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 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, future stock market returns, 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

Within the finance literature, it is well understood that orderflow is the conduit through which information about asset fundamentals are aggregated into prices. Empirical studies documenting 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. In a similar way, it is well understood within the macroeconomics literature that asset prices/returns help forecast the macroeconomy (see Stock and Watson (2003) for a survey of this literature). Given the aforementioned research, it is possible that orderflow may contain a whole array of information, macroeconomic fundamentals, future aggregate expected cashflows, risk preferences, discount rates, which are relevant for the macroeconomy as well as capital markets.

With this as background two important questions emerge as the focus of our analysis. First, what role does orderflow play in predicting macroeconomic fundamentals and individual markets both directly and in conjunction with prices/returns? Second, to the extent that orderflow has some predictive power, what is the exact nature of that information?

These questions are important because the predictive power of orderflow remains an open empirical question as orderflow may contain less, the same, or more information relative to the information contained in prices/returns. Orderflow may contain less information than prices/returns if public information resulting in instantaneous price adjustments (absent trade) is a substantial portion of the price formation process. Another possibility is that orderflow simply passes through information to asset prices/returns so that the information in orderflow and returns is identical. Finally, orderflow may contain more or unique information relative to prices/returns in that investors' trading behavior is not fully spanned by asset prices. This possibility may arise if orderflow reflects the *actions* of market participants while prices/returns reflect the *consequences* of a trading process with a number of potential frictions.

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 fundamentals – e.g., 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, an 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. Consistent with economic intuition, 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 both stock and bond markets, even after controlling for returns. While it is interesting that orderflow predicts the macro economy, stock market and bond market, what is most intriguing is that the linear combination of sector flows that *best* predicts the macro economy also contains the bulk of the explanatory power for predicting the stock and bond markets. Moreover, we demonstrate that our predictability results become significantly stronger after conditioning on low dispersion of orderflow *within* sectors. These results suggest that the information contained in sector orderflow is different than the information in returns and has more to do with sector allocation than stock picking. In addition, whatever information is contained in sector orderflow it appears to be important to the performance of both the macroeconomy as well as aggregate capital markets.

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 times, although it enjoys superior risk and return properties relative to the traditional market portfolio. Thus, taken together our results reveal that the

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

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 flows 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) study the relation between the common statistical factors within aggregate orderflow, liquidity and returns. 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, Keifer and O'Hara (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 flows appear to be related to styles and 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.

Within the extant literature, our paper is most closely aligned with Albuquerque, Francisco and Marques (2008) and Evans and Lyons (2007); the relation to these studies warrants further discussion. While orderflow is the focal point of all three papers, the questions addressed, methodology and scope are all different. Albuquerque, Francisco and Marques (2008) estimate a specific structural model and carry out their analysis of orderflow and exchange rates on 5 industries with an average of 6 firms in each. In contrast, we analyze orderflow of all stocks traded on the NYSE, Nasdaq and AMEX within ten large sectors, which dramatically increases the scope of our study and the breadth of the investor types analyzed. Like our paper, Evans and Lyons (2007) analyzes the relation between orderflow and macro fundamentals; however, there are a number of differences: First, they focus on exchange rate markets which reveal information on real interest rate differentials while we investigate the broader information embedded in the equity market. Second, our data is much more comprehensive as our sample period is considerably longer and our data is publically available. Finally, our analysis utilizes a real-time index of the macroeconomy while Evans and Lyons forecasts macroeconomic estimates of fundamentals as generated from a time-series econometric model. In summary, our analysis focuses on completely different information and is more comprehensive, in terms of the breadth of the data, the different macroeconomic environments covered, and the applicability to the types of traders.

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 flows 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 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, abbreviations and corresponding numbers). We then construct sector-level net orderflow by simply summing all orderflow for the individual stocks included in each sector and 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.

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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.

[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.

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 orderflow. We interpret active net orderflow as deliberate decisions 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 some extreme percentages during the economic downturn in 1999 and 2000. Materials and consumer staples have low fractions of orderflow while health care, information technology and telecommunications have high fractions of overall orderflow. 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).[5] 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.

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

[5] 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

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.

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.[6] This empirical specification has a number of advantages. First, our key variable reflects the orderflow that is entering a sector in

[6] 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.

excess of new funds flowing 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.[7] Recall that the construction of dollar sector orderflow is comparable to value-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 flows, 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.

Table 3 shows that flows into a number of the sectors forecast expansion/contractions in the macro economy, particularly for large orders. We find that active flows of large orders into the material sector predict higher levels of the expansion index both one and three months ahead, while active flows 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

[7] 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.

null hypothesis of no predictability from orderflow using 100,000 bootstrap replications. The 5% and 10% data-mining robust critical values for the T-statistics in Table 3, Panel A, are 3.01 and 2.71, respectively. Of the large sector orderflow, materials, financials and telecoms are still significant at least at the 10% level. Alternatively, under the null hypothesis of no predictability, there is a 18%, 7%, 4%, 2% probability to obtain at least three, five, seven, and nine models respectively out of 30 with a T-statistic greater than two. Empirically in Table 3, Panel A, we obtain nine 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.

In addition to the coefficients being statistically significant, they are also economically significant; as an example, a one-standard deviation shock to large flows 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 flows 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 flows 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.[8]

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 flows. 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 flows 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 flows 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. Notice that, consistent with the individual sector results, the large flow results are different from the small and medium flow results. Beginning with the three-month horizon, there appears to be some stratification of orderflow among sectors based on the size of the flow. For example, large flows 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 flows show a sharp contrast in their positioning. The materials and industrial sectors for the medium flows are aggressive (positive

[8] 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.

coefficients) as are the materials, consumer discretionary, information technology and telecommunication sectors for the small sized flows. Utilities are the one defensive sector for the small and medium flows.

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 flows, while health care and information technology are the most aggressive for medium and small flows, respectively. Consumer discretionary, financials, and telecommunications are the defensive sectors for large sized flows, 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 particular sectors able to forecast expansions/contractions up to one quarter ahead. Although, 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. Moreover, 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. 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 flow into utilities as well as medium and large-sized flows 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. 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 flows 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 flows, 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.[9] 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 flows 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 flows is materials and the most defensive is the financial sector (results not reported).

Since the cross-section of flows across sectors contains information about the future evolution of the economy, the bond market, and, to a lesser extent, the stock 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 now replace the dependent variable with the logarithmic change in the volatility index (VIX) one-month and one-quarter ahead.[10] While we find that flows have some predictive power, the results are far from substantial. For example, the active flows across sectors only predict up to 6% of the variation in the VIX change in one month (results not reported).

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

[10] VIX is a model-free implied volatility of S&P500 options with one-month to maturity computed by the CBOE and is commonly used as a measure of global risk-appetite. We also experiment with a realized volatility measure obtained from S&P500 returns, obtaining very similar results.

4.4 Relationship between Orderflow Information Predicting 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 flows 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 flows or excess sector returns, where the loadings are computed as those with the maximal correlation with each of the dependent variables, respectively.

Panels A, B and C of Table 7 display the results for the economic expansions, stock and bond markets respectively. Not surprisingly, 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 flows 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* appear 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 Dispersion within Sectors

While our results clearly demonstrate the predictive power of sector orderflow, 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.[11]

In order to test 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.[12] Then 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.

In Table 8, we present the results of forecasting the expansion indicator, the stock market and the bond market with the sector flows 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.[13] 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 flows doubles.

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

[12] 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.

[13] 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).

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. The Nature of Orderflow Information

While the predictive power of sector orderflow has been clearly established, what remains is to better understand the exact nature of the information contained therein. To that end, a number of questions come to mind. Do prices/returns contain the same or potentially more or less information than flows? Can sector orderflow movements be directly tied to the release of important macroeconomic information? Is the information in flows economically relevant? The next subsections will address each of these questions in turn.

5.1 Orderflow versus Returns

Others have investigated whether market level variables can be used to predict the economy. Specifically, our paper is related to Lamont (2001) and Hong et al. (2007), who 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 literature on returns, a natural question arises as to whether orderflow contains the same information as returns. On one hand, the two series 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 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 9 displays our results for the large-sized orderflow; for comparison we include the R^2 from the orderflow results contained in Table 3. The R^2 comparison reveals very little difference on average between the explanatory power of flows and the explanatory power of returns. However, further inspection reveals that the sector returns with predictive power are different than those for sector flows. For example, within the return regression, consumer discretionary and 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 flows into the materials sector and flows out of the financial and utility sectors are associated with an expanding economy.[14]

To complement the above analysis, we run 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 10 displays our results which compares the adjusted R^2 across the various sets of predictors. Panels A, B and C correspond to the economic expansion index, the stock market and the bond market respectively. The first item to note is that the cross-section of flows contains more explanatory power than returns for future economic expansions. The difference is more striking at the three-month horizon and for large-sized flows; specifically, adding flows 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 there less predictability, it is not clear whether flows dominate returns. At the one month horizon, flows of large-sized orders dominate while at the three month horizon

[14] 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.

excess sector returns offer better predictability. Finally, like the results for the economic expansion, the large-sized flows dominate returns in predicting the one-year maturity bond returns, strikingly so at the three-month horizon. In summary, these results clearly demonstrate that orderflow encompasses more information than is contained in returns.

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 and macroeconomic announcements would be consistent with our hypothesis and alleviate concerns that our results are driven by other latent factors.[15]

Our empirical design is to regress the orderflow factors with the highest correlation with the macro economy, stock market and bond market onto 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).[16] Orderflow is measured over the week and the month following the non-farm payroll release. If active flows are indeed capturing portfolio adjustments in response to changes in economic conditions, then the release of NFP news should trigger active flows in the sectors that are linked to the evolution of the economy. Therefore, if a positive NFP surprise signals an

[15] 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).
[16] We standardize the release by subtracting the announced figure from the median expectation and dividing by the standard deviation of the surprise.

expanding economy, we should subsequently observe active flows into materials and out of financials.

Table 11 displays our results. 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 expansion indicator regression suggests that the creation of new jobs (increase in non-farm payroll) predicts flows 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 flows 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 flows as the dependent variable. In contrast to the flow 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 flows, the nature of the information within returns and flows 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 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 flows 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 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 12 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, even with only 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 flows with a passive replication strategy of the S&P500 index (labeled S&P500 in Table 12). 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 nature of the 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 flows.

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 flows into percentage weight changes through a simple normal cumulative density function normalization. Like most other asset allocation techniques, our procedure has the potential to generate extreme and unrealistic weights. For example, an extremely positive (negative) active flow 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 viewed 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 3, 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 3 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.[17] Lastly, Panel C in Figure 3 shows that the sector weights appear to be well behaved ranging from a high of 30% to a low of 0% which argues for the feasible implementation of the orderflow mimicking portfolio.

[17] 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 assumptions. 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 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.[18]

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.

We find that sector orderflow movements predict changes in the expansion/contraction index, the future performance of the bond markets and, to a lesser extent, the equity markets. In

[18] 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.

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, 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 flows are less dispersed within sectors, lending further support to our conjecture that the sector flows 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 orderflow portfolio that enjoys superior risk and return properties relative to the traditional market portfolio or industry momentum portfolios. This suggests that flows contain asymmetric information in that it is primarily defensive in nature and largely related to wealth preservation.

Our analysis suggests that because sector orderflow aggregates the trading actions of market participants it necessarily synthesizes the collective risk preferences, expectations and information sets of market participants. Thus, utilizing the information within sector orderflow has the potential to reveal much about, not only the future performance of the economy and capital markets, but also concrete ways to improve our existing asset pricing models.

References

Albuquerque, R., E. de Francisco, and L. Marques, 2008, Marketwide Private Information in Stocks: Forecasting Currency Returns, *Journal of Finance*, forthcoming.

Andersen, T., T. Bollerslev, F. Diebold, and C. Vega., 2007, Real-Time Price Discovery in Stock, Bond and Foreign Exchange Markets," *Journal of International Economics* 73, 251-277.

Bansal, R., E. Fang and A. Yaron, 2005, Equity capital: A puzzle, Working paper, Duke University.

Beber, A., M. Brandt and K. Kavajecz, 2008, Flight-to-Quality or Flight-to-Liquidity? Evidence from the Euro-area bond market, *Review of Financial Studies*, forthcoming.

Boyd, J. H., J. Hu, and R. Jagannathan, 2005, The stock market's reaction to unemployment news: Why bad news is usually good for stocks, *Journal of Finance* 60, 649-672.

Brandt, M. and K. Kavajecz, 2004, Price discovery in the U.S. Treasury market: The impact of order flow and liquidity on the yield curve, *Journal of Finance* 59, 2623-2654.

Campbell, J., M. Lettau, B. Malkiel and Y. Xu, 2001, Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *Journal of Finance* 56, 1-43.

Campbell, J., T. Ramadorai and A. Schwartz, 2008, Caught on tape: Institutional trading, Stock Returns, and Earnings Announcements, *Journal of Financial Economics*, forthcoming.

Chordia, T., R. Roll, and A. Subrahmanyam, 2000, Commonality in Liquidity, *Journal of Financial Economics* 56, 3-28.

Chordia, T., R. Roll, and A. Subrahmanyam, 2001, Market Liquidity and Trading Activity, *Journal of Finance* 56, 501-530.

Chordia, T., R. Roll, and A. Subrahmanyam, 2002, Order Imbalance, Liquidity and Market Returns, *Journal of Financial Economics* 65, 111-130.

Cremers, K. and J. Mei, 2007, Turning over turnover, *Review of Financial Studies* 20: 1749-1782.

Evans, M., 2005, Where Are We Now?: Real-Time Estimates of the Macro Economy, *The International Journal of Central Banking* 1, 127-175.

Evans, M. and R. Lyons, 2002, Order flow and exchange rate dynamics, *Journal of Political Economy* 110: 170-180.

Evans, M. and R. Lyons, 2007, Exchange rate fundamentals and order flow, working paper, Georgetown University.

Froot, K. and M. Teo, 2008, Style Investing and Institutional Investors, *Journal of Financial and Quantitative Analysis*. forthcoming.

Glosten, L. and P. Milgrom, 1985, Bid, ask, and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 13: 71-100.

Hasbrouck, J., 1991, Measuring the information content of stock trades, *Journal of Finance* 46: 179-207.

Hasbrouck, J. and D. Seppi, 2001, Common factors in prices, orderflow and liquidity, *Journal of Financial Economics* 59: 383-411.

Hong, H., W. Torous and R. Valkanov, 2007, Do industries lead stock markets?, *Journal of Financial Economics* 83, 367-396.

Kyle, A., 1985, Continuous Auctions and Insider Trading, *Econometrica* 53: 1315-1335.

Lamont, O. A., 2001, Economic tracking portfolios, *Journal of Econometrics* 105, 161-184.

Lo, A. and J. Wang, 2000, Trading volume: Definitions, data analysis, and implications of portfolio theory, *Review of Financial Studies* 13: 257-300.

Lee, C. and M. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46: 733-746.

Stock, J. and M. Watson, 1999, Forecasting Inflation, *Journal of Monetary Economics*, 99: 293-335.

Stock, J. and M. Watson, 2003, Forecasting Output and Inflation: The Role of Asset Prices, *Journal of Economic Literature*, 16: 788-829.

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.

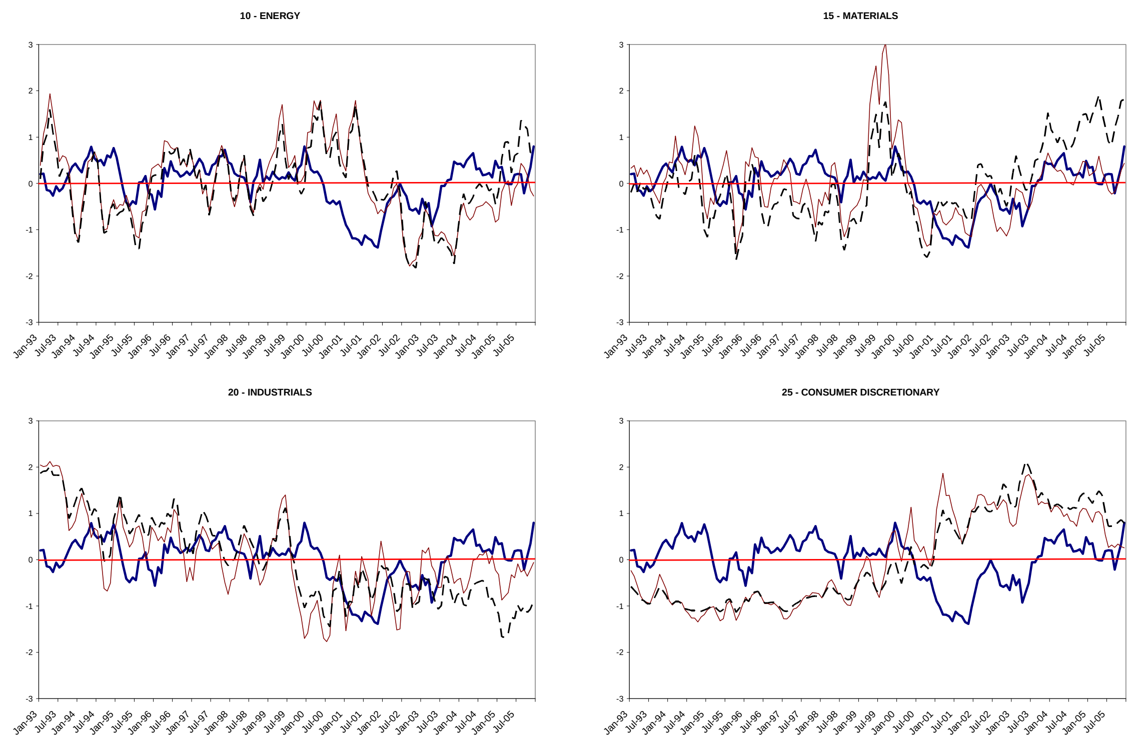


Figure 1 (continued)

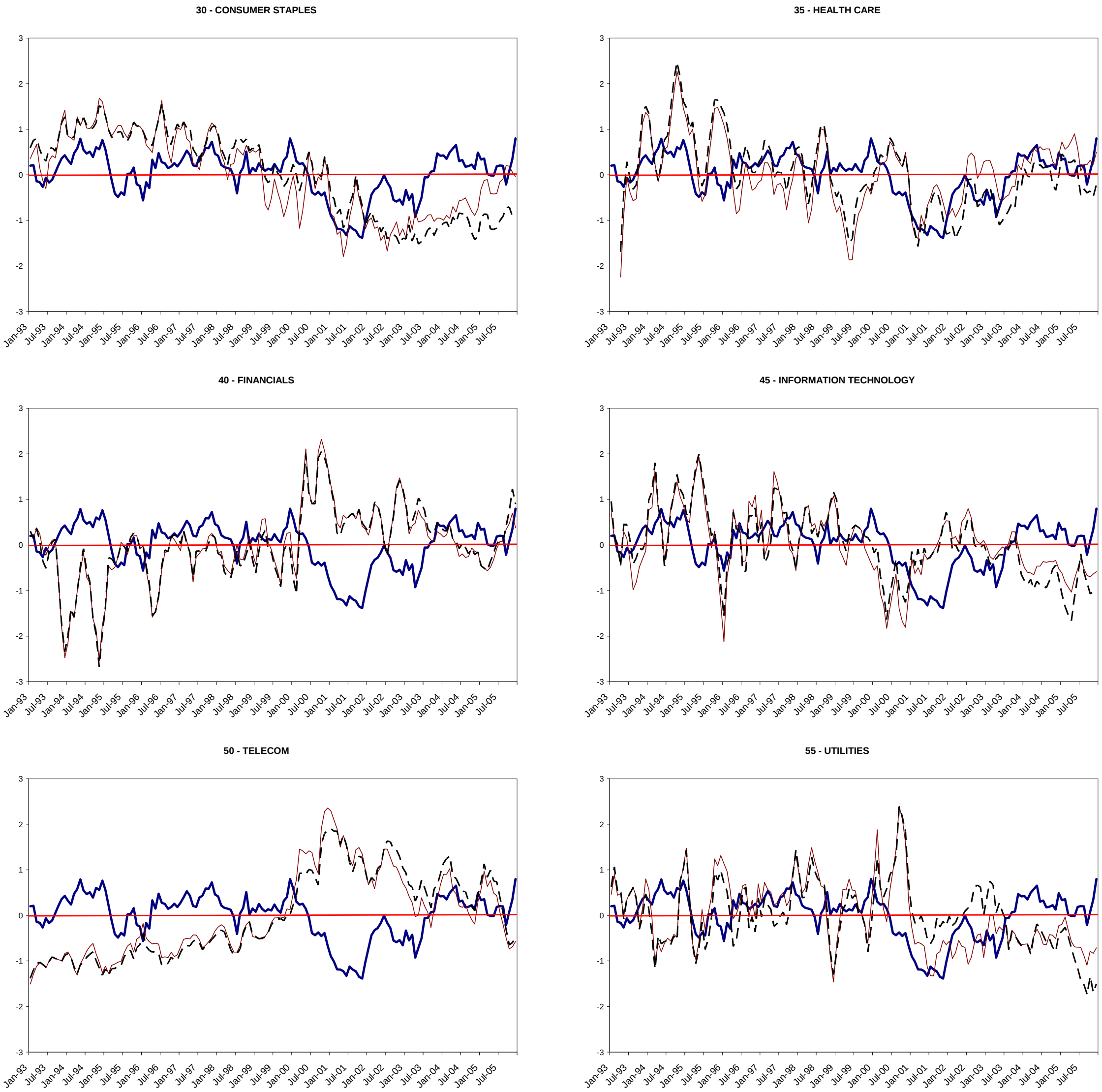
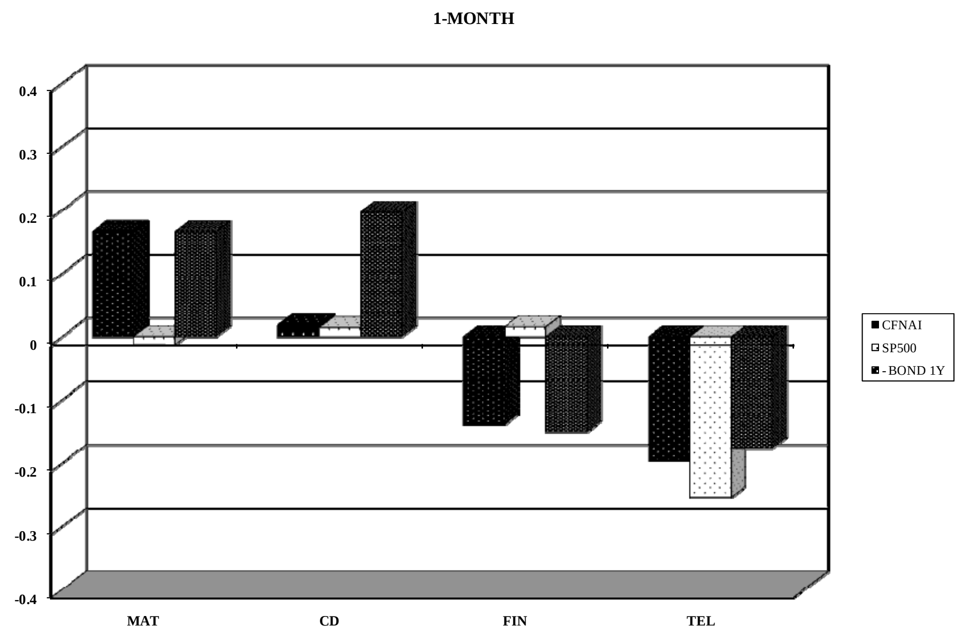


Figure 2

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.



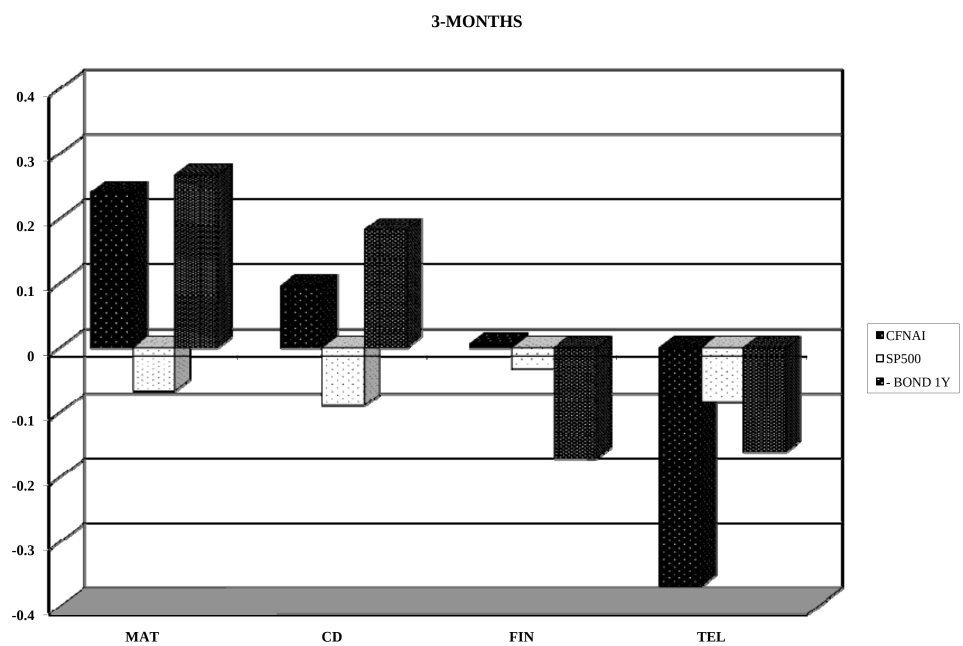
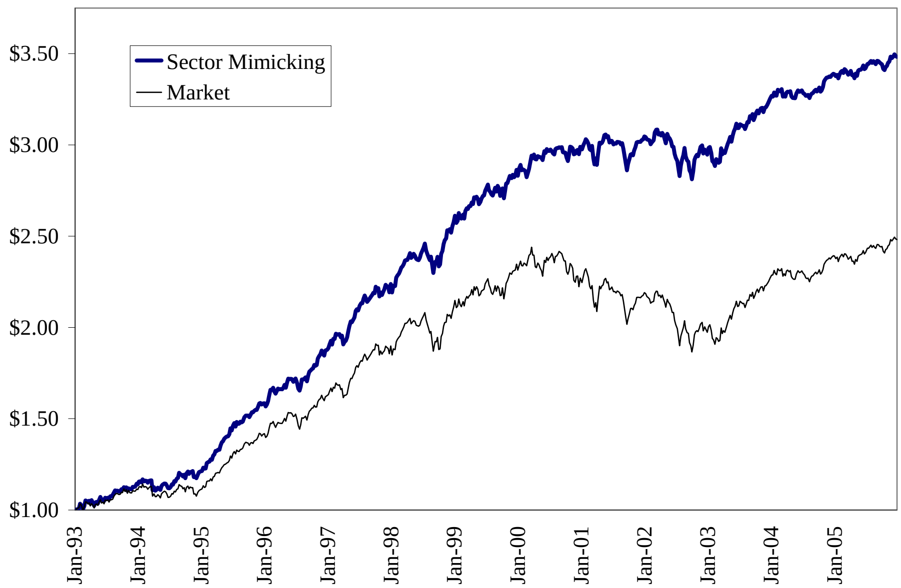


Figure 3

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

Figure 3, Continued

Panel C

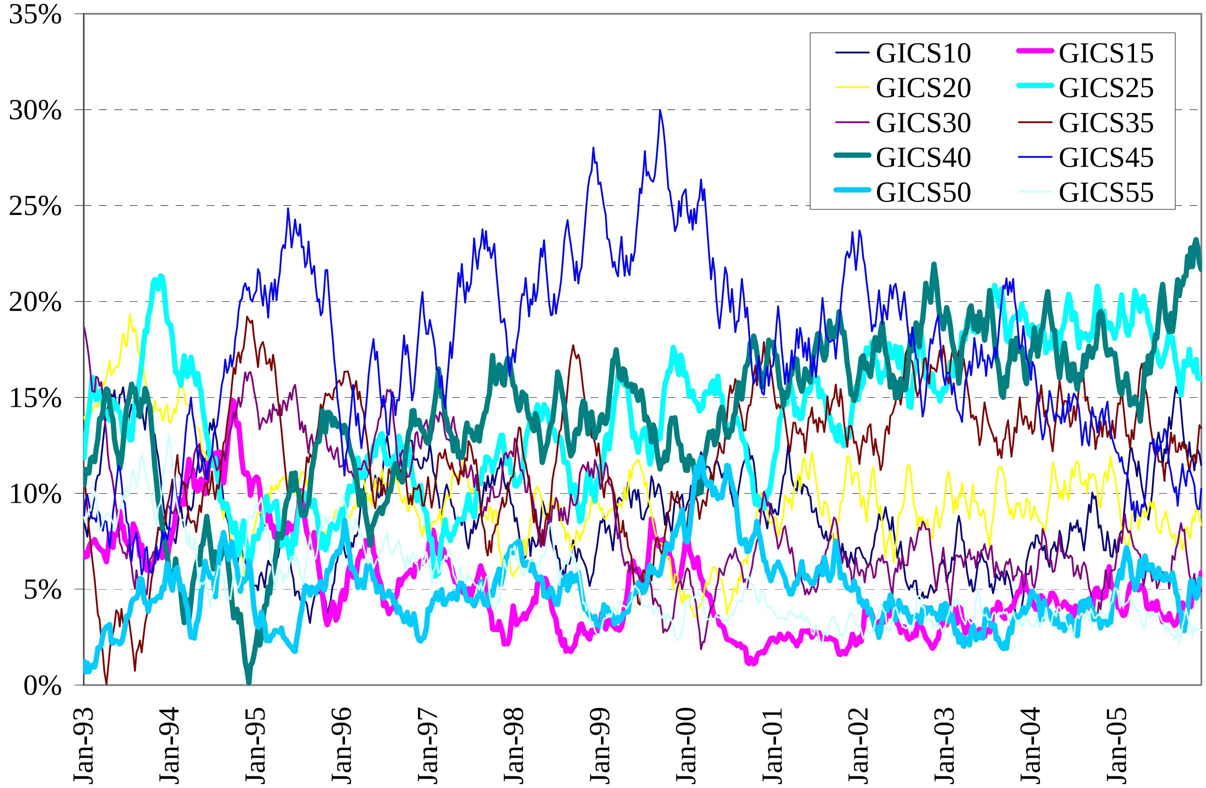


Table 1
Aggregate Orderflow Summary Statistics

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. Sector abbreviations are in the Appendix.

Panel A: All Orders

Sector		1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
10	ENE	12%	7%	6%	10%	9%	7%	9%	10%	9%	7%	7%	9%	14%
15	MAT	9%	12%	6%	7%	5%	4%	6%	3%	3%	4%	5%	6%	6%
20	IND	15%	9%	11%	10%	9%	9%	8%	7%	10%	9%	9%	10%	9%
25	CD	20%	11%	11%	13%	11%	13%	15%	12%	16%	18%	19%	19%	18%
30	CS	4%	11%	11%	12%	10%	9%	5%	7%	6%	6%	6%	6%	6%
35	HC	3%	14%	13%	11%	11%	13%	7%	15%	12%	13%	13%	13%	11%
40	FIN	11%	4%	13%	12%	15%	13%	14%	16%	16%	18%	18%	17%	18%
45	IT	11%	23%	19%	17%	20%	24%	27%	20%	21%	18%	17%	14%	12%
50	TEL	5%	4%	4%	3%	5%	4%	6%	7%	5%	3%	3%	3%	4%
55	UTI	9%	3%	6%	5%	4%	4%	3%	4%	3%	4%	4%	4%	3%
%		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
10	ENE	15%	8%	7%	11%	9%	7%	10%	10%	9%	6%	6%	8%	12%
15	MAT	8%	12%	6%	7%	5%	3%	7%	2%	2%	3%	4%	4%	4%
20	IND	16%	8%	10%	9%	8%	9%	8%	7%	10%	9%	10%	10%	8%
25	CD	22%	8%	9%	11%	10%	12%	16%	12%	15%	16%	19%	18%	18%
30	CS	3%	14%	13%	13%	11%	10%	5%	7%	6%	7%	6%	6%	6%
35	HC	0%	16%	14%	10%	11%	13%	7%	16%	13%	15%	14%	14%	13%
40	FIN	10%	3%	12%	10%	15%	13%	14%	17%	16%	18%	18%	17%	19%
45	IT	8%	20%	17%	18%	20%	23%	24%	15%	20%	19%	17%	14%	10%
50	TEL	5%	5%	5%	4%	5%	5%	6%	9%	6%	4%	3%	4%	6%
55	UTI	13%	5%	8%	7%	6%	5%	4%	4%	3%	3%	4%	4%	3%
%		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:

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

Net $\text{Orderflow}_{j,t}$, Passive Net $\text{Orderflow}_{j,t}$, $\text{Ret}_{j,t}$ represent the actual net orderflow, the passive net orderflow, and the value-weighted return within sector *j* over week/month *t*. $\text{Ret}_{mkt,t}$ 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. White heteroschedastic consistent standard errors are shown in parentheses and *, **, *** denote significance at the 10%, 5%, and 1% level.

Panel A: Weekly

Order Size	α	β	R^2	Obs.
Small	-1.1408	749.906 *	0.0002	6760
	(14.9799)	(480.896)		
Medium	-9.3829	6168.042 ***	0.0011	6760
	(52.5006)	(2033.755)		
Large	-32.2700	21213.430 ***	0.0050	6760
	(84.1257)	(4422.542)		
All Orders	-42.7918	28130.200 ***	0.0033	6760
	(136.5503)	(6156.423)		

Panel B: Monthly

Order Size	α	β	R^2	Obs.
Small	-4.6312	730.6475	0.0001	1550
	(814.952)	(1545.411)		
Medium	-31.5317	4974.594 **	0.0002	1550
	(3862.058)	(2298.435)		
Large	12.5099	-1973.620	0.0001	1550
	(5010.902)	(15356.10)		
All Orders	-23.6266	3727.440	0.0001	1550
	(9552.792)	(16945.52)		

Table 3
Relation between Expansions and past Active Net Orderflow

This table contains the results of the following unconditional regression:

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

where Net $\text{Orderflow}_{j,t}$, Passive Net $\text{Orderflow}_{j,t}$, $\text{Capsector}_{j,t}$ 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 regressor is standardized. White heteroschedastic consistent standard errors are shown in parentheses and *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: One-Month Lead

Sector		Small		Medium		Large		
		β	R^2	β	R^2	β	R^2	Obs.
10	ENE	-0.0197	0.1830	-0.0014	0.1820	0.0012	0.1820	155
15	MAT	0.0042	0.1821	0.0203	0.1831	0.1423 **	0.2317	155
20	IND	-0.0593	0.1911	0.0688	0.1937	0.0385	0.1859	155
25	CD	0.0141	0.1825	-0.0691	0.1938	-0.0971 **	0.2042	155
30	CS	-0.0345	0.1851	0.0503	0.1882	0.0878 *	0.2002	155
35	HC	0.0166	0.1827	0.0800	0.1963	-0.0033	0.1821	155
40	FIN	-0.0277	0.1840	-0.0988 **	0.2060	-0.1599 ***	0.2439	155
45	IT	0.0646	0.1927	-0.0065	0.1821	0.0498	0.1885	155
50	TEL	0.0461	0.1876	-0.1250 **	0.2181	-0.1675 ***	0.2427	155
55	UTI	-0.2032 ***	0.2796	-0.2080 ***	0.2894	-0.0256	0.1837	155

Panel B: Three-Month Lead

Sector		Small		Medium		Large		
		β	R^2	β	R^2	β	R^2	Obs.
10	ENE	-0.0021	0.2511	0.0095	0.2513	-0.0517	0.2581	153
15	MAT	0.0459	0.2558	0.0324	0.2536	0.1741 ***	0.3261	153
20	IND	-0.0908 *	0.2697	0.0811 *	0.2668	0.0670 *	0.2629	153
25	CD	0.0574	0.2587	-0.0181	0.2519	-0.0837 *	0.2675	153
30	CS	-0.0743	0.2635	0.0246	0.2521	0.0909 *	0.2706	153
35	HC	-0.0158	0.2517	0.0552	0.2577	-0.0021	0.2511	153
40	FIN	-0.0281	0.2529	-0.0356	0.2539	-0.1117 ***	0.2811	153
45	IT	0.0664	0.2622	-0.0387	0.2549	0.0236	0.2525	153
50	TEL	0.0663	0.2625	-0.1071 **	0.2778	-0.2112 ***	0.3484	153
55	UTI	-0.1491 ***	0.3028	-0.2057 ***	0.3495	-0.0391	0.2549	153

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 sector active orderflow:

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

where Net $\text{Orderflow}_{j,t}$, Passive Net $\text{Orderflow}_{j,t}$, $\text{Capsector}_{j,t}$ 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. 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.

Panel A: One-Month Lead

Sector		Small	Medium	Large
			Correlations	
10	ENE	-0.0638	0.0215	-0.0059
15	MAT	0.0042	0.0617	0.6146***
20	IND	-0.2385***	0.3101***	0.1786**
25	CD	0.0351	-0.3198***	-0.4624***
30	CS	-0.128	0.2541***	0.4311
35	HC	0.0867	0.3786***	0.0985
40	FIN	-0.1013	-0.4105***	-0.6781***
45	IT	0.2524***	-0.0617	0.2197***
50	TEL	0.1762**	-0.5173***	-0.6997***
55	UTI	-0.8188***	-0.7569***	-0.0275
R^2		0.3354	0.3720	0.3304

Panel B: Three-Month Lead

Sector		Small	Medium	Large
			Correlations	
10	ENE	0.0380	0.0863	-0.1777**
15	MAT	0.2305***	0.1454**	0.6232***
20	IND	-0.4256***	0.2970***	0.2417***
25	CD	0.2807***	-0.1111	-0.3583***
30	CS	-0.3541***	0.1005	0.3833***
35	HC	-0.095	0.2476***	0.1066
40	FIN	-0.0494	-0.1246*	-0.4274***
45	IT	0.2682***	-0.1882**	0.0974
50	TEL	0.3148***	-0.4473***	-0.7255***
55	UTI	-0.6879***	-0.7697***	-0.0584
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:

$$\mathrm{SP500}_t = \alpha + \beta \frac{\left(\text{Net Orderflow}_{j,t-1} - \textit{Passive}\text{ Net Orderflow}_{j,t-1}\right)}{\text{capsector}_{j,t-1}} + \varphi \mathrm{SP500}_{t-1} + \varepsilon_{j,t}$$

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. The regressor is standardized. White heteroschedastic consistent standard errors are shown in parentheses and *, **, *** denote significance at the 10%, 5%, and 1% level.

Panel A: One-Month Lead

Sector		Small		Medium		Large		
		β	R^2	β	R^2	β	R^2	Obs.
10	ENE	-0.0002	0.0005	-0.0010	0.0010	-0.0024	0.0038	155
15	MAT	-0.0035	0.0071	-0.0043	0.0107	0.0016	0.0019	155
20	IND	0.0003	0.0005	0.0048	0.0143	0.0032	0.0063	155
25	CD	-0.0014	0.0017	-0.0037	0.0085	-0.0060 *	0.0210	155
30	CS	0.0015	0.0018	0.0048	0.0137	0.0047	0.0131	155
35	HC	0.0022	0.0033	0.0067 *	0.0266	0.0013	0.0014	155
40	FIN	-0.0012	0.0013	-0.0020	0.0028	-0.0042	0.0109	155
45	IT	0.0040	0.0090	-0.0019	0.0024	0.0037	0.0082	155
50	TEL	-0.0025	0.0042	-0.0075 **	0.0327	-0.0097 ***	0.0547	155
55	UTI	-0.0070 **	0.0274	-0.0039	0.0080	0.0051	0.0156	155

Panel B: Three-Month Lead

Sector		Small		Medium		Large		
		β	R^2	β	R^2	β	R^2	Obs.
10	ENE	0.0020	0.0070	-0.0014	0.0061	-0.0009	0.0055	153
15	MAT	-0.0015	0.0062	-0.0024	0.0081	-0.0010	0.0056	153
20	IND	-0.0001	0.0050	0.0036	0.0123	0.0048	0.0188	153
25	CD	-0.0020	0.0072	-0.0036	0.0123	-0.0063 *	0.0277	153
30	CS	0.0021	0.0071	0.0056 *	0.0228	0.0063 *	0.0282	153
35	HC	0.0004	0.0051	0.0056 *	0.0229	0.0037	0.0128	153
40	FIN	-0.0050	0.0181	-0.0031	0.0100	-0.0038	0.0135	153
45	IT	0.0045 *	0.0159	-0.0033	0.0108	0.0007	0.0053	153
50	TEL	-0.0009	0.0055	-0.0049	0.0190	-0.0061 *	0.0263	153
55	UTI	-0.0054	0.0203	0.0022	0.0072	0.0026	0.0089	153

Table 6
Relation between Bond returns and past Active Net Orderflow

This table contains the results of the following unconditional regression:

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

where Net $\text{Orderflow}_{j,t}$, Passive Net $\text{Orderflow}_{j,t}$, $\text{Capsector}_{j,t}$ 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. The regressor is standardized. White heteroschedastic consistent standard errors are shown in parentheses and *, **, *** denote significance at the 10%, 5%, and 1% level.

Panel A: One-Month Lead

Sector		Small β	Small R^2	Medium β	Medium R^2	Large β	Large R^2	Obs.
10	ENE	-0.0001	0.0834	-0.0002	0.0890	-0.0001	0.0822	155
15	MAT	-0.0003 *	0.0925	-0.0004 **	0.1073	-0.0005 ***	0.1250	155
20	IND	0.0004 **	0.1067	0.0001	0.0822	0.0001	0.0827	155
25	CD	-0.0002	0.0885	-0.0001	0.0825	-0.0001	0.0822	155
30	CS	0.0003 *	0.0970	0.0001	0.0844	0.0001	0.0822	155
35	HC	0.0001	0.0842	0.0001	0.0821	0.0001	0.0835	155
40	FIN	0.0001	0.0823	0.0005 ***	0.1266	0.0005 ***	0.1165	155
45	IT	-0.0001	0.0828	-0.0001	0.0821	-0.0002	0.0866	155
50	TEL	-0.0005 **	0.1189	0.0001	0.0855	0.0003 *	0.0988	155
55	UTI	0.0004 **	0.1042	0.0007 ***	0.1497	0.0003 *	0.0942	155

Panel B: Three-Month Lead

Sector		Small β	Small R^2	Medium β	Medium R^2	Large β	Large R^2	Obs.
10	ENE	-0.0001	0.0344	-0.0001	0.0337	0.0003	0.0482	153
15	MAT	-0.0003 **	0.0490	-0.0004 ***	0.0608	-0.0008 ***	0.1277	153
20	IND	0.0004 **	0.0546	-0.0001	0.0327	-0.0001	0.0342	153
25	CD	-0.0003 **	0.0471	-0.0001	0.0331	0.0001	0.0324	153
30	CS	0.0004 **	0.0544	0.0001	0.0350	0.0001	0.0321	153
35	HC	0.0002	0.0395	-0.0001	0.0328	-0.0001	0.0324	153
40	FIN	-0.0002	0.0402	0.0003	0.0475	0.0006 ***	0.0860	153
45	IT	0.0001	0.0321	0.0001	0.0323	-0.0002	0.0367	153
50	TEL	-0.0004 **	0.0568	0.0001	0.0354	0.0004	0.0542	153
55	UTI	0.0003	0.0433	0.0008 ***	0.1248	0.0002	0.0386	153

Table 7
Restricted regressions

This table 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 flows or excess sector returns, where the loadings are computed as 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		-0.01	0.00
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 economy, financial markets and orderflow with low/high dispersion

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

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

where Y_t is either the CFNAI indicator, stock market returns, or bond market returns. Net $\text{Orderflow}_{j,t}$, Passive Net $\text{Orderflow}_{j,t}$, $\text{Capsector}_{j,t}$ 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.

	Comparison of R^2		
	CFNAI	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 9
Relation between Expansions and past excess sector returns

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

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

where $\text{Ret}_{j,t}$ represent the value-weighted return of sector *j* over month *t*, $\text{Ret}_{mkt,t}$ 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.

Sector		One-month lead			Three-month lead		
		β	R^2	R^2_{ofl}	β	R^2	R^2_{ofl}
10	ENE	-0.0586	0.1910	0.1820	-0.0217	0.2523	0.2581
15	MAT	-0.0468	0.1877	0.2317	-0.0055	0.2512	0.3261
20	IND	-0.0520	0.1891	0.1859	-0.0236	0.2525	0.2629
25	CD	-0.0857**	0.2012	0.2042	-0.0841**	0.2697	0.2675
30	CS	-0.1191***	0.2192	0.2002	-0.1004**	0.2776	0.2706
35	HC	-0.1317***	0.2273	0.1821	-0.0849**	0.2699	0.2511
40	FIN	-0.0822*	0.1997	0.2439	-0.0923**	0.2733	0.2811
45	IT	0.0747	0.1966	0.1885	0.0383	0.2549	0.2525
50	TEL	0.0359	0.1854	0.2427	0.0232	0.2525	0.3484
55	UTI	-0.1618***	0.2507	0.1837	-0.0998**	0.2773	0.2549
Ave			0.2047	0.2045		0.2631	0.2773

Table 10
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:

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

where 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. In Panel A, B, and C, Y_t is the CFNAI index, the S&P500 return, and the 1-year bond return, respectively.

Regressors	Adj-R^2 (1-mo ahead)	Adj-R^2 (3-mo ahead)
Panel A: CFNAI		
Small Active NOF	0.2843	0.3216
Medium Active NOF	0.3237	0.3844
Large Active NOF	0.2789	0.4250
Excess Returns	0.2473	0.2708
Large Active NOF + excess returns	0.3329	0.4396
Panel B: S&P500 return		
Small Active NOF	0.0034	0.0121
Medium Active NOF	0.0023	-0.0058
Large Active NOF	0.0160	-0.0319
Excess Returns	-0.0087	0.0178
Large Active NOF + excess returns	-0.0092	-0.0006
Panel C: 1-year Bond return		
Small Active NOF	0.1294	0.0334
Medium Active NOF	0.1694	0.1178
Large Active NOF	0.1284	0.1433
Excess Returns	0.0962	0.0159
Large Active NOF + excess returns	0.1562	0.1341

Table 11
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.
*, **, *** denote a significant coefficient at the 10%, 5%, and 1% level, with White-heteroschedastic consistent standard errors.

	Weekly		Monthly	
Dependent variable	β	R^2	β	R^2
		Panel A: Flows		
CFNAI	0.0439 **	0.02	0.0453 ***	0.03
SP500	-0.0004	0.00	0.0002	0.00
Bond	-0.0002 ***	0.03	-0.0001 **	0.01
		Panel B: Returns		
CFNAI	-0.0191	0.00	-0.0077	0.00
SP500	-0.0004	0.00	-0.0002	0.00
Bond	0.0001	0.01	0.0001	0.00

Table 12
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

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

where Net $\text{Orderflow}_{j,t}$, and Passive Net $\text{Orderflow}_{j,t}$, 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

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

where Net $\text{Flow}_{j,t}$, and Passive Net $\text{Flow}_{j,t}$, 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.

Sector		Core Corr	S&P Corr	Obs.
10	ENE	0.27**	-0.07	52
15	MAT	0.18	0.04	52
20	IND	0.06	0.10	52
25	CD	0.25*	-0.03	52
30	CS	0.30**	0.19	52
35	HC	0.30**	0.15	52
40	FIN	0.03	0.05	52
45	IT	0.16	0.24 *	52
50	TEL	0.04	-0.19	52
55	UTI	0.14	-0.36 **	52
	Average	0.17	0.01	
	Median	0.17	0.04	