

THE UNIVERSITY OF CHICAGO

CAN INSTITUTIONAL INVESTORS TRADE ON NEWS? EVIDENCE FROM  
FIRM-LEVEL AND MACROECONOMIC ANNOUNCEMENTS

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## ABSTRACT

Using the database of holding and trades of global institutional investors, we show that discretionary, long-only equity investors pay immediate attention to both macroeconomic and firm-level news. On earnings and macro announcement days, the number of traded positions and trade sizes increase by 20%-50%, regardless of news content, for both buy and sell trades. The increases in trading activities are high and persistent over time. However, not all trades on announcement days are informed. The informed trades lie in one domain - trading on the firm-specific information. Earnings announcement news helps investors make informed trades, especially the sell trades. The average sell performance on earnings announcement increases by about 1%-3% per year, compared to sell trades on non-announcement days. This skill on trading on firm-specific information is not subject to decreasing returns to scale. Investors who trade more on earnings announcement news also have higher fund alpha by nine basis points at the one-year horizon for every 1% increase in trading activity on earnings announcement. Despite increases in trading activities on macroeconomic announcement days, trading performances on those days add little value, and are worse than trades on non-macroeconomic announcement days on average. These results are consistent with the fractionation hypothesis and the difficulty in trading upon the macroeconomic information. Institutional investors overextend their domain of skills in trading on firm-specific information to other types of unfamiliar, hard-to-trade information.

# CHAPTER 1

## INTRODUCTION<sup>1</sup>

### 1.1 Introduction

In the 21st century, so much information is readily available that investors can be inundated with news they can choose to trade on. Institutional investors are compensated for monitoring and incorporating relevant information into their portfolios on a daily basis. However, to date, the academic literature provides little understanding on what information drives decisions of investors, especially sophisticated investors.<sup>2</sup> Typical market microstructure models often assume informed, actively-trading investors exist to correct mispricing in the market.<sup>3</sup> However, evidence from performance literature suggests such a group may not exist because the average returns of experts such as mutual funds are negative after fees. In this paper, we use a novel dataset of 783 global institutional investors and track daily holding and trading decisions to study investors' reaction to information. Our paper asks what types financial experts pay attention to and whether they make informed trading decisions on those sets of information.

We focus on two types of information in this paper: (1) firm-specific information and (2) economy-wide macroeconomic information. The main reason for this dichotomy is the breadth of securities that are affected by each type of information. In the first order,

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1. THIS DISSERTATION INCLUDING ALL CHAPTERS IS JOINT WITH RICK DI MASCIO, ALEX IMAS AND LAWRENCE SCHMIDT.

2. Constantinides and Gosh (2017) start their paper with the following quote: "An overload of worldwide macroeconomic, business, and political news inundates investors. Little is known as to how investors cope with this vast amount of information and, in particular, which subset of information they pay attention to."

3. Typical models in this area include Grossman-Stiglitz (1980), Kyle (1985), Diamond and Verrecchia (1981), Kyle, Obizhaeva, and Wang (2017), Kyle and Lee (2017). The typical assumption for the models to work is that some investors in the market have perfect information.

firm-specific information affects only related securities, whereas macroeconomic information affects all securities in the market.<sup>4</sup> Second, different types of investors specialize in trading on a specific set of information. For example, global macro funds focus on building portfolios across asset classes based on macroeconomic news and trends in different market conditions.<sup>5</sup> In this paper, investors in the dataset are long-only, long-term, equity investors with average holding periods of 480 days. Most of the investors in the sample are discretionary equity investors who carefully evaluate securities, perform careful due diligence and then invest in stocks of their highest conviction.<sup>6</sup> They are much less diversified than their benchmark or quantitative funds. Table 4.3 shows the distribution of the number of funds. On average, 38% of the funds in the sample hold less than 50 stocks, and 42% hold 50-100 stocks annually. Hence, this dataset presents a perfect setting to test the soundness of expert decision-making in response to news, because we can track investors' decisions upon information-release days. For tractability, we focus on the major news of each type of information. For firm-specific information, we analyze the decisions of portfolio managers around earnings announcement news. For macroeconomic information, we analyze the de-

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4. Indirect, second-order impacts on each type of information could exist. First, connected firms such as those with supplier/customer relationships could be affected by the release of firm-level supplier news. Second, although macroeconomic information affects all firms, each firm may have different exposure to macroeconomic news and respond differently on macroeconomic announcement days.

5. JP Morgan Asset Management explains its global macro investing as follows: "Themes and trends in the global economy are the biggest driver of asset price returns. Global macro investing seeks to take advantage of these changes by delineating macroeconomic thinking into a set of themes or trends and assigning certain levels of probability as to how these will evolve through time. To efficiently reflect macro themes in a portfolio, investors must draw on a broad set of asset classes. Macro investing typically aims to generate positive returns in different market environments, with a lower level of volatility than equities to limit falls in periods of market stress and achieve a smoother path of portfolio growth."

6. The following quote is an excerpt from Pedersen (2015), who interviewed Lee S. Ainslie III of Maverick Capital. Lee described his discretionary investment process: "We are trying to look out two or three years in every industry in which we invest, trying to identify who's winning and losing, and, perhaps most importantly, recognize the discrepancies between our view and the view of the markets. We have a deep and thorough process. I think we're unusual in that our typical ratio of primary positions to investment professionals is roughly four to one, which allows an uncommonly deep level of due diligence."

cisions around US, EU, and UK government macroeconomic releases of interest rate, GDP, PPI, and unemployment<sup>7</sup>. The results in the paper are robust to the choice of PPI and CPI.

The first part of this paper is concerned with investor attention and trading activities of discretionary equity investors. We measure attention to each type of information, using trading activities on the announcement days, relative to non-announcement days. We find the number of traded positions and trade sizes increase substantially, on the day of firm-level and macroeconomic information releases. On earnings announcement days, the average probability of trading increases by 14% to 58% and the average trade size increases by 42% to 105%. On macroeconomic announcement days, the average number of traded positions increases by 15% to 51% and the average trade size increases by 17% to 57%. However, on UK macroeconomic announcement days, investors do not increase trading activities, because the shares of UK in the global economy are smaller than the US and EU. The increase in trading activities continues for a day after the release of each news. Besides, funds, which are more discretionary, as proxied for by few positions and low assets under management(AUM), increase trading activities more in response to the news announcement. The increases in trading activities on announcement days are robust after we control for fund-level characteristics such as past performance, volatility, strategies, asset under management, and diversification, as well as position-level characteristics including past-position returns, holding length, and position's weights. The arrival of news explains most of the increases in trading activities. Content of the news, measured by surprises, explains little of the variations in the trading activities, and the effects of news surprises are small.

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7. Types of macroeconomic and firm-level news occur that are not analyzed in this paper. For convenience, we follow a similar list of the macroeconomic announcement in Savor and Wilson (2013). Our main focus is to compare the impact and informativeness of trading on the firm-specific and macroeconomic information. The analysis in this paper could be replicated using other events, as long as the date of the events is known.

Besides increases in trading activities, we document the behavior of the trade-based attention measures for each type of announcement over time and their correlation with each other. First, investors' attention to firm-level and macroeconomic information is persistent over time. In contrast to Kacperczyk et al. (2016), we do not find the trade-based attention measures vary over the business cycle, because institutional investors have an incentive to monitor all possible news that can affect their portfolios. On average, institutional investors in the sample pay consistently high attention to macroeconomic and firm-level news under all market conditions. Second, each investor concentrates his or her attention on a few types of information. For buy trades, the correlations of trading activities across news are weak. However, investors use both EU and US macroeconomic information to initiate sell trades on the announcement days. This result suggests each investor is unique and incorporates information he is familiar with.

In comparison to previous academic work, our measure of trading activities is new and estimated off the within-fund changes in trading activities, which represent changes on an intensive margin. Although similar trading measures can be constructed using aggregate trading volumes, those measures consist of both the intensive and extensive margins. In other words, aggregate trading volumes can change because (1) each investor trades differently (intensive margin) or (2) the composition of traders changes (extensive margin). Our trading measure estimates the first channel and can be easily interpreted as fund-level increases in trading activities.

The second part of the paper tests whether institutional investors have skills in incorporating firm-specific or macroeconomic information into investment decisions. We challenge the assumption of the existence of informed traders and test it directly by analyzing over four million trading decisions of institutional investors. To test whether financial experts are informed, we measure skills in incorporating information based on future performance of trades on information-release events, relative to a strategy that uses no infor-

mation. Similar to Akepanidaworn et al. (2018), we construct a counterfactual random-trade strategy whereby investors equally trade stocks that they hold on each day in order to benchmark actual trading performance. The critical insight from our previous paper is that institutional investors are good buyers but bad sellers because they allocate more resources to buy decisions and use heuristics such as extreme returns to make sell decisions.

A striking pattern on trading skills on different information events emerges. We find that institutional equity investors benefit from learning about and trading on firm-specific information, although they receive little benefits from trading on the macroeconomic information. When investors pay attention to and trade on earnings announcement news, their selling performance improves substantially. Although the average sell trades are bad and underperform a random sell strategy, the sell trades on earnings announcement days generate high positive returns by 1% over a one-year horizon. On average, their counterfactual sell returns on the earnings announcement days outperform counterfactual sell returns on non-earnings announcement days by 2.2% over a one-year horizon per stocks sold. We find no improvement in performance on trades initiated on macroeconomic announcement days even though investors in the sample trade substantially more on those days. In many cases, such as sell trades on the UK macroeconomic announcement days, the sell performance is worse than trades on days without macroeconomic announcements by 1% per position over the average holding period horizon.<sup>8</sup>

The results on trading skills of investors are robust to alternative explanations such as post-earnings announcement drifts or risk difference on announcement days. We rule out the alternative explanation that investors generate outperformance, by exploiting the post-earnings announcement drift strategy for two reasons. When trading on earnings an-

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8. This statement is not to say that institutional investors as a whole cannot trade on macroeconomic news. Investors in the sample are mainly discretionary fundamental investors. There can be subsets of investors such as Global Macro fund managers that are good at trading on macroeconomic information, but our sample is not composed of those investors.

nouncement news, investors make profitable trades regardless of earnings surprises, and even in the case of no surprise. Second, these trades are profitable in the long run exceeding one quarter, which is a typical profitable period of the post-earnings announcement drift strategy. We also perform various risk adjustments to the counterfactual returns, by looking at factor-neutral returns and subsetting sample into developed markets, where there are less of liquidity risks. We find that risk characteristics, measured by Fama-French four-factor loadings, CAPM betas, and announcement betas, are the same for stocks traded on the announcement and non-announcement days. Value added measures with risk adjustment show similar patterns as the raw returns, with slightly lower different magnitudes. Hence, our results are unlikely to be driven by changes in risks on announcements.

We further test whether the outperformance can be sustained as investors trade more on the firm-specific news and how it contributes to total returns of a portfolio. Although investors make the right sell trades on earnings announcement days, this right decision may not be scalable. If the investment opportunities on firm-level trades become rarer and good ideas are limited, investors who trade too much on earnings announcement news may run out of good ideas and eventually trade on uninformed ideas. In the data, we find no decreasing returns to trading scale. Trading on earnings announcement days has constant returns to scale, so investors - who trade more - do not make or lose more. Constant returns to scale in trading are a skill in itself as traditional mutual funds have decreasing returns to scale as their size increases. However, this skill is not persistent and reverts to a fund's average selling skills, which are positive. Because investors who trade more have positive scalable selling returns, the trading on earnings announcements statistically significantly predict higher future risk-adjusted returns. Investors - who increase their probability of trading on earnings announcement days by 1% - earn higher risk-adjusted returns by nine basis points per annum. Our estimate is in line with Puckett and Yan (2011), who estimate

interim trading yield returns of 20-26 basis points per year. Our estimate is lower because investors in our sample do not trade very often.

So, why do investors in the sample make poor trading decisions when they use macroeconomic news, whereas they make sound trading decisions when they use firm-specific news? Our explanation is fractionation - trading on two different types of news involves two separate tasks requiring different skill sets. Discretionary equity investors typically perform a fundamental analysis whereby they carefully interpret firm-level information and perform thorough due diligence to make investment decisions. Earnings announcements provide investors with potentially valuable and new information on both hard accounting information and soft information such as earnings calls and texts from quarterly or annual reports. Because they perform these tasks on a daily basis, they are likely able to identify profitable trading opportunities from the firm-specific information. On the other hand, macroeconomic announcements provide information about the overall state of the economy as well as future trends. How this macroeconomic information fits into the toolkits of discretionary equity investors and why long-horizon discretionary equity investors should take actions on the macroeconomic events are unclear. Investors who make profitable trades on macroeconomic events must be able to identify how a stock responds to macroeconomic shocks differently from all other stocks. This task is hard to estimate and uncommon for discretionary, fundamental investors. Investors who can successfully trade on firm-specific information may extrapolate that they can trade on all sorts of information and hence make neutral or value-destroying trades on other types of unfamiliar information.

Another potential explanation for our results is that macroeconomic information is much harder to trade than firm-specific information. Institutional investors are typically

compensated by relative performance, usually to some benchmarks.<sup>9</sup> When investors trade on firm-specific news, the news likely directly affects the returns of securities they are trading. The firm-specific news may indirectly affect other connected stocks, but the effect is likely to be smaller than the direct effects.<sup>10</sup> Macroeconomic news, however, affects both the securities that investors trade as well as all their other holdings and their benchmark. To make profitable trades on macroeconomic information, investors need to identify how macroeconomic news will affect the potential traded stocks differently from all other stocks in the portfolio and their benchmark. Trading on macroeconomic information is a hard task, especially when the number of stocks increases and when traders are not expert macroeconomists. Hence, trades initiated on macroeconomic announcement days may not add value because both traded stocks and a benchmark move similarly. Trades on earnings announcement days are more likely to be profitable, since any benchmark will not respond to firm-specific information as much as traded firms themselves.

## 1.2 Literature Review

The current analysis of this paper ties together three strands of literature: investor attention, investor trading and performance, and macroeconomic, earnings announcement. Our contributions are as follows:

Our paper contributes to investor-attention literature by documenting the micro-level details on how the attention institutional investors pay to different types of news. We directly measure investors' attention as trading responses to news when news arrives. Kacper-

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9. An emerging literature studies asset pricing behavior under the "relative performance" incentives of institutional investors. Basak and Pavlova (2013), and Lines (2016) model investors' objective as maximizing benchmark-adjusted returns.

10. Cohen and Frazzini (2007) show asset prices slowly incorporate news of related firms that have a supplier-consumer relationship.

sky et al. (2016) show theoretically that fund managers should optimally pay more attention more to aggregate signals during recessions and tilt portfolios to co-vary more with aggregate shocks. Peng and Xiong (2006) show theoretically that fund managers with limited attention will tend to process market-wide information rather than stock-specific information. Kacpersky et al. (2014) show empirically that fund managers' stock picking and timing skills vary over the business cycle. Sheng (2018) shows macroeconomic news increases investors' attention, abnormal trading volumes and the response of stocks to earnings news. Unlike the literature, we directly measure the intensive margins, by comparing trading activities of the same investor on announcement days to no-news days. We show that the changes in the intensive margins of discretionary investors in the sample are much larger (20%-50% increase) than the typical changes in the aggregate volume (4% increase).

For individual (retail) investors, researchers have extensively documented the attention behavior and the effect on stock prices. Barber and Odean (2008) uses retail brokerage account data to show that retail investors are net buyers of stocks on high-volume days following extreme positive one-day returns and stock's news in media or announcement. Da, Engleberg and Gao (2011) shows high attention, proxied by Google Search Volume Index (SVI), predicts reversal, which hints at over-reaction. Ben-Rephael, Da, Israelsen(2017) shows that the SVI is driven by trading of retail investors by comparing the SVI and the Abnormal Institutional Investor Attention(AIA) from Bloomberg search. The drift and subsequent reversal only occur for stocks with high SVI but low AIA. Liu and Pen (2015) shows Google Search Volume Index increases on macro news days, which suggest that retail investors also pay attention to macro news. Our paper contribution is the different focus - studying mainly the attention of sophisticated, and informed institutional investors.

Our paper is the first to measure institutional trading performance on news that investors use to trade. Most studies in this literature focus on quarterly changes in holdings of institutional investors and study the performance of funds based on the low-frequency measures.

Papers with detailed trading decisions usually study retail investors who might not be informed. Related papers find the following. Fang et al. (2014) show that some mutual funds trade considerably on media-covered stocks, and those that do so underperform. Grinblatt et al. (2012) show that high-IQ retail investors outperform low-IQ investors in trading. Kacperczyk and Seru (2007) measure the fund manager's use of public information and show that fund managers who use less public information perform better than managers who use more public information. This paper shows that investors can profit from trading on public firm-level information and this skill can be scaled up. Bernile and Tang (2014) show investors are informed on FOMC announcements, and their pre-announcement trades are profitable whereas their trades on other macro announcement are not as profitable.

This paper also contributes to the literature on macroeconomic announcements, and earnings announcements. We explicitly analyze how institutional investors react to, and how informed their trading decisions are. Most of the studies in this literature have focused on aggregate market reaction to news, not investor reactions. Savor and Wilson (2013) document that 60% of US equity premium is earned on macroeconomic announcement days, which comprises 13% of the year. Brusa, Savor and Wilson (2018) show that for global equities, only the US macroeconomic announcement explains the announcement premium and the cross-section of equity returns across the globe. Lucca and Moench (2015) show the US returns drift prior to FOMC announcement, whereas no other announcement generates the same patterns. Ederington and Lee (1993) show that future market and interest-rate markets react to information release within one minute of release and the profitable trading opportunity is short-lived. Medovikov(2016) shows market reacts most to bad macroeconomic news and discounts goods news. Gibert et al. (2017) show that timeliness and relation to fundamentals are two critical characteristics of the macroeconomic announcement that affect asset prices. Barber et al. (2016) show that stocks across countries have higher returns during the announcement month and higher trading volume on the day of earnings

announcement and one day afterward. Large literature since Bernard and Thomas (1989) studies post-earnings announcement drifts. We contribute to this literature by showing that institutional discretionary investors understand the content of earning news and make sound trading decisions on the earning release days. The outperformance of investors in the sample extends even beyond 60 trading days, which is the typical duration of the post-earnings announcement drift strategy.

### **1.3 Thesis Outline**

The remainder of the paper proceeds as follows. Chapter 2 discusses the dataset, methodology, and variable construction as well as developing testable hypotheses. Chapter 3 presents the result on (3.1) Trading Activities on news (4.2) Trading skills on news, and then performs robustness tests. We then conclude. Tables and figures are presented at the end of the paper in the Section 4.

## CHAPTER 2

### DATA AND METHODOLOGY

#### 2.1 Dataset

This section explains the dataset in details and the construction of the analysis sample. The dataset was first used in the finance literature by Di Mascio, Lines and Naik (2017), who discussed the data in greater detail. The data included portfolio holdings and trades of institutional investors that subscribe to Inalytics' services. Inalytics collects trade data in a real-time so our sample consists of daily trading and holding observations.

The dataset for this analysis includes long-only global equity portfolios from 2004 to 2015. The names of funds and portfolio managers are anonymized. Inalytics assigns a unique ID for each portfolio manager. Each portfolio has a client-specified benchmark against which fund managers are evaluated. Portfolios in the dataset are globally diversified, high-conviction, and low-turnover. The median number of distinct stocks is 58, and the average portfolio turnover is 4.1% per month. For each portfolio, we have a complete trading and holding history over a period in which a portfolio manager subscribes to Inalytics services.

We employ three-step screening procedures to select portfolios in our analysis sample. First, we exclude portfolios that do not have real-time trading data. We do so by computing the fraction of trades after the 27<sup>th</sup> of the month and exclude portfolios in which the average fraction trades occurring at the end of the month exceeds 50%. Second, we exclude portfolios that have less than 80% matches with external price series from CRSP, and Datastream. Third, we exclude portfolios that Inalytics identified as having problematic data, leaving us with 783 portfolios for the analysis.

The second dataset is the macroeconomic announcement database from Bloomberg. The Bloomberg economic calendar records the macroeconomic indicators of each country as well as its content on the level and the median forecast of each macroeconomic indicator. Bloomberg collects the median forecast by surveying professional forecasters in the industry. While the economic calendar contains lots of macroeconomic news, we focus our analysis on major macroeconomic news releases by governments. Savor and Wilson (2013) show that these four types of macroeconomic announcements are important, capturing 60% of the market equity premium. The macroeconomic news in this analysis includes (1) Central Bank meetings and interest rate decisions, (2) GDP releases, (3) PPI releases, and (4) unemployment releases. Because our portfolios are global, we consider the news from the US, EU, and UK. Table 4.2 shows the timing of macroeconomic news and its summary statistics of their average levels and surprises.

The third dataset is IBES, which provides earnings announcement date and the actual earnings of a company. IBES has excellent global coverage, especially for large-cap stocks. Our sample comprises of both large-cap and small-cap stocks. After merging the IBES dataset with the Analytics' holding data, we can match 49.3 million holding observations to stocks in IBES. Out of 49.3 million holding-date observations, 345,000 earnings announcement days occur in our sample.

We use various sources for the price series to supplement the holding and trading data, mainly to compute past and future returns. The main sources are CRSP and Datastream. When the securities do not have matches in either of these sources, Analytics provided us with its price series, which are sourced from MSCI and the portfolio managers respec-

tively. We converted all prices and returns to USD using exchange rates from Datastream, Inalytics, and Compustat<sup>1</sup>.

Table 4.1 presents the summary statistics. In the clean sample, we have 89 million holding observations and 4.4 million trades (2.4 million buy and 2 million sell trades). The average portfolio's market value is 573 million USD, and the average market value of trades is 0.34% of AUM per day. Median investors hold stocks for 314 days since they open a position and 57 days since their last buy. They infrequently trade, having a low monthly turnover of 2.5%: their probability of buying is 2.6%, and the probability of selling is 2.2%. Their portfolios are concentrated with the median number of stocks at 58. Hence, investors in the sample can be categorized as long-term, long-only, discretionary equity investors.

## 2.2 Methodology

This section first describes the variable constructions for variables used in the analysis. The main variables include (1) trading activities, (2) counterfactual returns, (3) fund returns, and (4) announcement surprises.

### 2.2.1 *Measuring trading activities*

We measure several trading characteristics including trade size and the number of positions traded. At the position-date level, we create an indicator for a buy trade and a sell trade. Trade size is measured as a dollar value of security traded divided by yesterday's total

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1. We compile data on exchange rates from three sources: Datastream, Compustat Global, and Inalytics' internal database, with Datastream being our primary source. In the vast majority of cases, at least two of these sources have identical exchange rates.

AUM. At the portfolio-date level, we aggregate trading activities by computing the scaled total number of trades and total scaled dollar value of trades as:

$$BuySize_{f,t}^{AUM} / SellSize_{f,t}^{AUM} = \frac{\sum_{s \in stock_{f,t}} P_{s,f,t} \times |\Delta Q_{s,f,t}| \times 1_{s,f,t}^{Buy/Sell}}{AUM_{f,t-1}}$$

$$BuyAct_{f,t}^{Nostock} / SellAct_{f,t}^{Nostock} = \frac{\sum_{s \in stock_f} 1_{s,f,t}^{Buy/Sell}}{NoStock_{f,t-1}}.$$

The scaling factor in denominator is the AUM for the trade size and the number of stocks, at the beginning of the day. The rationale for measuring trading activities in two ways is that movement in asset prices on each day can affect the trade size computed in dollars. In this regard, the raw quantity measures better capture the real trading activities in terms of the count of positions bought or sold, which are not affected by price movements. Our results are robust to different measurements of trading activities. For certain analyses, we aggregate trading activities at a yearly level instead of a daily level.

### 2.2.2 *Measuring trading performances*

Institutional investors are typically evaluated against a benchmark. Similar to Akepanidta-worn, Di Mascio, Imas, and Schmidt (2018), we use counterfactual returns to benchmark the performance of trading decisions<sup>2</sup>. The counterfactual returns capture the performance of trades relative to an alternative, randomly-trading strategy whereby investors equally trade all stocks held in their portfolios. We consider the counterfactual returns up to two years after the trading decisions are made. For a portfolio,  $f$ , on date  $t$ , the counterfactual returns at future  $k$  periods are defined as:

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2. All results still hold if we use client-specified benchmark in place of our counterfactual return measures

$$\begin{aligned}
\text{Counterfactual Buy}_{f,t \rightarrow t+k} &= \frac{\sum_{s \in \text{traded stock}_{f,t}} (R_{f,s,t+k}^{\text{Buy}} - R_{f,s,t+k}^{\text{hold}})}{N(\text{Stock Bought}_{f,t})} \\
\text{Counterfactual Sell}_{f,t \rightarrow t+k} &= \frac{\sum_{s \in \text{traded stock}_{f,t}} (R_{p,s,t+k}^{\text{hold}} - R_{p,s,t+k}^{\text{Sell}})}{N(\text{Stock Sold}_{f,t})}.
\end{aligned}$$

This measure directly captures the value added from trades to a fund's portfolio. When it is positive, it indicates a fund makes good trading decisions.<sup>3</sup> For instance, if the counterfactual buy returns are positive, a fund manager generates value by adding securities that outperform all existing holdings in the future. If the counterfactual sell returns are positive, a fund manager adds value by making good selling decisions - selling securities whose prices decrease more than or increases less than his or her existing holdings.

Apart from being a no-information benchmark for evaluating the trading decision, the counterfactual measure also serves as an alternative trading strategy. This counterfactual strategy is simple to implement by trading all held stocks equally and requires little information. In many cases that institutional investors make mistakes in trading, this counterfactual can help improve investor's traded returns.<sup>4</sup>

We compute standard errors using a simple Monte Carlo ("placebo") approach which is similar to construction of the counterfactual portfolios themselves. Specifically, rather than use the actual positions traded, we randomly allocate (without replacement) the same number stocks from the portfolio to be bought/sold as we observe in the data. We then form counterfactuals and aggregate across funds and time as we do in the data. When stocks traded are separated into multiple categories, we randomly allocate stocks to the different

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3. We also perform robustness checks using alternative return measures in place of the raw returns, including beta-neutral returns and daily alphas.

4. Our results also hold if the counterfactual portfolios include all existing stocks, rather than non-traded stocks. We present results for non-traded stocks in order to evaluate investors' stock-picking ability.

categories based on the observed number of stocks bought/sold in each category, and then form placebo counterfactuals.

### 2.2.3 Measuring fund overall performances

We measure fund performances by using (1) benchmark-adjusted returns, and (2) risk-adjusted returns using the Fama-French four-factor models.<sup>5</sup> Inalytics provides benchmark-adjusted returns of each fund at the daily level. To We run daily rolling regressions to estimate the fund's loading on each factor, using the past 12 months of data. In a month  $T$ , we use returns from the previous month to 12 months prior to compute alphas:

$$\begin{aligned}
R_{p,t} - r_{f,t} &= \alpha_T + \beta_T^{MKTRF} (R_t^m - r_{f,t}) + \beta_T^{SMB} (SMB)_t \\
&\quad + \beta_T^{HML} (HML)_t + \beta_T^{UMD} (UMD)_t, \quad t \in [T-12, T-1] \\
\alpha_{f,t} &= (R_{p,t} - r_{f,t}) - \left[ \beta_T^{MKTRF} (R_t^m - r_{f,t}) + \beta_T^{SMB} (SMB)_t + \beta_T^{HML} (HML)_t + \beta_T^{UMD} (UMD)_t \right] \\
\alpha_{f,t \rightarrow t+k}^{A-FF} &= \left( \prod_{s=1}^k (1 + \alpha_{f,t+s}) \right) - 1 \\
(R_f - R_{bench})_{t \rightarrow t+k} &= \left( \prod_{s=1}^k (1 + R_f - R_{bench})_{t \rightarrow t+k} \right) - 1.
\end{aligned}$$

The first two equations describe the estimation of our risk adjustment procedure and the calculation of the daily risk-adjusted returns(alphas). The last two equation describes the construction of cumulative benchmark-adjusted returns and risk-adjusted returns respectively for a given horizon k.

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5. Following Dimson (1988), we also measure performance adjusting for potential trading asynchronicity by including lead and lag terms at the daily level. To do so, we estimate the following specification:  $R_{p,t} - r_{f,t} = \alpha_T + \sum_{l=-1}^1 \{ \beta_{T-l}^{MKTRF} (R_{t-l}^m - r_{f,t-l}) + \beta_{T-l}^{SMB} (SMB)_{t-l} + \beta_{T-l}^{HML} (HML)_{t-l} + \beta_{T-l}^{UMD} (UMD)_{t-l} \}$ ,  $t \in [T-12, T-1]$ .

### 2.2.4 *Measuring content of macroeconomic and firm-level news.*

We measure the content of news in terms of the surprise elements.<sup>6</sup> The literature on macroeconomic announcements has shown surprise contents are the main drivers of market reactions. For example, Bernanke and Kuttner (2005) shows the surprise of FOMC is what drives the US stock market reaction to macroeconomic announcements, not the expected changes in FED policy. The literature on earnings announcements found market reacts to positive and negative earnings surprises and a strategy exploiting the post-earnings announcement drift generates annualized risk-adjusted returns of 0.6%<sup>7</sup>.

Following Balduzzi, Elton, and Green (2001), we measure the surprise content of macroeconomic news as the deviation from Bloomberg's survey expectation of the announcements( $a$ ) of a country( $c$ ), divided by the sample standard deviation of the same announcement over the past two years:

$$\text{Macro Surprise}_{a,c,t} = \frac{\text{Actual}_{a,c,t} - \text{SurveyExpectation}_{a,c,t}}{\sigma_{a,c,t}}$$
$$\sigma_{a,c,t} = SD(\text{Actual}_{a,c,t} - \text{SurveyExpectation}_{a,c,t}), t \in \{t - 730, t - 1\}.$$

This normalization allows us to compare the surprises across different macroeconomics announcements that originally vary in magnitudes. The surprise is measured in the standard deviation unit, and Table 4.2 provides the summary statistics for the  $\text{Macro Surprise}_{a,c,t}$  for each macroeconomic announcement.

Following Hartzmark and Shue (2017), we measure earning surprises as,

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6. We measure consensus surprises among forecasters for macroeconomic news and analysts for earnings news. However, the ideal measure to construct is the surprises of each portfolio manager in the data. This is difficult to estimate because we do not observe the expectations of each manager in the dataset.

7. The post-earnings announcement drift strategy is formed by taking long positions on stocks with positive earnings surprise and short positions on stocks with negative earning surprises.

$$Earning\ Surprise_{s,t} = \frac{Actual\ Earning_{s,t} - Median\ Forecast_{s,[t-15,t-2]}}{price_{s,t-3}}.$$

This definition of earnings surprise gets rid of stale prices in IBES because it uses the most recently updated analyst forecasts within the past 15 days to construct the measure. The earnings surprise is calculated in the percentage unit of a stock price( $price_{s,t-3}$ ). Table 4.1 provides summary statistics for  $Earning\ Surprise_{s,t}$  for stocks in the holding dataset.

## 2.3 Hypotheses

This paper goals are twofold. The first goal is to understand how institutional investors consume different types of news. The second goal is performance evaluation, assessing whether investors make informed decisions in investing on news. To do so, we conduct performance analysis on trading returns - comparing performance of trades on the news day to no-news days - to evaluate whether investors are skilled in incorporating news into their decisions.

Hypotheses 1-2 are concerned with investor's information choice, particularly how investors pay attention to news. The remaining hypotheses are on the informativeness of the trading decisions of institutional investors.

**Hypothesis 1:** Institutional investors pay attention to all types of news and trade immediately upon the arrival of news. Surprising news has a stronger effect on trading activities.

The daily tasks of institutional investors involve monitoring market activities and securities in their portfolio. When news - especially surprising news - arrives, financial market experts will be aware of it. So, investors will evaluate the news and adjust positions in their portfolios accordingly. Because they monitor their positions carefully, they have incentives to take actions immediately upon the arrival of news. For this paper, we study two

types of major news in the financial market – earnings announcements and macroeconomic announcements. The attention explanation posits that investors will pay attention to both types of news and increase trading activities to adjust their portfolios. If news is surprising, investors will trade more to incorporate the impact of surprises. Positive surprises will lead investors to buy more. To finance the buy trades, investors need to sell existing positions to raise capitals. For negative news, investors would sell positions that are strongly affected by the negative news. Because the expected returns on cash is 0, investors will put the proceeds from the sell trades into new positions that are not affected by negative news. Hence, investors will trade more overall.

**Hypothesis 2 :** Investors attention to news is persistent.

Investors who pay attention to news will keep track of the news over time. The information set that investors use to build their portfolios is likely to be sticky and consist of the same types of news over time. Hence, investors who take actions when a certain type of news arrives may believe they learn more about the news and its effect of stocks so they have incentives to trade on the same news again in the future.

After characterizing the trading behavior, we evaluate the performance of trading decisions on news. The goal is to evaluate whether financial market experts make informed trading decisions when they act on news. The main matrix through which we evaluate trading performance is the counterfactual returns. We evaluate the trading returns against the counterfactual random-trade strategy whereby investors equally trade non-traded stocks in their portfolios on a given day. We compute the difference by subtracting counterfactual returns on days with news from the counterfactual returns on days without news to measure whether the trading decisions are informed.

**Hypothesis 3:** Discretionary equity investors are skilled in trading on equity news and improve trading decisions on both buy and sell sides.

Earnings announcement news provides new public information on various key accounting variables and soft information such as management perspectives on the future of a firm. Because investors in the sample are 100% equity, they specialize in analyzing firm-level information and incorporating this information to their investment decisions. Hence, they understand well how the news will affect the returns of the firms and trade accordingly. In particular, skilled investors can pick right stocks to trade when news about those stocks arrive to the market.

Second, institutional investors are often evaluated against a certain benchmark. Earnings announcement news is idiosyncratic and affects only returns of the traded stocks in the first order.<sup>8</sup> Benchmark or counterfactual portfolios will be minimally affected because those portfolios are diversified, and the stocks with earnings announcement may not be included. If institutional investors make informed decisions regarding trading on earnings news, they are likely to generate positive counterfactual returns because the news will only affect the securities that have earnings announcements but not the benchmark or counterfactual portfolios.

It is unclear whether the performance of trading on firm-level news will be persistent over time. On the one hand, if investors learn more about their ability and firms over time through trading, they might make higher trading profits when they trade on firm-level news in the future. On the other hand, if firms are unique and the effect of earnings announcement of a firm is not informative of another firm's earnings announcement, investor's learning channel will be limited. Besides, good investment opportunities on earning announcement may become rarer over time as other market participants pay more attention to firms with surprising earning history. Hence, investors might find it harder to trade on earning news

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8. The second-order effect is the impact of the announcement of a stock on other correlated stocks. For example, the correlation can be through economic linkages such as a consumer-supplier relationship, as documented in Cohen and Frazzini (2008).

of the same firm repeatedly and will not necessarily generate higher trading profits when the trade on the firm-level news in the future.

**Hypothesis 4:** Discretionary equity investors have no skills in consuming macroeconomics news, and their trades on macroeconomics news do not perform better than their other trades.

The uninformative nature of macroeconomic signals to discretionary equity investors can be explained by fractionation. Even though this group of investors trades more on macroeconomic announcement days, they are typically not expert macroeconomists. The so-called fundamental analysis is their common analysis framework. It involves analyzing firm-level information and evaluating the company's management teams. This framework involves little to no macroeconomic information. For non-expert macroeconomists, to fully understand the effect of macroeconomic information on different stocks in their portfolios is a daunting task. Hence, discretionary equity investors should not be expected to pick the right stocks to trade on macroeconomic announcement days. The domain of this group of investors is the analysis of firm-specific information. The skills in this domain do not necessarily translate into the skills in other domains such as analyzing and trading on macroeconomic news.

Second, under the relative performance evaluation, making profitable trades based on macroeconomic signals is harder. Macroeconomic news is market-wide so it can equally affect both individual stock, benchmark, and counterfactual-strategy returns. Therefore, the net trading performance is unclear because benchmarks or counterfactual portfolios can move as much as the individual traded security.

**Hypothesis 5:** In the cross-section, investors who trade more on the firm-level news have higher future overall fund returns. Those who trade more on the firm-level news are not subject to decreasing returns to scale.

This hypothesis is about the nature of the trading skills across funds with varying degrees of trading on the firm-level information. First, investors who skillfully trade more on the firm-level information should also have higher overall fund returns. If the trades on the firm-specific information are informed, their future trading profits will be higher. This profits will result in higher overall fund returns, both in the risk-adjusted and benchmark-adjusted matrix. Also, if the trading activities on earnings announcement news proxies for how well investors evaluate firm-level news in general, funds who trade more on earnings announcement news will have higher returns.

There are some counter-arguments to this hypothesis. First, although funds make informed trades on earnings announcement news, the trade sizes are often small (0.25% of AUM) on average. Second, funds in the sample trade infrequently, and have a high average holding length of 484 days. Therefore, holdings and position sizing, rather than trades, will drive most of the fund returns.

The other cross-sectional pattern is that funds who are skilled in trading on firm-level information would not be subject to decreasing returns to scale. That is funds that trade more on earnings announcement days will not make lower profits as they trade more. The literature documented a negative relationship between the fund's AUM and overall performance, due to the liquidity effects or transaction costs.<sup>9</sup> However, if investors are skilled in trading on firm-level information, they must be able to source profitable trading opportunities continually on earning announcement news. It might not necessarily be more profitable opportunities, but at the very least, investors must not trade on inferior opportunities. Skilled discretionary investors, who trade more on the firm-specific information, should not have decreasing returns to scale.

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9. Several papers document decreasing returns to fund's size including Chen, Hong, Huang, and Kubik (2004), Edelen, Evans, and Kadlec (2007), Yan (2008), and McLemore (2018). Pastor et al. (2016) model and document positive turnover-performance relationship among the US equity mutual funds.

## CHAPTER 3

### RESULTS

#### 3.1 Results

In this section, we discuss key results of the paper in two steps. The first step is to characterize investor's trading decisions around the news release days. The second step is to analyze the trading performance, returns to scale of trading activities, and fund-level returns.

##### *3.1.1 Characterizing Trading Decisions on News*

We first consider at the trading activities around news including earnings announcements and macroeconomic announcements of the US, EU, and UK government. Discretionary equity investors in the sample pay attention to news and increase trading activities immediately upon the releases of news. On average, the number of stocks traded and the trade size increase for both buy and sell trades. Table 4.4 shows the daily trading activities on macro announcement days, relative to non-macro announcement days. Table 4.5 shows position-level trading activities around earnings announcement day relative to other positions without earnings announcement. We further perform regression tests to estimate trading activities around announcement days and show the coefficient estimates on Figure 4.4-4.6 for macroeconomic news and Figure 4.7 for earnings announcement news. For macroeconomic announcements, we run regressions at a fund-date level under the following specification, separately for each country( $c$ )<sup>1</sup>:

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1. Country-by-country regressions have easier interpretation. The coefficients can be interpreted as the changes in trading activities on macro news of a country, relative to the trading activities when that country has no macro news.

$$\begin{aligned}
Y_{f,t+k} &= \beta_c 1_{c,t}^{MacroAnn} + \gamma_c^+ Sur\_sd_{c,t}^+ + \gamma_c^- Sur\_sd_{c,t}^- \\
&+ Controls + Fund \times Year FE \\
Y_{f,t+k} &\in \{BuySize_{f,t+k}^{AUM} / SellSize_{f,t+k}^{AUM} / BuyAct_{f,t+k}^{Nostock} / SellAct_{f,t+k}^{Nostock}\}. \\
Controls &= \{PastR_{f,t}^{90-day}, \beta_{f,t-1}^{Mkt}, \beta_{f,t-1}^{SMB}, \beta_{f,t-1}^{hml}, \beta_{f,t-1}^{WML} \\
&, \log(AUM)_{f,t-1}, NoOfstock_{f,t-1}, \sigma_{f,t-1}^{Rf}, Realized Volatility_t, EPU_t\}
\end{aligned}$$

The dependent variables are the scaled number of trades and the scaled trade size trading activities for buy and sell trades on the  $k^{th}$  day around a date  $t$ . We consider three days around the macroeconomic announcement events ( $k = 3$ ). We control for fund-level characteristics including its past returns, loading on the Fama-French-four-international factors, AUM, the number of stocks and the prior 1-year average volatility. We also include market controls including the average realized volatility, and the economic policy uncertainty index (EPU) on each day, in order to test how market environment drives trading decisions of investors.<sup>2</sup> The coefficients of interests are the impact of each country  $c$ 's macro news ( $\beta_c$ ), positive macro surprises ( $\gamma_c^+$ ), and negative macro surprises ( $\gamma_c^-$ ) on trading activities. Standard errors are double-clustered at fund and date levels. The fixed effect (FE) is  $Fund \times Year$ , so coefficients are estimated off the within-fund variations in the same year. These regressions provide intensive-margin estimates, capturing the average trading activities on news days, compared to no-news days, within a year, of the same investor.

For earnings announcements, we run similar regressions at a position level under the following specification:

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2. The realized volatility is obtained from Oxford-Mann website. We construct a daily index realized volatility index for this analysis by averaging five-second realized volatility of S&P 500 and EP50 indexes. The economic policy uncertainty index (EPU) is obtained from the Economic Policy Uncertainty website. It is constructed and maintained by Bloom, Baker, and Davis. The daily EPU for the US economy is available.

$$\begin{aligned}
Y_{f,s,t+k} &= \beta \times 1_{s,f,t}^{E-day} + \beta^+ \times 1_{s,f,t}^{E-day} \times (\%Earning\ sur^+)_{s,f,t} + \beta^- \times 1_{s,f,t}^{E-day} \times (\%Earning\ sur^-)_{s,f,t} \\
&\quad + \sum_c \theta_c^+ 1_t^{MacroAnn} + \sum_c \theta_c^+ Sur\_sd_c^+ + \sum_c \theta_c^- Sur\_sd_c^- \\
&\quad + Controls + Fund \times Year\ FE \\
Y_{f,s,t+k} &\in \left\{ 100 \times \frac{|P_{s,f,t+k} \times \Delta Q_{s,f,t+k}|}{AUM_{s,f,t+k-1}} \times 1_{s,f,t+k}^{\{buy/sell\}}, 100 \times 1_{s,f,t+k}^{\{buy/sell\}} \right\} \\
Controls &= \{Fund\ Controls, Market\ Controls, Position\ Controls\}.
\end{aligned}$$

The dependent variables are the indicator of whether a stock is bought or sold and the trade size for buy and sell trades on the  $k^{th}$  day around a date  $t$ . Again, we consider three days around the macroeconomic announcement events ( $k = 3$ ). We include fund-level, market, and position level controls. Fund controls are similar to the daily-level specification. Market controls include daily realized volatility and EPU index. Position level controls include six bins of past 365-day capped benchmark-adjusted returns, beginning of the day stock weight and its square, holding length at the beginning of the day. The coefficients of interests are the impact of earnings announcement news ( $\beta$ ), positive earnings surprises ( $\beta^+$ ), and negative earnings surprises ( $\beta^-$ ) on trading activities. Standard errors are double-clustered at fund and date levels. The fixed effect (FE) is  $Fund \times Year$ , so coefficients are estimated off the within-fund variations in the same year. Because of the fund-year fixed effects, we are estimating the changes in trading activities on the intensive margin, and the coefficients can be interpreted as the average changes in trading activities relative to days without news of the same fund in a given year.

### 3.1.1.1 Macroeconomic announcements

For macroeconomic news, investors increase trading activities most in response to EU macro announcements, followed by US macro announcements. UK macro announcements

do not impact trading activities in a statistically significant way. Panel A of Table 4.4 summarizes percentage increases in the average number of positions traded on macro-news days relative to days without macro news, across funds with a different number of existing positions. On EU macro announcement days, investors increase the number of positions bought by 40.2% to 59.23% and the number of positions sold by 36.56% to 40.64%. On US macro announcement days, investors increase the number of positions bought by 22.6% to 36% and the number of positions sold by 25.67% to 39.32%. Similar to the number of positions traded, investors also increase trade size on EU and US macro announcement days relative to non-announcement days. Panel B of Table 4.4 summarizes the percentage difference in average trade sizes on macro announcement days, by the total assets of a fund. On EU macroeconomics news days, the average buy trade sizes are about 37%-49.65% higher and the average sell trade sizes are about 30%-44% higher. On US macroeconomic news days, the trade sizes are about 17.8% - 38.44% higher on the buy trades and 30.05% to 44.53% higher on sell trades.

The increase in trading activities on macroeconomic announcement days of the US and EU are statistically significant. We formally test trading behavior using reduced-form regression models with the trading activities around macroeconomic announcement days as dependent variables. Results are shown in Figure 4.4-4.6. We include various fund level controls including fund strategies, AUM, number of stocks, past fund returns, and fund volatility. We include fund-year fixed effects to estimate the trading activities around macroeconomic announcement days of the same fund in any given year. The standard errors are double-clustered at fund and date levels. In addition, we include daily market controls to ensure that the trading on the news are not driven by the fact that investors trade due to higher volatility or higher uncertainty on news days.

Figure 4.4 shows the regression coefficients on the probability of buying and selling in Panels A and on the trade size in Panels B. Trading activities increase on the EU and US

macroeconomic announcement days. All trading activities increase on the day of the arrival of macroeconomic news. The magnitude of the increases in the probability of buying is 0.4% on the EU macroeconomic announcement days and 0.6% on the US macroeconomic announcement days. Since the average buying probability is about 2.6%, the estimates represent 15.4% and 23% increases over the average buy trades for the EU and US announcements respectively. On the sell side, the arrival of macro news increases the probability of selling by 0.2% of EU macroeconomic announcement news (9%) and 0.25% (11.25%) on US macroeconomic announcement news. Most of the impact of EU macroeconomic announcements is contemporaneous, whereas trading activities increase the most one day after the US macroeconomic announcements. Panels B of Figure 4.4 show the regression estimates on the trade size around macroeconomic news. It has the same direction as the probability of trading. Trade sizes increase on the day of EU and US macroeconomic news. For EU macroeconomic news, buy size increases by 6 basis points, which is about 19.2% more than the average buy sizes across all dates. Sell size increases by 2 basis points, which is about 11% more than the average sell sizes. For US macroeconomic news, the buy size increases by 12 basis points contemporaneously, and the sell size increases by 4 basis points. The relative changes on the US announcements represent 35.2% and 22% increases over average buy and sell trade side respectively. For UK macroeconomic news, we do not have evidence that the news increases trading activities.

Next, we estimate the impact of macroeconomic news content in terms of surprises on trading activities. Additional impacts from news surprises on trading activities can occur that are not explained by the arrival of news. We find some evidence supporting this claim, but the impacts on trading activities are similar for positive news and negative news. This finding suggests that surprising news affects trading activities, and investors rebalance between stocks in a portfolio in response to news. Following Gilbert et al. (2010), we measure surprises in terms of an ex-ante standard deviation unit. Figure 4.5 shows the

effect of macro-news surprises on the number of trades, and Figure 4.6 shows the effect of macro-news surprises on trade sizes, relative to days without macro announcement.

The content of macroeconomic news in terms of surprises has little impact compared to the arrival of the news itself. Figure 4.5 shows that most estimates of trading activities on news surprises are not statistically significant. The only slightly significant impact is the positive EU macroeconomic news surprises on the number of buy trades. In that case, a one-standard-deviation increase in the size of positive surprise additionally increases the probability of buying by 0.2% (7.7% increase over the average buy probability). For trade size, the positive surprises can affect the buy size and sell size for EU and UK macro announcements. On EU macroeconomic announcements, a one-standard-deviation increase in the size of positive surprise increases by 6 basis points for buy trades and 2 basis points for sell trades, which are about a 17.6% and 11% increase over the average buy size and sell size, respectively. For the US macroeconomic announcement news, investors do not read into macroeconomic news surprises, so the contemporaneous effects of surprises are not statistically significant. For the UK macroeconomic announcements, Figure 4.4 shows the arrival of the news does not affect trading activities in a statistically significant way. However, when UK macro news is surprising, investors make a bigger bet. A one-standard-deviation increase positive UK macro-news surprise increases buy size by 3 basis points and sell size by 1.2 basis points. These increases are equivalent to a 9.6% increase over the average size of buy trades and a 6.3% increase over the average size of sell trades. Negative macro news surprises do not affect trading activities in a statistically significant way.

This result suggests that institutional investors in the sample trade more in response to the arrival of news itself, regardless of its content. This increase in trading activities on the US and EU news cannot be explained by the fund characteristics and the market environment on a day. Uncertainties and realized volatilities in the market cannot fully explain investor's increases in trading in response to macro news.

### 3.1.1.2 Earnings announcements

Discretionary equity investors respond not only to macroeconomic news, but also to the firm-level news. Earning news drives trading activities, both in terms of the number of stocks traded and trade sizes. In fact, it is the earnings news that drives trade size the most out of all the news we have considered. Table 4.5 shows the sample annual average trading activities on earnings announcement days (E-day) across funds, relative to trading activities on non-earnings announcement days. For the buy trades, the number of stocks bought increases by 20.43% to 58.21% and the buy size increases from 82.3% to 191.94%, relative to a position without earnings announcement news. For sell trades, the number of stocks sold increases by 14.75% to 52%, and the sell size increases by 42% to 105.18%, relative to a position without earnings announcement news.

We formally test trading activities around earnings announcement news using reduced-form regressions. We find trading activities increase in both economically and statistically significant ways. The arrival of earnings announcement news, not earning surprise, is what drives the number of positions traded and the trade sizes. In the regression, we run position-level regressions with current, lead, and lag trading activities as dependent variables. Apart from indicators for earning news, and measures of positive and negative earning surprises, we include fund-level, day, and position-level controls as well as fund-year fixed effects. The fund-level control includes the number of stocks held, fund strategies, log of AUM, and past benchmark-adjusted returns. Day controls include indicators for macroeconomic announcements for the US, EU and UK, and their surprises. Position-level controls include six bins of past position returns, holding length, holding length since the last buy, the stock's weight in a portfolio at the beginning of the day and the square of that weight at the beginning of the day. Figure 4.7 displays results for the probability of trading around earnings announcement days, and trade sizes around earnings announcement days.

Trade size shows patterns similar to the number of trades. Trade increases substantially with the arrival of earnings news and continues on the day afterward. On earnings announcement days, the buy size increases by about 0.3 basis points per position, and the sell size increases by 0.42 basis points per position and continue on the next day. Because the average buy size is about 1 basis point per position and the average sell size is 0.7 basis point per position, these increases represent a 30% increase over the average buy size and a 60% increase over the average selling size. The surprises of earnings announcement news affect buy sizes and sell sizes, and the negative earning surprise affects buy sizes, but these effects are of a smaller order of magnitude. A 1% increase in positive earning surprises decreases the buy size by 0.001 basis points and the sell size by 0.002 basis points. A negative earning surprise decreases buy size by 0.0005 basis points. Given the average trade size per position, the effect of surprises on trading activities is smaller and represents less than a 0.01% change over the average, although they are statistically significant. The economically significant effect comes from the arrival of earnings news itself.

### 3.1.1.3 Other characteristics of trading

To fully characterize trading activities, we document three additional dimensions of trading activities, including (1) correlation of trading activities on different types of news, (2) persistency of trading on news, and (3) risk of traded securities. The correlation of trading activities tests whether investors who specialize in trading on one type of news or investors trade on news across all types of news on average. The persistence of trading activities tests whether investors trade on a type of news over time. Table 4.11 shows the correlation of trading activities. Table 4.12 shows the persistence of trading activities.

We find some evidence that investors use more than one news signal to make sell decisions, but not as much on overall trades or buy trades. Table 4.11 shows these results on

correlations of trading activities across different types of information. We consider trading activities in two dimensions: (1) raw difference in probability of trading on news, and (2) percentage difference of trading activities on news. Investors use broad classes of macroeconomic signals to make selling decisions. The statistically significant correlation comes from the propensity to sell on US macroeconomic-news days and the propensity to sell on EU macroeconomic news. Investors who sell on US macro news are likely to sell more on EU macro news. However, for buy trades and overall trading activities, investors specialize in trading on one particular piece of news and do not incorporate broad sources of news to make buying or overall trading decisions. The last row of Table 4.11 shows investors specialize in using the same signal for buys and sells. Investors who buy more based on a piece of news tend to sell more based on that news as well, in both trading-activity measures.

We find strong persistence in trading activities. Investors who have traded on a particular piece of news tend to repeatedly trade on this news in the future. Table 4.12 presents the regression of fund's annual trading activity on each type of news on its previous two-year lags. We find strong persistence, on both buy and sell trades. Past trading activities are a strong predictor of current trading activities on all types of news. Trading activities on US macro news are the most persistent. The only persistence behavior that has a smaller economic magnitude is selling activities on earnings announcement news. Figure 4.8 plots the average investor's attention over time. Unlike Kacperczyk et al. (2016), we do not find the trade-based attention measures vary over the business cycle. Attention to US, EU, and firm-level news are statistically significant and do not vary much over the business cycle. Notably, investors in the sample still pay high attention and respond to firm-level news in the recessions, in the same way, that they do in the expansion.

We do not find evidence that investors alter risk exposure when they trade on announcement days. Table 4.7 performs position-level regressions of the stock-level factor loadings on trading and announcement day indicators. Most of the coefficients are not statistically

significant. Even when they are, the magnitude is economically small. They are in the order of magnitude of 4, which is much smaller than the factor loadings itself. As a result, the risk factor of traded securities on announcement days most likely represent less than 0.1% changes in average fund risk level. Investors in the sample trade stocks that are similar in risk profiles on announcement days as those traded on non-announcement days.

### *3.1.2 Trading skills*

The key component of this paper is to understand the trading skills of financial experts when they incorporate news into their trading decisions. Although institutional investors pay attention to most of the major news arriving on the market, they may not be able to profit from all types of news they trade on. As described in the hypotheses 3 and 4, we hypothesize that their domain of skills lies in trading on the firm-level news, but not necessarily on the macroeconomic news. Daily tasks of the discretionary equity investors heavily involve analyzing fundamental, firm-level information. Second, the firm-level news will not affect benchmark portfolios, but the macroeconomic news affects both individual traded stocks as well as benchmark portfolios. When institutional investors' performance is based on relative measures such as benchmark-adjusted or counterfactual returns, the firm-level news is more likely than macroeconomic news to generate trading profits.

To formally test investors' skills, we compute the average counterfactual returns of traded securities, going forward up to a one-year or 485-day horizon. We first compute average counterfactual returns across all stocks for each fund on a given day. For each type of trades, we report weighted average counterfactual returns across fund-date observations where the weight across observations is the number of trades for each type of trades of a fund. We compute standard errors using the Placebo method, described in the Section 2.2.1.

### 3.1.2.1 Average skills level

This subsection presents the results of the trading skills on news of institutional investors. We measure trading skills on news as the difference in the counterfactual returns on news event day minus the counterfactual returns on no-news days. Table 4.3 shows the average trading skills on earnings announcement days, and US,EU macroeconomic announcement days for both buy and sell trades, at one month to one-year horizons. We categorize each news item, based on its surprise content – no surprise, negative surprise, and positive surprise. Figure 4.1 shows the average trading counterfactual returns on overall buy and sell trades. Figure 4.2 shows the difference in the average counterfactual returns on each type of trade around days when traded stocks have no earnings announcements and days with earnings announcements. Figure 4.3 shows the average counterfactual returns on trades, taking place on the government macroeconomic announcement days.

The average trading skills of institutional investors are positive to buy trade and negative for sell trades. Akepanidaworn et al. (2018) document this aspect of skills in more details. Figure 4.2 shows that earnings announcement news helps investors make better average trades, especially on the sell side. Investors make bad sell trades on average, underperforming their hold portfolios by 0.6% over the one-year horizon; however, the trades on earnings announcement days outperform their hold portfolios by 1.1% over a one-year horizon. Investors display clear skills in selling on firm-specific information because the sell trades on earnings announcement days add value over the counterfactual hold portfolios in both short run and long run. Figure 4.3 paints different pictures for trades on macroeconomic news. Although the buy trades on macroeconomic news slightly add value over the hold portfolios, investors make worse mistakes when they sell on all macroeconomic announcements. In cases such as the US and UK macroeconomic announcements, investors make worse sell trades compared to their trades on non-macro-announcement days. The

average value, destroyed by sell trades on US-macro news, is about 0.6% at a one-year horizon, per positions sold. Table 4.6 tests the difference in trading performance in more detail. For each type of news, we measure the difference in the value-added counterfactual measures on news days minus the value-added counterfactual measures on no news days. The standard errors are computed using two-sample standard error for the difference.

Earnings announcement news does not help improve returns on the buy trades as much as on the sell trades. The average buy trades are already good decisions, outperforming the counterfactual random-buy portfolios. The buy trades on earnings announcements in most cases do not perform economically differently from the buy trades on no-announcement days. In some cases, earnings announcements improve buying performances, such as earnings news without surprise over the one year and the positive-surprise earnings news over the one-year horizon. In one case, buying on the negative earnings news at the one-year horizon leads to the significant underperformance of 2.48%. Overall, the earnings news help generate trading decisions that lead to positive returns, where most of the improvement comes from sell trades.

When investors sell on earnings announcement days, these sell trades add value more than all other trades, initiated on non-earnings-announcement days. Across all announcement, Table 4.6 shows the value added from trades on earnings announcements is about 1.79% per positions sold. Investors in the sample always make good sell trades, regardless of earnings surprises. At a one-year horizon, the most value added occurs on sell trades on earnings announcements with no surprises, whereby investors add value about 3.37% over their other sell trades. Even the case with positive surprises, whereby a stock tends to drift upwards for its next quarter, investors can pick the right stocks to sell, adding value by 0.91% over all other sell trades. If this skill in trading on earnings announcement news is explained by a post-earnings-announcement drift(PEAD) trading strategy, we would not be expected to sell the positive value added from selling on positive earning announcement

news or zero earning announcement news. The rationale is that these stocks tend to go up, so selling them will be a mistake, based on PEAD. The PEAD explanation suggests profitable sell trades on negative-surprise earnings news. Since best sell trades occur on no earnings surprise news and sell trades on positive earnings surprise news add values, we can rule out PEAD as an explanation. The observed selling skill is consistent with investors being able to pick right stocks to sell when reacting to firm-specific information.

For macroeconomic news, skills on sell trade paint different pictures. We find non-economically significant value added for buy trades, but sizable value destroyed on sell trades. The buy trades generally add little value, less than 0.5% at a one-year horizon, compared to other buy trades on macroeconomic announcement days. Most of the sell trades add less value than all other trades on non-macroeconomic announcement days. Those sell trades on macro announcements underperform non-macro-announcement sell trades by 0.35%-1.11% at a one-year horizon. In a shorter run, the sell trades initiated on macro announcement days also underperform. The underperformance becomes sizable at close to 0.3%-0.49% in just 90 days after selling. On EU macro announcement days, positive EU macro surprises help improve buy trades and sell trades over the one-year horizon, where the trading performance improves by approximately 1% at a one-year horizon. Nonetheless, Table 4.2 shows that most EU macro news has a negative surprise on average, so the instances in which trading performance improves are rare.

Based on these results, investors do not seem to be able to take profitable actions when trading on the macroeconomic news. Regardless of surprises, they make value-destroying sell trades that underperform all their other sells on non-macroeconomic announcement days, in both short, and long run. On macroeconomic announcement days, a random selling strategy would be able to help investors achieve higher returns on sell trades. Table 4.3 I shows that if investors were to implement a random sell strategy, their sell on US and EU macroeconomic announcements would improve by 0.57% and 0.63 %, for the same

amount of dollars sold. Therefore, we find evidence that discretionary equity investors are not skilled when trading on macroeconomic news.

### 3.1.2.2 Returns to scale of trading on news

Given the average returns on trading on earnings news, should investors trade more on that news to make more profits? On the one hand, as they trade more, investors may learn from and specialize in trading on earnings news. On the other hand, the more they trade, the more they may exhaust profitable trading opportunities and have to engage in bad trading opportunities. Table 4.8 shows the trading returns on earnings announcement days as a function of trading activities. We fit a quadratic function to allow for decreasing returns to scale after a certain level of trading activities.

Strong statistically significant evidence on increasing returns to scale or decreasing returns to scale is scant. On the buy side, the amount of trading activities and the profits that investors make are unrelated. On the sell side, across funds, some evidence exists of increasing returns to scale in the cross section. A fund that sells more on earnings announcement days also makes more, generating higher future 28-day and 485-day counterfactual returns. However, the trading profits are not statistically significant in the intermediate horizon. This finding suggests some learning activities occur when trading on earnings news. However, when one compares the trading activities of the same fund over time, the evidence for increasing returns to scale becomes weaker. On average, when investors trade more, they make more profits, but the relationship is not statistically significant.

Although earning news is rare, a fund can scale up its average skills when trading on earnings announcement news. Trading more also has no clear advantages, which may be because a fund in the sample carefully chooses which earnings news to trade on and is unaffected by trading too much on this news and facing bad outcomes of trading on wrong

earnings announcement news. The results suggest some evidence of learning whereby investors make more profits when they trade more on earnings announcement news. However, the learning channel is not statistically strong either. All in all, a fund can trade more on earnings announcement news, which does not seem to add or reduce overall trading returns.

### 3.1.2.3 Impact on fund-level alpha and benchmark-adjusted returns

The previous subsection shows that a fund that trades on earnings announcement news will have better future selling returns on average. Also, a fund manager seems to be able to scale up profitable trading on earning news without devastating effects, although he or she does not learn over time either. Hence, higher profits on trading on earnings news should translate, to some extent, into fund performance. In addition, the trading activities on news may also proxy for a manager's overall skill in tradings on that type of news. Therefore, fund managers, who are skilled at trading on earnings announcement news, may be skilled at interpreting and incorporating other firm-level information as well.

On the other hand, fund managers make many other trades on days without news, how much of the profitable trades on earnings announcements will contribute to fund-level risk-adjusted returns(alphas) is unclear. Furthermore, the majority of alphas can come from portfolio sizing, not from the trades. Returns from trades may constitute a small percentage of the fund's overall performance.

Table 4.9 tests the effect of trading characteristics on fund's overall returns, similar to Elison and Chavalier (1997). We regress the future fund alphas at various horizons on trading characteristics and other fund characteristics such as AUM, the number of stocks, and turnover. We find that funds that trade more on earning news have higher alpha. A 1% increase in the trading intensity on earning news leads to a 4.19 bp increase in three-month

alphas, a 7.91 bp increase in six-month alpha, and a 9.32 bp increase in one-year alpha. It also increases benchmark-adjusted returns by 8bp over the same period. We also have evidence of decreasing returns to scale where funds with higher AUM have lower alpha. Interestingly, in the cross section, other trading characteristics do not predict future alphas. Even a fund turnover itself, which the literature found to be a predictor of alphas, has less predictive power than trading activities on earnings news. Hence, we have evidence that trading profits on earnings news will get translated into fund returns. Measuring trading characteristics on the area in which a fund specializes is also essential, in order to better predict cross-sectional variations across future returns.

#### 3.1.2.4 Persistency of trading skills

We have shown that discretionary equity investors perform well when they trade on earnings announcement news on average. In this subsection, we try to understand if they can make profitable trades on the earning announcement consistently over time. So far, the literature has shown that mutual fund alphas are not persistent. Here, we try to understand whether the trading returns are persistent. However, note that this sample is not a perfect setting to test this hypothesis, because the availability of the data depends on the fund's relationship with the data vendor. Hence, we might have a short time series at the annual level for some funds.

Despite the issues, we test persistency by regressing a fund's annual average counterfactual returns on its past-year value, for funds with at least a full two-year worth of data. In the fund fixed-effects model, we find the opposite of persistency in trading returns. A mean reversion effect occurs. Table 4.10 presents this result.

A fund that makes high counterfactual returns in a particular year will make lower counterfactual returns in the next year, relative to the fund's average. If a counterfactual returns

increase by 1%, the next-year counterfactual returns will decrease by -0.18%-0.24%. This effect holds for both buy and sell trades. The magnitude of the mean reversion is not one-to-one, so it will not wipe out the future counterfactual returns. Because the counterfactual returns on earnings news exceed 1%, the mean-reversion effect decreases next-year returns, but fund managers will still make overall positive counterfactual returns in the next year. Note that with a fund fixed-effects model, mean reversion in stock returns can explain this pattern as well.

Another test is to estimate the model off the between-fund variations with year fixed effects. Here, we find no persistency or mean reversion. A fund that earns better profits when trading on earnings news this year, relative to other funds, does not necessarily earn higher or lower profits next year. In other words, past counterfactual returns are not a good predictor of trading performance.

## **3.2 Robustness**

In this section, we perform two robustness tests to ensure our baseline results, related to returns on tradings relative to counterfactuals, are valid. In addition, we perform robustness on trading activities and value-added measures by ungrouping macro announcements into different types of macroeconomic announcements.

### *3.2.1 Performance Robustness*

We consider more explicit adjustment for systematic risk and confirm that our main results are not driven by exposures to known, priced risk factors between stocks traded versus those held (which are constituents of the random sell counterfactual portfolios). Second, to address potential issues about measurement errors (e.g., stale, extreme prices) and/or liquidity, we re-run our main counterfactual analyses, only including stocks in developed

market that has strong four-factor structure and reliable price data.<sup>3</sup> Our key results are unchanged for this subsample.

The performance measures described above estimate the value-added that a given trade would create/lose relative to a randomly-selected, feasible alternative, where value-added can be interpreted as the expected change in benchmark-adjusted returns over a given horizon per dollar traded. Figure 4.1, and 4.3 demonstrate that stocks bought tend to increase more than randomly selected alternatives, and stocks sold also tend to increase more than these alternatives. Whereas the former helps performance, the latter acts as a drag on performance. A natural concern, therefore, is that stocks traded tend to have above average exposures to systematic risk, meaning that our estimates could be driven by risk compensation rather than skill. If this were the case, we would tend to overstate positive performance of buy trades and understate performance of sells, which is directionally consistent with our results above. Table 4.3 provides evidence that this explanation is unlikely because the risks of stocks traded are similar to the risks of held stocks.

To address this concern, we modify our counterfactual construction procedure so as to form “factor-netural” portfolios. We construct factor-netural portfolios as follows. We first estimate stock-level exposures to the Fama-French international four factors prior to the trade, then use these estimates to adjust our long short portfolios for ex-ante differences in these exposures.<sup>4</sup> For each stock-date, we subtract raw returns with the inner product of factor loadings and factor realizations, so factor-neutral returns are defined as:

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3. The set of developed markets are similar to Fama and French (2017), consisting of (i) North America (NA), including the United States and Canada; (ii) Japan; (iii) Asia Pacific, including Australia, New Zealand, Hong Kong, and Singapore; and (iv) Europe, including Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

4. The results also hold if we use daily alpha return measures, adjusting daily returns with stock-level exposures to the Fama-French four factors, every quarter into the future.

$$R_{s,t}^{Factor-neutral} = R_{s,t} - \sum_{i=1}^4 \hat{\beta}_{s,q(t)-1}^i R_t^{Factor}.$$

The set of factors include the standard international four factors. The estimated factor loadings,  $\hat{\beta}_{s,q(t)-1}^i$ , are estimated 1 year of daily data using data up to the end of the previous calendar quarter. These factor-neutral returns capture returns of a self-financing portfolio which, if factor loadings are estimated correctly and are stable, has zero exposure to the aggregate priced risk factors on each date. These factor-neutral returns are also an ex-ante valid, implementable trading strategy, by trading opposite trades to the actual trades and weighting securities by the estimated factor loadings. If the market has a strong factor structure,  $R_{s,t}^{Factor-neutral}$ , should earn zero expected excess returns, and capture only the idiosyncratic components. Therefore, randomly sold portfolios should have the same factor-neutral returns period-by-period as actual stocks sold. Next, we compute value-added measures as before, by compounding factor-neutral returns and compare cumulative factor-neutral returns of stocks traded with the average of cumulative factor-neutral returns of stocks held.

Table 4.3 reports the estimated value-added measures from the baseline specification, similar to Figures 4.2 and 4.3, as three alternatives. The second alternative is raw performance measure of developed markets, where we only include stocks in the developed market to construct counterfactual hold and actual trade portfolios. The third alternative is the factor-neutral performance, as described above. The last alternative is the factor-neutral performance in the developed market. In all cases, magnitudes are fairly similar between the baseline model and the three alternatives. At long horizons, factor-neutral and overall measures are within 10-50 bp of one another, except for earnings announcements, and the placebo standard errors are larger than that. So, the difference is not statistically significant. All the signs of the estimates are the same. Consistent with much trading activity not being concentrated among stocks with above-average systematic risk exposure,

we find fairly similar estimates of value-added for factor-neutral portfolios as the baseline estimates. Results in the developed only sample agree with the results in the full sample.

### *3.2.2 Different Type of Macroeconomic Announcements*

So far, we group all types of macroeconomic announcement into one category for each country. However, one might be concerned about the heterogeneous impact on trading activities and stock returns of different macroeconomic announcements. For example, Lucca and Moench (2005) show that only FOMC meetings lead to pre-announcement drifts, among all sets of macroeconomic news. To understand this effect of different macro news better, we ungroup the macroeconomic news into their original four set of news: (1) PPI, (2) Interest Rate, (3) Unemployment, and (4) GDP. We re-do our analysis on estimating trading activities, and re-run our counterfactual analyses for raw returns, for each of the four news.

Table 4.13 reports the results for the counterfactual analyses. We find a similar pattern that most of the sell trades are value-destroying after one quarter, especially sell trade on the US and UK macro news. There is substantial heterogeneity in trading performance. In the US, most value-destroying sell trades occur on FOMC meetings, followed by the GDP releases. For the EU macro news, most value-destroying sell trades occur on PPI releases and ECB meetings. For the UK macro news, most value-destroying sell trades occur on GDP and Unemployment releases. There are instances of value-added sell trades on some macroeconomic news such as sell trades on EU unemployment, but those magnitudes are small.

Table 4.14 reports the results for the trading activities on different types of macroeconomic announcements. Similar to counterfactual analyses, there is substantial heterogeneity on investor's response to each country's macro news. Investors' number of trades

and trade sizes have similar directions, for each type of macroeconomic news of a country. For the US macro news, investors trade considerably more on the FED meetings, and GDP releases, for both buy and sell trades. The increases in trading on US macro news also coincide with when the worst sell trades on US macroeconomic news. For the EU macro news, investors respond most to unemployment releases, for both buy and sell trades. Investors in the sample respond by placing larger sell trades on the ECB meeting days, which coincide with value-destroying sell trades on EU macro news. For the UK macro news, investors do not trade less in response to macro news. These results provide evidence that investors in the sample are not specialized in trading on macroeconomic news and make worse trading mistakes on macro news that they react to the most.

### 3.2.3 *CPI vs PPI*

One of the major pieces of the price-level news that investors and macroeconomists pay attention to is CPI. We perform robustness tests CPI on trading activities and the overall counterfactual returns, by replacing PPI with CPI. We found the trading activities on CPI days are higher than PPI days, when comparin Table 4.15 and Table 4.14. Hence, our baseline estimates on trading activities are on conservative side. Figure 4.9 presents overall counterfactual on macroeconomic announcement days. The results are similar to our baseline number in sign. The magnitude of CPI tends to be higher, which makes sell trades on US macro news statistically significantly worse than all other trades on N-days.

Our paper provides direct evidence on how institutional, discretionary equity investors incorporate news into their investment decisions. We focus on two main types of information: firm-specific news on earnings announcement, and aggregate news on macroeconomic announcements. We find that this group of investors pays extremely high attention to both aggregate and firm-specific news even though their investment process relies heavily on

the firm-specific information. On the day of information release, investors immediately increase trading activities by 20% to 50%, both in the number of trades and trade sizes, compared to their usual trading activities. Across all types of announcements, investors respond most to earnings announcements. Investors are also fast and respond immediately on the day of the news release. In addition, investors pay extremely high attention to news under all macroeconomic conditions. Each investor chooses to rely on one signal for buying decisions but incorporate multiple macroeconomic signals when making sell decisions.

Despite their high attention to the news, investors in the sample do not specialize in trading on all types of news. Investors in the sample perform poorly when they trade on the macroeconomic information, but they make better trades when selling on firm-specific information. Although the average sell trades underperform a random sell strategy, the sell trades on earnings-announcement days generate high positive returns by 1% over a one-year horizon and outperform counterfactual sell returns on non-earnings-announcement days by 1%-3.3% over a one-year horizon. We find no improvement in performance on trades initiated on macroeconomic announcement days even though investors in the sample trade considerably more on those days. In many cases, such as sell trades on the US and UK macroeconomic announcement days, trading performance is negative and worse than trades on days without macroeconomic news by 0.3% per position over a one-year horizon. We rule out alternative explanation such as trading on announcement drift and risk difference of traded stocks on announcement days. Investor's ability to profitably trade on firm-level news is a skill, and does not display decreasing returns to scale.

These results are consistent with the fractionation hypothesis whereby investors are skilled in some domains but overextend their ability to seemingly related but non-applicable domains. In this setting, discretionary equity investors are skilled in interpreting firm-specific information, but they may assume they are skilled in analyzing all types of news,

including macroeconomics news. The fractionation hypothesis can explain greater but non-performing trades on macroeconomic announcement days. The results are also consistent with the inherent difficulty in trading on the macroeconomic news, because the macroeconomic news affects both the traded stocks and non-traded stocks in the benchmark. Hence, the relative performance is likely to be neutral when investors trade on the macroeconomic news.

Various future research directions are possible. One direction is to understand retail investors' attention to news and their ability to trade on news in comparison to institutional investor behavior. Second, the quantitative models that feature investors' learning on each type of news with quantitative implications on portfolio performance can lead to better understanding of other channels that we might not empirically document here.

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**CHAPTER 4**  
**TABLES AND FIGURES**

Table 4.1: Summary Statistics

This table reports the summary statistics of the analysis dataset for 783 portfolios at various levels from 2004-2015. The fund level summary statistics are reported at monthly frequency. The position level summary statistics are reported at a fund-date level.

Variable	Count	Mean	Std	25th	50th	75th
Panel A: Fund level Summary (monthly)						
Asset Under Management(\$million)	51228	573.6	1169.3	71.70	201.8	499.0
Number of Stocks	51229	78.49	68.46	40.95	58.60	86.58
Turnover(%)	51223	4.10	5.76	0.927	2.54	5.03
% of distinct stocks sold	51221	10.14	12.13	1.923	5.695	13.70
% of distinct stocks bought	51221	14.86	17.68	3.788	8.820	19.23
% of distinct stocks bought minus % of distinct stocks sold	51221	4.675	16.87	-0.691	1.852	7.030
Monthly Benchmark Adjusted Returns	48786	0.217	1.767	-0.599	0.165	1.010
SD of daily Benchmark Adjusted Returns	48041	0.348	0.208	0.205	0.293	0.431
Market Beta	48705	0.971	0.259	0.807	0.943	1.121
Loading on SMB	48705	0.00669	0.497	-0.320	-0.0624	0.271
Loading on HML	48705	-0.0636	0.503	-0.358	-0.0655	0.215
Loading on Momentum	48705	0.0447	0.336	-0.133	0.0430	0.221
Panel B : Position Level Summary (daily)						
Buying Indicator	89.8M	0.0264	0.160	0	0	0
Selling Indicator	89.8M	0.0226	0.149	0	0	0
Holding Length since opening	89.8M	484.4	512.9	119	314	679
Holding Length since Last Buy	89.8M	112.3	152.4	18	57	144
Portfolio Weight(%)	89.7M	1.2	1.61	.24	.79	1.65
1-day Return	82.1M	0.0511	4.15	-1.11	0.0115	1.17
Future 7-day return	82.9M	0.205	5.830	-2.454	0.179	2.833
Future 28-day return	82.8M	0.781	11.04	-4.634	0.810	6.181
Future 90-day return	82.6M	2.561	20.16	-7.711	2.308	12.30
Future 180-day return	81.5M	5.315	30.51	-10.46	4.164	18.88
Future 270-day return	80.3M	7.873	38.54	-13.10	5.562	24.47
Future 365-day return	78.9M	10.37	44.84	-15.08	7.241	29.73
Future 485-day return	76.9M	13.43	51.12	-16.81	9.006	35.60
Future 605-day return	74.9M	16.73	58.82	-18.73	9.871	41.01
Future 665-day return	73.9M	18.53	62.94	-19.55	10.32	43.66
Future 730-day return	72.7M	20.40	66.82	-20.13	10.86	46.43
Earnings announcement Day Indicator	49.3M	0.007	0.08	0	0	0
Earnings Surprise	318,633	-0.03	0.027	-0.0016	0	0.0029

Table 4.2: Macroeconomic Announcement List

This table presents the set of macroeconomic announcements in our analysis. We pick the official government macroeconomic announcements of US, EU, and UK because our sample consists of global equity portfolios. The list includes 1) Central Bank Meeting & Interest Rate decisions 2) PPI Release 3) Government Unemployment release 4) GDP Release. We tabulate the frequency of releases, typical time of release, average surprises, actual rate, survey rate, and percentage change for each announcement. This table reports the average from 2001 to 2017.

Type	Frequency per year	Time of release	Surprise(sd)	Surprise	Actual	Survey	%Change
<b>Panel A: USA</b>							
FOMC Rate Decision(Meeting)	8*	2.00 PM EST	-0.052	0.204%	1.63%	1.55%	5.18%
PPI Ex Food and Energy (MoM)	12	8.30 AM EST	0.012	8.88%	0.156%	0.138%	-50.9%
Unemployment Rate	12	8.30AM EST	-0.22	-0.49%	6.2%	6.3%	0.055%
Annualized GDP (QoQ)	12	8.30 AM EST	-0.042	-1.24%	2.14%	2.16%	-2.47%
<b>Panel B: EU</b>							
ECB Main Refinancing Rate	12*	12.45 PM CET	-0.027	-0.6%	1.97%	1.95%	-2.3%
PPI YoY	12	10.00 AM CET	-0.01	-0.16%	1.56%	1.59%	5.19%
Unemployment Rate	12	10.00 AM CET	-0.13	-0.11%	9.42%	9.43%	-0.003%
GDP (YoY)	12	10.00 AM CET	0.06	2.18%	0.97%	0.94%	7.6%
<b>Panel C: UK</b>							
BOE Bank Rate	12	12.00 PM BST	-0.07	0.29%	2.46%	2.457%	-1.01%
PPI YoY	12	9.30 AM BST	0.09	3.74%	2.23%	2.21%	5.13%
Unemployment Rate	12	9.30 AM BST	-0.13	-0.17%	6.04%	6.06%	-0.61%
GDP (YoY)	12	9.30 AM BST	-0.10	0.43%	1.52%	1.53%	-6.18%

\* For EU, ECB meeting took place 8 times a year after 2014. For US, FOMC meets 10 times in 2008.

Table 4.3: Counterfactual Returns on Announcement days relative to Non-announcement days, weighted

This table presents the difference in the average value added measures (post-trade returns relative to a random sell counterfactual) for buy and sell trades under two measures of returns 1) returns and 2) factor-neutral returns, for the whole and the subsample of stocks from developed markets (see text for further details) on each type of announcements. We weigh observations inversely to a fund's trading activity. Standard errors are computed using the Placebo method.

Announcement	Return Measure	Panel A: Buy			Panel B: Sell		
	Horizon(days)	28	90	365	28	90	365
I: Earnings	Counterfactual	-0.22 (0.20)	-0.06 (0.35)	-0.47 (0.83)	0.40 (0.16)	0.67 (0.28)	2.20 (0.59)
	Counterfactual (Developed)	-0.26 (0.19)	0.40 (0.35)	-0.35 (0.82)	0.76 (0.20)	0.74 (0.38)	2.07 (0.80)
	Factorneutral	-0.14 (0.20)	-0.09 (0.35)	-0.90 (0.86)	0.46 (0.17)	0.55 (0.28)	2.47 (0.64)
	Factorneutral (Developed)	-0.25 (0.19)	0.03 (0.33)	-1.11 (0.90)	0.79 (0.20)	0.66 (0.34)	2.92 (0.76)
II: US Macro	Counterfactual	-0.06 (0.07)	-0.15 (0.12)	0.72 (0.27)	-0.11 (0.07)	-0.12 (0.14)	-0.46 (0.30)
	Counterfactual (Developed)	-0.13 (0.07)	-0.24 (0.12)	0.39 (0.26)	-0.08 (0.08)	-0.18 (0.14)	-0.34 (0.31)
	Factorneutral	-0.07 (0.07)	-0.22 (0.12)	0.65 (0.30)	-0.08 (0.07)	-0.11 (0.14)	-0.12 (0.31)
	Factorneutral (Developed)	-0.15 (0.07)	-0.36 (0.13)	0.38 (0.30)	-0.07 (0.08)	-0.16 (0.16)	-0.03 (0.36)
III: EU Macro	Counterfactual	-0.28 (0.06)	-0.29 (0.10)	0.01 (0.24)	-0.14 (0.07)	-0.03 (0.13)	0.35 (0.28)
	Counterfactual (Developed)	-0.28 (0.06)	-0.26 (0.11)	-0.08 (0.24)	0.00 (0.08)	0.11 (0.14)	0.73 (0.28)
	Factorneutral	-0.15 (0.06)	-0.22 (0.11)	-0.09 (0.27)	-0.11 (0.08)	0.10 (0.14)	0.27 (0.29)
	Factorneutral (Developed)	-0.18 (0.06)	-0.26 (0.11)	-0.19 (0.26)	-0.03 (0.08)	0.21 (0.15)	0.57 (0.31)
IV: UK Macro	Counterfactual	0.18 (0.06)	0.28 (0.10)	0.40 (0.25)	-0.26 (0.06)	-0.31 (0.12)	-0.40 (0.28)
	Counterfactual (Developed)	0.18 (0.06)	0.15 (0.11)	0.16 (0.25)	-0.27 (0.07)	-0.31 (0.13)	-0.34 (0.28)
	Factorneutral	0.10 (0.06)	0.17 (0.12)	0.19 (0.28)	-0.15 (0.07)	-0.36 (0.13)	0.38 (0.30)
	Factorneutral (Developed)	0.08 (0.06)	0.04 (0.11)	0.00 (0.27)	-0.33 (0.07)	-0.27 (0.13)	-0.48 (0.29)

Table 4.4: Trading Intensity on Macro Announcement Days

This table reports the trading activities and relative difference in trading on US, UK, and EU macroeconomic announcement days for buy and sell trades. Panel A reports the trading intensity in terms of the number of positions. Panel B reports trading intensity in terms of dollar volume. We report an average of these measures across fund-year observations with standard errors in parenthesis. We only include portfolios that exist more than half a year in a given year and winsorize fraction of AUM traded at 99%.

Panel A: Number of positions		Buy				Sell			
		<50	50-200	200-1000	>1000	<50	50-200	200-1000	>1000
Bin of No of Stocks									
Raw Average Number of Trades per day		1.19	1.89	3.88	8.06	0.83	1.46	3.15	6.05
Average fraction of positions traded per day		3.19%	2.78%	2.79%	2.05%	2.22%	2.14%	2.24%	1.60%
Relative Trading Activities on	US	22.56%	25.08%	36.00%	30.72%	25.67%	26.38%	39.32%	57.87%
om Macro Announcement	EU	(2.74%)	(2.96%)	(4.76%)	(11.19%)	(3.7%)	(2.96%)	(6.50%)	(21.92%)
vs other days	UK	51.22%	40.20%	43.49%	59.23%	40.64%	40.53%	36.56%	171.55%
		(5.55%)	(5.1%)	(4.50%)	(36.54%)	(4.61)	(4.57%)	(6.34%)	(119.30%)
		2.73%	5.23%	3.59%	2.15%	10.39%	7.92%	9.06%	7.68%
		(1.84%)	(1.42%)	(2.11%)	(5.15%)	(2.76%)	(1.76%)	(4.55%)	(7.68%)
Number of observations (Fund-year)		1567	1738	659	149	1567	1738	659	149
Panel B: Dollar values		Buy				Sell			
		<50M	50M-200M	200M-1B	>1B	<50M	50M-200M	200M-1B	>1B
Bin of AUM in dollars									
Average fraction of dollar value (%AUM) traded per day		0.35%	0.34%	0.30%	0.27%	0.18%	0.20%	0.19%	0.18%
Relative Trading Activities on	US	17.72%	23.22%	29.63%	38.44%	17.26%	26.67%	29.19%	59.47%
om Macro Announcement	EU	(2.79%)	(2.21%)	(2.24%)	(4.82%)	(3.77%)	(5.73%)	(7.3%)	(20.49%)
vs other days	UK	40.01%	37.05%	49.10%	49.65%	34.81%	30.05%	44.53%	35.49%
		(4.19%)	(2.47%)	(4.33%)	(5.13%)	(8.64%)	(2.71%)	(6.06%)	(5.02%)
		3.02%	0.17%	2.12%	2.01%	13.15%	7.40%	4.47%	3.46%
		(2.24%)	(1.26%)	(1.99%)	(2.36%)	(2.70%)	(1.86%)	(1.29%)	(2.95%)
Number of observations (Fund-year)		733	1234	1609	531	733	1234	1609	531

Table 4.5: Trading Intensity on Earnings Announcement Days (E-day)

This table reports the trading activities and the relative difference in trading on earnings announcement days for buy and sell trades. Panel A reports the trading intensity in terms of the number of positions. Panel B reports trading intensity in terms of dollar volume. We report the average of the measures across fund-year observations and their standard errors in parenthesis. We group portfolios into four bins by the average number of stock per year of a portfolio (less than 50 stocks, 50-200, 200-1000, more than 1000 stocks) in Panel A, and by the average asset under management (AUM) in panel B.

<b>Panel A: Number of positions</b>		<b>Buy</b>				<b>Sell</b>			
		<50	50-200	200-1000	>1000	<50	50-200	200-1000	>1000
Bin of No of Stocks									
Average fraction of positions traded		3.28%	2.93%	2.83%	2.06%	2.36%	2.38%	2.61%	1.93%
Relative trading activity on E-day		58.21%	35.89%	27.53%	20.43%	46.49%	51.79%	28.71%	14.75%
(se of Relative trading activity on E-day)		(22.15)	(5.55)	(5.53)	(9.51)	(7.52)	(7.18)	(6.34)	(7.78)
Number of observations (Fund-year)		1613	1786	685	147	1613	1786	685	147

<b>Panel B: Trade Size</b>		<b>Buy</b>				<b>Sell</b>			
		<50M	50M-200M	200M-1B	>1B	<50M	50M-200M	200M-1B	>1B
Bin of AUM in dollars									
Average trade size per position		0.015%	0.010%	0.009%	0.011%	0.009%	0.007%	0.005%	0.006%
Relative trading activity on E-day		191.94 %	129.29%	58.35%	82.30%	105.18%	86.25%	87.59%	42.00%
(se of Relative trading activity on E-day)		(90.56)	(85.53)	(9.93)	(23.01)	(21.42)	(10.20)	(9.67)	(9.31)
Number of observations (Fund-year)		1567	1738	659	149	1567	1738	659	149

Table 4.6: Counterfactual Returns on Announcement days relative to Non-announcement days, by announcement surprise, weighted

This table presents the difference of the value-added measures (post-trade returns relative to a random sell counterfactual) for buy and sell trades for earnings, US macro, and EU macro announcements with different announcement surprises. We present the difference between these measures for trades of stocks on their earnings/macro(US, EU) announcement days versus all other days, under different surprise on the announcement days. We first report the results for the earnings announcements, then the US macroeconomic announcements, and the EU macroeconomic announcements. Standard errors in parenthesis are computed using the Placebo method.

Announcement	Bins	Panel A: Buy			Panel B: Sell		
	Horizon(days)	28	90	365	28	90	365
I. Earning	No surprise	-0.96 (0.17)	-0.48 (0.32)	-0.67 (0.79)	0.40 (0.19)	1.24 (0.34)	3.22 (0.71)
	Negative surprise	-0.12 (0.15)	-0.40 (0.25)	-3.51 (0.56)	0.65 (0.14)	0.48 (0.28)	2.03 (0.63)
	Positive surprise	-0.01 (0.11)	0.19 (0.21)	2.24 (0.55)	0.16 (0.12)	0.71 (0.22)	1.83 (0.49)
II. US Macro	No surprise	0.04 (0.05)	-0.36 (0.08)	0.92 (0.19)	0.07 (0.05)	0.01 (0.08)	-0.15 (0.19)
	Negative surprise	-0.13 (0.04)	-0.13 (0.08)	-0.28 (0.19)	-0.14 (0.05)	-0.15 (0.08)	-0.55 (0.21)
	Positive surprise	-0.11 (0.05)	0.14 (0.09)	1.71 (0.22)	-0.30 (0.06)	-0.26 (0.11)	-0.76 (0.24)
III. EU Macro	No surprise	-0.17 (0.03)	-0.28 (0.05)	-0.36 (0.12)	-0.03 (0.03)	-0.05 (0.06)	0.40 (0.13)
	Negative surprise	-0.35 (0.06)	0.09 (0.11)	-0.13 (0.24)	-0.34 (0.06)	-0.25 (0.11)	-1.32 (0.31)
	Positive surprise	-0.25 (0.06)	-0.25 (0.11)	0.10 (0.29)	-0.27 (0.08)	0.53 (0.12)	1.30 (0.29)

Table 4.7: Regressions of Risk Exposures on different type of days

This table presents position-level regressions of changes in risk exposures on various announcement days. The stock-level risk exposures are estimated quarterly based on the Fama-French international four-factor model, using one-year prior daily returns. The key variables of interest are the interaction terms of each announcement with the buying and selling indicators. Each column represents loadings of each risk factor in the Fama-French international four factor models, as a dependent variable. For each risk factor, we run the following regressions at a position level:

$$\beta_{f,s,t}^{Factor} = \sum_{trade}^{\{Buy/Sell\}\{EU,US,UK\}} \sum_c \theta_{trade}^c 1_{c,t}^{Macro-Ann-Country} \times 1_{f,s,t}^{Trade} + \sum_{trade}^{\{Buy/Sell\}} \gamma_{trade}^{A-day-ES} 1_{s,t}^{EarningAnn} + \gamma^{BUY} 1_{f,s,t}^{BUY} + \gamma^{SELL} 1_{f,s,t}^{Sell} + \sum_{coun} \gamma^c 1_{c,t}^{Macro-Ann-Country} \times \gamma^{A-day-ES} 1_{s,t}^{EarningAnn} + Fund\ Controls + Fund \times Year\ FE.$$

Fund controls include past 90-day returns, prior 1-year volatility, prior fund-level loading on the four risk factors, number of stocks and AUM. We report the coefficient estimates and t-statistics of the interaction terms. The standard errors for each regression are clustered at a fund level. \* denotes statistical significance at 5% level, \*\* denotes statistical significance at 1% level and \*\*\* denotes statistical significance at 0.1% level.

Independent Variables	Model 1: Four-factor Betas				Model 2: CAPM Beta	
	$\beta^{MKTRF}$	$\beta^{SMB}$	$\beta^{HML}$	$\beta^{UMD}$	$\beta_{nonAnn}^{MKTRF}$	$\beta_{Ann}^{MKTRF}$
$A - day^{US} \times 1^{Buy}$	-0.000896 (-1.24)	-0.00104 (-0.75)	-0.00397 (-1.88)	0.000420 (0.29)	-0.0007 (-1.0)	-0.0009 (-1.5)
$A - day^{EU} \times 1^{Buy}$	-0.000294 (-0.43)	0.00225 (1.71)	-0.00336* (-2.32)	-0.000677 (-0.46)	-0.00009 (-0.1)	-0.00032 (-0.65)
$A - day^{UK} \times 1^{Buy}$	-0.000125 (-0.17)	-0.00484** (-3.24)	0.00325 (1.55)	0.00201 (1.27)	-0.0000 (-0.0)	-0.0002 (-0.03)
$E - day \times 1^{Buy}$	-0.000157 (-0.17)	0.00182 (1.02)	-0.00390 (-1.77)	0.00177 (0.90)	-0.00021 (-0.2)	-0.00009 (-0.1)
$A - day^{US} \times 1^{Sell}$	-0.000573 (-0.77)	0.000458 (0.26)	-0.000798 (-0.35)	-0.0000489 (-0.03)	-0.00041 (-0.62)	-0.00088 (-0.93)
$A - day^{EU} \times 1^{Sell}$	-0.00122 (-1.75)	-0.000651 (-0.50)	-0.00213 (-1.09)	0.00130 (0.83)	-0.00120 (-1.77)	-0.00132 (-1.72)
$A - day^{UK} \times 1^{Sell}$	0.0000979 (0.13)	-0.00334** (-2.74)	0.00138 (0.82)	-0.00130 (-0.91)	0.0001 (0.15)	0.00008 (0.11)
$E - day \times 1^{Sell}$	-0.000294 (-0.32)	0.00201 (1.20)	-0.00355 (-1.62)	0.00345 (1.78)	-0.00024 (-0.29)	-0.00037 (-0.38)
FE	Fund×Year	Fund×Year	Fund×Year	Fund×Year	Fund×Year	Fund×Year
$R^2$	0.886***	0.935***	0.732***	0.736***	0.889***	0.883***
N	47M	47M	47M	47M	47M	47M

**Table 4.8: Returns to Trading Scale on Earnings Announcement**

This table presents returns to levels of trading activity on earnings announcement days. We compute the annual fund's returns relative to random-trade strategies for buy/sell trades on earnings announcement days. We consider horizons after sells from 1 month to 2 years. The trading activities on announcement days are measured as the difference in the probability of trading on E-day and N-day. The returns to trading scales are estimated in the following regressions:

$$Counterfactual\ Return_{trade,f,y}^{Horizon,k} = \beta_1 (Trading\ Activity)_{trade,y,t} + \beta_2 (Trading\ Activity)_{trade,y,t}^2 + FE.$$

The fixed effects include 1) fund fixed effects. Panel A/B presents results for buy and sell trades respectively. The table reports regression coefficients and corresponding t statistics.

<b>Panel A: Buy Trade</b>									
Horizon	28	90	365	485	28	90	365	485	
Buy Intensity	-0.0310 (-0.61)	0.00809 (0.09)	-0.0568 (-0.30)	-0.222 (-1.03)	-0.0131 (-0.19)	0.107 (0.88)	0.116 (0.50)	0.0228 (0.08)	
Squared Buy Intensity	0.00129 (0.70)	0.00121 (0.41)	0.000393 (0.06)	0.00464 (0.61)	0.00247 (0.94)	-0.00446 (-1.11)	-0.00224 (-0.31)	0.0000475 (0.01)	
FE		Year				Fund			
r <sup>2</sup>	0.0566	0.0373	0.0318	0.0352	0.281	0.238	0.253	0.271	
N	2603	2603	2508	2429	2509	2509	2410	2335	

<b>Panel B: Sell Trades</b>									
Horizon	28	90	365	485	28	90	365	485	
Sell Intensity	0.168* (2.29)	0.178 (1.31)	0.280 (1.11)	0.765* (2.36)	0.131 (1.35)	0.148 (0.83)	0.164 (0.47)	0.702 (1.66)	
Squared Sell Intensity	-0.00780 (-1.31)	-0.00776 (-0.62)	-0.0100 (-0.50)	-0.0552 (-1.96)	-0.00304 (-0.42)	-0.00534 (-0.35)	0.00167 (0.06)	-0.0557 (-1.52)	
FE		Year				Fund			
r <sup>2</sup>	0.0599*	0.0355	0.0213	0.0256	0.244	0.215	0.251	0.231	
N	2445	2439	2351	2282	2358	2349	2259	2189	

Table 4.9: Fund Alpha on Trading Characteristics

This table presents the cross-sectional relationship between fund’s future returns and annual trading activities. The dependent variables include the following measures of fund returns(%): future alphas at three-month, six-month and one-year horizons, as well as cumulative one-year benchmark-adjusted returns. We compute alphas by compounding the residual from the Fama-French Cahart models with Dimson adjustment, whereby a loading on each month is estimated using prior one-year daily observations on a rolling basis. The trading activities are measured as fund’s difference in the probability of trading (buy or sell) on announcement days minus the probability of trading on no earnings announcement days, for each type of announcements, at an annual level. For each measure of fund’s future returns, we estimate the cross-sectional relationship with fund’s trading activities by running:

$$Future R_{f,y}^{Horizon k} = \sum \beta_{news}(Trading Intensity On News)_{f,y}^{news} + Fund Controls + YearFE$$

We include Year fixed effects, and fund characteristics controls including the average number of stocks held, and the average log of AUM. Standard errors are clustered at a fund level. The table reports regression coefficients and corresponding t statistics.

Variables	$\alpha^{+3month}$	$\alpha^{+6month}$	$\alpha^{+1Year}$	$(R - R^{bench})^{+1year}$
Trade Intensity EU-macro	-0.0510 (-1.20)	-0.0658 (-1.18)	-0.0147 (-0.18)	0.0855 (1.52)
Trade Intensity UK-macro	-0.0135 (-0.25)	-0.0385 (-0.54)	0.0398 (0.32)	0.0408 (0.50)
Trade Intensity US-macro	-0.0227 (-0.48)	0.0635 (0.98)	0.153 (1.30)	0.0486 (0.65)
Trade Intensity E-day	0.0419* (2.44)	0.0791** (3.20)	0.0932* (2.11)	0.0799** (2.60)
turnover_yearly	-0.0520 (-0.64)	-0.0967 (-0.90)	-0.0621 (-0.35)	0.207 (1.45)
logAUM	-0.135* (-2.48)	-0.323*** (-4.10)	-0.705*** (-5.59)	-0.436*** (-4.40)
Avg No of Stocks	-0.000199 (-0.37)	0.000486 (0.59)	-0.00285 (-1.39)	-0.00398*** (-3.62)
Fixed Effect	Year	Year	Year	Year
R <sup>2</sup>	0.138	0.122**	0.144***	0.0531***
N	3236	3236	3231	3231

Table 4.10: Persistency of Counterfactual Returns

This table presents persistency of fund's value added measures of trading on earnings announcement news. We compute the counterfactual returns on buy trades and sell trades on earnings announcement day at a fund-year level for each portfolio. The counterfactual buy returns are defined as the average future returns of buy trades on earnings announcement day minus the future average returns of stock held. The counterfactual sell returns are defined as the future average returns of stocks held minus the future average returns of sell trades on earnings announcement days. For each future horizon from 7 days to 2 years, we run the following regressions to estimate the persistence of trading skills on firm-specific news:

$$Counterfactual\ Return_{trade,f,y}^{Horizon\ k} = \beta(Counterfactual\ Return_{trade,f,y-1}^{Horizon\ k}) + FE.$$

We run regressions separately for each type of trades and each horizon. Standard errors are clustered at a fund level. The fixed effects include 1) fund fixed effects 2) Year fixed effects. Panel A presents results for buy trades, and Panel B presents results for sell trades. The table reports regression coefficients and corresponding t statistics. We require a fund to exist for full two years in this analysis.

Panel A: Buy Trade								
Horizon	7	28	90	365	7	28	90	365
Lag 1	-0.235*** (-8.34)	-0.196*** (-6.59)	-0.199*** (-7.49)	-0.249*** (-7.55)	-0.0464 (-1.40)	0.0484 (1.50)	-0.0144 (-0.54)	0.00645 (0.21)
FE	Fund				Year			
R <sup>2</sup>	0.313***	0.363***	0.333***	0.338***	0.0157	0.0606	0.0348	0.0300
N	1532	1532	1532	1460	1654	1654	1654	1581

Panel B: Sell Trades								
Horizon	7	28	90	365	7	28	90	365
Lag 1	-0.167*** (-5.41)	-0.182*** (-5.70)	-0.182*** (-5.70)	-0.182*** (-5.70)	-0.0268 (-1.08)	-0.0200 (-0.74)	-0.00357 (-0.12)	0.0135 (0.45)
FE	Fund				Year			
R <sup>2</sup>	0.275***	0.293***	0.303***	0.292***	0.0273	0.0710	0.0394	0.0184
N	1413	1413	1413	1347	1539	1539	1536	1473

Table 4.11: Correlation of Relative Trading Activities

This table reports the correlation of across relative trading activities between each announcement at a fund-year level. Panel A reports the correlation of relative trading activities (buy or sell). Panel B reports the correlation of buying intensity. Panel C reports the correlation of selling intensity. For each type of news, we measure trading activities on news in two ways: 1) the difference of probability of trading (buying/selling) between news release days and days without news, and 2) the percentage difference of probability of trading on news release days compared to days without news. Panel D reports the correlation between relative buy activities and relative sell activities of the same type of news. We exclude funds that exist less than half a year (120 trading days) in a particular year from this calculation.

Type of Trades	Bin	Measures of trading activities , relative to trading on no-news days							
		1) Raw Difference in probability				2) Percentage difference			
	News	E-day	US	UK	EU	E-day	US	UK	EU
Panel A:	E-day	1				1			
All	US	-0.00	1			0.01	1		
Trades	UK	0.08**	-0.09**	1		-0.02	0.00	1	
	EU	0.09**	0.03	0.19*	1	0.00	0.16**	-0.02	1
Panel B:	E-day	1				1			
Buy	US	-0.06**	1			-0.02	1		
Trades	UK	0.05**	-0.35**	1		0.01	-0.02	1	
	EU	0.03	0.00	0.00	1	0.01	0.06**	0.05**	1
Panel C:	E-day	1				1			
Sell	US	0.11**	1			0.01	1		
Trades	UK	0.08**	0.46**	1		0.00	0.07**	1	
	EU	0.11**	0.40**	0.30**	1	-0.00	0.56**	0.00	1
Panel D:									
Correlation across	Buy/Sell	0.12**	0.22**	0.36**	0.25**	0.05**	-0.40**	0.24**	0.35**

Table 4.12: Persistence of Trading Activities

This table reports the persistency of trading activities on news. The relative trading activities on each type of news at a fund-year level are defined as:

$$Relative\_Count\_Trade_{f,y,c} = 100 \times \left( \frac{\text{Average Num of Trade on News days of type } c_{f,y,c}}{\text{Average Num of Trade on no News days of type } c_{f,y,c}} - 1 \right).$$

To estimate persistency, we regress the relative trading activities on its prior two-year values with fund fixed effects. Standard errors are clustered at a fund level. The coefficients of interest are the loadings on lag terms. Panel A reports the regression results for buy trades and Panel B reports the regression results on sell trades.

**Panel A: Buy Trades**

Dependent Variable: <i>Relative_Count_Trade</i>	Announcement			
	Earnings	US Macro	UK Macro	EU Macro
Lag 1	0.268*** (4.41)	0.473** (2.70)	0.313** (3.15)	0.247*** (6.36)
Lag 2	0.167** (3.12)	0.353*** (3.51)	0.207*** (3.98)	0.146*** (4.13)
FE	Fund	Fund	Fund	Fund
$R^2$	0.157***	0.245***	0.140***	0.108***
N	2413	2695	2695	2695

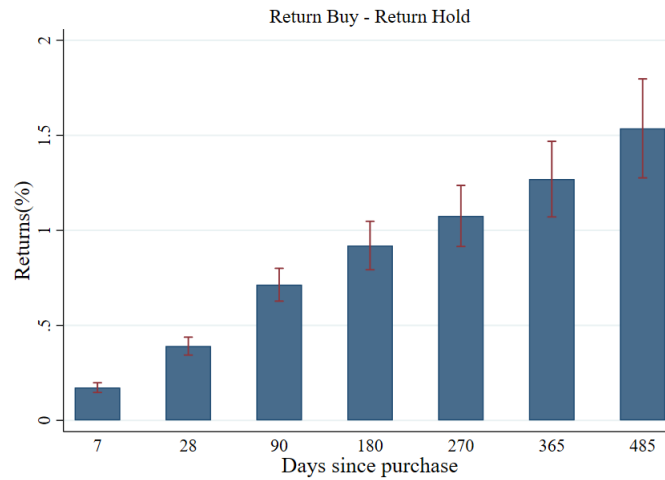
**Panel B: Sell Trades**

Dependent Variable: <i>Relative_Count_Trade</i>	Announcement			
	Earnings	US Macro	UK Macro	EU Macro
Lag1	0.0946* (2.36)	0.441** (2.86)	0.425*** (4.18)	0.328*** (3.62)
Lag2	0.0910** (3.26)	0.156*** (3.61)	0.170* (2.38)	0.161* (2.43)
FE	Fund	Fund	Fund	Fund
$R^2$	0.0337**	0.169**	0.174***	0.121***
N	2413	2695	2695	2695

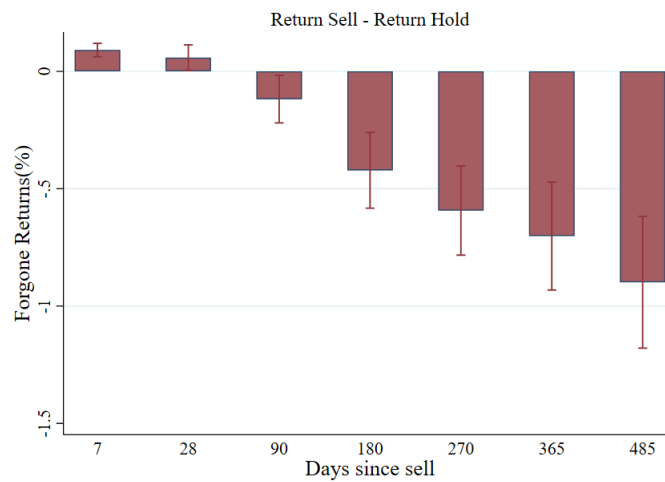
### Figure 4.1. Counterfactual Returns relative to Counterfactual Hold Portfolio

This figure presents the weighted average counterfactual returns for overall buy and sell trades. For each portfolio, the counterfactual returns for buy trades are computed by returns of stock bought minus returns of stocks held on each day. The counterfactual returns for sell trades are computed by returns of stock held minus stock sold. We then compute the average of counterfactual buy/sell returns across all portfolios and dates, weighted inversely to the number of trades per year of a fund. Each bar represents average counterfactual returns in percentage over a specified horizon on the x-axis. The range on the top of each bar is the 95% confidence interval of the average returns of a portfolio at each horizon. The standard errors are computed using the Placebo method.

#### Panel A: Buy Trades, weighted



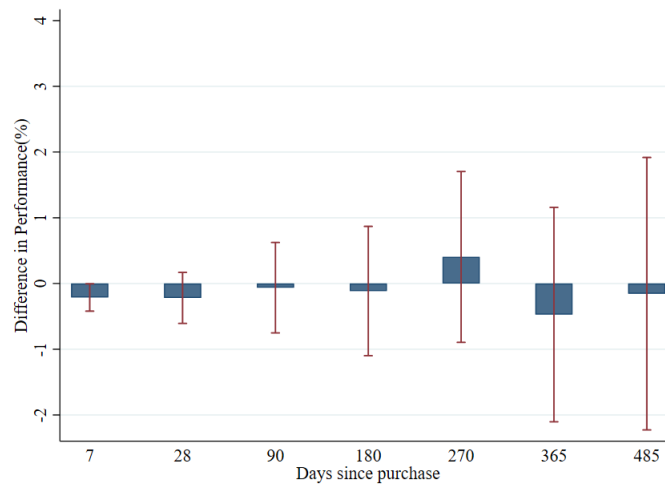
#### Panel B: Sell Trades, weighted



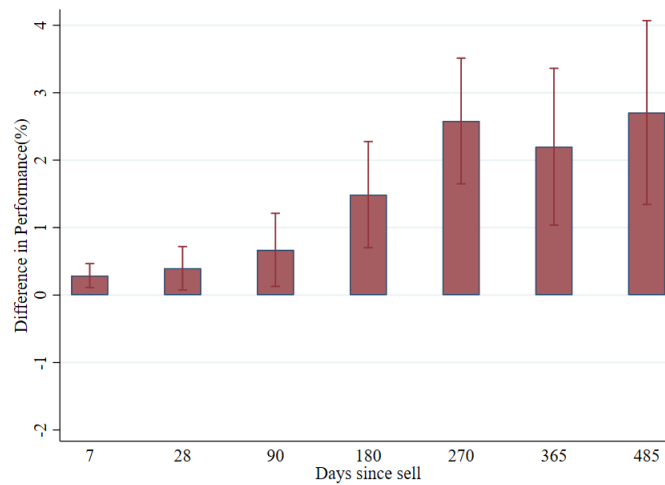
**Figure 4.2.** Difference in trading performance on earnings announcement vs other days

This figure presents weighted average returns relative to random buy/sell counterfactuals for trades that take place on firm's earnings announcement days (E-day) and trades that are on non-earnings announcement days (N-day). Earnings announcement dates are taken from the I/B/E/S database. We plot the difference between value added measures (post-trade returns relative to a random trade counterfactual) for trades of stocks on their earnings announcement days versus all other days, where weighted inversely to funds' trading activity. Each bar represents the average difference in value added measures on E-day in percentage over specified horizons on the x-axis. The range on the top of each bar is the 95% confidence interval of the average difference in value added measures at each horizon. The standard errors are computed using the Placebo method.

**Panel A: Buy Trades, weighted**



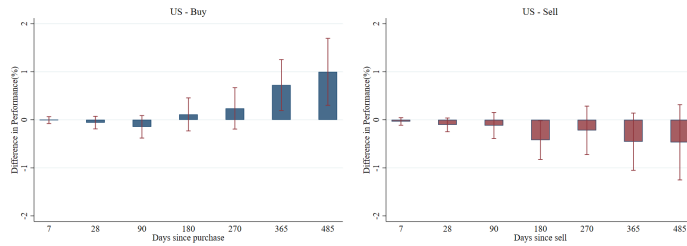
**Panel B: Sell Trades, weighted**



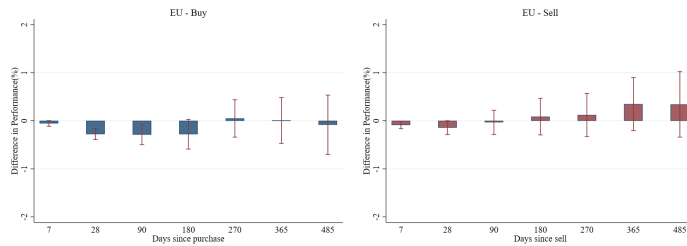
**Figure 4.3.** Counterfactual Returns relative to Counterfactual Hold Portfolio on Macro Announcement Days

This figure presents weighted average returns relative to random buy/sell counterfactuals for trades that take place on macroeconomic announcement days (A-day) and trades that are on non-earnings announcement days (N-day). Government macro news of UK, US and EU in Table 2 are considered. We plot the difference between value added measures (post-trade returns relative to a random trade counterfactual) for trades of stocks on their macroeconomic announcement days versus all other days, where weighted inversely to funds' trading activity, for each of the macro announcement. Each bar represents the average difference in value added measures on A-day in percentage over specified horizons on the x-axis. The range on the top of each bar is the 95% confidence interval of the average difference in value added measures at each horizon. The standard errors are computed using the Placebo method.

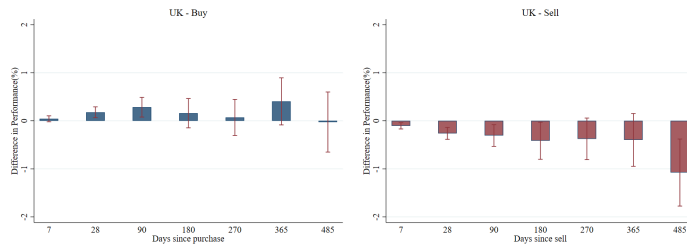
**Panel A: US Macro Announcement Days**



**Panel B: EU Macro Announcement Days**

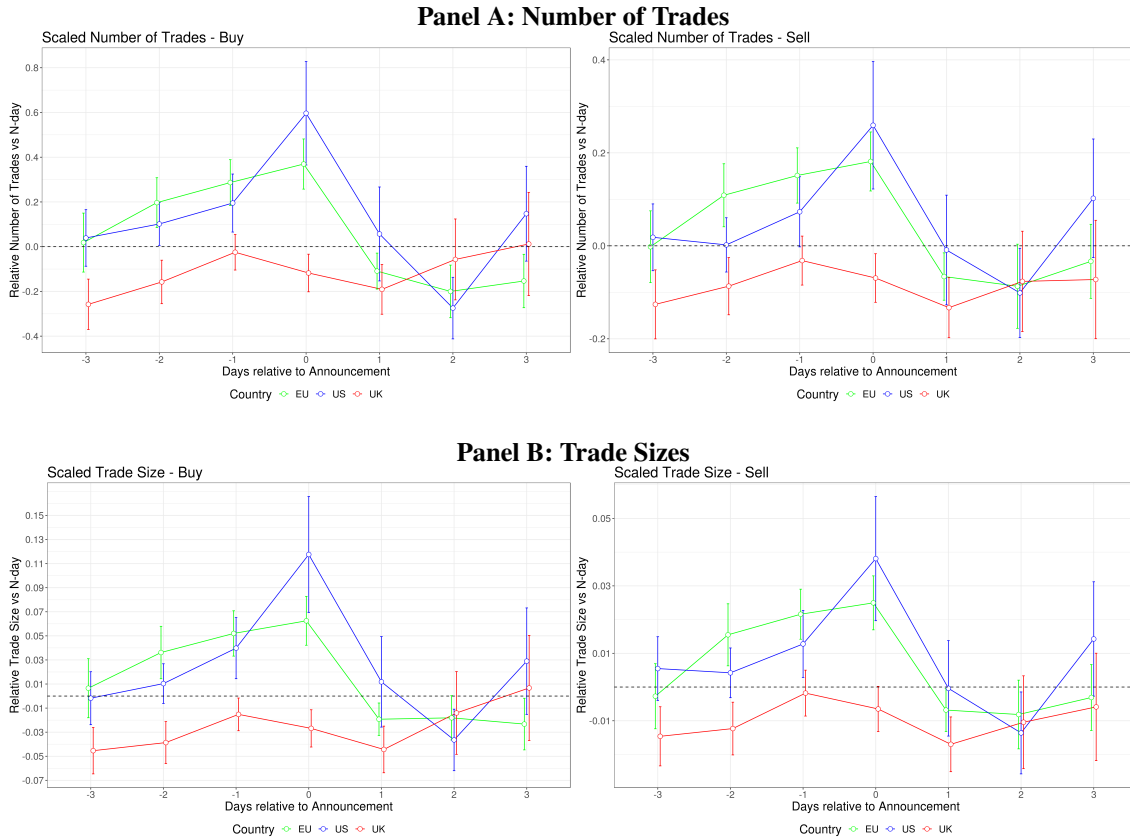


**Panel C: UK Macro Announcement Days**



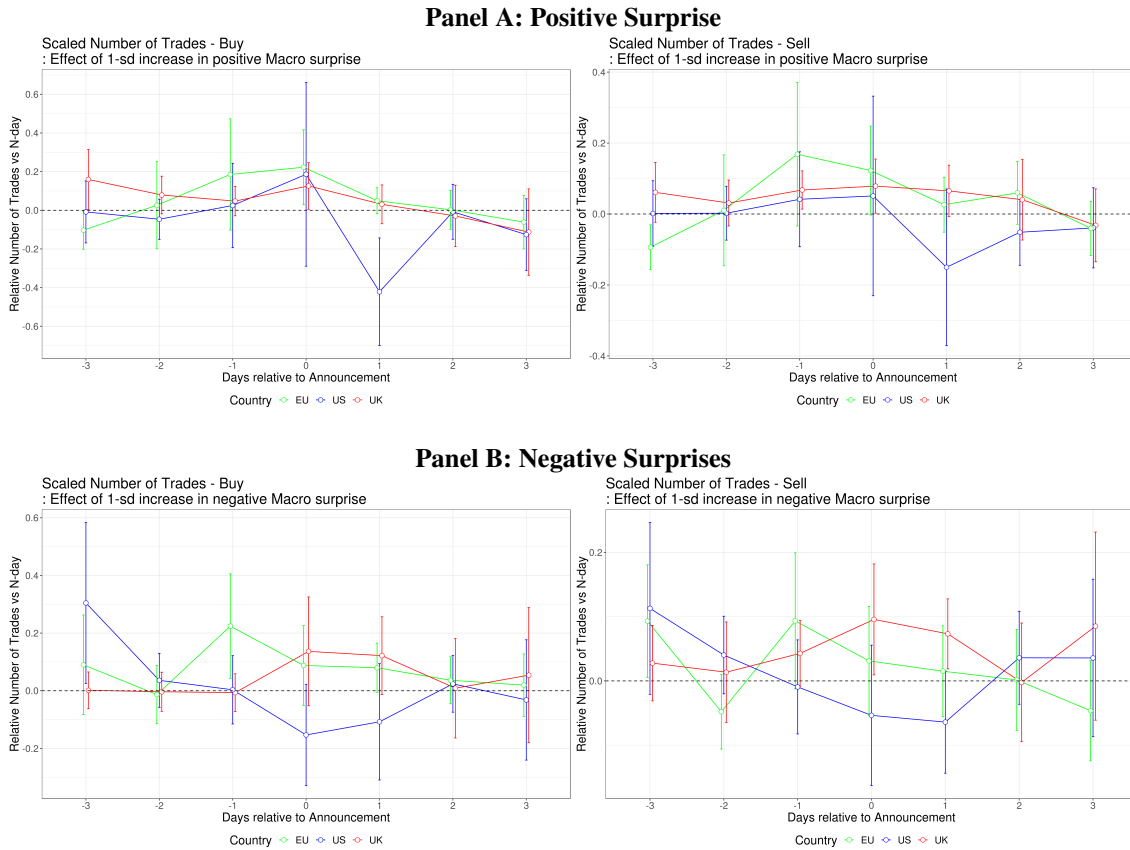
**Figure 4.4.** Trading Activities around Macroeconomic Announcement Days

This figure plots the trading intensity, measured by the scaled number of trades and the scaled trade size, around macroeconomic announcements. For each lead or lag ( $k$ ) around day  $t$  and a country,  $c$ , the trading intensities are estimated from the following regression at a fund-date level, described in the Section 3.3.1. The relative trading intensities on macroeconomic announcement days(A-day) relative to non-macroeconomic announcement days are represented by  $\beta_c$ . Each dependent variable is winsorized at a 99.5% level. Standard errors are double-clustered at fund and date levels. Panel A, B reports the coefficient estimates and their standard errors, for the scaled number of trades and trade size, respectively. along with their standard errors. The left figure in each panel reports results for buy trade and the right figure reports results for sell trades. The blue, red and green lines represent US, UK and EU macroeconomic news respectively.



**Figure 4.5.** The Effect of Macroeconomic News Surprises on Number of trades

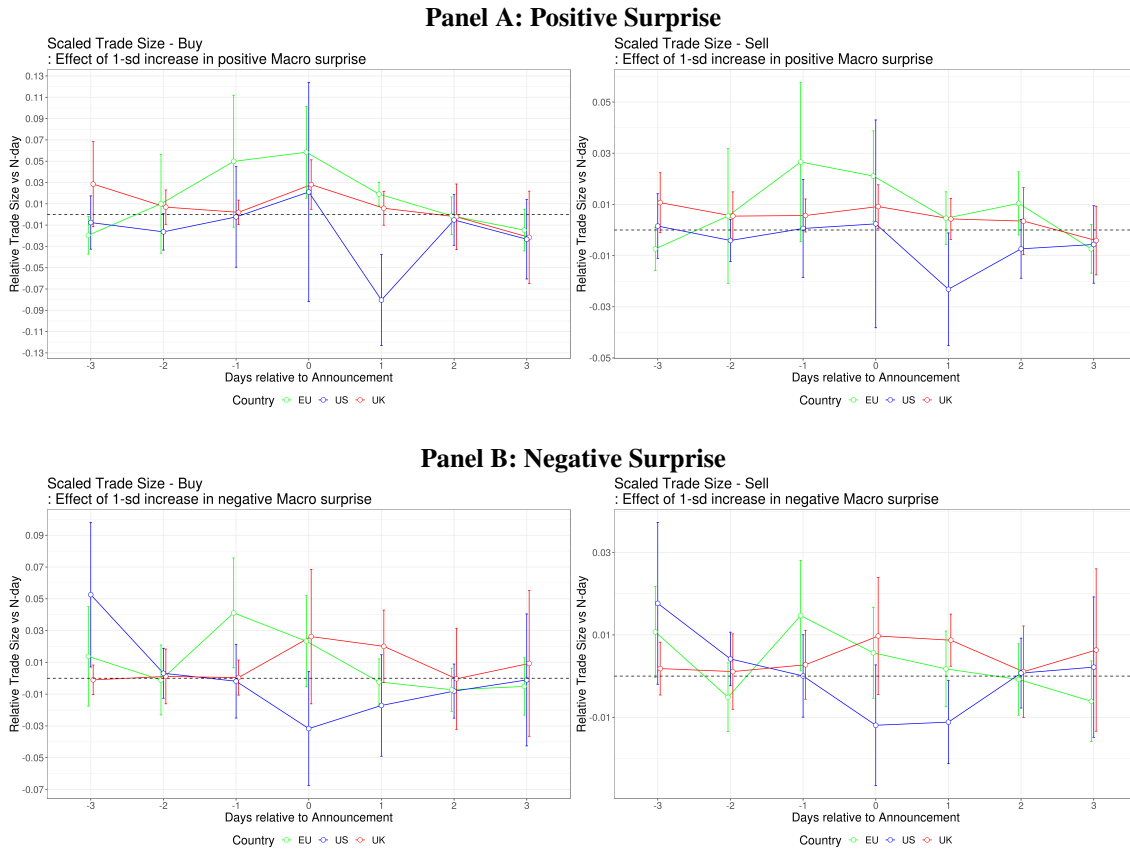
This figure plots the effect of macroeconomic news surprise on the scaled number of trades around macroeconomic announcements. For each lead or lag ( $k$ ) around day  $t$  and a country,  $c$ , the trading intensities are estimated from the following regression at a fund-date level, described in the Section 3.3.1. The effects of positive and negative surprises on the number of trades are represented by  $\gamma_c^+$ ,  $\gamma_c^-$ , shown respectively in Panel A and B, along with their 95% confidence interval. The scaled number of trade is winsorized at a 99.5% level. Standard errors are double-clustered at fund and date levels. The left figure in each panel reports results for buy trade and the right figure reports results for sell trades. The blue, red and green lines represent US, UK, and EU macroeconomic news respectively.



**Figure 4.6.** The Effect of Macroeconomic News Surprises on Trade Sizes

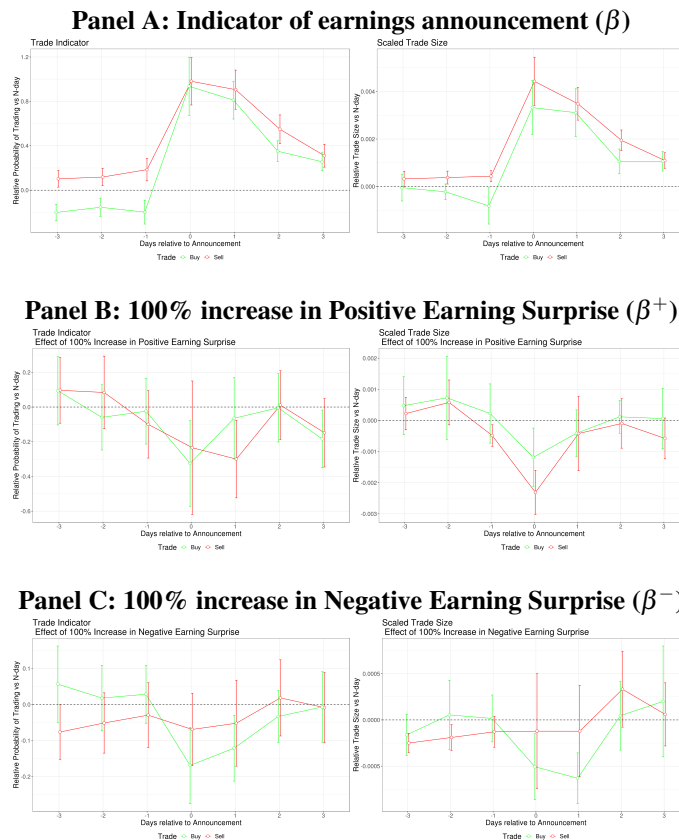
This figure plots the effect of macroeconomic news surprise on the scaled trade size around macroeconomic announcements. For each lead or lag ( $k$ ) around day  $t$  and a country,  $c$ , the trading intensities are estimated from the following regression at a fund-date level, described in the Section 3.3.1.

The effects of positive and negative surprises on the number of trades are represented by  $\gamma_c^+$ ,  $\gamma_c^-$ , shown respectively in Panel A and B, along with their 95% confidence interval. The scaled trade size is winsorized at a 99.5% level. Standard errors are double-clustered at fund and date levels. The left figure in each panel reports results for buy trade and the right figure reports results for sell trades. The blue, red and green lines represent US, UK, and EU macroeconomic news respectively.



### Figure 4.7. Trading Activities around Earnings Announcements

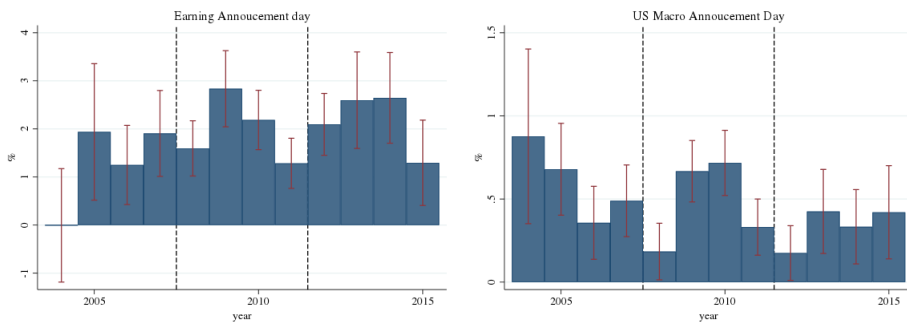
This figure presents the estimates the trading activities, in terms of the indicator of trading (in percentage) and the scaled trade size, around earning announcement news. For each lead or lag ( $k$ ) around time  $t$ . For each lead or lag ( $k$ ) around day  $t$  and a country,  $c$ , the trading intensities are estimated from the following regression at a fund-date level, described in the Section 3.3.1. The scaled trade size is winsorized at a 99.5% level. Panel A, B, and C report the regression coefficient estimates on the indicator of earnings announcements ( $\beta$ ), the magnitude of positive earnings surprise ( $\beta^+$ ), and the magnitude of positive earnings surprise ( $\beta^-$ ), respectively, along with their 95% confidence interval. Standard errors are double-clustered at fund and date levels. The green line represents buy trades, and the red line represents sell trades.



**Figure 4.8.** Investor's Attention over time

This set of figures presents investor's attention to various types of news over time. We measure investor's attention by the difference of the probability of trading (buying or selling) on news day minus the probability of trading on no news days at a fund-year level for four types of news, described in Table 2. We present the annual average investor's attention across funds over time. The blue bar represents the average attention, and the red bar represents the sample standard errors of the average investor's attention. The dash lines denote recession periods.

**Panel A: Earnings and US Macro Announcement Days**



**Panel B: EU and UK Macro Announcement Days**

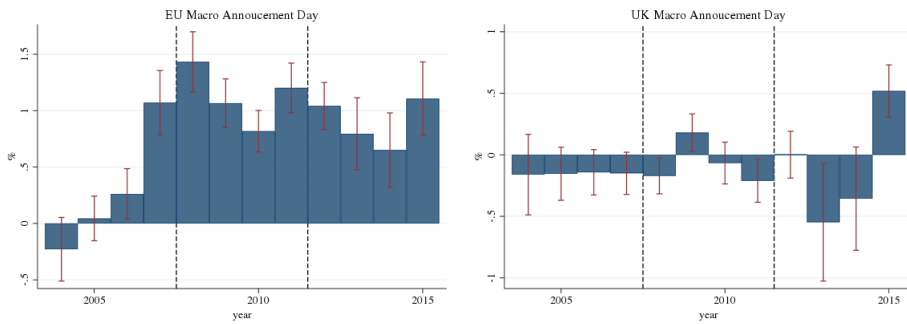


Table 4.13: Counterfactual Returns on Each Type of Macro Announcements

This table presents the value-added measures (post-trade returns relative to a random sell counterfactual) for buy and sell trades for each type of macroeconomic announcements of US, EU, and UK. We report the weighted average counterfactual returns for different types of announcements including (1) PPI, (2) Interest Rate, (3) EU Unemployment, and (4) GDP. For each type of announcement, we report weighted average value-added measures on each announcement days and non-announcement days, where we weigh observations inversely to a fund's trading activity. Standard errors are computed using the Placebo method.

Country	Announcement	Panel A: Buy			Panel B: Sell		
	Horizon	28	90	365	28	90	365
I.US	PPI	0.11 (0.14)	0.17 (0.23)	0.83 (0.58)	-0.13 (0.11)	0.01 (0.20)	0.66 (0.53)
	CB	-0.14 (0.14)	-0.57 (0.27)	-0.07 (0.57)	-0.17 (0.14)	-0.44 (0.27)	-0.81 (0.57)
	Unemployment	0.02 (0.11)	-0.27 (0.18)	-0.47 (0.43)	-0.22 (0.11)	-0.28 (0.18)	-0.66 (0.43)
	GDP	-0.21 (0.12)	-0.03 (0.20)	2.20 (0.49)	0.06 (0.12)	0.13 (0.20)	-0.96 (0.49)
II.EU	PPI	-0.23 (0.10)	-0.11 (0.19)	0.43 (0.44)	-0.34 (0.18)	-0.11 (0.24)	-1.05 (0.65)
	CB	-0.10 (0.08)	-0.19 (0.14)	0.11 (0.36)	-0.05 (0.08)	0.18 (0.15)	0.62 (0.34)
	Unemployment	-0.50 (0.14)	-0.68 (0.23)	-0.48 (0.50)	-0.09 (0.15)	-0.12 (0.29)	0.47 (0.62)
	GDP	-0.16 (0.12)	0.11 (0.22)	0.33 (0.51)	-0.17 (0.16)	-0.07 (0.30)	1.08 (0.57)
III.UK	PPI	-0.04 (0.12)	-0.21 (0.22)	-0.41 (0.60)	-0.57 (0.13)	-1.32 (0.27)	-1.02 (0.57)
	CB	0.28 (0.08)	0.26 (0.15)	0.33 (0.37)	-0.18 (0.09)	0.16 (0.17)	0.59 (0.41)
	Unemployment	0.35 (0.13)	0.75 (0.21)	1.19 (0.50)	-0.12 (0.11)	-0.04 (0.17)	-0.13 (0.44)
	GDP	0.11 (0.11)	0.30 (0.20)	0.44 (0.46)	-0.19 (0.12)	-0.09 (0.21)	-1.04 (0.60)

Table 4.14: Trading Intensity on Different Types of Macroeconomic Announcements(Baseline set of Macro Announcements)

This table reports the trading intensity, measured by the scaled number of trades and the scaled trade size, on different type of macroeconomic announcements in US, EU and UK. The trading intensities are estimated from the following regression at a fund-date level, described in the Section 3.3.1. Each dependent variable is winsorized at a 99.5% level. Standard errors are double-clustered at fund and date levels. Panel A, B reports the coefficient estimates and their standard errors in parenthesis, for the scaled number of trades and trade size, respectively.

Measure of Trading	Type of Macro Days	Buy			Sell		
		US	EU	UK	US	EU	UK
<b>Panel A:</b> Scaled Number Of Trades	PPI	-0.0631 (-1.00)	-0.0599 (-0.71)	-0.140 (-1.77)	-0.00917 (-0.13)	0.0339 (0.49)	-0.129* (-2.39)
	CB	0.484*** (3.38)	0.121* (2.06)	-0.0110 (-0.22)	0.365** (2.80)	0.0496 (1.12)	-0.0825* (-2.03)
	Unemployment	-0.327** (-3.24)	1.953*** (8.01)	-0.117* (-2.25)	0.0494 (0.76)	1.416*** (7.32)	-0.112** (-2.69)
	GDP	1.795*** (4.77)	0.168* (2.32)	-0.0407 (-0.29)	1.277*** (3.99)	0.0476 (0.85)	-0.0696 (-0.62)
<b>Panel B:</b> Scaled Trade Size	PPI	-0.0155 (-1.69)	0.000991 (0.09)	-0.0259* (-2.21)	-0.00254 (-0.29)	-0.00356 (-0.35)	-0.0209* (-2.08)
	CB	0.0933** (2.98)	0.0180 (1.87)	-0.01000 (-1.18)	0.0802** (2.80)	0.0117 (1.45)	-0.0124 (-1.67)
	Unemployment	0.00577 (0.17)	0.357*** (8.04)	-0.0255** (-2.71)	0.0631** (2.66)	0.292*** (7.45)	-0.0207* (-2.58)
	GDP	0.377*** (4.78)	0.0172 (1.38)	-0.0337 (-1.21)	0.291*** (4.28)	0.00648 (0.58)	-0.0279 (-1.18)

Table 4.15: Trading Intensity on Different Types of Macroeconomic Announcements( CPI instead of PPI)

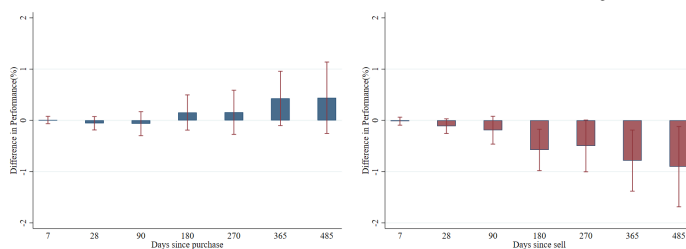
This table reports the trading intensity, measured by the scaled number of trades and the scaled trade size, on different type of macroeconomic announcements in US, EU and UK. The trading intensities are estimated from the following regression at a fund-date level, described in the Section 3.3.1. We replace PPI with CPI as price-level macro news. Each dependent variable is winsorized at a 99.5% level. Standard errors are double-clustered at fund and date levels. Panel A, B reports the coefficient estimates and their standard errors in parenthesis, for the scaled number of trades and trade size, respectively.

Measure of Trading	Type of Macro Days	Buy			Sell		
		US	EU	UK	US	EU	UK
<b>Panel A:</b> Scaled Number Of Trades	CPI	-0.125 (-1.48)	0.184* (2.52)	-0.0970 (-1.35)	-0.0368 (-0.66)	0.185** (2.75)	-0.0611 (-1.02)
	CB	0.480*** (3.32)	0.133* (2.26)	-0.00671 (-0.14)	0.356** (2.75)	0.0585 (1.32)	-0.0788 (-1.94)
	Unemployment	-0.320** (-3.28)	1.965*** (8.06)	-0.113* (-2.15)	0.0611 (0.84)	1.425*** (7.36)	-0.108** (-2.60)
	GDP	1.805*** (4.81)	0.179* (2.48)	-0.0363 (-0.26)	1.286*** (4.02)	0.0564 (1.01)	-0.0659 (-0.59)
<b>Panel B:</b> Scaled Trade Size	CPI	-0.0228* (-2.26)	0.0167 (1.49)	-0.0350*** (-3.66)	-0.00913 (-0.97)	0.0214 (1.93)	-0.0283** (-3.10)
	CB	0.0952** (3.02)	0.0192* (1.99)	-0.0101 (-1.18)	0.0788** (2.74)	0.0130 (1.61)	-0.0123 (-1.65)
	Unemployment	0.00764 (0.23)	0.358*** (8.06)	-0.0256** (-2.71)	0.0632** (2.76)	0.294*** (7.48)	-0.0206* (-2.56)
	GDP	0.379*** (4.80)	0.0182 (1.46)	-0.0337 (-1.21)	0.292*** (4.29)	0.00773 (0.70)	-0.0277 (-1.17)

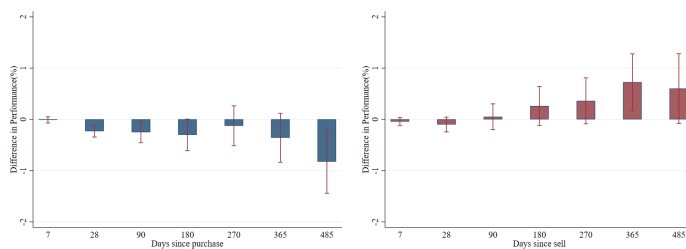
**Figure 4.9.** Counterfactual Returns relative to Counterfactual Hold Portfolio on Macro Announcement Days(CPI)

This figure presents weighted average returns relative to random buy/sell counterfactuals for trades that take place on macroeconomic announcement days (A-day) and trades that are on non-earnings announcement days (N-day). Government macro news of UK, US and EU in Table 2 are considered, except we replace PPI with CPI. For buy trades, we compute average returns of stocks bought minus returns of stocks held on each day. For sell trades, we compute average returns of stock held minus returns of stocks sold. For each portfolio, the counterfactual returns for buy trades are computed by returns of stock bought minus returns of stocks held on each day. The counterfactual returns for sell trades are computed by returns of stock held minus stock sold. We then compute the average of these performance measures across all portfolios and dates, weighted inversely to funds' trading activity. Each bar represents average counterfactual returns in percentage over specified horizons on the x-axis. The range on the top of each bar is the confidence interval of the average returns of a portfolio at each horizon. The standard errors are computed using Placebo method.

**Panel A: US Macro Announcement Days**



**Panel B: EU Macro Announcement Days**



**Panel C: UK Macro Announcement Days**

