Do Green Stocks Get You the Green? Differential Impacts of S&P 500 ESG Index Labels on Firm Stock Prices

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ABSTRACT

On January 28, 2019, the S&P Dow Jones Indices launched the ESG S&P 500 Index, aiming to create a sustainable index fund with a similar risk/return profile to the S&P 500 Index. This study assesses the causal mechanisms behind the performance of the S&P 500 ESG Index by running two difference-in-differences estimations using a panel data set of 698 companies. The first difference-in-differences estimation compares the stock prices of companies on the S&P 500 ESG Index to the stock prices of companies S&P 500 Index, determining if companies on the S&P 500 ESG Index received an "ESG label" price premium. Results show that in the short-term and the long-term, companies on the S&P ESG 500 Index experienced statistically significant negative stock price growth relative to companies only on the general S&P 500 Index; the "ESG label" appears to slow stock growth for companies on the S&P 500 ESG Index by \$48.24 in the short-term and \$65.29 in the long-term. The second difference-in-differences estimation compares the stock prices of companies on the S&P 500 ESG Index to the stock prices of companies with similar ESG qualifications that are not on an S&P Index, determining if companies in the S&P 500 ESG Index received an "S&P label" price premium. These results found that in both the short and the long run, companies on the S&P 500 ESG Index faced statistically significant positive stock price growth relative to companies with similar ESG qualifications; the "S&P label" seems to increase stock price growth for companies on the S&P 500 ESG Index by \$2.19 in the short-term and \$7.63 in the long-term.

JEL Classification: G2, G23, Q56

Keywords: ESG, S&P 500 ESG Index, Sustainable Investing

1. INTRODUCTION

The creation of the S&P 500 ESG Index on January 28, 2019 reflected the increasing importance of financial funds in the commitment to end climate change. As a publicly-traded index fund constructed similarly in industry weight and market capitalization to the S&P 500 Index, the S&P 500 ESG Index examines a firm's Environment, Social, and Governance (ESG) score in addition to financial performance as a criteria for index fund inclusion ("S&P 500 ESG Index | S&P Dow Jones Indices").[1]

The use of Environment-Social-Governance (ESG) scores in investing is, in theory, beneficial in the efforts to curtail climate change—ESG investing aims to focus investment into firms which do not have a negative impact on the environment, do not have a negative impact on society, and have good governance practices.[2] This criteria is met through the help of ESG raters like Sustainalytics, MSCI, RepRisk, Bloomberg, or S&P Global ("ESG Scores & Rating Agencies | Armanino"). These ESG raters collect information about a firm's environmental practices (carbon emissions, water management, recycling processes, etc.), social practices (working conditions, employee benefits, human rights, local impact, etc.), and governance practices (ethical standards, board diversity, stakeholder rights, etc.) to deliver an aggregate ESG score. By construction, the ESG score is reflective of a firm's ESG practices; while the magnitude and scale of the ESG score might vary by ESG rater, higher ESG scores reflect better ESG practices. In general, these ESG scores range from 0 - 100, but different private ESG raters might deliver slightly different ESG scores due to different methodology for calculating environmental, social, and governance impacts.

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[1] The Dow Jones industrial group, the group that runs the S&P 500 ESG Index, uses market capitalization value as a proxy for financial performance of a firm.

[2] S&P Global lists out the full criteria for their ESG scoring on their *ESG Scores* website, broken down by Social Dimensions Criteria Topics, Environmental Dimension Criteria Topics, and Governance & Economic Criteria Topics

Investors are now able to examine the information that ESG scores convey as an additional criteria for investment. If an investor has a preference for companies with better environmental impacts, for instance, they can select companies for investment based on the magnitude of that company's ESG score. This selection—focusing on firms with high ESG scores—is the practice of ESG investing. Firms with ESG scores have indeed benefitted from ESG investing, receiving a premium correlated with the magnitude of their ESG score (Shanaev and Ghimire, 2021). While investors can practice ESG investing on a firm-specific level, asset management firms have simplified this process by creating ESG funds, which are funds composed of companies with high ESG scores. Recently, investment in ESG funds have reached all time highs, growing about 12% between the end of the second quarter to the last quarter of 2022 to cumulate in $2.5 trillion of investment in 2022 (Baker et al., 2023). Indeed, the public has become increasingly aware of ESG and ESG funds—Google data shows that the term "ESG" was twice as popular as an online search term in 2022 than it was at the beginning of 2021 (Lellis, 2022). The S&P 500 ESG Index is one such ESG index fund gaining popularity.

1.1 The S&P 500 ESG Index

The S&P Dow Jones Indices (S&P DJI) created the S&P 500 ESG Index as a "broad-based, market-cap-weighted index that is designed to measure the performance of securities meeting sustainability criteria, while maintaining similar overall industry group weights as the S&P 500" (S&P Dow Jones Indices, 2024). S&P DJI, which also constructs and runs the general S&P 500 Index, specifically aims to target "75% of the market capitalization within each Global Industry Classification Standard (GCIS) industry group of the S&P 500, using the S&P DJI ESG Score" (S&P Dow Jones Indices, 2024). To construct the S&P 500 ESG index Dow Jones first aggregates the list of the 500+ companies already included on the general S&P 500 index—the general S&P 500 index is the S&P 500 ESG index's underlying index. A company cannot belong on only the S&P 500 ESG Index, they also have to belong on the general S&P 500 Index. This relationship is not reciprocal, however. A company can belong on the general S&P 500 Index but not the S&P 500 ESG Index.

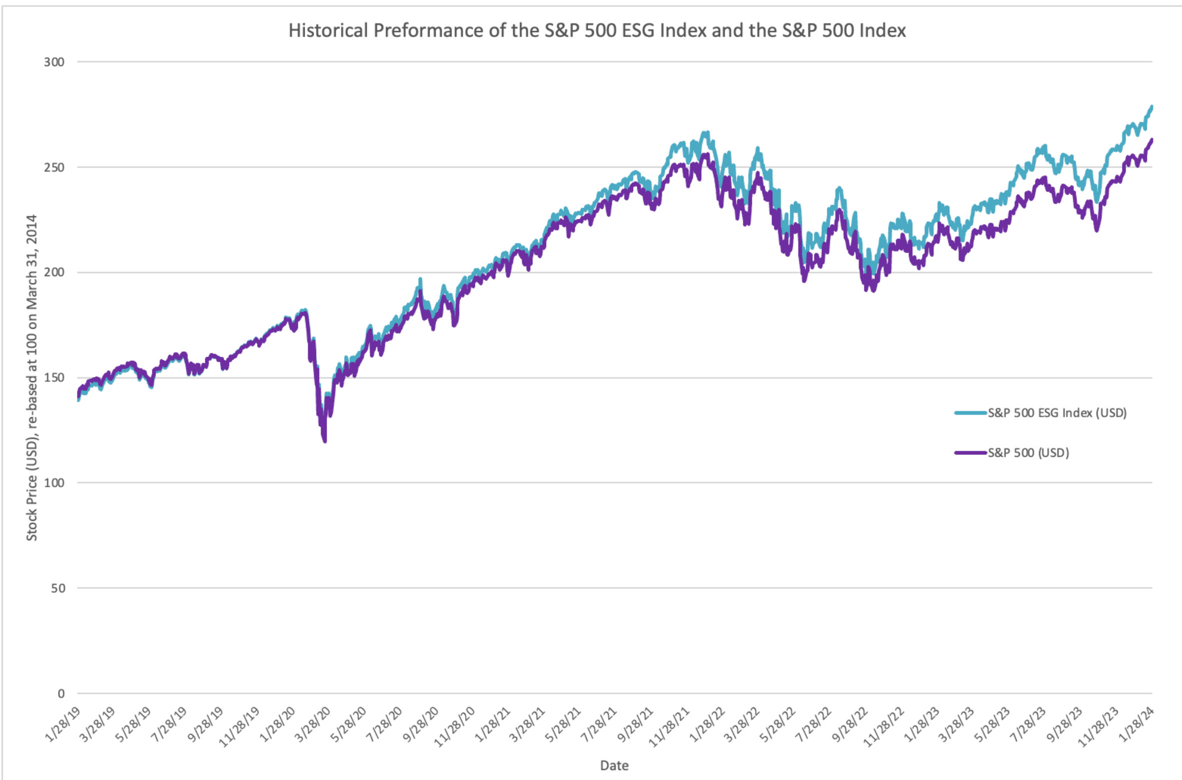
After assembling the list of the general S&P 500 Index constituents, S&P DJI eliminates companies based on a set of ESG non-compliance criteria (S&P Dow Jones Indices, 2024). First, S&P DJI disqualifies companies involved in controversial weapons, production or distribution of small arms, military contracting, coal mining, thermal coal mining, oil sand extraction or production, and the tobacco industry. Then, using Sustainalytics' Global Standards Screening (GSS), S&P DJI determines if a company is compliant with the United Nations Global Compact (UNGC). UNGC outlines a firm's fundamental responsibilities to human rights, labor freedom, environmental sustainability, and anti-corruption. If a firm is non-compliant, S&P DJI excludes the firm from inclusion in the S&P 500 ESG Index. Finally, S&P DJI excludes companies with ESG scores in the bottom 25% of their industry group.[3] The remaining firms are raked by their industry-relative ESG score—the S&P DJI goes down the list to select companies for inclusion on the S&P 500 ESG Index, weighting companies until they have reached their goal of 75% of the market capitalization value of the general S&P 500 Index.[4]

Following this criteria yields the S&P 500 ESG Index, wherein all ~300 constituents also comprise the general S&P 500 Index.[5] This criteria leaves ~190 companies which comprise the general S&P 500 Index but did not have the ESG capabilities for inclusion on the S&P 500 ESG

[3] Industry group as defined by the Global Industry Classification Standard, created by MSCI and S&P.
[4] Float-adjusted market capitalization is the total market value of all shares of stock available for public trading. It is one way to measure a company's worth in the stock market.
[5] Because the S&P 500 ESG Index has a named target to reach 75% of the float-adjusted market capitalization value of the general S&P 500 Index, the number of constituents of the S&P 500 ESG index has varied. It normally is above 300 but below 320 (S&P Dow Jones Indices, 2024).

Index. As the general S&P 500 has addition and deletion events every year, the makeup of the S&P 500 ESG Index also varies by year. Given the two indices have such similar makeup, it is unsurprising that their performance has largely paralleled each other over the past five years (Graph 1).

Graph 1: Historical Performance of S&P 500 ESG Index compared to the general S&P 500 Index



Note: Stock Price data is reported in USD and re-based at 100 on March 14, 2024. Stock prices are reported for the overall S&P 500 Index and S&P 500 ESG Index, not for the companies on each index. Data is from the S&P Dow Jones Indices

Understanding the causal mechanism driving the pressure on the S&P ESG 500's stock prices is essential for determining the potential futures of ESG funds and ESG scores themselves. Do the companies on the S&P 500 ESG Index receive an ESG label premium price that companies only on the general S&P 500 Index do not receive? Or, are investors driving up the cost of the S&P 500 ESG Index because it is another S&P DJI-created index fund—because they trust in the S&P label on the S&P 500 ESG Index? If the first case were true, that there is an ESG label premium, then this information strengthens the use of an ESG score as a tool during investments, pushing companies to invest in and raise their ESG score. If the second case were true, then the ESG label would not have a causal explanation for the S&P ESG 500 Index's performance, ultimately undermining the use of ESG score as an investment tool. Rather, the second case would strengthen the S&P Index's "branding" and show investors that any future indices S&P DJI creates and maintains could see similar stock price trends.

Examining the similarities and differences between three groups—1). the S&P 500 ESG Index, 2.) the general S&P 500 Index, and 3.) companies which are just as ESG compliant as the companies on the S&P 500 ESG Index, but did not meet the market capitalization lower bound for inclusion—can help determine which scenario helps to drive S&P 500 ESG Index's stock performance. Comparing the growth of these three groups, starting from before the creation of the S&P 500 Index, can determine if an ESG label effect or an S&P label effect exists. This comparison is the goal of this study—determining the exact ESG and S&P label effect which occurs around the creation of the S&P ESG 500 Index. Through answering this question, this study aims to determine what time period these effects exist in: the short term, the long term, or both.

2. LITERATURE REVIEW

2.1 Index Funds: The S&P 500

Current research finds a marked financial benefit for a firm's inclusion in index funds like the S&P 500 (Morck and Yang, 2001; Shleifer, 1986). One reason for this premium might be how inclusion on the S&P 500 increases information access. Martin et al. (2016) found that inclusion on the S&P 500 creates increased flow of public and private information and thereby reduces information asymmetry in the overall financial market. Once the S&P 500 announces the inclusion of a company, new shareholders and institutional investors examine the company for investment, increasing both the flow of private information membership and stock liquidity. Similarly, once a company is announced for inclusion on the S&P 500, third-party information intermediaries, newsmedia, and watchdog groups all subsequently examine a company's current operations, commenting on expected performance, management, and governance, thus increasing public information (Mola et al., 2012).

Elliot et al. (2008) and Morck and Yang (2001) find another reason for the increased stock valuation for companies included on the S&P 500—increased investor ease due to higher investor awareness, decreased information cost, and the ability for passive investment. This ease is partially due to the complicated nature of America's stock market—navigating the financial system is hard to understand for those without a formal education in finance. The S&P 500 does not require any specialized knowledge or training to navigate—retail investors can easily buy a couple shares and understand that they are buying not only a well-diversified portfolio, but a portfolio that has proven to yield stable returns (Robertson, 2020).

Furthermore, these studies argue that investing in the S&P 500 allows for passive, rather than active returns (Robertson, 2020). Retail investors with less familiarity with the stock market are able to invest their money into the S&P 500 Index and essentially ignore their investments. Once again, this passivity is another function of investor ease—those who do not have sophisticated knowledge of the financial industry are still able to participate and invest in portfolios that yield returns.

A firm's benefit from investor ease and increased investor awareness reflect in their valuation levels as well. Morock and Yang (2001) find that firms on the S&P 500 have a higher value for Tobin's Q, the ratio of a firm's market value to its total assets, than other similar firms that are excluded from the S&P 500. Thus, Morock and Yang's findings suggest inclusion to the S&P 500 leads to a premium in the market valuation of a firm.

Shleifer (1986) finds a similar benefit for companies on the S&P 500. When the news breaks that a company will be added to the S&P 500, a company's stock price increases by around 2.79%. Granger causality tests suggest addition to the S&P 500 Index causes this increase in value. While studies do not reject the reverse causality, it is less statistically important. Shleifer further asserts that this increase in stock price is not only significant, but also permanent—the effects of addition to the S&P 500 extend beyond just an initial buy-in period. An addition to an index fund increases share purchases, which then causes demand to increase, ultimately generating the observed sustained price increase. As indexing grows from 1978 to 1986, the S&P 500 membership value premium also increases in accordance (Shliefer, 1986). However, Harris and Gurel (1986) findings contradict Shliefer (1986). They determine that while addition to the S&P 500 does result in around a 3% increase in stock price, this increase is not permanent—it is almost fully reversed within two weeks. Harris and Gruel (1986) agree that changes in the S&P 500's construction affect stock demand and thus prices, but as the announcement of a company's addition to the S&P 500 fades, so does the demand from a volume-trading perspective. Thus, Harris and Gurel (1986) find that in the absence of new information, as demand for volume traded drops, so does the upward pressure on prices. Still, regardless of how long the economic premium lasts, Harris and Gruel (1986) and Shliefer (1986) do agree that upon addition to the S&P 500, there is a financial premium in the short term.

2.2 ESG and Stock Returns

For companies with ESG scores, many find a significant positive relationship between ESG ratings and a company's stock price—companies benefit economically from ESG scores (Shanaev and Ghimire, 2021; Engelhardt et al., 2021; Wang et. al, 2023; Wong et al., 2019; Mario La Torre et al., 2020; and Adams et al., 2020). However, there are asymmetric responses to increases and decreases in ESG score. Shanaev and Ghimire (2021) find that when an ESG score changes, the magnitude of that ESG score change correlates with a change in stock returns. For every unit increase in ESG score, there exists a 0.5% increase in stock return; for every unit decrease in ESG score, there exists a 1.2% decrease in stock return. These asymmetric responses may be due to the nature of media coverage; more negative news coverage of decreased ESG scores outweighs the limited positive news coverage of increased ESG scores. The changes in stock return are also larger for companies with higher proclaimed ESG agendas than those without higher ESG agendas.

ESG scores may also help in other ways. Wang et al. (2023) finds that higher ESG scores correlate with lower stock price fragility in Chinese markets: the higher the ESG score, the less sensitive investors are to stock performance. Wong et al. (2019) finds that when Malaysian firms receive an ESG score, the new information learned by the ESG score reduces their cost of capital by 1.2%, allowing Tobin's Q to increase by 31.9%.

Furthermore, the act of receiving an ESG score increases the public's trust in a company, thus allowing the company's valuation to increase. Engelhardt et al. (2021) show that ESG scores build trust between investors and firms, especially in low-trust companies with poor security regulations. Mario La Torre et. al (2020) explains that investors can consider ESG factors, "as a good proxy for firms' financial soundness." Indeed, when investigating why Malaysian firms' Tobin's Q increased after they received an ESG score, Wong et al (2019) determined the same causal mechanism to exist—that ESG scores increase investor trust in a company. This relationship between ESG rating and trust exists because in order to get an ESG score, companies must disclose their environmental impacts, governance practices, social impacts, and subject their company to review by an ESG rater. While companies that receive an ESG score may not disclose these practices to the public, they disclose their practices to an external third party. Adams et al (2022) find that investors see companies with ESG scores as more transparent than companies without ESG scores because of this disclosure. This increased transparency was essential during the 2020 COVID-19 pandemic; amidst a complex and unpredictable market, this increased transparency helped to especially increase public trust in ESG rated firms relative to others (Adams et al., 2022).

2.3 S&P 500 ESG Index

Unlike literature on individual company ESG stock, existing literature on ESG funds has been limited. While several studies have evaluated ESG disclosure, compliance, or performance for companies on the S&P 500 Index, existing literature has not studied the performance of the S&P 500 ESG Index. This thesis attempts to close this gap, examining the ESG and S&P label differentials the S&P 500 ESG Index offers. This thesis attempts to determine what inclusion effect ESG Index funds might have on company stock return as opposed to general inclusion in an Index fund.

3. DATA

For my analysis, I use data from the Center for Research in Security Prices (CRSP), collected by the University of Chicago Booth School of Business and accessed through the University of Pennsylannia Wharton's portal. CRSP has a named goal of providing accurate securities data for research by receiving and cleaning data from several indices like the S&P 500, NASDAQ, NYSE, and AMEX. According to CRSP, this data is reported from the indices themselves for CRSP to aggregate. Using the CRSP database, I access all data used in this study—daily and monthly values for company *i*'s stock price, GICS Industry Group, and Shares Outstanding, thus creating a panel data set for my three groups of interest. This constituted a total of 44,793 data points from CRSP.

3.1 Company Selection

My three groups of interest were the S&P 500 ESG Index, the general S&P 500 Index, and companies which had the ESG capabilities to make the S&P 500 Index, but did not have the market capitalization to do so. By examining these three groups, I identify two discontinuities in their constructions—first, the discontinuity between the companies on both the S&P 500 ESG Index and the general S&P 500 Index with the companies only on the S&P 500 Index, and second, the discontinuity between the companies on the S&P ESG 500 index and the companies which had ESG capabilities but did not have the market capitalization for inclusion on the S&P 500 ESG Index. The first discontinuity highlights the price premium that an ESG label can offer a company, while the second discontinuity highlights the premium gained by an S&P label to a company. For the rest of this thesis, I will be referring to the companies on both the S&P 500 ESG Index and the S&P 500 Index as Group A, the companies only on the general S&P 500

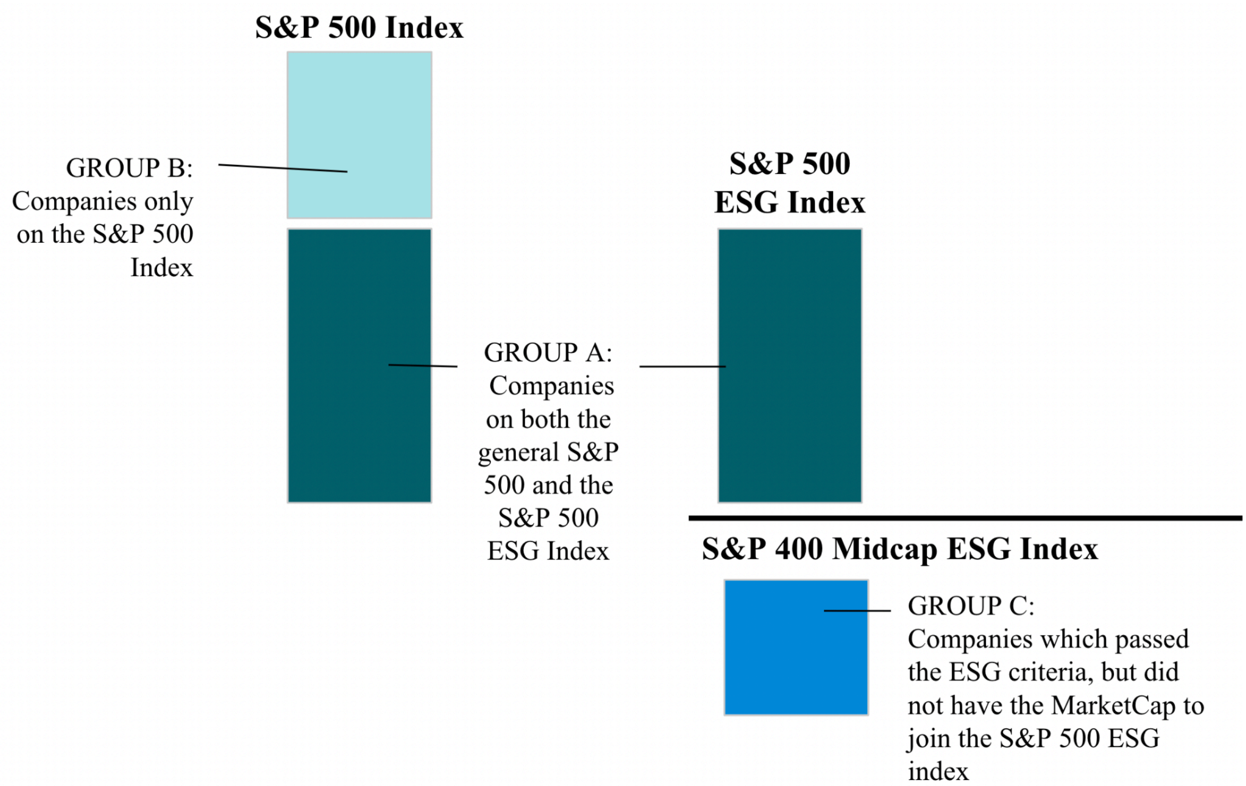
Index (and not the S&P 500 ESG Index) as Group B, and the ESG-compliant companies which did not make the S&P 500 ESG Index as Group C.

Groups C can be further identified by the S&P 400 MidCap ESG index. This is another index fund created by the S&P DJI with the same criteria and methodology for inclusion as the S&P 500 ESG Index, except the S&P 400 MidCap ESG index pulls from the general S&P 400 Midcap index as its underlying index. Because the same underlying methodology is used for inclusion in the S&P 400 Midcap ESG index, firms included on this index have the same ESG capabilities as those on the S&P 500 ESG Index (S&P Dow Jones Indices, 2024). However, the Dow S&P 400 Midcap ESG index was only launched on January 11, 2021—two years after the S&P 500 ESG Index ("S&P Midcap 400 ESG Index"). Therefore, as long as analysis is kept to a time period before January 11, 2021, I am able to use the companies on the S&P 400 Midcap ESG index as a collection of firms that are able to pass the ESG criteria, but do not have the S&P label on their company.

Barchart.com, an independent company that lists constituents of most major index funds, offers the list of firms for Groups A and B. Barchart.com receives this information from the S&P DJI. However, the S&P DJI has not published the constituents of their S&P MidCap 400 ESG index. Instead, the private company Xtrackers has created their own index, called the Xtrackers S&P MidCap 400 ESG ETF Index, a replica of the S&P Midcap 400 ESG index. To construct the Xtrackers S&P MidCap 400 ESG ETF Index, Xtrackers uses the same methodology as the construction of the S&P MidCap 400 ESG index, yielding the same result—a list of companies which meet the same ESG criteria as the S&P 500 ESG Index, but are not included on the S&P 500 ESG Index.

Both discontinuities found by the three groups of interest (Groups A, B, and C) are outlined on the diagram below. Comparing Group A to B yields the ESG premium, and comparing Group A to C yields the S&P label premium (Figure 2).

Figure 2: Diagram of the relationships between Group A, B, and C



Across Group A, B, and C, I examine a total of 698 companies, all belonging to either the S&P ESG 500 Index, the general S&P 500 Index, or the Xtrackers S&P Midcap 400 ESG Index. There are 505 companies belonging to the S&P 500 Index in total. 320 of these firms are also on the S&P 500 ESG Index—this overlap is where Group B of my regression falls, comprised of 185 companies. The Xtrackers S&P Midcap 400 ESG ETF Index consists of 193 companies in Group C.

To capture the differences between Groups A, B, and C, I have created two dummy variables—$EverinSP500_{it}$ and $EverinESG500_{it}$. These two dummy variables capture whether or not company i was part of the S&P 500 Index at time *t* (1 = on index, 0 = not on index) or the S&P 500 ESG Index (1 = on index, 0 = not on index). Group A is indicated by the group of firms that have a value of 1 for both $EverinSP500_{it}$ and $EverinESG500_{it}$. Group B is indicated by the group of firms that have a value of 1 for $EverinS\&P_{it}$ and 0 for $EverinESG500_{it}$. Group C is indicated by the group of firms that have a 0 for both $EverinSP500_{it}$ and $EverinESG500_{it}$.

3.2 Time-Period Selection

Given the goal of finding the S&P and ESG label effects in both the short and long run, I use two time periods of data. To see if a short-run effect existed, I examine daily high stock price values in the month before and after the creation of the S&P 500 ESG Index—from January 2, 2019 to February 28, 2019.[6] Harris and Gruel (1986) found that inclusion effects have largely reversed around two weeks after the addition of a company to the S&P 500 Index. This is why a time period of two months was chosen—it can capture if that same inclusion effect reversal exists for the stock prices of the companies on the S&P ESG 500. This time period of 40 business days for 688 companies yields 27,520 data points.[7]

Because of my company data set, there were certain restrictions on my long-run time period selection. The S&P 400 Midcap ESG Index was launched on January 11, 2021—my long-run data cannot surpass this date, otherwise it would risk losing the S&P label discontinuity created with the companies on the S&P 500 ESG Index. Furthermore, the S&P 500 ESG Index

[6] The S&P 500 ESG Index was created on January 28, 2019. January 1, 2019 is a bank holiday, where the market is closed for the new year. Data is collected starting January 2, 2019 as a result.
[7] In the short run, there are around 10 companies less than in the long run in the data set as they were added to the S&P 500 index in May 2019, after the end of the short-run data set.

reruns its inclusion methodology every year, adding or deleting firms as needed based off of changes in industry, market capitalization values, firm ESG scores, etc (S&P Dow Jones Indices, 2024). To avoid issues with addition and deletion, I only examine data in the year before and after the creation of the S&P 500 ESG Index—from January 2018 to January 2020. Over this two-year time period, I examine monthly close stock price data, for a total of 17,450 data points for my 698 companies over 24 months.

3.3 Control Selection

GICS Industry Group is used as a categorical variable control, allowing firms to be grouped and controlled for according to their industry, thus avoiding issues comparing higher-priced industries to lower-priced industries. Comparing the companies on the S&P 500 ESG Index to the companies which had the ESG capabilities but did not have the market capitalization values to join (Group A to Group C comparison) yields a discontinuity due to market capitalization value—market capitalization needs to be controlled for. Since market capitalization values are calculated directly from the stock price, which is also my outcome variable, I use the number of shares outstanding as an instrument for market capitalization. Shares outstanding vary directly with market capitalization, and do not affect the stock price in my data. Since the market capitalization discontinuity is only prevalent in the Group A to C comparison, I only use Shares Outstanding as a control for this comparison. Due to availability of data, in the long run, Common Shares Outstanding was used as the Shares Outstanding Control.

3.4 Summary Statistics

Table 1: Summary Statistics of Short-run Data — Company Daily Stock Prices in the Month Before and After the Creation of the S&P 500 ESG Index

Variable	Observations	Type	Mean	Standard Deviation	Min	Max
Date	27,520	Continuous	-	-	Jan 2, 2019	Feb 28, 2019
Shares Outstanding	27,520	Continuous	453,000,000	906,000,000	726,000	9,810,000,000
Industry Group	27,520	Categorical	426	239	110	850
Trading Volume	27,520	Continuous	3,535,527	8,486,309	0	348,000,000
Price High Daily	27,520	Continuous	546	11,601	2.87	313,960
Ever in S&P 500	19,960	Dummy	72.53%	-	0	1
Ever in S&P 500 ESG	12,600	Dummy	45.78%	-	0	1

Table 2: Summary Statistics of Long-run Data — Company Monthly Close Stock Price from Jan 2018 - Jan 2020

Variable	Observations	Type	Mean	Standard Deviation	Min	Max
Date	17,450	Continuous	-	-	Jan 31, 2018	Jan 31, 2020
Trading Volume	17,450	Continuous	68,500,000	139,000,000	204	348,000,000
Industry Group	17,233	Categorical	426	239	110	850
Common Shares	17,450	Continuous	465	901	3.58	10,176

Outstanding						
Price Close Monthly	17,233	Continuous	561	11,845	0.32	313,960
Ever in S&P 500	12,514	Dummy	72.62%	-	0	1
Ever in S&P 500 ESG	7,906	Dummy	45.88%	-	0	1

Histograms of all market variables are included in the Appendix.

4. THEORETICAL FRAMEWORK AND EQUATIONS

Because I am interested in the S&P and ESG label premiums following the launch of the S&P 500 ESG Index on January 28, 2019, I use a difference in differences regression, setting my treatment date as January 28, 2019. After that date, all firms added to the S&P 500 ESG Index (Group A) are "treated," and all firms that were not added to the S&P 500 ESG Index—Groups B and C—are "untreated." I run separate difference in differences regressions in the short and long run, each time comparing either of the "untreated" groups (Groups B or C) to the "treated" group (Group A).To go along with the difference in differences regression, I create an event study plot to map the change in β^{DID} for the ESG and S&P labels over time; this offers further insight into the future trends of each label. Jesse Shapiro and Liyang Sun outline both the creation of a difference in differences estimation and the creation of an event study plot in their NBER lecture, "SI 2023 Methods Lectures: Linear Panel Event Studies," forming the basis of the theoretical framework used in this thesis. I use Shapiro and Sun's framework to both run a difference in differences estimation and create event study plots on my three groups of interest (A, B, and C) and two comparisons (A to B and A to C) over two different time periods, yielding eight total equations used in this thesis. The equations are as follows:

4.1 Determining the ESG label effect

SHORT-RUN EFFECT

1. <u>Equation 1: Short-run effect — ESG Label Premium</u>

To determine the short-run ESG label effect, I use my short-run daily high data from January 1, 2019 to February 28, 2019 (one month before and after the creation of the S&P 500 ESG Index) for Groups A and B—excluding data for companies in Group C. I use *Equation 1* to determine the short-run effect:

Equation 1:

$$Y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 EverinESG_i + \beta_3 Post_t \times EverinESG_i + \beta_4 IndustryGroup_{it} + \mu_{it}$$

Y_{it} denotes stock price for firm i in time t, measured in Real USD. In *Equation 1*, time is measured in days. β_0 is my constant term, and $Post_t$ is a binary variable equal to 1 after the launch of the S&P 500 ESG Index on January 28, 2019. β_1 represents the average change in the stock price after the launch of the S&P 500 ESG Index on January 28, 2019, compared to before the launch. $EverinESG500_i$ is a binary variable indicating whether or not firm i has ever been included in the S&P 500 ESG Index (1 = on S&P ESG 500 index; 0 = not on S&P 500 ESG Index). Since my data excludes all data points for Group C, it is possible to identify the differences between Groups A and B through this single dummy variable. If a firm is on Group A, it has a value of 1 $EverinESG500_i$, and it is is a part of Group B, it is a value of 0 for $EverinESG500_i$. β_2, the coefficient on $EverinESG500_i$, represents the average difference in stock prices between firms included in the S&P 500 ESG Index and those not included, holding other variables constant; it captures the average difference in stock prices between Groups A and B. β_3 is an interaction term between $EverinESG500_i$ and $Post_t$. β_3 is my β^{DID} estimator—capturing the price differential effect of inclusion in the S&P 500 ESG Index over the general S&P 500 Index. If the coefficient is statistically significant and positive, it suggests that the impact of being included in the index on stock prices changes after the launch compared to before. Finally, I have controls for differences in a firm's industry through $IndustryGroup_{it}$, which is a categorical variable indicating which industry group a company belongs to. β_6 measures how these differences in industry groups affect their stock prices—some industries might have higher stock prices than others because of the nature of their business. μ_{it} is the error term. Thus, I am able to see the short-run effect of the creation of the S&P 500 ESG Index against firms not added to the S&P ESG 500 index from the general S&P 500 Index.

2. Equation 2: Short-run effect — ESG Label Premium Event Study

Now that I have determined the ESG effect in the short run, I can create an event study plot by mapping out how this ESG label effect changes over time. That is, how the β^{DID} from *Equation 1* shifts, yielding trends in the ESG label effect. I use *Equation 2* to run a short-run event study, using the same data used on *Equation 1* (only Groups A and B):

Equation 2:

$$Y_{it} = \beta_0 + \sum_{n=0}^{8} \alpha_n weeks\_since_t + \beta_1 EverinESG500_i +$$

$$\sum_{n=0}^{8} \delta_n weeks\_since_t \times EverinESG500_i + \beta_2 IndustryGroup_{it} + \mu_{it}$$

In *Equation 2*, Y_{it}, β_0, $EverinESG500_i$ and its associated coefficient, and $IndustryGroup_{it}$ and its associated coefficient is the same as *Equation 1*. However, now the time period indicating variable is a categorical variable, $weeks\_since_t$. $weeks\_since_t$ ranges from 0 - 8, indicating how many months it has been since January 1, 2019 my first data point for date in the short-run data set. α_n is the coefficient on $weeks\_since_t$ variable, reporting the average change in stock price each week. δ_n is the coefficient on the interaction term between $weeks\_since_t$ and

$EverinESG500_i$, capturing the differential effect of inclusion on the S&P 500 ESG Index over inclusion in the general S&P 500 Index each week. By examining how δ_n changes with week, I can see how the β^{DID} changes over time—specifically how it trends before and after the creation of the S&P 500 ESG Index in week 4. If δ_n is statistically significant after week 4, then results point to an ESG label effect.

LONG-RUN EFFECT

Equations 1 and *2* are essentially rerun with the long-run data set to see if short-run stock price behavior continues past one month.

3. Equation 3: Long-run effect — ESG Label Premium:

To determine the long-run ESG label premium, I compare Groups A and B using my long-run data set—monthly close values for the year before and after the creation of the S&P 500 ESG index. I use *Equation 3* to determine the long-run effect:

Equation 3:

$$Y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 EverinESG_i + \beta_3 Post_t \times EverinESG_i + \beta_4 IndustryGroup_{it} + \mu_{it}$$

All variables are the same as *Equation 1*, *Equation 3* differs from *Equation 1* in the data that it pulls from. Thus, I am able to measure the long-run ESG label effect by looking to the β^{DID} term found by β_3 .

4. Equation 4: Long-run effect — ESG Label Premium Event Study

I rerun my event study plot, this time using my long-run data. I use *Equation 4*, as outlined below:

Equation 4:

$$Y_{it} = \beta_0 + \sum_{n=0}^{24} \alpha_n months\_since_t + \beta_1 EverinESG500_i +$$

$$\sum_{n=0}^{24} \delta_n months\_since_t \times EverinESG500_i + \quad \beta_2 IndustryGroup_{it} + \mu_{it}$$

In *Equation 4*, $Post_t$, my time period variable, has been transformed into a categorical variable, $months\_since_t$. $months\_since_t$ ranges from 0 - 24, indicating how many months it has been since January 2019. α_n is the coefficient on $months\_since_t$ variable, reporting the average change in stock price each month. δ_n is the coefficient on the interaction term between $months\_since_t$ and $EverinESG500_i$, capturing the differential effect of inclusion on the S&P 500 ESG Index over inclusion in the general S&P 500 Index each month. Just like in my short-run event study, I can examine how δ_n changes over time to see how the β^{DID} changes over time. From this event study, I can determine if before the creation of the S&P 500 ESG Index in month 12, there was a statistically significant β^{DID}, or if the β^{DID} only started to become statistically significant after month 12.

4.2 Determining the S&P label effect

Now, I rerun *Equations 1 - 4* with my A versus C comparison, comparing all companies with ESG capabilities to join the S&P 500 ESG Index, but where Group C did not have the market capitalization values to gain access to the S&P 500 ESG Index and thus is not able to have the "S&P" label attached to their company in addition to the ESG label.

SHORT-RUN EFFECT

5. Equation 5: Short-run effect — S&P Label Premium

To determine the short-run S&P label effect, I use my short-run data from January 1, 2019 to February 28, 2019 for Groups A and C—excluding data for companies in Group B. I run *Equation 5* as follows:

Equation 5:

$$Y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 EverinESG_i + \beta_3 Post_t \times EverinESG_i + \beta_4 IndustryGroup_{it} + $$
$$+ \beta_5 SharesOutstanding_{it} + \mu_{it}$$

$SharesOutstanding_{it}$ is a control variable denoting the number of outstanding shares that company i has in time t. β_5 denotes the change in stock price for every increase in outstanding shares. All other variables are the same as *Equation 1*, except $EverinESG_i$ indicates which companies are from Group A (1 if on Group A) and which companies are from Group C (0 if on Group C). Thus, β_2, the coefficient on $EverinESG500_i$, represents the average difference in stock prices between firms included in the S&P 500 ESG Index and those not included, capturing the average difference in stock prices between Groups A and C. β_3 , still the β^{DID} estimator, now shows the differential effect of being in the S&P 500 ESG Index on stock prices before and after the launch. If the coefficient is statistically significant and positive, it suggests that the impact of being included in the index on stock prices changes after the launch.

6. Equation 6: Short-run effect — S&P Label Premium Event Study

I run the event study for the short-run effect in the same way that I did in *Equation 2* to determine how the β^{DID} changes for Groups A and C. I use *Equation 6* as follows

Equation 6:

$$Y_{it} = \beta_0 + \sum_{n=0}^{8} \alpha_n weeks\_since_t + \beta_1 EverinESG500_i +$$

$$\sum_{n=0}^{8} \delta_n weeks\_since_t \times EverinESG500_i + \beta_2 IndustryGroup_{it} + \beta_3 SharesOutstanding_{it} + \mu_{it}$$

All variables are the same as *Equation 2*, except *Equation 6 is* run with Group A and C data and now includes $SharesOutsanding$ as a control. Thus, the δ_n interaction term measures how the β^{DID} between Group A and C changes over time. If δ_n is statistically significant after week 4, then that does point to an S&P label effect in the US stock market.

LONG-RUN EFFECT

Once again, *Equations 5* and *6* are rerun using the long-run data.

7. Equation 7: Long-run effect — S&P Label Premium:

To determine the long-run S&P label premium, I compare Groups A and C using my long-run data set—monthly close values for the year before and after the creation of the S&P 500 ESG Index. I use *Equation 7* to determine the short-run effect:

Equation 7:

$$Y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 EverinESG_i + \beta_3 Post_t \times EverinESG_i + \beta_4 IndustryGroup_{it}$$
$$+ \beta_5 CommonSharesOutstanding_{it} + \mu_{it}$$

All variables are the same as *Equation 3,* except for $EverinESG_i$, which is now 1 if a company belongs to Group A and 0 if a company belongs to Group C. There is a new covariate,

$CommonSharesOutstanding_{it}$, which measures the number of Common Shares Outstanding that company i has in time t, and attempts to control for market capitalization value.

8. Equation 8: Long-run effect — S&P Label Premium Event Study

I rerun my event study model using my different long-run data for Groups A and C. I use *Equation 8*:

Equation 8:

$$Y_{it} = \beta_0 + \sum_{n=0}^{24} \alpha_n months\_since_t + \beta_1 EverinESG500_i +$$

$$\sum_{n=0}^{24} \delta_n months\_since_t \times EverinESG500_i + \quad \beta_2 IndustryGroup_{it}$$

$$+ \beta_3 CommonSharesOutstanding_{it} + \mu_{it}$$

All variables in *Equation 8* are the same as in *Equation 4* except for $EverinESG500_i$ and $CommonSharesOutstanding_{it}$, as Group A and C data is now being used. Once again, I look to examine how δ_n changes over time, and if it is statistically significant after month 12.

5. RESULTS[8]

5.1 ESG Label Effect

SHORT-RUN

Results from Equation 1: Short-run effect — ESG Label Premium are included below.

Table 3: Short-run Difference in Differences Effect of the Creation of the S&P ESG 500 Index on S&P 500 Index Stocks

VARIABLES	Price
Ever in ESG 500	-1,456
	(1,519)
Post	54.66***
	(6.046)
Post×EverinESG	-48.25***
	(7.610)
Constant	1,485
	(8,165)
Observations	19,960
Number of Firms	499
Overall R^2	0.100

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The coefficient on $EverinESG500_i$ is insignificant while the coefficients on $Post_t$ and the interaction term $EverinESG500_i \times Post_t$ are significant at the 99% level. This suggests the stock prices of the companies in Group A and the companies in Group B prices were statistically indistinguishable from each other until the S&P 500 ESG Index was launched. On average, all stock prices increased after the creation of the S&P 500 ESG Index, but companies without the ESG label grew at a higher rate than companies with the ESG label. In the short-run, one month

[8] All results for Industry Group in each of the 8 equations have been moved to the Appendix.

after the creation of the S&P 500 ESG Index, companies added to the S&P 500 ESG Index grew $48.25 dollars less than companies that were not added to the S&P 500 ESG Index. The companies that were on the general S&P 500 Index and were not included on the S&P 500 ESG Index (Group B) grew $54.66 dollars, while companies which were added to the S&P 500 ESG Index (Group A) grew only $6.41. This contradicts current literature, which has suggested that companies with higher ESG scores tend to see an upward jump in their stock price.

Now that I know there is a statistically significant difference in differences in the short run after the creation of the S&P 500 ESG Index, I run Equation 2: Short-run effect — ESG Label Premium Event Study. This event study calculates the difference in differences in each week as compared to the baseline week 4, the week when the S&P 500 ESG Index was launched. Equation 2 results are as follows:

Table 4: Weekly Difference in Differences Effect of the Creation of the S&P ESG 500 Index on S&P 500 Index Stocks

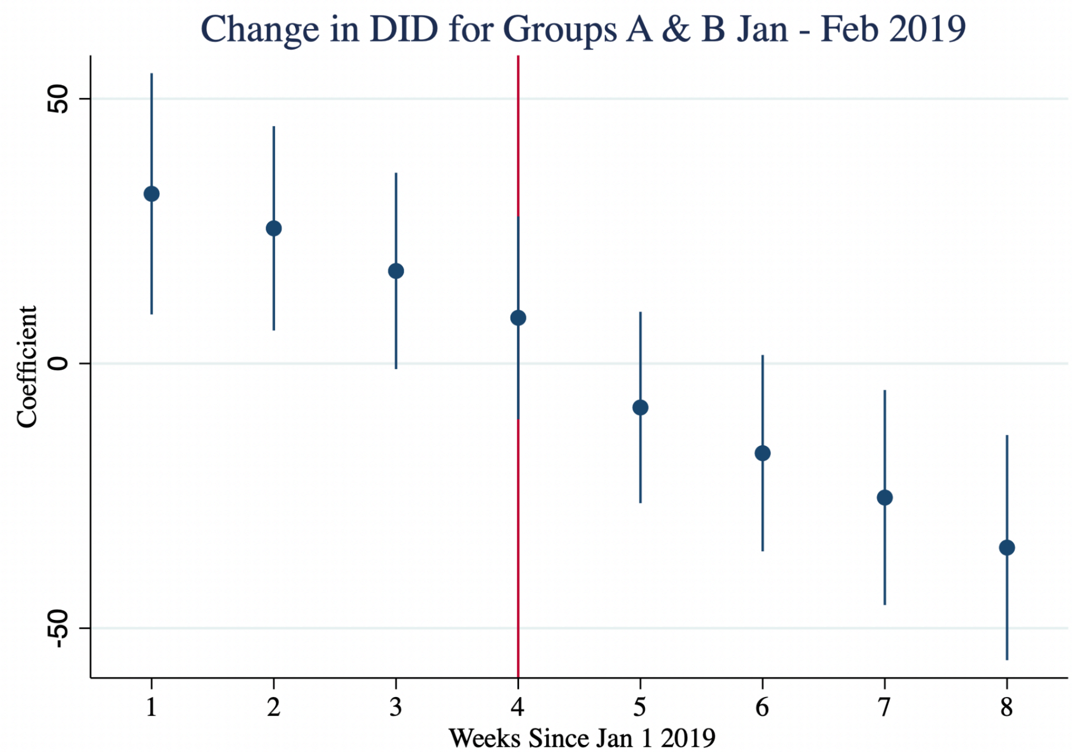
VARIABLES	Price
Ever in ESG 500	-1,483
	(1,519)
Weeks Since January 1, 2019	9.973***
	(1.216)
0 Weeks Since×EverinESG500 – Pre Treatment	32.05***
	(11.62)
1 Week Since×EverinESG500 – Pre Treatment	25.53***
	(9.843)
2 Weeks Since×EverinESG500 – Pre Treatment	17.48*
	(9.460)
3 Weeks Since×EverinESG500 – Pre Treatment	8.636
	(9.773)
4 Weeks Since×EverinESG500 – Treatment Week	0
	(0)
5 Weeks Since×EverinESG500 – Post Treatment	-8.305

	(9.223)
6 Weeks Since×EverinESG500 – Post Treatment	-16.94*
	(9.460)
7 Weeks Since×EverinESG500 – Post Treatment	-25.32**
	(10.36)
8 Weeks Since×EverinESG500 – Post Treatment	-34.78***
	(10.85)
Constant	1,476
	(8,165)
Observations	19,960
Number of Firms	499
Overall R^2	0.1003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Graphing the coefficients on the interaction terms $\sum_{n=0}^{8} \delta_n weeks\_since_t \times EverinESG500_i$, I get Graph 2, as shown below:

Graph 2: Weekly Change in Difference in Differences Effect of the Creation of the S&P ESG 500 Index on S&P 500 Index Stocks



Similarly to Table 3, The results from Table 4 and Graph 2 suggest that the creation of the S&P ESG 500 had a significant effect—companies added to the S&P 500 ESG Index grew less than companies that were not added to the S&P 500 ESG Index from the general S&P 500 Index. The coefficient on $EverinESG500_i$ is insignificant, agreeing with results from *Equation 1*. Interaction terms between my time period $Weeks\ Since\ January\ 1,\ 2019_t$ and indicator variable $EverinESG500_i$ are significant in week 0, 1, 2, 6, 7, and 8—every week but the weeks right before and after the creation of the S&P 500 ESG Index. While I am not able to consider the change of price in week 3 and 5 as statistically different from week 4, I am able to look at the change in β^{DID} graph for all other weeks, where it is clear to see a downward trend in the difference in differences as time progresses. Not only did the stocks of companies on the S&P 500 ESG Index grow less than the stocks of companies only on the general S&P 500 Index, but the slowing of growth occurred over time. That is, the treatment effect of reduced stock price growth increased over time. Still, *Graph 2* also suggests that this treatment might be independent of the creation of the S&P 500 ESG index, as β^{DID} had been downward trending before week 4, when the treatment went into effect.

LONG-RUN

Now that we have determined the short-run effect, I test to see if there is a long-run effect for inclusion in the S&P 500 ESG Index, and how this long-run effect compares to the short-run effect. I run Equation 3: Long-run effect — ESG Label Premium, and find results aggregated below:

Table 5: Long-run Difference in Differences Effect of the Creation of the S&P ESG 500 Index on S&P 500 Index Stocks

VARIABLES	Price
Ever in ESG 500	-1,467
	(1,537)
Post	75.47***
	(19.33)
Post×EverinESG	-65.29***
	(24.34)
Constant	1,498
	(8,296)
Observations	12,514
Number of Firms	505
Overall R^2	0.100

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Once again, the coefficient on $EverinESG500_i$ is insignificant—there is no statistically significant difference in price between Group A and Group B before the creation of the S&P 500 ESG Index. The statistically significant at the 99% level coefficients on $Post_t$ and the interaction term $EverinESG500_i \times Post_t$ also suggest similar findings in the long run as the short run—one year after the creation of the S&P 500 ESG Index, companies added to the S&P 500 ESG Index grew $65.29 dollars less than companies that were not added to the S&P 500 ESG Index from the general S&P 500 Index. Where companies that were on the general S&P 500 Index and were not included on the S&P 500 ESG Index (Group B) grew $75.47 dollars, companies which were added to the S&P 500 ESG Index (Group A) grew only $10.18.

Since a statistically significant difference in differences was found one year after the creation of the S&P 500 ESG Index, I create an event study plot to see how this difference in differences changes in each month. As the S&P 500 ESG Index was created in month 12 of the long-run data, this event study table is based in the difference from month 12. I run Equation 4: Long-run effect — ESG Label Premium Event Study and get results below:

Table 6: Monthly Difference in Differences Effect of the Creation of the S&P ESG 500 Index on S&P 500 Index Stocks

VARIABLES	Price
Ever in ESG 500	-1,507
	(1,544)
Months Since January 2018	7.328***
	(1.339)
0 Months Since×EverinESG500 — Pre Treatment	92.15*
	(54.69)
1 Month Since×EverinESG500 — Pre Treatment	79.96

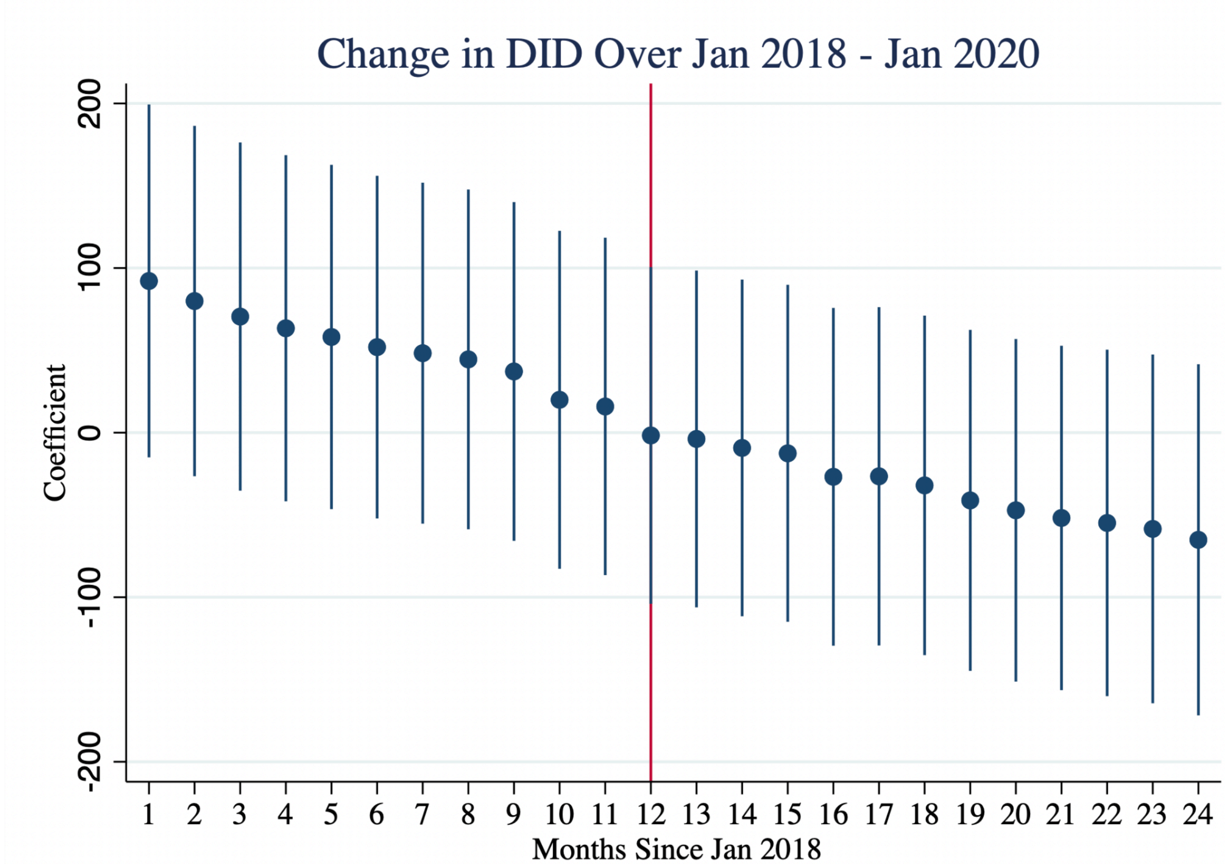
	(54.32)
2 Months Since×EverinESG500 — Pre Treatment	70.52
	(53.97)
3 Months Since×EverinESG500 — Pre Treatment	63.44
	(53.65)
4 Months Since×EverinESG500 — Pre Treatment	58.12
	(53.37)
5 Months Since×EverinESG500 — Pre Treatment	51.96
	(53.11)
6 Months Since×EverinESG500 — Pre Treatment	48.26
	(52.85)
7 Months Since×EverinESG500 — Pre Treatment	44.52
	(52.66)
8 Months Since×EverinESG500 — Pre Treatment	37.16
	(52.51)
9 Months Since×EverinESG500 — Pre Treatment	19.95
	(52.39)
10 Months Since×EverinESG500 — Pre Treatment	15.90
	(52.30)
11 Months Since×EverinESG500 — Pre Treatment	-1.717
	(52.21)
12 Months Since×EverinESG500 — Treatment Month	0
	(0)
13 Months Since×EverinESG500 — Post Treatment	-3.836
	(52.21)
14 Months Since×EverinESG500 — Post Treatment	-9.297
	(52.18)
15 Months Since×EverinESG500 — Post Treatment	-12.56
	(52.23)
16 Months Since×EverinESG500 — Post Treatment	-26.85
	(52.35)
17 Months Since×EverinESG500 — Post Treatment	-26.54
	(52.44)
18 Months Since×EverinESG500 — Post Treatment	-32.06
	(52.63)
19 Months Since×EverinESG500 — Post Treatment	-41.17
	(52.85)
20 Months Since×EverinESG500 — Post Treatment	-47.18
	(53.10)
21 Months Since×EverinESG500 — Post Treatment	-51.85

	(53.39)
22 Months Since×EverinESG500 — Post Treatment	-54.88
	(53.71)
23 Months Since×EverinESG500 — Post Treatment	-58.49
	(54.05)
24 Months Since×EverinESG500 — Post Treatment	-65.12
	(54.44)
Constant	1,450
	(8,333)
Observations	12,514
Number of Firms	505
Overall R^2	0.100

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Graphing the coefficients on the interaction terms, $\sum_{n=0}^{24} \delta_n months\_since_t \times EverinESG500_i$, I get Graph 3, as shown below:

Graph 3: Monthly Change in Difference in Differences Effect of the Creation of the S&P ESG 500 Index on S&P 500 Index Stocks



$months\_since_t$, statistically significant at the 99% level, suggests that as each month passes, all stocks increase by around $7.33. Other than in Month 0, the coefficients for the interaction terms between each month and $EverinESG500_i$ are insignificant—there is no statistically significant difference in stock price change between those on the S&P ESG 500 Index (Group A) and those only on the general S&P 500 Index (Group B). This does not mean that there is absolutely no change occurring, however—Table 5 shows that there is a statistically significant difference in differences after one year. Rather, the event study plot created in Table 6 might show that month to month, this change could be too small to determine as statistically different from 0. Indeed, Graph 3 suggests similar findings to Graph 2, which did have statistically significant results. Both graphs show downward trends in the β^{DID}

values—indicating that the treatment effect could be increasing over time. However, both graphs also show that this trend exists before the treatment effect started. Furthermore, Graph 3 does not have any statistically significant values other than Month 0—on its own, Graph 3 cannot draw any conclusions about the behavior of the monthly ESG label effect.

5.2 S&P Label Effect

Now that results have found an ESG label effect, I look to see if there is an S&P label effect occurring.

SHORT-RUN

Running Equation 5: Short-run effect — S&P Label Premium, I find the results aggregated below.

Table 7: Short-run Difference in Differences Effect of the Creation of the S&P ESG 500 Index on ESG-Compliant Stocks

VARIABLES	Price
Ever in ESG500	89.48***
	(10.20)
Post	4.126***
	(0.139)
Post×EverinESG	2.188***
	(0.176)
Shares Outstanding	-7.30e-08***
	(4.22e-09)
Constant	25.02
	(40.59)

Observations	20,160
Number of Firms	504
Overall R^2	0.301

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This time, when determining the S&P label effect, the coefficient on $EverinESG500_i$ is significant, indicating that before the creation of the S&P ESG 500 index, there was a $89.48 difference between the companies who would go on to comprise the S&P 500 ESG Index compared to those which would not. This statistical significance is in part measuring the S&P label before the launch of the S&P ESG 500 Index—all companies that would go on to comprise the S&P 500 ESG Index were pulled from the general S&P 500 Index. Thus, this $89.48 price premium on the $EverinESG500_i$ term is the difference between the companies who were on the general S&P 500 Index and companies which were not. The coefficient on $Post_t$ is also statistically significant at the 99% level, indicating that all companies grew on average by at least $4.13. Most notably, however, is the interaction term $EverinESG500_i \times Post_t$ — this is not only significant at the 99% level, but also positive. In the short run, one month after the creation of the S&P 500 ESG Index, companies added to the S&P 500 ESG Index grew $2.19 dollars more than companies that were not added to the S&P 500 ESG Index but had the ESG capabilities to do so. Over this time frame, the companies that were on the S&P 500 ESG Index (Group A) grew $6.32 dollars, while companies which were not included (Group C) only grew $4.13. This agrees with current literature—that inclusion in an index fund increases a company's stock price relative to companies which are not included on an index fund. In this case, it found that the S&P label not only gave $89.48 more to companies, but once those companies were added to the S&P 500 ESG Index they gained $2.19 more than other ESG-compliant companies.

$SharesOutstanding_{it}$ is statistically significant at the 99% level, but extremely small; the coefficient on $SharesOutstanding_{it}$ suggests that for each Share Outstanding, stock price decreased by $-0.0000000730.

Now, I run Equation 6: Short-run effect — S&P Label Premium Event Study to determine how this difference in differences shifts over time. This event study is based at week 4, when the S&P 500 ESG Index was created, thus tracking the difference relative to week 4. Results from Equation 6 are as follows:

Table 8: Weekly Difference in Differences Effect of the Creation of the S&P ESG 500 Index on ESG-Compliant Stocks

VARIABLES	Price
Ever in ESG 500	89.00***
	(10.18)
Weeks Since January 1, 2019	0.993***
	(0.0266)
0 Weeks Since×EverinESG500 – Pre Treatment	-3.780***
	(0.258)
1 Week Since×EverinESG500 – Pre Treatment	-1.324***
	(0.218)
2 Weeks Since×EverinESG500 – Pre Treatment	-0.436**
	(0.210)
3 Weeks Since×EverinESG500 – Pre Treatment	-0.330
	(0.217)
4 Weeks Since×EverinESG500 – Treatment Week	0
	(0)
5 Weeks Since×EverinESG500 – Post Treatment	0.644***
	(0.205)
6 Weeks Since×EverinESG500 – Post Treatment	1.003***
	(0.210)
7 Weeks Since×EverinESG500 – Post Treatment	1.546***

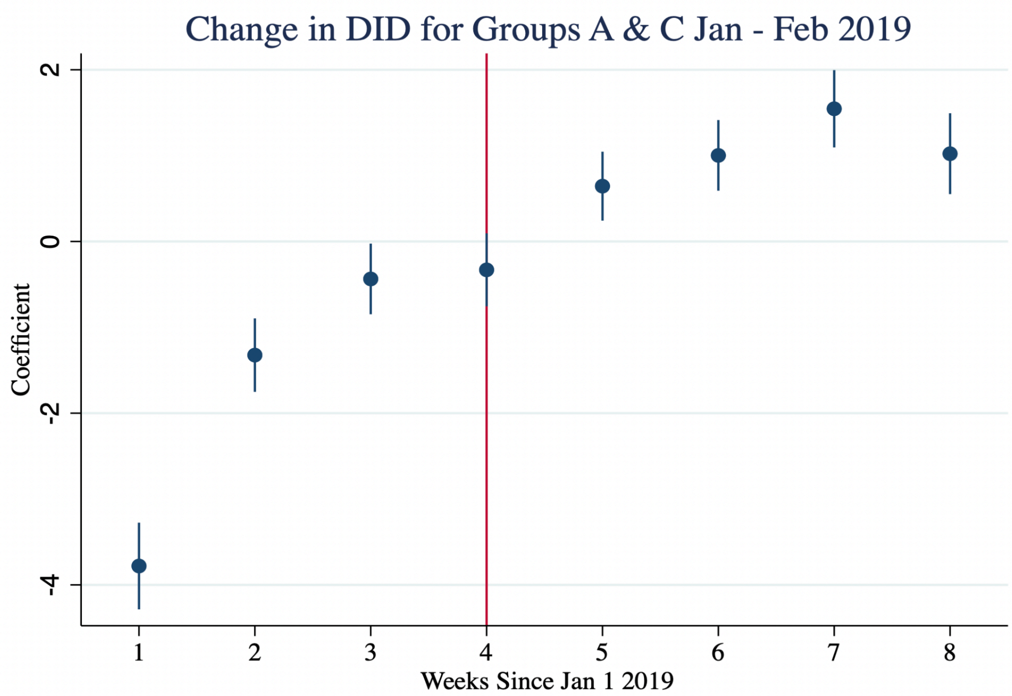
	(0.230)
8 Weeks Since×EverinESG500 – Post Treatment	1.022***
	(0.240)
Shares Outstanding	-6.98e-08***
	(4.13e-09)
Constant	22.34673
	(40.552)
Observations	20,160
Number of Firms	504
Overall R^2	0.3083

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Graphing the coefficients from the interaction terms of Table 8,

$\sum_{n=0}^{8} \delta_n weeks\_since_t \times EverinESG500_i$, I get the graph below:

Graph 4: Weekly Change in Difference in Differences Effect of the Creation of the S&P ESG 500 Index on ESG-Compliant Stocks



Results in this event study agree with findings from Table 7—the coefficients on $EverinESG500_i$ and my time variable, $weeks\_since$ are statistically significant. Not only was there a price difference between Group A and C before the creation of the S&P 500 Index, all companies increased in price over the two-month short-run period. Apart from the coefficient for the interaction term belonging to week 3, all other interaction terms per week are statistically significant. Thus, looking at Graph 4, I can see that in the short-run, the difference in differences increases until week 7, where it decreases slightly in week 8—in the short run, the treatment effect of inclusion on the S&P 500 ESG index increased a company's stock prices, and this treatment effect increased until week 7. These findings agree with current literature—that the S&P inclusion effect increases and then starts to decrease as "hype" surrounding the inclusion of an index fund slows down.

LONG RUN

In order to compare the short-run effect to the long-run effect, I run Equation 7: Long-run effect — ESG Label Premium. Results are aggregated below.

Table 9: Long-run Difference in Differences Effect of the Creation of the S&P ESG 500 Index on ESG-Compliant Stocks

VARIABLES	Price
Ever in ESG 500	48.35***
	(10.24)
Post	2.554***
	(0.565)
Post×EverinESG	7.630***
	(0.713)
Common Shares Outstanding	-0.000149
	(0.000484)
Constant	2.705
	(42.25)
Observations	12,625
Number of Firms	513
Overall R^2	0.375

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9 suggests similar findings to Table 7—that is, the long-run and short-run results agree with each other. Once again, the coefficients on $EverinESG500_i$ and $Post_t$ are statistically significant at the 99% level, indicating that before the creation of the S&P ESG 500 index, there was a $48.35 difference between the companies who would go on to comprise the S&P 500 ESG Index compared to those which would not. $Post_t$'s coefficient indicates that all companies grew on average by at least $2.55 in the long run. Additionally, the interaction term

$EverinESG500_i \times Post_t$ is significant at the 99% level, and positive—in the long run, the companies added to the S&P 500 ESG Index grew $7.63 more than the companies which were not added. This is around double the difference in differences effect identified in the short run in Table 8.

I run Equation 8: Long-run effect — S&P Label Premium Event Study to determine exactly how this difference in difference shifts. This event study is based at Month 12, when the S&P 500 ESG Index was created. Results from Equation 8 are as follows:

Table 10: Monthly Change in Difference in Differences Effect of the Creation of the S&P ESG 500 Index on ESG-Compliant Stocks

VARIABLES	Price
Ever in ESG 500	46.19***
	(10.32)
Months Since January 2018	0.216***
	(0.0380)
0 Months Since×EverinESG500 — Pre Treatment	6.827***
	(1.563)
1 Month Since×EverinESG500 — Pre Treatment	1.741
	(1.552)
2 Months Since×EverinESG500 — Pre Treatment	-0.588
	(1.538)
3 Months Since×EverinESG500 — Pre Treatment	-0.565
	(1.529)
4 Months Since×EverinESG500 — Pre Treatment	1.235
	(1.521)
5 Months Since×EverinESG500 — Pre Treatment	2.179
	(1.514)
6 Months Since×EverinESG500 — Pre Treatment	5.595***
	(1.507)
7 Months Since×EverinESG500 — Pre Treatment	8.960***

	(1.501)
8 Months Since×EverinESG500 — Pre Treatment	8.712***
	(1.497)
9 Months Since×EverinESG500 — Pre Treatment	-1.384
	(1.494)
10 Months Since×EverinESG500 — Pre Treatment	1.680
	(1.491)
11 Months Since×EverinESG500 — Pre Treatment	-8.828***
	(1.488)
12 Months Since×EverinESG500 — Treatment Month	0
	(0)
13 Months Since×EverinESG500 — Post Treatment	3.275**
	(1.488)
14 Months Since×EverinESG500 — Post Treatment	4.925***
	(1.488)
15 Months Since×EverinESG500 — Post Treatment	8.768***
	(1.489)
16 Months Since×EverinESG500 — Post Treatment	1.595
	(1.493)
17 Months Since×EverinESG500 — Post Treatment	9.016***
	(1.495)
18 Months Since×EverinESG500 — Post Treatment	10.60***
	(1.500)
19 Months Since×EverinESG500 — Post Treatment	8.602***
	(1.506)
20 Months Since×EverinESG500 — Post Treatment	9.710***
	(1.514)
21 Months Since×EverinESG500 — Post Treatment	12.15***
	(1.522)
22 Months Since×EverinESG500 — Post Treatment	16.23***
	(1.531)
23 Months Since×EverinESG500 — Post Treatment	19.73***
	(1.541)
24 Months Since×EverinESG500 — Post Treatment	20.22***
	(1.551)
Common Shares Outstanding	4.65e-05
	(0.000472)
Constant	1.366
	(42.39)

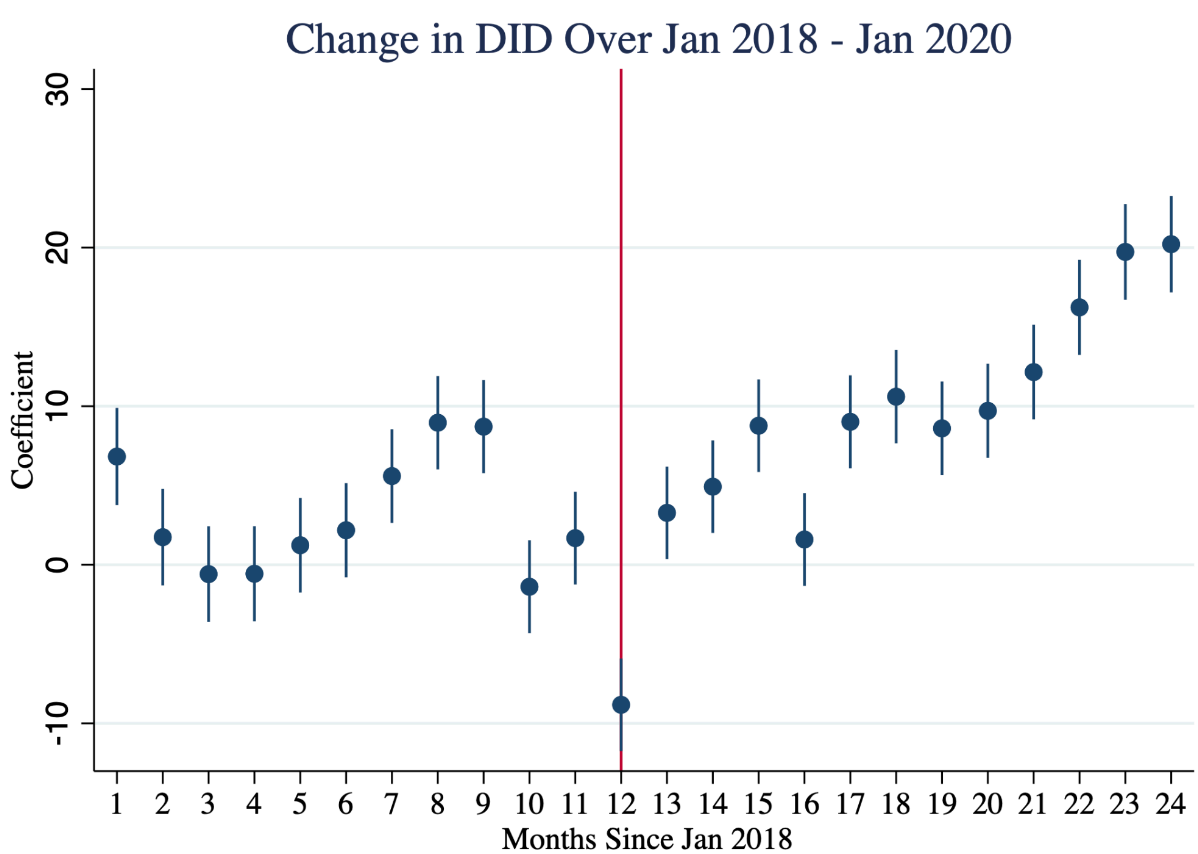
Observations	12,625
Number of Firms	513
Overall R^2	0.376

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Graphing the coefficients from the interaction terms calculated in Equation 8,

$\sum_{n=0}^{24} \delta_n months\_since_t \times EverinESG500_i$, I get Graph 5, included below:

Graph 5: Monthly Change in Difference in Differences Effect of the Creation of the S&P ESG 500 Index on ESG-Compliant Stocks



Once again, event study results agree with all earlier findings—the coefficients on $EverinESG500_i$ and the time variable, $months\_since$, are statistically significant, indicating that there was a difference before the creation of the S&P 500 Index. Furthermore, all companies increased in price over the year-long-run period. The statistical significance of the difference in difference for each month, however, is not consistent. In Months 0, 6 - 8, 11 - 15, and 17 - 24, the coefficient for the interaction is significant. In general, Table 10 and Graph 5 an upward trend for the difference in differences coefficient. While there are outliers when the difference in differences coefficient dips from Month 1 - 4, Month 10, or Month 16, the overall trend suggests similar findings to Graph 4—that the treatment effect of inclusion on an S&P index not only increases stock price relative to companies that were not included on an S&P index, but that this treatment effect grows with time—their difference in their differences increases. This long-run event study table shows us that the slight decrease in the difference in differences seen in week 8 of Graph 4 does not extend to the long-run; the long-run results do not agree with current literature that the inclusion effect decreases over time.

6. CONCLUSION

6.1 ESG Label Effect

Ultimately, Equations 1 - 4 demonstrated that in both the month and the year following the creation of the S&P 500 ESG Index, companies on the S&P 500 ESG Index (companies with the ESG label) lost money relative to companies which stayed only on the general S&P 500 Index (companies without the ESG label). It also showed that this treatment effect did not reverse itself after two weeks, as predicted by Harris and Gruel (1986). Rather, it showed that in the short-run, the treatment effect increased week-to-week. In the long-run, no statistically significant difference was found month-to-month. Yet, from the short to the long-run, the difference in differences increased by around 35%, going from $48.24 after one month to $65.29 after one year.

This result is surprising considering that current literature has suggested that an ESG label on a company would increase its stock price (Shanaev and Ghimire, 2021; Engelhardt et al., 2021; Wang et. al, 2023; Wong et al., 2019; Mario La Torre et al., 2020; and Adams et al., 2020). The reason for disagreement could lie within the American stock market in particular—most of the ESG research included in this literature review focused on the European or the Asian markets. Dorfleitner et al. (2020) finds controversy in the American markets around the ESG term and companies involved in ESG—this could be pushing down the stock prices of companies on the S&P ESG 500 and keeping them down longer than previous literature has identified. Additionally, the ESG literature reviewed focused on companies which received an ESG score; it determined the effect of the magnitude of that score. This study, on the other hand, does not test receiving an ESG score or magnitude of that score. Rather, I test the inclusion in an ESG-based index fund. These small differences—the American controversy surrounding ESG and inclusion in an ESG-based fund, are more areas to explore where the future of ESG could lie.

6.2 S&P Label Effect

Equations 5 - 8 demonstrate that in both the month and the year following the creation of the S&P 500 ESG Index, companies on the S&P 500 ESG Index (companies with the S&P label) gained money relative to those which had the ESG qualifications but were not added to the Index (companies without the S&P label). In the short run, one month after the creation of the S&P 500 ESG index, the difference in differences is found to be \$2.19. This difference in differences increased both week-to-week and month-to-month; in the long run, the difference in differences of company stock prices reached \$7.63, a 248.40% increase from the short-run difference in differences. Additionally, the coefficient term $EverinESG500_i$—the average difference in stock price before the creation of the S&P 500 ESG Index— was statistically significant in both the short and the long run with a large value, always above ~\$45. As Group A was pulled from the existing general S&P 500 Index, this large magnitude on $EverinESG500_i$ shows the importance that investors place on the S&P label.

The results both agree and disagree with current literature review. For one, the results agree with Morck and Yang (2001) and Shleifer (1986) that inclusion in an S&P index fund fares better for a company than non-inclusion. However, where Harris and Gurel (1986) says that this inclusion effect will almost completely reverse itself in the long run, the long-run event study created in this paper showed that the S&P inclusion effect continued on until the end of the year.

6.3 Takeaways

While current literature covers the magnitude and effect of ESG scores and the effect of S&P index fund inclusion, no current studies have determined the causal effects behind the price changes in the S&P 500 ESG Index. Through this difference in differences approach, I have attempted to complete this gap in the existing literature and point to what drives the price performance of stocks on the S&P 500 ESG Index—the ESG label or the S&P label. Results ultimately suggest that future upward price performance of the S&P 500 ESG Index has less to do with its ESG capabilities and more to do with the S&P label on the index fund—S&P Dow Jones is a prominent company in the financial world, and investors, it seems, invest more positively in a company with an S&P label than it does in one with an ESG label.

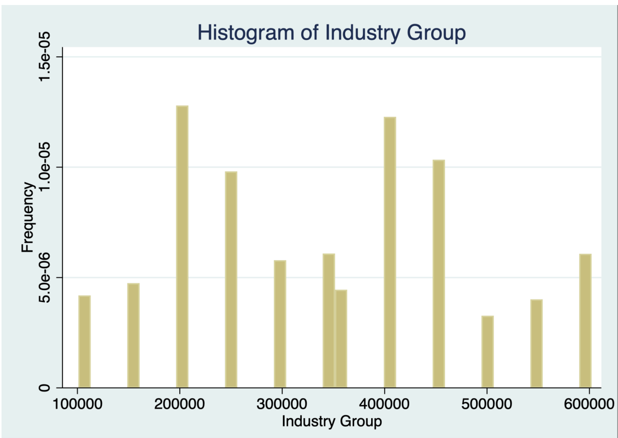
6.4 Limitations & Potential Future Research Areas

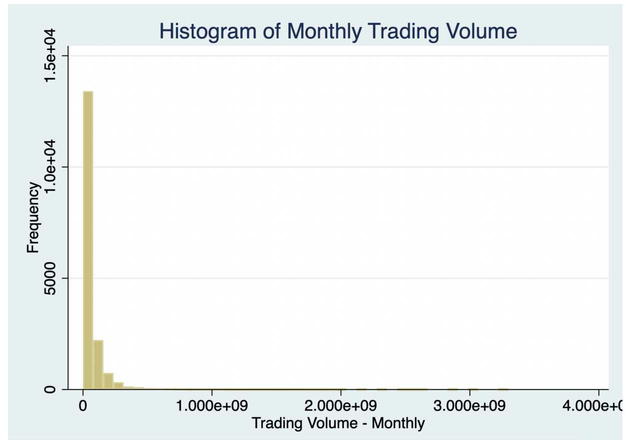
My study had several limitations with data access—I was not able to obtain the list of companies on the S&P 400 Midcap ESG Index, nor was I able to obtain S&P Global's ESG score, or additions and deletions to the S&P 500 ESG Index. While the Xtrackers S&P 400 Midcap ESG Index is used as a replica for the S&P 400 Midcap ESG Index, results would have stronger S&P label conclusions with the S&P 400 Midcap ESG Index; the real S&P 400 Midcap ESG Index has the same company going through the ESG inclusion methodology for the S&P 400 Midcap ESG index and the S&P 500 ESG Index. Additionally, the S&P is currently facing reporting issues; they are not able to report the accurate S&P Global ESG score to CRSP's database. Not only does CRSP have a warning about their S&P Global ESG score data, but when investigated, every company on CRSP's database was found to have two different ESG scores reported for the same time period. This data could not be relied upon. Finally, I was not able to find a list of companies which had been added and deleted from the S&P 500 ESG Index over time, which prevented me from extending the long run difference in differences estimation past one year.

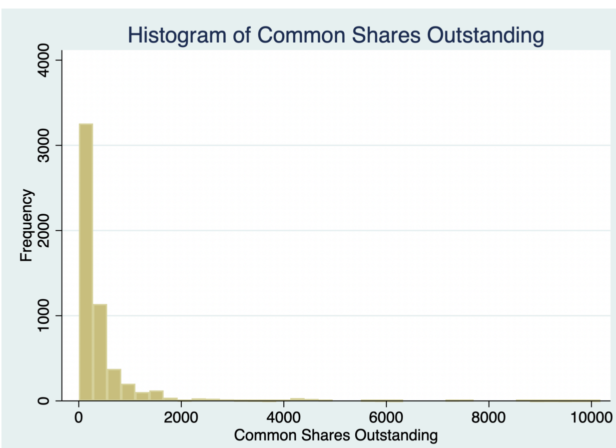
An area for future research is not only extending the long-run regression to 5 years, but also determining what occurs once the S&P 400 Midcap ESG index is created on January 11, 2021. This could further add insight into the differences between the S&P label effect and ESG label effect—if it exists for the S&P 400 Midcap ESG Index, and if the directions of the label effects point in the same direction as is found in this study.

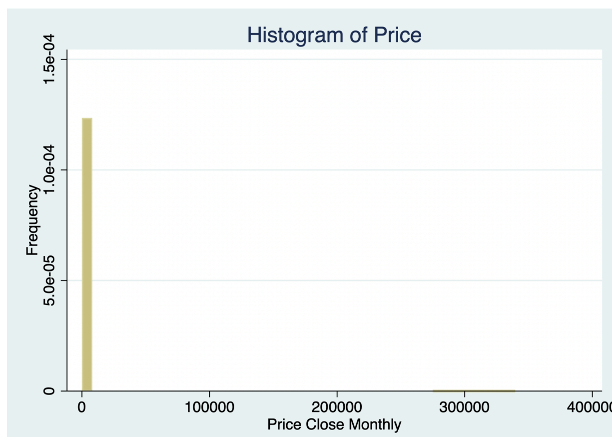
7. APPENDIX

7.1 Histograms of Long-run Market Variable Data

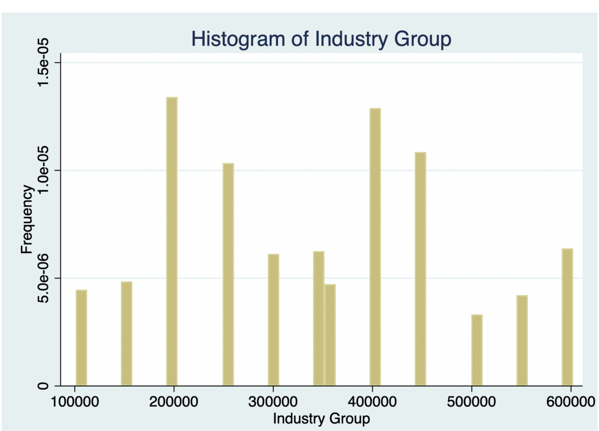


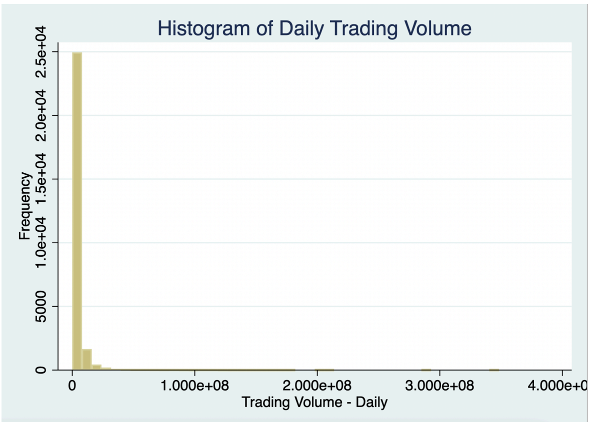


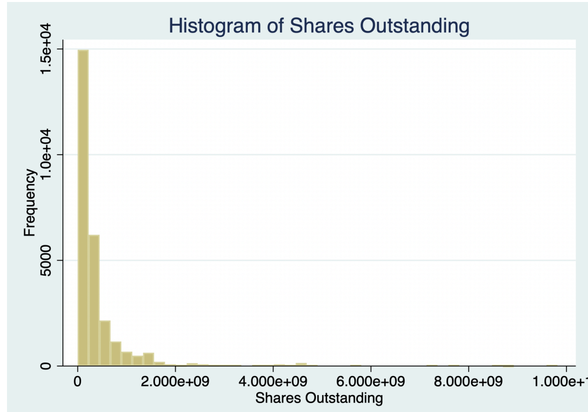




7.2 Histograms of Short-run Market Variable Data







7.3 Results of Equation 1: Short-run effect — ESG Label Premium, Industry Group Control Categorical Variable

VARIABLES	Price
EverinESG500	-1,456
	(1,519)
Post	54.66***
	(6.046)
Post_EverinESG	-48.25***
	(7.610)
101020.IndustryGroup	-342.1
	(8,612)
151010.IndustryGroup	-334.9
	(8,851)
151020.IndustryGroup	-1,371
	(12,776)
151030.IndustryGroup	-559.9
	(10,166)
151040.IndustryGroup	-739.5
	(10,640)
151050o.IndustryGroup	-
201010.IndustryGroup	-1,325
	(9,178)
201020.IndustryGroup	-969.3
	(9,878)
201030.IndustryGroup	1.128
	(16,046)
201040.IndustryGroup	-532.1
	(10,166)
201050.IndustryGroup	-903.7
	(11,391)
201060.IndustryGroup	-17.21
	(8,743)
201070.IndustryGroup	-860.0
	(11,391)
202010.IndustryGroup	-536.0
	(10,166)
202020.IndustryGroup	-594.8
	(9,289)
203010.IndustryGroup	-293.4
	(10,620)
203020.IndustryGroup	-1,089
	(10,674)
203030o.IndustryGroup	-
203040.IndustryGroup	-201.3
	(10,153)
251010.IndustryGroup	24.49
	(12,685)
251020.IndustryGroup	88.50
	(11,346)
252010.IndustryGroup	-573.0
	(9,455)
252020.IndustryGroup	55.11
	(16,046)
252030.IndustryGroup	-236.9
	(10,153)
253010.IndustryGroup	-391.1
	(8,686)
253020o.IndustryGroup	-
255010.IndustryGroup	-1,422
	(11,447)
255030.IndustryGroup	546.5
	(11,346)
255040.IndustryGroup	-643.5
	(9,089)
301010.IndustryGroup	-123.5
	(9,410)
302010.IndustryGroup	-100.2
	(9,149)
302020.IndustryGroup	-164.3
	(8,791)
302030.IndustryGroup	-1,453
	(12,776)
303010.IndustryGroup	-823.9
	(10,189)
303020.IndustryGroup	108.3
	(16,046)
351010.IndustryGroup	-577.4
	(8,663)
351020.IndustryGroup	-264.6
	(8,751)
352010.IndustryGroup	-46.27
	(9,410)
352020.IndustryGroup	-331.7
	(9,415)
352030.IndustryGroup	-510.0
	(8,928)
401010.IndustryGroup	-667.5
	(8,817)
402010.IndustryGroup	29,660***
	(9,193)
402020.IndustryGroup	37.03
	(10,613)
402030.IndustryGroup	21.76
	(8,553)
402040o.IndustryGroup	-
403010.IndustryGroup	-284.5
	(8,559)
451020.IndustryGroup	-1,393
	(9,709)
451030.IndustryGroup	-667.5
	(8,739)
452010.IndustryGroup	86.77
	(10,148)
452020.IndustryGroup	-468.6
	(9,839)
452030.IndustryGroup	-765.0
	(9,302)
453010.IndustryGroup	-618.6
	(8,631)
501010.IndustryGroup	10.30
	(12,685)
501020.IndustryGroup	-1,447
	(16,117)
502010.IndustryGroup	39.45
	(9,408)
502020.IndustryGroup	-304.4
	(9,415)
502030.IndustryGroup	239.2
	(10,620)
551010.IndustryGroup	-988.9
	(8,805)
551020.IndustryGroup	-1,420
	(16,117)
551030.IndustryGroup	-1,003
	(9,209)
551040.IndustryGroup	62.23
	(16,046)
551050.IndustryGroup	-1,500
	(16,117)
601025.IndustryGroup	33.92
	(16,046)
601030.IndustryGroup	-14.95
	(16,046)
601040.IndustryGroup	94.12
	(12,685)
601050.IndustryGroup	22.74
	(11,346)
601060.IndustryGroup	-556.4
	(9,611)
601070.IndustryGroup	-238.5
	(10,153)
601080.IndustryGroup	-343.3
	(9,159)
602010.IndustryGroup	-557.3
	(12,708)
Constant	1,485
	(8,165)
Observations	19,960
Number of firm_id	499
overall R2	0.100

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.4 Results of Equation 2: Short-run effect — ESG Label Premium Event Study, Industry Group Control Categorical Variable (Industry Group called _stub)

VARIABLES	(3) Price
_stub2	-342.1
	(8,612)
_stub3	-334.9
	(8,851)
_stub4	-1,371
	(12,776)
_stub5	-559.9
	(10,166)
_stub6	-739.5
	(10,640)
_stub8	-1,325
	(9,178)
_stub9	-969.3
	(9,878)
_stub10	1.128
	(16,046)
_stub11	-532.1
	(10,166)
_stub12	-903.7
	(11,391)
_stub13	-17.21
	(8,743)
_stub14	-860.0
	(11,391)
_stub15	-536.0
	(10,166)
_stub16	-594.8
	(9,289)
_stub17	-293.4
	(10,620)
_stub18	-1,089
	(10,674)
_stub20	-201.3
	(10,153)
_stub21	24.49
	(12,685)
_stub22	88.50
	(11,346)
_stub23	-573.0
	(9,455)
_stub24	55.11
	(16,046)
_stub25	-236.9
	(10,153)
_stub26	-391.1
	(8,686)
_stub28	-1,422
	(11,447)
_stub29	546.5
	(11,346)
_stub30	-643.5
	(9,089)
_stub31	-123.5
	(9,410)
_stub32	-100.2
	(9,149)
_stub33	-164.3
	(8,791)
_stub34	-1,453
	(12,776)
_stub35	-823.9
	(10,189)
_stub36	108.3
	(16,046)
_stub37	-577.4
	(8,663)
_stub38	-264.6
	(8,751)
_stub39	-46.27
	(9,410)
_stub40	-331.7
	(9,415)
_stub41	-510.0
	(8,928)
_stub42	-667.5
	(8,817)
_stub43	29,660***
	(9,193)
_stub44	37.03
	(10,613)
_stub45	21.76
	(8,553)
_stub47	-284.5
	(8,559)
_stub48	-1,393
	(9,709)
_stub49	-667.5
	(8,739)
_stub50	86.77
	(10,148)
_stub51	-468.6
	(9,839)
_stub52	-765.0
	(9,302)
_stub53	-618.6
	(8,631)
_stub54	10.30
	(12,685)
_stub55	-1,447
	(16,117)
_stub56	39.45
	(9,408)
_stub57	-304.4
	(9,415)
_stub58	239.2
	(10,620)
_stub59	-988.9
	(8,805)
_stub60	-1,420
	(16,117)
_stub61	-1,003
	(9,209)
_stub62	62.23
	(16,046)
_stub63	-1,500
	(16,117)
_stub64	33.92
	(16,046)
_stub65	-14.95
	(16,046)
_stub66	94.12
	(12,685)
_stub67	22.74
	(11,346)
_stub68	-556.4
	(9,611)
_stub69	-238.5
	(10,153)
_stub70	-343.3
	(9,159)
_stub71	-557.3
	(12,708)
Constant	1,476
	(8,165)
Observations	19,960
Number of firm_id	499
overall R2	0.100

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.5 Results of Equation 3: Long-run effect — ESG Label Premium, Industry Group Control Categorical Variable

VARIABLES	(1) Price
101020.IndustryGroup	-347.3
	(8,751)
151010.IndustryGroup	-293.4
	(8,893)
151020.IndustryGroup	-1,366
	(12,982)
151030.IndustryGroup	-475.2
	(9,998)
151040.IndustryGroup	-750.7
	(10,813)
151050o.IndustryGroup	-
201010.IndustryGroup	-1,329
	(9,325)
201020.IndustryGroup	-979.0
	(10,038)
201030.IndustryGroup	-0.208
	(16,306)
201040.IndustryGroup	-534.6
	(10,331)
201050.IndustryGroup	-916.1
	(11,575)
201060.IndustryGroup	-15.19
	(8,885)
201070.IndustryGroup	-874.4
	(11,575)
202010.IndustryGroup	-536.8
	(10,331)
202020.IndustryGroup	-595.3
	(9,439)
203010.IndustryGroup	-294.6
	(10,792)
203020.IndustryGroup	-1,105
	(10,847)
203030o.IndustryGroup	-
203040.IndustryGroup	-426.3
	(9,998)
251010.IndustryGroup	27.07
	(12,891)
251020.IndustryGroup	82.69
	(11,530)
252010.IndustryGroup	-524.5
	(9,608)
252020.IndustryGroup	60.87
	(16,306)
252030.IndustryGroup	-241.7
	(10,317)
253010.IndustryGroup	-391.0
	(8,826)
253020o.IndustryGroup	-
255010.IndustryGroup	-1,438
	(11,632)
255030.IndustryGroup	571.0
	(11,530)
255040.IndustryGroup	-650.6
	(9,236)
301010.IndustryGroup	-123.2
	(9,562)
302010.IndustryGroup	-96.91
	(9,297)
302020.IndustryGroup	-165.0
	(8,933)
302030.IndustryGroup	-1,469
	(12,982)
303010.IndustryGroup	-837.2
	(10,354)
303020.IndustryGroup	125.0
	(16,306)
351010.IndustryGroup	-579.8
	(8,803)
351020.IndustryGroup	-274.3
	(8,893)
352010.IndustryGroup	-66.63
	(9,562)
352020.IndustryGroup	-338.4
	(9,568)
352030.IndustryGroup	-509.1
	(9,073)
401010.IndustryGroup	-675.5
	(8,960)
402010.IndustryGroup	30,299***
	(9,341)
402020.IndustryGroup	41.18
	(10,785)
402030.IndustryGroup	32.07
	(8,691)
402040o.IndustryGroup	-
403010.IndustryGroup	-285.1
	(8,698)
451020.IndustryGroup	-1,406
	(9,865)
451030.IndustryGroup	-670.5
	(8,880)
452010.IndustryGroup	87.71
	(10,313)
452020.IndustryGroup	-467.1
	(9,998)
452030.IndustryGroup	-771.5
	(9,453)
453010.IndustryGroup	-618.5
	(8,770)
501010.IndustryGroup	8.227
	(12,891)
501020.IndustryGroup	-1,468
	(16,378)
502010.IndustryGroup	32.34
	(9,296)
502020.IndustryGroup	-310.2
	(9,568)
502030.IndustryGroup	266.3
	(10,792)
551010.IndustryGroup	-1,002
	(8,947)
551020.IndustryGroup	-1,439
	(16,378)
551030.IndustryGroup	-1,016
	(9,358)
551040.IndustryGroup	65.56
	(16,306)
551050.IndustryGroup	-1,522
	(16,378)
601025.IndustryGroup	36.78
	(16,306)
601030.IndustryGroup	-17.50
	(16,306)
601040.IndustryGroup	96.75
	(12,891)
601050.IndustryGroup	17.79
	(11,530)
601060.IndustryGroup	-564.1
	(9,767)
601070.IndustryGroup	-248.9
	(10,317)
601080.IndustryGroup	-339.1
	(9,307)
602010.IndustryGroup	-529.0
	(12,914)
Constant	1,498
	(8,296)
Observations	12,514
Number of firm_id	505
overall R2	0.100

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.6 Results of Equation 4: Long-run effect — ESG Label Premium Event Study , Industry Group Control Categorical Variable (Industry Group called _stub)

VARIABLES	(1) Price
_stub2	-347.2
	(8,790)
_stub3	-293.8
	(8,932)
_stub4	-1,366
	(13,040)
_stub5	-475.9
	(10,043)
_stub6	-750.6
	(10,861)
o._stub7	-
_stub8	-1,329
	(9,367)
_stub9	-978.9
	(10,082)
_stub10	-0.208
	(16,379)
_stub11	-534.5
	(10,377)
_stub12	-916.0
	(11,627)
_stub13	-15.18
	(8,925)
_stub14	-874.3
	(11,627)
_stub15	-536.7
	(10,377)
_stub16	-595.2
	(9,481)
_stub17	-294.6
	(10,840)
_stub18	-1,105
	(10,895)
o._stub19	-
_stub20	-429.9
	(10,043)
_stub21	27.07
	(12,948)
_stub22	82.69
	(11,581)
_stub23	-524.4
	(9,651)
_stub24	60.87
	(16,379)
_stub25	-241.7
	(10,363)
_stub26	-391.0
	(8,866)
o._stub27	-
_stub28	-1,437
	(11,684)
_stub29	571.0
	(11,581)
_stub30	-650.6
	(9,277)
_stub31	-123.2
	(9,605)
_stub32	-96.93
	(9,338)
_stub33	-165.0
	(8,973)
_stub34	-1,469
	(13,040)
_stub35	-837.1
	(10,400)
_stub36	125.0
	(16,379)
_stub37	-579.7
	(8,842)
_stub38	-274.3
	(8,932)
_stub39	-66.52
	(9,605)
_stub40	-338.4
	(9,611)
_stub41	-509.0
	(9,113)
_stub42	-675.4
	(9,000)
_stub43	30,299***
	(9,383)
_stub44	41.18
	(10,833)
_stub45	32.08
	(8,730)
o._stub46	-
_stub47	-285.1
	(8,737)
_stub48	-1,405
	(9,909)
_stub49	-670.4
	(8,920)
_stub50	87.71
	(10,359)
_stub51	-467.0
	(10,043)
_stub52	-771.4
	(9,495)
_stub53	-618.4
	(8,809)
_stub54	8.227
	(12,948)
_stub55	-1,468
	(16,451)
_stub56	32.01
	(9,337)
_stub57	-310.2
	(9,611)
_stub58	266.3
	(10,840)
_stub59	-1,002
	(8,987)
_stub60	-1,439
	(16,451)
_stub61	-1,016
	(9,400)
_stub62	65.56
	(16,379)
_stub63	-1,522
	(16,451)
_stub64	36.78
	(16,379)
_stub65	-17.50
	(16,379)
_stub66	96.75
	(12,948)
_stub67	17.79
	(11,581)
_stub68	-564.0
	(9,810)
_stub69	-248.9
	(10,363)
_stub70	-339.3
	(9,349)
_stub71	-528.9
	(12,971)
Constant	1,450
	(8,333)
Observations	12,514
Number of firm_id	505
overall R2	0.100

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.7 Results of Equation 5: Short-run effect — S&P Label Premium, Industry Group Control Categorical Variable

VARIABLES	(1) Price
101020.IndustryGroup	3.821
	(45.03)
151010.IndustryGroup	20.22
	(47.72)
151020o.IndustryGroup	-
151030.IndustryGroup	-10.06
	(59.76)
151040.IndustryGroup	6.286
	(54.91)
151050.IndustryGroup	7.419
	(106.6)
201010o.IndustryGroup	-
201020.IndustryGroup	13.55
	(59.74)
201030.IndustryGroup	1.600
	(63.73)
201040.IndustryGroup	20.96
	(54.90)
201050.IndustryGroup	526.1***
	(111.6)
201060.IndustryGroup	20.03
	(45.76)
201070.IndustryGroup	9.100
	(80.55)
202010.IndustryGroup	35.43
	(56.97)
202020.IndustryGroup	28.98
	(49.35)
203010.IndustryGroup	-5.516
	(69.95)
203020.IndustryGroup	-18.49
	(80.53)
203030.IndustryGroup	-20.99
	(106.6)
203040.IndustryGroup	34.32
	(53.28)
251010.IndustryGroup	-7.194
	(63.69)
251020.IndustryGroup	137.0*
	(70.02)
252010.IndustryGroup	12.98
	(53.31)
252020.IndustryGroup	17.40
	(63.73)
252030.IndustryGroup	32.62
	(53.28)
253010.IndustryGroup	11.46
	(46.88)
253020.IndustryGroup	74.11
	(106.6)
255010o.IndustryGroup	-
255030.IndustryGroup	314.3***
	(59.74)
255040.IndustryGroup	47.89
	(51.99)
301010.IndustryGroup	22.59
	(52.05)
302010.IndustryGroup	46.01
	(51.08)
302020.IndustryGroup	-6.542
	(46.93)
302030o.IndustryGroup	-
303010.IndustryGroup	84.65
	(80.74)
303020.IndustryGroup	39.30
	(106.7)
351010.IndustryGroup	50.20
	(46.20)
351020.IndustryGroup	46.30
	(46.91)
352010.IndustryGroup	87.29*
	(50.08)
352020.IndustryGroup	89.33*
	(53.42)
352030.IndustryGroup	141.9***
	(52.12)
401010.IndustryGroup	58.08
	(45.70)
402010.IndustryGroup	80.08
	(54.87)
402020.IndustryGroup	-0.860
	(59.80)
402030.IndustryGroup	36.28
	(45.00)
402040.IndustryGroup	83.93
	(106.7)
403010.IndustryGroup	6.567
	(45.31)
451020o.IndustryGroup	-
451030.IndustryGroup	85.45*
	(48.13)
452010.IndustryGroup	55.98
	(54.91)
452020.IndustryGroup	73.83
	(59.90)
452030.IndustryGroup	39.84
	(52.01)
453010.IndustryGroup	32.24
	(46.50)
501010.IndustryGroup	228.0***
	(71.00)
501020o.IndustryGroup	-
502010.IndustryGroup	17.15
	(51.02)
502020.IndustryGroup	22.18
	(57.18)
502030.IndustryGroup	704.9***
	(69.97)
551010.IndustryGroup	3.469
	(59.95)
551020.IndustryGroup	49.34
	(69.92)
551030.IndustryGroup	-20.36
	(69.94)
551040.IndustryGroup	-9.579
	(106.7)
551050.IndustryGroup	32.22
	(106.6)
601025.IndustryGroup	28.12
	(69.76)
601030.IndustryGroup	-14.53
	(80.53)
601040.IndustryGroup	28.60
	(54.92)
601050.IndustryGroup	-10.70
	(56.95)
601060.IndustryGroup	39.70
	(63.92)
601070.IndustryGroup	13.52
	(53.29)
601080.IndustryGroup	39.87
	(50.11)
602010.IndustryGroup	-47.48
	(106.7)
Constant	25.02
	(40.59)
Observations	20,160
Number of firm_id	504
overall R2	0.301

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.8 Results of Equation 6: Short-run effect — S&P Label Premium Event Study, Industry Group Control Categorical Variable (Industry Group called _stub)

VARIABLES	(1) Price
_stub2	4.183
	(44.99)
_stub3	21.83
	(47.67)
o._stub4	-
_stub5	-8.627
	(59.70)
_stub6	6.556
	(54.86)
_stub7	8.004
	(106.5)
o._stub8	-
_stub9	14.46
	(59.68)
_stub10	2.734
	(63.67)
_stub11	22.22
	(54.85)
_stub12	501.5***
	(111.3)
_stub13	21.81
	(45.72)
_stub14	10.68
	(80.48)
_stub15	36.83
	(56.92)
_stub16	30.36
	(49.31)
_stub17	-3.736
	(69.89)
_stub18	-17.76
	(80.46)
_stub19	-20.10
	(106.5)
_stub20	35.32
	(53.23)
_stub21	-5.815
	(63.63)
_stub22	134.1*
	(69.95)
_stub23	14.39
	(53.26)
_stub24	18.59
	(63.67)
_stub25	33.64
	(53.23)
_stub26	12.68
	(46.84)
_stub27	74.98
	(106.5)
o._stub28	-
_stub29	315.2***
	(59.68)
_stub30	48.57
	(51.94)
_stub31	22.73
	(52.00)
_stub32	46.16
	(51.04)
_stub33	-5.408
	(46.89)
o._stub34	-
_stub35	82.17
	(80.67)
_stub36	41.45
	(106.6)
_stub37	51.09
	(46.16)
_stub38	47.72
	(46.87)
_stub39	88.06*
	(50.04)
_stub40	86.87
	(53.37)
_stub41	144.0***
	(52.07)
_stub42	56.75
	(45.66)
_stub43	79.83
	(54.82)
_stub44	-0.155
	(59.75)
_stub45	37.68
	(44.96)
_stub46	80.58
	(106.6)
_stub47	7.987
	(45.27)
o._stub48	-
_stub49	85.12*
	(48.09)
_stub50	55.90
	(54.86)
_stub51	71.13
	(59.84)
_stub52	41.12
	(51.96)
_stub53	32.27
	(46.46)
_stub54	218.1***
	(70.88)
o._stub55	-
_stub56	17.56
	(50.97)
_stub57	23.57
	(57.13)
_stub58	706.9***
	(69.90)
_stub59	4.874
	(59.90)
_stub60	50.16
	(69.86)
_stub61	-18.87
	(69.88)
_stub62	-7.311
	(106.6)
_stub63	33.09
	(106.5)
_stub64	28.95
	(69.70)
_stub65	-14.09
	(80.45)
_stub66	29.58
	(54.87)
_stub67	-9.768
	(56.90)
_stub68	41.87
	(63.86)
_stub69	14.90
	(53.24)
_stub70	41.36
	(50.06)
_stub71	-45.72
	(106.6)
Constant	22.35
	(40.55)
Observations	20,160
Number of firm_id	504
overall R2	0.308

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.9 Results of Equation 7: Long-run effect — S&P Label Premium, Industry Group Control

Categorical Variable

	(1)
VARIABLES	Price
101020.IndustryGroup	11.89
	(46.91)
151010.IndustryGroup	49.07
	(48.83)
151020o.IndustryGroup	-
151030.IndustryGroup	12.60
	(59.35)
151040.IndustryGroup	13.79
	(57.20)
151050.IndustryGroup	22.52
	(111.1)
201010o.IndustryGroup	-
201020.IndustryGroup	39.70
	(62.22)
201030.IndustryGroup	33.05
	(66.37)
201040.IndustryGroup	51.24
	(57.16)
201050.IndustryGroup	-43.89
	(111.1)
201060.IndustryGroup	64.02
	(47.61)
201070.IndustryGroup	51.93
	(83.88)
202010.IndustryGroup	74.49
	(59.32)
202020.IndustryGroup	64.51
	(51.38)
203010.IndustryGroup	33.79
	(72.83)
203020.IndustryGroup	-2.684
	(83.88)
203030.IndustryGroup	-0.884
	(111.1)
203040.IndustryGroup	61.71
	(55.48)
251010.IndustryGroup	29.98
	(66.32)
251020.IndustryGroup	62.91
	(72.83)
252010.IndustryGroup	52.75
	(55.50)
252020.IndustryGroup	52.11
	(66.37)
252030.IndustryGroup	56.65
	(55.48)
253010.IndustryGroup	42.25
	(48.81)
253020.IndustryGroup	102.9
	(111.1)
255010o.IndustryGroup	-
255030.IndustryGroup	346.7***
	(62.22)
255040.IndustryGroup	67.73
	(54.15)
301010.IndustryGroup	24.96
	(54.22)
302010.IndustryGroup	55.68
	(53.21)
302020.IndustryGroup	20.83
	(48.86)
302030o.IndustryGroup	-
303010.IndustryGroup	27.27
	(84.04)
303020.IndustryGroup	105.0
	(111.1)
351010.IndustryGroup	69.81
	(47.56)
351020.IndustryGroup	68.16
	(48.13)
352010.IndustryGroup	91.69*
	(52.16)
352020.IndustryGroup	33.64
	(55.54)
352030.IndustryGroup	200.8***
	(54.22)
401010.IndustryGroup	29.01
	(47.57)
402010.IndustryGroup	82.15
	(57.16)
402020.IndustryGroup	18.23
	(62.29)
402030.IndustryGroup	78.42*
	(46.83)
402040.IndustryGroup	6.013
	(111.1)
403010.IndustryGroup	42.96
	(47.16)
451020o.IndustryGroup	-
451030.IndustryGroup	81.60
	(50.14)
452010.IndustryGroup	53.24
	(57.20)
452020.IndustryGroup	18.92
	(62.29)
452030.IndustryGroup	73.34
	(54.15)
453010.IndustryGroup	42.26
	(48.44)
501010.IndustryGroup	-1.909
	(72.68)
501020o.IndustryGroup	-
502010.IndustryGroup	19.50
	(51.48)
502020.IndustryGroup	50.42
	(59.54)
502030.IndustryGroup	788.5***
	(72.83)
551010.IndustryGroup	37.24
	(62.42)
551020.IndustryGroup	66.91
	(72.83)
551030.IndustryGroup	13.45
	(72.83)
551040.IndustryGroup	45.54
	(111.1)
551050.IndustryGroup	57.71
	(111.1)
601025.IndustryGroup	50.69
	(72.67)
601030.IndustryGroup	-6.597
	(83.88)
601040.IndustryGroup	54.22
	(57.20)
601050.IndustryGroup	7.716
	(59.32)
601060.IndustryGroup	88.14
	(66.51)
601070.IndustryGroup	39.53
	(55.48)
601080.IndustryGroup	82.56
	(52.16)
602010.IndustryGroup	-7.070
	(111.1)
Constant	2.705
	(42.25)
Observations	12,625
Number of firm_id	513
overall R2	0.375

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.10 Results of Equation 8: Long-run effect — S&P Label Premium Event Study, Industry Group Control Categorical Variable (Industry Group called _stub)

	(1)
VARIABLES	Price
_stub2	11.92
	(47.06)
_stub3	48.79
	(48.99)
o._stub4	-
_stub5	11.94
	(59.54)
_stub6	13.82
	(57.38)
_stub7	22.55
	(111.4)
o._stub8	-
_stub9	39.76
	(62.42)
_stub10	33.12
	(66.58)
_stub11	51.30
	(57.35)
_stub12	-45.27
	(111.5)
_stub13	64.14
	(47.76)
_stub14	52.03
	(84.16)
_stub15	74.58
	(59.51)
_stub16	64.60
	(51.54)
_stub17	33.91
	(73.06)
_stub18	-2.625
	(84.16)
_stub19	-0.823
	(111.4)
_stub20	61.77
	(55.66)
_stub21	30.07
	(66.53)
_stub22	62.76
	(73.06)
_stub23	52.83
	(55.68)
_stub24	52.13
	(66.58)
_stub25	56.72
	(55.66)
_stub26	42.33
	(48.97)
_stub27	103.0
	(111.4)
o._stub28	-
_stub29	346.7***
	(62.42)
_stub30	67.79
	(54.33)
_stub31	24.95
	(54.40)
_stub32	55.65
	(53.38)
_stub33	20.91
	(49.02)
o._stub34	-
_stub35	27.15
	(84.31)
_stub36	105.2
	(111.4)
_stub37	69.81
	(47.71)
_stub38	68.13
	(48.29)
_stub39	91.81*
	(52.33)
_stub40	33.52
	(55.72)
_stub41	200.9***
	(54.40)
_stub42	28.94
	(47.73)
_stub43	82.14
	(57.35)
_stub44	18.29
	(62.49)
_stub45	78.52*
	(46.99)
_stub46	5.819
	(111.4)
_stub47	43.05
	(47.31)
o._stub48	-
_stub49	81.60
	(50.30)
_stub50	53.22
	(57.38)
_stub51	18.78
	(62.49)
_stub52	73.43
	(54.33)
_stub53	42.28
	(48.60)
_stub54	-2.446
	(72.91)
o._stub55	-
_stub56	19.26
	(51.65)
_stub57	50.40
	(59.73)
_stub58	788.6***
	(73.06)
_stub59	37.35
	(62.62)
_stub60	66.96
	(73.06)
_stub61	13.56
	(73.06)
_stub62	45.69
	(111.4)
_stub63	57.76
	(111.4)
_stub64	50.76
	(72.90)
_stub65	-6.555
	(84.16)
_stub66	54.29
	(57.38)
_stub67	7.783
	(59.51)
_stub68	88.28
	(66.73)
_stub69	39.62
	(55.66)
_stub70	82.66
	(52.33)
_stub71	-6.944
	(111.4)
Constant	1.366
	(42.39)
Observations	12,625
Number of firm_id	513
overall R2	0.376

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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