmetry while at the same time, due to investors' difficulties to assess the value relevance of the new information, they might be hesitant to trade the respective stocks. Furthermore, as indicated above, turnover is expected to be also related to other factors than information asymmetry, and therefore ESG scores might exhibit conflicting effects on trading volumes via different channels.

To investigate whether the effect on information asymmetry differs across regions, we split our sample into four geographical areas, i.e., Asia-Pacific (including Australia and New Zealand), Europe, Japan, and North America (including the US and Canada). The release of the Sustainalytics ESG scores on Bloomberg significantly reduces information asymmetry for companies that are primarily traded in Japan and North America, however not for Asian-Pacific and European companies (see Table 6). We explain this pattern by the fact that investors in countries with strong environmental and social norms (such as Europe) have already considered the ESG performance of investment opportunities before the event (Dyck et al., 2019), and thus, the release has not shifted the beliefs of the investors to a significant extent.

Table 5: Summary statistics of Sustainalytics ESG scores by region: treated sample.

	mean	p50	sd	min	max	p5	p95
All (N=1212)							
SUST_SCORE	53.22	53.95	29.07	0.00	100.00	5.77	96.55
North America (N=493)							
SUST_SCORE	48.57	48.28	28.07	0.00	100.00	5.56	91.95
Europe (N=317)							
SUST_SCORE	71.79	80.00	25.87	1.23	100.00	22.08	100.00
Japan (N=289)							
SUST_SCORE	42.01	40.77	24.90	0.00	95.83	3.37	83.33
Asia-Pacific (N=113)							
SUST_SCORE	50.12	50.00	28.08	0.00	99.52	2.70	92.79

Notes: These summary statistics include all stocks in the treated sample.

In countries with weaker environmental and social norms (such as the US), the release of the Sustainalytics ESG scores on Bloomberg may have added substantially new company-specific information to investors. Table 5 supports this argumentation by showing that Sustainalytics ESG scores in Europe (mean 71.79, sd 25.87) exhibit a high average valuation with low variation compared to the North American sample (mean 48.57, sd 28.07). Due to strong social and environmental norms, European companies differentiate less in ESG aspects and thus, show lower variation in the cross-section of ESG scores. In regions with a less severe regulatory environment concerning ESG aspects, the opportunity to differentiate in ESG from competitors is higher, and results in higher variation in the cross-section of ESG scores. The opportunity to differentiate also increases information asymmetry, since investors cannot rely on the regulatory environment but need to be aware of company-specific ESG activities. Thus, the release of ESG scores for such companies may have stronger capital market effects.

Finally, and to determine whether our findings on information asymmetry remain robust to the selected observation period, we estimate the DiD regression model for different periods, ranging from six (nine) months before the event and three months after the event. The reported results in Table A.15 in the appendix suggest that lengthening the pre-event period does not substantially alter our findings. Despite slightly lower coefficients, the results remain qualitatively the same after this amendment. Furthermore, the differences-in-differences model is conducted with two placebo dates, three months, respectively one year before the treatment date. We choose the date three months before the event because the ESG scores were back-filled until February 27th, 2014, at the time the data was uploaded. Therefore, we have the Sustainalytics ESG scores available for the treated sample at the placebo event date. The placebo test one year before the event helps us to assess if seasonality-linked aspects drive our results. With the placebo dates, we cannot document a reduction in liquidity measures (*ln*(SPREAD) and *ln*(VOLATILITY)) as of February, 27th, 2014 or May, 27th 2013.

Table 6: Difference-in-Differences model in different regions.

	Dependent variable								
	ln($SPREAD_{it}$)			*ln*($VOLATILITY_{it}$)			*ln*($REL\_TURNOVER_{it}$)		
	all	above median	below median	all	above median	below median	all	above median	below median
North America									
DiD	−0.117***	−0.144***	−0.086**	−0.022**	−0.035***	−0.008	−0.026*	−0.020	−0.030
	(−3.85)	(−3.40)	(−1.99)	(−2.50)	(−2.77)	(−0.69)	(−1.66)	(−0.95)	(−1.37)
#Obs.	114,668	57,667	57,001	115,020	57,911	57,109	114,234	57,742	56,492
p-value	0.000	0.039	0.003	0.006	0.001	0.179	0.187	0.000	0.059
Europe									
DiD	0.021	0.024	0.010	−0.058***	−0.056***	−0.060***	0.037*	0.025	0.049
	(0.82)	(0.79)	(0.26)	(−4.77)	(−3.38)	(−3.35)	(1.68)	(0.80)	(1.63)
#Obs.	65,627	33,593	32,034	71,756	36,235	35,521	71,112	35,962	35,150
p-value	0.290	0.000	0.998	0.000	0.005	0.025	0.000	0.000	0.000
Japan									
DiD	−0.073***	−0.114***	−0.033*	−0.051***	−0.058***	−0.044***	−0.047**	−0.035	−0.058**
	(−5.78)	(−6.53)	(−1.90)	(−5.33)	(−4.25)	(−3.23)	(−2.50)	(−1.34)	(−2.15)
#Obs.	69,405	34,738	34,667	69,821	34,992	34,829	69,818	34,992	34,826
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001
Asia-Pacific									
DiD	0.076	0.012	0.095	−0.052**	−0.055**	−0.046	−0.004	−0.017	0.004
	(1.26)	(0.15)	(1.24)	(−2.39)	(−2.30)	(−1.29)	(−0.09)	(−0.32)	(0.06)
#Obs.	25,747	12,795	12,952	26,009	12,929	13,080	26,007	12,927	13,080
p-value	0.009	0.010	0.002	0.008	0.179	0.007	0.043	0.082	0.060

Notes: This table reports the estimates of the DiD coefficients in the regression analysis following Equation 2 for three measures of liquidity (spread, volatility, and rel_turnover) separated by four regions (North America, Europe, Japan, and Asia-Pacific). The first column (all) of each of the three sets of columns contains the results estimated based on the entire sample. The last two columns of each of the three sets of columns contain the results for two sub-samples, one including all companies with Sustainalytics ESG scores above the sample median and one including all companies with scores below the sample median. We ran these regressions for a period of three months before and three months after the event (February 27th, 2014 to August 27th, 2014) based on daily observations. We included company and day fixed-effects, and clustered standard errors at the company level. The coefficients of the control variables are unreported in this table. t-values are in parentheses. $^{*}p < .1$, $^{**}p < .05$, $^{***}\ p < .01$.

IV. Stock prices and ESG scores in an event study approach

A. Estimating abnormal returns

In the next step, we calculate daily abnormal returns, based on the total return index, to answer the question of whether the release of the Sustainalytics ESG scores impacted market equilibrium prices. We follow a standard event study methodology and determine an estimation and an event window. We consider the event to be exogenous, since the release of the Sustainalytics ESG scores was not advertised in advance. The press release of the Sustainalytics ESG score release was published at 09:18 Eastern Time on May 27th, 2014, and thus the new information impacted trading in Europe, Japan, and Asia Pacific on May 28th, 2014. Accordingly, we define the event for companies of the respective regions. Our estimation window of 220 trading days ends one day before the respective event day. The event window spans one month of trading days, i.e., 23 days. The reason for this choice is the fact that Sustainalytics ESG scores are published on a monthly basis and an update of the ESG scores became available 24 days after the initial publication. We exclude all stocks that have less data points than 150 in the estimation window and less than 11 data points in the event window.

To analyze the impact of the Sustainalytics ESG scores on stock prices, we calculate cumulative abnormal returns (CAR) for treated and control companies for the entire event window. In detail, for each company i and each day t in the event window, we calculate the daily abnormal return $AR_{i,t}$ as the difference of the actual return of the company $R_{i,t}$ and its expected return $\hat{R}_{i,t}$. We estimate the expected return $\hat{R}_{i,t}$ in market regressions with the five common risk factors reported in Fama and French (2015).

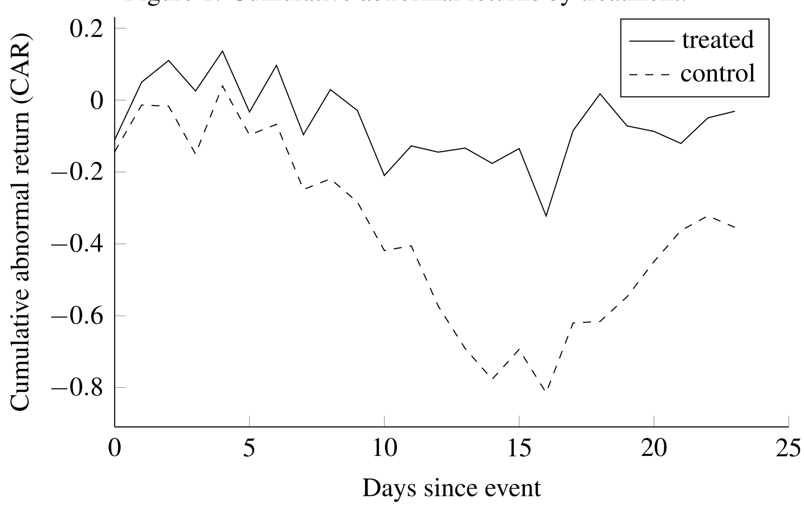
$$AR_{i,t} = R_{i,t} - \hat{R}_{i,t} = R_{i,t} - (a_{i,t} + \sum_{f=1}^{F} \beta_f \cdot \text{FF5-Factor}_f) \tag{3}$$

Next, we calculate cumulative abnormal returns $CAR_i[\tau_0, \tau_1]$ for each company i as the sum of the respective abnormal returns for the 23-day period $[0, 23]$:

$$CAR_i[0, 23] = \sum_{t=0}^{23} AR_{i,t} \tag{4}$$

Figure 1 shows cumulative abnormal returns of treated and control companies in the respective period. Treated companies show higher cumulative abnormal returns in the event period as compared to the control sample.

Figure 1: Cumulative abnormal returns by treatment.



B. Empirical results

We investigate whether the effect identified on CARs (see Figure 1) is indeed linked to the treatment (i.e., the release of the ESG scures on Bloomberg) or if other company-level characteristics drive the difference in CAR between treated and control companies. Therefore, we run a cross-sectional regression to explain the variation in the CAR by a treatment dummy, several control variables (SIZE, PRICE_BOOK, INST_OWN, *ln*(LEVERAGE) and ROA), and robust standard errors.[6] The control variables have been documented to drive returns around different events (see for example Ramelli et al., 2018; Wagner et al., 2018). We do not include industry fixed-effects because we implicitly control for the industry as it is an exact matching variable and therefore corresponding for control and treated firms.

The variable of our interest, TREATMENT is significant for the entire sample (Column "all" in Table 7), indicating that treated companies earn 0.786% higher cumulative abnormal returns in the period after the event even after controlling for stock characteristics. In line with our liquidity analysis that revealed the strongest effect for companies with above median ESG scores, we also investigate the return impact according to the level of the Sustainalytics ESG scores (Columns 2 and 3 of Table 7). In the case of abnormal returns, the effects is equally strong for companies with above and below average ESG ratings, indicating that the

[6]The sample size is smaller in this analysis as we excluded all companies (and their matching partners) with less than 150 observations in the estimation window, respectively less than 11 observations in the event window.

capital-market effect is largely driven by the reduction in information asymmetry, irrespective of the qualitative content of the new information. A potential argument in favor of this finding is the fact that to date, the relationship between ESG performance and stock market risk and return characteristics is still somewhat ambiguous and not clearly revealed by existing research. The above-median sustainability performance of a specific stock does therefore not necessarily imply a positive adjustment of an investors' belief about future stock price performance.

Table 7: Cumulative abnormal returns in the cross-section.

	Dependent Variable: CAR						
	all	above median	below median	North America	Europe	Japan	Asia-Pacific
TREATMENT	0.786***	0.845**	0.777**	1.349***	−0.640	1.293*	1.432
	(2.81)	(1.98)	(2.06)	(3.04)	(−1.25)	(1.84)	(1.39)
SIZE	−0.195**	−0.230	−0.201	−0.500***	0.400**	−0.391	−0.287
	(−1.97)	(−1.63)	(−1.34)	(−2.96)	(2.08)	(−1.47)	(−0.72)
PRICE_BOOK	0.000	0.012***	−0.017***	−0.026	0.003	0.053	−0.082
	(0.05)	(3.70)	(−3.86)	(−1.07)	(0.25)	(0.10)	(−1.48)
ln(LEVERAGE)	−0.112	−0.036	−0.174	0.025	−0.420***	0.090	0.246
	(−1.36)	(−0.32)	(−1.46)	(0.12)	(−2.83)	(0.67)	(0.55)
ROA	−0.022	−0.061	0.012	−0.024	−0.049	0.082	−0.007
	(−0.88)	(−1.55)	(0.39)	(−0.63)	(−1.05)	(0.94)	(−0.10)
CONSTANT	1.603**	1.800*	1.697	3.817**	−1.895	1.777	0.618
	(2.07)	(1.65)	(1.44)	(2.27)	(−1.19)	(0.99)	(0.16)
#Obs.	2256	1124	1132	892	594	559	211
p-value	0.041	0.000	0.000	0.014	0.047	0.355	0.487

Notes: This table shows the results of a regression with the cumulative abnormal return based on the Fama and French (2015) model in the period $t = 0$ to $t = 23$ as dependent variable. The set of control variables includes company size, price-to-book ratio, leverage, and return on assets (ROA). The first column displays the results for the overall sample. Columns two to five show results separately for the four regions North America, Europe, Japan, and Asia-Pacific. Abnormal returns are expressed in percentage points. Robust standard errors included. Standard errors are in parentheses. $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

We furthermore test the difference in cumulative abnormal returns between treatment and control for different regions. The effect in the entire sample appears to be driven mainly driven by the North American sample, as separate regressions reveal that the effect is not significant in Europe and Asia-Pacific, and only slightly significant in Japan. Results on the information asymmetry already pointed to the fact that the reduction in information asymmetry linked to the event is strongest in North America, which is arguably confirmed by a significant effect on stock prices in the month following the event. However, while we find a reduction in information asymmetry for the Japanese sample, the effect does not strongly materialize in an adaption of stock price performance.

Furthermore, in line with the liquidity analysis, we run two placebo event studies based on the Fama and French (2015) model three months before the true event as well as one year before the event. We do not find significant differences in cumulative abnormal returns between the treated and the control sample for the two placebo event dates (see Table A.17).

V. Bloomberg Disclosure Scores

Bloomberg was one of the first large financial data providers that had already reported ESG disclosure scores that account for non-financial disclosure before May 27th, 2014, to its subscribers. Thus, Bloomberg ESG disclosure scores have been available to Bloomberg subscribers already before the release of Sustainalytics scores. Like Sustainalytics ESG scores, Bloomberg ESG disclosure scores are presented in absolute numbers distributed between 0 and 100. However, these

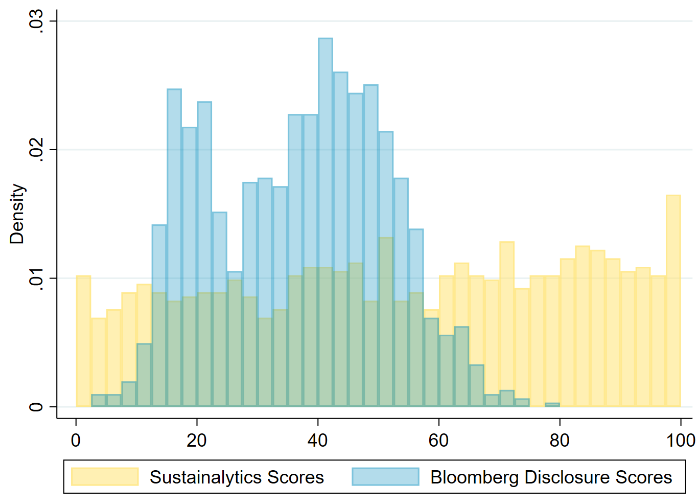
ESG disclosure scores do not give indications about companies' performance or quality to ESG aspects, but only indicates to which extent a company reports on ESG-related aspects. After May 27th, 2014, Bloomberg subscribers who examine a specific stock with regards to its ESG performance get both scores displayed side by side.

Investors may react differently to the newly published Sustainalytics ESG scores compared to already existing Bloomberg ESG disclosure scores differently. Although both scores may be perceived as ESG scores informing about the quality of a company's ESG activities, there might be (1) investors who are unaware of the differing concepts captured by these two ESG scores and (2) investors who are aware of the difference and gain additional insight from the comparison. More generally, the information gain from Sustainalytics ESG scores conditional on existing knowledge about Bloomberg ESG disclosure scores may lead to updates in information and respective expectations.

Therefore, we investigate the capital-market effects of the Sustainalytics ESG score release conditional on the Bloomberg ESG disclosure scores in the following. We collected annual ESG disclosure scores from Bloomberg for all treated companies from 2010 to 2018. Despite both scores ranging from 0 to 100, they considerably differ in terms of distribution, as depicted in Figure 2. The figure displays the ESG scores of all companies in our treated sample, which have both scores (Bloomberg and Sustainalytics) available as of May 27th, 2014. In total, this sample comprises 1212 treated companies. While the distribution of the Sustainalytics ESG scores mimics a uniform distribution on the entire range of scores

0 to 100, the distribution of the Bloomberg ESG disclosure scores is bimodal, with one maximum of around 20 and the other around 40. Moreover, the Bloomberg ESG disclosure scores spread over a narrower interval (5 to 80), although they also cover a range of 0 to 100 in theory.

Figure 2: Distribution of Sustainalytics ESG scores vs. Bloomberg ESG disclosure scores as of May 27th, 2014. This figure includes all stocks in the treated sample for which both scores are available as of May 27th, 2014.



Descriptive statistics reported in Table 8 show the heterogeneity of the two ESG scores and across different regions. European companies obtained the highest Sustainalytics ESG scores and Bloomberg ESG disclosure scores as of May 27th, 2014, compared to all other regions. However, while Japanese companies exhibit the lowest average Sustainalytics ESG scores, they show the second-highest average Bloomberg ESG disclosure score among the regions.

Table 8: Summary statistics of Sustainalytics ESG and Bloomberg ESG disclosure scores: treated sample.

	mean	p50	sd	min	max	p5	p95	skew	kurt	corr
All (N=1212)										
S	53.22	53.95	29.07	0.00	100.00	5.77	96.55	−0.12	1.83	0.65***
B	36.72	38.02	14.42	2.89	78.07	14.83	59.50	0.00	2.17	
North America (N=493)										
S	48.57	48.28	28.07	0.00	100.00	5.56	91.95	0.01	1.82	0.64***
B	32.37	30.14	14.81	8.33	74.79	14.05	57.02	0.52	2.26	
Europe (N=317)										
S	71.79	80.00	25.87	1.23	100.00	22.08	100.00	−0.92	2.81	0.64***
B	44.65	46.89	13.31	5.79	78.07	17.77	63.22	−0.59	3.09	
Japan (N=289)										
S	42.01	40.77	24.90	0.00	95.83	3.37	83.33	0.12	1.98	0.55***
B	36.34	39.67	11.99	2.89	60.74	12.81	52.89	−0.62	2.74	
Asia-Pacific (N=113)										
S	50.12	50.00	28.08	0.00	99.52	2.70	92.79	−0.14	1.97	0.64***
B	34.42	34.21	12.13	9.92	64.32	14.46	55.97	0.21	2.51	

Notes: These summary statistics include all stocks in the treated sample for which both scores are available as of May 27th, 2014. The first row ("S") in each panel contains the statistics of the Sustainalytics ESG scores, the second row ("B") those of the Bloomberg ESG disclosure scores. The column "corr" reports the Pearson correlation between the Sustainalytics ESG scores and the Bloomberg ESG disclosure scores on the event day.

To examine whether companies with high (low) Bloomberg ESG disclosure scores also exhibit high (low) Sustainalytics ESG scores, we divide the companies into two groups, one containing all companies with ESG scores above the respective median and one group with all companies with ESG scores below the respective median.[7] Approximately 70% (=(428+423)/1212) of the companies in our treated sample are classified into the same median category for the Sustain-

[7]Respective median refers to the type of ESG score and the (sub)sample.

alytics ESG score and the Bloomberg ESG disclosure scores (see Table 9). For 181 companies (15%), the Sustainalytics ESG scores represent a "positive surprise" (in terms of the median classification) compared to the Bloomberg ESG disclosure score.

Table 9: Difference in median classification for the treated sample.

		Above median: Bloomberg		
		0	1	Total
Above median: Sustainalytics	0	428	180	608
	1	181	423	604
	Total	609	603	1212

Notes: This table displays the frequency of classification into above and below median classes for Sustainalytics and Bloomberg disclosure scores. The amount of stocks classified into above or below median with regards to Bloomberg disclosure scores marginally differs compared to the other classifications as more stocks fall exactly on the 50th percentile.

The classification in the above and below median groups is only a rough measure to illustrate the correlations structure of the two types of scores. To investigate the surprise of the Sustainalytics ESG scores in more detail, we calculate two types of a differential between the newly available Sustainalytics ESG scores and the Bloomberg ESG disclosure scores. Our first measure is the *difference between raw scores*

$$\Delta_{raw,i} = ESG_{S,i} - ESG_{B,i}$$

where S refers to the Sustainalytics ESG score of company i and B refers to the Bloomberg ESG disclosure score of company i. This measure accounts for the quantities investors face on their Bloomberg terminals without further knowledge about ESG score distributions.

Our second measure is the *difference between normalized scores*

$$\Delta_{norm,i} = \frac{ESG_{S,i} - \overline{ESG_S}}{\sigma(ESG_S)} - \frac{ESG_{B,i} - \overline{ESG_B}}{\sigma(ESG_B)}$$

where $\overline{ESG_*}$ is the sample average of the ESG_* scores with $* \in \{S,B\}$ and $\sigma(ESG_*)$ refers to the sample standard deviation of the ESG_* scores with $* \in \{S,B\}$. This measure represents the difference in the Sustainalytics ESG score and Bloomberg ESG disclosure score of a company after normalizing the respective ESG score with its cross-sectional mean and standard deviation. Consequently, this measure demands knowledge about the cross-sectional structure of the respective ESG scores. For an average sample company i with a Sustainalytics ESG score of $ESG_{S,i} = 48.57$ and a Bloomberg ESG disclosure score of $ESG_{B,i} = 32.37$, the two measures yield values of $\Delta_{raw,i} = 48.57 - 32.37 = 16.20$ and $\Delta_{norm,i} = \frac{48.57-48.57}{28.07} - \frac{32.37-32.37}{14.81} = 0$. Thus, the difference between these two measures represents the situation of an investor unaware of the cross-section of ESG scores and therefore considering the Sustainalytics score as a "positive surprise" (following a positive $\Delta_{raw,i}$). In contrast, an investor aware of the cross-section of ESG scores realizes that the Sustainalytics ESG score supports the Bloomberg ESG disclosure score assessment, i.e., that the company has an average assessment in both rating approaches.

Considering these two possible states of information of investors, we therefore use both the absolute and the normalized delta measures to classify our sample.

Table 10 presents summary statistics of the two different approaches for calculating the score-differences between Sustainalytics ESG scores and the Bloomberg ESG disclosure scores in the entire sample and separated for the four different regions.

To investigate the impact of positive and negative surprise of the Sustainalytics ESG scores, we classify companies into two samples, both based on the normalized and the absolute difference. We define a positive surprise if the delta measure is above the median (ABOVE MEDIAN) and a negative surprise if the delta measure is below the median (BELOW MEDIAN). Companies with a larger gap than the median (normalized or absolute) difference for a given region are classified into the ABOVE MEDIAN category and vice versa. Thus, for companies being classified into the ABOVE MEDIAN category, the release of Sustainalytics ESG scores depicted a “positive surprise” compared to other stocks which are traded in the same region. The sharp regional contrast in magnitudes supports our classification approach, i.e., comparing the score-differences to the respective region’s median. Each treated stock’s matching partner is classified into the same respective category.

Table 10: Summary statistics of differences in raw scores and normalized scores by region.

	mean	p50	sd	min	max	p5	p95	skewness	kurtosis
All (N=1212)									
Δ_{raw}	16.50	18.17	22.52	−48.65	69.05	−21.16	50.45	−0.17	2.24
Δ_{norm}	−0.00	0.02	0.93	−3.26	2.83	−1.55	1.45	−0.13	2.98
North America (N=493)									
Δ_{raw}	16.20	17.84	21.85	−44.63	69.05	−19.32	49.59	−0.13	2.34
Δ_{norm}	−0.16	−0.14	0.84	−3.26	2.14	−1.57	1.16	−0.29	3.49
Europe (N=317)									
Δ_{raw}	27.14	31.05	20.07	−48.65	62.81	−10.23	55.38	−0.63	3.01
Δ_{norm}	0.64	0.68	0.80	−2.42	2.83	−0.87	1.95	−0.39	3.74
Japan (N=289)									
Δ_{raw}	5.66	4.09	20.88	−33.66	58.94	−26.52	42.30	0.21	2.26
Δ_{norm}	−0.39	−0.39	0.89	−2.94	2.61	−1.78	1.16	0.24	2.93
Asia-Pacific (N=113)									
Δ_{raw}	15.71	15.45	22.40	−43.12	54.74	−22.88	48.14	−0.20	2.28
Δ_{norm}	−0.11	−0.10	0.84	−2.64	1.99	−1.52	1.10	−0.34	2.97

Notes: This table reports summary statistics of the raw (Δ_{raw}) and normalized (Δ_{norm}) differences between the Sustainalytics ESG score and the Bloomberg ESG disclosure score of all treated companies as of May 27th, 2014.

We consistently run our DiD analysis considering the normalized and absolute score differences (Δ_{raw} and Δ_{norm}) to gauge the value of the new information relative to previously available information in the form of Bloomberg disclosure scores. Results in Table 11 shows that the effect on *ln*(SPREAD) prevails only for stocks which experience a "positive surprise" with the newly available Sustainalytics ESG scores, both based on Δ_{raw} and Δ_{norm}. Interestingly, even though the distribution of the two ESG scores differs, the analysis of the absolute score difference yields comparable results as the analysis of the difference in normalized scores (Δ_{norm}). The size and significance of the effect identified for the volatility measure prevails for both forms of difference calculation and for the companies above and below the median. These findings are comparable with our main results, previously outlined in Table 4.

Table 11: Difference-in-difference model for differences in Bloomberg ESG disclosure scores and normalized Sustainalytics ESG scores.

	Δ_{raw}		Δ_{norm}	
	ABOVE MEDIAN	BELOW MEDIAN	ABOVE MEDIAN	BELOW MEDIAN
Dependent variable: ln(SPREAD$_{it}$)				
DiD	−0.084***	−0.018	−0.066***	−0.035
	(−3.39)	(−0.76)	(−2.71)	(−1.45)
#Obs.	136,749	137,385	134,925	139,209
F-statistic	5.950	3.289	2.620	6.728
p-value	0.000	0.003	0.016	0.000
Dependent variable: ln(VOLATILITY$_{it}$)				
DiD	−0.044***	−0.035***	−0.038***	−0.041***
	(−5.20)	(−4.06)	(−4.47)	(−4.74)
#Obs.	140,701	140,461	139,154	142,008
F-statistic	6.895	5.035	5.626	7.623
p-value	0.000	0.000	0.000	0.000
Dependent variable: ln(TURNOVER$_{it}$)				
DiD	−0.015	−0.018	−0.010	−0.023
	(−0.98)	(−1.20)	(−0.64)	(−1.59)
#Obs.	140,138	139,601	138,446	141,293
F-statistic	0.557	2.248	0.760	2.553
p-value	0.765	0.037	0.602	0.018

Notes: This table shows the estimates of the DiD coefficients of the difference-in-differences regression to explain the variation of the liquidity measures following Equation 2. We sorted the sample by the surprise of the Sustainalytics ESG score compared to the Bloomberg ESG disclosure score. We ran the estimation for three months before to three months after the event (February 27th, 2014 to August 27th, 2014). All regressions included the set of earlier used control variables (unreported in this table), and company and day fixed-effects. Moreover, we clustered standard errors on company level. t-values are in parentheses. $^{*}p < .1$, $^{**}p < .05$, $^{***}\ p < .01$

To evaluate the relevance of this additional analysis, we investigate whether companies classified into the ABOVE MEDIAN category based on ESG score differences are essentially in line with the companies categorized into the ABOVE MEDIAN category based on Sustainalytics ESG scores (used in Section III). In other words we aim to elicit whether the two approaches, our main results and the analysis based on ESG score differences, yield the same classification and thus, to similar results. The upper part of Table 12 shows that the classification based on the raw score difference yields to approximately 87% (=(528+524)/1212) overlapping stocks. However, the classification based on the difference of normalized scores (lower part of Table 12) yield to an overlap of approximately 62% (=(379+375)/1212). Thus, nearly 40% of the stocks are classified into a different category when investigating the score differences. While we acknowledge the partially overlapping classification, we conclude that the magnitude of difference between the two scores indeed plays a role in the extent to which market participants react.

Table 12: Difference in median classification for regression analyses.

Sustainalytics Above median	Δ_{raw} Above median: 0	1	Total
0	528	80	608
1	80	524	604
Total	608	604	1212

Sustainalytics Above median	Δ_{norm} Above median: 0	1	Total
0	379	229	608
1	229	375	604
Total	608	604	1212

Notes: This table displays the frequency of classification into above or below median classes. We compare the classification for our main results (according to Sustainalytics scores) with the classification based on the score difference and normalized score differences.

Lastly, we run the cross-sectional regression of the cumulative abnormal returns in the event month using the two developed categories representing the difference between the Sustainalytics ESG scores and the Bloomberg ESG disclosure scores. The results show that the positive effects are largely driven by the companies where the new ESG scores present positive surprises (above median Δ_{raw} and Δ_{norm}) also with respect to cumulative abnormal returns (see Table 13). While this effect did not prevail when we investigated the absolute levels of the Sustainalytics ESG scores in Section IV, the effect seems to be rather linked to the relevance of the new information vis à vis the previously published Bloomberg ESG disclosure scores.

Table 13: Cumulative abnormal returns in the cross-section: relevance of Δ_{raw} and Δ_{norm}.

	Dependent Variable: CAR			
	Δ_{raw}		Δ_{norm}	
	ABOVE MEDIAN	BELOW MEDIAN	ABOVE MEDIAN	BELOW MEDIAN
TREATMENT	0.862**	0.691*	0.986**	0.631
	(2.02)	(1.84)	(2.43)	(1.61)
SIZE	−0.209	−0.148	−0.376**	−0.023
	(−1.41)	(−1.08)	(−2.36)	(−0.18)
PRICE_BOOK	0.011***	−0.018***	0.011**	−0.015***
	(3.30)	(−3.96)	(2.37)	(−3.55)
ln(LEVERAGE)	−0.134	−0.094	−0.103	−0.093
	(−1.14)	(−0.82)	(−0.91)	(−0.77)
ROA	−0.057	0.012	−0.018	−0.023
	(−1.53)	(0.36)	(−0.50)	(−0.65)
CONSTANT	1.896*	1.082	3.137***	0.003
	(1.68)	(0.98)	(2.64)	(0.00)
#Obs.	1127	1120	1116	1131
p-value	0.001	0.000	0.007	0.000

Notes: This table shows the results of a regression with the cumulative abnormal return based on the Fama and French (2015) model in the period $t = 0$ to $t = 23$ as dependent variable. The set of control variables includes company size, price-to-book ratio, leverage, and return on assets (ROA). The first two columns display the results for companies with above and below median absolute score differences between Sustainalytics and Bloomberg scores. Columns three and four show results for above and below median results with respect to normalized score differences. Abnormal returns are expressed in percentage points. Robust standard errors included. Standard errors are in parentheses. $^{*}p < .1$, $^{**}p < .05$, $^{***}\ p < .01$.

VI. Conclusions

In this paper, we investigate capital-market effects of an unexpected release of ESG scores. We consider the publication of Sustainalytics ESG scores on Bloomberg on May 27th, 2014, as an exogenous shock to study the link between

ESG scores and (1) cost of adverse selection assessed using measures of stock market liquidity and (2) equilibrium market prices. Our findings support the hypothesis that ESG scores are indeed value-relevant. Liquidity increased significantly for companies that obtained newly available ESG scores on Bloomberg relative to a matched control sample. We also document higher cumulative abnormal returns in the month directly following the publication of the new ESG information. However, our findings are sensitive to the geographical region in which a company is primarily listed on an exchange. While in the US and Canada, the score release has the largest impact on stock market liquidity and abnormal returns, companies listed on European exchanges show no significant effect on stock market liquidity or stock market performance after the release.

We furthermore show that the effect is sensitive to the level of ESG information published. For companies in the upper half of the ESG score spectrum, we observe an impact on adverse selection costs measured using the bid ask spread after the event. However, for companies with below-median ESG scores, the ESG score release did not result in a reduction of these costs. Besides the bid-ask spread, our findings suggest a decrease in average stock price volatility among treated firms (compared to their peers) after the ESG score release. Notably, these findings persist irrespective of the firms' ESG performance.

Due to the complex structure of ESG data and the divergence of reported scores across data providers, investors' level of information about the sustainability of different companies may have diverged before the event. Our results are in favor of this situation and highlight the importance of the access to reliable ESG data for capital market participants. In particular, the most-prominent capital-market effect prevails for companies experiencing a large positive surprise in comparison with the Bloomberg ESG disclosure scores, i.e., the largest positive updates in ESG information for investors. A further investigation of the resulting adjustment of investors' beliefs about future stock price performance, based on the newly available ESG ratings, could provide an avenue for future research.

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Appendix A. Appendix

Table A.14: Variable definitions.

Variable	Element of	Type	Retreived from	Description	Frequency
ASK	$\mathbb{R}^+$	continuous	Datastream	Ask [USD]	Daily
AFTER_BLOOMBERG	$\{0,1\}$	binary	calculated	1 if after May 27th, 2014; 0 else	Static
BB_SCORE	[0,100]	continuous	Bloomberg	Bloomberg disclosure score	yearly
BID	$\mathbb{R}^+$	continuous	Datastream	Bid [USD]	Daily
BID_ASK	$\mathbb{R}$	continuous	Datastream	Ask−Bid [USD]	Daily
COUNTRY_PL		categorical	Eikon	Country of primary listing	Static
Asia-Pacific	$\{0,1\}$	binary	calculated	1 if Country_PL is in Asia-Pacific, Australia or New Zealand, 0 else	Static
Europe	$\{0,1\}$	binary	calculated	4 if Country_PL is in Europe, 0 else	Static
Japan	$\{0,1\}$	binary	calculated	5 if Country_PL is in Japan, 0 else	Static
North America	$\{0,1\}$	binary	calculated	6 if Country_PL is in US or Canada, 0 else	Static
INVPrice	$\mathbb{R}^+$	continuous	calculated	1/Price	Daily
ISIN/ISIN1		categorical	Datastream	ISIN of company, (string or long)	Static
INDUSTRY	$\{1,2,3,4,5,6,7,8,9,10,11\}$	categorical	Eikon	01 Basic Materials 02 Consumer Discretionary 03 Consumer Staples 04 Energy 05 Financials 06 Health Care 07 Industrials 08 Real Estate 09 Technology 10 Telecommunications 11 Utilities	Static
INST_OWN	$[0,100]$	continuous	Eikon	% held by institutional investors	Monthly
LEVERAGE	$\mathbb{R}^+$	continuous	Datastream	Total Debt % Common Equity	Daily
MARKET_VALUE	$\mathbb{R}^+$	continuous	Datastream	Market Value [million USD]	Daily
PRICE_BOOK	$\mathbb{R}^+$	continuous	Datastream	PtB	daily
ROA	$\mathbb{R}$	continuous	Datastream	Return on Assets	Daily
REGION	$\{1,2,3,4,5,6\}$	categorical	calculated	1 if Ex_NA == 1 2 if Ex_Europe == 1 3 if Ex_Japan == 1 4 if Ex_APAC == 1	Static
RI_Return_USD	$\mathbb{R}$	continuous	calculated	$RI\_USD_t/RI\_USD_{t-1}-1$	Daily
RI_USD	$\mathbb{R}^+$	continuous	Datastream	Total Return Index [USD]	Daily
SHARES_OUT	$\mathbb{R}^+$	continuous	Datastream	Shares Outstanding	Daily
SIZE	$\mathbb{R}^+$	continuous	calculated	ln(Total_Assets)	Daily
SPREAD	$\mathbb{R}$	continuous	calculated	Bid_Ask/Price	Daily

SustBloomberg	$\{0,1\}$	binary	Sustainalytics	1 if treated (received Sustainalytics rating on the event date), 0 if untreated (not received Sustainalytics rating on the event date)	Static
Sust_Score	$[0,100]$	continuous	Bloomberg	Sustainalytics Rating	Monthly, (Japan Static)
TOTAL_ASSETS	$\mathbb{R}^+$	continuous	Datastream	Total Assets	Daily
REL_TURNOVER	$\mathbb{R}^+$	continuous	calculated	rel_turnover= Volume/(shares*1000) (multiply by 1000 for units reasons)	Daily
VOLUME	$\mathbb{R}^+$	continuous	Eikon	Trading Volume	Daily

Figure A.3: Common trends mean ln(SPREAD). The graph exhibits common trends of the mean ln(Spread) for treatment and control companies throughout a period of six months around the event.

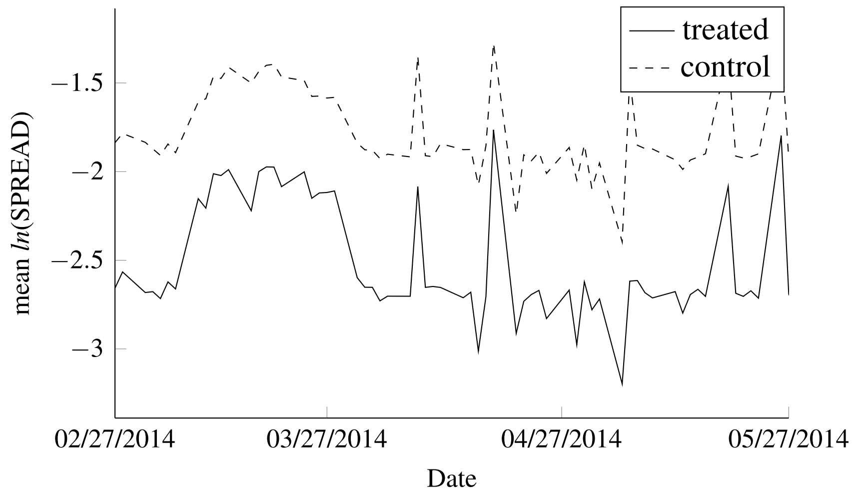

Figure A.4: Common trends mean ln(VOLATILITY). The graph exhibits common trends of the mean ln(VOLATILITY) for treatment and control companies throughout a period of six months around the event.

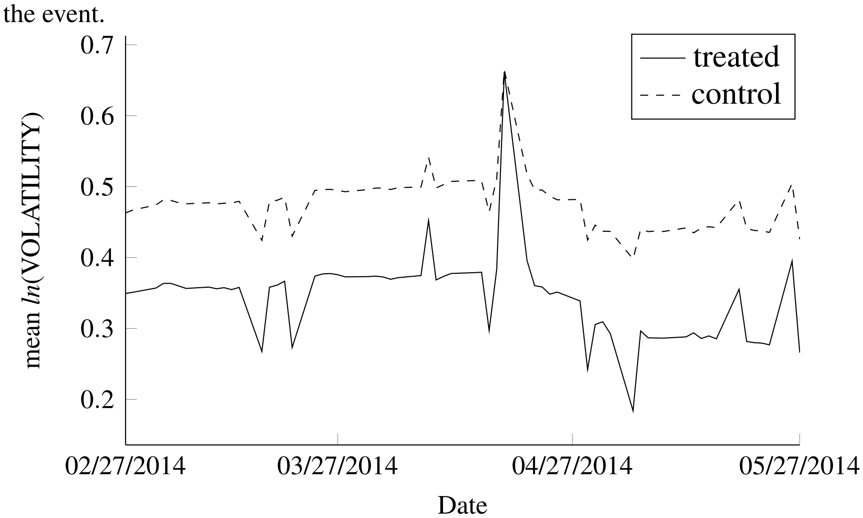

Figure A.5: Common trends mean ln(REL_TURNOVER). The graph exhibits common trends of the mean ln(REL_TURNOVER) for treatment and control companies throughout a period of six months around the event.

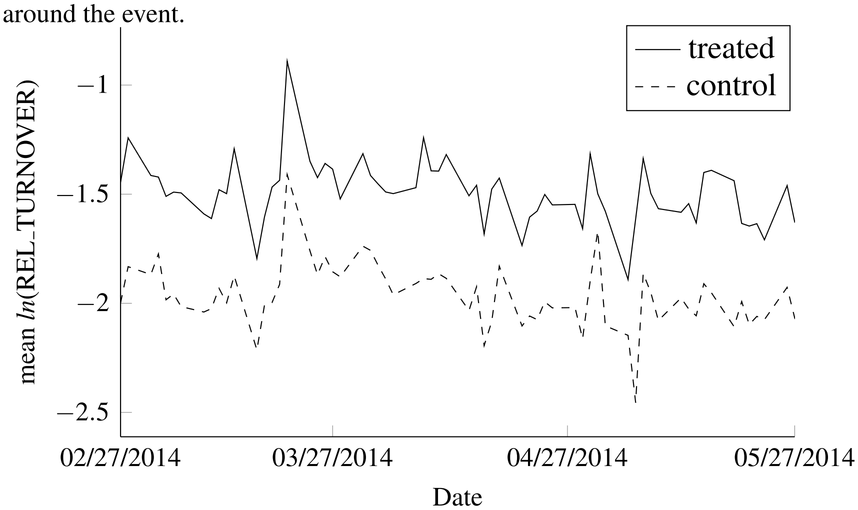

Table A.15: Difference-in-Difference model robustness: six months before and 3 months after the event.

	all	above median	below median
Dependent variable: ln(SPREAD$_{it}$)			
DiD	−0.037***	−0.060***	−0.014
	(−2.85)	(−3.20)	(−0.76)
Daily FE	Yes	Yes	Yes
Institution FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
#Obs.	406,662	204,884	201,778
F-statistic	20.068	15.499	7.746
p-value	0.000	0.000	0.000
Dependent variable: ln(VOLATILITY$_{it}$)			
DiD	−0.044***	−0.052***	−0.036***
	(−7.34)	(−6.26)	(−4.18)
Daily FE	Yes	Yes	Yes
Institution FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
#Obs.	417,198	209,730	207,468
F-statistic	13.469	10.571	4.320
p-value	0.000	0.000	0.000

Notes: This table shows the results of a difference-in-differences analysis for six months before and three months after the event: November 27th, 2013 - August 27th, 2014. We include company and day fixed effects and cluster standard errors by company. t-values in parentheses. $^{*}p < .1$, $^{**}p < .05$, $^{***}\ p < .01$

Table A.16: Difference-in-Difference model robustness: placebo dates February 27th, 2014 and May 27th, 2013.

	February 27th, 2014			*May 27th, 2013*		
	all	above median	below median	all	above median	below median
Dependent variable: ln($SPREAD_{it}$)						
DiD	0.031**	0.031	0.032	−0.026*	−0.023	−0.030
	(2.18)	(1.54)	(1.53)	(−1.92)	(−1.17)	(−1.55)
Daily FE	Yes	Yes	Yes	Yes	Yes	Yes
Institution FE	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
#Obs.	264,771	133,425	131,346	278,824	140,238	138,586
F-statistic	15.646	10.417	7.090	9.002	3.495	7.153
p-value	0.000	0.002	0.000	0.000	0.002	0.000
Dependent variable: ln($VOLATILITY_{it}$)						
DiD	−0.008	−0.010	−0.007	0.037***	0.036***	0.038***
	(−1.44)	(−1.21)	(−0.86)	(5.47)	(3.82)	(3.95)
Daily FE	Yes	Yes	Yes	Yes	Yes	Yes
Institution FE	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
#Obs.	271,673	136,603	135,070	286,596	143,736	142,860
F-statistic	7.541	5.741	3.462	11.341	6.701	5.268
p-value	0.000	0.000	0.000	0.000	0.000	0.000

Notes: This table shows the results of a difference-in-differences analysis for three months before and three months after two placebo event dates: February 27th, 2014 and May 27th, 2013. We include company and day fixed effects and cluster standard errors by company. t-values in parentheses. $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

Table A.17: Cumulative abnormal returns Placebo dates.

	Dependent Variable: CAR				
	Overall	North America	Europe	Japan	Asia-Pacific
Three months before the event: February 27th, 2014					
TREATMENT	0.136	−0.049	0.325	−0.590	0.633
	(0.353)	(0.512)	(0.712)	(0.815)	(1.231)
Control variables	Yes	Yes	Yes	Yes	Yes
Constant	2.790***	−0.643	4.206**	3.290	2.647
	(1.068)	(1.834)	(1.774)	(2.806)	(4.513)
#Obs.	2290	907	604	562	217
One year before the event: May 27th, 2013					
TREATMENT	0.057	0.402	−0.091	−0.996	0.338
	(0.390)	(0.615)	(0.648)	(1.009)	(1.311)
Control variables	Yes	Yes	Yes	Yes	Yes
Constant	2.790***	−0.643	4.206**	3.290	2.647
	(1.068)	(1.834)	(1.774)	(2.806)	(4.513)
#Obs.	2242	888	587	555	212

Notes: This table shows the results of a regression with the cumulative abnormal return based on the Fama and French (2015) model in the period $t = 0$ to $t = 23$ as dependent variable on the two placebo dates (May 27th 2013 and February 27th, 2014). The first column displays the results for the overall sample. Columns 2 to 5 show results separately for the four regions North America, Europe, Japan and Asia-Pacific. Abnormal returns are expressed in percentage points. Robust standard errors included. t-values in parentheses. $^{*}p < .1$, $^{**}p < .05$, *** $p < .01$