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To G.P.

Preface

The dissertation consists of three essays in the fields of information and market efficiency. It is submitted in fulfilment of the requirements for the degree of PhD in Economics at the Università della Svizzera italiana and of SFI PhD in Finance.

The first chapter is a single-authored paper titled *"Institutional Trading around FOMC Meetings: Evidence of Fed Leaks"*. In this paper, I show that institutional investors exhibit and exploit an informational advantage that allows them to trade profitably on the stock market ahead of FOMC meetings. Although it may seem unlikely from an institutional point of view, there is instead a building amount of direct and indirect circumstantial evidence that financial institutions are on the receiving end of Fed leaks. Direct evidence includes news articles, newsletters, FOMC minutes (Cieslak et al., 2019 and Finer, 2018); indirect evidence includes asset pricing patterns and anomalies, such as the pre-FOMC announcement drift (Lucca and Moench, 2015a), that can be explained by the presence of investors who trade on privileged information before FOMC meeting dates. An important question is: should we care about these leaks? To some extent, informal communication of the Fed with the financial sector can offer the Fed many advantages including flexibility and the opportunity of learning from the market (Vissing-Jorgensen, 2020b). However, if leaks are actively exploited to front-run monetary policy decisions and execute profitable trades, then there are risks of giving some investors an unfair advantage and undermining public's trust in the central bank, leading to market distortions. In this paper, using detailed transaction records from the Ancerno database, I find evidence consistent with informed institutional trading on the stock market on the days before FOMC scheduled announcements. I show that the institutional trading imbalance on stocks that are highly exposed to monetary policy shocks – in the sense of Ozdagli (2017) – is in line, on the days before FOMC meeting dates, with the subsequent monetary policy shock itself. The magnitude of this result is economically meaningful – in anticipation of a 1% surprise rate increase, the institutional trading imbalance is 0.43 bps higher for highly exposed stocks –, and the characteristics of the institutions that front-run monetary surprises are in line with an information-leakage story. Informed trades are stronger before easing monetary surprises, when market reaction is positive, and for the hedge funds, consistent with previous literature that finds that hedge funds tend to trade more on strategies that are not based on public and widely disseminated news (Gargano et al., 2017). Moreover, geographical proximity appears to enhance information transmission, and the informational advantage is stronger for institutions that are headquartered closer to Fed officials. Finally, I show that informed trades are more likely to be executed by Ancerno's managers located in the regional Fed districts that are currently represented in the FOMC by alternate members. This result can be explained by a loss-compensation hypothesis: in years without the right to vote, regional Fed presidents seek to compensate for the loss of the formal voting right by making more intense use of informal communication. Since disclosure ties the hand of the committee, non-voting policymakers may seek to advocate for their preferred policy by selectively disclosing internally-known information that supports their view. These findings contribute to an information-based explanation of the pre-FOMC drift on the stock market (Lucca and Moench, 2015a) and, from a policy perspective, suggest that any benefits of Fed unofficial communication must be balanced against the risk of unequal access to monetary-related information, with some investors possibly gaining and exploiting an unfair advantage.

The second chapter is a paper titled *"Insurance companies as liquidity providers: The case of mutual funds' bond sales"*, co-authored with Sirio Aramonte (Bank for International Settlements) and developed during a Ph.D. fellowship at the BIS. In this paper, we investigate the liquidity supply ecosystem in the corporate bond market. After the 2008 financial crisis, mutual funds focused on corporate bonds have grown rapidly, contributing – due to their redemption mechanism – to time-varying liquidity demand and to the risk of fire sales (Goldstein et al., 2017). Over the same period, liquidity provision by dealers declined (Adrian et al., 2017). These developments raise questions about the nature and reliability of liquidity supply in corporate-bond markets. We contribute to the literature on liquidity provision in corporate bond markets by analyzing trading patterns between mutual funds and insurance companies. While insurers can also engage in forced sales when bond downgrades raise their regulatory capital, they do not face the same outflow pressures as mutual funds. As a result, they have the flexibility to buy bonds that mutual funds are keen to divest. That is, insurers can provide liquidity to mutual funds. Studies highlight that reverse-tournament incentives lead certain mutual funds to reduce risk exposure to contain future redemptions. Our analysis focuses on "derisker" funds (Cutura et al., 2020), because their sales likely reflect stronger liquidity demand. We characterize trading patterns between mutual funds and insurers, finding that they tend to trade in opposite directions in the case of high-yield bonds, which are often sold by derisking funds, and during periods of low market risk. This relation is more pronounced after large increases in dealers' balance sheets, which lower their risk-taking capacity, suggesting that insurers can complement the activity of dealers. The link between insurers and mutual funds is weakened by factors known to impinge on liquidity provision, such as large unexpected losses and the risk of sharply higher capital requirements. Consistent with liquidity provision, portfolios that go long bonds bought by insurers and go short those sold by insurers (among bonds sold by mutual funds) earn sizeable risk-adjusted returns. Returns mostly accrue around the introduction and implementation of the Volcker Rule, when strains in the liquidity provision ecosystem were more likely (Bao et al., 2018). On balance, our work indicates that, in good times, insurance companies can provide liquidity to corporate-bond mutual funds, helping to reduce fragility in this sector and also complementing dealers when they are more likely to be constrained. As market or industry conditions deteriorate, the link between the activity of insurers and mutual funds weakens, hinting at a fair-weather undertone in insurers' liquidity provision.

The third chapter is a paper titled *The Green Side of Sell-Side Analysts*, co-authored with Silvia Dalla Fontana (USI Lugano and SFI), Laurent Frésard (USI Lugano and SFI), and Roberto Tubaldi (BI Norwegian Business School). In this paper, we focus on the relation between sell-side analysts and sustainability. A growing literature is studying the implications of incorporating environmental, social, and governance concerns into finance (Matos, 2020). However, the role played by sustainability as a source of information for sell-side analysts is still overlooked. Our work aims at filling this gap. Analysts are information intermediaries who gather, analyze, and produce information for the investment community, with the potential to influence asset prices (Kothari et al., 2016). Moreover, analysts coverage has real effects for firms, as it decreases information asymmetry and, hence, the cost of capital (Derrien and Kecskés, 2013). We identify sustainable analysts by looking at the average ESG score of the firms that they follow, and we uncover several findings. First, we show that starting in 2013 the sustainability of analysts has increased sharply, due to analysts rebalancing their portfolios toward firms with higher ESG scores. Second, we find that the fraction of total coverage that goes to high ESG firms has risen substantially over the past 10 years. Third, consistent with analysts responding to a demand for high-ESG factors – where investors usually have longer-term horizons –, sustainable analysts are more likely to disclose long-term-growth forecasts than other analysts. Finally, we study sell-side analysts' skills in producing and interpreting information in the ESG space. We find that sustainable analysts are less influential when releasing a recommendation, and make bigger forecast errors, mainly because they are too optimistic about ESG firms. Taken together, these findings suggest that sell-side analysts are responding to a growing demand for information related to sustainability, but at the current time they are failing to produce or process valuable information for the investment community. While further research is required to study this channel, we conjecture that this might be due to the high complexity of the sustainability informational environment.

Nicola Mano
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List of Papers

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Mano N., "Institutional Trading around FOMC Meetings: Evidence of Fed Leaks".

Paper II

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Paper I

Institutional Trading around FOMC Meetings: Evidence of Fed Leaks

Mano Nicola

Abstract

Fed leaks to the financial sector are actively exploited by institutional investors to trade ahead of the Federal Open Market Committee (FOMC) meetings. Using detailed transaction records from Ancerno, I find evidence consistent with informed institutional trading on the stock market on the days before FOMC scheduled announcements. The institutional trading imbalance on highly exposed stocks is in the same direction of the subsequent monetary policy surprise. The magnitude of this result is economically significant. I find that trades in anticipation of FOMC meetings are particularly strong before easing monetary policy shocks - when the aggregate market reaction is positive -, for the most-active traders, and for the hedge funds that are headquartered close to one of the regional reserve banks. Fed informal communication with the financial sector seems to be driven by the non-voting members of the Federal Open Market Committee. These findings contribute to an information-based explanation of the pre-FOMC drift and, from a policy perspective, suggest that any benefits of Fed unofficial communication must be balanced against the risk of giving some investors an unfair advantage.

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I.1 Introduction

Recent literature investigates the role of informal communication of Fed officials with the media and financial sector as a channel through which news about monetary policy reaches the market. Cieslak et al. (2019) argue for a central role for informal communication in explaining the pre-FOMC announcement drift (Lucca and Moench (2015b)) and the bi-weekly pattern of aggregate market returns over the FOMC calendar. They lay out motives for the Fed's systematic informal communication including flexibility, explaining policy, and learning from the market. Informal communication can also be motivated by disagreement between policymakers and used to gain tactical advantage in the policymaking process (Vissing-Jorgensen (2020a)). From a public policy perspective, however, any benefits must be balanced against the risk of undermining the public's trust in the central bank and of giving some investors an unfair advantage (Vissing-Jorgensen (2020c)).

Seemingly unlikely from an institutional viewpoint, there is instead a building amount of circumstantial evidence that Fed decisions leak into the market before the official announcement (Auerbach (2008)). Cieslak et al. (2019) and Vissing-Jorgensen (2020a) document several examples of news articles, newsletters, and over one hundred FOMC minutes that evidence leaks of confidential monetary policy information to financial institutions. The investigation that led to the resignation in 2017 of Richmond Fed President Jeffrey Lacker, who admitted to speaking with a MGA analyst in 2012, is only one well-known example of leak to financial institutions. Intriguingly, Finer (2018) exploits a novel database of New York's yellow taxi records to document abnormally high interactions between Federal Reserve Bank of New York and commercial bank headquarters around FOMC meetings. These meetings often occur outside business hours and also during the blackout period before FOMC dates.

However, while informal communication of the Fed with the financial sector and the media seems a fact, there is no clear evidence of whether these leaks are actively exploited, and, if yes, what are the consequences of this. In this paper, I show that institutional traders exhibit and exploit an informational advantage that allows them to trade on the stock market ahead of FOMC meetings. I document that the institutional trading imbalance on the days before FOMC meetings is in the same direction of the subsequent monetary policy surprise, and the characteristics of the institutions that front-run monetary surprises are consistent with an information-leakage story. While informal communication of the Fed is not necessarily bad (Cieslak et al. (2019)), the fact that leaks are actively exploited to front-run monetary surprises implies that some investors have an unfair advantage, if not illegal, and this eventually results in market distortions. Focusing on the stock market is particularly interesting because any evidence of information asymmetry ahead of FOMC meetings testifies in favour of an information-leak-based explanation of the pre-FOMC drift (Lucca and Moench (2015b)): information contained in some macroeconomic announcements might leak to a certain group of investors so that their uncertainties are resolved in advance, lowering the equity premium and leading to higher realized stock returns. Additionally, by using Ancerno, a high-frequency and stock-level proprietary database of institutional trades, I can zoom-in on detailed institutional trades and link them to institutions' characteristics. This approach complements and extends in scope Bernile et al. (2016), who rely on aggregate E-mini Standard & Poor's 500 futures' abnormal order imbalances on a 30-minute window before FOMC announcement, and attribute informed trades to leaks originated from accredited news agencies that violate embargo agreements.

Initially, I build upon the seminal works of Bernanke and Kuttner (2005) and Rigobon and Sack (2003), who document large responses of the stock market to surprise movements in the Fed funds rate. Extending their original analysis, I find that this result holds true also for the time period of the Ancerno's sample. From 1999 to 2014, the average policy sensitivity of the CRSP value-weighted index is −2.54 percentage points (significant at the 5% level), meaning that, for a 1% unexpected increase to the Fed funds rate, the market return falls on average by 2.54% on the day of a FOMC announcement. This estimate is in line with Gurkaynak et al. (2005).

In a first step, as preliminary evidence of informed trade, I find that the positive correlation between the realized stock returns in excess of the market and the previous days' institutional trading imbalance, defined as shares purchased minus shares sold and scaled by the firm's total shares outstanding, is significantly greater on FOMC dates. This result suggests that, on top of the price pressure effect (Lakonishok et al. (1992)), institutions are tilting their trading imbalances towards stocks that are going to experience higher returns, thus anticipating the monetary policy effect on the stock market.

For an investor who knows in advance the post-announcement Fed Funds rates, the most naive strategy would be to buy the market right before the announcement if the Fed announces a surprise cut in rates, and short the market right before the Fed announces a surprise increase in rates. However, this strategy is unlikely to be implemented by a fund manager for at least two reasons. First, most of the institutions in the Ancerno's sample are long-only mutual funds and pension funds, and for them the short leg of the strategy is not implementable; second, this strategy would have a large impact on the fund's trading strategy and overall portfolio exposure. Given the large differences in the cross-sectional monetary policy sensitivity of individual stocks (Figure I.1), a more reasonable strategy would imply buying in advance the stocks that will perform well after the monetary policy shock, and - in absence of short sales constraints - selling in advance those that will perform poorly after the shock.

In line with this intuition, I aggregate all trades at the firm-date level and look at the institutional trading imbalance on stocks that are more exposed to the monetary policy. As a first proxy for the monetary policy exposure, I use the Capital Asset Pricing Model (CAPM) beta and define exposed stocks as those belonging to the higher quintile of the cross-sectional distribution of betas, recomputed before each FOMC date. High beta industries are more sensitive to Fed announcements (Bernanke and Kuttner (2005)), and stock market beta is strongly related to average returns on FOMC dates (Savor and Wilson (2014)). As for the monetary shock, I compute the expected and unexpected (surprise, or shock) components of monetary policy changes as the changes in Fed fund future prices computed in a 1-day window around the FOMC announcement dates, as in Kuttner (2001) and Bernanke and Kuttner (2005). All results are qualitatively robust to the use of alternative measures of monetary policy shock, such as the policy news shock of Nakamura and Steinsson (2018), which is constructed using changes in interest rates at various maturities. I find that the institutional trading imbalance on high beta stocks on the three days before a FOMC date is significantly and negatively correlated with the yet-to-be realized *surprise* component of the monetary policy change. What drives market reaction is the unexpected monetary change, and the negative coefficient is consistent with the fact that a positive monetary shock determines a negative market reaction (Bernanke and Kuttner (2005)). In anticipation of a 1% positive monetary shock, that in the Ancerno's sample is associated to an average -2.5% market return, on the three days before FOMC dates, high beta stocks have a normalized trading imbalance that is 0.45 bps lower than the non-high-beta stocks. This corresponds to about one-third of the standard deviation of the trading imbalance computed in the sample. In the specifications, I control for firm-level characteristics and for the effect of the *expected* component of the revisions. Therefore, I exclude that the result is driven by institutional trades based on the expectation of the monetary revision. It is worth noticing that the 3-day window before FOMC meetings falls in the Federal Reserve blackout period during which policy-makers and staff are required to abstain from policy-related interactions with the public. In contrast to FOMC announcements, I find no evidence of informed trading ahead of Bureau of Labour Statistics' announcements (Gross Domestic Product, the CPI Inflation Rate, and the Civilian Unemployment Rate)[1].

In a recent contribution, Ozdagli and Velikov (2020) argue that CAPM beta has limited predictive power for the cross-sectional differences in the monetary policy sensitivity of individual stocks, and this is due to the fact that CAPM does not correctly price the risk exposure when there are multiple aggregated shocks. Therefore, in the next step, I build a FOMC-specific measure of stock-level monetary policy exposure in the same spirit of Ozdagli and Velikov (2020). This measure overcomes the limited predictive powers of the CAPM beta in explaining the cross-sectional differences in the monetary policy sensitivity of individual stocks. In order to create this measure, I interact policy surprises with firm characteristics that are linked to monetary policy transmission mechanisms and policy sensitivity by previous literature (e.g. Chava and Hsu (2020) and Weber (2018)). This approach yields a MPE index based on the contribution of each characteristic to the monetary policy exposure. Firms with high MPE tend to perform well when there is a tightening monetary policy shock, and firms with a low MPE tend to perform poorly when there is a tightening monetary policy shock. Consistently with previous results, I find that, on the three days before the FOMC meetings, the direction of institutional trades on high MPE shocks is positively correlated to the unexpected component of the monetary policy change. The magnitude of these results is significant: in anticipation of a 1% surprise rate increase, the institutional trading imbalance is 0.43 bps higher for high-MPE stocks (i.e. with MPE above the median) as compared to low-MPE stocks. This result holds throughout the Ancerno's sample (1999-2014), but it is stronger in 2006-2014, when the Fed chairman was Ben Bernanke. Informed trading is particularly strong before negative monetary policy shocks, when the market is expected to rise. This suggests that institutions are more likely to buy the stocks that will perform good, rather than to sell those that will perform badly: this is not surprising, since the majority of Ancerno's institutions are long-only mutual funds and pension funds. Moreover, there is no evidence of anticipatory trades before unscheduled FOMC meetings, when the monetary policy decisions tend to be reactive or endogenous, such as the FOMC announcement following the Long-Term Capital Management (LTCM) crisis on September 23, 1998, and the market impact of monetary shocks negligible (Ozdagli (2017)).

In a second step, I aggregate the Ancerno database at the manager-firm-date level. This allows to test for the robustness of the main specification to different choices of fixed effects, and to exploit the heterogeneity of Ancerno's institutions. Although Ancerno's clients are always anonymous, I follow the

[1]This result is presented in Table I.1.

procedure in Di Maggio et al. (2021) and Çötelioğlu et al. (2020) to identify hedge funds and mutual funds. The formers are identified by matching the names of Ancerno's management companies with a list of hedge fund names built from quarterly 13F mandatory filings, a Thomson Reuters proprietary list of hedge funds, ADV filings, industry listings, the Lipper/TASS Hedge Fund Database, Morningstar CISDM, and Hedge Fund Research; the latter are identified by comparing the transaction data in Ancerno with the quarterly holdings data in the Thomson Reuters Databases. This matching procedure allows to identify 417 mutual funds, 99 hedge funds, and 338 pension funds. I find significant evidence of informed trading for mutual funds and, with a higher coefficient, for hedge funds. This is consistent with Gargano et al. (2017), that finds that hedge funds trade more on strategies that are not based on public and widely disseminated news. Hedge funds, that in general are free from short-sale constraints, appear also to be more active than mutual funds before positive monetary shocks, when the market experiences negative returns and a profitable strategy would be to short highly-exposed stocks. In contrast, pension funds, that have a longer horizon and trade with lower frequency, seem to trade less in anticipation of monetary shocks. By exploiting trade execution characteristics to further characterize the institutional investors, I find that the biggest, most-active and median-skilled institutions are those that tend to trade more in anticipation of FOMC news. I also investigate the persistence of trading performance on FOMC dates and find that it is significant and almost entirely driven by high-performance funds (in line with Puckett and Yan (2011)).

The Federal Open Market Committee (FOMC) has 12 voting members, including all seven members of the Board of Governors and five Reserve Bank presidents. The New York Fed is directly involved in carrying out monetary policy operations, so its president has a permanent vote on the FOMC. The four remaining voting seats are filled by the other 11 Reserve Bank presidents on a rotating basis, holding one-year terms (the "voting" members). It is important to note, however, that also the other non-voting Federal Reserve bank presidents (the "alternate" members) get the same pre-meeting materials, attend the FOMC meetings, participate in the discussions, give their assessments of national and regional economic conditions and share their views on appropriate policy. In a next step, I collect the locations of Ancerno's institutions and match them with the corresponding regional Fed districts. Out of the 1067 Ancerno's managers, I can identify the location of 848 US managers, based on their names. I find that informed trades in anticipation of FOMC meetings are more likely to be executed by Ancerno's managers located in the regional Fed districts that are currently represented in the Federal Open Market Committee by alternate members. This result appears consistent with a loss-compensation hypothesis (e.g. Crawford and Sobel (1982) and Milgrom and Roberts (1986)) and with Vissing-Jorgensen (2020a). In years without the right to vote, Fed presidents seek to compensate for the loss of the formal voting right by making more intense use of *informal* communication: since disclosure ties the hand of the committee, non-voting policy makers may seek to advocate for their preferred policy by selectively disclosing internally-known information that supports their view. This result complements Ehrmann et al. (2021), who find that speeches by presidents in years they do not have the right to vote are more informative for the market (albeit they make less intense use of *public* inter-meeting speeches and meeting interventions).

To further address the concern that anticipatory trades are due just to luck, I exploit the location of Ancerno's institutions to see if the informational advantage is stronger for institutions that are headquartered closer to Fed officials. Recent literature suggests that information spreads more effectively among fund managers that are geographical or socially connected, so it is natural to ask whether a similar effect plays out also for what concerns information leakages ahead of FOMC meetings (Hong et al. (2005) and Pool et al. (2015)). I hand-collect locations of Ancerno's fund managers using the reported name and then match with the borders of each regional Fed district and the location of Federal Reserve branches. I focus on the subsample of hedge funds, for which the baseline results are stronger, and find that hedge funds that are located closer to a regional Fed branch (within 20 km) exhibit superior information advantage in trading before FOMC dates. This result is robust to alternative choices of the threshold for the distance.

Contribution to the literature. This paper contributes to the literature in at least three ways. First, by providing empirical evidence about the informativeness of institutional trading imbalances in the equity space before FOMC announcements, I contribute to research on information asymmetry, a vein of the literature that goes back to Kyle (1985) and Akerlof (1970). My results are in line with the Cieslak et al. (2019) and Bernile et al. (2016) hypothesis and anecdotal evidence on the Fed informally or indirectly sharing information about the announcements. Here I report two examples of leaks borrowed from Cieslak et al. (2019). The first one is a leak to Bank of America retrieved from a FOMC Transcript dated August 16, 2007: "MR. LACKER. Vice Chairman Geithner, did you say that (the banks) are unaware of what we're considering or what we might be doing with the discount rate? VICE CHAIRMAN GEITHNER. Yes. MR. LACKER. Vice Chairman Geithner, I spoke with Ken Lewis, President and CEO of Bank of America, this afternoon, and he said that he appreciated what Tim Geithner was arranging by way of changes in the discount facility. So, my information is different from that." The second is a leak to a former Fed governor, W. Angell, retrived from an "Advice to clients" of the Bear, Stern & Co. (as reported by D. Wessel, Wall Street Journal of July 7, 1995): "One Fed watcher who called it right - barely - was former Fed governor Wayne Angell; now an economist at Bear, Stearns & Co. Mr. Angell had been among those confidently predicting that the Fed would hold rates steady at this week's meeting. But on Wednesday - after joining current Fed officials and others the night before to watch Fourth of July fireworks from the roof of the Fed's building in Washington - Mr. Angell abruptly announced that he had changed his view and anticipated a one-quarter-point cut." More recently, Mr. Kaplan and Mr. Rosengren, the presidents of the Federal Reserve banks of Boston and Dallas, resigned following reports of the two leaders' investment trading that prompted calls for their departures and a central-bank review of its ethics rules. The two banks gave different reasons for the exits. Dallas Fed President acknowledged in a statement released by the bank that his stock trading distracted from the Federal Reserve's work, while Boston Fed President decision follows the recent disclosure that he traded stocks and other investments related to the real-estate industry in 2021 while also helping to set monetary policy [2].

Second, I contribute to existing work documenting abnormal stock market movements before FOMC announcements are made (Lucca and Moench (2015b)). The reason for this premium is still debated in the literature. Lucca and Moench (2015b) suggest that the pre-FOMC announcement drift has to be characterized as an expected return. However, none of the off-the-shelf risk-based theories that they discuss match the empirical evidence, leading them to conclude the paper with a significant remark: "as of this paper writing, the pre-FOMC announcement drift is a puzzle". More recently, Laarits (2019) suggests the pre-FOMC drift represents a risk premium associated with the resolution of uncertainty about the announcement type, and Ai et al. (2021) explain it in a Grossman-Stiglitz model with endogenous information acquisition. Abdi and Wu (2018) find that U.S. corporate bond market movements during the days preceding FOMC announcements have predictive power for the fund rate surprises. Albeit the timing of the empirical evidence of leaks does not perfectly match the timing of the pre-FOMC annoucement drift as documented in Lucca

[2]"Fed Leaders Eric Rosengren, Robert Kaplan to Resign Following Trading Controversy; Dallas Fed President Kaplan said his stock trading distracted from the work of the central bank". Michael S. Derby, Wall Street Journal (September 28, 2021).

and Moench (2015b), my paper provides supporting evidence to the alternative information-based explanation proposed by Cieslak et al. (2019), and in line with Ying (2020) and Zhu (2021). Pre-FOMC stock returns may be due to information leaks intended to influence the investors' interpretation of the FOMC statements and to reduce the downside risk via a promise to act as needed: these leaks reduce the amount or price of uncertainty, thereby lowering the equity premium and leading to subsequent higher realized stock returns.

Third, I provide an additional channel through which institutions make abnormal profits from their intra-quarter trades (Puckett and Yan (2011)). From a policy perspective, in the same spirit of Kurov et al. (2016), my work suggests that to ensure fairness in financial markets, strict release procedures need to be implemented for all market-moving announcements including announcements originating in the private sector.

The rest of this paper is organized as follows. The next section describes the methodology and data. Section III presents the empirical results including robustness checks. Institutional heterogeneity and locations are exploited in Section IV, and a brief discussion concludes in Section V.

I.2 Data, Measures and Summary Statistics

I.2.1 Stock prices and firm characteristics

This analysis requires different data sources. Daily stock prices are retrieved from CRSP and annual firm characteristics from Compustat. I exclude utilities and financial firms (SIC codes between 4900 and 4999 or between 6000 and 6999), and firms whose stock price is below $5 (penny stocks). Data about the VIX index and the Fed fund futures are gathered from Thomson Reuters Datastream. Institutional trade data come from the Ancerno Ltd database.

I.2.2 Ancerno's institutional trading data

Institutional trade-level data derive from Ancerno Ltd. (formerly Abel Noser Solutions Corporation), which collects its institutional clients' transaction records for which such clients use Ancerno's trade cost analysis service. The dataset, that spans the period from January 1999 to December 2014, contains detailed information regarding institutions' trading times, execution price, trading amounts, and whether execution is a buy or sell. Ancerno's institutions include mutual funds, hedge funds, and pension funds. The fact that clients submit this information to Ancerno to obtain objective evaluations of their trading costs, and not to advertise their performance, suggests that self-reporting should not bias the data. Moreover, Ancerno is free of survivorship bias as it includes information about institutions that report in the past but at some point terminated their relationship with Ancerno.

To study the aggregate institutional trades around earning announcements and other event days, I first aggregate the trades of all the institutions in the Ancerno data by stock and day. Following the literature, e.g. Irvine et al. (2007), I compute both the total number of shares traded regardless of trading direction (i.e. shares purchased plus shares sold, ot total institutional trading) and the net shares traded (shares purchased minus shares sold, or institutional trading imbalance). I then standardize the daily number of stocks traded by the total number of shares outstanding

$$imbalance_{j,t} = \frac{\Delta shares_{j,t}}{sharesout_{j,t}} \tag{I.1}$$

where $sharesout_{j,t}$ is the total number of shares outstanding for stocks j on day t. I keep only the FOMC date-firm observations for which there is at least one institutional trade on a $[-9;+9]$ window around it. Ancerno does not provide reliable information on the identity of the individual fund that is executing the trade within a fund management company (Çötelioğlu et al. (2020)). For this reason, when exploiting the heterogeneity across institutions, I work on trades aggregated at the management company level and normalized by the number of shares outstanding, as above. For simplicity, I will simply refer to hedge funds or mutual funds when talking about the asset management companies. Before merging with the other variables, the Ancerno sample includes 7836 firms and 978 fund management companies. As shown in Table I.1, the average normalized institutional trading imbalance of FOMC dates is -0.55, with a standard deviation of 1.405.

I.2.3 Monetary policy shocks

I calculate the surprise element of policy actions by using the price of Fed funds futures contracts following the standard procedure outlined in Kuttner (2001) and Bernanke and Kuttner (2005). I start in 1994 as from this year onwards, FOMC meetings became regularly scheduled events known to the public at the beginning of each year and less contaminated by other macro announcements. The main idea is to back out the unexpected target rate changes by looking at the changes in prices of the current-month futures contracts right before and right after FOMC event days. These contracts, officially referred to as "30 Day Federal Funds Futures" are traded on the Chicago Board of Trade.

The implied futures rate is equal to 100 minus the contract price. Shocks to monetary policy based on Fed funds futures are computed as

$$MPShock = \frac{D}{D-d}\left(f^0_{m,d} - f^0_{m,d-1}\right) \tag{I.2}$$

where $f^0_{m,d}$ is the current-month futures contract prices, D is the number of days in the month, and d is the calendar day of the month. The fraction $D/(D-d)$ is to account for the fact that the Fed fund future contract settlement price is based on the average monthly Fed funds rate. In order to minimize the effect of any month-end noise in the effective funds rate, the unscaled change in the 1-month futures rate is used to calculate the funds rate surprise when the change falls on one of the last 3 days of the month. The expected component of the rate change is defined as the actual change ($MPDelta$) minus the surprise

$$MPExpected = MPDelta - MPShock \tag{I.3}$$

Fed funds futures summarize the average expected Fed funds target rates in the month of the expiration. I use only the FOMC announcements made on dates scheduled in advance because unscheduled meetings tend to be reactive or endogenous, such as the FOMC announcement following the Long-Term Capital Management (LTCM) crisis. This choice minimizes the contamination of monetary policy surprises by other macroeconomic news (Ozdagli (2017)). This approach also minimizes delays in the incorporation of information to stock prices, thereby improving identification, because the dates of scheduled meetings are known well in advance. The final sample includes 127 scheduled FOMC meetings from February 1999 to December 2014, with an average $MPShock$ equal to 1.23 basis points and an average rate change of -0.79 basis points.

As a robustness check, to recover the unexpected part of the monetary policy shock I also use the high-frequency methodology of Gurkaynak et al. (2005) and Nakamura and Steinsson (2018), and the ex-ante measuree of Bernile et al. (2016). These shocks of Nakamura and Steinsson (2018) are computed from tick-by-tick data on Fed funds futures and eurodollar futures. One of the strength's in their approach is that they include longer horizon interest rates in their analysis rather than just focusing on short term Fed funds futures. As in Gurkaynak et al. (2005), the high-frequency data allows to better identify pure monetary policy shocks as changes in the policy indicator are computed in a 30-minute window around scheduled FOMC announcements, from 10 minutes before the FOMC announcement to 20 minutes after it. The rationale behind this procedure is that during these 30 minutes the policy indicator is mostly influenced by the news coming from the FOMC announcements and thus only capture information about future monetary policy. The policy change indicator developed by Nakamura and Steinsson (2018) is built using changes in interest rates at various maturities. Specifically, this indicator is the first principal component of unanticipated changes that occur during FOMC announcements for 5 different interest rates covering the term structure up to one year [3]. This policy indicator is able to capture the effects of forward guidance, a special tool used by central banks to influence, with their own forecasts, market expectations about future changes in interest rates. The measure of Bernile et al. (2016) differs from Bernanke and Kuttner (2005) in that, to estimate the expected federal funds target rate, they use the changes of implied rate on the day before the trades take place, while the difference between the expected federal funds rate and the announced target rate is the measure of surprise.

I.2.4 Monetary policy exposure

Figure I.1 gives the cross-sectional distribution of how stock prices react to monetary policy (5% - 95% range). Monetary policy sensitivity comes from equation:

$$r_{i,t} = \alpha_i + \beta_i * MPShock_t + \epsilon_{i,t} \tag{I.4}$$

where $r_{i,t}$ is the return of stock i of day t, and $MPShock_t$ is the monetary shock as in Bernanke and Kuttner (2005). This regression is estimated on FOMC dates and the time sample is the same of the Ancerno data (from 1999 to 2014). Following previous literature, I drop event days surrounding QE: November 25, 2008, December 1, 2008, December 16, 2008, January 28, 2009, and March 18, 2009. The FOMC announcement on March 18, 2008 is considered an outlier because on that day the $S\&P500$ index increased by about 4% after the positive news about the purchase of Bearn Stearns by JP Morgan. The reaction of 90% of the firms to a 1-percentage-point policy surprise lies between -37.1 and 64.9 percentage points, suggesting large differences across firms. Using this sample, the average policy sensitivity of the CRSP value-weighted index is -2.54 percentage points (significant at the 5% level). Therefore, for a 1% unexpected increase to the Fed funds rate, the market return falls by 2.54% on the day of an FOMC announcement. This estimate is in line with Gurkaynak et al. (2005).

[3] The time-series of policy news shocks are available to download in Emi Nakamura's (website)

For an investor who knows in advance the post-announcement Fed Funds rates, the most naive strategy would be to buy the market right before the announcement if the Fed announces a surprise cut in rates, and short the market right before the Fed announces a surprise increase in rates. However, this strategy is unlikely to be implemented by a fund manager for at least two reasons. First, most of the institutions in the Ancerno's sample are long-only mutual funds and pension funds, and for them the short leg of the strategy is not implementable; second, this strategy would have a large impact on the fund's trading strategy and overall portfolio exposure. Given the large differences in the cross-sectional monetary policy sensitivity of individual stocks (Figure I.1), a more reasonable strategy would imply buying in advance the stocks that will perform well after the monetary policy shock, and - in absence of short sales constraints - selling in advance those that will perform poorly after the shock.

Since stock market beta is strongly related to average returns on FOMC days Savor and Wilson (2014), in a first set of regression I use the CAPM beta as a proxy for the monetary policy exposure. However, Ozdagli (2017) shows that the CAPM beta has limited predictive power for the cross-sectional differences in the monetary policy sensitivity of individual stocks. Moreover, Ozdagli and Velikov (2020) argues that while CAPM holds on FOMC dates, it does very poorly on other dates, and this is due to the fact that CAPM does not correctly price the risk exposure when there are multiple aggregated shocks. Therefore, I build a measure of stock-level monetary policy exposure in the same spirit of Ozdagli and Velikov (2020). In order to create this measure, I interact policy surprises with firm characteristics that are linked to monetary policy transmission mechanisms and policy sensitivity by previous literature. This approach yields a MPE index based on the contribution of each characteristic to the monetary policy exposure. In Appendix I.6, I provide a brief description of the relevant firm characteristics.

Table I.2 reports coefficients estimates from panel regressions estimated at the FOMC meeting-firm level. Specifications in Columns (1)-(6) follow:

$$r_{i,t} = \alpha + \sum_{k=1}^{n} \beta_k x_{i,t}^k + \sum_{k=1}^{n} \gamma_k MPShock_t \times x_{i,t}^k + \epsilon_{i,t} \tag{I.5}$$

Where $r_{i,t}$ is the stock return of firm i on FOMC meeting day t, and $MPShock$ is the monetary policy surprise computed as in Bernanke and Kuttner (2005). The $x_{i,t}^k$ are the variables that capture the exposure of a firm to monetary polity: cash, cash flow volatility, the size-age index to proxy for financial constraints, cash flow duration and operating profitability. These variables are winsorized at the 1% percentile on both tails. Columns (1)-(6) show the results about how different characteristics capture the exposure of stock prices to monetary policy. The negative coefficient in column (2) is consistent with the intuition that the interest rate is the opportunity cost of holding cash. The negative coefficient in column (3), albeit not significant, is consistent with the fact that firms with higher cash flow volatility are more prone to rely on external financing. The negative coefficient in column (4) is in line the results of Chava and Hsu (2020), and with the intuition that higher interest rates lead to higher interest expenses and this can worsen the condition of financially distressed firms. Column (5) shows that, consistently with the discount rate effect, firms with higher cash flow duration have lower returns after a positive monetary surprise. Finally, the negative coefficient in column (6) is consistent with a theory of sticky prices. Using the estimates of column (7), the monetary policy exposure (MPE) index is built as

$$MPE_{i,t} = \sum_{k=1}^{n} \hat{\gamma}_k \times x_{i,t}^k \tag{I.6}$$

That is

$$\begin{aligned} MPE = -0.133\% * Cash - 0.215\% * CFVol - 0.208\% * SAIndex + \\ - 0.014\% * Duration + 1.089\% * OpProf \end{aligned} \tag{I.7}$$

In the final sample, as shown in Table I.1, the average MPE is 0.5%, with a standard deviation of 0.43%. Following Ozdagli and Velikov (2020), I evaluate the ability of the MPE measure in capturing stocks' response to monetary policy announcements. In unreported result, I regress stock returns on the interaction of MPE with the monetary policy shocks, finding a positive coefficient (very close to 1 by construction) and significant at the 5% level. Therefore, as expected, stocks with high MPE respond better to tightening monetary policy surprises.

I.3 Empirical Analysis

I.3.1 Total institutional trading activity around FOMC dates

In a first test, I check if the total institutional trading activity is higher than usual around FOMC dates, meaning higher than outside a $[-6, +6]$ window around the announcement date. Table I.3 reports the coefficient estimates of the cross-sectional regression by pooling all firm-level total institutional trading (shares purchased plus shares sold scaled by the firm's total shares outstanding). The dependent variable is the total institutional trading around each FOMC date, and the independent variable is a dummy that takes value 1 on the days of scheduled FOMC meetings, and 0 on the days outside a $[-6,+6]$ window around the announcement date. On days $[-6;-1]$ the coefficient is positive and significant at the 1% level, meaning that the total trading activity is higher than in the non-FOMC dates by about 12 to 17 bps, i.e. about 12% to 17% given that the sample mean of the total trading imbalance is close to 1. This higher trading activity is consistent with institutions that, as the FOMC date approaches, execute trades based on information about the upcoming monetary policy announcement. In the following sections, I investigate more in depth how this trading activity is linked to the monetary policy shock.

I.3.2 Institutional trades and stock returns on FOMC dates

In this test, I check if the institutional trading imbalance on the days before a FOMC date is higher for the firms that perform better on the FOMC date itself. In Table I.4 I run the following regression

$$IMB_{i,t} = \alpha + \beta * HighRet_{i,t} * FOMC_t + HighRet_{i,t} + Controls_{i,t} + FE_{i,t} + \epsilon_{i,t} \tag{I.8}$$

Where $IMB_{i,t}$ is the institutional trading imbalance for stock i around each date t. $HighRet_{i,t}$ is a dummy that is equal to 1 when the stock i's return on the focal date $t = [0;0]$ is above the median of the cross-section of stock returns, recomputed each date. $FOMC_t$ is a dummy that takes value 1 if day t is a day with a scheduled FOMC meetings, and 0 otherwise. As firm-level controls, I include lagged book-to-market ratio, debt-to-equity ratio, return-on-equity, log market value and the one-year standard deviation of past stock returns. Date and firm fixed-effects are also included. It is known in the literature that the institutional trading generates a price pressure (e.g. Huang et al. (2020)). What is worth noticing here is that this effect is higher before FOMC dates, suggesting that, on top of the price pressure effect, institutions seem to anticipate stocks' returns due the monetary policy shocks by buying more on the days before FOMC dates the firms that will perform better on the FOMC dates themselves.

I.3.3 Institutional trades on high beta stocks

In the previous test, I used the ex-post realized stock return as a proxy for the monetary policy exposure. Here, as a proxy for the exposure, I use stocks' ex-ante market beta. The stock beta is computed according to the CAPM using a 1-year rolling window that ends before each FOMC date. In Table I.5, I run on FOMC dates the following regression

$$
\begin{aligned}
&IMB_{i,t} = \alpha + \beta * MPShock_t * HighBeta_{i,t} + \\
&+ \gamma * MPExp_t * HighBeta_{i,t} + \delta * HighBeta_{i,t} + Controls_{i,t} + FE_{i,t} + \epsilon_{i,t}
\end{aligned} \tag{I.9}
$$

Where IMB is the institutional trading imbalance around each FOMC date. $HighBeta$ is a dummy variable that is equal to 1 if the stock is in the top quintile of the cross-sectional distribution of betas, recomputed on each date, and 0 otherwise. $MPShock$ ($MPExp$) is the unexpected (expected) component of the monetary policy. In columns (1)-(5), the monetary policy components are computed according to Bernanke and Kuttner (2005), that is, using the changes in Fed fund future prices computed in a 1-day window around the FOMC announcement. In columns (6)-(10), the monetary policy components are computed similarly, but looking at the 30-minute window around the announcement. In columns (11)-(15), I use the "policy news shock" by Nakamura and Steinsson (2018), that is, the first principal component of the unanticipated change over the 30-minute windows in the following five interest rates: the Fed funds rate immediately following the FOMC meeting, the expected Fed funds rate immediately following the next FOMC meeting, and expected three-month eurodollar interest rates at horizons of two, three, and four quarters. In this case, since the shock has no scale, the expected component cannot be recovered. In columns (16)-(20), I use the ex-ante measure of monetary surprise by Bernile et al. (2016). I add date and firm controls, and book-to-market ratio, debt-to-equity ratio, return-on-equity, log market value and the one-year standard deviation of past stock returns as firm-level controls.

I find positive and significant (at the 1% level) coefficients of the interaction between the monetary policy shock and the high beta dummy on the $[-3; -1]$ window before FOMC dates. This means that the institutional net trade on high beta stock before a FOMC date is negatively related to the unexpected component of the monetary policy change, that is what drive stocks' price reaction on FOMC dates. In anticipation of a 1% positive monetary shock, that in the Ancerno's sample is associated to an average -2.5% market return, on the three days before FOMC dates, high beta stocks have a normalized trading imbalance that is 0.45 bps lower than the non-high-beta stocks. This corresponds to about one-third of the standard deviation of the trading imbalance computed in the sample. On the other days, the correlation is not significant. It is worth noticing that the 3-day window falls in the Federal Reserve blackout period during which policy-makers and staff are required to abstain from policy-related interactions with the public. This result hold also if I include the expected component of the monetary change in the regression, and it is robust to the choice of different measures of monetary policy shock.

This result complements Di Maggio et al. (2021), who find that institutional investors (both hedge funds and mutual funds) on average sell on the day immediately before scheduled FOMC announcements. They explain this behavior as motivated by uncertainty avoidance and they find it to be stronger for hedge funds and mutual funds with a more volatile capital base.

I.3.4 Institutional trades on high MPE stocks

Next, instead of using the CAPM beta as a proxy for the exposure, I use the measure of monetary policy exposure as computed in a previous section following Ozdagli and Velikov (2020). This measure is shown to outperform the beta in explaining the cross-sectional differences in returns on FOMC dates. In Table I.6, I run on FOMC dates the following regression

$$\begin{aligned} IMB_{i,t} = \alpha + \beta * MPShock_t * MPE_{i,t} + \\ \gamma * MPExp_t * MPE_{i,t} + \delta * MPE_{i,t} + Controls_{i,t} + FE_{i,t} + \epsilon_{i,t} \end{aligned} \tag{I.10}$$

Where $IMB_{i,t}$ is the institutional trading imbalance for stock i around each FOMC date t. MPE is the monetary exposure measure described above: high MPE stocks perform better after a monetary policy tightening, and vice-versa. $MPShock$ ($MPExp$) is the unexpected (expected) component of the monetary policy change. All specifications include firm-level control and date and firm fixed-effects. In Panel A, I show the results using the continuous MPE measure. In Panel B, I use a dummy ($HighMPE$) that identifies the firms whose MPE is above the median. Consistently with results in the previous sections, I find that high MPE stocks are bought significantly in anticipation of a positive monetary policy shocks (on a $[-3; -1]$ window before the FOMC date). In anticipation of a 1% surprise rate increase, the institutional trading imbalance on high-MPE stocks is 43 bps higher than for low-MPE stocks. There is no evidence of significative correlation between the trading imbalance and the monetary surprise before day [−3] or after the monetary policy announcement. Moreover, given the sign of the coefficients in Columns (4)-(5) institutions do not quickly revert their trades after the FOMC meeting. In untabulated regressions, the MPE is estimated with data from 1994 to 2003, and the regressions are run with data from 2004 to 2014, to alleviate the concern of forward-looking coefficients. The results remain very similar.

In Table I.7, I check if the institutional trading behavior changes in anticipation of positive/negative and scheduled/unscheduled monetary policy shocks. This is done by adding to the specification of Table I.6 a triple-interaction term:

$$IMB_{i,t} = \alpha + \beta * MPShock_t * MPE_{i,t} * MPType_t + \gamma * MPShock_t * MPE_{i,t} + \delta MPType_t + \eta * MPE_{i,t} + Controls_{i,t} + FE_{i,t} + \epsilon_{i,t} \tag{I.11}$$

where $MPType_t$ is a dummy variable that is equal to 1 when the monetary policy shock is positive, and zero if it is negative (Columns (1)-(3)); and a dummy variable that is equal to 1 when the FOMC date is unscheduled, and zero otherwise (Columns (4)-(6)). I find that the coefficient of the interaction with $MPPos$ is negative, significant and close in magnitude to the coefficient of the baseline effect. Therefore, informed trading is particularly strong before negative monetary policy shocks, when the market is expected to rise. This is reasonable, since most Ancerno's institutions - namely, mutual funds and pension funds - are long-only, and consistent with anticipatory trades aimed at taking advantage of positive market movements. Moreover, there is no evidence of anticipatory trades before unscheduled FOMC meetings, when the monetary policy decisions tend to be reactive or endogenous, such as the FOMC announcement following the Long-Term Capital Management (LTCM) crisis on September 23, 1998, and the market impact of monetary shocks negligible (Ozdagli (2017)).

Then, I aggregate the Ancerno database at the manager-firm-date level. This allows to test for the robustness of the main specification to different choices of fixed effects, and to exploit the heterogeneity of Ancerno's institutions. Panel A of Table I.8 shows the coefficient estimates of the main specification with different combinations of fixed-effects. All columns refer to the [−3; −1] window before FOMC dates, and results are consistent if I include a manager FE, a manager#date FE or a manager#firm FE. In Panel B, I run the same regressions but conditioning on the direction of the institutional trading imbalance. The coefficient is statistically significant only for the subsample of observations with a positive imbalance: this suggests that institutions buy stocks according to the yet-to-be-realized monetary shock, rather than sell. In anticipation of a 1% monetary shock, the positive trading imbalance for high-MPE stocks is 0.065 bps higher (i.e. about 40% higher) than for low-MPE stocks. Instead, the negative side of the institutional trading imbalance is uncorrelated with the monetary surprise.

Next, I check if anticipatory trades have increased or decreased over time. To do so, I run the main specification on two sub-samples: the first one goes from January 1999 (beginning of Ancerno's data) until January 2006; the second one goes from February 2006 until January 2014. In the first period the chairman of the Fed Board of Governors was Alan Greenspan, in the second period Ben S. Bernanke. Given the magnitude and significance of the coefficients, it appears that the effect, if anything, has increased over time (Table I.9). Cieslak et al. (2019) reports several examples of leaks of nonpublic FOMC meeting contents both before and after 2006. In particular, the most well-known example of leak to financial institutions is the October 3, 2012 leak to Medley Global Advisors (MGA), a policy intelligence firm. The subsequent investigations led to the resignation in 2017 of Richmond Fed President Jeffrey Lacker, who admitted to speaking with a Medley analyst the day before report was sent to clients. Vissing-Jorgensen (2020a) reports the number of FOMC documents per year with leak discussions from 1943 to 2013 and find a slight upward trend.

In unreported results, I re-estimate the MPE using the Nakamura and Steinsson (2018)'s monetary policy shocks and repeat the analysis. The results remain significant and qualitatively unchanged.

I.3.5 Persistence of institutional trading profits around FOMC dates

An important question at this point is whether there is persistence in managers' trading profitability ahead of FOMC dates. If anticipatory trades stem from information leakage, it is reasonable to expect that these leaks are received by fund managers with some persistence. To address this question, I follow Barbon et al. (2019) and compute the profitability of trades by manager m on stock j over the window $\pi = [-3, 0]$ as

$$Prof_{i,t} = (MarkToMarket_{m,j,\pi} - CashFlows_{m,j,\pi})/|CashFlows_{m,j,\pi}| \tag{I.12}$$

Here, $MarkToMarket_{m,j,\pi}$ is the marked-to-market dollar value of the position at the end of the FOMC date, defined as the product of the share position cumulated from day -3 to day -1 with the closing market price of stock j on day 0, and $CashFlows_{m,j,\pi}$ is the dollar amount spent to build the position over the window $[-3, 0]$, that is, the dollar volume of each transaction in the stock (based on execution prices). In order to account for the pre-FOMC drift, I market-adjust this profitability measure by subtracting the cumulative market return over the window $[-3, 0]$. I divide all managers into five quintiles based on the market-adjusted profitability measure on any FOMC date, and then I report the average adjusted profitability for these quintiles during the date of portfolio formation and for the subsequent four announcement dates. Results are reported in Table I.10. Consistently with Puckett and Yan (2011), I find evidence that, on FOMC dates, past trading performance is related to future trading performance only for the top quintile of institutions. Quintile 1 funds have the worst profitability in the quarter of portfolio formation (-0.423%) and continue to have negative or statistically zero profitability during the subsequent four quarters. Quintile 5 funds have the best profitability during the portfolio formation quarter (0.492%) and continue to display positive and significant profitability of 0.520%, 0.028% 0.024%, 0.17%, and 0.17%, during the following four quarters.

I.4 Heterogeneity across institutions

I.4.1 Hedge funds, mutual funds, and pension funds

A unique feature of the Ancerno dataset is that each trade is associated to the fund management company that executed it. Therefore, it is natural to ask if the results shown before are robust across different types of institutions. Previous literature shows that some subset of institutions are more skilled at trading ahead of news (e.g. Hendershott et al. (2015)), so it is possible that anticipatory trades before FOMC dates are more frequent for specific types of institutions, relative to all institutions.

Although Ancerno's clients are always anonymous, I follow the procedure in Di Maggio et al. (2021) and Çötelioğlu et al. (2020) to identify hedge funds and mutual funds. Corresponding to the company identifier, Ancerno gives the name of the management company to which the trade pertains (the variable *manager*). This variable is crucial for the identification of hedge funds. I identify hedge funds among Ancerno managers by matching the names of the management companies with two sources. The first source is a list of hedge funds that is based on quarterly 13F mandatory filings. The second source is the combined data from three commercial databases - the Lipper/TASS Hedge Fund Database, Morningstar CISDM, and Hedge Fund Research - which contain hedge-fund-level information at the monthly frequency. In the identification process, I make sure to select exclusively "pure-play" hedge fund management companies, that is, institutions whose core business is managing hedge funds. In the end, the matching procedure allows me to identify 99 distinct hedge fund management companies that are present in Ancerno at various times throughout the sample. To identify pension funds, I use the *ClientType* variable, as done in e.g. Puckett and Yan (2011). A value of *ClientType* equal to 1 denotes pension funds, and a value of 2 indicates mutual funds. In some instances, this classification might be incorrect - for example, when the client is a pension fund, but the trades are executed by a mutual fund on its behalf. Therefore, I also perform a manual match of the Ancerno manager name with S12 mandatory filings data. Based on this procedure, I identify 357 distinct pension fund managing companies for the analysis. After excluding the managers that mainly perform brokerage activities (for which $ClientType = 3$), I identify 417 mutual funds residually as the managers that are neither hedge funds nor pension funds.

In Panel A of Table I.11, using Ancerno at the manager-firm-date level, I calculate the institutional trading imbalance for each type of institutions (hedge funds, mutual funds and pension funds) and run separate regressions. Given the magnitude and significant of the coefficients in Columns (1), (4), and (7), I find that hedge funds trade more in anticipation of the yet-to-be-realized monetary policy surprise than mutual funds and pension funds. The coefficient for the hedge funds is equal to 6.21, almost three times larger than the coefficient for the mutual funds (although it is also positive and significant at the 1%). This is consistent with previous literature that find that hedge funds in general trade more on strategies that are not based on public and widely disseminated news. For instance, Gargano et al. (2017) find that hedge funds actively exploit the Freedom of Information Act to gather non-public information from the Food and Drug Administration about results of clinical trials of new drugs. Pension funds, instead, being more long-term oriented, seem to be engage less in anticipatory trades. In Panel B of Table I.11, I look at another scheme of classification based on trading frequency. Using an institution's total number of trades in the previous year, I sort institutions into the bottom, middle, and top terciles, respectively, as the least-active, median-active, and most-active traders. Given the significance of coefficients in Columns (1), (4), and (7), I find evidence that only the most-active and median-active traders are those that trade in anticipation of FOMC meetings. Panel C of Table I.11 presents the results for another classification based on the average trade execution quality.

Following Hu (2009) and Henry and Koski (2017), I define the execution quality measure as

$$\text{Execution Quality} = \frac{\text{Execution Price} - \text{Benchmark Price}}{\text{Benchmark Price}} \times \text{Sign} \tag{I.13}$$

where the Benchmark Price is the volume-weighted average price of all available institutional market transactions. The execution quality is computed for each trade, and then each institution's daily average execution quality is computed as the volume-weighted average execution quality for all its trades during the day. Further, each institution's annual execution quality is then obtained as the annual average of its daily execution quality. Based of the previous-year execution quality, I sort institutions into the bottom, middle, and top terciles, respectively, as the less-skilled, median-skilled, and most-skilled institutions. Coefficients in Columns (1), (4), and (7) show that only the median-skilled and the less-skilled institutions are able to trade ahead of the FOMC dates. Therefore, skill in the quality of execution seems to be unrelated to the ability to trade before FOMC days. This finding appears consistent with Huang et al. (2020): institutions that trade on non-public news demand immediate execution, and this lead to lower execution quality. In Panel D of Table I.11, each year I sort institutions into terciles based on the dollar-volume of the trades executed the year before. This can be thought of as a proxy for the size of the institutions. Given the magnitude and significance of the coefficients, only big- and medium-size institutions appear to trade in anticipation of FOMC announcement days.

Mutual funds and hedge funds are very different in terms of the trading strategies that they can implement. Mutual funds are limited in their ability to hedge their positions through short-sales and derivatives use; in contrast, derivatives and short positions are critical in most hedge fund strategies (Stulz (2007)). In Table I.12, I analyse the differential behavior of hedge funds and mutual funds ahead of positive and negative monetary surprises. I do so by adding to the baseline regression a tripe-interaction term with a dummy (HF) that is equal to one if the trade is executed by a hedge fund, and zero if it is executed by a mutual fund, and conditioning on the sign of the monetary surprise.

$$IMB_{i,t} = \alpha + \beta * MPShock_t * MPE_{i,t} * HF_{i,t} + \\ \gamma * MPShock_t * MPE_{i,t} + \delta MPType_t + \eta * MPE_{i,t} + Controls_{i,t} + FE_{i,t} + \epsilon_{i,t} \tag{I.14}$$

Hedge funds, that in general are free from short-sale constraints, appear to be more active than mutual funds before positive monetary shocks, when the market experiences negative returns and a profitable strategy would be to short highly-exposed stocks. Instead, there is no significant difference between the trading behavior of the two groups of funds before negative shocks.

In the next analysis, I focus on the risk-adjusted profits earned by institutional investors on the trades executed just before FOMC announcements. I consider separately each institution type, and set up a long-short portfolio that goes long (short) the stocks that the institution net buys (sells) on the three days before FOMC date. This portfolio is assumed to be fixed on FOMC dates, when returns are earned. Table I.13 displays the coefficients of portfolio returns regressed on Fama-French risk factors including momentum. The regressions are estimated separately for each category of institutions, and the coefficients are to be interpreted as the average across institutions. In the first three columns, the stocks of each portfolio's leg are equally weighted, while in the last three columns, the stocks are weighted by their net trading amount. It appears that mutual funds and hedge funds earn on average a positive and statistically significant alpha on FOMC dates for the trades they set up on the three days before. The magnitude of these daily alpha is economically sizeable. Looking at the equally weighted portfolios, it is equal to 0.066% for mutual funds (it corresponds to 1.39% on a monthly basis), and 0.123% for hedge funds (it corresponds to 2.58% on a monthly basis). As highlighted before, anticipatory trades appear to be more profitable for hedge funds than for mutual funds, whereas they are not statistically distinguishable from zero for pension funds. Results obtained for net-trade-weighted portfolios are qualitatively in line.

I.4.2 Managers' locations and FOMC composition

To further address the concern that anticipatory trades are due just to luck, I exploit the location of Ancerno's institutions to see if the informational advantage is stronger for institutions that are headquartered closer to Fed branches. Recent literature suggests that information spreads more effectively among fund managers that are geographical or socially connected, so it is natural to ask whether a similar effect plays out also for what concerns information leakages ahead of FOMC meetings (Hong et al. (2005) and Pool et al. (2015)). I hand-collect the geographical locations of the headquarters of Ancerno's institutions. By using Orbis, Bloomberg, and SEC filings, and the reported fund names, I could reliably identify the location of 848 fund management companies. Figure I.2 shows the geographical location of Ancerno's institutions in the US. These locations are then matched with the borders of each regional

Fed district and the locations of Federal Reserve branches. For this analysis, I focus on the subsample of hedge funds, for which trades ahead of FOMC are more intense and, additionally, it is more reasonable to assume that the location of the corporate headquarter coincides with the location of the management teams' offices.

Table I.14 displays the results of this analysis. I run the baseline regression with a triple-interaction term with a dummy variable (*Close*) that is equal to one when the linear distance between the headquarters of the hedge funds and the closest regional Fed branches is lower than 20 km (Columns (1)-(3)) or lower than 50 km (Columns (4)-(6)). The coefficient of the triple-interaction term is positive and significant in Columns (1) and (3), meaning that, indeed, the hedge funds that are located closer to a regional Fed branch exhibit superior information advantage in trading before FOMC dates.

In a next test, I investigate whether institutional trades ahead of FOMC meetings are linked to the FOMC composition. The Federal Open Market Committee (FOMC) has 12 voting members, including all seven members of the Board of Governors and five Reserve Bank presidents. The New York Fed is directly involved in carrying out monetary policy operations, so its president has a permanent vote on the FOMC. The four remaining voting seats are filled by the other 11 Reserve Bank presidents on a rotating basis, holding one-year terms (the "voting" members). It is important to note, however, that also the other non-voting Federal Reserve bank presidents (the "alternate" members) get the same pre-meeting materials, attend the FOMC meetings, participate in the discussions, give their assessments of national and regional economic conditions and share their views on appropriate policy. To test how institutional trades ahead of FOMC meetings are linked to the FOMC composition, I link fund locations with the borders of each regional Fed district[4], and then I hand-collect the composition of the FOMC for each announcement date[5]. In Table I.15, I run the baseline regression for two subsamples of institutions: in Columns (1)-(3), for each FOMC date, I focus on institutions located in a Fed district that is represented in the Federal Open Market Committee by an alternate member (non-voting member); in Columns (4)-(6), instead, I focus on institutions that are represented by voting members. The results suggest that institutions tend to trade more in anticipation of monetary surprises when the Fed bank of the area in which they are located is represented in the FOMC by an alternate

[4]I use the Federal Reserve District County Shapefiles provided by Colton Tousey of Federal Reserve Bank of Kansas City. It is available at https://www.kansascityfed.org/research/technical-briefings-sub/federal-reserve-district-county-shapefiles/

[5]As reported in the FOMC website: https://www.federalreserve.gov/monetarypolicy/fomc.htm

member. This result appears consistent with a loss-compensation hypothesis (e.g. Crawford and Sobel (1982) and Milgrom and Roberts (1986)) and with Vissing-Jorgensen (2020a). In years without the right to vote, presidents seek to compensate for the loss of the formal voting right by making more intense use of *informal* communication: since disclosure ties the hand of the committee, non-voting policy makers may seek to advocate for their preferred policy by selectively disclosing internally-known information that supports their view. This result complements Ehrmann et al. (2021), who find that speeches by presidents in years they do not have the right to vote are more informative for the market (albeit they make less intense use of *public* inter-meeting speeches and meeting interventions).

I.4.3 Bid-ask spread around FOMC dates

One question might arise. If institutions, and hedge funds in particular, have a strong and reliable informational advantage before FOCM dates, they should be willing to trade infinite amount of money on these signals. They don't do so, probably, for two reasons. The first is not to reveal themselves as informed traders. The second could depend on the fact that if market makers are aware of the information asymmetries before FOMC meetings, they would require a higher average bid-ask spread on trades around these dates. To test if this is the case, I compute stock-level daily bid-ask spread using the Trades and Quotes (TAQ) dataset and regress it on a dummy that identifies scheduled FOMC dates. Results are reported in Table I.16. In Panel A, the dependent variable is $log(1+Realspread)$, where $Realspread$ is the share-weighted percent realised spread around any focal date. In Panel B, the dependent variable is $log(1+Effspread)$, where $Effspread$ is the dollar-weighted percent effective spread around any focal date. $Realspread$ is equal to $2D_k(P_k - M_{k+5})$, where M_{k+5} is the bid-ask mid-point five minutes after the kth trade. $Effspread$ is equal to $2D_k(P_k - M_k)/M_k$, where M_k is the bid-ask mid-point for the kth trade. I aggregate the spreads to the daily level by taking the dollar-volume weighted average across all trades in the day. The firm-level bid-ask spread is 0.4% higher (significantly at the 5% level) before *scheduled* FOMC meetings than on non-FOMC date. Remarkably, the bid-ask spread before unscheduled FOMC meetings is not statistically different from zero. TAQ data are available only after 2003, and to check for robustness I run the same analysis with a daily bid-ask spread estimated with the procedure of Corwin and Schultz (2012): results are qualitatively consistent.

I.5 Conclusions

Using detailed institutional transaction records from Ancerno, I find evidence consistent with informed trading on the days before the Federal Open Market Committee (FOMC) scheduled announcements. The informal communication of Fed officials with the financial sector, well supported by anecdotal evidence, allows some market participants to front-run monetary policy revisions. The institutional trading imbalances on stocks that are highly exposed to monetary shocksare in the direction of the subsequent monetary policy surprises. In particular, on the three days before a 1% surprise rate increase, the institutional trading imbalance is 0.43 bps higher for high-MPE stocks as compared to low-MPE stocks. This result is economically meaningful, and is particularly strong before easing monetary policy shocks - when the aggregate market reaction is positive -, for the most-active traders, and for the hedge funds that are headquartered close to one of the regional reserve banks. This effect does not disappear over time and contributes to an information-based explanation of the pre-FOMC announcement drift. The Fed's informal communication with the financial sector seems to be driven by the non-voting members of the Federal Open Market Committee. From a policy perspective, these findings reinforce concerns about unequal access to information, with some investors gaining a persistent and unfair advantage. These concerns strengthen also because big-name hedge funds, including for instance BlueMountain and Paulson & Co., have made a practice of hiring former central bankers and other government officials as their funds grow in size and scope [6]. Overall, these findings are consistent with a hypothesis of systematic informal communication of Fed officials with the financial sector, provide an additional channel through which institutions make abnormal profits from their intra-quarter trades, and contribute to an information-based explanation of the pre-FOMC drift.

[6] Source: https://www.reuters.com/article/hedgefunds-bluemountain/hedge-fund-bluemountain-hires-form-fed-governor-as-consultant-idINL2N0WQ1BK20150324

Figures and Tables

Table I.1: Summary Statistics This Table reports the summary statistics for firms in the Ancerno's sample on FOMC dates: mean; standard deviation; minimum; 25th, 50th, and 75th percentiles; maximum. $MPShock$ ($MPExp$) is the unexpected (expected) component of the monetary policy, computed using the changes in Fed fund future prices computed in a 1-day window around the FOMC announcement (in percent). The undexpected component $MPExp$ is equal to the actual rate change ($RateChange$), in percentage, minus the unexpected component. $TradingImbalance$ is equal to shares purchased minus shares sold scaled by the firm's total shares outstanding, and $TotalTrading$ is equal to shares purchased plus shares sold scaled by the firm's total shares outstanding. Beta is the CAPM beta, and MPE the measure of monetary policy exposure. The sample includes 127 scheduled FOMC meetings from 1999 to 2014.

VARIABLES	(1) N	(2) mean	(3) sd	(4) p25	(5) p50	(6) p75	(7) min	(8) max
	Monetary Policy Changes							
MPShock (%)	127	0.012	0.129	-0.003	0	0.005	-0.400	0.850
MPExp (%)	127	-0.023	0.236	-0.007	0	0.020	-1.251	0.417
Rate Change (%)	127	-0.008	0.197	0	0	0	-0.750	0.500
	Ancerno's sample (firm-date level) on FOMC dates							
Trading Imbalance (bps)	404,261	-0.006	1.405	-0.098	0	0.132	-7.191	6.976
Total Trading (bps)	404,261	0.991	2.023	0	0.210	1.021	0	14.42
Beta	332,479	1.062	0.582	0.641	1.028	1.423	-0.063	2.728
MPE	239,748	0.005	0.004	0.002	0.005	0.008	-0.019	0.026
Book-to-market	320,664	0.582	0.477	0.266	0.464	0.753	0.032	3.050
Log(Market Value)	402,727	20.24	1.783	19.01	20.12	21.35	11.56	27.27
ROE	318,916	-0.048	0.586	-0.045	0.082	0.164	-4.027	0.984
DE ratio	326,926	1.277	2.925	0.356	0.815	1.593	-11.51	17.96
Stock Ret SD	393,554	0.035	0.019	0.021	0.030	0.042	0.010	0.112
	Ancerno's sample (manager-firm-date level) on FOMC dates							
Trading Imbalance (bps)	6,392,050	0.001	0.178	0	0	0	-1.568	1.652
Buy Trading Imb. (bps)	794,429	0.163	0.321	0.004	0.022	0.127	0	1.652
Sell Trading Imb. (bps)	763,015	-0.162	0.324	-0.122	-0.017	-0.002	-1.568	0

Table I.2: Monetary Policy Exposure This table reports the coefficients from panel regression estimated at the FOMC meeting-firm level. Specifications (1)-(6) follow $r_{i,t} = \alpha + \sum_{k=1}^{n} \beta_k x_{i,t}^k + \sum_{k=1}^{n} \gamma_k MPShock_t \times x_{i,t}^k + \epsilon_{i,t}$, where $MPShock_t$ is the monetary policy surprise. The other variables x_i include cash, cash flow volatility, the size-age index for financial constraints, cash flow duration, and operating profitability. Standard errors are clustered at the firm level and reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) ret	(2) ret	(3) ret	(4) ret	(5) ret	(6) ret
MPShock * Cash	-0.0012***					-0.0013***
	(0.0002)					(0.0003)
MPShock * CF volatility		-0.0028***				-0.0022***
		(0.0005)				(0.0006)
MPShock * SA Index			-0.0022***			-0.0021***
			(0.0002)			(0.0003)
MPShock * Duration				-0.0002***		-0.0001*
				(4.52e-05)		(7.82e-05)
MPShock * Op Prof					0.0138***	0.0109***
					(0.0018)	(0.0022)
Cash	0.0002***					7.00e-05
	(5.68e-05)					(6.75e-05)
CF volatility		0.0002*				0.0001
		(0.0001)				(0.0001)
SA Index			-6.29e-06			7.74e-05
			(0.0001)			(0.0001)
Duration				1.38e-05		1.04e-05
				(1.08e-05)		(1.63e-05)
Operating Profitability					0.0031***	0.0007
					(0.0006)	(0.0007)
MPShock	-0.0117***	-0.0149***	-0.0054***	-0.0051***	-0.0120***	
	(0.0007)	(0.0015)	(0.0005)	(0.0009)	(0.0006)	
Observations	601,639	434,459	601,702	601,702	601,702	434,406
Adjusted R-squared	0.005	0.006	0.005	0.005	0.005	0.131
Date FE	NO	NO	NO	NO	NO	YES
Firm FE	YES	YES	YES	YES	YES	YES

Table I.3: Total Trading Activity around FOMC days This table reports the coefficient estimates of the cross-sectional regression by pooling all firm-level total institutional trading (shares purchased plus shares sold scaled by the firm's total shares outstanding). The dependent variable is the total institutional trading around each date. FOMC is a dummy that takes value 1 on the days of scheduled FOMC meetings, and 0 otherwise (I exclude a 6-day window around the announcement from the control group). As firm-level controls, I include book-to-market ratio, debt-to-equity ratio, return-on-equity, log market value and the one-year standard deviation of past stock returns. Firm and year fixed-effects are also included. Standard errors are double-clustered at the firm and time level and reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) $[-7;-9]$	(2) $[-6;-4]$	(3) $[-3;-1]$	(4) $[0;0]$	(5) $[+1;+3]$	(6) $[+4;+6]$
FOMC	0.0767	0.171***	0.122***	0.102***	0.248***	-0.0457
	(0.0468)	(0.0426)	(0.0454)	(0.0223)	(0.0616)	(0.0462)
Observations	6,145,663	6,155,263	6,165,196	6,175,548	6,161,165	6,153,663
Adjusted R-squared	0.196	0.196	0.196	0.120	0.197	0.200
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

Table I.4: Institutional trades and stock returns on FOMC dates This table reports the coefficient estimates of the cross-sectional regression by pooling all firm-level institutional trading imbalance (shares purchased minus shares sold scaled by the firm's total shares outstanding). The dependent variable is the institutional trading imbalance around each date. For each date, *HighRet* is a dummy that is equal to 1 when the stock return is above the median of the cross-section of stock returns. FOMC is a dummy that takes value 1 on the days of scheduled FOMC meetings, and 0 otherwise. As firm-level controls, I include book-to-market ratio, debt-to-equity ratio, return-on-equity, log market value and the one-year standard deviation of past stock returns. Date and firm fixed-effects are also included. Standard errors are double-clustered at the firm and time level and reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	[−6; −4]	[−3; −1]	[0; 0]	[+1; +3]	[+4; +6]
HighRet * FOMC	0.0180	0.0433***	0.0213*	0.0327	0.0169
	(0.0128)	(0.0138)	(0.0113)	(0.0242)	(0.0140)
HighRet	0.00320	0.0141***	0.194***	0.303***	0.0929***
	(0.00242)	(0.00266)	(0.00336)	(0.00458)	(0.00267)
Observations	9,812,168	9,823,146	9,834,052	9,817,225	9,800,425
Adjusted R-squared	0.009	0.009	0.012	0.011	0.009
Date FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES

Table I.5: Institutional trades on high beta stocks This table reports the coefficient estimates of the cross-sectional regression by pooling all firm-level institutional trading imbalance (shares purchased minus shares sold scaled by the firm's total shares outstanding) over the FOMC dates. The dependent variable is the institutional trading imbalance around the FOMC dates. $High\_Beta$ is a dummy variable that is equal to 1 if the stock is in the top quintile of the cross-sectional distribution of betas, recomputed on each date, and 0 otherwise. The stock beta is computed according to the CAPM using the past year daily returns. $MPShock$ ($MPExp$) is the unexpected (expected) component of the monetary policy. In columns (1)-(5), the monetary policy components are computed according to Bernanke and Kuttner (2005), that is, using the changes in Fed fund future prices computed in a 1-day window around the FOMC announcement. In columns (6)-(10), the monetary policy components are computed similarly, but looking at the 30-minute window around the announcement (Gürkaynak, Sack, and Swanson (2005)). In columns (11)-(15), I use the "policy news shock" by Nakamura and Steinsson (2018), that is, the first principal component of the unanticipated change over the 30-minute windows in the following five interest rates: the Fed funds rate immediately following the FOMC meeting, the expected Fed funds rate immediately following the next FOMC meeting, and expected three-month eurodollar interest rates at horizons of two, three, and four quarters. In this case, since the shock is has no scale, the expected component cannot be recovered. In columns (16)-(20), I build an ex-ante measure of policy surprises in the same fashion of Bernile, Hu and Tang (2016): the change in the 30-day federal funds futures on the day before the trades take place is used as a proxy for the expected federal fund target rate, and the unexpected monetary change is the announced Federal funds target rate minus the expected rate. Levels are not included due to collinearity with the fixed-effects. As firm-level controls, I include book-to-market ratio, debt-to-equity ratio, return-on-equity, log market value and the one-year standard deviation of past stock returns. Date and firm fixed-effects are also included. Standard errors are double-clustered at the firm and time levels. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	Bernanke and Kuttner (2005)					Gürkaynak, Sack, and Swanson (2005)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	[-6;-4]	[-3;-1]	[0;0]	[+1;+3]	[+4;+6]	[-6;-4]	[-3;-1]	[0;0]	[+1;+3]	[+4;+6]
MPShock * HighBeta	0.037	-0.454**	0.001	0.043	-0.031	-0.082	-1.426***	0.169	0.030	-0.540
	(0.156)	(0.197)	(0.0943)	(0.188)	(0.184)	(0.377)	(0.504)	(0.263)	(0.577)	(0.374)
MPExp * HighBeta	-0.019	-0.251**	-0.065	-0.026	0.063	-0.087	-0.269**	-0.106	-0.065	0.008
	(0.106)	(0.118)	(0.062)	(0.132)	(0.108)	(0.106)	(0.122)	(0.074)	(0.161)	(0.111)
HighBeta	0.003	-0.024	-0.008	0.001	-0.059***	0.012	-0.020	-0.004	-0.000	-0.056**
	(0.023)	(0.024)	(0.011)	(0.024)	(0.021)	(0.024)	(0.024)	(0.012)	(0.026)	(0.022)
Observations	308,515	308,635	308,751	308,349	308,014	270,966	270,991	271,026	270,684	270,387
Adjusted R-squared	0.003	0.002	0.010	0.005	0.002	0.003	0.002	0.012	0.005	0.002
Date FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

	Nakamura and Steinsson (2018)					Bernile, Hu and Tang (2016)				
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
VARIABLES	[-6;-4]	[-3;-1]	[0;0]	[+1;+3]	[+4;+6]	[-6;-4]	[-3;-1]	[0;0]	[+1;+3]	[+4;+6]
MPShock * HighBeta	-0.444	-1.618***	0.256	0.171	-0.344	-0.025	-0.402***	0.001	0.043	-0.031
	(0.509)	(0.519)	(0.303)	(0.536)	(0.491)	(0.105)	(0.120)	(0.094)	(0.188)	(0.184)
MPExp * HighBeta						0.019	1.803***	-0.065	-0.026	0.063
						(0.186)	(0.612)	(0.062)	(0.132)	(0.108)
HighBeta	0.012	-0.015	-0.005	-0.001	-0.054**	0.004	-0.023	-0.008	0.001	-0.059***
	(0.024)	(0.025)	(0.012)	(0.026)	(0.023)	(0.023)	(0.024)	(0.011)	(0.024)	(0.021)
Observations	270,966	270,991	271,026	270,684	270,387	308,515	308,635	308,751	308,349	308,014
Adjusted R-squared	0.003	0.002	0.012	0.005	0.002	0.003	0.002	0.010	0.005	0.002
Date FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table I.6: Institutional trades on high MPE stocks This table reports the coefficient estimates of the cross-sectional regression by pooling all firm-level institutional trading imbalance (shares purchased minus shares sold scaled by the firm's total shares outstanding) over the FOMC dates. The dependent variable is the institutional trading imbalance around the FOMC dates. The independent variables include the stocks' monetary policy exposures (MPE) interacted with the yet-to-be-realized unexpected component of the monetary policy change ($MPShock$), and with the ex-post expected component of the monetary policy change ($MPExp$). As in Bernake and Kuttner (2005), the shock is computed as the change in the current-month Fed fund future contracts relative to the day prior to the policy action. The expected component of the rate change is defined as the actual change minus the surprise. The MPE measure is computed based on several accounting measures with a similar procedure as Ozdagli and Velikov (2020), but using one-day shocks instead of 30-minute shocks: the interpretation is that a firm with high MPE tends to perform well when there is a tightening monetary policy surprise. In Panel A, I use the interactions with the continuous MPE measure. In Panel B, I use the interaction with a dummy ($HighMPE$) that is equal to 1 when the firm's MPE is above the median, and 0 otherwise. Levels are not included because they are collinear with fixed effects structure. As firm-level controls, I include book-to-market ratio, debt-to-equity ratio, return-on-equity, log market value and the one-year standard deviation of past stock returns. Date and firm fixed-effects are also included. Standard errors are double-clustered at the firm and time levels. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Panel A: Continuous MPE					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	$[-6;-4]$	$[-3;-1]$	$[0;0]$	$[+1;+3]$	$[+4;+6]$
MPShock * MPE	2.945	41.59***	16.31	15.94	18.96
	(12.12)	(13.70)	(18.09)	(12.88)	(11.64)
MPExp * MPE	10.28	19.54**	9.704	8.322	21.00***
	(8.885)	(9.801)	(8.736)	(8.041)	(8.018)
MPE	11.74***	12.71***	2.365	12.23***	10.50***
	(3.885)	(4.072)	(1.937)	(4.107)	(3.770)
Observations	227,497	227,566	227,619	227,385	227,179
Adjusted R-squared	0.003	0.004	0.013	0.006	0.002
Date FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Panel B: High MPE is above median					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	$[-6;-4]$	$[-3;-1]$	$[0;0]$	$[+1;+3]$	$[+4;+6]$
MPShock * HighMPE	0.089	0.436***	0.194	0.228	0.148
	(0.112)	(0.128)	(0.159)	(0.154)	(0.115)
MPExp * HighMPE	0.102	0.162**	0.0593	0.109	0.186**
	(0.084)	(0.081)	(0.072)	(0.082)	(0.079)
HighMPE	0.051**	0.073***	0.017	0.077***	0.073***
	(0.025)	(0.025)	(0.012)	(0.024)	(0.024)
Observations	227,497	227,566	227,619	227,385	227,179
Adjusted R-squared	0.003	0.004	0.013	0.006	0.002
Date FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES

Table I.7: Institutional trades on high MPE stocks - Announcement characteristics This table reports the coefficient estimates of the cross-sectional regression by pooling all firm-level institutional trading imbalance (shares purchased minus shares sold scaled by the firm's total shares outstanding) over the FOMC dates. The dependent variable is the institutional trading imbalance around the FOMC dates. The independent variables include the stocks' monetary policy exposures (MPE) interacted with the yet-to-be-realized unexpected component of the monetary policy change ($MPShock$), and with the ex-post expected component of the monetary policy change ($MPExp$). $MPPos$ is a dummy variable equal to 1 when $MPShock$ is greater or equal to zero, and 0 otherwise. $Unsched$ is a dummy variable that is equal too 1 when the FOMC meeting is unscheduled, a 0 otherwise. Columns (1)-(3) include all scheduled FOMC meetings (127). Columns (4)-(6)include all scheduled (127) and unscheduled (24) meetings. Levels are not included because they are collinear with the fixed effects structure. As firm-level controls, I add book-to-market ratio, debt-to-equity ratio, return-on-equity, log market value and the one-year standard deviation of past stock returns. Date and firm fixed-effects are also included. Standard errors are double-clustered at the firm and time levels. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

VARIABLES	(1) $[-3;-1]$	(2) $[0;0]$	(3) $[+1;+3]$	(4) $[-3;-1]$	(5) $[0;0]$	(6) $[+1;+3]$
MPE * MPShock * MPPos	-74.63***	8.676	-82.37**			
	(26.78)	(21.55)	(33.38)			
MPE * MPPos	1.958	5.643	3.684			
	(6.035)	(4.829)	(5.218)			
MPE * MPShock * Unsched				-39.50***	-4.207	-7.272
				(14.68)	(11.65)	(15.32)
MPE * Unsched				-7.032	0.0422	-7.480
				(4.642)	(2.699)	(4.645)
MPE * MPShock	78.62***	-7.623	73.71**	23.57**	7.917	12.70
	(23.91)	(19.66)	(28.98)	(11.08)	(10.58)	(11.93)
MPE	21.62***	2.896	20.66***	15.49***	3.575**	14.10***
	(6.927)	(3.809)	(5.383)	(3.980)	(1.771)	(3.802)
Observations	118,955	119,001	118,856	272,083	272,139	271,865
Adjusted R-squared	0.003	0.017	0.008	0.005	0.012	0.008
Date FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

Table I.8: Institutional trades on high MPE stocks - Manager level This is similar to Table I.6, but here trades are aggregated at the manager-firm-date. This allows to test different specifications of fixed-effects. All regressions are run for a [-3;-1] window relative to the FOMC announcement date, and different combinations of fixed-effects are displayed. As firm-level controls, I include book-to-market ratio, debt-to-equity ratio, return-on-equity, log market value and the one-year standard deviation of past stock returns. Date and firm fixed-effects are also included. Standard errors are triple-clustered at the firm, date and manager levels. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Dependent Variable	**Trading Imbalance**			
	(1)	(2)	(3)	(4)
VARIABLES	[-3;-1]	[-3;-1]	[-3;-1]	[-3;-1]
MPShock * MPE	2.786***	2.722***	2.669***	2.776***
	(0.887)	(0.888)	(0.977)	(0.947)
MPExp * MPE	1.232**	1.220*	1.154*	1.141*
	(0.614)	(0.618)	(0.670)	(0.623)
Observations	4,355,212	4,355,217	4,249,917	4,352,194
Adjusted R-squared	0.003	0.002	-0.014	0.008
Date FE	YES	YES	YES	NO
Firm FE	YES	YES	NO	YES
Manager FE	YES	NO	NO	NO
Manager#Date	NO	NO	NO	YES
Manager#Firm	NO	NO	YES	NO
Controls	YES	YES	YES	YES
Dependent Variable	$Imbalance > 0$		$Imbalance < 0$	
	(4)	(5)	(6)	(7)
VARIABLES	[-3;-1]	[-3;-1]	[-3;-1]	[-3;-1]
MPShock * MPE	9.052***		1.175	
	(2.976)		(2.901)	
MPExp * MPE	2.976*		0.853	
	(1.633)		(1.819)	
MPShock * HighMPE		0.065***		0.016
		(0.020)		(0.020)
MPExp * HighMPE		0.019*		0.008
		(0.011)		(0.013)
Observations	980,196	980,196	962,688	962,688
Adjusted R-squared	0.187	0.187	0.195	0.195
Date FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Manager FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES

Table I.9: Institutional trades on high MPE stocks - Greenspan vs Bernanke This is similar to Table I.6, but here I run the specification for two subsamples: the first from January 1999 to January 2006 included, the second from February 2007 included to January 2014. In the first period Alan Greenspan was the chairman of the board of governors of the U.S. Federal Reserve; in the second period he was succeeded by Ben S. Bernanke. As firm-level controls, I include book-to-market ratio, debt-to-equity ratio, return-on-equity, log market value and the one-year standard deviation of past stock returns. Date and firm fixed-effects are also included. Standard errors are double-clustered at the firm and time levels. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	Greenspan (1999 - 2006)			Bernanke (2006 - 2014)		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	[-3;-1]	[0;0]	[+1;+3]	[-3;-1]	[0;0]	[+1;+3]
MPShock * MPE	45.23***	24.58	33.08**	64.70***	-2.662	8.588
	(15.82)	(20.79)	(13.50)	(16.56)	(17.62)	(33.73)
MPExp * MPE	31.12**	15.54	21.43**	2.160	0.280	2.827
	(11.98)	(10.68)	(10.18)	(9.839)	(7.802)	(14.91)
Observations	105,890	105,943	105,837	110,503	110,503	110,411
Adjusted R-squared	0.005	0.021	0.007	0.005	0.009	0.008
Date FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

Table I.10: Trading performance and persistence of performance on FOMC dates This Table reports results on the persistence of institutional trades profitability on FOMC dates. The profitability of trades by manager m on stock j over the window $\pi = [-3, 0]$, is defined as $(MarkToMarket_{m,j,\pi} - CashFlows_{m,j,\pi})/|CashFlows_{m,j,\pi}|$. Here, $MarkToMarket_{m,j,\pi}$ is the marked-to-market dollar value of the position at the end of the FOMC date, defined as the product of the share position cumulated from day -3 to day -1 with the closing market price of stock j on day 0, and $CashFlows_{m,j,\pi}$ is the dollar amount spent to build the position over the window $[-3, 0]$, that is, the dollar volume of each transaction in the stock (based on execution prices). I divide all managers into five quintiles based on the market-adjusted profitability measure, and then I report the average adjusted profitability for these quintiles during the date of portfolio formation and for the subsequent four announcement dates. Numbers in parentheses are t-statistics, which are computed based on two-way clustered standard errors. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	Current FOMC date mkt-adj profitability quintiles				
	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Announcement 0	-.42252***	-.06215***	8.77E-05	.06439***	.49151***
	(-29.688)	(-21.460)	(0.059)	(19.452)	(29.060)
Announcement 1	-.01232*	0.00615	.01234*	0.01031	.05180***
	(-1.820)	(0.958)	(1.710)	(1.555)	(6.710)
Announcement 2	-0.00369	.01625***	0.00935	.01504**	.02830***
	(-.508)	(2.818)	(1.258)	(2.492)	(3.825)
Announcement 3	0.00516	0.00883	.01121*	.01598**	.02351***
	(0.747)	(1.603)	(1.750)	(2.487)	(2.930)
Announcement 4	0.00391	.01189*	.02544***	0.00755	.01715**
	(0.579)	(1.941)	(3.906)	(1.252)	(2.275)
Announcement 5	0.00415	0.00241	.01262*	.02378***	.01682**
	(0.602)	(0.398)	(1.769)	(3.480)	(2.282)

Table I.11: Institutional trades on high MPE stocks - Managers' Heterogeneity In this Table trading imbalance is calculated for different types of institutions and separate regressions are run. In Panel A, I look at hedge funds (99 funds), mutual funds (417 funds) and pension funds (357 funds). In Panel B, at less-active traders, median-active traders and most-active traders. In Panel C, at more-skilled, median-skilled and less-skilled institutions. In Panel D, at high $-volume, median $-volume and low $-volume institutions. As firm-level controls, I include book-to-market ratio, debt-to-equity ratio, return-on-equity, log market value and the one-year standard deviation of past stock returns. All regressions include date, firm and manager fixed-effects. Standard errors are triple-clustered at the firm, time, and manager levels. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A	Hedge Funds			Mutual Funds			Pension Funds		
VARIABLES	[-3;-1]	[0;0]	[+1;+3]	[-3;-1]	[0;0]	[+1;+3]	[-3;-1]	[0;0]	[+1;+3]
MPShock * MPE	6.210**	1.872*	4.292**	2.348***	0.967**	1.484***	1.768**	0.396	0.0154
	(2.258)	(0.906)	(2.007)	(0.668)	(0.408)	(0.339)	(0.786)	(0.535)	(0.752)
MPExp * MPE	2.406	1.451**	2.483	0.879	0.317	1.225	1.451***	0.330	1.278*
	(1.458)	(0.520)	(1.474)	(0.671)	(0.247)	(0.739)	(0.479)	(0.317)	(0.620)
MPE	0.325	0.442**	0.598	0.474*	0.117	0.643***	0.663***	0.0839	0.656**
	(0.422)	(0.183)	(0.509)	(0.244)	(0.0716)	(0.217)	(0.204)	(0.0952)	(0.234)
Observations	254,613	254,592	254,613	3,342,217	3,341,962	3,342,217	447,511	447,466	447,511
Adjusted R-squared	0.014	0.010	0.011	0.003	0.002	0.003	0.012	0.015	0.015
Panel B	Most-Active Traders			Median-Active Traders			Less-Active Traders		
MPShock * MPE	2.551***	1.066**	1.580***	1.786**	0.342	1.059	1.995	0.858	-2.940
	(0.710)	(0.412)	(0.404)	(0.775)	(0.833)	(1.106)	(3.529)	(1.292)	(2.603)
MPExp * MPE	1.065	0.432*	1.430*	0.477	-0.00455	0.0927	-0.358	-0.295	-1.174
	(0.721)	(0.237)	(0.755)	(0.583)	(0.396)	(0.633)	(1.897)	(1.029)	(2.221)
MPE	0.467*	0.122	0.602**	0.441	0.000299	0.608	0.0187	-0.165	-0.468
	(0.249)	(0.0786)	(0.212)	(0.252)	(0.0934)	(0.362)	(0.506)	(0.201)	(0.778)
Observations	3,364,069	3,363,832	3,364,069	454,874	454,854	454,874	107,212	107,201	107,212
Adjusted R-squared	0.003	0.002	0.003	0.016	0.018	0.016	0.034	0.024	0.037
Panel C	Most-Skilled Institutions			Median-Skilled Institutions			Less-Skilled Institutions		
MPShock * MPE	2.162	1.061	0.997	2.851***	0.868**	0.927	1.965***	1.371*	2.863**
	(1.765)	(0.671)	(1.607)	(0.834)	(0.334)	(1.019)	(0.550)	(0.753)	(1.167)
MPExp * MPE	0.985	0.314	0.444	0.718	0.241	1.219	1.240*	0.674**	1.477**
	(1.251)	(0.256)	(1.027)	(0.681)	(0.242)	(0.959)	(0.652)	(0.246)	(0.635)
MPE	0.571	-0.0331	-0.0192	0.377	0.105	0.728***	0.484*	0.182*	0.611*
	(0.479)	(0.245)	(0.210)	(0.304)	(0.0707)	(0.203)	(0.229)	(0.0894)	(0.331)
Observations	652,608	652,555	652,608	2,198,470	2,198,330	2,198,470	1,075,223	1,075,147	1,075,223
Adjusted R-squared	0.006	0.006	0.006	0.004	0.002	0.003	0.005	0.005	0.007
Panel D	High $-volume Institutions			Median $-volume Institutions			Low $-volume Institutions		
MPShock * MPE	2.313***	1.038**	1.456***	3.829***	0.983*	1.740**	-0.286	-0.283	2.469
	(0.753)	(0.443)	(0.452)	(1.001)	(0.493)	(0.750)	(1.915)	(0.874)	(2.053)
MPExp * MPE	0.976	0.416	1.335	0.952	0.195	1.206**	0.0319	0.121	0.873
	(0.792)	(0.268)	(0.850)	(0.546)	(0.277)	(0.511)	(1.069)	(0.359)	(1.342)
MPE	0.496*	0.139*	0.669***	0.0675	-0.166	0.0302	0.494	0.0712	-0.101
	(0.252)	(0.0780)	(0.205)	(0.216)	(0.134)	(0.319)	(0.380)	(0.184)	(0.624)
Observations	3,272,268	3,272,037	3,272,268	492,509	492,480	492,509	161,442	161,433	161,442
Adjusted R-squared	0.003	0.002	0.003	0.014	0.012	0.015	0.021	0.032	0.027
Date FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Manager FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table I.12: Institutional trades on high MPE stocks - Managers' Heterogeneity and Shock This table reports the coefficient estimates of the cross-sectional regression by pooling all firm-manager-level institutional trading imbalance over the FOMC dates. The dependent variable is the institutional trading imbalance. The explanatory variables include the MPE measure (MPE), the monetary policy shock ($MPShock$), a dummy for the hedge funds (HF), and their interactions. In Columns (1) to (3) I keep the FOMC events for which the monetary surprise is greater than zero. In Columns (4) to (6), I keep the FOMC events with a negative monetary surprise. As firm-level controls, I include book-to-market ratio, debt-to-equity ratio, return-on-equity, log market value and the one-year standard deviation of past stock returns. All regressions include date, firm and manager fixed-effects. Standard errors are triple-clustered at the firm, date and manager levels. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$MPShock > 0$			$MPShock < 0$		
VARIABLES	$[-3;-1]$	$[0;0]$	$[+1;+3]$	$[-3;-1]$	$[0;0]$	$[+1;+3]$
MPE * MPShock * HF	5.917***	-0.0525	-0.0187	1.615	0.753	4.920
	(1.612)	(1.849)	(1.137)	(4.431)	(2.279)	(4.246)
MPE * MPShock	0.786	0.377	0.0972	2.948**	1.823	3.839**
	(1.103)	(0.395)	(1.494)	(1.263)	(1.070)	(1.328)
MPShock * HF	0.00594	0.00826*	-0.00365	0.00966	-0.00897	-0.0447**
	(0.00772)	(0.00445)	(0.0104)	(0.0202)	(0.00723)	(0.0143)
MPE * HF	-0.832	0.141	0.801*	0.714	0.118	0.902*
	(0.885)	(0.497)	(0.399)	(0.549)	(0.333)	(0.416)
MPE	0.937**	0.228	1.239**	0.997**	0.295*	1.141**
	(0.374)	(0.140)	(0.420)	(0.439)	(0.155)	(0.481)
Observations	924,023	924,000	924,023	910,371	910,277	910,371
Adjusted R-squared	0.005	0.004	0.004	0.005	0.004	0.006
Date FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Manager FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

Table I.13: Risk-adjusted returns The dependent variable is the returns of a portfolio that on the FOMC dates goes long (short) the stocks that institutional investors net buy (sell) on the three days *before* the FOMC dates. Portfolio returns are regressed on the three Fama-French factors and the momentum factor. Portfolio and factor returns are expressed in percent. In columns (1)-(3) the portfolio is equally weighted, and in columns (4)-(6) returns are weighted by the net amount traded by each institution in the three days ahead of FOMC dates. "MF", "HF", and "PF" refer to mutual funds, hedge funds, and pension funds, respectively. Net trading amounts and returns are winsorized at the 1% level on both tails. Standard errors are clustered at the date and fund levels. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Equally Weighted			Value Weighted		
VARIABLES	MF	HF	PF	MF	HF	PF
MKT-RF	0.0308***	-0.0398	0.0451*	0.0381***	-0.0419	0.0338
	(0.0104)	(0.0386)	(0.0272)	(0.0113)	(0.0402)	(0.0305)
SMB	0.0196	0.0328	-0.0537	0.0178	0.0178	-0.0272
	(0.0208)	(0.0845)	(0.0604)	(0.0279)	(0.0914)	(0.0699)
HML	0.0275**	0.0385	0.00281	0.0585***	0.0541	0.0521
	(0.0131)	(0.0696)	(0.0576)	(0.0191)	(0.0905)	(0.0652)
UMD	0.0260*	-0.0725	-0.0108	0.0362**	-0.0780	0.0195
	(0.0132)	(0.0547)	(0.0385)	(0.0173)	(0.0600)	(0.0390)
α	0.0660***	0.123***	0.0472	0.0274*	0.103**	0.0160
	(0.0128)	(0.0420)	(0.0349)	(0.0159)	(0.0463)	(0.0377)
Observations	20,202	2,889	5,560	20,072	2,867	5,290
Adjusted R-squared	0.001	0.001	0.001	0.001	0.001	-0.000

Table I.14: Hedge Funds proximity to regional Fed branches This table reports the coefficient estimates of the cross-sectional regression by pooling all firm-manager-level institutional trading imbalance over the FOMC dates. The dependent variable is the trading imbalance of Ancerno's hedge-fund managers. The explanatory variables include the MPE measure (MPE), the monetary policy shock ($MPShock$), and a dummy ($Close$) that is equal to one when the distance between the headquarter of the hedge fund and the closest regional Fed branch is lower that 20 km (in Columns (1) to (3)) or lower than 50 km (in Columns (4) to (6)). As firm-level controls, I include book-to-market ratio, debt-to-equity ratio, return-on-equity, log market value and the one-year standard deviation of past stock returns. All regressions include date, firm and manager fixed-effects. Standard errors are triple-clustered at the firm, date and manager levels. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	Close means within 20 km			Close means within 50 km		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	$[-3;-1]$	$[0;0]$	$[+1;+3]$	$[-3;-1]$	$[0;0]$	$[+1;+3]$
MPE * MPShock * Close	10.30**	-1.319	4.581*	11.71***	0.315	4.135
	(4.211)	(1.790)	(2.318)	(4.391)	(1.421)	(2.818)
MPE * MPShock	-2.937	3.111**	0.213	-4.247*	1.726**	0.538
	(2.384)	(1.555)	(1.432)	(2.414)	(0.722)	(1.889)
MPE * Close	0.236	-0.288	0.653	0.171	-0.343	0.694
	(1.143)	(0.234)	(0.537)	(1.321)	(0.245)	(0.570)
MPShock * Close	-0.010	-0.002	-0.005	-0.010	-0.004	-0.004
	(0.026)	(0.005)	(0.013)	(0.027)	(0.005)	(0.014)
MPE	0.187	0.717***	-0.016	0.241	0.774***	-0.069
	(1.064)	(0.234)	(0.506)	(1.238)	(0.253)	(0.559)
Observations	249,328	249,308	249,328	249,328	249,308	249,328
Adjusted R-squared	0.013	0.010	0.010	0.013	0.010	0.010
Date FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Manager FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

Table I.15: Anticipatory trades and FOMC compositions This Table reports results on the informed trading and trading performance on FOMC dates. The dependent variable is the trading imbalance of Ancerno's funds managers. I match each manager with the district of the regional Fed to which it belongs. In the Columns "Voting", I use the trades of the managers located in the districts that are represented in the Federal Open Market Committee by a *voting* member. In the Columns "Alternate", I use the trades of the managers located in the district that are represented in the Federal Open Market Committee by an *alternate* member. I reports the coefficient estimates of the baseline cross-sectional regressions, for the two categories of institutions as above. Standard errors are triple-clustered at the firm, date and manager levels. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	Alternate			Voting		
	$[-3;-1]$	$[0;0]$	$[+1;+3]$	$[-3;-1]$	$[0;0]$	$[+1;+3]$
MPShock * MPE	5.191***	1.579***	2.846	0.197	0.643	-0.229
	(3.349)	(2.657)	(1.524)	(0.165)	(1.131)	(-0.130)
MPExp * MPE	2.570***	0.722**	2.311***	-0.411	0.175	0.034
	(3.348)	(2.144)	(4.934)	(-0.535)	(0.580)	(0.042)
MPE	0.321	0.0615	0.486	0.665**	0.166*	0.813***
	(1.239)	(0.670)	(1.624)	(2.283)	(1.765)	(2.730)
Observations	1,708,727	1,708,595	1,708,727	2,000,098	1,999,932	2,000,098
Adjusted R-squared	0.005	0.003	0.004	0.004	0.003	0.003
Date FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Manager FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

Table I.16: Bid-ask spread around scheduled and unscheduled FOMC meetings In Panel A, the dependent variable is $log(1 + Realspread)$, where $Realspread$ is the share-weighted percent realised spread around any focal date. In Panel B, the dependent variable is $log(1 + Effspread)$, where $Effspread$ is the dollar-weighted percent effective spread around any focal date. $Realspread$ is equal to $2D_k(P_k - M_{k+5})$, where M_{k+5} is the bid-ask mid-point five minutes after the kth trade. $Effspread$ is equal to $2D_k(P_k - M_k)/M_k$, where M_k is the bid-ask mid-point for the kth trade. I aggregate the spreads to the daily level by taking the dollar-volume weighted average across all trades in the day. $FOMCscheduled$ ($FOMCunscheduled$) is a dummy variable that takes value one when a scheduled (unscheduled) FOMC meeting takes place on the focal date, and zero otherwise. As firm-level controls, I include book-to-market ratio, debt-to-equity ratio, return-on-equity, log market value and the one-year standard deviation of past stock returns. Year and firm fixed-effects are also included. Standard errors are double-clustered at the firm and date levels. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Panel A	Percent Realised Spread					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	[-3;-1]	[0;0]	[+1;+3]	[-3;-1]	[0;0]	[+1;+3]
FOMC scheduled	0.00475**	-0.00366**	0.00902***			
	(0.00220)	(0.00182)	(0.0045)			
FOMC unscheduled				-0.000634	0.0125	-0.00367
				(0.00936)	(0.0130)	(0.00542)
Observations	3,703,290	3,700,189	3,701,245	5,600,906	5,596,162	5,598,833
Adjusted R-squared	0.597	0.387	0.515	0.596	0.386	0.512
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Panel B	Percent Effective Spread					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	[-3;-1]	[0;0]	[+1;+3]	[-3;-1]	[0;0]	[+1;+3]
FOMC scheduled	0.00740**	-0.00377	0.0164***			
	(0.00347)	(0.00337)	(0.00558)			
FOMC unscheduled				-0.000750	0.0203	-0.00315
				(0.0112)	(0.0192)	(0.0103)
Observations	3,703,531	3,700,998	3,701,464	5,601,264	5,597,348	5,599,198
Adjusted R-squared	0.761	0.657	0.722	0.759	0.655	0.718
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

Figure I.1: The figure gives the cross-sectional distribution of how stock prices react to monetary policy (5% - 95% range). Monetary policy sensitivity comes from equation: $r_{i,t} = \alpha_i + \beta_i * MPShock_t + \epsilon_{i,t}$ estimated on FOMC dates. The sample is the same of the ANcerno data (from 1999 to 2014). $r_{i,t}$ are expressed in decimals, while $MPShock_t$ are in percentage points. Following previous literature, I drop event days surrounding QE: November 25, 2008, December 1, 2008, December 16, 2008, January 28, 2009, and March 18, 2009. The FOMC announcement on March 18, 2008 is dropped as an outlier because on that day the SP 500 index increased by about 4% reflecting the positive news about JP Morgan's purchase of Bearn Stearns. Using this sample, the policy sensitivity of the CRSP value-weighted index is -2.54 percentage points (significant at the 5% level).

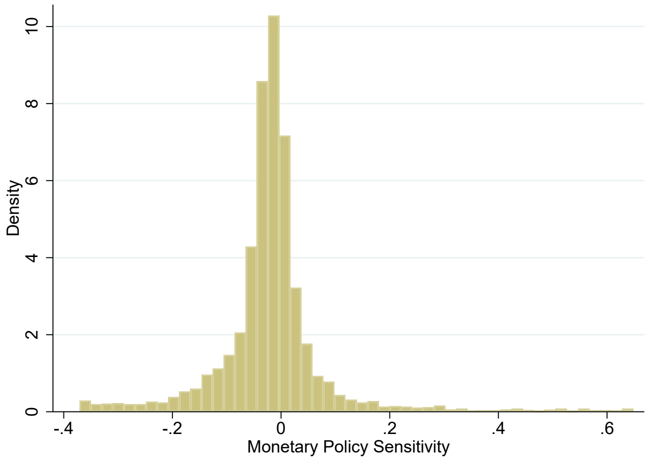
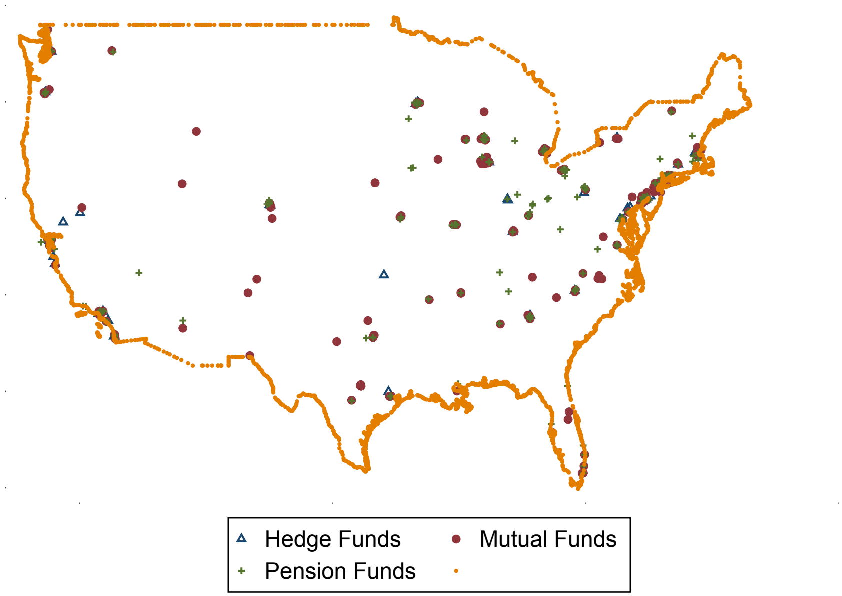


Figure I.2: The figure shows the location of institutions that appear in the Ancerno's sample. Hedge funds, mutual funds, and pension funds are plotted, for a total of 848 institutions.



I.6 Appendix: Construction of MPE Measure

In this Appendix, I provide a brief description of the variables that enter in the computation of the monetary policy exposure, mainly following Ozdagli (2017). These variables have been shown by previous literature to be associated to stock-level sensitivity to monetary policy surprises.

Financial Constraints. The effect of firms' financial constraints on monetary policy transmission has been widely discussed in the literature, with conflicting results. On one side, Ozdagli (2017) finds that more constrained firms earn higher returns after a positive monetary shock, and this is due to the fact that these firms rely less on external finance. On the other side, in a contemporaneous work, Chava and Hsu (2020) find that financially constrained firms earn a significantly lower return following surprise interest rate increases as compared to unconstrained firms. In their interpretation, a tight monetary policy can increase interest expenses and reduce net cash flows to the firm thereby weakening its financial condition. This is particularly bad for financially constrained firms. Although they both use the Withed-Wu measure of financial constraints, these conflicting results derive from the use of slightly different specifications and choices in terms of the control variables and the sample window. I use the Size-Age (SA) measure of financial constraints from Hadlock and Pierce (2010), that is constructed as

$$SA = -0.737Size + 0.043Size^2 - 0.040Age, \tag{I.15}$$

where $Size$ is equal to the logarithm of total assets (AT) adjusted in 2004 dollars and winsorized above at \$4.5 billion, and Age is number of years the firms is listed with a non-missing fiscal year end stock price on Compustat, winsorized above at 37 years.

Cash and short-term investments (liquidity effect). These are the most liquid assets of the firm and are directly related to the monetary base, broadly defined. On the one hand, firms with a higher amount of cash can react more negatively to a policy rate increase because the interest rate is the opportunity cost of holding cash (Baumol, 1952); on the other hand, corporate cash reserves can dampen the effect of monetary policy by making investment less sensitive to policy (Gao et al., 2018). This measure is computed as cash (CHE) scaled by market capitalization.

Cash flow duration (discount rate effect). Ozdagli (2017) finds that firms that expect to have cash flows further in the future, and therefore have greater equity duration, are more affected by monetary policy, consistent with the notion that the present value of later cash flows are more affected by the changes in discount rate. This measure is computed as in Dechow et al. (2004) and Weber (2018). It resembles the traditional Macaulay duration for bonds, and hence reflects the weighted average time to maturity of cash flows

$$CFDuration_{i,t} = \frac{\sum_{s=1}^{T} s \times CF_{i,t+s}/(1+r)^s}{P_{i,t}} \tag{I.16}$$

where $CFDuration_{i,t}$ is the cash-flow duration of firm i at the end of fiscal year t, $CF_{i,t+s}$ denotes the cash flow at time $t+s$, $P_{i,t}$ is the current price, and r is the expected return on equity. The expected return on equity is constant across both stocks and time. Contrary to bonds, stocks do not have a well-defined finite maturity, $t+T$, and cash flows are not known in advance. Therefore, the duration formula is split into a finite detailed forecasting period and an infinite terminal value, and assume the latter is paid out as level perpetuity to deal with the first complication.

$$\begin{aligned} CFDuration_{i,t} = &\frac{\sum_{s=1}^{T} s \times CF_{i,t+s}/(1+r)^s}{P_{i,t}} + \\ &\left(T + \frac{1+r}{r}\right) \times \frac{P_{i,t} - \sum_{s=1}^{T} s \times CF_{i,t+s}/(1+r)^s}{P_{i,t}} \end{aligned} \tag{I.17}$$

Cash flows are measured assuming clean surplus accounting

$$CF_t = E_t - (BV_t - BV_{t-1}) = BV_{t-1} \times \left[\frac{E_t}{BV_{t-1}} - \frac{BV_t - BV_{t-1}}{BV_{t-1}}\right] \tag{I.18}$$

Based on recent findings in the financial statement analysis literature, Dechow et al. (2004), return on equity (ROE) is assumed to follow a first-order autoregresive process with an autocorrelation coefficient equal to the long-run average rate of mean reversion in ROE and a long-run mean equal to the cost of equity, whereas the growth in book equity (BE) similarly follows a first-order autoregressive process with an autocorrelation coefficient equal to the long-run average rate of mean reversion in sales growth and a mean equal to the long-run gross domestic product (GDP) growth rate. Following previous literature, e.g. Dechow et al. (2004), I assume ROE has an $AR(1)$ coefficient of 0.57 and BV of 0.24. I assume a discount rate r of 0.12, a steady-state average cost of equity capital of 0.12, an average long-run nominal growth rate of 0.06, and a detailed forecasting period of 10 years.

Cash flow volatility. Cash flow volatility may capture the monetary policy sensitivity of a firm's stock price in multiple ways, as explained in Ozdagli (2017). On the one hand, firms with lower volatility may have lower default likelihood and therefore longer lives and higher duration of cash flows. On the other hand, lower volatility may also imply a lower value of the option to delay investment and therefore firms with lower volatility may increase cash flow duration by increasing investment today in exchange for cash flows in the future. This is measured as the standard deviation over the last 20 quarters of cash flows, measured by operating cash flow scaled by total assets. Operating cash flow is measured by sales (SALE) minus cost of goods sold (COGS) minus selling, administrative, and general expenses (XSGA) minus working capital change (WCAP minus lagged WCAP). A minimum of three consecutive years is required.

Operating profitability. If firms' output prices are more sticky than their input prices, an expansionary monetary policy will lead to a greater increase in input costs than the firms' revenues, eating away their profits, and thus reducing their stock prices. However, this reduction would be smaller in percentage terms for firms with higher profitability. This is measured as sales (SALE) minus cost of goods sold (COGS), scaled by market value of assets. Market value of assets equals total assets (AT) minus shareholder equity (SEQ) plus market capitalization.

Table I.1: Institutional trades on high-beta stock before non-FOMC macro announcements This is similar to Table I.5, but here I focus on three non-FOMC news announcements: the Gross Domestic Product, the CPI Inflation Rate, and the Civilian Unemployment Rate. The dependent variable is the institutional trading imbalance around the release dates of each of these macro news. *HighBeta* is a dummy variable that is equal to 1 if the stock is in the top quintile of the cross-sectional distribution of betas, recomputed on each date, and 0 otherwise. The stock beta is computed according to the CAPM using the past year daily returns. *Forecast* is the one-step ahead forecasted value of each type of macroeconomic announcements, as provided by the Federal Reserve Bank of Philadelphia in their quarterly Survey of Professional Forecasters (SPF). *Shock* is computed as a forecast error (*Shock* = (*Forecast* - *Realized*) / *Realized*), where *Realized* is the actual value of the macroeconomic indicator, gathered from the U.S. Bureau of Labor Statistics (BLS), and *Forecast* is the outstanding consensus (median) among the Professional Forecasters. For each macroeconomic announcement type, I compute the shock on the date in which the actual value is published by the U.S. Bureau of Labor Statistics. The error statistics for the Survey of Professional Forecasters (SPF) are publicly available in the website of the Federal Reserve Bank of Philadelphia: https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/error-statistics. The historical release date of the BLS's macro news are reported in the website of the Federal Reserve Bank of St. Louis, e.g. for the GDP news at the following link: https://alfred.stlouisfed.org/release/downloaddates?rid=53. As firm-level controls, I include book-to-market ratio, debt-to-equity ratio, return-on-equity, log market value and the one-year standard deviation of past stock returns. Date and firm fixed-effects are also included. Standard errors are double-clustered at the firm and date levels. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	CPI	GDP	UNEMP
	(1)	(2)	(3)
VARIABLES	[−3; −1]	[−3; −1]	[−3; −1]
Shock * HighBeta	-0.014	-0.053	1.214
	(0.046)	(0.079)	(1.627)
Forecast * HighBeta	0.019	0.020	0.019
	(0.023)	(0.023)	(0.013)
HighBeta	-0.073	-0.076	-0.172*
	(0.054)	(0.104)	(0.097)
Observations	154,846	154,904	154,644
Adjusted R-squared	0.002	0.007	0.002
Date FE	YES	YES	YES
Firm FE	YES	YES	YES
Controls	YES	YES	YES

Paper II

Insurance companies as liquidity providers: The case of corporate-bond mutual funds

Aramonte Sirio, Mano Nicola

II

Abstract

The retrenchment of dealers after the Great Financial Crisis has amplified mutual-fund fragility risks. We study whether insurance companies help to contain these risks by providing liquidity to corporate-bond mutual funds. We find that insurers often buy bonds sold by mutual funds, mainly when sales are not driven by fundamental factors. Consistent with liquidity provision, insurers complement dealers' risk capacity and earn positive returns on bonds sold by mutual funds. In a sign of fair-weather liquidity supply, insurers retrench when market risk is high and shy away from bonds that could sharply raise regulatory capital. Overall, our work suggests that policy efforts to address mutual-fund fragility concerns should consider insurance companies as important players in the liquidity provision ecosystem.

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II.1 Introduction

Structural changes in financial intermediation that arc back to the 1980s transformed the ecosystem that supplies corporate credit. Technological and regulatory developments in the U.S. banking sector (Berger et al., 1995) contributed to the rise in marketable securities such as corporate bonds, which offset the declining share of bank loans in corporate debt (Martin-Buck, 2019). Trading in bonds has traditionally been facilitated by dealers, which match client trades or use their own inventory to accommodate client transactions. In line with their increasingly prominent role, the balance sheets of dealers rose quickly starting in the 1980s (Adrian and Shin, 2010). The 2008 Great Financial Crisis (GFC) ushered two important shifts. First, dealers reduced liquidity provision, for reasons that include changes in business models and evolving regulations (Adrian et al., 2017 and Di Maggio et al., 2017). Second, strong appetite for corporate bonds led to a rapid expansion of corporate-bond mutual funds (Goldstein et al., 2017).

Open-ended mutual funds engage in liquidity transformation, which generates spikes in liquidity demand and can contribute to broad dislocations.[1] The reason is that bonds take time to sell at full price, while fund shares can be redeemed daily at fair value, meaning that liquidity discounts are borne by the remaining shareholders. As a result, there is a first-mover advantage that creates run risk and makes mutual funds inherently fragile (Goldstein et al., 2017 and Falato et al., 2021b), especially if they hold more illiquid assets or reach for yield (Choi et al., 2021 and Choi and Kronlund, 2018). In response to run risk, fund managers hoard liquidity in anticipation of large redemptions (Morris et al., 2017 and Huang, 2020).

In this paper, we explore the role of insurance companies in an environment characterized by rising liquidity demand by mutual funds and more limited liquidity supply by dealers. Insurers hold substantial amounts of corporate bonds,[2] and represent a stable investor base (Coppola, 2021), hence they are well positioned to exploit mispricing that arises from selling pressure. We are particularly interested in whether they provide liquidity to “derisker”

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[1]The market turmoil at the onset of the Covid-19 pandemic led to large and sustained outflows from corporate-bond mutual funds (Breckenfelder et al., 2021 and Falato et al., 2021a), which strained market functioning (Ma et al. (2020)). With constrained liquidity supply from dealers (Kargar et al., 2021 and O’Hara and Zhou, 2021), central-bank interventions were crucial to ease these strains (Gilchrist et al., 2021).

[2]In 2019, U.S. insurers held about \$1.80 trillion in U.S. corporate bonds (Fringuellotti and Santos, 2021), or about 20% of the \$8.87 trillion total estimated by SIFMA’s U.S. Corporate Bond Statistics. The share is higher for investment-grade corporate bonds (Nanda et al., 2019).

mutual funds, which attempt to contain future redemptions by shedding riskier securities (Cutura et al., 2020). These flows do not reflect fundamental factors that could also drive insurers' trading, hence they are a useful laboratory to study liquidity provision. Liquidity supply by insurers would help to contain the effects of mutual-fund fragility, chiefly spillovers within and across asset classes (Koch et al., 2016, Chernenko and Sunderam, 2020 and Manconi et al., 2012). In this sense, it would complement regulation[3] and funds' own liquidity management. The latter consists of holding small amounts of easily tradeable instruments that are sold to meet redemptions, while the underlying securities can be divested over time at full price (Choi et al., 2020).

Our work contributes to the literature on the complex liquidity-provision ecosystem that emerged from the GFC. Crucially, it relies on a composite set of intermediaries, including those traditionally focused on long-term investing (Anand et al., 2013). The benefits of diversification are balanced by a more tangible risk of systemic liquidity crises (Aramonte et al., 2022), largely due to the procyclicality in risk-taking capacity highlighted by the literature on intermediary asset pricing (He and Krishnamurthy, 2013 and He et al., 2017) and that largely arises from the interplay of funding conditions and leverage (Brunnermeier and Pedersen, 2009, Adrian et al., 2014, Macchiavelli and Zhou, 2022). The nature of liabilities can also be an important determinant of liquidity provision. For instance, the activity of hedge funds (Aragon and Strahan, 2012 and Cotelioglu et al., 2021) is sensitive to the chance of large outflows (Ben-David et al., 2012), with potentially disruptive effects on the markets for the underlying assets (Kruttli et al., 2022).

Our analysis comprises three steps and is designed to understand whether purchases by insurers represent liquidity supply to mutual funds. In particular, we study insurers' trading through the lens of factors that affect or reflect liquidity provision, including activity by dealers, risk-capacity constraints experienced by insurers, and risk-adjusted returns earned by insurers on bonds divested by mutual funds.

We start by characterizing trading patterns, finding that insurers tilt their trading towards purchases when mutual tend to sell, particularly if market risk is low. This negative correlation also emerges at the security level for

[3]For instance, regulations allow fund managers to use swing pricing, whereby redeemers receive lower prices than implied by NAV to reflect liquidity discounts (Capponi et al., 2020). These provisions appear to reduce outflows during periods of market stress (Jin et al., 2021), however they may lead to lower cash buffers (Lewrick and Schanz, 2017) and increase moral hazard (Cutura et al., 2020), potentially carrying reputational costs. In general, actions with reputational costs can accelerate redemptions, since investors fear that managers may take steps detrimental to portfolio value when trying to avoid taking these actions (Fecht and Wedow, 2014).

high-yield bonds (which are often sold by deriskers) and after controlling for insurer and mutual-fund characteristics and bond and period fixed-effects. To address endogeneity concerns, we study the relation between insurers' trades and lagged mutual fund trades, since offloading a position can take time (Cai et al., 2019) and dealers likely intermediate some transactions with temporary inventory expansion (Anand et al., 2013). Once again, the effect is largely confined to periods of low market risk. This regularity is consistent with liquidity provision, since elevated market risk generally degrades liquidity as the risk-taking capacity of intermediaries falls (Shin, 2008).

In the second step, we consider the role of balance-sheet constraints in shaping the trading link between insurers and mutual funds. We find that the link is stronger after large increases in dealers' balance sheets, which arguably reduce the ability of these key intermediaries to provide additional liquidity. As such, insurers seem to complement dealer activity. We next focus on the balance sheets of insurers, and consider the effects of costly natural disasters that impose losses on the insurance industry.[4] In these instances, the link between insurers' and mutual funds' trading disappears, in line with the findings of Massa and Zhang (2021) that hurricane Katrina led to meaningful bond sales by insurers. Finally, we explore the effect of large prospective increases in regulatory capital. Previous studies highlight that bond downgrades from investment grade (IG) to high yield (HY), which raise insurers' capital requirements substantially, lead to fire sales (Ellul et al., 2011, Merrill et al., 2021 and Murray and Nikolova, 2021).[5] Consistent with insurers wishing to avoid fire sales, their activity decouples from that of mutual funds for bonds with the lowest IG ratings.

In the third step, we focus on the returns accrued to bonds sold by mutual funds and bought by insurers. Studies typically characterize activity as liquidity provision based on both the direction and price of trades, with purchases at discounted prices being important evidence (e.g., Da et al., 2011 and Anand et al., 2013). From this perspective, our asset-pricing analysis is key to qualify insurers' trading with mutual funds as liquidity supply. We find that, among

[4]Losses impair liquidity provision because they reduce economic capital. However, they can also affect risk-taking incentives through career concerns (see the discussion in Aramonte and Szerszen, 2020 and references therein). Besides the corporate-bond market (Gissler, 2017 and Choi et al., 2019), losses experienced by key intermediaries also reduce liquidity and generate liquidity comovement in equities (Coughenour and Saad, 2004 and Comerton-Forde et al., 2010) and in foreign-exchange (Karnaukh et al., 2015).

[5]As a result of the risks connected to possible fire sales, bonds with a high share of insurers among holders have higher yields (Nanda et al., 2019). Fire sales exacerbate general procyclicality in trading by insurers (Becker and Ivashina, 2015). Trading across insurers also tends to be correlated and to exert a meaningful impact on prices (Girardi et al., 2021), especially during periods of stress.

bonds sold by mutual funds, a portfolio that goes long (short) those bought (sold) by insurers earns sizable returns, also after controlling for systematic factors relevant for corporate bonds (Bai et al., 2019). In addition, returns on this portfolio are higher after the Volcker Rule was adopted and around its entry into force. This regulation, which limited the ability of banks to engage in proprietary trading, had substantial effects on corporate-bond liquidity (Allahrakha et al., 2019 and Bao et al., 2018). It appears that insurers earned higher profits around events that temporarily unsettled the liquidity-provision ecosystem.

Our paper is closely related to the work of Cai et al. (2019) on herding among institutional investors in the corporate bond market. They find that trading tends to be correlated, markedly more so than for stocks (Wermers, 1999). In line with studies showing that certain mutual funds act as liquidity providers (Da et al., 2011, Ng et al., 2019, Wang et al., 2020, and Anand et al., 2021), they highlight that mutual funds increase their holdings of bonds offloaded by insurers after the securities are downgraded to HY status. Relative to Cai et al. (2019), we are interested specifically in liquidity supply by insurers in favor of mutual funds, especially those more likely to engage in sales not driven by fundamental factors. The key question that motivates our analysis is whether insurers can help contain the fragility of corporate-bond mutual funds (Goldstein et al., 2017).

In the remainder of the article, Section II.2 describes the research design and data. Section II.3 analyzes trading patterns between mutual funds and insurers, and studies the role of dealers' balance sheets and of natural disasters. Section II.4 focuses on risk-adjusted returns earned by insurers. Section II.5 concludes.

II.2 Data and research design

The first part of our analysis focuses on changes in bond exposures for insurers and mutual funds. We refer to these changes as "trades", as in Cai et al. (2019). The main dataset we use is Thomson Reuters eMAXX, which reports quarterly holdings of individual bonds by institutional investors, including those no longer active to avoid survivorship bias. We consider fixed-coupon, dollar-denominated corporate bonds issued by US companies and held by US-based institutional investors.[6] To focus on *active* trading decisions, we follow Cai et al. (2019) and

[6]In eMAXX, corporate bonds are identified by the first letter of the variable *MarketSectorString*, which is equal to "C". Insurance companies have *SubAccountClassCode* equal to "INS","LIN","PIN","RIN". Mutual funds have *SubAccountClassCode* equal to "MUT".

exclude bonds issued or maturing within one year, as well as those traded by less than five institutional investors in a given quarter. Bond characteristics are from eMAXX and Mergent FISD through Wharton Research Data Services (WRDS). The baseline results cover the period ranging from the start of our eMAXX data in 2004 to 2019, excluding the Covid-19 pandemic to ensure that the conclusions are not driven by the early 2020 dislocations. We also discuss evidence spanning the full sample period through 2020.

The key motivating question for our work is whether liquidity provision by insurers can help to ameliorate fragility in corporate-bond mutual funds. By and large, this fragility arises from liquidity transformation, which can give rise to sharp selling pressure through runs (Goldstein et al., 2017). Portfolio managers can also generate selling pressure by hoarding liquidity when run risk picks up (Morris et al., 2017) or by derisking to contain future outflows (Cutura et al., 2020). Given that runs on mutual funds are infrequent, we focus on *derisking* mutual funds and explore whether insurers provide liquidity to them. Deriskers are defined as mutual funds whose change in risk taking from quarter to quarter is below the median of the quarterly cross-sectional distribution. Following Cutura et al. (2020), the change in risk taking for fund j is defined as:

$$\Delta Risk_{j,t} = \sum_{i=1}^{N_{j,t}} w_{i,j,t} Riskiness_{i,t-1} - \sum_{i=1}^{N_{j,t-1}} w_{i,j,t-1} Riskiness_{i,t-1}, \qquad \text{(II.1)}$$

where $Riskiness_{i,\cdot}$ is the highest credit rating among those assigned to bond i by Standard and Poor's, Moody's, and Fitch, and $w_{i,j,t}$ is the quarter-t weight of bond i in fund j's portfolio of $N_{j,t}$ bonds, based on par amounts.

After characterizing broad trends in transactions between mutual funds and insurers, we study trading patterns using panel regressions that include fund- and insurer-level controls. Fund characteristics like expense ratios, turnover and flows are from the CRSP Survivor-Bias-Free US Mutual Funds database. Data for insurance companies are from Compustat. We match eMAXX, CRSP Mutual Fund and Compustat manually by fund name. We only consider U.S. mutual funds focused on corporate bonds, which we select based on names and by reviewing portfolio allocation if needed.

In order to understand the drivers of trading patterns, we condition the analysis on changes in dealers' holdings of corporate and foreign bonds as a measure of their risk capacity (from table L.130 of the Financial Accounts of the United States) and on the occurrence of hurricanes, which impose exogenous losses on the insurance industry and spur bond sales (Massa and Zhang, 2021).

Data on hurricanes, including their costs, are from the Natural Centers for Environmental Information[7].

The profitability of insurers' trading with mutual funds is essential to understand whether their activity amounts to liquidity provision. Since eMAXX tracks quarterly changes in holdings, rather than transactions, we rely on a portfolio approach to assess whether insurers earn a profit from purchasing bonds sold by mutual funds. Bond returns are capped at $\pm 50\%$. We evaluate risk-adjusted returns using the factors of Bai et al. (2019). These variables, available on Tarun Bali's website, track a variety of systematic risks, including liquidity.

We also study the liquidity characteristics of the underlying bonds, relying on three measures also used by Cutura et al. (2020). All three are computed as quarterly medians of daily values based on data from WRDS. The first one is the daily average bid-ask spread for all transactions on a given day. The second proxy quantifies the price impact of trades (Amihud, 2002). For each corporate bond, it is the daily average of trade price impact divided by trading volume Q_j (in million U.S. dollars):

$$Amihud_t = \frac{1}{N_t} \sum_{j=1}^{N_t} \sqrt{\frac{|p_j/p_{j-1} - 1|}{Q_j}} \tag{II.2}$$

where N_t is the number of transactions for a given bond in day t, while p_j and p_{j-1} are the prices of trade j and of the previous one, respectively. At least two transactions are required on a given day. The third proxy is the inter-quartile range of prices, computed as follows:

$$IQR_t = \frac{P^{75}_{j,t} - P^{25}_{j,t}}{\overline{P_t}}, \tag{II.3}$$

where $\overline{P}$, P^{75}, and P^{25} are the average and the 75^{th} and 25^{th} percentiles, respectively, of traded prices on day t. At least three daily observations are required.

II.2.1 Descriptive Statistics

The participation of insurers and mutual funds in the corporate-bond market is broad based. As shown in Figure II.1, the 20% share of outstanding held by insurers (see Footnote 1) translates into nearly 3,000 firms investing in close

[7] https://www.ncdc.noaa.gov/

to 15,000 bonds. The numbers are somewhat lower for mutual funds, with about 1,000 institutions holding 10,000 bonds. Reflecting the strong growth of corporate-bond mutual funds after the 2008 financial crisis, both the numbers of funds and the bonds they hold increased markedly over time. In terms of par amount, insurers in our sample had about $1.5 trillion worth of bonds, compared to less than $1 trillion for mutual funds. Overall, these figures are close to those reported by Cai et al. (2019), except that the number of mutual funds and the corresponding holdings in mid-2014 (the end of their sample) are lower in our data. The reason is that we focus on corporate bond funds, for instance excluding balanced funds.

The average insurer in the sample has book assets worth about $30 billion (Table II.1), with the presence of very large intermediaries that skew the distribution (the median size is $9 billion). The average mutual funds has a track record of 27 quarters, total net assets of $522 million, and received 2.4% net inflows per quarter. The distributions of fund size and flows are also skewed, with noticeably lower medians than means.

Turning to the bonds held by insurers and mutual funds, most of the sample includes IG securities. The number of bond/investor observations is three times as large for IG bonds than for their HY counterparts. Deriskers tend to offload considerably more bonds than non-deriskers, both in the IG and HY spaces. The negative mean for changes in exposures reflect that we do not track the initial purchase of a bond, but only changes of already established positions. As a result, the naturally high turnover of a bond mutual fund, largely due to targeting a certain portfolio maturity, leads to a negative average for position changes. Exposure changes are more negative for deriskers due to the added layer of risk rebalancing. On average, liquidity tends to be lower for HY bonds, which also have shorter duration. However, differences are less pronounced when considering medians.

II.3 Analysis of trading patterns

An early indication that insurers can provide liquidity to mutual funds emerges from the share of trades in which mutual funds sell and insurers buy the same bond. Between 2005 and 2016, this share – as a fraction of the overall transactions in which these intermediaries engage – stayed range bound between 15% and 20%, with little difference across derisking and non-derisking funds (Figure II.2). A rapid increase in 2017 was accompanied by the opening of a relatively wide gap between fund types, as trading with insurers became more common for deriskers. This change occurred shortly after the approval of regulations intended to improve mutual-fund liquidity management,[8] which might have led mutual funds to seek a broader set of liquidity providers.

To the extent that insurers supplied liquidity, we would expect that, in aggregate, they tilted towards buying when mutual funds tilted towards selling. In Table II.2, we explore the comovement between mutual funds' sales, expressed as a percentage of their total trading activity, and insurers' purchases, also in terms of their total trading. We condition the link on the level of market risk. The table shows coefficients from the following regression:

$$Share_t^{IC,buy} = \alpha + \beta_1 Share_t^{MF,sell} + \beta_2 VIX_t + \beta_3 Share_t^{MF,sell} \times VIX_t + \epsilon_t. \tag{II.4}$$

In Panels A and B, $Share_t^{IC,buy}$ is defined as the number of insurers' buy trades over the total number of their transactions during quarter t. In Panels C and D, $Share_t^{IC,buy}$ is the log-dollar volume of purchases divided by overall log-dollar volume of trades. $Share_t^{MF,sell}$ is defined similarly, but using mutual-fund sales.

Focusing on derisking mutual funds, there is a positive and significant correlation between funds' buy trading activity and insurers' sell activity. The result is considerably stronger for the post-2010 sample, which coincides with lower liquidity provision by dealers following the GFC. All variables are standardized, hence the coefficients in Panels A and C imply that a one-standard deviation increase in mutual-fund sales (as a share of total trades) corresponds to a 0.4-standard deviation increase in the share of insurers' purchases. The coefficient of the interaction between $Share_t^{MF,sell}$ and VIX is negative and strongly statistically significant, meaning that the comovement between deriskers' sales and insurers' purchases is only present when market risk is low (Panels B and D). This result is consistent with the link between mutual funds and insurance companies reflecting liquidity provision, which tends to decline when market risk increases and risk-taking capacity declines.

II.3.1 Evidence from bond-level trading

A granular bond-level analysis allows us to study the link between trading by insurers and derisking mutual funds while controlling for intermediary characteristics. We use a set of panel regressions that include bond and time fixed effects, together with variables that summarize key aspects of the insurers and mutual funds involved. The main specification is as follows:

$$\Delta_{i,t-1}^{deriskers} = \alpha + \beta \Delta_{i,t}^{IC} + \gamma \Delta_{i,t}^{others} + Controls_{i,t-2} + \mu_i + \nu_t + \epsilon_{i,t}, \tag{II.5}$$

[8] https://www.sec.gov/rules/final/2016/33-10233.pdf

where $\Delta^{\cdot}_{i,t}$ is the change in the holdings of bond i between quarters $t-1$ and t for the indicated intermediary type. The labels "deriskers", "IC", and "others" refer to derisking mutual funds, insurance companies, and non-derisking mutual funds, respectively. The bond and quarter fixed effects are μ_i and ν_t, and average insurer and mutual-fund characteristics are grouped in $Controls_{i,t-2}$. These variables, which are lagged by two quarters to avoid that they are jointly determined with trading decisions, are: $size$, $leverage$, $income/size$ (for insurers), and age, $assets$, $expenses$, $turnover$, $flows$ (for mutual funds)[9]. Standard errors are double clustered by time and bond.

Changes in mutual-fund holdings are lagged by one quarter, for two reasons. First, doing so reduces the possibility that $\Delta^{deriskers}_{i,\cdot}$ and $\Delta^{IC}_{i,\cdot}$ are subject to the same market-wide developments. Second, it can take time for mutual funds to sell the bonds they have decided to divest (Cai et al., 2019), and funds may not trade with insurers directly, even if the bonds are eventually bought by insurers. Rather, dealers may intermediate transactions, expanding their balance sheets to purchase from funds before shrinking them over time by selling to other institutional investors (Anand et al., 2013). From this perspective, liquidity provision can be a two-step process, with insurers playing a central but delayed role.

The first set of results from the regressions in (II.5) is shown in Panel A of Table II.11. We study IG and HY bonds separately, and we further split the sample into periods of low and high market risk. The coefficient on $\Delta^{IC}_{i,t}$ is negative in all cases, indicating that mutual funds and insurers trade in opposite directions. It is also statistically significant and markedly larger in absolute value for HY bonds, especially when market risk is low. In this case, out of every dollar of insurers' purchases, about 10 cents are used to buy bonds sold by derisking mutual funds in the previous quarter. These findings are consistent with Cutura et al. (2020), who highlight that derisking funds often sell HY

[9]For insurance companies, $size$ is the logarithm of an insurer's total assets (Compustat item atq); lev_t is the ratio of total assets over stockholders' equity ($seqq$); and $income/size$ is net income (ni) divided by the size. For mutual funds, age is the logarithm of the number of quarters since the fund first appeared in the CRSP Mutual Funds database; $assets_t$ is the logarithm of total net assets (CRSP item tna_latest); $expenses$ is the expense ratio, defined as the asset-weighted average of item exp_ratio across share classes; $turnover$ is the turnover ratio, defined as the asset-weighted average of item $turn\_ratio$ across share classes; $flows_t$ is the net fund flow (i.e., inflows minus outflows) defined for month m as:

$$Flow_m = 100 \times \frac{TNA_m - TNA_{m-1} * (1 + R_m)}{TNA_{m-1}}$$

and then aggregated at quarterly level, as standard in the literature (e.g. Coval and Stafford (2007). This variable is winsorized at the 1% level on both tails.

bonds, and with the literature on the link between market risk and risk-taking capacity. In Panel B of Table II.11 we also include the period covering the early Covid-19 pandemic through 2020:Q4, when our data end. The results show substantially higher IG activity in the additional one year, with observations climbing from 19,000 to 30,000. At the same time, the coefficient on $\Delta_{i,t}^{IC}$ increases in magnitude and becomes statistically significant. While market risk generally leads to a weaker relation between the activity of derisking mutual funds and insurers, this was clearly not the case during during the Covid-19 pandemic.

II.3.2 The role of balance-sheet constraints

The observation that the link between insurers and mutual funds is generally tenuous when market risk is elevated, but strengthens in periods of severe market disruption, highlights the complex effect of balance-sheet constraints within the liquidity-provision ecosystem. On the one hand, deteriorating markets have a broadly adverse effect, as discussed by an extensive literature (see, among others, the early contribution of Shin, 2008). On the other hand, certain intermediaries may be affected more acutely and – especially if they are central to liquidity provision – their retrenchment could open profitable opportunities that entice other normally less active institutions. Indeed, Anand et al. (2013) find evidence that buy-side investors, like pension funds, have a stronger incentive to provide liquidity when dealers are constrained. This patterns fits within models that tie capital availability and expected returns to trading activity and ultimately liquidity (Gromb and Vayanos, 2018). In the remainder of this section, we explore how the link between deriskers and insurers responds to different types of balance-sheet constraints.

We start with developments that can limit the risk capacity of insurers. The first is large natural disasters, which generate considerable losses for property-and-casualty insurers and reinsurance companies. Massa and Zhang (2021) find that the very costly hurricane Katrina led affected insurers to shed substantial amounts of corporate bonds. The economic impact of hurricanes is also difficult to assess much in advance, hence the losses they inflict can be considered exogenous. Building on these considerations, we augment the regression in (II.5) as follows:

$$\begin{aligned}\Delta_{i,t-1}^{deriskers} = \alpha + \beta_1 \Delta_{i,t}^{IC} + \beta_2 D_{90} \times \Delta_{i,t}^{IC} + \beta_3 D_{75-90} \times \Delta_{i,t}^{IC} + \\ \beta_4 D_{90} + \beta_5 D_{75-90} + +\gamma \Delta_{i,t}^{others} + Controls_{i,t-2} + \mu_i + \nu_y + \epsilon_{i,t}.\end{aligned} \tag{II.6}$$

The specification includes interactions of $\Delta_{i,t}^{IC}$ with dummies for quarters with hurricane damages above the 90^{th} percentile (D_{90}), or between the 75^{th} and the 90^{th} percentiles (D_{75-90}) of their distribution. Note that time fixed effects are now yearly. As shown in Table II.4, the coefficient on $D_1 \times \Delta^{IC}_{i,t}$ is positive and statistically significant. It is also larger than the absolute value of the (negative) coefficient on $\Delta^{IC}_{i,t}$. As a result, the marginal effect of $\Delta^{IC}_{i,t}$ is positive, meaning that insurers start trading in the same direction as derisking mutual funds, prefiguring a shift from liquidity provision to liquidity demand that is consistent with the findings of Massa and Zhang (2021).

The second type of constraint that can reduce insurers' activity pertains to prospective increases in regulatory capital. Bond downgrades from IG to HY often precipitate fire sales by insurers (Ellul et al., 2011 and Murray and Nikolova, 2021). The reason is that regulatory capital requirements rise as ratings decline, and the most sizable increase for life insurance companies – the largest holders of corporate bonds – occurs between IG and HY (see Table 1 in Murray and Nikolova, 2019). We posit that insurers become less willing to transact with mutual funds for bonds with low IG ratings. The reason is that these bonds are, all else equal, more likely to be downgraded to HY, leading to costly fire sales. As a result, it is reasonable to expect that the coefficient on $\Delta^{IC}_{i,t}$ in equation (II.5) declines in absolute value for IG ratings closest to HY, before increasing again for HY bonds, which already command higher capital requirements and are priced accordingly. Figure II.3 shows precisely such pattern, with a clear discontinuity at the threshold between IG and HY. This result implies that insurers' liquidity provision to mutual funds declines with prospective jumps in the cost of balance-sheet usage.

The activity of insurers can also be affected by the risk-taking capacity of other intermediaries. Dealers are likely to exert a particularly strong influence, since they play an important role in corporate bond markets. Shortfalls in their liquidity supply can raise the returns earned by accommodating mutual funds' trades, enticing other investors. We use changes in dealers' holdings of corporate and foreign bonds (the two are reported together in the Federal Reserve's National Accounts of the United States). We add an interaction term to the baseline regression (II.5) that conditions $\Delta^{IC}_{i,t}$ on aggregate lagged changes in dealers' balance sheets in $t-1$ ($ChgDeal_{t-1}$). The specification, with yearly fixed effects, is:

$$\begin{aligned} \Delta^{deriskers}_{i,t-1} = \alpha + \beta_1 ChgDeal_{t-1} \times \Delta^{IC}_{i,t} + \beta_2 \Delta^{IC}_{i,t} + \beta_3 ChgDeal_{t-1} + \\ + \gamma \Delta^{others}_{i,t} + Controls_{i,t-2} + \mu_i + \nu_y + \epsilon_{i,t}, \end{aligned} \tag{II.7}$$

The marginal effect of $\Delta^{IC}_{i,t}$, conditional on various percentiles of $ChgDeal_{t-1}$, is shown in Table II.5. The link between the activity of insurers and mutual funds is statistically significant only for relatively elevated values of $ChgDeal_{t-1}$. The result indicates that large increases in dealers' holdings, which arguably reduce their ability to take on additional risk, strengthen the activity of insurers. On balance, there is evidence of complementarity between dealers and insurers in providing liquidity.

II.4 Asset-pricing and liquidity analysis

Evaluating the profitability of insurers' trades is important to characterize the nature of their activity, since liquidity providers are expected to earn profits (see, among others, Da et al., 2011 and Anand et al., 2013). To this end, we focus on bonds that are sold by mutual funds in a given quarter, and we construct portfolios based on transactions made by insurers. The portfolios go long bonds bought by insurers and short those that they sell, with quarterly rebalancing. Portfolios differ in terms of weighting (equally or by outstanding notional), bond rating, and whether they are sold by derisking mutual funds.

With standard asset-pricing regressions, we compute risk-adjusted portfolio returns relative to a set of factors known to span returns on corporate bonds (Bai et al., 2019). The regressions take following form:

$$PortRet_t = \alpha + \beta_1 MKT_t + \beta_2 DRF_t + \beta_3 CRF_t + \beta_4 LRF_t + \epsilon_t, \qquad \text{(II.8)}$$

where MKT is the excess returns on the corporate bond market, DRF represents downside risk, CRF measures credit risk, and LRF quantifies liquidity risk.

In Table II.6, Panel A shows that insurers earn up to 1% in quarterly risk-adjusted returns (α) on the bonds they buy from derisking mutual funds, relative to those they sell. Consistent with the patterns we find in the panel regressions in Section II.3, regression intercepts are considerably larger when focusing on HY bonds during quarters with low market risk. Risk-adjusted returns returns are much smaller when considering bonds sold by non-derisking mutual funds (Panel B). This difference suggests that deriskers sell at a discount, while other funds do not. As shown in Table II.7, the results carry through for equally weighted portfolios, but statistical significance wanes when including the 2008-2009 financial crisis in the sample. The reason is that bond factors experienced extreme observations during that period, confounding their link with portfolio returns. See Figure II.4 for an illustration.

On balance, return patterns indicate that insurers provide liquidity to mutual funds wishing to divest bonds relatively quickly. Further evidence emerges from the timing of return accrual. Studies highlight that the Volcker

Rule, which constrains banks' ability to engage in proprietary trading, had adverse effects on corporate-bond liquidity (Bao et al., 2018 and Allahrakha et al. (2019)). The Rule was part of the Dodd-Frank Act, which was approved in July 2010. It came into force in July 2015, after a relatively long regulatory implementation process. Most likely, the liquidity-provision ecosystem was temporarily unsettled by changes in business models arising from, first, early voluntary compliance (Keppo and Korte, 2016) and, second, adherence to the final Rule. If so, liquidity provision would have commanded a higher premium *after* the Volcker Rule was introduced and *around* its implementation. Indeed, Figure II.5 shows that buying bonds sold by mutual funds was particularly profitable for insurers *after* 2010:Q2 and *around* 2015:Q2.

The results reported in Table II.6 show that the coefficients on the liquidity factor LFR are statistically insignificant in all specifications. This pattern is consistent with similar liquidity characteristics for the bonds bought and sold *by insurers*, a result we show in Table II.8 (following Cutura et al., 2020, we use the the bid-ask spread, the Amihud (2002) measure, and the inter-quartile range, or IQR).[10] The liquidity profile of bonds bought and sold *by mutual funds* is also quite similar. This evidence indicates that the returns earned by insurers arise from price discounts, rather than from structural differences in liquidity characteristics. Note that the various statistics are computed with regressions that include time fixed effects, hence they do not reflect changes in the economic backdrop.

However, gaps emerge when market risk is elevated. Table II.9 reports coefficients from regressions of median liquidity differences between bonds sold and bought by mutual funds (ΔLiq) on market risk (VIX) and on corresponding median differences in bond yield ($\Delta yield$) and in duration ($\Delta duration$):

$$\Delta Liq_{t-2} = \alpha + \beta_1 VIX_{t-2} + \beta_2 \Delta yield_{t-2} + \beta_3 \Delta duration_{t-2} + \epsilon_{t-2}, \quad \text{(II.9)}$$

where t is the transaction quarter. The coefficient β_1 is positive, especially when focusing on large declines in exposure vs. small declines/increases in exposure, rather than simply sales vs. purchases. Since higher values of the measures indicate lower liquidity, the implication is that mutual funds tend to sell less liquid bonds in periods of elevated volatility. This evidence of liquidity hoarding during market stress is in line with the findings of Morris et al. (2017), Cutura et al. (2020), and Jiang et al. (2020).

[10] Here and in the next table, the liquidity indicators are lagged by two quarters to avoid that the measurement of liquidity is affected by noise correlated with factors that also affect the decision to trade.

II.5 Conclusions

The corporate-credit intermediation landscape has evolved substantially over time. Non-banks currently provide considerable amounts of credit, often by purchasing and then trading marketable securities. After the 2008 financial crisis, mutual funds focused on corporate bonds have grown rapidly, contributing – due to their redemption mechanism – to time-varying liquidity demand and to the risk of fire sales. Over the same period, liquidity provision by dealers declined. These developments raise questions about the nature and reliability of liquidity supply in corporate-bond markets. As highlighted by the dislocations that occurred at the onset of the Covid-19 pandemic, liquidity dry-ups can be costly enough that central banks intervene as "market makers of last resort".

We contribute to the literature on liquidity provision in corporate bond markets by analyzing trading patterns between mutual funds and insurance companies. While insurers can also engage in forced sales when bond downgrades raise their regulatory capital, they do not face the same outflow pressures as mutual funds. As a result, they have the flexibility to buy bonds that mutual funds are keen to divest. That is, insurers can provide liquidity to mutual funds. Studies highlight that reverse-tournament incentives lead certain mutual funds to reduce risk exposure to contain future redemptions. Our analysis focuses on "derisker" funds, because their sales likely reflect stronger liquidity demand.

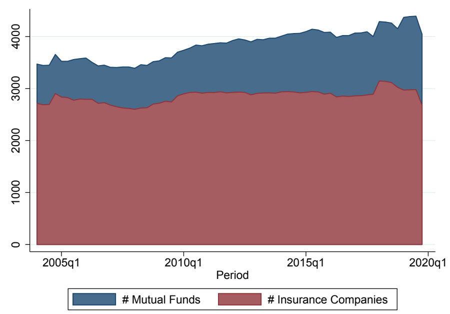
We characterize trading patterns between mutual funds and insurers, finding that they tend to trade in opposite directions in the case of high-yield bonds, which are often sold by derisking funds, and during periods of low market risk. This relation is more pronounced after large increases in dealers' balance sheets, which lower their risk-taking capacity, suggesting that insurers can complement the activity of dealers. The link between insurers and mutual funds is weakened by factors known to impinge on liquidity provision, such as large unexpected losses and the risk of sharply higher capital requirements. Consistent with liquidity provision, portfolios that go long bonds bought by insurers and go short those sold by insurers (among bonds sold by mutual funds) earn sizable risk-adjusted returns. Returns mostly accrue around the introduction and implementation of the Volcker Rule, when strains in the liquidity provision ecosystem were more likely.

On balance, our work indicates that, in good times, insurance companies can provide liquidity to corporate-bond mutual funds, helping to reduce fragility in this sector and also complementing dealers when they are more likely to be constrained. As market or industry conditions deteriorate, the link between the activity of insurers and mutual funds weakens, hinting at a fair-weather undertone in insurers' liquidity provision.

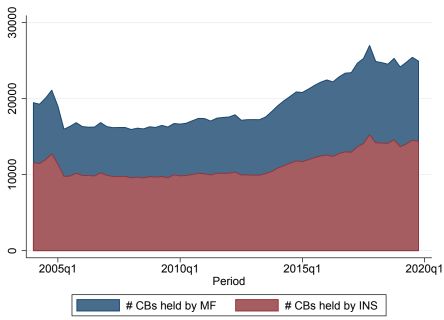
Figures and Tables

Figure II.1: Participation of insurers and mutual funds.

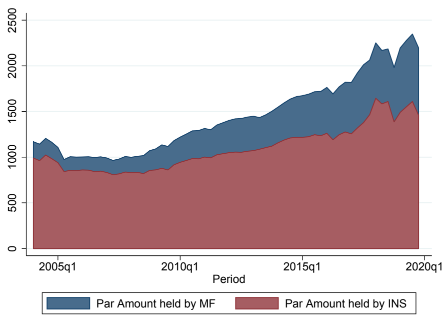
The charts illustrate key trends in the participation of U.S.-based insurers and mutual funds in the corporate bond market. Panel A plots the number of institutions that hold fixed-coupon dollar-denominated corporate bonds issued by U.S. companies, excluding bonds issued or maturing within one year and requiring that bonds are traded by at least five institutional investors in a given quarter (see Cai et al., 2019). The sample ranges from 2004 to 2019. Panel B shows the number of corporate bonds held by mutual funds and insurance companies. Panel C plots the dollar par amount of these bonds, expressed in billion U.S. dollar.



Panel A: Number of institutions.



Panel B: Number of corporate bonds held.



Panel C: Holding amount of corporate bonds.

Figure II.2: Trends in bonds sold by mutual funds and bought by insurers

The figure plots the share of bond trades in which mutual funds sell and insurers buy, as a percentage of the total number of trades within a given year. Note that, in line with the literature, we refer to bond-level quarterly changes in exposures as "trades". The solid line is based on derisking mutual funds, and the dashed line on non-derisking mutual funds. Derisking (non-derisking) mutual funds are those whose change in risk taking over consecutive quarters is below (above) the median of the cross-sectional distribution, recomputed each quarter t.

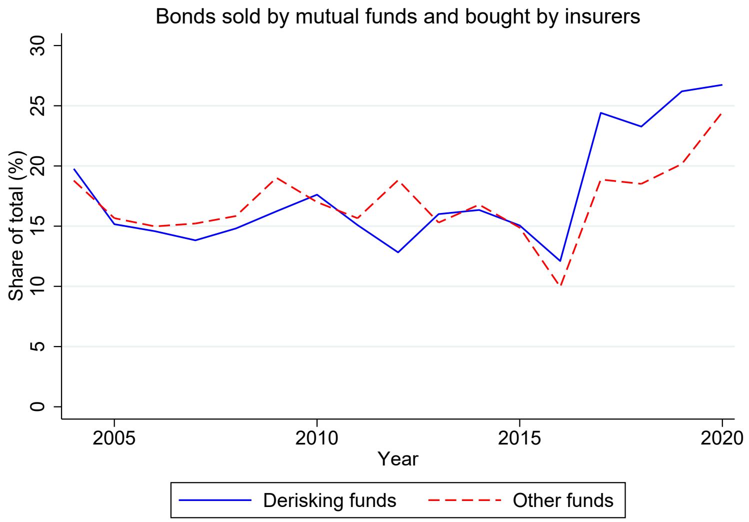


Figure II.3: Trading activity by bond rating

The chart shows the coefficient on $\Delta_{i,t}^{IC}$ from the baseline regression in equation (II.5), computed using bonds with the indicated Moody's rating. The chart contrasts bonds with the bottom three investment-grade ratings (Baa3 and better, three leftmost bars) and those with the top three high-yield ratings (Ba1 and lower, three rightmost bars). The reported 90% confidence interval is based on standard errors clustered by quarter and bond.

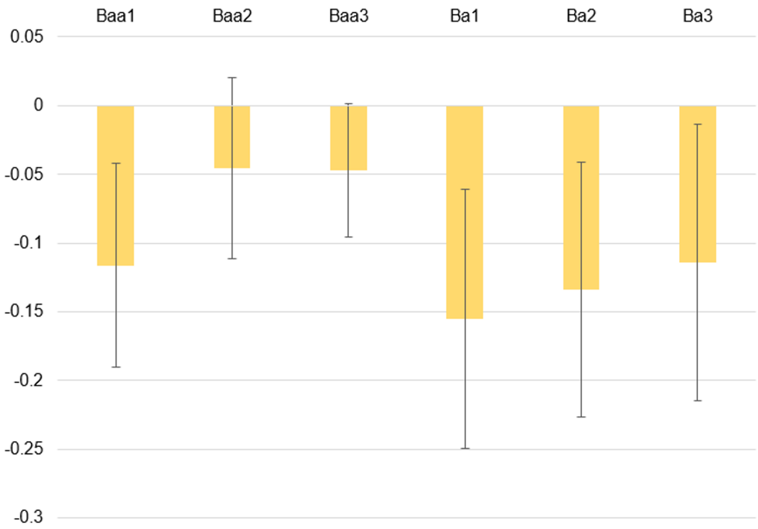


Figure II.4: The effect of outliers in pricing factors during the Great Financial Crisis.

The top chart plots the returns on the bond liquidity factor (Bai et al., 2019). The bottom figure is a partial regression plot of returns on the bond portfolio that tracks the profitability of insurers' activity (see Table II.6) on the liquidity factor. The blue dot on the right corresponds to 2009:Q2. The sample covers 2004:Q3 to 2019:Q4.

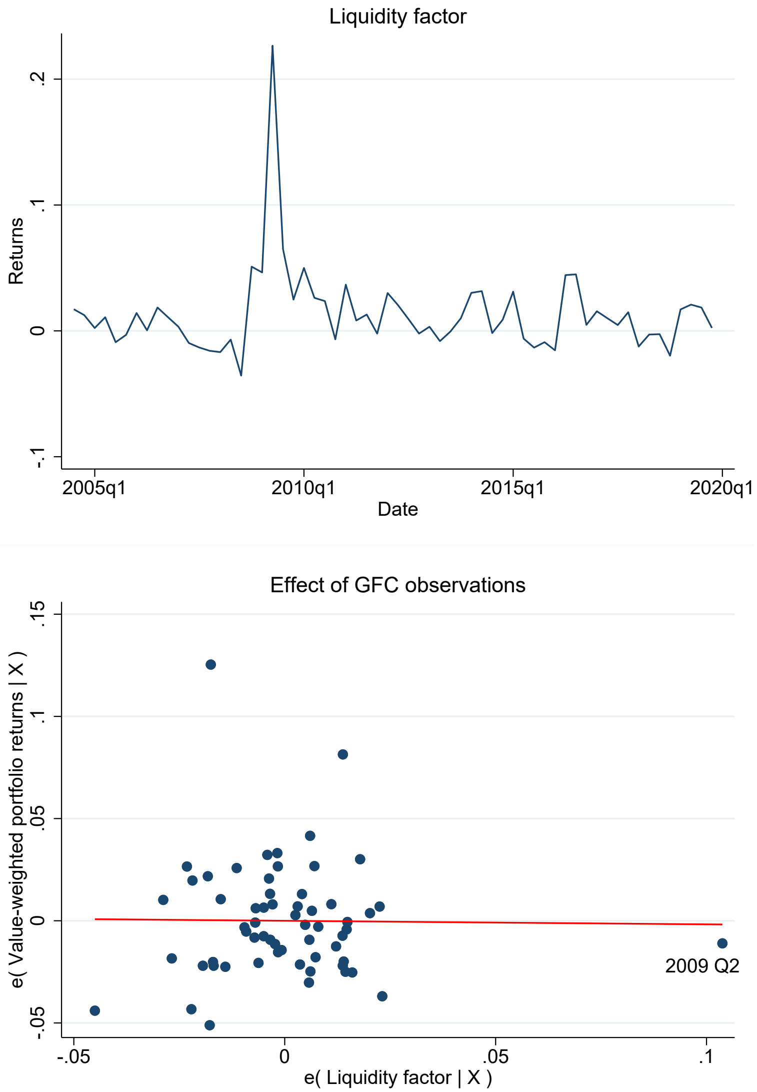


Figure II.5: The profitability of insurers' trades.

The figure plots the cumulative return on a portfolio that buys (sells) corporate bonds that are bought (sold) by insurance companies in the previous quarter. The sample is restricted to bonds sold by mutual funds. The first vertical line corresponds to 2010:Q2, just before the Dodd-Frank Act was approved in July 2010. The second vertical line corresponds to 2015:Q2, prior to the Volcker Rule coming into force in July 2015. The red part of the line, on the right, corresponds to 2020, when corporate credit markets suffered dislocations due to the Covid-19 pandemic.

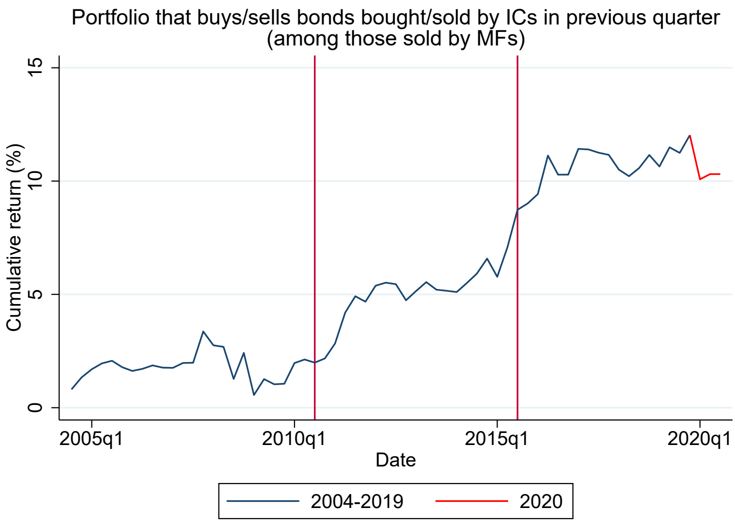


Table II.1: Summary statistics

The table shows selected summary statistics for the insurers, mutual funds, and bonds in our sample. For each variable, we report the number of observations, the mean, the standard deviation, the 5^{th}, 25^{th}, 50^{th}, 75^{th}, and 95^{th} percentiles. For insurance companies, *Size IC* is total book assets, *Leverage IC* is the ratio of total book assets to stockholders' equity, *Income/Size IC* is the ratio of net income to size (in percent). For mutual funds, *Age MF* is the number of quarters since the fund first appeared in the CRSP Mutual Funds database, *Assets MF* is total net assets (in million U.S. dollar), *Expenses MF* is the expense ratio (in percent), *Turnover MF* is the turnover ratio (in percent), and *Flows MF* is the net fund flow in percent. Panels B and C report selected characteristics for high-yield and investment-grade bonds. $\Delta^{deriskers}$, Δ^{others}, Δ^{IC} are the quarterly changes in holdings of corporate bonds for derisking mutual funds, non-derisking mutual funds, and insurers, respectively (in thousand U.S. dollar). *Return* is the quarterly bond return (in percent), while *Bid-Ask Spread* (in percent), *Amihud*, and *IQR* (in percent) are bond liquidity measures, defined as explained in Section II.2. *Duration* is bond duration. All variables are winsorized at the 1% level in both tails.

Panel A	Insurers and mutual funds							
	Obs.	Mean	St. Dev.	5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
Size IC	24,173	30,880	38,369	182.4	1,298	9,067	61,738	95,565
Leverage IC	24,103	7.512	5.357	2.093	3.373	5.774	10.24	17.53
Income/Size IC (%)	24,108	0.456	1.021	-0.596	0.148	0.320	0.826	2.001
Age (quarters) MF	27,445	27.50	16.17	5	15.70	25.00	37.28	59.00
Assets MF	27,322	521.8	1,382	2.422	16.71	68.01	302.1	2,786
Expenses MF (%)	26,842	0.755	0.315	0.218	0.531	0.760	0.965	1.295
Turnover MF (%)	26,933	1.108	0.985	0.264	0.504	0.764	1.333	3.280
Flows MF (%)	27,287	2.365	8.504	-4.381	-1.277	0.150	2.564	17.92

Panel B	High-yield corporate bonds							
	Obs.	Mean	St. Dev.	5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
Δ Derisker	55,350	-2,202	30,697	-62,585	-13,150	-530	9,717	54,502
Δ Others	55,350	-189.7	28,063	-52,588	-10,020	0	9,635	51,735
Δ IC	55,350	-2,004	10,553	-19,390	-2,590	0	603	9,340
Return (%)	55,350	-0.0179	7.661	-11.82	-1.854	0.001	2.271	10.81
Bid-Ask Spread (%)	54,901	0.660	0.609	0.122	0.266	0.462	0.836	1.860
Amihud	55,201	0.248	0.202	0.0310	0.0794	0.198	0.367	0.634
IQR (%)	54,098	0.705	0.679	0.121	0.267	0.477	0.888	2.079
Duration	53,991	4.596	2.392	1.543	3.005	4.216	5.527	9.834

Panel C	Investment-grade corporate bonds							
	Obs.	Mean	St. Dev.	5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
Δ Derisker	162,779	-738.3	22,937	-39,252	-6,632	25	6,328	35,013
Δ Others	162,779	-56.04	21,924	-34,997	-5,981	0	5,300	36,350
Δ IC	162,779	-1,721	14,580	-27,864	-4,667	0	2,484	20,055
Return (%)	162,779	0.284	3.971	-5.326	-1.231	0.0453	1.774	6.147
Bid-Ask Spread (%)	159,289	0.541	0.506	0.0820	0.224	0.395	0.680	1.500
Amihud	162,076	0.254	0.191	0.0361	0.113	0.207	0.343	0.633
IQR (%)	157,139	0.531	0.523	0.0888	0.194	0.360	0.679	1.570
Duration	162,372	6.738	4.521	1.441	3.081	5.436	10.66	15.28

Table II.2: Comovement between tilts in trading activity

The table reports the coefficients of regressions that explore the comovement between the tilt towards purchasing for insurers (the share of bonds bought as a fraction of their overall trades, or IC^b) and the tilt towards selling for mutual funds (the share of bonds sold as a fraction of their overall trades, or MF^s). The dependent variable IC^b, while the independent variables include MF^s, the implied volatility index VIX (VIX), and the interaction between VIX and MF^s. In panels A and B, shares are based on the number of bonds traded; in panels C and D, they are based on the dollar volume of bonds traded. The t-statistics are based on robust standard errors.

Shares based on trade *numbers*

Panel A	All funds	Deriskers	Deriskers ≥2010	Panel B	β_{MF^s} conditional on: Low VIX	High VIX
MF^s	-0.049	0.218*	0.429***			
	(-0.30)	(1.74)	(3.46)	All funds	-0.025	-0.073
VIX	-0.006	-0.006	-0.458***		(-0.11)	(-0.04)
	(-0.06)	(-0.06)	(-4.41)			
$MF^s \cdot VIX$	-0.024	-0.107	-0.481***	Deriskers	0.326*	0.111
	(-0.20)	(-0.93)	(-3.60)		(1.87)	(0.67)
Obs.	62	62	40	Deriskers	0.910***	-0.051
Adj.R^2	-0.049	0.014	0.327	≥2010	(8.04)	(-0.22)

Shares based on trade *volumes*

Panel C	All funds	Deriskers	Deriskers ≥2010	Panel D	β_{MF^s} conditional on: Low VIX	High VIX
MF^s	-0.003	0.238*	0.449***		Low VIX	High VIX
	(-0.02)	(1.93)	(4.12)	All funds	0.030	-0.036
VIX	-0.006	-0.012	-0.517***		(0.14)	(-0.17)
	(-0.06)	(-0.12)	(-4.74)			
$MF^s \cdot VIX$	-0.033	-0.095	-0.547***	Deriskers	0.333*	0.143
	(-0.24)	(-0.84)	(-4.43)		(1.87)	(0.92)
Obs.	62	62	40	Deriskers	0.996***	-0.099
Adj.R^2	-0.051	0.022	0.363	≥2010	(9.03)	(-0.48)

Table II.3: Linking the trading activity of funds and insurers: Bond-level analysis

The two panels of the table report coefficients from regressions of lagged trading activity undertaken by derisking mutual funds on insurers' trading activity and twice-lagged control variables, in addition to time and bond fixed effects. For readability, the coefficients on *age*, *assets*, *turnover*, and *expenses* are multiplied by 1,000. Constants are not reported. The various columns refer to different sub-samples based on bond ratings and market-risk levels, measured with the implied volatility index VIX. Columns labeled "Low VIX" and "High VIX" comprise samples focused on the bottom and top quartiles of the distribution of VIX, respectively. In Panel A, the data span 2004 through 2019; in Panel B, 2020 is also included. Bond and quarter FEs are included. The reported t-statistics are based on errors double clustered by bond and quarter.

Panel A: 2004-2019

Dep.Var.: $\Delta^{deriskers}_{i,t-1}$	IG	HY	IG Low VIX	IG High VIX	HY Low VIX	HY High VIX
$\Delta^{others}_{i,t}$	0.385***	0.455***	0.424***	0.367***	0.495***	0.398***
	(11.32)	(18.06)	(7.50)	(8.15)	(11.60)	(4.18)
$\Delta^{IC}_{i,t}$	-0.017	-0.044*	-0.041	-0.009	-0.095***	-0.065
	(-1.28)	(-1.89)	(-1.33)	(-0.40)	(-3.71)	(-1.31)
$size^{IC}_{t-2}$	-430.284**	479.465*	189.271	-851.038	1,462.617**	31.814
	(-2.09)	(1.82)	(0.43)	(-1.11)	(2.79)	(0.07)
lev^{IC}_{t-2}	-74.005	-26.721	-51.303	-105.693	157.454	-311.237
	(-0.87)	(-0.38)	(-0.30)	(-0.59)	(0.98)	(-1.70)
$income/size^{IC}_{t-2}$	-510.664	455.618	1,255.648	274.290	3,311.659**	426.224
	(-1.22)	(0.87)	(1.27)	(0.33)	(2.58)	(0.40)
age^{MF}_{t-2}	-3.408***	4.071***	-3.266*	-3.099*	5.716**	3.001
	(-4.80)	(4.32)	(-1.89)	(-2.08)	(2.37)	(1.34)
$assets^{MF}_{t-2}$	-2.682***	-3.799***	-2.501***	-3.646***	-3.234***	-5.770***
	(-12.29)	(-10.54)	(-8.93)	(-7.86)	(-6.19)	(-4.66)
$expenses^{MF}_{t-2}$	-8.317***	-10.066***	-4.453	-17.374***	-2.227	-20.782***
	(-5.28)	(-3.73)	(-1.71)	(-7.28)	(-0.42)	(-4.67)
$turnover^{MF}_{t-2}$	-0.643	1.052	-0.397	-4.163**	3.329**	0.769
	(-1.04)	(1.60)	(-0.63)	(-2.74)	(2.25)	(0.58)
$flows^{MF}_{t-2}$	-34.935	173.651**	53.439	-115.093	123.948	-306.267
	(-0.72)	(2.23)	(0.95)	(-1.32)	(1.26)	(-1.73)
Obs.	151,101	58,993	46,985	18,112	18,722	8,319
Adj.R^2	0.290	0.278	0.345	0.132	0.337	0.164

Panel B: 2004-2020

Dep.Var.: $\Delta^{deriskers}_{i,t-1}$	IG	HY	IG Low VIX	IG High VIX	HY Low VIX	HY High VIX
$\Delta^{IC}_{i,t}$	-0.025*	-0.032	-0.041	-0.066*	-0.095***	-0.014
	(-1.89)	(-1.55)	(-1.33)	(-1.91)	(-3.71)	(-0.29)
	Coefficients on other variables are not reported					
Obs.	167,466	64,432	46,985	29,858	18,722	12,073
Adj.R^2	0.286	0.274	0.345	0.180	0.337	0.178

Table II.4: The role of insurers' risk-taking capacity: The effect of hurricanes

The coefficients shown in this table are from augmented versions of the specifications shown in Table II.11; see equation (II.6) in the main text. We evaluate the effects of constraints on insurers' risk-taking capacity, in the form of losses from hurricanes, on the link between the trading activity of mutual funds and insurers. The main explanatory variable ($\Delta^{IC}_{i,t}$) is interacted with dummies that identify quarters with elevated hurricane costs, namely between the 75^{th} and 90^{th} percentiles of their distribution (D_{75-90}) and above the 90^{th} percentile (D_{90}). Regressions include bond and year fixed effect. t-statistics are based on errors clustered by bond and year.

Dep.Var.: $\Delta^{deriskers}_{i,t-1}$	(1) HY	(2) HY, low VIX
$\Delta^{IC}_{i,t} \cdot D_{90}$	0.235*	0.445**
	(1.88)	(2.34)
$\Delta^{IC}_{i,t} \cdot D_{75-90}$	-0.014	0.131
	(-0.14)	(1.25)
$\Delta^{IC}_{i,t}$	-0.073	-0.251***
	(-1.13)	(-5.16)
Coefficients on other variables not reported		
Obs.	58,993	18,722
Adj.R^2	0.174	0.302

Table II.5: The role of dealers' balance-sheet growth

The table reports coefficients from panel regressions that condition the link between the trading activity of mutual funds and insurers on the growth of dealers' balance sheets, which proxies for their spare risk-taking capacity; see equation (II.7) in the main text. The table shows the coefficient $\Delta_{i,t}^{IC}$ for different percentiles of the quarterly growth of dealers' holdings of corporate and foreign bonds, using data from table L.130 of the Financial Accounts of the United States (columns (1) and (2)), and from the NY Fed for primary dealers (columns (3) and (4)). For the period after April 2013, the NY Fed reports the breakdown of primary dealers' holdings for HY and IG bonds. The sample spans from 2004 to 2019. In columns (2) to (4), we only consider HY bonds and periods in which market risk is low, with VIX remaining in the bottom quartile of its distribution. The t-statistics are based on errors clustered by bond and time.

	Conditional coeff. on $\Delta_{i,t}^{IC}$			
Regression sample	All bonds	HY/LowVIX	HY/LowVIX	HY/LowVIX
Change in lagged dealers inventories	All bonds, all dealers	All bonds, all dealers	HY bonds, primary dealers	IG bonds, primary dealers
10th p.tile	0.010	0.115	0.130	0.01
	(0.24)	(0.14)	(0.40)	(0.06)
25th p.tile	-0.012	0.04	0.041	-0.055
	(-0.37)	(0.10)	(0.16)	(-0.42)
50th p.tile	-0.032	-0.027	-0.033	-0.128
	(-1.13)	(0.08)	(-0.15)	(-1.34)
75th p.tile	-0.077***	-0.178***	-0.339***	-0.144
	(-2.92)	(-3.05)	(-7.98)	(-1.58)
90th p.tile	-0.109***	-0.285***	-0.365***	-0.423*
	(-3.15)	(-3.05)	(-7.85)	(-1.91)

Table II.6: Asset pricing analysis

We evaluate the asset-pricing properties of value-weighted portfolios that buy (sell) corporate bonds bought (sold) by insurers in the previous quarter, out of those sold by mutual funds. Returns on the portfolios are regressed on several factors that span risks relevant for corporate bonds, including market risk (MKT), downside risk (DRF), credit risk (CRF), and liquidity risk (LRF). The factors are from Bai et al. (2019). Panels A and B focus on derisking and non-derisking mutual funds, respectively. The column "All" includes all corporate bonds, while columns "IG" and "HY" consider IG and HY separately. The column "HY, no high VIX" focuses on HY bonds and excludes quarters with VIX above its 75^{th} percentile. The years 2008 and 2009 are excluded from the sample. The t-statistics are based on robust standard errors.

Dependent Variable: Portfolio returns				
	All	IG	HY	HY, no high VIX
Panel A: Deriskers, value weighted				
MKT	0.0398	0.0352	0.5277***	0.3705
	(0.74)	(0.66)	(2.87)	(1.56)
DRF	0.0284	0.0473	-0.3358**	-0.2722
	(0.74)	(1.52)	(-2.54)	(-1.57)
CRF	-0.0938***	-0.0262	-0.2867***	-0.2880***
	(-2.74)	(-0.94)	(-2.99)	(-2.86)
LRF	0.0122	0.0301	0.0090	-0.0040
	(0.14)	(0.59)	(0.04)	(-0.01)
α	0.0024***	0.0008	0.0088***	0.0094***
	(2.75)	(1.49)	(3.00)	(2.88)
Obs.	52	52	52	52
Adj. R^2	0.1835	0.2638	0.2928	0.2274
Panel B: Other funds, value weighted				
α	0.0013	0.0011	-0.0032	-0.0021
	(1.45)	(1.53)	(-0.38)	(-0.24)
Obs.	52	52	52	52
Adj. R^2	0.2425	0.2828	0.0407	0.0339

Table II.7: Asset pricing analysis: additional results

This table extends the analysis reported in Table II.6 and shows the intercepts of factors regressions for different subsamples. For reference, Panel A reports the baseline value-weighed portfolio; Panel B refers to an equally-weighted portfolio; Panel C is similar to Panel A but includes 2009; Panel D includes both 2008 and 2009. The t-statistics are based on robust standard errors.

Sample:	All	IG	HY	HY, no high VIX
Panel A: deriskers, value-weighted, excl. 2008-2009				
α	0.0024***	0.0008	0.0088***	0.0094***
	(2.75)	(1.49)	(3.00)	(2.88)
Panel B: deriskers, equally weighted				
α	0.0020**	0.0008	0.0081***	0.0083***
	(2.42)	(1.57)	(3.28)	(3.20)
Panel C: deriskers, value weighted, including 2009				
α	0.0026***	0.0010	0.0080**	0.0092***
	(3.15)	(1.59)	(2.47)	(3.00)
Panel D: deriskers, value weighted, including 2008 and 2009				
α	0.0023**	0.0006	0.0090**	0.0085**
	(2.52)	(1.05)	(2.56)	(2.30)

Panel E: alphas for various quarters after the portfolio formation.
The sample is restricted to HY bonds.

Qtr after ptf formation	0	1	2	3
α	0.0058*	0.0088***	0.0003	0.0022
	(1.96)	(3.00)	(0.06)	(0.66)

Table II.8: The liquidity of bonds traded by insurers and mutual funds

The table explores differences in the liquidity of bonds bought and sold by insurers and mutual funds. Row 1) shows the average of several liquidity measures for all bonds in the sample (for all measures, higher values indicate lower liquidity; see Section II.2). Row 2) reports differences between bonds sold and bought by derisking mutual funds. Row 3) lists differences between bonds bought and sold by insurance companies (among those sold by derisking mutual funds). These statistics are computed with regressions that include time fixed-effect, while standard errors are clustered at the time and bond level. The measures are lagged by two quarters relative to when the changes in exposures occur. Values for the bid-ask spread and for IQR are multiplied by 100 for readability. The sample covers 2004 through 2019.

Variable:	Bid-ask spread	Amihud	IQR
1) Sample mean	0.665	0.243	0.787
2) Difference between sell and buy samples	-0.033** (-2.04)	-0.013*** (-2.67)	-0.0096 (-0.48)
3) Among MF sales, difference between IC purchases and sales	-0.063*** (-3.42)	-0.020*** (-4.14)	-0.092*** (-3.71)

Table II.9: Differences in liquidity conditional on market risk

The table reports coefficients from regressions of liquidity differences between bonds sold and bought by derisking mutual funds on corresponding differences in yields ($\Delta yield$) and duration ($\Delta duration$) and on market risk (VIX). In a given quarter, bonds sold (bought) are those for which the change in exposure is below or above zero (results shown in columns (a)). Alternatively, bonds with large (small) declines in exposures are those for which the change in exposure is below or above the 25^{th} percentile of the distribution (results shown in columns (b)). All variables are standardized. The liquidity proxies are the bid-ask spread, the Amihud (2002) measure, and the interquartile range of prices (IQR). The liquidity measures are lagged by two quarters to avoid that they reflect noise correlated with factors that also affect the decision to trade. The t-statistics are based on heteroskedasticity-consistent standard errors. The sample covers 2004 to 2019.

	Bid-ask spread		Amihud		IQR	
	(a)	(b)	(a)	(b)	(a)	(b)
VIX	0.103	0.144*	0.061	0.194*	0.232**	0.276**
	(1.27)	(1.86)	(0.53)	(1.89)	(2.40)	(2.41)
$\Delta yield$	0.566***	0.609***	0.337***	0.256*	0.653***	0.497***
	(4.65)	(7.50)	(2.78)	(1.95)	(6.05)	(4.44)
$\Delta duration$	0.154	0.318***	0.252**	0.159	0.109	0.165**
	(1.52)	(3.34)	(2.16)	(1.35)	(1.41)	(2.01)
Obs.	60	60	60	60	60	60
Adj.R^2	0.331	0.457	0.130	0.117	0.529	0.414

II.6 Appendix

Table II.10: Bond-level analysis for laggard funds

This table reports coefficients from regressions of lagged trading activity undertaken by laggard mutual funds on insurers' trading activity and twice-lagged control variables, in addition to time and bond fixed effects. For readability, the coefficients on *age*, *assets*, *turnover*, and *expenses* are multiplied by 1,000. Constants are not reported. Laggard mutual funds are funds whose past return is below the median: columns (1) and (2) refer to year-to-date returns; columns (3) and (4) to last 12-month returns. The various columns refer to different sub-samples based on bond ratings and market-risk levels, measured with the implied volatility index VIX. In particular, columns labeled "Low VIX" comprise samples focused on the bottom quartiles of the distribution of VIX. The data span 2004 through 2019. Bond and quarter FEs are included. The reported t-statistics are based on errors double clustered by bond and quarter.

	(1)	(2)	(3)	(4)
Dep.Var.: $\Delta_{i,t-1}^{laggard}$	Laggard: YTD ret		Laggard: 12-month ret	
	ALL	HY and low VIX	ALL	HY and low VIX
$\Delta_{i,t}^{others}$	0.1454***	0.1578***	0.1074***	0.0631**
	(2.85)	(3.16)	(2.86)	(2.36)
$\Delta_{i,t}^{IC}$	0.0087	-0.0593**	-0.0015	-0.0343*
	(0.42)	(-2.48)	(-0.10)	(-1.74)
$size_{t-2}^{IC}$	362.5617	720.6755	299.7415	-355.4531
	(1.10)	(1.02)	(0.61)	(-0.47)
lev_{t-2}^{IC}	44.0352	23.6037	58.4736	178.1459
	(0.53)	(0.19)	(1.03)	(1.15)
$income/size_{t-2}^{IC}$	479.6183	1,475.7874	266.4548	2,229.6601*
	(0.62)	(1.23)	(0.43)	(2.02)
age_{t-2}^{MF}	-7.297***	-0.325	-6.207***	-2.281
	(-4.44)	(-0.11)	(-3.20)	(-0.67)
$assets_{t-2}^{MF}$	-2.077***	-2.203**	-2.193***	-1.876**
	(-4.46)	(-2.66)	(-4.38)	(-2.23)
$expenses_{t-2}^{MF}$	-0.333	-6.254***	1.540	-2.115
	(-0.14)	(-3.61)	(0.59)	(-0.46)
$turnover_{t-2}^{MF}$	-0.133	0.190	0.024	0.125
	(-0.23)	(0.19)	(0.04)	(0.13)
$flows_{t-2}^{MF}$	-136.9083	-100.9375	-117.0104	-70.2497
	(-1.20)	(-0.74)	(-1.31)	(-0.49)
Obs.	145,128	8,288	135,534	8,148
Adj R^2	0.1213	0.4549	0.1335	0.5875

Table II.11: Bond-level analysis for derisking funds

This table report coefficients from regressions of lagged trading activity undertaken by laggard mutual funds on insurers' trading activity and twice-lagged control variables, in addition to time and bond fixed effects. For readability, controls and the constant are not reported. All columns refer to high-yield bonds and low VIX quarters. Column (1) reports the baseline result. Column (2) excludes bonds sold by deriskers and with lagged quarterly returns in the bottom quintile of the distribution. Column (3) excludes bonds sold by deriskers and with lagged quarterly returns in the top quintile of the distribution. The data span 2004 through 2019. The reported t-statistics are based on errors double clustered by bond and quarter. Bond and quarter FEs are included.

	(1)	(2)	(3)
	Baseline	NO bonds low ret & sold by derisker	NO bonds high ret & sold by derisker
Dep.Var.: $\Delta_{i,t-1}^{deriskers}$	HY and low VIX	HY and low VIX	HY and low VIX
$\Delta_{i,t}^{others}$	0.495***	0.512***	0.475***
	(11.60)	(12.05)	(10.92)
$\Delta_{i,t}^{IC}$	-0.095***	-0.063**	-0.119***
	(-3.71)	(-2.24)	(-3.93)
Observations	18,722	13,834	13,543
Adjusted R-squared	0.337	0.345	0.312

Paper III

The Green Side of Sell-Side Analysts

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Abstract

Over the past years investors have been showing increasing interest for sustainability in finance. As analysts play a crucial role in gathering, analyzing and producing information for the investment community, this paper investigates whether sell-side analysts are also moving their focus toward sustainable firms. We test if firms with high ESG ratings are able to attract more analysts' coverage, and whether analysts are developing specific skills in issuing influential recommendations and timely and correct earnings forecasts. The paper reports two main findings. First, starting in 2013, analysts are updating their portfolio of firms to portfolios with higher overall ESG scores. We estimate that the fraction of total coverage that goes to high ESG firms has increased from 6% to more than 25% in our sample. Second, we show that sustainable analysts are on average less influential, less precise, and more optimistic. Overall, analysts appear to be responding to a rapidly increasing demand for information on ESG factors, though the specific skills needed to navigate this new information environment seem to be lagging behind.

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III.1 Introduction

A growing literature in finance covers both the asset pricing and corporate finance implications of sustainable investing Matos (2020). Marking the increasing demand for information related to sustainability, the CFA institute launched on March 2021 the first certificate in environmental, social and governance (ESG) investing, a program that seeks to deliver the knowledge and skills required by investment professionals to integrate ESG factors into the investment process.[1]. Analysts are information intermediaries who gather, analyze, and produce information for the investment community, with the potential to influence asset prices (Kothari et al. (2016)). Moreover, analysts coverage has real effects for firms, as it decreases information asymmetry and, hence, the cost of capital (Derrien and Kecskés (2013)).

Despite the crucial role that analysts play for the investment community, and investors' increasing interest toward sustainability, previous studies overlooked the interaction between sell-side analysts and sustainability. This paper aims at filling this gap by studying whether analysts are moving toward sustainable firms, and if by doing so they are also developing specific skills that allow them to correctly interpret the rich information environment produced by ESG scores providers.

Similar to the approach used in the mutual funds literature (Hartzmark and Sussman (2019)), we define sustainable analysts by looking at the ESG score of firms in their portfolios. In particular, each year, we compute the average score at the analyst level and then sort analysts based on this measure. Sustainable analysts are those in the top 50% of this distribution. We implement this measure of analyst's sustainability for a panel covering 6,739 analysts and 6,883 firms over the period 1993-2019[2]. In our main analysis we use ESG scores provided by KLD, for which the sample is longer. However, provided that the existing literature has uncovered low correlations among different ESG scores (Berg et al. (2020)), we also run the analysis using an alternative provider for robustness check. All the results in the paper are qualitatively similar when we use Thomson Reuters ASSET4, which is available from 2004 onward.

The paper reports two main findings. First, starting in 2013, analysts modify their portfolio of firms and choose one that has higher overall ESG score. Second, we show that sustainable analysts tend to perform worse

[1] See https://www.cfainstitute.org/en/about/press-releases/2021/cfa-institute-launches-first-global-certificate-in-ESG-investing (Visited on May 18, 2021).

[2] These statistics refer to the sample of analysts' recommendations that we use in our main tests. However, our analysis require different samples. We provide a detailed description of the different samples in the data section.

when compared to other analysts. Taken together, our findings suggest that while the increased demand for information on sustainability coming from the investment sector might have pushed sell-side analysts toward more sustainable portfolios, they might not have yet fully incorporated the tools needed to add specific information value and be influential in this market. On the one hand, ESG scores increase the information available at the firm level; on the other hand, analyzing and understanding this information can be a complicated task. Indeed the link between a firm's valuation and sustainability depends on many different factors, such as a firm's specific exposure to ESG issues, the firm's comparative advantage in having impact, or the materiality of stakeholders (Edmans (2020)).

To shed light on the evolution of analysts sustainability, we first plot the time-series of analysts' ESG scores and uncover a sharp increase in the last 10 years. However, this might just be the byproduct of more high-ESG firms in the market. To address this concern, we breakdown the analyst's score into its determinants to study what drives this change. We find that about 77% of the score change is explained by a rebalancing of the analyst's portfolio, suggesting that analysts are actively choosing firms with higher ESG scores.

To further address this point, we look at the other side of the coin and ask whether analyst coverage is indeed higher for more sustainable firms. We find that between 2001 and 2019 the fraction of total coverage that goes to high-ESG firms has increased from 6% to more than 25%. We confirm this time-series prediction using a formal OLS regression with firm and time fixed-effects. We find that, within firm, coverage increases sharply by more than 7 percentage points when an ESG score becomes available. The results are even more pronounced when we look at the cross-section. In a regression with time fixed-effects, we estimate a 21% increase in coverage for firms with an available ESG score, after controlling for several firm's characteristics, such as size, market-to-book ratio, age and profitability. In the year when the ESG score is first available, our analysis suggests a 12% jump in coverage. These results are robust to the inclusion of firm level controls and the use of alternative ESG scores. Furthermore, we estimate a linear probability model to test if the ESG score correlates with the probability of losing analysts' coverage, and we find that within firm when an ESG score becomes available, the probability of completely losing analyst coverage decreases by 3.2%, after controlling for the firm's size, market-to-book ratio, age and profitability.

Starks et al. (2017) show that high-ESG stocks are mostly held by long-horizon investors, provided that these firms overperform in the long-run. Therefore, if analysts are moving toward sustainability in order to respond to the increasing demand for ESG information, we conjecture that they will be more likely to disclose long-term information. Our hypothesis is that disclosing this information could be a valuable tool to attract new clients interested in sustainability. Consistent with our conjecture, we find that sustainable analysts have roughly 2 percentage points higher probability of issuing a long-term forecast, compared to another analyst that follows the same firm in the same year. The economic magnitude is sizeable as this corresponds to an increase of about 8% from the sample average.

Next, we study the performance of sustainable analysts in producing information. Following Loh and Stulz (2011), we look at recommendation changes. We define a recommendation as influential if it is followed by significant abnormal returns, which cannot be ascribed to information releases other than that of the analyst. Using this measure of influential recommendation changes as outcome variable, we run a linear probability model, where the main explanatory variable is an analyst's sustainability. After controlling for analyst and firm characteristics that Loh and Stulz (2011) have shown to be the main drivers of influential recommendations, we find that sustainable analysts are 50 bps less likely to issue an influential recommendation. While this number might seem economically small, it is worth noting that only a small set of analysts are influential. Similarly to Loh and Stulz (2011), we find that for the entire sample, only 16% of recommendations are influential. Notably, we show that sustainable analysts tend to be less influential when they issue recommendations on brown firms, suggesting that they shift their focus toward ESG issues.

Analysts add value to financial markets also by providing timely and precise earnings forecasts. Therefore, we study the performance of sustainable analysts when they release a forecast of annual earnings. Our analysis shows that sustainable analysts, on average, have 9 percentage points higher forecast errors, when compared to other analysts releasing forecasts for the same firm in the same year. In addition, we provide evidence that this underperformance is concentrated on firms with high ESG score. This result might be driven by an excess optimism of analysts on the future prospects of the firms that they follow. To test this hypothesis, we estimate a linear probability model for issuing a forecast that is above the actual earning value, and find evidence that sustainable analysts have higher probability of being optimistic. By looking at the dispersion of analysts' forecast, we also find that the greater is the fraction of sustainable analysts covering a firm, the lower is the forecast dispersion. This results suggest herding behavior among sustainable analysts, meaning that they rely heavily on the forecasts issued by their peers.

This paper contributes to two strands of literature[3]. We contribute to the literature on financial analysts and on the role of climate and sustainability in finance. The literature on sell-side analysts is a well-developed body of research that investigates along several dimensions the determinants of analysts' skills in producing relevant firm-level information. The seminal work of Loh and Stulz (2011) suggests that only a small fraction of recommendation changes is influential. More recently, Crane and Crotty (2020) found that while the vast majority of analysts are able to process information, only top analyst display skills in information production. We contribute by showing that sustainable analysts are even less influential than the average analyst in the sample, suggesting low or bad information production of analysts in the ESG space.

Another dimension on which analysts can be evaluated is their ability in forecasting future earnings. The general consensus in the literature is that accuracy is the single most important aspect of the quality of an analyst's output (Gu and Wu (2003)). We find that analysts' sustainability leads to less precise forecasts. This seems to clash with the fact that analysts with a specific industry expertise are on average more accurate (Gilson et al. (2001)) and that analysts produce better output in industries with higher competition (Merkley et al. (2017)). However, sustainable analysts might be still in the process of acquiring specific skills in this new dimension, and competition might be relatively low at this early stage of transition toward sustainability.

Besides accuracy, another attribute of forecasts is whether they exhibit a bias. A number of explanations have been proposed in the literature to account for the empirical evidence of analysts showing excessive optimism in their forecasts, such as self-selection into firms for which they are genuinely optimistic (McNichols and Brien (1997)), strategic reporting bias (Hilary and Hsu (2013)), or first impression and confirmation bias (Pouget et al. (2017), Hirshleifer et al. (2021)) . Our paper shows that sustainable analysts are optimistically biased in their forecasts, possibly because they are inclined to think that ESG is linked to performance.

Finally, the analysts' literature studied coverage. He and Tian (2013) suggest that coverage is negatively linked to innovation, therefore the sharp increase in coverage for high-ESG firms that we uncover in this paper, might undermine the relevance of their innovation. Beyer et al. (2010) discuss the lack of knowledge of the factors that drive analysts' decisions. Moreover, Derrien and Kecskés (2013) find that coverage has important implication for corporate investments

[3]Albeit the results are robust to several specifications and to the use of different ESG score, we acknowledge that endogeneity might still be an issue in defining sustainable analysts and sustainable firms. We plan to address these concerns in future versions of this work.

and financing policies, because it helps alleviate information asymmetry and reducing the firm's cost of capital. We contribute by showing that a firm's ESG score is an important factor that influences how analysts select portfolio companies.

The literature studying the role of climate change and sustainability on firms and investors behaviors has been booming over the past years. Recently, investors showed increasing interest for firms with high ESG ratings. The existing literature shows that investors are willing to accept lower financial returns from firms with high ESG scores, because they derive non-pecuniary utility from sustainable investing (Baker et al. (2018), Hartzmark and Sussman (2019), Bonnefon et al. (2019), Bauer et al. (2021), Barber et al. (2021)), or because they perceive firms with high ESG ratings to be less risky (Dunn et al. (2018), Krueger et al. (2020), Ilhan et al. (2020)) and more trustworthy (Amiraslani et al. (2019)). We provide evidence that also other players in the financial markets, sell-side analysts, show an increasing preference for sustainability.

Investors' interests on sustainable firms result in a price pressure that pushes up the risk-adjusted value of stocks (Brandon et al. (2020)). Azar et al. (2020) and Dyck et al. (2019) show that big institutional investors are successful in helping to reduce carbon emissions of the firms where they hold a large stake. This increasing importance of sustainability for institutional investors might have generated an increase demand for information production in these firms. In this paper we show that sell-side analyst are keen to fill this gap by focusing more and more on ESG stocks. Cao et al. (2019) study the implications of socially responsible investing on price efficiency and find that high-ESG stocks entail less quantitative information, and thus respond less to mispricing signals. This is consistent with our findings that sell-side analysts do not seem to contribute significantly to the informational environment of high-ESG firms.

The paper is organized as follows, Section III.2 describes the data used in the analysis and our definition of sustainable analysts, Section III.3 studies whether and how analysts' coverage has moved toward high-ESG firms, while we focus on sustainable analysts' skills in Section III.4. Section III.5 concludes.

III.2 Data

Our analysis requires different data sources. First, we define the firms universe by selecting all firms in the CRSP-Compustat annual database for the period 1994-2019, that satisfy the following requirements. We exclude financials (SIC 6000-6999), utilities (SIC 4900-4999) , and international affairs and non-operating establishments (SIC 9000-9999). We also only keep ordinary shares (share code 10 and 11) traded on mayor exchanges (exchange code 1, 2, 3, 31, 32, 33). Finally, we exclude firms with negative or missing annual total assets.

We retrieve information on sell-side analysts from I/B/E/S. In particular, we use the recommendation and the detail estimates files. We refer to section III.4 and III.8 for a description of how we filter these samples.

Finally, our identification requires the use of ESG scores. Our primary source is the MSCI ESG KLD STATS database (formerly known as KLD). The scores measure the firm-level social performance, including community relations, product characteristics, environmental impact, employee relations, workforce diversity, and corporate governance. The database covers both the social benefits and harms of a firm, and therefore reflects both negative and positive screening process of socially responsible investing. The ESG data are published close to the end of each calendar year, and we use this information for the next calendar year. Following Cao et al. (2019), we consider five dimensions, including environment, community, diversity, employee relationship, and corporate governance. We consider both the social benefits (strengths) and harms (concerns) of the company. For each category, we compute the difference between strengths and concerns. Then, we sum up the net score in each dimension and obtain a firm-level social performance measure for each year in the sample. A higher ESG score indicates better sustainability performance. For robustness, we also incorporate an alternative data source for ESG score: Thomson Reuters ASSET4, and the results are consistent[4].

We describe the variables used in the analysis in Table III.1, and report summary statistics for all the different samples in Table III.2. Panel A reports statistics for the firm-year sample that we use to study coverage in Section III.3. Panel B, C and D focus on the analysts' recommendation and forecast samples of Section III.4. Note that the number of observation in Panel C differs from that in Panel D, because the former includes only annual forecasts, while the latter is an analyst-firm-year level sample that includes analysts isuing either a short-term (quarterly or yearly) or a long-term-growth forecast.

Sustainable Analysts

Our main analysis relies on the definition of sustainable analysts. Similar to the approach used for mutual funds (Hartzmark and Sussman (2019)), we compute the average ESG score at the analyst-year level as the yearly average ESG

[4]We use the overall ESG scores, which are percentile rank scores, and are scaled to range between 0 (minimum score) and 100 (maximum score). See, e.g., Berg et al. (2020) for a detail description of this database.

score of the firms in their portfolio. Therefore, we obtain a continuous score for each year and for each analyst in our sample. In most of the analysis, we define as sustainable those analysts for which the score is above the median in a given year.

Table III.3 reports characteristics for both sustainable and non-sustainable analysts. We find that, along several dimensions such as age, experience, number of industries followed, portfolio size and the probability of working for a top 5% brokerage house, the two groups of analysts do not seem to differ substantially. This provides an important starting point for our analysis, since we can rule out that any observable analyst characteristic drives the results of this paper.

Figure III.1 plots the time-series of analysts ESG scores. We get yearly averages from a regression of analyst score onto a series of year dummies. In the regression we control for analyst's breadth, experience and broke size, and include analysts fixed effects. We retain year 1993 as a baseline. The figure also displays the 95% confidence interval for standard errors clustered at the analyst and year level. We find a sharp increase in the average analyst ESG score starting in 2013. While this finding is reassuring that the ESG dimension is of interest for sell-side analysts, we cannot by far disentangle whether the increase stems from (i) analysts voluntarily tilting their portfolios towards high-ESG firms, (ii) new firms getting an ESG score, or (iii) firms already covered by analysts increasing their ESG score. The next section proposes an in-depth study of the different components of the rise in analyst-level ESG score.

III.3 Analysts' Response to Increasing Demand for Sustainability?

This section discusses whether and how analysts have been responding to the increasing demand for ESG-related factors coming from the investment community. In particular, we analyze the determinants of the variation in analysts' ESG scores, the evolution of coverage of high-ESG firms, and the disclosure of long-horizon forecasts by sustainable analysts.

Determinants of Analysts' Sustainability

We start by studying the determinants of an analyst change in her overall ESG score. Figure III.1 suggests that the sustainability of analysts has increased sharply over the last few years. Nevertheless, this finding might be driven by at least three possible effects, that is, (i) firms that experience an increase in their

ESG score, (ii) more firms having an ESG score, and (iii) sell-side analysts actively tilting their portfolio toward firms with higher ESG score. Therefore, we decompose the change in the score of analyst j from year $t-1$ to year t as follows:

$$\Delta\, Score_{j,t} = \Delta\, Fixed\ Portfolio_{j,t} + \Delta\, Initiation_{j,t} + \Delta\, Rebalancing_{j,t}\,, \tag{III.1}$$

where $\Delta\, Score_{j,t}$ is the difference between the score in year t and that in year $t-1$, and $\Delta\, Fixed\ Portfolio_{j,t}$ is the change in score exclusively due to the change in the score of firms already followed by the analyst in year $t-1$, net of $\Delta\, Initiation_{j,t}$; that is, the change due to firms already present in $t-1$ but that obtain an ESG score for the first time in year t. Finally, $\Delta\, Rebalancing_{j,t}$ is computed as a residual component after subtracting the first and second element of equation III.1 from $\Delta\, Score_{j,t}$, and represents the change in score coming from new firms; that is firms that are followed by an analyst in year t for the first time.

We use the sample of analysts recommendations to compute the three elements of equation III.1 and express them as a percentage of $\Delta\, Score_{j,t}$. ESG scores are from KLD. Figure III.2 displays the results. We find that the change in score coming from firms already in the portfolio, and that from initiations, combined, can account for only 23% of the total year-to-year change. Therefore, the main driver of the change in analysts' sustainability appears to be the active rebalancing of their portfolio, which accounts for roughly 77% of the total change. Combining the results of Figure III.1and Figure III.2, we show that sell-side analysts have become more sustainable in the past few years, and this change is due in large part to a shift in analysts preferences, that start following firms with higher ESG score.

Coverage and Sustainability

Another way of studying whether sell-side analysts have become more sustainable, is to look at analysts' coverage at the firm level. We first provide graphical evidence that coverage of high-ESG firms has increased over time. Figure III.3 reports the evolution of the percentage of the total coverage that goes to ESG firms. We define total coverage as the total number of analyst-firm pairs in a given year, and total ESG coverage as the same figure computed only for firms with an above-median ESG score. As above, we compute coverage from the analysts recommendation sample and use ESG scores provided by KLD.

Figure III.3 shows a steady increase in the percentage of total coverage that goes to ESG firms, which started in the early 2000s. ESG coverage could account for only 6% of the total coverage in 2001, while in 2019 reached 25%, marking a four-fold increase in less than 20 years.

We next study coverage in a more formal regression setting. In particular, we analyse how analysts' coverage has evolved with respect to sustainability both in the cross-section and in the time-series. Using a firm-year panel, we run the following regressions:

$$LogCoverage_{i,t} = \beta\, ESG_{i,t} + \gamma^{'}\, \mathbf{X_{i,t}} + \alpha_i + \delta_t + \varepsilon_{i,t}\,, \tag{III.2}$$

where $LogCoverage_{i,t}$ is defined as the log of 1 plus the number of analysts that issue a recommendation for firm i in year t[5], $ESG_{i,t}$ is either a dummy variable equal to one if firm i has an ESG score in year t, or an indicator for the year in which firm i has a score for the first time. $\mathbf{X}$ is a vector of control variables that includes log-size, market-to-book ratio, firm's age and profitability. Finally, α_i and δ_t represent firm and year fixed-effects respectively. We add δ_t alone in the cross-sectional regressions, while we include both α_i and δ_t to study the time-series. Table III.4 shows the estimates together with t-statistics for standard errors clustered at the firm and year level.

Columns (1)-(2) and (5)-(6) report results for the cross-sectional regression. We show that after controlling for firm characteristics, having an ESG score is related to an increase in coverage of $exp(0.191) - 1 = 21.05\%$ (column (2)), while the initiation of a score is linked to an 11.9% rise in coverage.

Looking at the time-series, columns (3)-(4) and (7)-(8) of Table III.4 confirm the graphical evidence of Figure III.3. In particular, adding firm fixed-effects to the regression provide a positive and significant coefficient of 0.076 linked both to the presence or initiation of an ESG score. Therefore, within firm, having an ESG score increases coverage by roughly 8% per year.

Finally, Table A1 shows that using ESG scores from Thomson Reuters provides qualitatively similar results.

A related question is whether ESG scores are also correlated with the probability of losing analysts' coverage. In table III.5 we therefore estimate a linear probability model where the dependent variable is one if the firm has no coverage and 0 otherwise. The main explanatory variable is either a dummy for higher than median ESG ratings, the continuous ESG score, a dummy equal to one if the firm has an ESG, or a dummy equal to one if the firms has an ESG score for the first time (initiation). We use time and firm fixed effects to test this probability within firm. Results are significant with all ESG measures.

[5]We include also firms in the CRSP-Compustat universe without coverage.

We find that within firm when an ESG score becomes available, the probability of completely losing analyst coverage decreases by 3.2%, after controlling for the firm's size, market-to-book ratio, age and profitability.

Disclosure of Long-Horizon Forecasts

Starks et al. (2017) show that investment horizon is an important determinant of investors' decisions regarding the ESG profile of their portfolio. In particular, their findings suggests that investors with longer horizon tend to prefer ESG firms, provided that the implementation of ESG strategies might pay out only in the long run. This peculiarity of ESG investors is likely to create demand for firms' long-term information. Therefore, we conjecture that if sell-side analysts are moving toward ESG firms, then they would be more likely to disclose their long-horizon-growth forecast, in order to respond to the change in demand for information and attract more clients.

To test this hypothesis, we use a panel at the analyst-firm-year level and run a linear probability model, where the dependent variable is a dummy equal to one if the analyst discloses her long-term-growth forecast in a given year for a given firm. The main explanatory variable is an indicator for Sustainable Analysts. We report results in Table III.6, where column (1) displays estimates for the full sample, while we consider the sub-sample of firms with high ESG scores, firms with low ESG score, and firms without ESG scores, in columns (2), (3), and (4), respectively. In each specification, we control for a set of analysts characteristics including the size of the brokerage house where the analyst works, the breadth of the analyst's portfolio, and her experience. In order to look at the cross-section of analysts in a given year, we include the interaction of firm and year fixed effects. Standard errors are clustered at the analyst, firm, and time level.

Confirming our hypothesis, column (1) of Table III.6 shows that sustainable analysts are 1.5 percentage points more likely to report a long-term-growth forecasts than analysts with a low portfolio ESG score. This corresponds to a 6% increase from the average value. Interestingly, columns (2)-(4) suggests that this result stems primarily from firms that have an ESG score, and therefore have the potential of entering both legs of the long-short portfolios of ESG investors. Moreover, Table A3 shows that similar results follow when we use ESG scores provided by Thomson Reuters.

Taken together, the results of this section suggest that sell-side analysts respond to the widespread demand for information related to sustainability. The next section will assess whether analysts are equipped with skills to add value in this new informational environment.

III.4 Are Sustainable Analysts' Skilled?

This sections ask the question of whether sustainable analysts have the skills to produce and interpret information regarding the firms that they follow.

Influential Recommendations

We start by studying the performance of sustainable analysts in producing information, and ask whether they are better than the others recommendation changes. In doing so, we follow the approach of Loh and Stulz (2011).

From the I/B/E/S recommendation sample, we compute the recommendation change for U.S. firms as the difference between the current ad previous recommendation by the same analysts. We exclude observations where there is no outstanding prior recommendation from the same analyst, or reiterations, that is zero recommendation change. Our focus is on gauging the performance of sustainable analysts in producing information that the market deems relevant. We therefore exclude recommendations that occur in the three days around quarterly earnings announcements, and days in which multiple analysts issue a recommendation for the same firm, which could be potential firm-specific news events.

We identify influential recommendations by looking at the cumulative buy-and-hold DGTW abnormal return in the window [0, 2] around the recommendation. Day 0 is either the recommendation date or the next trading day (for recommendations on non-trading days or recommendations between 4:30 PM and 11:59 PM on a trading day). We remove observations where the lagged price is less than one dollar on day 0 to prevent our results from being driven by low-priced stocks. We classify a recommendation change as influential if the CAR is in the correct direction and statistically significant[6]. Similar to Loh and Stulz (2011), only a small fraction, 16.6%, of recommendations changes are influential.

With this definition of influential recommendation, we run the following model:

$$Influential_{j,i,t} = \beta\, Sustainable\, Analyst_{j,t} + \gamma^{'} \mathbf{X_{j,i,t}} + \alpha_{i,j,t,v} + \varepsilon_{j,i,t}\ , \quad \text{(III.3)}$$

where, $Influential_{j,i,t}$ is a dummy equal to 1 if the recommendation change issued by analyst j on firm i on date t is influential, and $Sustainable\, Analyst_{j,t}$

[6]Statistically significant means that the absolute value CAR exceeds $1.96 \times \sqrt{2} \times \sigma_{\varepsilon}$. σ_{ε} is the idiosyncratic volatility, computed as the standard deviation of residuals from a daily time-series regression of past three-month (trading days -69 to -6) firm returns against market returns and the Fama-French factors SMB and HML.

is either the average ESG score of the analysts' portfolio computed for a given year, or an indicator for analyst's score above the median value. $\mathbf{X_{j,i,t}}$ is vector of analysts and firm characteristics. We pick characteristics that are shown to drive influential recommendations Loh and Stulz (2011); namely, recommendations away from the consensus, whether the analyst has been influential in the past, the market-to-book ratio, the firm's size, the level of institutional ownership, and the previous 3-months forecast dispersion and analysts' activity in the firm for which the recommendation is released. Finally, $\alpha_{i,j,t,v}$ include different specifications of firm i, analyst j, time t and industry v[7] fixed-effects. We report results in Table III.7.

The main coefficient of interest in equation III.3 is β, which is shown in the first row of the table. In Panel A, we look at the full sample of firms, while in Panel B we split the sample in firms with high ESG scores, firms with low ESG scores, and firms without a score. In both Panel A and B, columns (1)-(3) show results when *Sustainable Analyst* is a dummy variable, while we use a continuous variable in columns (4)-(6). We use ESG scores from KLD to define sustainable analysts.

Looking at Panel A, we include time and industry fixed-effects in column (1) and (4). Analyst, firm and time fixed-effects are considered in columns (2) and (5), while we include firm-year fixed-effects in columns (3) and (6). All the different specifications provide a negative and significant estimate of the coefficient on *Sustainable Analyst*, ranging from -0.003 to -0.006. Using column (2) to provide an interpretation of the results, the coefficient of -0.006 means that a sustainable analyst is 60 basis-point less likely to be influential than a non-sustainable analyst. Provided that in our sample only 16.6% of the analysts are influential, this translates into sustainable analysts having a probability of being influential that is about 4% lower than the average.

Moreover, in Panel B we show that this underperformance of sustainable analysts is mainly driven by recommendations released on low-ESG firms, while we find a positive, yet non statistical significant, coefficient for high-ESG firms. Table A4 confirms the results using Thomson Reuters scores.

Forecast Error, Bias and Dispersion

Another way of measuring analysts performance is to look at the error of their earnings forecasts. Intuitively, a bigger error is a sign of less precise forecasts. We therefore test the performance of sustainable analysts using a model similar to equation III.3, where we use as dependent variable the forecast error, defined

[7]We identify industries using 2-digit sic codes.

as the absolute value of the difference between the realized earnings and the forecasted earnings. We express this quantity as a percentage of realized earnings. Following prior literature[8], we restrict the sample to annual earnings forecasts ($fpi = 1, 2$) on U.S. firms, made during the first 11 months of a fiscal year, that is, with a minimum forecast horizon of 30 days. The 11-month requirement is imposed based on the assumption that active analysts would supply forecasts for the firms they follow during this period. An analyst who only releases forecasts more than 12 months prior to the period end is not likely to be following companies very closely. Similarly, an analyst who only releases forecasts less than 30 days prior to the period end is more likely to be mimicking the forecasts of other analysts, rather than following the companies herself. Finally, in accordance with the most common cut-off rule used in this type of studies (e.g. Capstaff et al. (1998)), we remove forecasts in excess of 100% of the actual value. These outliers are likely to reflect data errors or transient factors, such as M&As and other atypical events.

Table III.8 reports the results. In each specification, we include firm-year fixed effects and control for broker size, analyst's breadth and experience, and forecast horizon. Given the fixed-effects specification, our results shall be interpreted as a cross-sectional regression across analysts for a given firm in a given year. Our coefficient of interest is the one for sustainable analyst, defined as a dummy variable equal to one if the average KLD ESG score for an analyst in a given year is above the median.

We find that sustainable analysts have bigger forecast errors. For example, the coefficient in column (1) suggests that the forecast error of sustainable analysts is about 9 basis points bigger than that of other analysts. When we focus on firms with high ESG scores, the coefficient is 20 basis points. These results seem to confirm that sustainable analysts tend to underperform other analysts, particularly for the subset of high-ESG firms.

We want to understand where this forecast error comes from by studying the direction of the forecast bias. In particular we conjecture that, since ESG firms have better long-term prospects and given the general positive hype that has surrounded sustainability in the past few years, sustainable analysts tend to make bigger forecast error because they tend to be more optimistic on the prospects of the firms that they follow.

To test this hypothesis we run a regression similar to that of Table III.8, but change the dependent variable with a dummy equal to one if the forecast error is negative; that is, if the analyst made a prediction that is bigger than the realized value of earnings. Therefore, we run a linear probability model for the

[8]See, e.g., Clement (1999) and Harford et al. (2019).

likelihood of issuing an optimistic forecast. Table III.9 confirms our conjecture. We find that sustainable analysts are between 60 and 80 basis points more likely to issue an optimistic forecast than non-sustainable analysts, or about 2% more optimistic when considering the average value of the dependent variable.

Finally, we study the dispersion in analysts' earnings forecasts, as a proxy for differences in opinions and herding behaviors among investors Diether et al. (2002). For each firm-year, we test how the dispersion of analysts' forecasts changes in relation with the fraction of sustainable analysts covering the firm. Given that the forecast dispersion does not have a well-behaved distribution, we define a "high dispersion" dummy in terms of the median of the distribution. Table III.10 shows that for firms followed by a higher fraction of sustainable analysts, the forecast dispersion is lower. In particular, for a 10% increase in the fraction of sustainable analysts, there is 50 bps less probability of being included in the high-dispersion bucket. The results is stronger for firms with a low ESG score.

For robustness we re-run the analysis of this section using ESG scores provided by Thomson Reuters, and report the results in Table A5 and Table A6. Overall, the results are largely unchanged also when using an alternative data provider.

This section has shown that sustainable analysts tend to issue less influential recommendations, while producing more biased earnings forecasts and herding more. Taken at face value, these results might suggests that sell-side analysts become sustainable only to respond to an increasing demand for ESG-related information coming from the investment sector, but fail to produce relevant analysis. Nevertheless, these results might be consistent with at least two alternative non-mutually exclusive stories. First, analysts might have rushed into the sustainability space, without yet possessing the specific skills required in this new market. Second, interpreting how sustainability will affect the future performance of a firm is likely to be a tough task, provided that this type of information cannot be found in financial statements. We plan to further study these mechanisms in future versions of the paper.

III.5 Conclusions

This paper studies the relation between sell-side analysts and sustainability. A growing literature is studying the implications of incorporating environmental, social and governance concerns into finance. However, the role played by sustainability as a source of information for sell-side analysts is still overlooked.

This paper aims at filling this gap. We identify sustainable analysts by looking at the average ESG score of the firms that they follow, and we uncover several findings. First, we show that starting in 2013 the sustainability of analysts has increased sharply, due to analysts rebalancing their portfolios toward firms with higher ESG scores. Second, we find that the fraction of total coverage that goes to high ESG firms has risen substantially over the past 10 years. Third, consistent with analysts responding to a demand for high-ESG factors -where investors usually have longer-term horizons-, sustainable analysts are more likely to disclose long-term-growth forecasts than other analysts. Finally, we study sell-side analysts' skills in producing and interpreting information in the ESG space. We find that sustainable analysts are less influential when releasing a recommendation, and make bigger forecast error, mainly because they are too optimistic on ESG firms.

Taken together, these findings suggest that sell-side analysts are responding to a growing demand for information related to sustainability, but at the current time they are failing to produce or process valuable information for the investment community. While further research is required to study this channel, we conjecture that this might be due to the high complexity of the sustainability informational environment.

Further research should address endogeneity concerns stemming from our identification of sustainable analysts, while deepening the analysis and study whether and how sustainable analysts can be valuable for investors and the market in general.

Figures and Tables

Figure III.1: The evolution of analysts' ESG scores This figure displays the coefficients of a regression of analyst's sustainability onto time dummies. Analyst's sustainability is defined as the average ESG score of the firms for which the analyst provides a recommendation in a given year. We use KLD scores following the approach of Cao et al. (2020). In the regression we add analysts fixed-effect and control for breadth, size of the brokerage company, and analyst experience. Each point estimate is accompanied by its 95% confidence interval for standard errors clustered at the analyst and time level.

Figure III.2: What explains analysts' ESG score? This figure shows what drives the change in the ESG score at the analyst level. The ESG score of an analyst portfolio can be driven by three factors: the analyst changes the firms she follows (rebalancing), the firms in the portfolio change ESG score (fixed portfolio), and/or the firms in the portfolio start having an ESG score (initiation). 76% of the change of an analyst ESG rating in our sample is due to the analyst rebalancing her portfolio and covering more firms with higher ESG ratings.

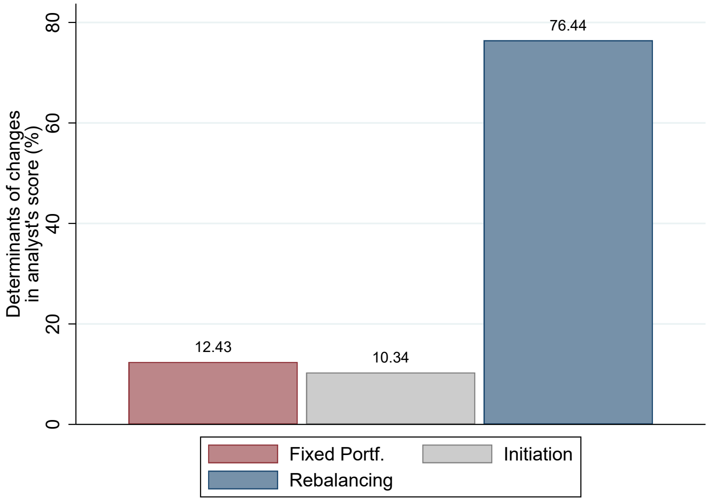

Figure III.3: Evolution of the sustainability of total coverage. The figure displays the % of total analyst-firm coverage that goes to sustainable firms in a certain year. Sustainable firms are identified as firms having ESG ratings above the median of ratings. In 1993, 10% of analysts coverage in the total market was toward sustainable firms, in 2019 this number increased to 26%.

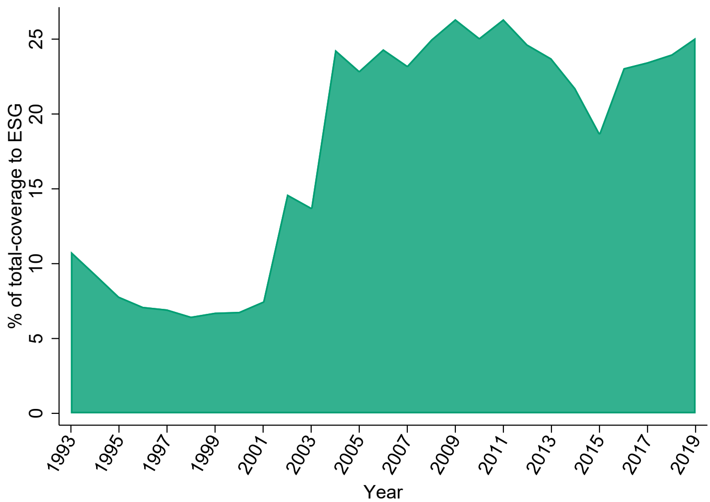

Table III.1: Variable Definitions

Age (analyst)	The total number of years that analyst j 's appeared in I/B/E/S database.
Experience	The total number of years since analyst j's first earnings forecast for firm i.
Number of Industries	Number of two-digit SICs followed by analyst j in year t (SIC2)
Portfolio Size	The number of firms for which analyst j issues recommendations in year t.
Top 5% brokerage house	Indicator variable that is equal to one if an analyst works at a top quintile brokerage in year t
Size	The natural log of market capitalization of the covered firm (in $thousands) at the end of year $t-1$.
Market-to-Book	It is defined as $(at - ceq + (csho * prccf))/at$, where at are total assets, ceq are common equity, $csho$ are common shares outstanding and $prccf$ the close price at the fiscal year end.
Profitability	It is defined as $oibdp/at$, where at are total assets and $oibdp$ are operating income before depreciation.
Coverage	The total number of analysts that follow firm i in year t.
Sustainable Analyst	It is a dummy equal to one for analysts that have ESG score of their portfolio above the median of the cross-sectional distribution, recomputed each year.
Away from Consensus	For each analyst and each recommendation, this is a dummy equal to one if the new recommendation has a distance from the oustanding consensus higher than the previous one.
Influential Recomm.	A recommendation change if influential if its associated abnormal return is in the same direction as the recommendation change and is statistically significant (with respect to the distribution of past abnormal returns).
Institutional Ownership	The dollar amount of institutional investment in firm i , calculated as firm i 's market capitalization at the end of year $t-1$, multiplied by the percentage of equity held by all institutions.
Forecast Dispersion	For each firm i and time t, it is equal to the standard deviation of analysts' forecasts, normalized by the absolute value of the mean forecast.
Analysts' Actitivity	At time t, it is equal to the number of recommendations that the analyst j released for firm j in the three months before.
Forecast Error	For each analyst j, firm i and time t, it is equal to the realized earnings minus the forecasted earnings, divided by the absolute value of the realized earnings.
Broker Size	It is equal to the natural logarithm of the number of analysts that work for a given brokerage house in year t.
Breadth	The natural logarithm of the number of firms for which analyst j issues earnings forecasts in year t.
Forecast Horizon	It is equal to the number of days between the earnings forecast issuance and the earnings announcement.

Table III.2: Summary Statistics This table displays summary statistics for the main variables used in the sample. We provide statistics for all the different samples used in the analysis. Panel A uses the firm-year sample used for the analysis of analysts' coverage. In Panel B and and C we focus on an analyst-firm-year-recommendation (forecast) sample for the tests of influential recommendations and forecast error, respectively. Finally, Panel D shows statistics for the analyst-firm-year sample that we use to test the probability of issuing a long-term-growth forecast. All continuous variables are winsorized at the 1% level and we report number of observations, mean, standard deviation, minimum, median and maximum.

Panel A: Summary Stats for Coverage Sample						
	N	Mean	SD	Min	Median	Max
Log-Coverage	92,839	1.074	0.906	0.000	1.099	2.996
Size	92,839	5.469	2.095	1.305	5.350	10.640
Market-to-Book	92,839	2.228	1.887	0.598	1.589	12.070
Age	92,839	16.650	15.350	1.000	12.000	77.000
Profitability	92,839	0.039	0.251	-1.187	0.105	0.401
Has KLD Score	92,839	0.338	0.473	0.000	0.000	1.000
Initiation of KLD Score	92,839	0.047	0.211	0.000	0.000	1.000
Has TR Score	52,606	0.255	0.436	0.000	0.000	1.000
Initiation of TR Score	52,606	0.036	0.186	0.000	0.000	1.000
Panel B: Summary Stats for Recommendations Sample						
	N	Mean	SD	Min	Median	Max
Influential Recommendation	133,521	0.166	0.372	0.000	0.000	1.000
Away from Consensus	133,521	0.282	0.450	0.000	0.000	1.000
Influential Before	133,521	0.787	0.409	0.000	1.000	1.000
Market-to-Book	133,521	2.280	1.587	0.802	1.760	10.460
Size	133,521	7.557	1.768	3.235	7.541	11.640
Institutional Ownership	133,521	0.708	0.243	0.006	0.751	1.160
Forecast Dispersion	133,521	0.819	0.232	0.000	0.835	1.410
Analysts' Activity	133,521	14.290	8.753	1.000	12.750	38.000
Sustainable Analyst Dummy (KLD)	133,521	0.498	0.500	0.000	0.000	1.000
Sustainable Analyst Continuous (KLD)	133,521	-0.025	0.465	-2.783	-0.082	4.000
Sustainable Analyst Dummy (TR)	73,544	0.518	0.500	0.000	1.000	1.000
Sustainable Analyst Continuous (TR)	73,544	38.710	14.950	1.570	37.670	93.890

Panel C: Summary Stats for Forecast Error Sample						
	N	Mean	SD	Min	Median	Max
Absolute Forecast Error (%)	547,914	10.480	17.110	0.000	3.764	100.000
Optimistic Forecast	547,914	0.358	0.479	0.000	0.000	1.000
Broker Size	547,914	3.572	1.085	0.000	3.738	5.775
Breadth	547,914	16.250	9.302	1.000	15.000	144.000
Experience	547,914	1.074	0.819	0.000	1.099	3.611
Forecast Horizon	547,914	124.100	76.480	30.000	101.000	365.000
Sustainable Analyst Dummy (KLD)	547,914	0.514	0.500	0.000	1.000	1.000
Sustainable Analyst Continuous (KLD)	547,914	0.066	0.420	-0.808	0.000	1.423
Sustainable Analyst Dummy (TR)	358,192	0.504	0.500	0.000	1.000	1.000
Sustainable Analyst Continuous (TR)	358,192	38.500	12.530	11.950	38.070	69.590
Panel D: Summary Stats for Long-Horizon Sample						
	N	Mean	SD	Min	Median	Max
Probability of Long-Term-Growth	622,625	0.246	0.431	0.000	0.000	1.000
Broker Size	622,625	3.645	1.087	0.000	3.807	6.073
Breadth	622,625	18.320	10.760	1.000	17.000	155.000
Experience	622,625	1.079	0.819	0.000	1.099	3.611
Sustainable Analyst Dummy (KLD)	622,625	0.512	0.500	0.000	1.000	1.000
Sustainable Analyst Continuous (KLD)	622,625	0.052	0.405	-0.810	-0.008	1.357
Sustainable Analyst Dummy (TR)	396,673	0.502	0.500	0.000	1.000	1.000
Sustainable Analyst Continuous (TR)	396,673	38.000	12.350	11.790	37.620	68.550

Table III.3: Analysts' Characteristics This table reports the summary statistics at the analyst-year level, where analysts are divided into sustainable and other analysts, based on the average ESG score of the firms in their portfolio. Sustainable analysts are those with an ESG rating in the top 50% of the distribution, in a certain year. All continuous variables are winsorized at the 1% level and we report number of observations, mean, standard deviation, minimum, median and maximum.

	Panel A: Sustainable Analysts					
	N	Mean	SD	Min	Median	Max
Age	15,522	7.196	6.310	2.000	11.000	26.000
Experience	15,522	3.770	1.850	1.000	3.385	9.938
Number of Industries	15,522	2.898	1.813	1.000	2.000	9.000
Portfolio Size	15,522	8.473	5.245	1.000	7.000	27.000
Top 5% brokerage house	15,522	0.743	0.437	0.000	1.000	1.000
	Panel B: Other Analysts					
	N	Mean	SD	Min	Median	Max
Age	15,305	6.925	6.318	2.000	12.000	26.000
Experience	15,305	3.926	1.919	1.000	3.538	9.938
Number of Industries	15,305	2.821	1.789	1.000	2.000	9.000
Portfolio Size	15,305	8.462	5.113	1.000	8.000	27.000
Top 5% brokerage house	15,305	0.757	0.429	0.000	1.000	1.000
Number of Analysts	6,739					
Total number of firms covered	6,883					

Table III.4: Coverage This table reports the results of an OLS regression of analysts' log-coverage on firms characteristics. Size, Market-to-Book , Age and Profitability are control variables at the firm level. The main explanatory variable is a dummy variable that equals one for firms that have an ESG score in that year (columns 1-4), and a dummy variable that equals 1 for firms that start having and ESG score in that year (columns 5-8). All specifications include Year Fixed Effects, columns 3-4 and 7-8 also include Firm Fixed Effects. Standard errors are clustered at the firm and time level and t-statistics reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are standardized.

Dependent variable	Log-coverage							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Has ESG Score	0.895***	0.191***	0.249***	0.076***				
	(25.554)	(7.486)	(13.142)	(5.691)				
Initiation of ESG Score					0.366***	0.112***	0.132***	0.076***
					(4.342)	(3.343)	(5.368)	(4.482)
Size		0.642***		0.601***		0.683***		0.620***
		(48.506)		(29.543)		(51.996)		(31.466)
Market-to-Book		0.245***		0.167***		0.255***		0.168***
		(26.264)		(22.641)		(26.219)		(22.969)
Age		-0.128***		-0.229***		-0.121***		-0.215***
		(-14.762)		(-3.668)		(-14.923)		(-3.427)
Profitability		0.013		0.054***		0.016		0.053***
		(0.819)		(7.055)		(1.010)		(6.973)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	100,638	92,839	99,641	91,532	100,638	92,839	99,641	91,532
R-squared	0.206	0.518	0.727	0.778	0.055	0.514	0.722	0.778

Table III.5: Probability of Losing Coverage This table reports the results of a linear probability model where the dependent variable is a dummy equal to 1 if analysts' coverage is zero. The main explanatory variable is a proxy for sustainability. We use a dummy variable for above median ESG scores in columns (1)-(2), the continuous ESG score in column (3)-(4), an indicator for availability of ESG scores (columns (5)-(6)), and a dummy for initiations of firm-level ESG scores (columns (7)-(8)). All specifications include year and firm fixed effects. Size, Market-to-Book , Age and Profitability are control variables at the firm level. Standard errors are clustered at the firm and time level and t-statistics reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are standardized.

Dependent variable	Probability of Losing Coverage							
Sustainability	High ESG score		Continuous ESG score		Has ESG score		Initiation of ESG score	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Proxy for Sustainability	-0.006*	-0.006*	-0.006***	-0.007***	-0.093***	-0.025**	-0.057***	-0.032***
	(-1.817)	(-1.831)	(-2.846)	(-3.118)	(-11.233)	(-2.594)	(-8.372)	(-4.776)
Size		-0.094***		-0.094***		-0.227***		-0.233***
		(-9.305)		(-9.334)		(-23.539)		(-27.555)
Market-to-Book		-0.025***		-0.025***		-0.062***		-0.062***
		(-8.479)		(-8.594)		(-19.328)		(-19.447)
Age		0.009		0.005		0.045		0.041
		(0.351)		(0.183)		(1.536)		(1.377)
Profitability		-0.011**		-0.011**		-0.036***		-0.035***
		(-2.229)		(-2.231)		(-7.094)		(-6.949)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,758	30,727	30,758	30,727	99,641	91,532	99,641	91,532
R-squared	0.563	0.568	0.563	0.568	0.578	0.610	0.575	0.610

Table III.6: Forecast Horizon The table reports the OLS estimates obtained by regressing a dummy variable that equals 1 when the forecast issued is long-term-growth. The main explanatory variable, Sustainable Analyst, is a dummy variable that equals 1 for analysts that have an ESG score in the top 50% of the distribution in that given year. Analysts control variables include Broker Size, Breadth, Experience and Forecast Horizon. All specifications have Firm-Year Fixed Effects. Column 1 estimates are obtained by the whole sample of firms. Columns 2, 3 and 4 focus on the subsample of firms with ESG ratings above the year median, below, and without ESG ratings, respectively. Standard errors are clustered at the analyst, firm and time level and t-statistics reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Probability of Issuing a Long-Term-Growth Forecast			
	All sample	High ESG firms	Low ESG firms	Firms without score
	(1)	(2)	(3)	(4)
Sustainable Analyst	0.015***	0.019***	0.023***	0.003
	(3.429)	(3.285)	(4.398)	(0.621)
Broker Size	0.053***	0.066***	0.049***	0.042***
	(18.296)	(17.380)	(15.637)	(13.513)
Breadth	-0.025***	-0.018***	-0.022***	-0.032***
	(-5.292)	(-2.734)	(-5.008)	(-7.045)
Experience	-0.014***	-0.015***	-0.012***	-0.013***
	(-6.159)	(-4.968)	(-5.014)	(-5.481)
Firm-Year FE	Yes	Yes	Yes	Yes
Observations	622,625	200,087	201,435	221,103
R-squared	0.189	0.140	0.162	0.247

Table III.7: Influential recommendations This table reports the estimates of an OLS regression of influential recommendations on analysts and firms characteristics. Analysts' recommendations are defined influential following the methodology in Loh and Stulz (2011): a recommendation is influential if it is followed by significant abnormal returns, which cannot be ascribed to information releases other than that of the analyst. Panel A includes the full sample of firms that are issued a recommendation, Panel B focuses on subsamples of firms following the firms ESG scores: Sustainable Firms are those in the top 50% of the ESG ratings distribution, Brown Firms in the bottom 50% and columns 3 and 6 of panel B include firms with no ESG score in that year. The main explanatory variable, Sustainable Analyst, in columns 1-3 is a dummy variable that equals 1 for analysts that have an ESG score in the top 50% of the distribution, in a given year, in columns 4-6 Sustainable Analyst is a continuous variable that equals the average ESG score of firms in the analyst portfolio in a given year. Analysts control variables include Away from Consensus, Influential Before, Analysts Activity. Firms controls are Market-to-Book value, Size and Institutional Ownership. For Panel A Columns 1 and 4 include Year FE and Industry FE, where Industry is defined by the firs two-digit of the SIC code. Columns 2 and 5 include Firm, Year and Analysts FE and 3 and 6 Firm-Year FE. For Panel B fixed effects are at the firm-year level. Standard errors are clustered at the firm-time level and t-statistics reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Full Sample						
Dependent variable	Influential Recommendation					
Sustainable Analyst	Dummy variable			Continuous variable		
	(1)	(2)	(3)	(4)	(5)	(6)
Sustainable Analyst	-0.006**	-0.005*	-0.005	-0.003*	-0.004**	-0.004
	(-2.044)	(-1.737)	(-1.341)	(-1.693)	(-2.233)	(-1.387)
Sustainable Analyst × Recent Sample			-0.001			-0.000
			(-0.213)			(-0.091)
Away from Consensus	-0.017***	-0.013***	-0.013***	-0.017***	-0.013***	-0.013***
	(-7.082)	(-4.792)	(-4.792)	(-7.088)	(-4.797)	(-4.797)
Influential Before	-0.058***	0.023***	0.023***	-0.058***	0.023***	0.023***
	(-13.428)	(7.881)	(7.885)	(-13.409)	(7.862)	(7.861)
Market-to-Book	0.001			0.001		
	(0.268)			(0.259)		
Size	-0.000			-0.000		
	(-0.047)			(-0.043)		
Institutional Ownership	0.009***			0.009***		
	(4.139)			(4.128)		
Forecast Dispersion	-0.010***			-0.010***		
	(-6.910)			(-6.900)		
Analysts' Activity	-0.007**			-0.007**		
	(-2.169)			(-2.179)		
Time FE	Yes	No	No	Yes	No	No
Firm FE	Yes	No	No	Yes	No	No
Analyst FE	Yes	No	No	Yes	No	No
Industry FE	No	No	No	No	No	No
Firm-Year FE	No	Yes	Yes	No	Yes	Yes
Observations	131,772	123,241	123,241	131,772	123,241	123,241
R-squared	0.157	0.289	0.289	0.157	0.289	0.289

Panel B: Subsamples by Firm ESG scores						
Dependent variable	Influential Recommendation					
Green Analyst	Dummy variable			Continuous variable		
	High ESG firms	Low ESG firms	Firms without score	High ESG firms	Low ESG firms	Firms without score
	(1)	(2)	(3)	(4)	(5)	(6)
Green Analyst	0.003	-0.014***	-0.004	0.002	-0.018***	-0.001
	(0.541)	(-2.725)	(-0.634)	(0.729)	(-4.828)	(-0.206)
Away from Consensus	-0.021***	-0.006	-0.011**	-0.021***	-0.006	-0.011**
	(-4.843)	(-1.382)	(-2.077)	(-4.839)	(-1.355)	(-2.077)
Influential Before	0.032***	0.022***	0.010*	0.032***	0.024***	0.010*
	(6.615)	(4.932)	(1.696)	(6.626)	(5.286)	(1.705)
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,169	47,471	30,601	45,169	47,471	30,601
R-squared	0.263	0.282	0.342	0.263	0.282	0.342

Table III.8: Forecast Error This table reports the estimates of an OLS regression of the absolute value of forecast error on analysts characteristics. The main explanatory variable, Sustainable Analyst, is a dummy variable that equals 1 for analysts that have an ESG score in the top 50% of the distribution in that given year. Analysts control variables include Broker Size, Breadth, Experience and Forecast Horizon. All specifications have Firm-Year Fixed Effects. Column 1 estimates are obtained by the whole sample of firms. Columns 2, 3 and 4 focus on the subsample of firms with ESG ratings above the year median, below, and without ESG ratings, respectively. Standard errors are clustered at the analyst, firm and time level and t-statistics reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Absolute Value of Forecast Error %							
	All sample		High ESG firms		Low ESG firms		Firms without score	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sustainable Analyst	0.089*	0.060	0.206***	0.225*	0.058	0.082	0.021	-0.043
	(1.925)	(0.979)	(2.862)	(1.739)	(0.794)	(0.862)	(0.279)	(-0.547)
Sustainable Analyst × Recent Sample		0.077		-0.037		-0.057		0.324
		(0.854)		(-0.242)		(-0.400)		(1.584)
Broker Size	-0.087*	-0.088*	-0.026	-0.026	-0.098*	-0.097*	-0.173***	-0.176***
	(-2.036)	(-2.044)	(-0.642)	(-0.632)	(-1.765)	(-1.747)	(-3.337)	(-3.418)
Breadth	0.124***	0.123***	0.052	0.052	0.064	0.064	0.220***	0.218***
	(2.852)	(2.833)	(1.148)	(1.148)	(1.093)	(1.098)	(4.143)	(4.112)
Experience	-0.244***	-0.244***	-0.244***	-0.244***	-0.261***	-0.261***	-0.230***	-0.230***
	(-9.565)	(-9.558)	(-9.956)	(-9.961)	(-6.164)	(-6.165)	(-4.588)	(-4.581)
Forecast Horizon	3.638***	3.637***	3.077***	3.077***	3.691***	3.691***	4.188***	4.188***
	(23.893)	(23.891)	(18.951)	(18.952)	(25.994)	(25.991)	(18.795)	(18.795)
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	547,914	547,914	184,437	184,437	181,741	181,741	181,736	181,736
R-squared	0.632	0.632	0.599	0.599	0.608	0.608	0.657	0.657

Table III.9: Forecast Bias The table reports the OLS estimates obtained by regressing a dummy variable that equals 1 when the forecast is optimistic, i.e., the realized earnings are lower than the forecasted earnings, on analysts characteristics. The main explanatory variable, Sustainable Analyst, is a dummy variable that equals 1 for analysts that have an ESG score in the top 50% of the distribution in that given year. Analysts control variables include Broker Size, Breadth, Experience and Forecast Horizon. All specifications have Firm-Year Fixed Effects. Column 1 estimates are obtained by the whole sample of firms. Columns 2, 3 and 4 focus on the subsample of firms with ESG ratings above the year median, below, and without ESG ratings, respectively. Standard errors are clustered at the analyst, firm and time level and t-statistics reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Probability of Optimistic Forecast			
	All sample	High ESG firms	Low ESG firms	Firms without score
	(1)	(2)	(3)	(4)
Sustainable Analyst	0.006***	0.008**	0.008***	0.003
	(2.890)	(2.293)	(2.813)	(1.344)
Broker Size	-0.008***	-0.008***	-0.008***	-0.007***
	(-6.874)	(-6.480)	(-5.219)	(-4.577)
Breadth	0.004**	0.004*	0.004**	0.003*
	(2.683)	(1.806)	(2.514)	(1.766)
Experience	-0.003***	-0.004***	-0.003*	-0.003*
	(-3.906)	(-3.259)	(-1.760)	(-1.940)
Forecast Horizon	0.047***	0.043***	0.047***	0.051***
	(11.542)	(9.050)	(10.419)	(11.503)
Firm-Year FE	Yes	Yes	Yes	Yes
Observations	547,914	184,437	181,741	181,736
R-squared	0.496	0.469	0.481	0.533

Table III.10: Forecast Dispersion This table reports estimates for the probability of having high forecast dispersion. The dependent variable is a dummy variable that equals 1 when the average forecast dispersion for a firm in a given year is above median . The main explanatory variable, Sustainable Analyst, is equal to the fraction of Sustainable Analysts that cover the firm in a given year. In columns (3) and (4) we interact this variable with Has ESG Score, an indicator for the availability of ESG scores in a given year for a given firm. In columns (5) and (6) the interaction is with a dummy equal to 1 for high and ESG firms. High (low) is defined with respect to the median ESG score i a given year. In these specifications we use firms without an ESG score as base group. We include firm- and analyst-level control variables. Firm controls include Size, Age, Profitability, and log-Coverage. Analysts control variables include Broker Size, Breadth, Experience and Forecast Horizon. All specifications have Year Fixed Effects. Standard errors are clustered at the firm and time level and t-statistics reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	High Forecast Dispersion Dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
Sustainable Analyst	-0.086***	-0.053***	-0.043**	-0.023*	-0.042**	-0.023*
	(-4.183)	(-4.062)	(-2.753)	(-1.709)	(-2.750)	(-1.708)
Sustainable Analyst × Has ESG Score			-0.085***	-0.075***		
			(-3.206)	(-3.414)		
Sustainable Analyst × High ESG					-0.064*	-0.050
					(-1.818)	(-1.662)
Sustainable Analyst × Low ESG					-0.049*	-0.074***
					(-1.833)	(-3.072)
Has ESG Score			-0.131***	-0.008		
			(-7.282)	(-0.569)		
High ESG					-0.165***	-0.032
					(-6.773)	(-1.537)
Low ESG					-0.128***	-0.003
					(-7.210)	(-0.195)
Size		-0.062***		-0.054***		-0.054***
		(-7.174)		(-5.971)		(-5.977)
Market-to-Book		-0.068***		-0.065***		-0.065***
		(-7.400)		(-7.200)		(-7.191)
Age		-0.030***		-0.029***		-0.029***
		(-5.985)		(-5.697)		(-5.690)
Profitability		-0.097***		-0.096***		-0.095***
		(-9.167)		(-8.997)		(-9.001)
Coverage		0.031***		0.033***		0.033***
		(4.315)		(4.632)		(4.661)
Broker Size		-0.017***		-0.016***		-0.016***
		(-4.007)		(-3.883)		(-3.904)
Breadth		0.006		0.006		0.006
		(1.239)		(1.137)		(1.144)
Experience		-0.013**		-0.010		-0.010
		(-2.086)		(-1.641)		(-1.620)
Forecast Horizon		0.039***		0.039***		0.039***
		(8.727)		(8.902)		(8.887)
P-value (High ESG v. Low ESG)					0.6280	0.4100
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,554	61,960	65,554	61,960	65,554	61,960
R-squared	0.004	0.081	0.025	0.083	0.026	0.083

Appendix

Table A1: Coverage This table replicates Table III.4 using ESG scores from Thomson Reuters ASSET4. Standard errors are clustered at the firm and time level and t-statistics reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Log-coverage							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Has ESG Score	0.944***	0.084***	0.129***	0.003				
	(18.531)	(3.059)	(5.921)	(0.175)				
Initiation of ESG Score					0.399**	0.091*	0.045	0.034
					(2.350)	(2.094)	(1.605)	(1.290)
Size		0.682***		0.558***		0.701***		0.558***
		(32.171)		(16.092)		(41.858)		(16.611)
Market-to-Book		0.267***		0.164***		0.273***		0.164***
		(16.634)		(13.817)		(18.088)		(14.016)
Age		-0.121***		-0.218**		-0.119***		-0.224***
		(-11.688)		(-2.715)		(-11.528)		(-3.039)
Profitability		-0.024		0.031***		-0.024		0.031***
		(-1.337)		(3.217)		(-1.402)		(3.195)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	55,688	52,606	55,008	51,808	55,688	52,606	55,008	51,808
R-squared	0.171	0.491	0.761	0.795	0.012	0.491	0.760	0.795

Table A2: Coverage This table replicates Table III.5 using ESG scores from Thomson Reuters ASSET4. Standard errors are clustered at the firm and time level and t-statistics reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Probability of Losing Coverage							
Sustainability	High ESG score		Continuous ESG score		Has ESG score		Initiation of ESG score	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Proxy for Sustainability	-0.003	-0.002	-0.009**	-0.007**	-0.042***	0.007	-0.014	-0.013
	(-0.457)	(-0.287)	(-2.479)	(-2.321)	(-4.879)	(0.723)	(-1.704)	(-1.393)
Size		-0.057***		-0.056***		-0.214***		-0.213***
		(-4.574)		(-4.601)		(-18.459)		(-19.034)
Market-to-Book		-0.014***		-0.014***		-0.055***		-0.054***
		(-3.455)		(-3.427)		(-14.242)		(-14.381)
Age		0.041***		0.043***		0.063*		0.067*
		(3.490)		(3.440)		(1.949)		(2.082)
Profitability		-0.004		-0.004		-0.018***		-0.018***
		(-0.631)		(-0.623)		(-3.179)		(-3.096)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,462	12,997	13,462	12,997	55,008	51,808	54,560	51,417
R-squared	0.669	0.677	0.670	0.677	0.596	0.622	0.595	0.622

Table A3: Forecast Horizon This table replicates Table III.6 using ESG scores from Thomson Reuters ASSET4. Standard errors are clustered at the analyst, firm and time level and t-statistics reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Probability of Issuing a Long-Term-Growth Forecast			
	All sample	High ESG firms	Low ESG firms	Firms without score
	(1)	(2)	(3)	(4)
Sustainable Analyst	0.010***	0.021***	0.022***	-0.003
	(5.763)	(7.024)	(6.244)	(-1.071)
Broker Size	0.057***	0.087***	0.060***	0.031***
	(82.853)	(76.711)	(44.707)	(29.526)
Breadth	-0.017***	-0.018***	-0.012***	-0.018***
	(-18.185)	(-11.586)	(-6.048)	(-12.717)
Experience	-0.016***	-0.015***	-0.018***	-0.016***
	(-21.707)	(-12.752)	(-11.063)	(-13.391)
Firm-Year FE	Yes	Yes	Yes	Yes
Observations	396,673	122,040	88,302	186,331
R-squared	0.172	0.134	0.144	0.214

Table A4: Influential recommendations This table replicates Table III.7 using ESG scores from Thomson Reuters ASSET4. Standard errors are clustered at the firm-time level and t-statistics reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A	Dependent variable: Influential Recommendation			
	All sample	High ESG firms	Low ESG firms	Firms without score
	(1)	(2)	(3)	(4)
Sustainable Analyst	-0.014***	-0.010	-0.028***	-0.008
	(-3.179)	(-1.404)	(-3.531)	(-1.148)
Away from Consensus	-0.015***	-0.017***	-0.019***	-0.012*
	(-4.489)	(-3.002)	(-2.824)	(-1.924)
Influential Before	0.028***	0.027***	0.027***	0.031***
	(6.338)	(4.332)	(3.421)	(3.653)
Firm-Year FE	Yes	Yes	Yes	Yes
Observations	73,544	25,820	19,122	28,602
R-squared	0.278	0.224	0.256	0.324

Table A5: Forecast Error This table replicates Table III.8 using ESG scores from Thomson Reuters ASSET4. Standard errors are clustered at the analyst, firm and time level and t-statistics reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Absolute Value of Forecast Error %			
	All sample	High ESG firms	Low ESG firms	Firms without score
	(1)	(2)	(3)	(4)
Sustainable Analyst	0.081	0.171**	0.084	0.007
	(1.500)	(2.364)	(0.721)	(0.099)
Broker Size	-0.004	-0.059	0.007	0.011
	(-0.106)	(-1.445)	(0.088)	(0.208)
Breadth	0.083	-0.056	0.073	0.198**
	(1.272)	(-0.844)	(0.726)	(2.311)
Experience	-0.248***	-0.201***	-0.300***	-0.294***
	(-7.898)	(-5.504)	(-6.501)	(-5.922)
Forecast Horizon	3.472***	2.625***	3.485***	4.133***
	(23.077)	(17.003)	(21.316)	(24.690)
Firm-Year FE	Yes	Yes	Yes	Yes
Observations	358,192	114,703	80,876	162,613
R-squared	0.624	0.589	0.586	0.639

Table A6: Forecast Bias This table replicates Table III.9 using ESG scores from Thomson Reuters ASSET4. Standard errors are clustered at the analyst, firm and time level and t-statistics reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Probability of Optimistic Forecast			
	All sample	High ESG firms	Low ESG firms	Firms without score
	(1)	(2)	(3)	(4)
Sustainable Analyst	0.006**	0.009**	0.002	0.006**
	(2.712)	(2.339)	(0.640)	(2.723)
Broker Size	-0.006***	-0.008***	-0.006***	-0.005***
	(-4.589)	(-4.188)	(-3.360)	(-3.075)
Breadth	0.004	0.004	0.006**	0.002
	(1.652)	(0.998)	(2.636)	(1.127)
Experience	-0.004***	-0.004***	-0.003*	-0.004***
	(-4.473)	(-3.028)	(-1.848)	(-5.569)
Forecast Horizon	0.042***	0.038***	0.041***	0.045***
	(8.835)	(7.364)	(6.970)	(8.927)
Firm-Year FE	Yes	Yes	Yes	Yes
Observations	358,192	114,703	80,876	162,613
R-squared	0.489	0.455	0.465	0.519

Table A7: Forecast Dispersion This table replicates Table III.10 using ESG scores from Thomson Reuters ASSET4. Standard errors are clustered at the firm and time level and t-statistics reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	High Forecast Dispersion Dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
Sustainable Analyst	-0.200***	-0.069**	-0.099***	-0.028	-0.099***	-0.028
	(-5.537)	(-2.677)	(-3.901)	(-1.361)	(-3.896)	(-1.364)
Sustainable Analyst × Has ESG Score			-0.193***	-0.149***		
			(-6.278)	(-4.921)		
Sustainable Analyst × High ESG					-0.138***	-0.118**
					(-2.952)	(-2.499)
Sustainable Analyst × Low ESG					-0.165***	-0.145***
					(-4.545)	(-3.971)
Has ESG Score			-0.102***	-0.014		
			(-4.955)	(-0.796)		
High ESG					-0.159***	-0.044
					(-4.533)	(-1.316)
Low ESG					-0.091***	-0.006
					(-4.937)	(-0.416)
Size		-0.073***		-0.048***		-0.048***
		(-6.929)		(-4.364)		(-4.192)
Market-to-Book		-0.088***		-0.081***		-0.081***
		(-11.960)		(-11.056)		(-10.873)
Age		-0.031***		-0.027***		-0.026***
		(-5.196)		(-4.363)		(-4.310)
Profitability		-0.074***		-0.076***		-0.076***
		(-7.418)		(-7.583)		(-7.656)
Coverage		0.041***		0.043***		0.043***
		(4.483)		(4.895)		(4.883)
Broker Size		-0.016***		-0.017***		-0.018***
		(-2.959)		(-3.212)		(-3.229)
Breadth		-0.012		-0.014		-0.014
		(-1.494)		(-1.717)		(-1.718)
Experience		-0.027***		-0.026***		-0.026***
		(-3.721)		(-3.648)		(-3.620)
Forecast Horizon		0.051***		0.051***		0.051***
		(16.243)		(16.687)		(16.576)
P-value (High ESG v. Low ESG)					0.6021	0.6245
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,641	38,855	40,641	38,855	40,641	38,855
R-squared	0.020	0.099	0.049	0.104	0.049	0.104

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