Does Green Fund Ownership Impact Liquidity and Analyst Following?

by

Nicole Ann Holden

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Roger White, Chair
Jenny Brown
Steve Kaplan

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ABSTRACT

I examine whether a stock's inclusion in green exchange traded funds and mutual funds (GMFs) affects liquidity and analyst following. I base these predictions on prior literature that establishes that a firm's pro-ESG (Environmental, Social, and Governance) orientation can spur investors' interest and mitigate investors' agency concerns (by signaling that managers are pro-social). I test these predictions using difference-in-differences models of monthly turnover, bid-ask spread, and analyst coverage to examine whether firm liquidity, trading costs, and analyst following improve post-GMF inclusion. I find support for all three predictions, even though GMF ownership in my sample is exceedingly modest. Importantly, I identify my treatment effects as incremental to the liquidity boost firms receive when added to conventional mutual funds and exchange traded funds (ETFs). Together, these results suggest that GMF inclusion is perceived as an informative signal of a firm's green credentials, which leads to more trading volume, lower trading costs, and more analyst participation.

DEDICATION

To my beloved parents, who have been my guiding lights and pillars of strength throughout my journey. Mom, your endless love and encouragement have been the driving force behind my every achievement. Dad, though you are no longer with us, your wisdom and unwavering faith in me continue to inspire and motivate me to be the best version of myself. Your presence is deeply missed, but your spirit lives on in everything I do. I dedicate this accomplishment to both of you, with heartfelt gratitude and love that knows no bounds. Your sacrifices and support have made all the difference, and I am eternally grateful.

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CHAPTER 1

INTRODUCTION

The integration of environmental, social, and governance (ESG) information into investment decisions has been one of the most significant developments in financial markets in recent years. This change is mainly driven by increased awareness, pressure from regulators[1] and investors to adhere to ESG standards, and the changing preferences of investors, resulting in increased funds being allocated to ESG-compliant investments (Clarkson, Li, Richardson, and Vasvari, 2019; Eccles and Serafeim, 2013). Consequently, researchers, regulators, and investors are calling for more studies on how ESG affects financial markets (Christensen, Serafeim and Sikochi, 2022; Serafeim and Yoon, 2022).[2,3] Despite this demand for information, the market's understanding of ESG (green) signals is surprisingly unclear. I add to this literature by examining a new signal of a firm's ESG credentials, being added to a "green" mutual fund (GMF), and analyze how stock market participants react to this inclusion.

Measuring this new dimension of a firm's green status is important, namely because little is known about how market participants react to ESG signals beyond firm-level ESG disclosures or third-party ESG ratings (commonly utilized by researchers, e.g., Whelan *et al.,* 2022; Berg, Koelbel and Rigobon, 2022). GMF inclusion offers an alternative signal regarding a firm's "green" credentials that is easily identifiable and clear to market

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[1] https://www.sec.gov/rules/proposed/2022/33-11042.pdf
[2] For instance, the SEC recently issued an Investor Bulletin focusing on ESG-focused mutual funds and exchange-traded funds. See https://www.sec.gov/oiea/investor-alerts-and-bulletins/environmental-social-and-governance-esg-funds-investor-bulletin
[3] The increasing demand for academic studies on ESG issues has resulted in new academic journals emerging on the topic, such as *Accountability in a Sustainable World Quarterly* .

participants. Market participants may perceive this green credentialing signal as meaningful, as GMF inclusion is based on green mutual fund managers, who have "skin in the game" in terms of investment dollars, identifying companies with strong sustainability practices. This identification relies on fund managers' assessments of a firm's ESG performance, sustainability practices, business activities, engagement, and disclosure. Accordingly, market participants may view GMF inclusion as a legitimate signal of a firm's pro-environmental orientation, as it originates from a relatively objective third party with similar incentives (i.e., to identify green investments). Prior research suggests that green stocks are particularly attractive to a growing subset of environmentally conscious investors, which suggests that GMF inclusion could subsequently lead to liquidity improvements by attracting new, green investors (Gutsche and Ziegler, 2019; MacAskill *et al.,* 2021; Pástor, Stambaugh and Taylor, 2021; Siemroth and Hornuf, 2023; Riedl and Smeets, 2017). Furthermore, previous research establishes that an ESG orientation boosts market participants' trust in managers (Amiraslani *et al.,* 2022; Atkinson and Rosenthal, 2014; Bae, Lee and Luan, 2023; Hoepner *et al.,* 2018). If GMF inclusion similarly signals that a firm's managers are socially conscious, trustworthy, and pro-social, it could lower investors' concerns regarding the risks of self-dealing, fraud, and empire-building.

Following these research streams, I hypothesize that GMF inclusion (1) mitigates concerns relating to agency problems and information asymmetry, by signaling managers' pro-social credentials, and (2) promotes market participation by attracting green-focused market participants. I predict that both channels will operate to boost the liquidity of firms added to a GMF, *incremental* to the liquidity improvement expected from a firm being added to a general mutual or exchange traded fund.

The first channel, related to agency concerns, builds off prior literature suggesting that information asymmetry can be a significant obstacle for individual investors, particularly those with limited financial resources. Investors seek to reduce investment risk by researching and monitoring firms (Cohn *et al.,* 1975; Noe, 2002; Olsen, 1997). However, the cost of conducting research can outweigh the benefit, especially when agency concerns, like information asymmetries, are prominent (Hughes, Liu and Liu, 2007; Lang, Lins and Miller, 2004). As a result, investors typically search for more accessible methods of credible information (signals) or refrain from investing in a particular equity. Prior research suggests that investors and other stakeholders perceive ESG-oriented firms as more trustworthy (Amiraslani *et al.,* 2022; Atkinson and Rosenthal, 2014; Bae, Lee and Luan, 2023), and if market participants view a firm's addition to a GMF as a similar signal of a firm's pro-ESG orientation and trustworthiness, then GMF inclusion may temper investors' agency concerns.

I expect that if GMF inclusion does lessen agency concerns, GMF inclusion may lead to improvements in liquidity via narrowing bid-ask spreads, even after controlling for trading volume effects. This prediction is based on an extensive line of market microstructure research that documents a relation between information asymmetry problems, like adverse selection risk, and price protection in bid-ask spreads (Hrazdil, 2009; Ravi and Hong, 2015; Xie, 2013). If GMF inclusion induces uninformed outside investors to believe that managers are more trustworthy and pro-social, then these investors may have fewer adverse selection concerns and may accordingly be willing to trade with less price protection (Welker, 1995; Blankespoor, Miller and White, 2014). This would result in lower trading costs via narrower bid-ask spreads.

My second channel also predicts that GMF inclusion boosts liquidity, but via a different mechanism. Specifically, prior research documents that a growing minority of investors have strong preferences for green investments, to the point that they are willing to accept lower returns in sustainable investments (Gutsche and Ziegler, 2019; MacAskill *et al.,* 2021; Pástor, Stambaugh and Taylor, 2021; Siemroth and Hornuf, 2023). If GMF inclusion sometimes acts as a new signal of a firm's sustainability credentials, then these investors with green preferences may be more interested in said firm's stock after GMF inclusion. Moreover, ESG signals like GMF inclusion can also shape a firm's reputation among stakeholders, influencing the firm's access to capital and overall financial performance (Eccles, Newquist and Schatz, 2007). A positive reputation as a result of GMF inclusion may attract a broader range of investors and enhance the firm's ability to secure financing, further contributing to the liquidity improvement. Accordingly, I predict that the inclusion of a firm into a green mutual fund will boost trading volume, *incremental* to the expected boost in demand from being added to a general mutual or exchange-traded fund (Boujelbene and Besbes, 2012; Leuz and Verrecchia, 2000; Pevzner, 2007).

Beyond liquidity, I also examine whether GMF inclusion affects analyst following. Analysts tend to avoid companies with significant information asymmetries, since asymmetries make predicting stock returns more difficult (Lang, Lins and Miller, 2004). If GMF inclusion is an informative and value-relevant signal of a firm's managers being more

ESG conscious and less self-interested, then analysts may feel less concerned with agency problems, like asymmetry, and more confident in issuing guidance for a stock (Amiraslani *et al.,* 2022; Arya and Mittendorf, 2007; Atkinson and Rosenthal, 2014; Bae, Lee and Luan, 2023). Relatedly, previous research also indicates that firms with robust ESG practices are more transparent and predictable, making it easier for analysts to forecast their earnings (Dhaliwal *et al.,* 2012; Cheng, Ioannou and Serafeim, 2014). Both factors suggest that pro-ESG firms have more predictable earnings, which I expect may make such firms more appealing to analysts.

I summarize this prediction about analyst coverage, along with my prior predictions about how GMF inclusion affects liquidity, in the below hypothesis, stated in the alternative form:

H1: *Green mutual fund (GMF) inclusion leads to a reduction in information asymmetry and caters to the preferences of sustainability-driven investors, resulting in increased liquidity and analyst following, compared to firms included in conventional mutual funds alone.*

Importantly, I acknowledge that prior evidence indicates that the general inclusion of a stock into any mutual and exchange traded fund can map mechanically to higher volume and lower spreads (Edmister, Graham and Pirie, 1996; Elliott *et al.,* 2006; Green and Jame, 2011) . Thus, I control for general fund inclusion and attempt to isolate the *incremental* effect of GMF inclusion. In other words, my tests control for inclusion in regular, conventional funds and then isolate whether a fund being "green" has any extra effect on stock market participants' interest.

I anticipate that firms included in GMFs will experience a higher increase in liquidity compared to those included in conventional mutual funds. Furthermore, I expect that firms included in GMFs will attract incrementally more analyst coverage, even after controlling for trading volume.

I test these predictions by examining fund holdings data from 2008 to 2019. In line with prior research (Ammann *et al.,* 2019; Dolvin, Fulkerson and Krukover, 2019), I code funds (mutual funds and ETFs) as GMFs if they are a part of the Morningstar ESG Funds and ETF lists.[4] The "inclusion" variable in my study indicates whether a firm is included or not included in a mutual fund or ETF on Morningstar's ESG Funds and ETF list. This binary variable takes a value of either 0 or 1 and activates the month a firm is added to a GMF. A value of 0 signifies that the firm is not included in a GMF, while a value of 1 indicates that the firm is included in a GMF. This variable is also persistent, meaning it remains constant until the firm is removed from the GMF. I use this treatment variable to estimate differences-in-differences regressions that model the post-inclusion shifts in turnover, bid-ask spread, and analyst following for regular mutual funds compared to green mutual funds, while controlling for firm and year characteristics. I estimate my diff-in-diff

[4] A strategy is a "Sustainable Investment" by Morningstar if the prospectus or other regulatory filings state it as concentrating on sustainability, impact, or environmental, social, and governance (ESG) issues. https://www.morningstar.com/esg-funds; In 2019, the Morgan Stanley Institute for Sustainable Investing released a publication called "Sustainable Reality: Analyzing Risk and Returns of Sustainable Funds". The report examined the performance of mutual and exchange-traded funds (ETFs) focused on ESG factors, as defined by Morningstar, compared to traditional funds from 2004 to 2018. The analysis used total returns and downside deviation and concluded that sustainable funds did not have a financial trade-off in returns compared to traditional funds and exhibited lower downside risk. Additionally, during a period of heightened market volatility, the study found robust statistical evidence supporting the stability of sustainable funds.

models at the firm-month level and include firm-year fixed effects.[5] Because of my research design, the variation in month-to-month GMF ownership within each firm-year identifies the treatment effect of GMF inclusion. These short-window changes (by month within each firm-year) provide comfort that my models are not identifying shifts in firm-level fundamentals, where changes are more significant on a year-to-year basis (Davies *et al.,* 2006). My model, rather, identifies short-window changes from one month to the next, around a firm being added to a green fund by third-party mutual fund managers.

I find that while GMF ownership is exceedingly small (the largest stakes GMFs take in my sample firms is only about 2%), monthly turnover significantly increases after GMF inclusion *beyond* the trading boost firms receive when added to conventional mutual funds or ETFs. Furthermore, monthly bid-ask spreads shrink after GMF inclusion, even when controlling for the increased volume. Analyst following also increases after GMF inclusion, beyond the predicted increase associated with the trading volume bump. My findings suggest that GMF inclusion is a clear signal to market participants about a firm's green credentials, which boosts the appeal of said firms to market participants like investors and analysts.

This result contributes to the ESG literature by providing more, and particularly cleanly identified, evidence that investors and analysts have preferences for green stocks. I make a unique contribution to this literature in documenting that signals outside of ESG ratings agencies and firms' disclosures can meaningfully shift market participants'

[5] Results are robust to dynamic panel data model following Arellano and Bond (1991). Due to the high number of ts in the study, the bias seen by combining fixed effects with lagged dependent variables converges to zero.

judgements about firms' green credentials. Relatedly, my results also demonstrate that managers at green funds impact investors' perceptions of firms' green credentials.

Beyond these contributions, GMF inclusion could be a potentially useful tool for other researchers interested in measuring firms' ESG orientations. The advantages of using GMF inclusion, including its firm-quarter specific granularity and objective, simple measurement, could be useful in various settings. Researchers using short-window settings may find this measure particularly useful, as it allows for variation in a firm's green credentials within a firm-year.

I detail this GMF inclusion measure, and my related research design, in the next section. Later sections discuss my empirical results and robustness checks, followed by a brief conclusion.

CHAPTER 2

DATA, RESEARCH DESIGN, AND DESCRIPTIVE EVIDENCE

2.1 Data

I measure GMF inclusion using institutional holdings data from the CRSP holdings database, which includes mutual fund and ETF holdings across the United States over the 2008 to 2019 period.[6] I base my analysis on a comprehensive sample of the monthly effective dates of firm GMF inclusion. My classification of a fund as a "green" fund (GMF) comes from Morningstar's ESG Fund and ETF lists.[7] I draw analyst following data from I/B/E/S and liquidity data from the CRSP monthly stock file.

2.2 Research Design

I employ a difference-in-differences approach to investigate my hypothesis. These regressions estimate post-GMF inclusion shifts in my variables of interest within each firm-year. The sample comprises firms included in green mutual funds and ETFs (main treatment sample), those held by conventional funds (comparison sample), and those not held by any fund (control sample). This approach enables me to isolate the *incremental* effect of being added to a green mutual fund over and above the effect of being added to a non-green fund. That is, if a GMF owns 1% of a firm's stock and non-green funds own 3% of the firm's stock, I code "total" fund ownership as 4%, so that my GMF variable picks up *incremental* effects of GMF ownership after controlling for "total" fund ownership

[6] The date choice is 2008-2019 due to Zhu (2020) findings that the data has errors before 2008. I exclude years after 2019 to avoid the COVID 19 shock.
[7] The results are robust to using Bloomberg ESG fund lists.

(Puhani, 2012). The appendix provides a summary of the treatment variable and my set of controls (outlined below).

I have two main variables of interest, *% SHROUT GMF*, which equals the percentage of a firm's shares held by green mutual funds, and *GMF_INDICATOR,* an indicator variable that equals *1* if a firm is held by any green mutual fund during the month. To control for unobserved firm and time factors, I (1) cluster standard errors by firm and (2) include fixed effects for firm-year and year-month.[8] Accordingly, my treatment effect captures within firm-year variation in GMF inclusion. This setting allows me to interpret results in a shorter window and abstract from firm-year level changes in fundamentals. For instance, strategic shifts may affect liquidity year-over-year but are much less likely to add noise from one month to the next. However, investor perception of a firm's green credentials can shift in that shorter window around addition to a GMF.

2.2.1 Liquidity

To test H1, I examine two measures of liquidity: (1) turnover and (2) bid-ask spreads. I measure turnover, my first liquidity proxy, as shares traded over a month as a percentage of shares outstanding, consistent with prior literature that often uses trading volume as a proxy for underlying liquidity and investors' willingness to trade (Boujelbene and Besbes, 2012; Leuz and Verrecchia, 2000; Pevzner, 2007). In estimating turnover, I control for several variables that covary with liquidity, namely, (1) the lagged values of turnover (*Lag Turnover*) and the natural log of lagged market capitalization (*Lag Log(Mkt*

[8] Results are robust to a dynamic panel data model following Arellano and Bond (1991). Due to the high number of time periods in the study, the bias seen by combining fixed effects with lagged dependent variables converges to zero.

Cap)) to capture volume and size trends, (2) the lagged value of the closing bid-ask spread (*Lag Bid-Ask Spread*) to proxy for information asymmetry and trading costs, (3) the natural log of share price (*Log(Share Price)*), (4) the number of shares outstanding (*Log(Shares Outstanding)*), and (5) the signed (*Signed Return*) and absolute values of stock returns (*Absolute Return*) as proxies for information shocks (Brown, Stice and White, 2015).

The estimated coefficient of *% SHROUT GMF* tests my first prediction. A significantly positive coefficient would suggest that turnover (i.e., firm liquidity) surges with increasing GMF ownership, incremental to the general impact of that firm being owned by conventional ETFs or mutual funds. This rationale extends to *GMF_INDICATOR* (which is an *indicator variable* denoting GMF inclusion).

Beyond modelling turnover, my second proxy for liquidity is the monthly closing bid-ask spread. Spreads are a combination of order processing and inventory costs, reflecting the operational costs of the market maker, and adverse selection costs (Aitken and Comerton-Forde, 2003; Chordia, Roll and Subrahmanyam, 2000). This adverse selection cost component of bid-ask spread operates through price protection, required by potential traders to transact with a potentially informed counterparty. When this fear of adverse selection increases in the minds of potential buyers, they require more of a discount in buying shares, which subsequently pushes bid-ask spreads upwards, and vice-versa (i.e., when adverse selection fears subside, there is less price protection and bid ask spreads shrink) (Copeland and Galai, 1983; Easley and O'Hara, 1987; Glosten and Milgrom, 1985).

My related empirical tests estimate panel-data regressions of closing bid-ask spreads at the firm-month level. These regressions estimate post-inclusion shifts in monthly bid-ask spread using the closing bid-ask spread (*Bid-Ask Spread*) as my dependent variable while controlling for concurrent and lagged liquidity (*Turnover* and *Lag Turnover*) and other stock characteristics. I control for liquidity effects to ensure that my results are not attributable to liquidity surges accompanying fund inclusion, as my goal is to detect shifts in adverse selection risk, as opposed to volume-induced drops in order processing costs (another major component of bid-ask spread) (Brockman and Chung, 1999). I expect the coefficient on *% SHROUT GMF* and *GMF_INDICATOR* to be significantly negative, indicating that bid-ask spread decreases upon addition to a GMF, which signals an increase in liquidity and a decrease in information asymmetry concerns, potentially arising from a signal that a firm's management is socially oriented.

2.2.2 Analyst Following

My first two tests of H1 examine investor-facing measures of liquidity (trading volume and trading costs). As a second setting to test whether GMF inclusion boosts a firm's appeal to market participants, I model whether said inclusion spurs more analyst coverage. I use both *Number of Estimates* and an indicator variable, *ANALYST_INDICATOR,* to test the effects of GMF inclusion on analyst coverage. If GMF inclusion decreases information asymmetries and subsequently lessens market participants' agency concerns, then analysts may be more willing to cover the firm in question after GMF inclusion. Importantly, when modelling analyst coverage, I control for liquidity and spreads, as I want to ensure that any result I identify are not attributable to GMF-related increases in liquidity driving higher analyst coverage. Rather, my goal is to examine whether, controlling for liquidity, analysts are more likely to cover firms that receive a clear signal of green credentials.

2.3 Descriptive Evidence

Table 1 provides descriptive statistics of the variables used in my study. Average monthly traded turnover in my sample is about 23% (shares traded during the month divided by shares outstanding). The average closing monthly bid-ask spread is 0.075, or about $0.08. Roughly 82% of the sample firms are held by at least one mutual fund, and about 42% of the sample firms are held by at least one GMF. On average, 47% of my sample firms receive analyst coverage. In Panel B I analyze the distribution of green and non-green fund firm-months. Green funds are those that invest in environmentally sustainable projects, while non-green funds invest more broadly and are not on the Morningstar lists. I grouped the data into four categories based on the number of funds firm-months (0, 1, 2-5, >5). The GMF_INCLUSION variable measures changes in firms that jump from 0 to 1. Green funds have a range of 0-24 funds per firm, while non-green funds have a range of 0-880. 40.9% of the fund firm-months are in GMFs.

In Table 2, I present Pearson and Spearman correlation statistics between my independent, dependent, and control variables.

CHAPTER 3

EMPIRICAL RESULTS

3.1 Liquidity Results

I report my main results estimating the effect of GMF inclusion on trading volume in Table 3. Model 1 presents a baseline monthly turnover regression, which includes controls used in prior literature (Brown, Stice and White, 2015). Model 2 presents my post-treatment continuous variable, *% SHROUT GMF*, and my set of control variables. Model 3 presents my post-treatment dummy variable, *GMF_INDICATOR*, and my set of control variables. Green fund ownership predicts statistically significantly higher turnover in both models. The positive coefficient of 4.9831 (*t*-statistic = 1.68, *p*-value = 0.093) on *% SHROUT GMF* suggests that a one standard deviation shift in GMF ownership leads to a 0.52% change in the trading volume.[9] The positive coefficient of 0.0820 on *GMF_INDICATOR* (*t*-statistic = 5.16, *p*-value = 0.00) suggests that trading volume increases by about 3.47% of the unconditional mean of turnover when a firm is included in a GMF.

It is important to note that these models account for the predicted boost in trading volume firms receive for addition to any mutual fund or ETF (captured in Model 3 via the *MF_INDICATOR* control, which equals one if the mutual fund or ETF holds the firm during the month). Accordingly, this suggests that in Model 3, for example, the *GMF_INDICATOR* coefficient identifies an *incremental* liquidity boost that firms receive when added to GMFs (incremental to the liquidity boost expected from inclusion by

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[9] Results hold with entropy balancing.

conventional funds). This result supports H1 and suggests that GMF inclusion increases firm liquidity.

This GMF-induced surge in volume should operate to decrease bid-ask spreads in GMF-held firms. I want to control for this mechanical relation in modeling bid-ask spreads and focus more directly on information asymmetry-driven price protection. To do so, in my next table I examine whether GMF ownership directly reduces bid-ask spreads *after* controlling for traded volume. Table 4 Model 1 presents a baseline monthly closing bid-ask spread regression, which includes controls used in prior literature (Brown, Stice and White, 2015). Model 2 presents my post-treatment continuous variable, *% SHROUT GMF*, and my set of control variables. Model 3 presents my post-treatment dummy variable, *GMF_INDICATOR*, and my set of control variables. In Model 2, the *% SHROUT GMF* coefficient is negative and statistically significant at -0.1796 (t-statistic = -2.42, *p*-value = 0.016). In terms of economic significance, a one standard deviation shift upwards in GMF ownership predicts a 0.59% decrease in traded spreads (at the mean). This result offers further support for H1 and indicates that GMF inclusion improves liquidity. In summary, Tables 3 and 4 indicate that a firm's inclusion in a GMF leads to more liquidity *incremental* to the effects of a firm's inclusion in a mutual fund or ETF in general.[10]

3.2 Analyst Following Results

In Table 5 Panel A, I test my related prediction that GMF inclusion boosts analyst coverage (beyond any trading volume effects of GMF inclusion). Following prior research, I predict analysts avoid firms with information asymmetry problems. If GMF inclusion

[10] In additional analysis, the signal to the market is sticky in nature, meaning that the investors do not change their perception of the firm if they lose the GMF designation.

suggests that firm managers are pro-socially oriented insiders who are unlikely to exploit information asymmetries, then analysts may be more inclined to cover the firm in question. After estimating a baseline specification in Model 1, I present in Model 2 my post-treatment continuous variable, *% SHROUT GMF*, and my set of control variables. Model 3 similarly presents my post-treatment dummy variable, *GMF_INDICATOR*, and my set of control variables. Green fund ownership predicts higher analyst following in both specifications. In Model 2, the *% SHROUT GMF* coefficient of 0.9133 (t-statistic = 3.74, *p*-value = 0.00) predicts that a one standard deviation increase in GMF ownership boosts analyst coverage by 0. 26%. The corresponding dummy variable treatment effect in Model 3 similarly predicts a 1.44% increase in analyst following for firms newly added to a GMF. Note that these models control for trading volume, which suggests that GMF inclusion has *direct* effects on analyst coverage decisions beyond the indirect effects driven by liquidity.

Panel B reports related results using the analyst following indicator as a dependent variable. *% SHROUT GMF* is significant at 0.5085 (t-stat = 2.41, p-value = 0.016), indicating a 0.27% increase in the likelihood that a firm receives analyst coverage for a one standard deviation increase in GMF. The *GMF_INDICATOR* is significant at 0.0128 (t-stat = 6.78, p-value < 0.01), indicative of a 2.72% increase in the likelihood of a firm receiving analyst coverage, above the unconditional mean, for firms newly added to a GMF. Together, these Table 5 results suggest that analysts are more likely to cover firms that are added to GMFs, *incremental* to the boost in coverage that firms receive when added to a mutual fund in general *and* the boost in coverage predicted from GMF-driven improvements in liquidity. This finding supports my prediction that GMF inclusion signals that a firm's managers are socially conscious, which lessens analysts' asymmetry concerns and subsequently increases their willingness to provide coverage.

CHAPTER 4

ADDITIONAL ANALYSES

4.1 Materiality

If GMF inclusion spurs investor interest and relaxes adverse selection concerns, then I expect that this signal will be most informative in industries with particularly negative environmental or social impacts (Khan, Serafeim and Yoon, 2016). The idea behind this expectation is that GMF inclusion serves as a signal that a company is committed to environmental and social responsibility. In industries where environmental and social concerns are particularly pronounced, such as fossil fuels or manufacturing, this signal may be even more valuable for investors who are looking to align their investments with their values. Companies in these industries may be more likely to face negative public perception and scrutiny, making it even more important for them to signal their commitment to ESG principles. Therefore, if GMF inclusion can effectively mitigate adverse selection concerns and signal a company's commitment to sustainability in these industries, it could be a particularly valuable tool for investors seeking to make socially responsible investments. This expectation is supported by prior research in Khan, Serafeim and Yoon (2016), who find that ESG ratings are particularly informative in environmentally-sensitive industries. To test whether this relation similarly emits in my setting, I examine whether "dirty" industries see larger liquidity improvements following GMF inclusion.

To investigate my cross-sectional prediction for industry materiality, I include interactions between *% SHROUT GMF* and *GMF_INDICATOR* with indicators for those industries that have more material, green-related problems (*MAT_INDICATOR*) (i.e., "dirty" industries). I classify industries as "dirty" using the Sustainability Accounting Standards Board Materiality Map linked to the Fama-French 12 industry schema.[11] I code Fama-French industries #1 (consumer non-durables, such as food) and #4 (energy such as oil, gas, and coal extraction) as those with the most significant concerns about environmental sustainability.

I test this materiality prediction in Table 6, where I estimate whether my treatment effects are stronger for firms in industries with notable environmental impact. Model 1 presents my baseline monthly closing bid-ask spread regression, and Models 2 and 3 present my post-treatment variables interacted with *MAT_INDICATOR* to signify that the firm is in an industry materially affected by sustainability issues (using the continuous treatment variable in Model 2 and the indicator in Model 3). These interaction terms are not statistically significant in either model, which does not support my prediction that GMF inclusion improves firm liquidity by a larger margin in "dirty" industries.[12] Put differently, although GMF inclusion spurs interest and relaxes adverse selection concerns by signaling a manager's pro-social orientation, this signal is not more informative in industries with particularly negative environmental or social impacts. While this non-result does not support Khan, Serafeim and Yoon (2016), it is broadly in line with other research on materiality in the ESG sector and its idiosyncratic variation (Berchicci and King, 2022; King and Berchicci, 2022).

[11] https://materiality.sasb.org/

[12] This finding is similar when using *Turnover* as the dependent variable.

4.2 Analyst Coverage as a Moderator

One channel through which I expect my liquidity results to operate, as explained previously, is through GMF inclusion signaling that firm's managers are pro-social, which could lessen agency concerns from prospective investors and analysts. If these agency concerns, like adverse selection risk and information asymmetries, are important channels for my prediction, then I expect my results to be moderated in settings in which other forces constrain self-dealing by insiders. Analyst monitoring has such an effect, as more attention from analysts discourages managers' self-dealing (Adhikari, 2016; Dhiensiri and Sayrak, 2010; Doukas and Pantzalis, 2010). Following this line of reasoning, in my next analysis, I examine whether my results indicate GMF inclusion boosts liquidity to a smaller degree in firms with significant analyst following.

I present this analysis in Table 7, where I expect that more analyst coverage will moderate the relation between GMF inclusion and liquidity improvements (e.g., firms with higher analyst coverage have a lower level of adverse selection risk to begin with, as this risk largely drives information asymmetries that analysts help resolve). Table 7 Model 1 presents my baseline monthly closing bid-ask spread regression. Model 2 presents my post-treatment continuous variable interacted with Log(*Number of Estimates)* to signify the number of analysts following the firm, *% SHROUT GMF * Log(Number of Estimates)*, and my set of control variables. Model 3 presents my post-treatment dummy variable interacted with analyst following*, GMF_INDICATOR * Log(Number of Estimates)*, and my set of control variables. The *GMF_INDICATOR* interaction in Model 3 loads with a positive and significant coefficient, suggesting that the analyst coverage moderates the improvements in spreads brought on by GMF inclusion. In terms of economic significance, a one standard deviation increase in analyst coverage almost completely moderates the improvements in trading costs spurred GMF inclusion. Broadly, this result suggests that the pro-social orientation of managers that is signaled by GMF inclusion is meaningful in reducing market participants' agency concerns, and that the associated GMF inclusion-related improvements in liquidity are significantly weaker in settings where these concerns are limited.

CHAPTER 5

CONCLUSION

I examine how green fund inclusion affects a firm's liquidity and analyst following. I find that a firm's inclusion in a green fund boosts market participants' interest and trading volume. Beyond this first-order liquidity affect, I also provide evidence that GMF ownership reduces investors' agency concerns, perhaps by providing a signal that a firm's managers are pro-socially oriented (Amiraslani *et al.,* 2022; Bae, Lee and Luan, 2023). Investors price agency risks into bid-ask spreads, which likely explains why my models predict that spreads narrow in response to a firm being included in a GMF, incremental to the effects of greater liquidity and being added to a fund in general. This relation is weaker, however, in firms with fewer agency concerns (Table 7), which further supports agency concerns being one channel through which my results operate.

Beyond investors, I also examine how GMF inclusion predicts analyst coverage. Prior research suggests that agency problems and information asymmetries discourage analyst coverage, and in line with this notion I find that analysts are more willing to cover firms after their inclusion in GMFs. Importantly, the treatment effects of GMF inclusion that I observe for liquidity and analyst coverage capture effects that are *incremental* to that predicted by general mutual fund ownership and inclusion. That is, a firm newly included in a *green* fund sees incrementally higher trading volume and analyst coverage, as well as incrementally lower bid-ask spreads, than if it were added to a non-green mutual fund or ETF. My research contributes to the growing body of knowledge about the impact of changes in the way information dissemination occurs among market participants in financial markets, particularly with respect to signals about a firm's environmental friendliness. Specifically, I identify the impact of inclusion in a GMF on a boosting a firm's appeal to market participants and the subsequent improvements in firm liquidity. I am the first to document such a relation, and in doing so I make a novel contribution to the literature in documenting a unique signal of a firm's green credentials that market participants seem to value.

This unique signal of a firm's green credentials, GMF inclusion, could be useful for future researchers and market observers trying to proxy for firms' environmental friendliness. This measure offers some advantages over other ESG proxies based on firm-level disclosures and ESG scores. Notably, GMF inclusion can be easily measured across all firms in a granular (quarterly) manner. Admittedly, however, this measure is only a binary indicator of a company's sustainability practices, which means it does not consider the relative importance of various ESG factors or provide investors and researchers the nuance of continuous or count-type ESG scores. For some settings, though, the advantages provided by GMF inclusion of easy measurement, clear interpretation, and granular availability may outweigh the drawbacks of a binary score. In those settings, GMF inclusion could serve to provide researchers and observers with a straightforward measure of a firm's green status.

Lastly, I note that my analysis also provides avenues for future research. Previous finance literature suggests that both analyst coverage (Trueman, 1996) and liquidity are priced (Albuquerque, Song and Yao, 2020; Amihud, 2002; Chaieb, Errunza, and Langlois, 2021). If these relations hold in my setting, then GMF inclusion may incrementally boost stock prices, beyond that predicted by general mutual fund inclusion, given the incremental improvements in liquidity and analyst coverage that I document in response to GMF inclusion. Investigating this relation is beyond the scope of this study, but it could be a straightforward extension for other researchers interested in the broad question of how firms' ESG orientation affects stock returns (see Gillan, Koch and Starks, 2021 for a recent review of this growing literature).

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APPENDIX A

VARIABLE DEFINITIONS

APPENDIX: Variable Definitions

Primary Variables	
Turnover	Total number of shares traded for each firm divided by the total number of shares outstanding based on CRSP data. I measure Turnover at the monthly levels in my analyses.
Bid-Ask Spread	The closing spread in my monthly panel data is measured at the close of the last trading day of the month. I collect data on closing bid and ask prices from CRSP.
% SHROUT GMF	Equals the number of green mutual fund (GMF) shares as a percentage of shares outstanding. Indicates the incremental effect. GMF indication comes from 2021 Morningstar ESG Funds and ETF Lists.
% SHROUT MF	Equals the number of total mutual fund shares, including GMF, as a percentage of shares outstanding.
GMF_INDICATOR	Equals 1 beginning in the month when the firm is added to a GMF, and zero otherwise. Indicates the incremental effect of being added to a GMF.
MF_INDICATOR	Equals 1 beginning in the month when the firm is added to a mutual fund, and zero otherwise.
MAT_INDICATOR	Equals 1 if the firm is in a "dirty" industry (one that has more material, green-related issues), and zero otherwise. I classify industries as "dirty" using the Sustainability Accounting Standards Board Materiality Map linked to the Fama-French 12 industry schema. I code Fama-French industries #1 (consumer non-durables such as food) and #4 (energy such as oil, gas, and coal extraction).
Log(Number of Estimates)	The natural log of the number of analysts providing one-year-ahead earnings forecasts in I/B/E/S for a given firm as of the calendar quarter closest to each firm-month in the monthly panel data. I assume firms without forecasts in I/B/E/S have zero analyst following.
ANALYST_INDICATOR	Equals 1 beginning in the month when the firm has an analyst forecast, zero otherwise.
Control Variables	
Lag Log(Market Cap)	The natural log of the lagged market capitalization, computed using CRSP data.
Signed Return	The signed value of monthly return from CRSP.
Absolute Return	The absolute value of monthly stock return from CRSP.
Log(Share Price)	The natural log of closing share price at the end of the month from CRSP.
Log(Shares Outstanding)	The natural log of the number ofshares outstanding from CRSP.

Table 1: Descriptive Statistics

Panel A: Summary Statistics

Variable	n	Mean	Std. Dev.	1st Quartile	Median	3rd Quartile
Turnover	1,009,662	2.3619	4.4663	0.5300	1.1566	2.3062
Bid-Ask Spread	1,004,525	0.0753	0.1574	0.0100	0.0200	0.0600
% SHROUT GMF	1,032,666	0.0009	0.0025	0.0000	0.0000	0.0003
% SHROUT MF	1,032,666	0.1520	0.1714	0.0024	0.0719	0.2824
GMF_INDICATOR	1,032,666	0.4147	0.4927	0.0000	0.0000	1.0000
MF_INDICATOR	1,032,666	0.8243	0.3805	1.0000	1.0000	1.0000
Log(Number of Estimates)	1,032,666	0.8736	1.0752	0.0000	0.0000	1.7918
ANALYST_INDICATOR	1,032,666	0.4713	0.4992	0.0000	0.0000	1.0000
Log(Market Cap)	1,004,565	12.7550	2.2157	11.2365	12.7173	14.2575
Signed Return	998,401	0.0066	0.1521	−0.0473	0.0047	0.0523
Absolute Return	998,401	0.0850	0.1263	0.0200	0.0500	0.1067
Log(Share Price)	1,004,565	2.8910	1.0918	2.2225	2.9781	3.6434
Log(Shares Outstanding)	1,018,306	9.9874	1.8841	9.0546	10.1959	11.1515

Panel B: Distribution of Green and Non-Green Fund Ownership in Firm-Months

	Number of Firm-Months	
Number of Funds	Green	Non-Green
0	604,432	181,421
1	138,864	60,536
2-5	168,993	106,547
>5	111,751	675,536
Total	1,024,040	1,024,040

Table 1 Panel A presents selected descriptive statistics for the sample period 2008-2019. Please see Appendix for variable descriptions. To mitigate the influence of outliers, each variable is winsorized at the 1st and 99th percentile. Panel B presents the distribution of green and non-green fund ownership of my sample firm-months. I coarsen fund ownership into four categories based on the number of funds with an ownership stake per firm-month (0, 1, 2-5, >5).

Table 2: Pearson/Spearman Correlation Matrix

	Turnover	*Bid-Ask Spread*	*% SHROUT GMF*	*% SHROUT MF*	*GMF_ INDICATOR*	*MF_ INDICATOR*	*Log(Number of Estimates)*	*ANALYST_ INDICATOR*	*Log(Market Cap)*	*Signed Return*	*Absolute Return*	*Log(Share Price)*	*Log(Shares Outstanding)*
Turnover	1.000	-0.283	0.269	0.257	0.233	0.024	0.254	0.174	0.281	0.010	0.165	0.277	0.195
Bid-Ask Spread	-0.063	1.000	-0.330	-0.358	-0.333	-0.284	-0.312	-0.267	-0.413	0.013	-0.091	0.151	-0.630
% SHROUT GMF	0.037	-0.107	1.000	0.714	0.948	0.357	0.639	0.563	0.620	0.040	0.080	0.300	0.542
% SHROUT MF	-0.007	-0.192	0.396	1.000	0.721	0.644	0.678	0.644	0.618	0.042	0.127	0.223	0.546
GMF_INDICATOR	-0.026	-0.197	0.444	0.698	1.000	0.376	0.620	0.569	0.599	0.040	0.091	0.256	0.533
MF_INDICATOR	-0.065	-0.162	0.167	0.404	0.376	1.000	0.348	0.363	0.429	0.021	0.114	-0.033	0.447
Log(Number of Estimates)	-0.023	-0.210	0.390	0.651	0.618	0.329	1.000	0.935	0.584	0.041	0.130	0.232	0.535
ANALYST_INDICATOR	-0.069	-0.186	0.295	0.596	0.569	0.363	0.873	1.000	0.473	0.035	0.157	0.129	0.444
Log(Market Cap)	-0.016	-0.260	0.336	0.540	0.582	0.442	0.605	0.463	1.000	0.095	-0.047	0.528	0.801
Signed Return	0.034	0.003	0.007	0.017	0.016	0.017	0.021	0.022	0.056	1.000	0.037	0.127	0.018
Absolute Return	0.165	-0.028	-0.011	-0.001	-0.003	0.046	0.025	0.062	-0.105	0.392	1.000	-0.265	0.123
Log(Share Price)	0.108	0.138	0.207	0.303	0.262	-0.016	0.274	0.145	0.532	0.078	-0.272	1.000	0.011
Log(Shares Outstanding)	-0.088	-0.398	0.260	0.433	0.508	0.527	0.529	0.443	0.820	0.007	0.069	-0.043	1.000

Table 2 presents the Pearson (below the diagonal) and Spearman (above the diagonal) correlations for the variables. All variables defined in the Appendix.

Table 3: Panel Regressions of Monthly Turnover

			DV: *Turnover*
Variable	Model 1	Model 2	Model 3
% SHROUT GMF		4.9831*	
		(2.970)	
% SHROUT MF		2.6748***	
		(0.181)	
GMF_INDICATOR			0.0820***
			(0.016)
MF_INDICATOR			0.1014***
			(0.025)
Lag Log(Mkt Cap)	0.4583***	0.4232***	0.4538***
	(0.100)	(0.101)	(0.100)
Lag Bid-Ask Spread	−0.1677***	−0.1520***	−0.1659***
	(0.036)	(0.036)	(0.036)
Lag Turnover	0.2787***	0.2770***	0.2786***
	(0.005)	(0.005)	(0.005)
Signed Return	0.5416***	0.5447***	0.5405***
	(0.141)	(0.141)	(0.141)
Absolute Return	3.9972***	3.9868***	3.9981***
	(0.149)	(0.148)	(0.148)
Log(Share Price)	−0.2666**	−0.2732**	−0.2657**
	(0.128)	(0.128)	(0.128)
Log(Shares Outstanding)	−1.8788***	−1.8240***	−1.8810***
	(0.103)	(0.104)	(0.103)
Observations	990,300	990,300	990,300
Adjusted R-squared	0.823	0.823	0.823
R^2	0.8383	0.8386	0.8384
F	759.7536	617.4719	592.4737
Frequency	Monthly	Monthly	Monthly

Table 3 reports panel regression results using the monthly turnover. The monthly panel is a pooled sample consisting of all firm-month observations firms with available data from 2008 to 2019 to compute my regression variables. I winsorize all continuous variables at the 1% and 99% levels to control for outliers. All variables defined in the appendix. Model 1 estimates the baseline effect of monthly turnover. Models 2–3, respectively, estimate separate regressions of the differential effect of the number of green mutual fund shares as a percentage of shares outstanding *(% SHROUT GMF)* and the indicator variable for GMF inclusion during the month *(GMF_INDICATOR)*, respectively. Each regression includes fixed firm-year and year-month effects. I compute robust t-statistics using standard errors clustered by the firm. I present the standard errors in parentheses below each estimated coefficient. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.

Table 4: Panel Regressions of Monthly Closing Bid-Ask Spreads

		DV: *Bid-Ask Spread*	
Variable	Model 1	Model 2	Model 3
% SHROUT GMF		−0.1796**	
		(0.074)	
% SHROUT MF		−0.0186***	
		(0.004)	
GMF_INDICATOR			−0.0004
			(0.001)
MF_INDICATOR			−0.0023***
			(0.001)
Lag Bid-Ask Spread	0.0610***	0.0609***	0.0609***
	(0.004)	(0.004)	(0.004)
Turnover	−0.0007***	−0.0007***	−0.0007***
	(0.000)	(0.000)	(0.000)
Lag Turnover	−0.0005***	−0.0005***	−0.0005***
	(0.000)	(0.000)	(0.000)
Lag Log(Mkt Cap)	−0.0132***	−0.0131***	−0.0131***
	(0.001)	(0.001)	(0.001)
Log(Share Price)	0.0560***	0.0562***	0.0559***
	(0.001)	(0.001)	(0.001)
Observations	990,286	990,286	990,286
Adjusted R-squared	0.709	0.709	0.709
R^2	0.7350	0.7350	0.7350
F	372.2370	268.7259	268.5253
Frequency	Monthly	Monthly	Monthly

Table 4 reports panel regression results using the monthly closing bid-ask spread. The monthly panel is a pooled sample consisting of all firm-month observations firms with available data from 2008 to 2019 to compute my regression variables. I winsorize all continuous variables at the 1% and 99% levels to control for outliers. All variables defined in the appendix. Model 1 estimates the baseline effect of monthly closing bid-ask spread. Models 2–3, respectively, estimate separate regressions of the differential effect of the number of green mutual fund shares as a percentage of shares outstanding *(% SHROUT GMF)* and the indicator variable for GMF inclusion during the month *(GMF_INDICATOR)*, respectively. Each regression includes fixed firm-year and year-month effects. I compute robust t-statistics using standard errors clustered by the firm. I present the standard errors in parentheses below each estimated coefficient. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.

Table 5: Panel Regressions of Monthly Closing Analyst Following

Panel A: Number of Estimates

	DV: *Log(Number of Estimates)*		
Variable	Model 1	Model 2	Model 3
% SHROUT GMF		0.9133***	
		(0.244)	
% SHROUT MF		0.1580***	
		(0.012)	
GMF_INDICATOR			0.0126***
			(0.002)
MF_INDICATOR			0.0076***
			(0.001)
Lag Log(Number of Estimates)	0.6030***	0.6010***	0.6026***
	(0.003)	(0.003)	(0.003)
Turnover	0.0000	−0.0001	0.0000
	(0.000)	(0.000)	(0.000)
Lag Turnover	0.0005***	0.0004***	0.0005***
	(0.000)	(0.000)	(0.000)
Lag Log(Mkt Cap)	0.0036***	0.0031***	0.0030***
	(0.001)	(0.001)	(0.001)
Log(Share Price)	0.0379***	0.0356***	0.0380***
	(0.002)	(0.002)	(0.002)
Observations	990,346	990,346	990,346
Adjusted R-squared	0.987	0.987	0.987
R^2	0.9880	0.9880	0.9880
F	6,435.84	4,602.77	4,662.57
Frequency	Monthly	Monthly	Monthly

Table 5: Panel Regressions of Monthly Closing Analyst Following Cont.

Panel B: Analyst Indicator

		DV: *Analyst Indicator*	
Variable	Model 1	Model 2	Model 3
% SHROUT GMF		0.5085**	
		(0.211)	
% SHROUT MF		0.1280***	
		(0.011)	
GMF_INDICATOR			0.0128***
			(0.002)
MF_INDICATOR			0.0107***
			(0.002)
Turnover	−0.0003***	−0.0004***	−0.0003***
	(0.000)	(0.000)	(0.000)
Lag Turnover	0.0002**	0.0001	0.0002*
	(0.000)	(0.000)	(0.000)
Lag Log(Mkt Cap)	−0.0047***	−0.0052***	−0.0054***
	(0.001)	(0.001)	(0.001)
Log(Share Price)	0.0419***	0.0400***	0.0421***
	(0.003)	(0.003)	(0.003)
Observations	990,346	990,346	990,346
Adjusted R-squared	0.958	0.958	0.958
R^2	0.9620	0.9621	0.9620
F	68.0261	67.5755	59.4951
Frequency	Monthly	Monthly	Monthly

Table 5 reports panel regression results using the monthly number of analyst estimates in Panel A and analyst indicator in Panel B. The monthly panel is a pooled sample consisting of all firm-month observations firms with available data from 2008 to 2019 to compute my regression variables. I winsorize all continuous variables at the 1% and 99% levels to control for outliers. All variables defined in the appendix. Model 1 estimates the baseline effect of monthly turnover. Models 2–3, respectively, estimate separate regressions of the differential effect of the number of green mutual fund shares as a percentage of shares outstanding *(% SHROUT GMF)* and the indicator variable for GMF inclusion during the month *(GMF_INDICATOR)*, respectively. Each regression includes fixed firm-year and year-month effects. I compute robust t-statistics using standard errors clustered by the firm. I present the standard errors in parentheses below each estimated coefficient. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.

Table 6: Panel Regression of Monthly Closing Bid-Ask Spread with Industry Materiality

		DV: *Bid-Ask Spread*	
Variable	Model 1	Model 2	Model 3
% SHROUT GMF		−0.1853***	
		(0.082)	
% SHROUT MF		−0.0177***	
		(0.004)	
GMF_INDICATOR			−0.0005
			(0.001)
MF_INDICATOR			−0.0021**
			(0.001)
MAT_INDICATORSHROUT GMF		0.0250	
		(0.178)	
MAT_INDICATORSHROUT MF		−0.0085	
		(0.008)	
*MAT_INDICATOR*GMF_INDICATOR*			−0.0012
			(0.001)
*MAT_INDICATOR*MF_INDICATOR*			0.0066
			(0.004)
Lag Bid-Ask Spread	0.0610**	0.0607***	0.0608***
	(0.004)	(0.004)	(0.004)
Turnover	−0.0007***	−0.0007***	−0.0007***
	(0.000)	(0.000)	(0.000)
Lag Turnover	−0.0005***	−0.0005***	−0.0005***
	(0.000)	(0.000)	(0.000)
Lag Log(Mkt Cap)	−0.0132***	−0.0131***	−0.0131***
	(0.001)	(0.001)	(0.001)
Log(Share Price)	0.0560***	0.0562***	0.0559***
	(0.001)	(0.001)	(0.001)
Observations	990,286	990,691	990,691
Adjusted R-squared	0.709	0.709	0.709
R^2	0.7350	0.7352	0.7352
F	372.2370	208.5374	208.4169
Frequency	Monthly	Monthly	Monthly

Table 6 reports panel regression results using the monthly closing bid-ask spread. The monthly panel is a pooled sample consisting of all firm-month observations firms with available data from 2008 to 2019 to compute our regression variables. I winsorize all continuous variables at the 1% and 99% levels to control for outliers. All variables defined in the appendix. Model 1 estimates the baseline effect of monthly closing bid-ask spread. Models 2–3, respectively, estimate separate regressions of the interaction effect of the number of green mutual fund shares as a percentage of shares outstanding *(% SHROUT GMF)* and the indicator variable for GMF inclusion during the month *(GMF_INDICATOR)* with an indicator variable for "dirty" industries *(MAT_INDICATOR)*, respectively. Each regression includes fixed firm-year and year-month effects. I compute robust t-statistics using standard errors clustered by the firm. I present the t-statistics in parentheses below each estimated coefficient. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.

Table 7: Panel Regression of Monthly Closing Bid-Ask Spread with Analyst Following

	DV: *Bid-Ask Spread*		
Variable	Model 1	Model 2	Model 3
% SHROUT GMF		−0.2443	
		(0.170)	
% SHROUT MF		−0.0199***	
		(0.005)	
GMF_INDICATOR			−0.0020*
			(0.001)
MF_INDICATOR			−0.0017*
			(0.001)
Log(Number of Estimates)		−0.0056***	
		(0.001)	
*Log(Number of Estimates)*SHROUT GMF*		0.0405	
		(0.071)	
*Log(Number of Estimates)*SHROUT MF*		0.0034	
		(0.002)	
*Log(Number of Estimates)*GMF_INDICATOR*			0.0018***
			(0.001)
*Log(Number of Estimates)*MF_INDICATOR*			−0.0094***
			(0.002)
Lag Bid-Ask Spread	0.0610***	0.0608***	0.0608***
	(0.004)	(0.004)	(0.004)
Turnover	−0.0007***	−0.0007***	−0.0007***
	(0.000)	(0.000)	(0.000)
Lag Turnover	−0.0005***	−0.0005***	−0.0005***
	(0.000)	(0.000)	(0.000)
Lag Log(Mkt Cap)	−0.0132***	−0.0130***	−0.0130***
	(0.001)	(0.001)	(0.001)
Log(Share Price)	0.0560***	0.0565***	0.0562***
	(0.001)	(0.001)	(0.001)
Observations	990,286	990,286	990,286
Adjusted R-squared	0.709	0.709	0.709
R^2	0.7350	0.7351	0.7351
F	372.2370	190.1937	191.4145
Frequency	Monthly	Monthly	Monthly

Table 7 reports panel regression results using the monthly closing bid-ask spread. The monthly panel is a pooled sample consisting of all firm-month observations firms with available data from 2008 to 2019 to compute our regression variables. I winsorize all continuous variables at the 1% and 99% levels to control for outliers. All variables defined in the appendix. Model 1 estimates the baseline effect of monthly closing bid-ask spread. Models 2–3, respectively, estimate separate regressions of the interaction effect of the number of green mutual fund shares as a percentage of shares outstanding *(% SHROUT GMF)* and the indicator variable for GMF inclusion during the month *(GMF_INDICATOR)* with analyst following *(Number of Estimates)*, respectively. Each regression includes fixed firm-year and year-month effects. I compute robust t-statistics using standard errors clustered by the firm. I present the t-statistics in parentheses below each estimated coefficient.*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.