WHAT DOES EQUITY SECTOR ORDERFLOW TELL US ABOUT THE ECONOMY?

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ABSTRACT

Investors rebalance their portfolios as their views about expected returns and risk change. We use empirical measures of portfolio rebalancing to back out investors' views, specifically their views about the state of the economy. We show that aggregate portfolio rebalancing across equity sectors is consistent with sector rotation, an investment strategy that exploits perceived differences in the relative performance of sectors at different stages of the business cycle. The empirical foot-print of sector rotation has predictive power for the evolution of the economy and future bond market returns, even after controlling for relative sector returns. Contrary to many theories of price formation, trading activity therefore contains information that is not entirely revealed by resulting relative price changes.

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1.   Introduction

It is well documented that asset prices and returns help forecast business cycles (see Stock and Watson (2003) for a survey of this literature). The motivation behind this literature is that the information about the current and future states of the economy collected and processed by investors is revealed by the (change in) relative prices of the securities traded in response to this new information. Asset prices are therefore a leading, and often thought of as sufficient statistic, for the public or private information available to agents.

Orderflow, the act of initiating the purchase or sale of securities, is the conduit through which information about economic fundamentals are aggregated into asset prices. Theoretical and empirical studies demonstrating the role of orderflow in price formation include Glosten and Milgrom (1985), Kyle (1985) and Hasbrouck (1991) for equities, Evans and Lyons (2002) for foreign exchange, and Brandt and Kavajecz (2004) for fixed income.

Combining these two observations, that asset prices help forecast business cycles and that orderflow is the mechanism by which asset prices change, raises the question of how orderflow itself is related to current and future economic conditions. Does orderflow forecast the state of the economy by itself and in conjunction with asset prices? To the extent that orderflow has (marginal) predictive power, what is the exact nature of this information?

Orderflow may contain less, the same, or more information than prices or returns. Orderflow may contain less information if a substantial portion of the price formation process is due to unambiguous public information resulting in instantaneous price

adjustments (absent contemporaneous or subsequent trade). Alternatively, orderflow might simply pass through information to asset prices so that the information contained in orderflow and returns is identical. Finally, orderflow may contain more or unique information relative to prices in that investors' trading behavior is not fully spanned by asset prices. This possibility arises if standing between orderflow, (which reflects the *actions* of investors) and returns (which reflect the *consequences)* is a trading process with a number of potential frictions. A whole host of frictions can impact the mapping of actions (orderflow) into consequences (returns), such as noise trading, non-strategic liquidity providers (e.g. stale limit orders), multiple signals channeled through a single price, decentralized trading venues, etc. Each of these frictions has the potential to dampen or mask the transfer of a signal from orderflow to prices or returns; thus, it is conceivable that orderflow may contain more or different information than is contained in prices or returns. In the end, whether orderflow contains less, the same, or more information about the macroeconomy than asset prices or returns is an empirical question – one that we wish to answer in this paper.

It is important to note, however, that this last possibility does not hinge on the nature of the information that prompted the orderflow, in particular, whether the information is public or private. Both public information with heterogeneous beliefs and/or heterogeneous decision processes (i.e., different investors using proprietary priors or models to process public information) and private information in the traditional sense have the potential to generate informative orderflow. As our empirical results do not depend on this distinction, we do not model explicitly how or why market participants decide to trade. We simply argue that agents are taking in information, some may be

private while other information is public, and they are processing it with their own beliefs and models, to arrive at an orderflow action.

There are many different settings that could be used to investigate these questions as there are numerous ways in which investors adjust their portfolios in response to changes in their views about economic fundamentals – e.g., they change their stock/bond/cash allocation, change their positions in real assets such as gold or inflation-indexed Treasury securities, or change their relative equity allocation within different sectors of the economy. We focus our analysis on the last case of sector rotation, a highly publicized investment strategy that exploits perceived differences in the relative performance of sectors at different stages of the business cycle. This setting allows us to study a very common strategy that is implemented by institutional and retail traders alike as well as utilize data within a single dataset. Specifically, we analyze the dynamics of orderflow across ten U.S. equity sectors to investigate whether sector adjustments to investor portfolios is related to the current and future state of the macro economy as well as the aggregate stock and bond markets.

With regard to orderflow predictability, our results show that while sector orderflow movements are inconsistent with naive portfolio rebalancing techniques, such as buy-and-hold (no rebalancing) or a constant-mix strategy, it appears that market participants shift funds between equity sectors according to their collective information about changes in the macro economy as much as three months ahead. Our results show that large-sized active orderflow into the material sector forecasts an expanding economy, while large-sized active orderflow into consumer discretionary, financials, and

telecommunications forecasts a contracting economy.[1] We also find that the cross-section of sector orderflow contains information that predicts the evolution of bond markets, even after controlling for relative sector returns and traditional low-frequency forecasting variables. While it is interesting that orderflow predicts the macro economy and bond market, what is most intriguing is that the linear combination of sector orderflow that *best* predicts the evolution of the macro economy also contains the bulk of the explanatory power for predicting the bond markets. Moreover, we demonstrate that our predictability results become significantly stronger after conditioning on low dispersion of orderflow *within* sectors indicating a true sector view as opposed to a view on a few stocks within the sector. Together, these results suggest that the information contained in sector orderflow is different than the information in returns; moreover, the information contained therein has more to do with sector allocation than stock picking.

Our results also reveal three characteristics regarding the nature of information contained in sector orderflow. First, we show that the information in sector orderflow is directly related to the release of macroeconomic fundamentals, specifically the release of the prominent non-farm payroll figures. Second, our results show that sector orderflow movements are related to independent mutual fund flows, which suggests market participants are making *active decisions* regarding their equity market allocations. Lastly, sector orderflow movements are inherently defensive in nature. By constructing an orderflow mimicking portfolio, whereby a well-diversified portfolio is tilted according to sector orderflow movements, we are able to show that the resulting portfolio is focused primarily on wealth preservation by investing in low risk stocks during difficult economic

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[1] Active sector orderflow refers to orderflow within a sector in excess of the proportion of total aggregate orderflow into or out of the aggregate equity market based on the sector's market capitalization.

times, albeit it enjoys superior risk and return properties relative to the traditional market portfolio. Thus, taken together our results reveal that the information in aggregate sector orderflow is directly related to macroeconomic fundamentals, is consistent with deliberate reallocation strategies by market participants and is defensive in nature.

Section 2 discusses the related literature. Section 3 describes our data and methodology. Section 4 investigates the predictive power of sector orderflow. Section 5 examines the nature of sector orderflow information and Section 6 concludes.

2. Related literature

The role of orderflow in a trading environment has received a fair amount of attention in the recent finance literature. Despite the growing number of papers that analyze orderflow, each can be partitioned into two broad strands of the literature based on their research focus. One strand of the literature takes a macro view of orderflow, by investigating how aggregate orderflow is related to market-level variables. Chordia, Roll and Subraymanyam (2000, 2001, and 2002) analyze the connection between orderflow movements into and out of equities and market-wide liquidity, while Evans and Lyons (2007) relate proprietary foreign exchange orderflow with output/money growth and inflation. Lo and Wang (2000) and Cremers and Mei (2007) investigate the implications of two-fund separation on aggregate share turnover, while Hasbrouck and Seppi (2001) find that returns and orderflow in the equity market are characterized by common factors. Finally, Bansal, Fang, and Yaron (2005) demonstrate that there appears to be no relation between macroeconomic sectoral wealth and the return and volatility of sectoral returns.

The other strand of the orderflow literature takes a micro view, by investigating whether disaggregated (by individual security or mutual fund) orderflow can be used to forecast subsequent asset returns. In particular, Albuquerque, Francisco and Marques (2008) estimate the Easley, Kiefer, O'Hara, and Paperman (1996) structural model on a set of stocks with international exposure to investigate the relation between orderflow and exchange rates. Froot and Teo (2008) analyze institutional orderflow from State Street Global Advisors to investigate whether orderflow movements are related to mutual fund style returns. They find that fund flows appear to be related to styles and interestingly, sector rotation is a specific investment style that they were able to identify. Campbell, Ramadorai and Schwartz (2008) also investigate institutional orderflow; however, their data source is a match of the TAQ database with the 13-F institutional ownership filings. The latter two studies find that institutional orderflow has a significant effect on subsequent asset returns.

Our paper is positioned between these two strands of the orderflow literature. The focus of our orderflow analysis is distinct in that we investigate the extent to which the dynamics of orderflow between sectors is related to the macro economy as well as broad markets rather than less aggregate series related to liquidity, volatility or specific mutual fund returns. Our aim is to understand whether trading activity contains information that is not entirely captured by resulting relative price changes and then to understand the nature of that information. Thus, our contribution to the literature rests importantly in the paper's focus being on the connection between market participants' decisions about sector orderflow and the larger macroeconomy and capital markets.

3.   Data and variable construction

At the center of our empirical analysis are equity orderflow data constructed using the Trades and Quotes (TAQ) dataset over the sample period 1993 through 2005. Our universe of common stock equities is generated from the stocks covered in the *CRSP* dataset.

We construct our orderflow data through a number of steps. For each stock and each day in the sample period, we apply the following procedure. First, to ensure data integrity, we eliminate non-positive spreads, depths and trade prices as well as records where the size of the quoted spread and/or effective spreads are large relative to the median quoted for that specific stock. Second, we match the sequence of outstanding quotes with the sequence of trades applying the standard 5-second rule.[2] Third, we aggregate all trades that are executed at the same price which do not have an intervening quote change. Fourth, we utilize the Lee and Ready (1991) algorithm to sign each trade as being initiated by a buyer or a seller which allows us to identify the liquidity provider and liquidity demander. Lastly, each trade is assigned to a dollar size category whose cutoffs are defined as follows: small ($< \$25,000$), medium ($\$25,000$ to $\$250,000$) and large ($>\$250,000$).[3] The rationale for using dollar orderflow is that by summing the net dollar orderflow into sectors we are implicitly value-weighting, this is unlike stock returns that are expressed on a homogeneous (scale-free) basis across size. This

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[2] This rule has been standard practice in the literature and was certainly applicable during the first part of our sample; however, recent advances in technology and speed of transacting may call into question its use (Bessembinder, 2003). In the interest of consistency, we apply it uniformly across the entire sample period.
[3] Trades were also separated into size categories based on shares instead of dollars. We focus on dollars throughout the analysis because partitioning by shares places a disproportionate fraction within the small and medium categories.

procedure results in a set of daily orderflow series for each security: small, medium and large buys and small, medium and large sells.[4]

We assign each stock to one of the ten sectors defined by the Global Industry Classification Standard (GICS) developed by Morgan Stanley Capital International (MSCI) and Standard & Poor's (see the appendix for specific sector descriptions). We then construct sector-level net orderflow by simply summing all orderflow for the individual stocks included in each sector; net orderflow to the stock market as a whole is the analogous sum of net orderflow of each sector. Likewise, we define sector level capitalization as the sum of the capitalizations (shares outstanding multiplied by end of month price) of the individual stocks in the sector. Throughout the paper/tables the sectors are ordered with respect to their cyclicality with the U.S. business cycle. We use as an objective sector ordering the MSCI/Barra partition of the ten sectors into three groups: pro-cyclical (information technology, materials and industrials), neutral (consumer discretionary, financials, energy and telecommunications), and counter-cyclical (utilities, consumer staples and health care).[5] As a robustness check we also conducted our own regressions regarding each sectors degree of cyclicality; our results largely confirmed the MSCI ordering.

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[4] We acknowledge that breaking up orderflow by trade-size to identity the broad type of trader (institutional vs. retail) can be difficult. In particular, while it is well understood that institutional traders do not trade large quantities exclusively nor do retail traders solely trade small or medium trades; as a general rule we believe the likelihood of large trades originating from institutions remains high. In addition, we are able to provide evidence (upon request) that all our key results hold irrespective of whether we use large or all trade orderflow.

[5] For more information about the MSCI/Barra sector ordering see Using Sector Performance Across Business Cycles, 2009, MSCI/BARRA Research Bulletin, November, http://www.mscibarra.com/research/articles/2009/Sector_Performance_Across_Business_Cycles_Nov_2009.pdf

Once the basic sector and stock market level net orderflow measures have been constructed, it is possible to define our two key measures of net orderflow, *active* and *passive*. Passive net orderflow for a given sector is defined as the total net orderflow to the stock market multiplied by the weight of that sector in the market portfolio. Effectively, the definition of passive net orderflow amounts to the null hypothesis that orderflow entering the stock market is distributed across sectors by their weight in the market portfolio. Active net orderflow for each sector is the difference between sector-level total net orderflow and passive net orderflow thereby measuring the excess or shortfall in orderflow relative to a market capitalization weighted distribution of total orderflow. We interpret active net orderflow as deliberate decisions/actions by market participants about their capital allocation within the equity market.

Table 1 displays our total aggregate orderflow by sector and year expressed as a percentage of the total net orderflow for the year. While the percentage of orderflow across years remains fairly stable, there are certainly variation across years particularly, leading up to, and during, the economic downturn in 1999 and 2000. In addition, these shifts in the shares of orderflow across sectors appear more pronounced for large orders (Panel B) relative to all orders (Panel A), suggesting that market participants placing large orders may be more aggressive and/or savvy in positioning their portfolio ahead of changes in the economy.

We supplement the equity sector orderflow with information about the current state of the economy, stock and bond market performance (returns) as well as non-farm payroll expectations and announcement information. For the non-farm Payroll announcement we obtain the release dates, actual reported (announced) values and

median forecasts from Money Market Services. The performances of the stock and bond markets are measured using the returns of the S&P500 index and the returns of the Fama-Bliss CRSP discount bonds. Finally, we measure the state of the economy using the Chicago Federal Reserve Bank National Activity Index (CFNAI). The CFNAI index is a weighted average of a number of monthly indicators of economic activity first developed by Stock and Watson (1999).[6] Note that an index value above (below) zero indicates economic growth above (below) the trend. In contrast to the NBER expansion and recession periods, the CFNAI index has the advantage of being a coincident indicator, a measure of economic conditions available in real time. In addition, our sample covers a relatively balanced period of economic growth and decline, with the former occurring in 58% of the months in our analysis. To provide a visual sense of our key variables, we plot the active net orderflow of large and all orders along with the CFNAI index for each individual sector in Figure 1.

4.   The Information in Equity Sector Orderflow

4.1   Preliminaries

As we have argued above, aggregate orderflow is a collection of all market participants trading strategies and therefore embeds their preferences, expectations, and information. Consequently, if we are interested in the information component of orderflow as it relates to the macro economy it is important to disentangle, or control for, any systematic portion of aggregate orderflow.

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[6] The CFNAI index is constructed to be a single summary measure (with mean zero and standard deviation of one) of the activity in four broad categories of the economy: production and income; employment, personal consumption which includes housing; and sales, orders, and inventories. For more detailed information concerning the CFNAI index see
http://www.chicagofed.org/economic_research_and_data/cfnai.cfm

At the most fundamental level, the systematic portion of equity market orderflow could simply be the result of movements into and out of the equity market as a whole. We investigate this possibility by conducting a principal component decomposition of sector orderflow. While our untabulated results reveal one dominant factor explaining 68% of orderflow movements, consistent with Hasbrouck and Seppi (2001), there are at least five other significant factors that are important in explaining orderflow. Given this result, we can quickly dispel the notion that aggregate equity orderflow simply blankets the equity sectors uniformly.

As a further diagnostic along these lines, we also compute the cross-correlation of sector orderflow within the cyclical and countercyclical sectors, where cyclicality is defined by the MSCI/Barra classification. Aggressive sectors have a very low average correlation of 0.03, while defensive sector orderflows are relatively more correlated, with an average of 0.24. Overall, this is suggestive evidence that information in different aggressive and defensive sector orderflow is quite heterogeneous. Furthermore, when we compare the simple correlations between large active sector orderflow and the excess sector returns, all of them are positive, significantly different from zero, and are on average equal to 0.35. Similarly to the equity market evidence presented in Hasbrouck and Seppi (2001), this is evidence that sector orderflow and returns have some degree of commonality but also show different dynamics.

Portfolio rebalancing of sector positions is another common motive for trade. If market participants engage in a buy-and-hold strategy (thereby effectively not rebalancing their portfolios), we would expect to see no relation between aggregate sector orderflow and the previous performance of the sector, while a negative relation between

sector orderflow and previous performance would be consistent with a constant mix strategy. To investigate these possibilities, we analyze the temporal relation between sector orderflow and the corresponding lagged sector returns at both a weekly and monthly frequency. We suspect that the monthly aggregation may be more appropriate as it is better able to cancel out components that are related to liquidity and inventory, yet retain the components of orderflow that are related to long-lived information. Specifically, we regress active net orderflow standardized by sector market capitalization on the sector return in excess of the return of the market portfolio.

Our results for the weekly horizon (shown in Table 2, panel A) reject both the buy-and-hold and defensive rebalancing (constant mix strategy) as market participants appear extremely eager to increase the weight of a sector after a period of positive performance (positive excess returns). One way of interpreting these results is that in aggregate, market participants chase performance (or act as momentum traders) at the industry level. When we repeat the same analysis using a monthly frequency (shown in Table 2, panel B), the results on small and large orders are no longer significant while the results for medium orders are less significant than at the weekly horizon. At this lower frequency, orderflow simply does not appear to respond to previous excess returns. Thus, at the sector level, neither defensive rebalancing nor momentum trading appear to be a pervasive determinant of orderflow patterns at the monthly frequency.

These results show little evidence that in aggregate market participants defensively rebalance their portfolios. If anything, orderflow seems to respond positively to past sector returns, but only at a weekly frequency. These findings combined with the evidence from the principal components analysis, suggest that orderflow is driven by

more than simple indiscriminant or defensive trading strategies and therefore, has the potential to reveal aggregate investor information related to beliefs, expectations and risk preferences.

4.2   Sector Orderflow and the Economy

In this section we explore whether the collective trades of market participants across asset classes contain information about the expected state of the macro economy. Our conjecture is that market participants are continually digesting news about the macro economy; as they process this news, it impacts their preferences, expectations and risk tolerances, which in turn induce them to trade.

Our analysis involves aggregating orderflow to the monthly frequency and testing whether sector orderflow has predictive power for the CFNAI expansion indicator. In particular, we regress the current CFNAI index on active net sector orderflow normalized by the market capitalization of each sector and the lag of the CFNAI index.[7] This empirical specification has a number of advantages. First, our key variable reflects the orderflow that is entering a sector in excess of new funds invested into the stock market. Second, standardization by sector market capitalization enjoys the intuitive interpretation of market share and also avoids the practical difficulty of overweighting the largest sectors.[8] Recall that the construction of dollar sector orderflow is comparable to value-

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[7] We repeat all the regressions in the paper including three lags of the explanatory variables and the key results are confirmed. Therefore, in the interest of parsimony we keep the simpler specification without lags. However, in the few marginal cases where the results differ, we mention the difference in the exposition.

[8] We measure the sector market capitalization using stock prices at the beginning of the month to avoid any spurious effects of a given month's return on the weight of a specific sector. As a robustness check we also repeat our analysis using the sector market capitalization for each day of the month, obtaining the similar results.

weighting sector returns. Lastly, we are careful to control for the current level of the expansion indicator to ensure that coefficients on the orderflow do not pick up any contemporaneous relation with the economy.

At the outset, we investigate whether active monthly orderflow, within each separate sector, have predictive power for the expansion index one and three months into the future. Our rationale for investigating each sector in isolation is to understand, in an unconditional and unconstrained environment, which sector orderflow series are most closely associated with economic expansions and contractions. The results, shown in Table 3, formalize the individual sector comparison with the CFNAI index displayed visually in the ten panels of Figure 1. As a reminder, note that the sectors are ordered by their cyclicality, pro-cyclical sectors at the top of the table, neutral in the middle and counter-cyclical at the bottom.

Intuition suggests that pro-cyclical sectors (top of the table) would have positive coefficients and counter-cyclical sectors would have negative coefficients (bottom of the table). While in general this intuition is bore out, it is certainly not universal, with exceptions being more prevalent for small sized orderflow. In addition, Table 3 shows that orderflow into a number of the sectors are able to forecast expansion/contractions in the macro economy, particularly for large orders. Specifically, we find that active orderflow of large orders into the material sector predict higher levels of the expansion index both one and three months ahead, while active orderflow of large orders into financials, telecommunications and consumer discretionary predict lower levels of the expansion index at the one and three month horizons.

In order to be conservative in our interpretation of the results, we compute data-mining robust critical values for the largest *t-statistic* across the thirty alternative orderflow regressors (orderflow in ten sectors across three trading sizes) in the forecast of the CFNAI indicator. In particular, we construct the finite-sample empirical distribution of the largest *t-statistic* under the null hypothesis of no predictability from orderflow using 100,000 bootstrap replications. Our methodology consists of a block bootstrap approach which specifically accounts for both the cross-sectional correlation across sectors as well as the autocorrelation within each sector by drawing sets of observations across all sectors at a point in time as well as a time-series window within each sector.[9] In choosing the block length we follow Politis and Romano (1994) for a random length, and Hall, Horowitz and Jing (1995) for fixed optimal length; however, critical values are similar in either case. For example, the 5% and 10% data-mining robust critical values for the *t-statistics* in Table 3, Panel A, with a random block bootstrap are 2.93 and 2.64, respectively and they are 3.01 and 2.68 with a fixed-length block bootstrap.

Of the large sector orderflow, materials, financials and telecoms are significant at least at the 5% level across the one and three-month horizon, while small and medium sector orderflow show utilities as significant at the 1% level. Further evidence of the information contained in the orderflow series can be gleaned from comparing the baseline R^2 absent the orderflow series (shown in the last row of each panel within Table 3) to the R^2 including the respective orderflow series. An alternate way of digesting the result is that under the null hypothesis of no predictability, there is a 5% and 2.5% probability to obtain six and eight models, respectively, out of 30 with a *t-statistic* greater than two. In Table 3, Panel A, we

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[9] There is an average of 0.55 autocorrelation for the first lag of large orders across sectors.

obtain eight models with *t-statistics* greater than two, consequently we believe this is strong evidence that our findings are robust to the number of regressions that we execute.

One last methodological concern is the bias that could arise in small samples when regressors are persistent (e.g., Stambaugh, 1999), even though the degree of persistence of active sector orderflow is much lower compared to the typical dividend yield predictor extensively examined in the literature (e.g., the first order autocorrelation on average across sector orderflow is 0.55). In any case, we use the block-bootstrap technology described above to derive an empirical distribution for the R^2. In Table 3 panel A, for example, we find that the hypothesis of no predictability implies an increase in R^2 over the AR(1) model below 4.5% in 95% of the cases. Empirically, large active orderflow in materials, financials and telecoms all imply R^2 increases that are above that threshold. We thus conclude that in these cases the increase in explanatory power is significant.

In addition to the coefficients being statistically significant, they are also economically significant; as an example, a one-standard deviation shock to large orderflow in the materials sector implies a 0.14 higher expansion index one month later, and such a move is approximately 10% of the maximum value of the expansion index within our sample. While the relation between sector orderflow and the macro economy is quite compelling for the large orders, the forecasting power of the medium and small-sized orderflow is dramatically lower with only active orderflow into utilities being consistently (negatively) associated with the expansion index. The contrast between the large and small/medium orderflow results is interesting because it suggests the information, expectations, preferences and risk tolerance of the market participants

behind the different size trades is dramatically different. Under the simple assumption

that large orders are more likely to originate from institutional investors, while small and

medium orders are more likely to originate from retail investors, our results suggest that

institutional investors are better able to position their trades in anticipation of changes in

the economy than are retail investors. Retail investors appear to have a very coarse

partition of the sectors with utilities showing up as the only defensive sector and no

significant expansion sectors being employed.[10]

     After investigating the relation between the expansion index and sector orderflow

by individual industry, we now turn to an analysis of the cross-section of orderflow.

Specifically, we are interested in determining the orderflow factor (i.e., the set of sector

loadings) with the highest correlation to the state of the macro economy. As before, the

numerators of the active net orderflow variables represent deviations from passive

allocations, thus their sum is equal to zero. As a result, the ten sectors have orderflow

that are highly collinear and the coefficients in the multivariate regression are difficult to

interpret. Therefore, we refrain from showing the coefficients of the multivariate

regression and instead present the correlations between each sector orderflow and the best

linear combination of sector orderflow estimated in the multivariate regression. Lamont

(2001) encounters the same problem when using the returns of the base assets and

concludes that "the portfolio weights have no particular meaning".

     Table 4 presents the cross-sectional results. Consistent with intuition, the large

orderflow results display positive coefficients for pro-cyclical sectors which tend to

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[10] We acknowledge that with the increased importance of algorithmic trading recently, institutions can optimally break up their trades to minimize price impact and disguise their actions. Therefore, it might not be necessarily true that small trades correspond exclusively to retail investors. Despite this development, large orders are still likely to originate from institutional investors.

negative coefficients as sectors become more counter-cyclical; the one exception being consumer staples. We are puzzled by the results for consumer discretionary and consumer staples and hypothesize that the categories are so large and heterogeneous that it is difficult to get a clear signal about pure discretionary and necessity purchases. However, the puzzle is consistent across both orderflow and return regressions, which lends credibility to a feature that is systematic across various measures within our data.

Also, consistent with the individual sector results, the large orderflow results are different from the small and medium results. Beginning with the three-month horizon, there appears to be some stratification of orderflow among sectors based on the size of the trades. For example, large orderflow show that materials, industrials, and consumer staples are aggressive economic sectors, while energy, consumer discretionary, financials, and telecommunications are all defensive sectors relative to the expansion/contraction index. The small and medium sized orderflow show a sharp contrast in their positioning with no clear pattern relative to the cyclicality of the sectors. For example, the materials and industrial sectors for the medium orderflows are aggressive (positive coefficients) but so are consumer staples and health care; on the defensive side (negative coefficients), information technology, telecommunications and utilities are significant.

Fewer sectors have significant correlations at the one-month horizon, which suggests that one quarter ahead of an expansion (contraction) market participants perform a broad portfolio reallocation (three-month results), while the final adjustments before a turn in the economy appear to be concentrated into (out of) fewer sectors (one-month results). At the one-month horizon, the materials sector is the most aggressive sector for

large orderflow, while health care and information technology are the most aggressive for medium and small orderflow, respectively. Consumer discretionary, financials, and telecommunications are the defensive sectors for large sized orderflow, while utilities remain the one defensive sector for small and medium sized orderflow.

In summary, it is clear that the link between aggregate sector orderflow and the macro economy is strong, with large-sized active orderflow in specific sectors able to forecast expansions/contractions up to one quarter ahead. Both the univariate and multivariate regression results show greater predictability (higher R^2 in Table 3 and 4) the longer the horizon, for all trade sizes. In addition, large-sized sector orderflow, which is likely to originate from institutional investors, appears to contain the bulk of the predictive power in aggregate orderflow. Finally, the target sectors in our results for trading on the macro economy are consistent with common financial wisdom concerning sector rotation and portfolio allocation tactics.

4.3   Sector Orderflow and Markets

To the extent that financial markets are tied to economic expansions and contractions, it is an empirical question whether sector orderflow contains pertinent information about the performance of the equity and bond markets and how that information compares to the information that is useful for predicting the macro economy.

In this section, we regress equity market returns on individual sector orderflow in order to understand whether market participants overweight/underweight sectors in anticipation of higher/lower future stock market returns. Table 5 presents our results which are presented in a manner consistent with Table 3 (and Table 6) for comparison purposes. Clearly the predictive power for the equity market is much weaker than results

for the macro economy. For example, at the 1-month horizon, small sized orderflow into utilities as well as medium and large-sized orderflow into the telecommunication sector seems to predict lower future stock market returns. Moreover, the economic significance is striking in that a one-standard deviation shock to the telecommunication sector predicts a 1% monthly return. However interestingly, these results are not sustained at the 3-month horizon with weak and sporadic significance displayed among the sectors. Admittedly, the number of significant regressors for the stock market are in line with chance. We also compute the correlations between each sector's active orderflow and the linear combination of ten sector factor loadings that best predict the stock market, similar to the analysis presented in Table 4 for the macroeconomy. We find that the most aggressive sector for large-sized orderflow is information technology and the most defensive is the telecommunication sector, consistent with the univariate results (results not reported).

We perform the same analysis on the bond market (1-year maturity), see Table 6. Not surprisingly, the results are stronger than the corresponding results for the equity market, which is consistent with the received wisdom that the macro economy and the fixed income market may have more in common with each other than either has in common with the equity market. For the medium and large sized orderflow, the materials sector has a negative sign and the financials and utilities sectors have a positive sign, which is exactly the opposite result found for the expansion indicator.[11] Furthermore, these results hold at both the 1 and 3-month horizons. As an example of the substantial economic impact of these results consider that a one standard deviation shock to

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[11] Regressions were also run using the 3-year and 5-year bond returns. The results were similar and are available upon request.

orderflow into the material sector predicts a 0.0005 lower monthly bond return (0.6%

lower annual return), which is about ten times the average one-year bond return in our

sample. Moreover, the analysis of the correlations between each sector's active

orderflow and the linear combination of ten sector factor loadings that best predict the

bond market, confirms that the most aggressive sector for large-sized orderflow is

materials and the most defensive is the financial sector (results not reported).[12]

4.4   Relation between Orderflow Information within the Economy and Markets

To further investigate the predictability of sector orderflow, we consider whether

the orderflow factors which have the maximal correlation with economic expansions, the

stock market and the bond market each have predictive power over the other dependent

variables. For example, does the maximal linear combination of sector orderflow which

best predicts economic expansions have any ability to predict the stock and bond market

returns and vice versa? Specifically, Table 7 shows the explanatory power of regressing

future values of the expansion indicator, the stock market return, and the bond market

return on the current value of the dependent variable and a forecasting factor. The

forecasting factor is a linear combination of either active orderflow or excess sector

returns, where the loadings are computed as those with the maximal correlation with each

of the dependent variables, respectively.

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[12] Since the cross-section of orderflow across sectors contains information about the future evolution of the economy and the bond market, one could also envision that it contains information about future volatilities. Specifically, investors could re-allocate towards defensive sectors not only when they believe the economy is transitioning into a recession, but also when they think the risk of such an event is higher. We investigate this hypothesis using the same empirical specification adopted before to predict the economy, where we replace the dependent variable with the logarithmic change in the volatility index (VIX) (a model-free implied volatility of S&P500 options with one-month to maturity) and the change in realized volatility obtained from S&P500 returns, one-month and one-quarter ahead. While we find that orderflow has some predictive power, the results are far from substantial. For example, the active orderflow across sectors only predict up to 6% of the variation in the VIX change in one month (results not reported).

Panels A, B and C of Table 7 display the results for the economic expansions, stock and bond markets respectively. As one would intuit, the results show that own orderflow and own returns have predictive power across the three panels. Beyond this, Table 7 highlights four observations about the interaction among the three independent variables that reveals much about the predictability of sector orderflow. First, the orderflow factor with the maximal correlation with the expansion indicator has the ability to predict not only the expansion index, but also the 1-year bond return and to a lesser extent the stock market return (at least at the 1-month horizon). Specifically, at the one-month horizon, the best linear combination of the cross-section of sector orderflow for the expansion index is statistically significant and generates a R^2 of 32%, 2% and 13% for the expansion index, stock and bond markets respectively. The lower explanatory power for the stock market is likely due to the relative importance of information about cash flows and discount rates changing over time, as shown in Boyd et al. (2005). Second, there is a high degree of reciprocity among factors; the combination of sector orderflow which best predicts the stock market (bond market) also has predictive power over the CFNAI index, with a statistically significant R^2 of 22% (26%). Third, forecasting factors based on linear combinations of *excess returns* appears to have little explanatory power beyond their own market, which suggests that orderflow contains more cross market information than returns. Fourth, the sector orderflow coefficients are relatively stable across the three regressions (see Figure 2 for a summary of the orderflow coefficients across select sectors). Thus, the reciprocity of orderflow's predictive power across the regressions coupled with the coefficients stability across sectors implies the existence of a single orderflow forecasting factor, which is strongly related to macroeconomic

information and has the ability to forecast performance within the economy and capital markets.

4.5   Orderflow versus Returns

While the predictive power of sector orderflow has been clearly established, it remains to be seen whether prices/returns contain the same or potentially more or less information than orderflow.

As a matter of background, there is an established literature which shows that low frequency, market-level variables such as the dividend yield, the corporate default spread (BAA less AAA yields) and the term spread (10-year less 3-month Treasury yields) have predictive power for the economy as well as for equity and fixed income markets (see, Keim and Stambaugh, 1986; Campbell and Shiller, 1988; Fama and French, 1988; among others). Armed with these results, others have investigated whether returns have incremental predictive power. Specifically, Lamont (2001) and Hong et al. (2007), show that the cross-section of *returns* across sectors predicts the economy and the stock market. Thus, when juxtaposing our orderflow results with results from the existing literature, a natural question arises as to whether orderflow contains the same information as returns. On one hand, returns and orderflow are related through the interaction of the demand and supply of shares (orderflow) which generates the equilibrium price (returns) and quantity (volume); on the other hand, the two series are distinct as orderflow is an aggregation of market participant *actions* while returns are an aggregation of trading *consequences*. Nonetheless, it remains an empirical question whether orderflow, returns or both, contain information about the future of the economy and the various capital markets, as well as what the specific nature of the respective information sets may be.

To formalize this comparison, we predict the expansion indicator CFNAI with excess sector returns rather than orderflow, sector by sector.   Table 8 displays our results; for comparison we include the R^2 from the large-sized orderflow results in Table 3. The R^2 comparison reveals very little difference on average between the explanatory power of orderflow and the explanatory power of returns. However, further inspection reveals that the sector returns with predictive power are different than those for sector orderflow. For example, within the return regression, consumer discretionary and consumer staples, health care, financials and utilities are all negatively related to economic expansion, which suggests that a negative excess return in these sectors predicts an expansionary economy.   In contrast, recall that the orderflow regression showed that orderflow into the materials sector and orderflow out of the financial and utility sectors are associated with an expanding economy.[13] Thus, Table 8 suggests that the information contained in orderflow and returns is at a minimum, different.

To complement the above analysis, we run two auxiliary sets of regressions on the economic expansion index, the stock market return and the bond market return varying the set of independent variables among the various orderflow and return series. Table 9 displays our results which compare the adjusted R^2 across small, medium and large sized active net orderflow predictors along with returns at the 3-month horizon. The first item to note is that the cross-section of orderflow contains more explanatory power than returns do for future economic expansions, specifically, adding orderflow to the current level of the index generates a twofold increase in the explanatory power, while adding returns alone only increases the R^2 by about 2%. For the stock market return, not only is

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[13] As a robustness check, we also estimate a sector-by-sector regression where we include both returns and orderflow as independent variables. The results that obtain are both quantitatively and qualitatively similar and available upon request.

there less predictability, it is not clear whether orderflow dominate returns. Finally, like

the results for the economic expansion, the large-sized orderflow dominate returns in

predicting the one-year maturity bond returns. In summary, these results demonstrate that

orderflow encompasses more information than is contained in returns.

While Table 8 and 9 suggest that there appears to be more information in

orderflow and that information is materially different than information contained in

returns, it is possible that orderflow is merely proxying for low frequency variables such

as the dividend yield, the default spread (BAA less AAA yields) and the term spread (10-

year less 3-month), variables that the literature has already demonstrated has predictive

power for the economy and other capital markets. The final set of auxiliary regressions,

contained in Table 10, addresses this concern. The regressions compare the predictive

ability of nested sets of variables: Equations 1 and 2 provide the baseline regression,

Equations 3 and 4 add returns and active net orderflow respectively, and Equations 5 and

6 investigates if active net orderflow explains the residual of the return equation

(Equation 3) and vice versa.[14] However, it is difficult to interpret the individual

coefficient estimates for two reasons. First, in equation 3 and 4 there is collinearity

induced by regressors expressed as deviations from a passive benchmark. Second, in

equation 5 and 6 the dependent variable is a residual and, as a result, the signs of the

explanatory variables are not meaningful. For these reasons, Table 10 simply displays the

number of significant regressors and the R^2 in order to provide some sense of the

economic significance.

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[14] We also augment the set of low-frequency market-level predictors with the three-month Treasury bill and the volatility index VIX in equation (2), (3) and (4). Our empirical findings are practically unchanged and therefore we only report the results for the more parsimonious specifications.

As is evident from comparing the results in Equation 5 and 6, active net orderflow explains more of the residual after controlling for returns and other low frequency forecasting variables (Equation 3), than returns explain of the residual after controlling for active net orderflow and the same low frequency forecasting variables (Equation 4) for both the macroeconomy and to a lesser extent the bond market. Specifically, returns have no additional explanatory power beyond market-level forecasting variables and orderflow, whereas orderflow explains 12% and 5% of the variation of the economy and the bond market respectively, left unexplained by market-level forecasting variables and returns. Thus, the results contained in Table 10 suggest that active net orderflow provides more and materially different information than that contained in returns and traditional low frequency market variables.

5. The Nature of Orderflow Information

Our results thus far show that orderflow contains different information than returns, what remains is to better understand the exact nature of the information contained therein. To that end, a number of questions come to mind. Is the composition of active sector orderflow important to its ability to forecast? Can sector orderflow movements be directly tied to the release of important macroeconomic information? Does sector orderflow reflect the information of a particular category of institutional investors? Is the information in orderflow economically relevant? The next subsections will address each of these questions in turn.

5.1 Orderflow Dispersion within Sectors

We conjecture that, beyond the level, the composition of active sector orderflow may also be important. Specifically, we hypothesize that the variability of orderflow

among stocks contained in the sector is related to the strength of the macroeconomic signal.

To illustrate, consider that up to now, we have measured sector net orderflow as the simple sum of all orderflow for the individual stocks included in that sector. Thus, a large net orderflow in one sector could be the result of investors increasing the weight of that sector in their portfolios or it could also be the result of a heavily traded single stock within the sector for reasons unrelated to expected economic conditions (e.g., stock picking based on private information). If our hypothesis is correct, the predictive power of our results should be stronger whenever orderflow within one sector is more homogeneous across stocks in that sector.[15]

In order to measure whether investors are trading the whole sector or just select stocks, we calculate the standard deviation of active orderflow for each stock as a measure of dispersion of orderflow within each sector.[16] Next we average sector orderflow dispersion at the market level using two different weighting schemes. The first dispersion measure (σ_1) uses weights corresponding to the monthly market capitalization of each sector. This method gives more importance to the dispersion of orderflow within large sectors. The second dispersion measure (σ_2), weights orderflow dispersion by the absolute value of the correlations reported in Table 4, normalized to sum to one. This method gives more importance to the dispersion of orderflow within the sectors that matter more for predicting the economy.

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[15] Beber, Brandt, and Kavajecz (2008) is another example of a conditional analysis of orderflow and returns.

[16] The results are very similar if we use the range between the maximum and minimum value of active orderflow or the absolute value of the orderflow skewness.

In Table 11, we present the results of forecasting the expansion indicator, the stock market and the bond market with the sector orderflow in high and low dispersion states. In a given month, dispersion is high (low) when the aggregate standard deviation is above (below) its median in the last 12 months.[17] Our conjecture is clearly confirmed. When orderflow has low dispersion weighted by market capitalization (σ_1), the explanatory power is between 1.47 and 1.83 times higher than with high dispersion. If we give more weight to the sectors that are more relevant for predicting the economy and the asset markets (σ_2), the results are even more striking; in months with low dispersion the average explanatory power of orderflow doubles.

In summary, the predictive power of active sector orderflow is much stronger when we condition on low dispersion of orderflow within sectors. Moreover, the results obtain no matter which weighting scheme is used or what market is analyzed.

5.2   Orderflow and Macroeconomic News

One potential concern is that our results could be driven by some latent variable unrelated to economic news which alters market participants' fundamentals views of, and attitude toward, the macroeconomy, which in turn induces trade. To address this concern, we investigate whether sector orderflow responds directly to important macroeconomic announcements which we know are signals, albeit noisy, of the current state of the economy. Thus, a significant relation between aggregate sector orderflow

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[17] The rolling threshold is preferred to a static threshold to avoid that conditional results pick up specific subsample periods. The results are robust to the choice of the rolling span (from 12 months to 36 months) and to the choice of the percentile (e.g., low dispersion as bottom quartile and high dispersion as top quartile).

and macroeconomic announcements would be consistent with our hypothesis and alleviate concerns that our results are driven by other latent factors.[18]

Our empirical design is to investigate the relation between orderflow factors with the highest correlation with the macro economy, stock market and bond market with the standardized non-farm payroll (NFP) announcement surprise, which is commonly understood to be the first, and most influential, macro announcement within a given month, (see, Andersen, Bollerslev, Diebold, and Vega, 2007).[19] Orderflow is measured over the week and the month following the non-farm payroll release. If active orderflow is indeed capturing portfolio adjustments in response to changes in economic conditions, then the release of NFP news should trigger active orderflow in the sectors that are linked to the evolution of the economy. Our investigation encompasses two complimentary approaches: measuring cumulative sector orderflow following non-farm payroll releases (Figure 3) and a regression of the orderflow factors onto the non-farm payroll surprise.

Figure 3 cumulates orderflow by sector following non-farm payroll announcements. We distinguish sectors in three groups according to a predictive regression of the CFNAI indicator on sector orderflow (see Table 3, Panel A): financials, consumer discretionary and telecom sectors act in a counter-cyclical fashion, materials and consumer staples act in a pro-cyclical fashion, while the remainder of the sectors are not significant. The cumulative orderflow series are further partitioned by whether the announcement was a positive (Panel A) or negative (Panel B) surprise relative to

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[18] In this sense, our paper fits into the literature that uses the relation between macroeconomic announcements and asset prices to provide real-time estimates of the current state of the economy (e.g., Evans, 2005).

[19] We standardize the release by subtracting the announced figure from the median expectation and dividing by the standard deviation of the surprise.

expectations. Consistent with having strong direct tie to macroeconomic news, the orderflow results show that the financials, consumer discretionary and telecom sectors shed (accumulate) orderflow after positive (negative) surprises, while materials and to a lesser extent, consumer staples sectors have the opposite pattern.

Table 12 displays our complementary regression results.[20] The dependent variable is a linear combination of sector orderflow or returns in the period following the NFP release, where the loadings are the ones with a maximal correlation with the CFNAI index, stock returns, or bond returns. Panel A shows that both the orderflow factor for the macro economy and the bond market are significantly related to the non-farm payroll announcement, while the orderflow factor for the stock market appears to have no relation. The positive sign on the CFNAI indicator regression suggests that the creation of new jobs (increase in non-farm payroll) predicts orderflow into those sectors which are associated with a macroeconomic expansion. The negative sign on the bond market is consistent with new jobs being associated with orderflow from the bond market into more risky assets, which in turn puts downward pressure on bond returns. Panel B replicates the above analysis using returns instead of orderflow as the dependent variable. In contrast to the orderflow results, the return factors are unrelated to the non-farm payroll release. This suggests that not only do returns carry less pertinent information relative to orderflow, the nature of the information within returns and orderflow appears to be markedly different.

The remaining two sub-sections address the economic significance of our findings. In particular, we study the sector orderflow behavior of an identifiable set of

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[20] Note that the t-statistics in Table 12 are determined using bootstrapped standard errors.

institutional investors as well as the profitability of trading on sector orderflow movements.

5.3   Orderflow and Mutual Fund Flows

A drawback of the empirical measures of orderflow used in the literature and in our paper is that the identity of the trader is unknown and thus it is not possible to determine the category of investors that is primarily responsible for orderflow into a group of stocks of the same sector. Mutual Funds, however, are one category of institutional investors for which we can obtain low-frequency information on flows invested in stocks of different sectors. The data we utilize for this portion of the analysis is obtained from two mutual fund databases. The first database is the TFN/CDA Spectrum database that contains quarterly portfolio holdings for all U.S. equity mutual funds and the second mutual fund database is available from CRSP and contains detailed information on the style of the fund provided by Lipper. While the Spectrum database spans our sample period, unfortunately, the Lipper style categories data begins in 1998. Thus, we backfill the style designations over the initial five years of our sample using the first available styles in Lipper. We note that by backfilling data we are implicitly assuming low mobility across fund categories in the first part of our sample. Additional details on the two databases and the process to match funds are provided in Wermers (2000).

Once the data is compiled, we apply a series of filters to make sure that we are properly and timely measuring mutual fund flows. Specifically, we require the quarterly reporting date to be within two months of the stock holding reporting date and not more than a quarter away from the previous reporting date. We also exclude all funds that do

not exhibit positive stock holdings in all the ten sectors throughout our sample period. This filter effectively excludes international funds, bond funds, gold funds, real estate funds, and all other sector specific funds, which are unlikely to be responsible for the orderflow patterns documented earlier in this paper.

For each of the style categories, we compute quarterly stock holding changes in dollars broken down by the ten GICS sectors. According to the same logic used before to compute the active component of orderflow, we calculate the active part of the sector mutual fund flows. Specifically, we compute the passive part of flows in a sector within a particular category of mutual funds as the sector allocation that would match a passive market replication strategy. For example, if the total dollar flow in the category equity income mutual funds is $100 in one specific quarter and the market cap weight of the industrial sector at that time is 20%, we calculate that the passive dollar flows to industrial is $20 and deviations from this level constitute active allocation strategies. Similarly to the previous empirical analysis for orderflow, we standardize the active flows by the market capitalization of each sector.

We aggregate sector orderflow data of large orders by quarters to match the frequency of mutual fund holding data and we compute the correlation between the standardized active components of sector orderflow and sector mutual fund flows. We do not expect to find a significant correlation between sector orderflows and mutual fund flows in an analysis of *all* mutual funds, because there would be plenty of confounding effects, like passive index mutual funds or mutual funds that are constrained to invest in only one sector. In contrast, we focus our attention on the Lipper 'core' category without distinction for size because we assume that the categories of mutual funds that are most

likely to implement sector rotation strategies are those with an investment objective that are not constrained to a particular category of stocks.

Table 13 shows the correlation results by sector for the mutual funds with the 'core' investment objective, i.e. a blend of value and growth. All ten sector flows in core mutual funds exhibit a positive correlation with sector net orderflow of large orders. In four of the sectors, this positive correlation is statistically significant, despite the small sample (52 observations). This result is notable, given the number of confounding influences on quarterly mutual fund holdings. This is strong evidence that our active net orderflow variables are measuring the rebalancing strategies of within core funds. As benchmark, we also include the correlation of sector net orderflow with a passive replication strategy of the S&P500 index (labeled S&P500 in Table 13). By definition, these correlations should be unrelated to sector rotation strategies. As expected, the average correlation is close to zero with only six of ten sectors being positive correlations and two cases of correlations that are significantly different from zero, one positive and one negative.

5.4   The Orderflow Mimicking Portfolio

Thus far, our results are consistent with the notion that the magnitude, direction and timing of orderflow across sectors reflect information about the risk preferences, expectations and overall trading strategies of market participants.

If we continue this line of reasoning within an asset pricing framework, then the result that market-wide sector orderflow reflects the aggregate preferences and expectations within the entire market suggest that market participants must necessarily hold portfolios that are different than the market portfolio. Therefore, as a capstone to

our analysis we investigate the practical nature of information contained in the movement of orderflow across sectors by constructing an orderflow mimicking portfolio.

Specifically, we construct and analyze a portfolio that mirrors the aggregate equity asset allocation of the investors initiating large trades, i.e. orderflow of large-sized orders. The intuition behind our empirical strategy is that movements of orderflow across the various sectors represent tilts to the market portfolio which define an orderflow mimicking portfolio. These tilts define a market-wide portfolio that is potentially different from the traditional CAPM market portfolio which will provide an evaluation of the economic importance of the information contained in the cross-section of sector orderflow.

To implement such an orderflow portfolio, we start at the beginning of our sample with an equity portfolio where the allocations across sectors are determined by market capitalization weights. As before, we compute the weekly net *active* orderflow of large-sized orders in different sectors as the difference between total orderflow for each sector and the *passive* orderflow, that is, orderflow expected given the market capitalization weight of each sector the previous week. Thus, active orderflow represents the proportion of the orderflow to the aggregate stock market that deviates from the current allocation based on *current* portfolio weights. We translate dollar orderflow into percentage weight changes through a simple normal cumulative density function transformation. Like most other asset allocation techniques, our procedure has the potential to generate extreme and unrealistic weights. For example, an extremely positive (negative) active orderflow in one sector may translate into a 100% increase (decrease) in the weight of that sector in the orderflow portfolio. Since we rebalance the portfolio weekly, we impose a reality

constraint of 1% on the maximum weekly adjustment, so that the largest possible change in a sector weight is 1% every week. Economically, this constraint on the sector weights might be interpreted as a transaction costs, implementation constraint, or even a risk management technique.

The orderflow mimicking portfolio that we constructed has properties that are not only interesting, but also consistent with our earlier results pertaining to the information content of sector orderflow. For example, Figure 4, Panel A, shows the cumulative return performance of investing $1 in the orderflow portfolio compared with the market portfolio over our sample period. Clearly the orderflow portfolio outperforms the traditional market portfolio by approximately 40% over the sample period ($3.50 versus $2.50). Moreover, a closer examination of the figure reveals that the orderflow portfolio does not suffer the 1999-2000 down-turn in the market portfolio, which is consistent with the orderflow portfolio being largely a defensive allocation strategy. Panel B of Figure 4 confirms this intuition as the orderflow portfolio loads heavily on low beta stocks over the course of the 1999-2000 recession. Furthermore, the orderflow portfolio enjoys superior risk and return metrics compared to the market portfolio; the orderflow portfolio has an annual return, standard deviation and Sharpe ratio of 19.7%, 14.5% and 1.36 respectively, compared to 11.8%, 15.7% and 0.75 for the market portfolio.[21] Lastly, the sector weights are well behaved ranging from a high of 30% to a low of 0% which argues for the feasible implementation of the orderflow mimicking portfolio.

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[21] We have also examined the performance of the orderflow portfolio conditional on the dispersion of flows within sector, i.e. the tilts to the market portfolio are implemented only when flows' dispersion is low or high. Consistent with previous results, the Sharpe ratio of the low dispersion strategy is higher than in the case of the high dispersion strategy.

We acknowledge that a number of assumptions were made to generate these results; however, our results are robust to a wide range of parametric permutations. For example, the orderflow portfolio results still obtain (1) relaxing the dollar to percentage transformation, (2) utilizing a 1% to 100% weekly threshold range, and (3) irrespective of the timeframe analyzed (starting date).

Finally, it is important to be clear on what should be inferred from these results. Certainly the reader should not be surprised to know that a portfolio can be constructed that dominates the S&P500, this is just another manifestation of the Roll Critique. What is remarkable though is that the information contained in orderflow across sectors has striking economic implications as reflected through our orderflow mimicking portfolio dominating the market portfolio. Moreover, the information contained in the orderflow portfolio is directly related to the macro economy, tends to be defensive in nature, and goes beyond the information captured by sector excess returns.[22]

6.   Conclusion

There is mounting evidence in the literature that the trade decisions of market participants incorporate their risk preferences, expectations and actual or perceived information. Armed with this evidence, we investigate what orderflow movements among equity sectors are able to tell us about the macro economy as well as the near term performance of the equity and bond markets.

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[22] A potential concern might be that the results are proxying for other factors known to be priced. One specific concern might be the momentum factor at the industry level, which reflect information contained in sector returns. However, our results show that the orderflow portfolio is different from the momentum portfolio that has an annual return, standard deviation and Sharpe ratio of 22.4%, 25.1% and 0.89, respectively. Therefore, even though the momentum factor has superior returns, on a risk adjusted basis the orderflow portfolio produces superior performance and must therefore contain different information than merely momentum.

We find that sector orderflow movements predict changes in the expansion/contraction index and the future performance of the bond markets. In comparing the various orderflow factors which predict the economic expansion, stock and bond markets, we find that not only does orderflow contain more and different information compared to returns and traditional low-frequency forecasting variables, but the nature of the information is common across the three markets and explicitly linked to information about the macro economy as seen through its relation to the non-farm payroll announcement. In addition, our results are stronger when orderflow is less dispersed within sectors, lending further support to our conjecture that the sector orderflow measures indeed reflect the empirical foot-prints of sector rotation.

Finally, we investigate the nature and economic relevance of the information contained in sector orderflow movements within a portfolio context. The correlation between active sector orderflow and mutual fund flows in core categories suggests our orderflow measures are indeed capturing institutional trader flows. Moreover, when we translate sector orderflow movements into tilts to the market portfolio in order to produce an orderflow mimicking portfolio, the result is that the orderflow portfolio enjoys superior risk and return properties relative to the traditional market portfolio or industry momentum portfolios. This suggests that orderflow contain asymmetric information in that it is primarily defensive in nature and largely related to wealth preservation.

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Appendix

Sector definitions

The sectors are defined according to the Global Industry Classification Standard (GICS). The GICS was developed by Morgan Stanley Capital International and Standard & Poor's. The GICS structure consists of ten sectors, defined as follows.

[10] ENE: Energy Sector – The GICS Energy Sector comprises companies whose businesses are dominated by either of the following activities: The construction or provision of oil rigs, drilling equipment and other energy related service and equipment, including seismic data collection. Companies engaged in the exploration, production, marketing, refining and/or transportation of oil and gas products, coal and other consumable fuels.

[15] MAT: Materials Sector – The GICS Materials Sector encompasses a wide range of commodity-related manufacturing industries. Included in this sector are companies that manufacture chemicals, construction materials, glass, paper, forest products and related packaging products, and metals, minerals and mining companies, including producers of steel.

[20] IND: Industrials Sector – The GICS Industrials Sector includes companies whose businesses are dominated by one of the following activities: The manufacture and distribution of capital goods, including aerospace & defense, construct ion, engineering & building products, electrical equipment and industrial machinery, the provision of commercial services and supplies, including printing, employment, environmental and office services and the provision of transportation services, including airlines, couriers, marine, road & rail and transportation infrastructure.

[25] CD: Consumer Discretionary Sector – The GICS Consumer Discretionary Sector encompasses those industries that tend to be the most sensitive to economic cycles. Its manufacturing segment includes automotive, household durable goods, textiles & apparel and leisure equipment. The services segment includes hotels, restaurants and other leisure facilities, media production and services, and consumer ret ailing and services.

[30] CS: Consumer Staples Sector – The GICS Consumer Staples Sector comprises companies whose businesses are less sensitive to economic cycles. It includes manufacturers and distributors of food, beverages and tobacco and producers of non-durable household goods and personal products. It also includes food & drug retailing companies as well as hypermarkets and consumer super centers.

[35] HC: Health Care Sector – The GICS Health Care Sector encompasses two main industry groups. The first includes companies who manufacture health care equipment and supplies or provide health care related services, including distributors of health care products, providers of basic health-care services, and owners and operators of health care facilities and organizations. The second regroups companies primarily involved in the research, development, production and marketing of pharmaceuticals and biotechnology products.

[40] FIN: Financial Sector – The GICS Financial Sector contains companies involved in activities such as banking, mortgage finance, consumer finance, specialized finance, investment banking and brokerage, asset management and custody, corporate lending, insurance, and financial investment, and real estate, including REITs.

[45] IT: Information Technology Sector – The GICS Information Technology Sector covers the following general areas: firstly, Technology Software & Services, including companies that primarily develop software in various fields such as the Internet, applications, systems, databases management and/or home entertainment, and companies that provide information technology consulting and services, as well as data processing and outsourced services; secondly Technology Hardware & Equipment, including manufacturers and distributors of communications equipment, computers & peripherals, electronic equipment and related instruments; and thirdly, Semiconductors & Semiconductor Equipment Manufacturers.

[50] TEL: Telecommunications Services Sector – The GICS Telecommunications Services Sector contains companies that provide communications services primarily through a fixed-line, cellular, wireless, high bandwidth and/or fiber optic cable network.

[55] UTI: Utilities Sector – The GICS Utilities Sector encompasses those companies considered electric, gas or water utilities, or companies that operate as independent producers and/or distributors of power.

Figure 1

Chicago Fed National Activity Index (CFNAI) and Sector Orderflow

We plot 3-month moving averages of the CFNAI index (bold line), *active* net orderflow of large orders (continuous line) and *active* net orderflow of all orders (dashed line) for each sector. The CFNAI index is constructed to be a single summary measure (with mean zero and standard deviation of one) of the activity in four broad categories of the economy: production and income; employment, personal consumption which includes housing; and sales, orders, and inventories. For more detailed information concerning the CFNAI index see http://www.chicagofed.org/economic_research_and_data/cfnai.cfm . The *active* orderflow series are constructed as the difference between sector total net orderflow and sector *passive* net orderflow (stock market orderflow that would be allocated to the sector based on its market share) scaled by the sector market capitalization and standardized to have mean equal to zero and standard deviation equal to one.

Figure 1 (continued)

30 - CONSUMER STAPLES

35 - HEALTH CARE

40 - FINANCIALS

45 - INFORMATION TECHNOLOGY

50 - TELECOM

55 - UTILITIES
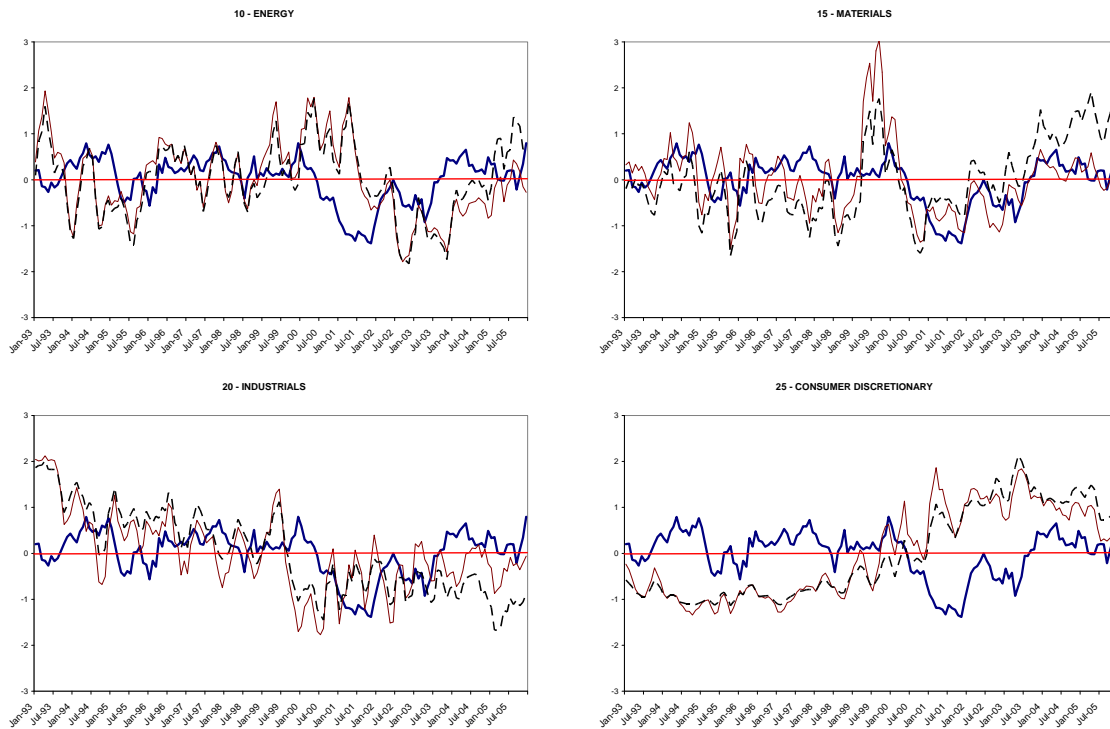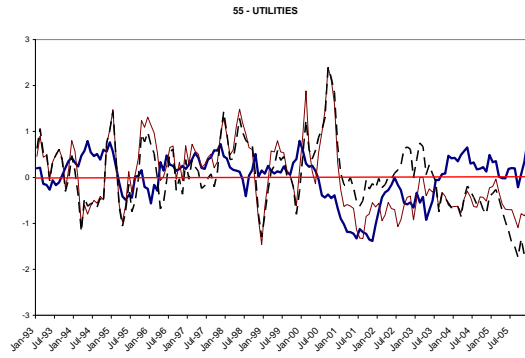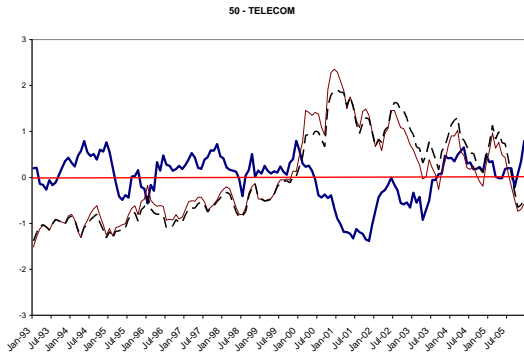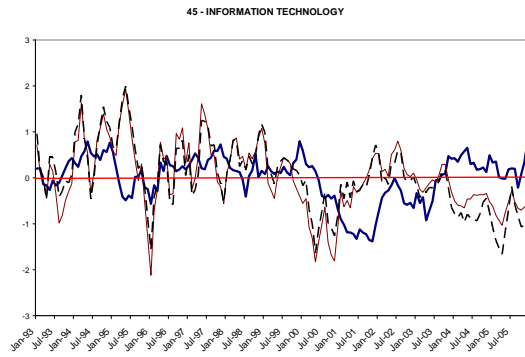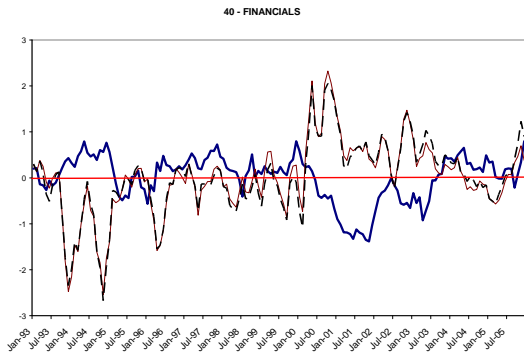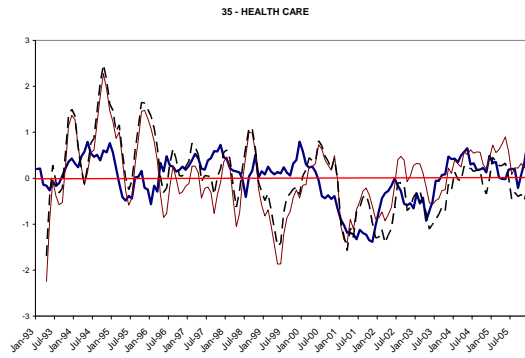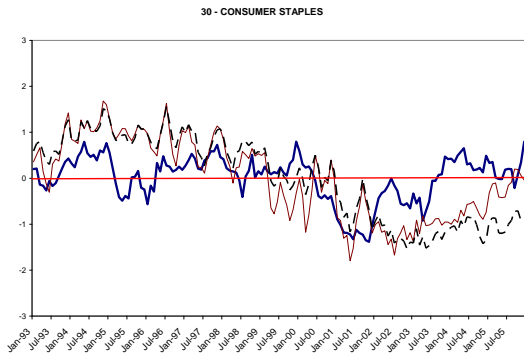
Figure 2

Sector Coefficients from the Restricted Regressions

This figure shows the coefficients on the orderflow of the four most significant sectors, materials, consumer discretionary, financials, telecommunications, predicting the expansion indicator (CFNAI), the stock market, and 1-year bond returns multiplied by -1, for the one and three month horizons.
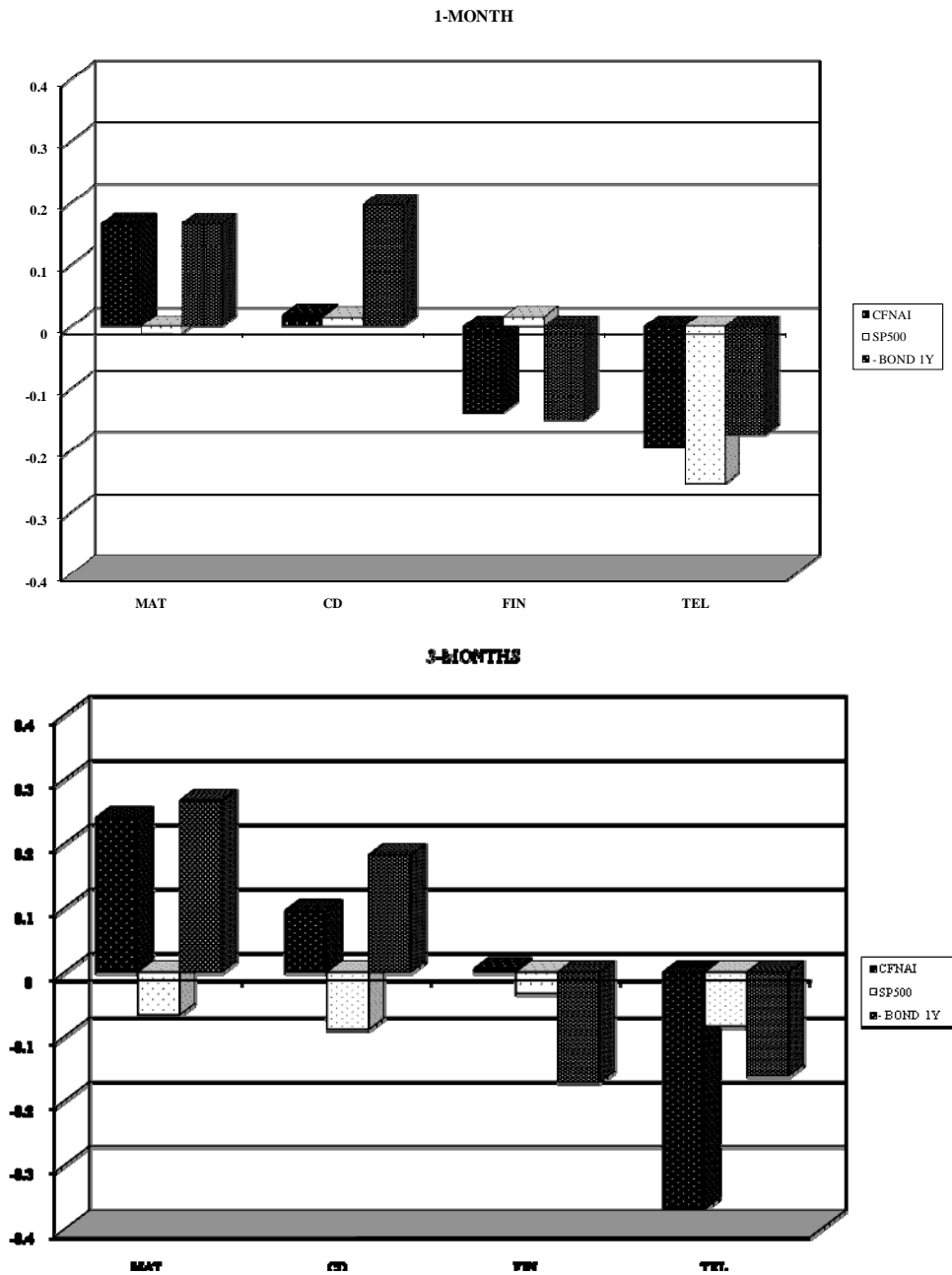
Figure 3

Cumulative Active Orderflow after Non-Farm Payroll Surprises

Panels A and B of this figure show the cumulative active orderflow following the release of the Non-Farm payroll data for positive and negative surprises respectively. Triangles denote pro-cyclical sectors, squares denote counter-cyclical sectors, the remainder are non-significant sectors, as defined by regressing the expansion indicator on sector orderflow (see Table 3, Panel A, for details).

Panel A: Positive NFP Surprise

Panel B: Negative NFP Surprise
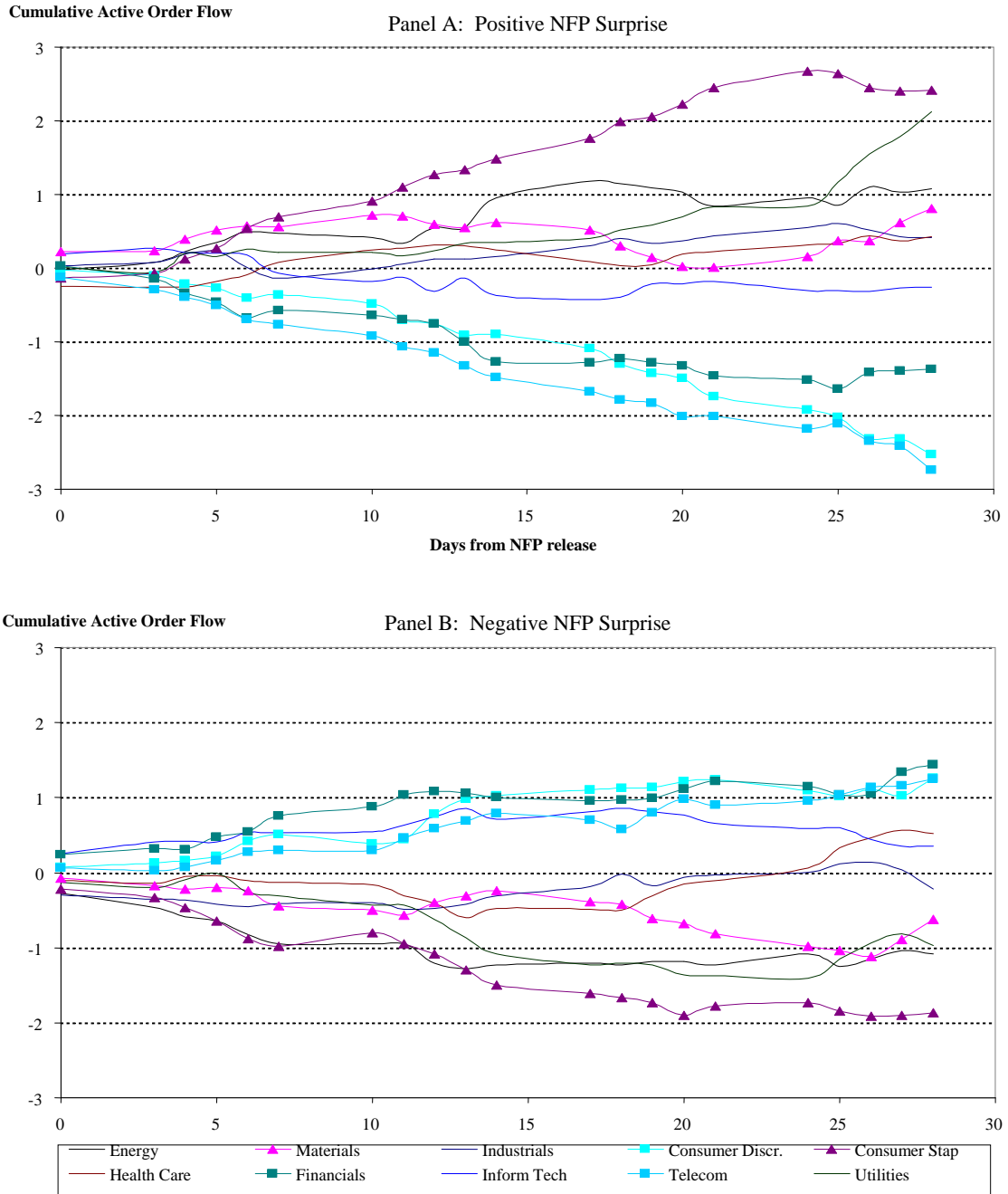
Figure 4

Characteristics of the orderflow portfolio

Panel A of this figure shows the cumulative return performance of investing $1 in the orderflow portfolio compared with the market portfolio during our sample period. Panel B displays the rolling betas of the orderflow portfolio. Panel C graphs the sector weights of the orderflow portfolio.
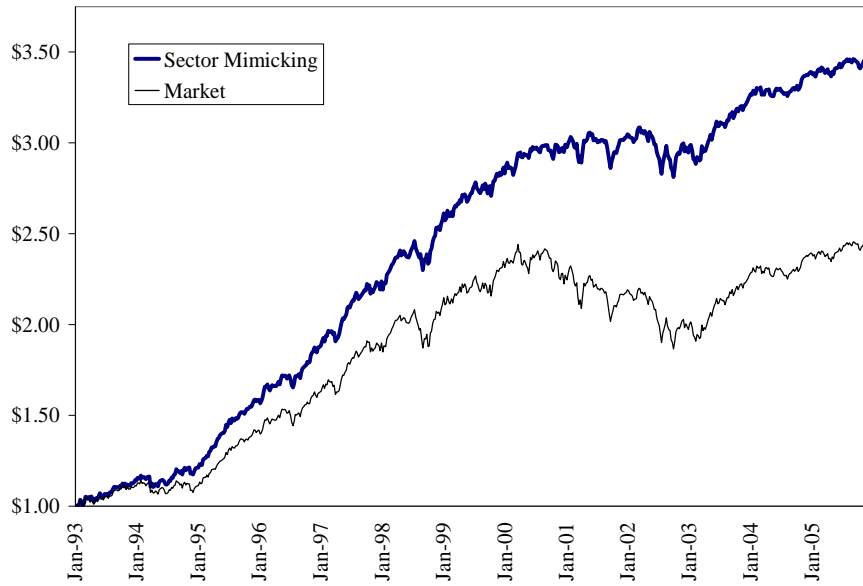
Panel A

Panel B

Table 1
Aggregate Orderflow Summary Statistics

This table displays aggregate net orderflow figures by sector and year expressed as a percentage of the total dollar net orderflow expressed in millions of dollars. Sectors are ordered down the column from pro-cyclical to neutral to counter-cyclical.

Panel A: All Orders

Sector	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Information Tech	11%	23%	19%	17%	20%	24%	27%	20%	21%	18%	17%	14%	12%
Industrials	15%	9%	11%	10%	9%	9%	8%	7%	10%	9%	9%	10%	9%
Materials	9%	12%	6%	7%	5%	4%	6%	3%	3%	4%	5%	6%	6%
Consumer Discr.	20%	11%	11%	13%	11%	13%	15%	12%	16%	18%	19%	19%	18%
Financials	11%	4%	13%	12%	15%	13%	14%	16%	16%	18%	18%	17%	18%
Energy	12%	7%	6%	10%	9%	7%	9%	10%	9%	7%	7%	9%	14%
Telecom	5%	4%	4%	3%	5%	4%	6%	7%	5%	3%	3%	3%	4%
Utilities	9%	3%	6%	5%	4%	4%	3%	4%	3%	4%	4%	4%	3%
Consumer Staples	4%	11%	11%	12%	10%	9%	5%	7%	6%	6%	6%	6%	6%
Health Care	3%	14%	13%	11%	11%	13%	7%	15%	12%	13%	13%	13%	11%
%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
$	1,031	1,076	2,009	2,662	3,619	5,398	6,622	10,261	12,255	12,301	12,282	14,047	13,583

Panel B: Large Orders

Sector	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Information Tech	8%	20%	17%	18%	20%	23%	24%	15%	20%	19%	17%	14%	10%
Industrials	16%	8%	10%	9%	8%	9%	8%	7%	10%	9%	10%	10%	8%
Materials	8%	12%	6%	7%	5%	3%	7%	2%	2%	3%	4%	4%	4%
Consumer Discr.	22%	8%	9%	11%	10%	12%	16%	12%	15%	16%	19%	18%	18%
Financials	10%	3%	12%	10%	15%	13%	14%	17%	16%	18%	18%	17%	19%
Energy	15%	8%	7%	11%	9%	7%	10%	10%	9%	6%	6%	8%	12%
Telecom	5%	5%	5%	4%	5%	5%	6%	9%	6%	4%	3%	4%	6%
Utilities	13%	5%	8%	7%	6%	5%	4%	4%	3%	3%	4%	4%	3%
Consumer Staples	3%	14%	13%	13%	11%	10%	5%	7%	6%	7%	6%	6%	6%
Health Care	0%	16%	14%	10%	11%	13%	7%	16%	13%	15%	14%	14%	13%
%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
$	622	829	1,317	1,957	2,436	3,765	4,491	7,027	7,648	6,803	5,963	6,444	5,157

Table 2
Unconditional Relation between Active Net Order Flow and Lagged Excess Returns

This table contains the results of the following unconditional regression:

$$\frac{\text{Net Orderflow}_{j,t} - Passive \text{ Net Orderflow}_{j,t}}{\text{Capsector}_{j,t}} = \alpha + \beta(\text{Ret}_{j,t-1} - \text{Ret}_{mkt,t-1}) + \varepsilon_{j,t}$$

Net Orderflow$_{j,t}$, Passive Net Orderflow$_{j,t}$, Ret$_{j,t}$ represent the actual net orderflow, the passive net orderflow, and the value-weighted return within sector j over week/month t. Ret$_{mkt,t}$ represents the value-weighted return on the stock market index. We compute the passive net orderflow for sector j as the total net orderflow to the stock market multiplied by the weight of sector j in the market. Panel A shows the results for orderflow and returns cumulated over a week, while Panel B shows the results for orderflow and returns cumulated over a month. T-statistics in parenthesis are calculated using White heteroschedastic consistent standard errors..

Panel A: Weekly

Order Size	α	β	R^2	Obs.
Small	-1.1408	749.906	0.0002	6760
	(-0.0762)	(1.5594)		
Medium	-9.3829	6168.042	0.0011	6760
	(-0.1787)	(3.0328)		
Large	-32.2700	21213.430	0.0050	6760
	(-0.3836)	(4.7967)		
All Orders	-42.7918	28130.200	0.0033	6760
	(-0.3134)	(4.5692)		

Panel B: Monthly

Order Size	α	β	R^2	Obs.
Small	-4.6312	730.6475	0.0001	1550
	(-0.0057)	(0.4728)		
Medium	-31.5317	4974.594	0.0002	1550
	(-0.0082)	(2.1643)		
Large	12.5099	-1973.620	0.0001	1550
	(0.0025)	(-0.1285)		
All Orders	-23.6266	3727.440	0.0001	1550
	(0.0025)	(0.2199)		

Table 3
Relation between Expansions and past Active Net Orderflow

This table contains the results of the following unconditional regression:

$$\text{CFNAI}_t = \alpha + \beta \frac{\left(\text{Net Orderflow}_{j,t-1} - \textit{Passive } \text{Net Orderflow}_{j,t-1}\right)}{\text{Capsector}_{j,t-1}} + \varphi\text{CFNAI}_{t-1} + \varepsilon_{j,t}$$

where Net Orderflow$_{j,t}$, Passive Net Orderflow$_{j,t}$, Capsector$_{j,t}$ represent the actual net orderflow, the passive net orderflow, the capitalization of sector j over month t. We compute the passive net orderflow for sector j as the total net orderflow to the stock market multiplied by the weight of sector j in the market portfolio. T-statistics are calculated using White heteroschedastic consistent standard errors. Sectors are grouped by cyclicality as per the MSCI ranking in three broad groups, pro-cyclical, neutral and counter-cyclical respectively.

Panel A: One-Month Lead

Sector	Small β	T-stats	R^2	Medium β	T-stats	R^2	Large β	T-stats	R^2
Inform. Tech	0.0646	1.1247	0.1927	-0.0065	-0.1450	0.1821	0.0498	1.1136	0.1885
Industrials	-0.0593	-1.5358	0.1911	0.0688	1.5199	0.1937	0.0385	0.9007	0.1859
Materials	0.0042	0.0823	0.1821	0.0203	0.4458	0.1831	0.1423	2.2909	0.2317
Consumer Discr.	0.0141	0.3241	0.1825	-0.0691	-1.4798	0.1938	-0.0971	-2.0532	0.2042
Financials	-0.0277	-0.6915	0.1840	-0.0988	-2.2222	0.2060	-0.1599	-3.9209	0.2439
Energy	-0.0197	-0.3754	0.1830	-0.0014	-0.0273	0.1820	0.0012	0.0265	0.1820
Telecom	0.0461	1.1100	0.1876	-0.1250	-2.4950	0.2181	-0.1675	-3.4458	0.2427
Utilities	-0.2032	-4.2848	0.2796	-0.2080	-4.9156	0.2894	-0.0256	-0.5760	0.1837
Consumer Stap.	-0.0345	-0.8267	0.1851	0.0503	1.0792	0.1882	0.0878	1.7793	0.2002
Health Care	0.0166	0.3583	0.1827	0.0800	1.4162	0.1963	-0.0033	-0.0682	0.1821
Lagged CFNAI			0.1820			0.1820			0.1820

Panel B: Three-Month Lead

Sector	Small β	T-stats	R^2	Medium β	T-stats	R^2	Large β	T-stats	R^2
Inform. Tech	0.0664	1.3308	0.2622	-0.0387	-0.9881	0.2549	0.0236	0.5326	0.2525
Industrials	-0.0908	-1.7857	0.2697	0.0811	1.7976	0.2668	0.0670	1.8251	0.2629
Materials	0.0459	0.9055	0.2558	0.0324	0.7157	0.2536	0.1741	4.1176	0.3261
Consumer Discr.	0.0574	1.2011	0.2587	-0.0181	-0.3880	0.2519	-0.0837	-1.8146	0.2675
Financials	-0.0281	-0.6384	0.2529	-0.0356	-0.7363	0.2539	-0.1117	-2.5986	0.2811
Energy	-0.0021	-0.0393	0.2511	0.0095	0.1924	0.2513	-0.0517	-1.3129	0.2581
Telecom	0.0663	1.4682	0.2625	-0.1071	-2.1602	0.2778	-0.2112	-4.7493	0.3484
Utilities	-0.1491	-3.1334	0.3028	-0.2057	-4.9160	0.3495	-0.0391	-0.8518	0.2549
Consumer Stap.	-0.0743	-1.4955	0.2635	0.0246	0.4110	0.2521	0.0909	1.9063	0.2706
Health Care	-0.0158	-0.3604	0.2517	0.0552	1.0268	0.2577	-0.0021	-0.0510	0.2511
Lagged CFNAI			0.2511			0.2511			0.2511

Table 4
Relation between Expansions and past Active Net Orderflow

This table contains pairwise correlations between the best linear combination of active orderflow that predicts the economy (CFNAI) and each specific sector's active orderflow:

$$\frac{\left(\text{Net Orderflow}_{j,t-1} - Passive \text{ Net Orderflow}_{j,t-1}\right)}{\text{Capsector}_{j,t-1}}$$

where Net Orderflow$_{j,t}$, Passive Net Orderflow$_{j,t}$, Capsector$_{j,t}$ represent the actual net orderflow, the passive net orderflow, the capitalization of sector j over month t. We compute the passive net orderflow for sector j as the total net orderflow to the stock market multiplied by the weight of sector j in the market portfolio. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively. At the bottom of each panel, we also report the R^2 of the multivariate regression of the expansion indicator on the active orderflow in all ten sectors that we use to obtain the best linear combination. Sectors are grouped by cyclicality as per the MSCI ranking in three broad groups, pro-cyclical, neutral and counter-cyclical respectively.

Panel A: One-Month Lead

Sector	Small	Medium	Large
		Correlations	
Inform. Tech	0.2524 ***	-0.0617	0.2197 ***
Industrials	-0.2385 ***	0.3101 ***	0.1786 **
Materials	0.0042	0.0617	0.6146 ***
Consumer Discr.	0.0351	-0.3198 ***	-0.4624 ***
Financials	-0.1013	-0.4105 ***	-0.6781 ***
Energy	-0.0638	0.0215	-0.0059
Telecom	0.1762 **	-0.5173 ***	-0.6997 ***
Utilities	-0.8188 ***	-0.7569 ***	-0.0275
Consumer Stap.	-0.128	0.2541 ***	0.4311
Health Care	0.0867	0.3786 ***	0.0985
R^2	0.3354	0.3720	0.3304

Panel B: Three-Month Lead

Sector	Small	Medium	Large
		Correlations	
Inform. Tech	0.2682 ***	-0.1882 **	0.0974
Industrials	-0.4256 ***	0.2970 ***	0.2417 ***
Materials	0.2305 ***	0.1454 **	0.6232 ***
Consumer Discr.	0.2807 ***	-0.1111	-0.3583 ***
Financials	-0.0494	-0.1246 *	-0.4274 ***
Energy	0.0380	0.0863	-0.1777 **
Telecom	0.3148 ***	-0.4473 ***	-0.7255 ***
Utilities	-0.6879 ***	-0.7697 ***	-0.0584
Consumer Stap.	-0.3541 ***	0.1005	0.3833 ***
Health Care	-0.095	0.2476 ***	0.1066
R^2	0.3707	0.4289	0.4666

Table 5
Relation between Stock Market and past Active Net Orderflow

This table contains the results of the following unconditional regression:

$$SP500_t = \alpha + \beta \frac{\left(\text{Net Orderflow}_{j,t-1} - \textit{Passive } \text{Net Orderflow}_{j,t-1}\right)}{\text{capsector}_{j,t-1}} + \varphi SP500_{t-1} + \varepsilon_{j,t}$$

where Net Orderflow$_{j,t}$, Passive Net Orderflow$_{j,t}$, Capsector$_{j,t}$ represent the actual net orderflow, the passive net orderflow, the capitalization of sector j over month t. We compute the passive net orderflow for sector j as the total net orderflow to the stock market multiplied by the weight of sector j in the market.   T-statistics are calculated using White heteroschedastic consistent standard errors. Sectors are grouped by cyclicality as per the MSCI ranking in three broad groups, pro-cyclical, neutral and counter-cyclical respectively.

Panel A: One-Month Lead

	Small			Medium			Large		
Sector	β	T-stats	R^2	β	T-stats	R^2	β	T-stats	R^2
Inform. Tech	0.0040	1.7011	0.0090	-0.0019	-0.5644	0.0024	0.0037	1.2528	0.0082
Industrials	0.0003	0.1098	0.0005	0.0048	1.6526	0.0143	0.0032	1.1078	0.0063
Materials	-0.0035	-1.4185	0.0071	-0.0043	-1.4475	0.0107	0.0016	0.4200	0.0019
Consumer Discr.	-0.0014	-0.5168	0.0017	-0.0037	-1.0781	0.0085	-0.0060	-1.6626	0.0210
Financials	-0.0012	-0.3986	0.0013	-0.0020	-0.6093	0.0028	-0.0042	-1.3889	0.0109
Energy	-0.0002	-0.1052	0.0005	-0.0010	-0.2898	0.0010	-0.0024	-0.7133	0.0038
Telecom	-0.0025	-0.9325	0.0042	-0.0075	-2.0155	0.0327	-0.0097	-2.7412	0.0547
Utilities	-0.0070	-1.9101	0.0274	-0.0039	-1.1756	0.0080	0.0051	1.5191	0.0156
Consumer Stap.	0.0015	0.5953	0.0018	0.0048	1.4463	0.0137	0.0047	1.3520	0.0131
Health Care	0.0022	0.7962	0.0033	0.0067	1.8686	0.0266	0.0013	0.4139	0.0014
Lagged SP500			0.0005			0.0005			0.0005

Panel B: Three-Month Lead

	Small			Medium			Large		
Sector	β	T-stats	R^2	β	T-stats	R^2	β	T-stats	R^2
Inform. Tech	0.0045	1.8921	0.0159	-0.0033	-1.0524	0.0108	0.0007	0.2240	0.0053
Industrials	-0.0001	-0.0175	0.0050	0.0036	1.1828	0.0123	0.0048	1.3937	0.0188
Materials	-0.0015	-0.5567	0.0062	-0.0024	-0.7781	0.0081	-0.0010	-0.3263	0.0056
Consumer Discr.	-0.0020	-0.7643	0.0072	-0.0036	-1.1870	0.0123	-0.0063	-1.8845	0.0277
Financials	-0.0050	-1.4934	0.0181	-0.0031	-0.9516	0.0100	-0.0038	-1.1888	0.0135
Energy	0.0020	0.8063	0.0070	-0.0014	-0.4109	0.0061	-0.0009	-0.2525	0.0055
Telecom	-0.0009	-0.3126	0.0055	-0.0049	-1.3619	0.0190	-0.0061	-1.5447	0.0263
Utilities	-0.0054	-1.4662	0.0203	0.0022	0.6038	0.0072	0.0026	0.6435	0.0089
Consumer Stap.	0.0021	0.7387	0.0071	0.0056	1.6100	0.0228	0.0063	1.7041	0.0282
Health Care	0.0004	0.1491	0.0051	0.0056	1.6539	0.0229	0.0037	1.1876	0.0128
Lagged SP500			0.0050			0.0050			0.0050

Table 6
Relation between Bond returns and past Active Net Orderflow

This table contains the results of the following unconditional regression:

$$1yBondRet_t = \alpha + \beta \frac{\left(\text{Net Orderflow}_{j,t-1} - Passive\ \text{Net Orderflow}_{j,t-1}\right)}{\text{capsector}_{j,t-1}} + \varphi\ BondRet_{t-1} + \varepsilon_{j,t}$$

where Net Orderflow$_{j,t}$, Passive Net Orderflow$_{j,t}$, Capsector$_{j,t}$ represent the actual net orderflow, the passive net orderflow, the capitalization of sector j over month t. We compute the passive net orderflow for sector j as the total net orderflow to the stock market multiplied by the weight of sector j in the market portfolio. T-statistics are calculated using White heteroschedastic consistent standard errors. Sectors are grouped by cyclicality as per the MSCI ranking in three broad groups, pro-cyclical, neutral and counter-cyclical respectively.

Panel A: One-Month Lead

Sector	Small β	T-stats	R^2	Medium β	T-stats	R^2	Large β	T-stats	R^2
Inform. Tech	-0.0001	-0.3451	0.0828	-0.0001	-0.0308	0.0821	-0.0002	-0.8172	0.0866
Industrials	0.0004	2.1830	0.1067	0.0001	0.1181	0.0822	0.0001	0.3301	0.0827
Materials	-0.0003	-1.6734	0.0925	-0.0004	-2.3860	0.1073	-0.0005	-2.5736	0.1250
Consumer Discr.	-0.0002	-1.2885	0.0885	-0.0001	-0.2959	0.0825	-0.0001	-0.1026	0.0822
Financials	0.0001	0.1717	0.0823	0.0005	2.5622	0.1266	0.0005	2.1213	0.1165
Energy	-0.0001	-0.5052	0.0834	-0.0002	-1.1487	0.0890	-0.0001	-0.1161	0.0822
Telecom	-0.0005	-2.8804	0.1189	0.0001	0.7865	0.0855	0.0003	1.6272	0.0988
Utilities	0.0004	1.8333	0.1042	0.0007	3.6760	0.1497	0.0003	1.5880	0.0942
Consumer Stap.	0.0003	1.8381	0.0970	0.0001	0.6670	0.0844	0.0001	0.1463	0.0822
Health Care	0.0001	0.7986	0.0842	0.0001	0.0350	0.0821	0.0001	-0.4790	0.0835
Lagged BondRet			0.0821			0.0821			0.0821

Panel B: Three-Month Lead

Sector	Small β	T-stats	R^2	Medium β	T-stats	R^2	Large β	T-stats	R^2
Inform. Tech	0.0001	0.0019	0.0321	0.0001	0.1593	0.0323	-0.0002	-0.7581	0.0367
Industrials	0.0004	2.1005	0.0546	-0.0001	-0.3248	0.0327	-0.0001	-0.6320	0.0342
Materials	-0.0003	-2.1676	0.0490	-0.0004	-2.4886	0.0608	-0.0008	-4.2266	0.1277
Consumer Discr.	-0.0003	-2.0157	0.0471	-0.0001	-0.4597	0.0331	0.0001	0.2012	0.0324
Financials	-0.0002	-1.3154	0.0402	0.0003	1.4831	0.0475	0.0006	2.5323	0.0860
Energy	-0.0001	-0.8528	0.0344	-0.0001	-0.5152	0.0337	0.0003	1.6374	0.0482
Telecom	-0.0004	-2.2341	0.0568	0.0001	0.6948	0.0354	0.0004	1.4338	0.0542
Utilities	0.0003	1.5359	0.0433	0.0008	4.0032	0.1248	0.0002	0.8089	0.0386
Consumer Stap.	0.0004	2.3708	0.0544	0.0001	0.7571	0.0350	0.0001	0.0555	0.0321
Health Care	0.0002	1.3968	0.0395	-0.0001	-0.2693	0.0328	-0.0001	-0.1612	0.0324
Lagged BondRet			0.0321			0.0321			0.0321

Table 7
Relation between orderflow information within the economy and markets

This table shows the explanatory power of regressing future values of the CFNAI expansion indicator, the stock market return, and the bond market return on the current value of the dependent variable and a forecasting factor. The forecasting factor is a linear combination of either active sector orderflows or excess sector returns. The loadings in the linear combination are the ones with the maximal correlation with each of the dependent variables in turn.
We report only the adjusted-R2. *, **, *** denote a significant coefficient on the factor at the 10%, 5%, and 1% level, with White heteroschedastic consistent standard errors.

Panel A: Dependent Variable CFNAI

Regressor	Loadings with maximal correlation on	1-mo ahead Adj-R^2	3-mo ahead Adj-R^2
Current CFNAI		0.18 ***	0.25 ***
Active orderflow	CFNAI	0.32 ***	0.46 ***
	SP500	0.22 ***	0.27 ***
	1-y Bond	0.26 ***	0.39 ***
Excess returns	CFNAI	0.29 ***	0.31 ***
	SP500	0.18	0.25
	1-y Bond	0.26 ***	0.29 ***

Panel B: Dependent Variable S&P500

Regressor	Loadings with maximal correlation on	1-mo ahead Adj-R^2	3-mo ahead Adj-R^2
Current CFNAI		0.00	0.01
Active orderflow	CFNAI	0.02 **	0.00
	SP500	0.07 ***	0.03 **
	1-y Bond	0.00	-0.01
Excess returns	CFNAI	-0.01	0.00
	SP500	0.05 ***	0.08 ***
	1-y Bond	-0.01	-0.01

Panel C: Dependent Variable 1-y bond returns

Regressor	Loadings with maximal correlation on	1-mo ahead Adj-R^2	3-mo ahead Adj-R^2
Current CFNAI		0.08 ***	0.03 ***
Active orderflow	CFNAI	0.13 ***	0.14 ***
	SP500	0.08	0.02
	1-y Bond	0.18 ***	0.19 ***
Excess returns	CFNAI	0.13 ***	0.05 **
	SP500	0.07	0.02
	1-y Bond	0.15 ***	0.06 ***

Table 8
Relation between Expansions and past excess sector returns

This table contains the results of the following bivariate unconditional regression:

$$CFNAI_t = \alpha + \beta\,(\mathrm{Ret}_{j,t} - \mathrm{Ret}_{mkt,t}) + \phi CFNAI_{t-1} + \varepsilon_{j,t}$$

where $\mathrm{Ret}_{j,t}$ represent the value-weighted return of sector j over month t, $\mathrm{Ret}_{mkt,t}$ represents the value-weighted return on the stock market index, and CFNAI is the expansion indicator. We report the R^2 of the regressions together with R^2ofl, which is the R^2 of the large orderflow regressions reported in Table 3. The excess return regressor is standardized.
*, **, *** denote significance at the 10%, 5%, and 1% level with White heteroschedastic consistent standard errors. Sectors are grouped by cyclicality as per the MSCI ranking in three broad groups, pro-cyclical, neutral and counter-cyclical respectively.

Sector	One-month lead			Three-month lead		
	β	R^2	R^2_{ofl}	β	R^2	R^2_{ofl}
Inform. Tech	0.0747	0.1966	0.1885	0.0383	0.2549	0.2525
Industrials	-0.0520	0.1891	0.1859	-0.0236	0.2525	0.2629
Materials	-0.0468	0.1877	0.2317	-0.0055	0.2512	0.3261
Consumer Discr.	-0.0857 **	0.2012	0.2042	-0.0841 **	0.2697	0.2675
Financials	-0.0822 *	0.1997	0.2439	-0.0923 **	0.2733	0.2811
Energy	-0.0586	0.1910	0.1820	-0.0217	0.2523	0.2581
Telecom	0.0359	0.1854	0.2427	0.0232	0.2525	0.3484
Utilities	-0.1618 ***	0.2507	0.1837	-0.0998 **	0.2773	0.2549
Consumer Stap.	-0.1191 ***	0.2192	0.2002	-0.1004 **	0.2776	0.2706
Health Care	-0.1317 ***	0.2273	0.1821	-0.0849 **	0.2699	0.2511
Average		0.2047	0.2045		0.2631	0.2773

Table 9
Relation between Business Cycle, Stock Market Returns, Bond Market Returns
and past Active Net Orderflow and returns

This table contains the results of the following unconditional regression:

$$Y_{t+2} = \alpha + \sum_{j=1}^{10} \beta_j \frac{\left(\text{Net Orderflow}_{j,t-1} - Passive \text{ Net Orderflow}_{j,t-1}\right)}{\text{capsector}_{j,t-1}}$$

$$+ \sum_{j=1}^{10} \delta_j \left(\text{Ret}_{j,t-1} - \text{Ret}_{mkt,t-1}\right) + \varphi Y_{t-1} + \varepsilon_{j,t}$$

where Y_t is either the CFNAI indicator, the S&P500 return, or the 1-year bond return, Net Orderflow$_{j,t}$, Passive Net Orderflow$_{j,t}$, Capsector$_{j,t}$, Ret$_{j,t}$ represent the actual net orderflow, the passive net orderflow, the capitalization, the value-weighted return, of sector j over month t. Ret$_{mkt,t}$ represents the value-weighted return on the stock market index. We compute the passive net orderflow for sector j as the total net orderflow to the stock market multiplied by the weight of sector j in the market.

Regressors	Adjusted-R^2 (3-months ahead)		
	CFNAI	S&P500 Return	1-Year Bond Return
Only Y_{t-1}	0.2461	-0.0016	0.0258
Small Active NOF	0.3216	0.0121	0.0334
Medium Active NOF	0.3844	-0.0058	0.1178
Large Active NOF	0.4250	-0.0319	0.1433
Excess Returns	0.2708	0.0178	0.0159
Large Active NOF + excess returns	0.4396	-0.0006	0.1341

Table 10
Relation between Business Cycle, Stock Market Returns, Bond Market Returns, past Large Active Net Orderflow, past excess returns and other predictors

This table contains the adjusted R^2 of estimating the following six specifications in turn:

(1) $Y_{t+2} = \alpha_1 + \varphi_{11}Y_{t-1} + \varepsilon_{t+2,1}$

(2) $Y_{t+2} = \alpha_2 + \varphi_{12}Y_{t-1} + \varphi_{22}DIV_{t-1} + \varphi_{32}DEF_{t-1} + \varphi_{42}TERM_{t-1} + \varepsilon_{t+2,2}$

(3) $Y_{t+2} = \alpha_3 + \varphi_{13}Y_{t-1} + \varphi_{23}DIV_{t-1} + \varphi_{33}DEF_{t-1} + \varphi_{43}TERM_{t-1} + \sum_{j=1}^{10}\delta_j \, (\text{Ret}_{j,t-1} - \text{Ret}_{mkt,t-1}) + \varepsilon_{t+2,RET}$

(4) $Y_{t+2} = \alpha_4 + \varphi_{14}Y_{t-1} + \varphi_{24}DIV_{t-1} + \varphi_{34}DEF_{t-1} + \varphi_{44}TERM_{t-1} + \sum_{j=1}^{10}\beta_j \, \dfrac{\left(\text{Net Orderflow}_{j,t-1} - Passive \text{ Net Orderflow}_{j,t-1}\right)}{\text{capsector}_{j,t-1}} + \varepsilon_{t+2,NOF}$

(5) $\varepsilon_{t+2,RET} = \alpha_5 + \sum_{j=1}^{10}\beta_j \, \dfrac{\left(\text{Net Orderflow}_{j,t-1} - Passive \text{ Net Orderflow}_{j,t-1}\right)}{\text{capsector}_{j,t-1}} + \varepsilon_{t+2,5}$

(6) $\varepsilon_{t+2,NOF} = \alpha_6 + \sum_{j=1}^{10}\delta_j \, (\text{Ret}_{j,t-1} - \text{Ret}_{mkt,t-1}) + \varepsilon_{t+2,6}$

where Y_t is either the CFNAI indicator, the S&P500 return, or the 1-year bond return, DIV_t; DEF_t, $TERM_t$ represent the dividend yield, the default spread (difference between corporate BAA and AAA yields) and term spread (difference between Treasury 10-year and 3-months), respectively. Net Orderflow$_{j,t}$, Passive Net Orderflow$_{j,t}$, Capsector$_{j,t}$, Ret$_{j,t}$ represent the actual large net orderflow, the passive large net orderflow, the capitalization, the value-weighted return, of sector j over month t. Ret$_{mkt,t}$ represents the value-weighted return on the stock market index. We compute the passive net orderflow for sector j as the total net orderflow to the stock market multiplied by the weight of sector j in the market.

Equation	CFNAI		S&P 500 Return		1-Yr Bond Return	
	No. signif. Regressors	Adj-R^2 (3-mo ahead)	No. signif. Regressors	Adj-R^2 (3-mo ahead)	No. signif. Regressors	Adj-R^2 (3-mo ahead)
(1)	1 of 1	0.25	0 of 1	-0.00	1 of 1	0.03
(2)	1 of 4	0.27	0 of 4	0.01	1 of 4	0.04
(3)	1 of 14	0.28	2 of 14	0.02	0 of 14	0.02
(4)	10 of 14	0.42	0 of 14	-0.04	5 of 14	0.14
(5)	4 of 10	0.12	0 of 10	-0.04	2 of 10	0.05
(6)	1 of 10	0.00	2 of 10	0.00	0 of 10	-0.03

Table 11
Relation between economy, financial markets and orderflow with low/high dispersion

This table contains the R^2 of the following regression:

$$Y_t = \alpha + \sum_{j=1}^{10} \beta_j \frac{\left(\text{Net Orderflow}_{j,t-1} - \text{Passive Net Orderflow}_{j,t-1}\right)}{\text{Capsector}_{j,t-1}} + \varphi Y_{t-1} + \varepsilon_{j,t}$$

where Y_t is either the CFNAI indicator, stock market returns, or bond market returns. Net Orderflow$_{j,t}$, Passive Net Orderflow$_{j,t}$, Capsector$_{j,t}$ represent the actual net orderflow, the passive net orderflow, the capitalization of sector j over month t. We compute the passive net orderflow for sector j as the total net orderflow to the stock market multiplied by the weight of sector j in the market portfolio.

The regression is estimated conditional on low or high dispersion of orderflow within sectors. We measure dispersion as the standard deviation of active flows within each sector. We aggregate dispersion at the market level using either the market capitalization of each sector (σ_1) or the absolute value of the correlations reported in Table 4 and normalized to sum up to one (σ_2). In a given month, dispersion is high (low) when the standard deviation is above (below) its median in the last 12 months.

	CFNAI	Comparison of R^2 Stock Market	Bond Market 1y
	Dispersion with Market Cap Weights (σ_1)		
Low dispersion	0.54	0.22	0.28
High dispersion	0.34	0.12	0.19
Ratio (Low/High)	1.59	1.83	1.47
	Dispersion with Correlation Weights (σ_2)		
Low dispersion	0.47	0.20	0.31
High dispersion	0.28	0.08	0.16
Ratio (Low/High)	1.68	2.50	1.94

Table 12
Relation between equity flows and non-farm Payroll surprises

This table shows the results of estimating the following regression:

$$F_{t,t+\tau} = \alpha + \beta \frac{\left(NFP_{ACT,t} - NFP_{EXP,t}\right)}{\sigma_S} + \varepsilon$$

where F is a linear combination of sector flows or returns in the period τ following the non-farm Payroll release at t, $NFP_{ACT,t}$ is the actual NFP release, $NFP_{EXP,t}$ is the median forecast, and σ_s is the standard deviation of the NFP surprise. τ is either one week or one month. The loadings in the linear combination are the ones with maximal correlation with changes in the expansion index (CFNAI), stock market returns (SP500), or 1-year bond returns. T-statistics are calculated using bootstrapped standard errors.

Dependent variable	Weekly			Monthly		
	β	T-stat	R^2	β	T-stat	R^2
Panel A: Flows						
CFNAI	0.0439	1.78	0.02	0.0453	2.74	0.03
SP500	-0.0004	-0.28	0.00	0.0003	0.29	0.00
Bond	-0.0002	-2.12	0.03	-0.0001	-1.40	0.01
Panel B: Returns						
CFNAI	-0.0191	-1.35	0.01	-0.0077	-0.46	0.00
SP500	-0.0004	-0.40	0.00	-0.0002	-0.22	0.00
Bond	0.0001	1.49	0.01	0.0001	0.41	0.00

Table 13
Relation between Active Net Order Flow and Mutual Fund Flows

This table contains pairwise sector correlations between active net orderflow and active mutual fund flows. Active net orderflow is defined as

$$\frac{\text{Net Orderflow}_{j,t} - Passive \text{ Net Orderflow}_{j,t}}{\text{Capsector}_{j,t}},$$

where Net Orderflow$_{j,t}$, and Passive Net Orderflow$_{j,t}$, represent the actual net orderflow and the passive net orderflow, within sector j over quarter t. We compute the passive net orderflow for sector j as the total net orderflow to the stock market multiplied by the weight of sector j in the market. Active mutual fund flow is defined as

$$\frac{\text{Net Flow}_{j,t,L} - Passive \text{ Net Flow}_{j,t,L}}{\text{Capsector}_{j,t}}$$

where Net Flow$_{j,t}$, and Passive Net Flow$_{j,t}$, represent the actual flow and the passive flow, within sector j over quarter t in the mutual fund category L. We compute the passive net flow for sector j in mutual fund category L as the total flows to the category L multiplied by the weight of sector j in the market. *, **, *** denote significance at the 10%, 5%, and 1% level. The Core investment objective represents a blend of the value and growth styles, while the S&P investment objective represents the passive style of replicating the S&P 500 index. Sectors are grouped by cyclicality as per the MSCI ranking in three broad groups, pro-cyclical, neutral and counter-cyclical respectively.

Sector	Core Correlation	S&P Correlation		Obs.
Inform. Tech	0.16	0.24	*	52
Industrials	0.06	0.10		52
Materials	0.18	0.04		52
Consumer Discr.	0.25 *	-0.03		52
Financials	0.03	0.05		52
Energy	0.27 **	-0.07		52
Telecom	0.04	-0.19		52
Utilities	0.14	-0.36	**	52
Consumer Stap.	0.30 **	0.19		52
Health Care	0.30 **	0.15		52
Average	0.17	0.01		
Median	0.17	0.04		