What Can Equity 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. This empirical foot-print of sector rotation has strong predictive power for the evolution of the economy, future stock returns, and future bond returns, even after controlling for relative sector returns. Contrary to many theories of price formation, trading activity therefore contains information that is not entirely captured by resulting relative price changes. Moreover, we find that a portfolio that mimics the observed aggregate rebalancing across equity sectors dominates the market portfolio, particularly during economic downturns.

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Introduction

Asset prices reflect investors' views about economic fundamentals, and it is well understood that orderflow is the mechanism by which these views are aggregated. Empirical studies documenting the role of orderflow in price formation include Glosten and Milgrom (1985) and Hasbrouck (1991) for equities, Evans and Lyons (2002) for foreign exchange, and Brandt and Kavajecz (2004) for fixed income. There is a rich literature documenting that asset prices help forecast economic fundamentals (see Stock and Watson (2003) for a survey of this literature in a macroeconomic context), but the predictive role of orderflow by itself and in conjunction with asset prices has not been explored in such depth. One possibility is that, since orderflow is only one component of the price formation process (public information resulting in instantaneous price adjustments being another), prices contain the same or potentially more information. Alternatively, however, investors' trading behavior may contain information that is not fully spanned by asset prices. The aim of our paper is to empirically shed some light on this issue.

We focus on investors' views about macroeconomic fundamentals (i.e., the stage of the business cycle), rather than firm-level views. There are many ways in which investors may rebalance their portfolios as their views about fundamentals are updated – 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 allocation to equities in different sectors of the economy. We consider 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. We choose this case not because it is obviously the most informative about investors' views about economic fundamentals but because it allows us to study orderflow within a single dataset (TAQ) as opposed to multiple data sets covering different trading platforms.

We analyze the dynamics of orderflow across ten U.S. equity sectors to investigate whether systematic portfolio rebalancing is related to the current and future state of the macro economy. If orderflow reveals information about the economy, which we find it does, it may contain information about both future aggregate expected cash flows and future discount rates, which in turn should also be important for predicting the stock and bond markets. Thus, we also investigate whether the level and nature of the information within sector orderflow is able to predict stock and bond market returns.

Our results show that sector orderflow movements are inconsistent with naive portfolio rebalancing techniques, such as buy-and-hold (no rebalancing) or a constant-mix strategy. Instead, it appears that market participants shift funds between equity sectors according to their collective information about the macro economy. Specifically, we demonstrate that equity sector orderflow predicts the state of the macro economy up to three months ahead. Consistent with intuition, large-sized unexpected orderflow in the material sector forecasts an expanding economy, while large unexpected orderflow in consumer discretionary, financials, and telecommunications forecasts a contracting economy. Small-sized unexpected orderflow into information technology and telecommunications predicts expansions, while unexpected orderflow into utilities predicts a contraction.

We also find that the cross-section of orderflow across sectors contains relevant information to predict the evolution of the stock and bond markets, even after controlling for returns. While it is interesting that the orderflow predicts the macro economy, stock market and bond market, what is most intriguing is that the linear combination of sector flows which predicts the macro economy is the same factor that contains the bulk of explanatory power for predicting the stock and bond markets. In addition, we confirm that the sector orderflow factor is directly related to the release of the Non-farm Payroll figures. Finally, we show that our results become much stronger when we condition on low dispersion of flows within sectors, which is a typical feature of sector rotation as opposed to stock picking.

As a capstone to our analysis, we investigate the information contained in the movement of orderflow across sectors in a portfolio context. Specifically, we translate sector orderflow movements into "tilts" to the market portfolio thereby producing what we call an orderflow mimicking portfolio. This orderflow mimicking portfolio enjoys superior risk and return properties relative to the traditional market portfolio. Furthermore, the orderflow mimicking portfolio tends to be defensive in that it dominates the market portfolio during times of economic contractions.

Section 2 discusses the related literature. Section 3 describes our data and methodology. Section 4 reports our empirical results. Section 5 introduces our notion of an orderflow mimicking portfolio and Section 6 concludes.

2. Related literature

The role of orderflow within 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. Specifically, there is a series of papers, Chordia, Roll and Subraymanyam (2000, 2001, and 2002) which investigate the connection between orderflow movements into and out of the equity market and market-wide liquidity measures. 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 and Yaron (2005) demonstrate that there appears to be no relation between macro-economic 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 orderflow can be used to forecast subsequent asset returns. In particular, Froot and Teo (2004) analyze institutional orderflow from State Street Global Advisors to investigate how orderflow movements are related to mutual fund style returns. They find that flows appear to be related to styles and they identify sector rotation as one of those investment styles. Campbell, Ramadorai and Vuolteenaho (2005) also investigate institutional orderflow; however their data source is a match of the TAQ database with the 13-F institutional ownership filings. Both 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 among sectors is able to explain the larger macro economy as well as large markets rather than less aggregate series related to liquidity, volatility or specific mutual fund returns. Understanding how orderflow movements respond to the trading environment has the potential to reveal much about the asset characteristics that are valued implicitly by market participants. Thus, our contribution to the literature rests importantly in the paper's focus being about the connection between market participants' decisions about sector orderflow and the larger macro economy.

3. Data and variable construction

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

The construction of our orderflow data is accomplished through a number of steps. Specifically, for each stock, and each day within 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. 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. Lastly, each trade is assigned to a size category (small, medium or large) for orderflow specified in shares or in dollars. The shares cutoffs are small (<1,000 shares), medium (1,000 to 10,000 shares) and large (>10,000 shares), whereas the cutoffs for dollar orderflow are small (< $25,000), medium ($25,000 to $250,000) and large (>$250,000) The result is a set of daily orderflow series for each security, small, medium and large buys and small, medium and large sells.

Each stock is then assigned to one of the ten sectors defined by the Global Industry Classification Standard (GICS) that was developed by Morgan Stanley Capital International and Standard & Poor's, see the appendix for specific sector descriptions and corresponding numbers. Once stocks are assigned to a sector, sector net orderflow is simply the sum of all orderflow for the individual stocks included in that sector. Sector capitalization is defined by the sum of the capitalizations (shares outstanding multiplied by end of month price) of the individual stocks within the sector. Lastly, expected net orderflow for a given sector is defined as the total net orderflow to the stock market as a whole multiplied by the weight of that sector in the market portfolio. Effectively, the definition of expected net orderflow amounts to the null hypothesis that orderflow to the stock market is distributed across sectors by their weight in the market portfolio. Table 1 displays our total aggregate orderflow by sector and year expressed as a percentage of the total net orderflow for the year. Note that while the percentage of orderflow across years remains fairly stable, there are some extreme percentages during the economic downturn in 1999 and 2000. Materials [15] and consumer staples [30] have low fractions of orderflow while health care [35], information technology [45] and telecommunications [50] have high fractions of overall orderflow. In addition, these shifts in the shares of orderflow across sectors appear more pronounced for large orders relative to all orders, suggesting that market participants placing large orders may be more active 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. We measure the state of the economy using the Chicago Fed National Activity Index (CFNAI). The CFNAI index is a weighted average of a number of monthly indicators of economic activity which was first developed by Stock and Watson (1999).[1] Unlike the NBER expansion and recession periods, the CFNAI index has the advantage of being

[1] 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

a coincident indicator, a measure of economic conditions available in real time. Figure 1 displays the 3-month moving average of the CFNAI index over our sample period. Note that an index value above (below) zero indicates economic growth above (below) the trend. Our sample covers a relatively balanced period of economic growth and decline, with the former occurring in 58% of the months in our analysis. The performance 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 as in Cochrane and Piazzesi (2005), respectively. Finally, for the Non-Farm Payroll announcement we have the release dates, actual reported (announced) values and median forecasts from Money Market Services.

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

Portfolio rebalancing of sector positions is another common motive for trade. If market participants engage in a buy-and-hold strategy (effectively do not rebalance their portfolios), we would expect to see no relation between aggregate sector orderflow and the previous performance of the sector, while a constant mix strategy would suggest that sector orderflow has a negative relation with previous relative performance of the sector. To investigate these possibilities, we analyze the temporal relation between sector orderflow and 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 and yet retain the components of orderflow that are related to long-lived information.

Our results for the weekly horizon (shown in Table 2, panel A) reject both the buy-and-hold and defensive rebalancing strategy (constant mix) 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 seem to be a pervasive determinant of orderflow patterns over a full month.

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 that there are many factors driving orderflow dynamics, 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 stream of news it impacts their preferences, expectations and risk tolerances, which in turn induce market participants 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 construct a measure of unexpected orderflow, which we standardize by the market capitalization of each sector. This empirical specification has a number of advantages. First, this measure reflects the orderflow that is entering a sector in 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. We control for the current level of the expansion indicator to make sure that loadings on the flows do not pick up the contemporaneous relation with the economy.

At the outset, we investigate whether unexpected 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.

Our results in Table 3 show that flows into a number of the sectors forecast expansion/contractions in the macro economy, particularly for large orders. Specifically, we find that unexpected flows of large orders into the material sector [15] predict higher levels of the expansion index both one and three months ahead while unexpected flows of large orders into financials [40], telecommunications [50] and consumer discretionary [25] predict lower levels of the expansion index at the one and three month horizons. Moreover, the coefficients are also economically significant; as an example, a one-standard deviation shock to large flows in the materials sector implies a 0.1423 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 are quite compelling for the large orders, the forecasting power of the medium and small-sized orderflow is dramatically lower with only unexpected flows into utilities [55] being consistently (negatively) associated with the expansion index.

The contrast between the large and small/medium orderflow results is interesting because it suggests that 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.

After investigating the relation between the expansion index and orderflow sector by individual sector, we turn to an analysis of the cross-section of flows. Specifically, we are interested in determining the orderflow factor with the highest correlation to the state of the macro economy. Table 4 presents the correlation of each sector unexpected orderflow with the linear combination of factor loadings on the ten sectors that best predict the macro economy. 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 [15], industrials [20], and consumer staples [30] are aggressive economic sectors, while energy [10], consumer discretionary [25], financials [40], and telecommunications [50] 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 [15] and industrial [20] sectors for the medium flows are aggressive (positive coefficients) as are the materials [15], consumer discretionary [25], information technology [45] and telecommunication [50] sectors for the small sized flows. Utilities [55] 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) only fewer sectors (one-month results). At the one-month horizon, materials [15] is the most aggressive sector for large flows, while health care [35] and information technology [45] are the most aggressive for medium and small flows, respectively. Consumer discretionary [25], financials [40], and telecommunications [50] are the defensive sectors for large sized flows while utilities [55] remains 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 unexpected orderflow in particular sectors able to forecast expansions/contractions up to one quarter ahead. In addition, large 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

We have demonstrated that sector orderflow aggregates the preferences, expectations and information of market participants such that their trades forecast the state of the macro economy. To the extent that markets within the economy feed into 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 with the equity market is much weaker than results on the macro economy. For example, at the 1-month horizon, small sized flow into utilities [55] as well as medium and large flows into the telecommunication sector [50] seems to predict lower future stock market returns. Moreover, the economic significance is striking in that a one-standard deviation shock to the telecom sector predicts a 1% monthly return. However interestingly, these results are not sustained at the 3-month horizon with only a few sectors displaying weak and sporadic significance. We also compute the correlations between each sector unexpected orderflow and the linear combination of factor loadings on the ten sectors that best predict the stock market, similarly to the analysis presented in Table 4 for the macroeconomy. We find that the most aggressive sector for large 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) as well, see Table 6. Not surprisingly, the results are stronger than the corresponding results for the equity market, which is consistent with the common wisdom that the macro economy and the fixed income market may have more in common with each other than does the equity market. For the medium and large sized flows, the materials sector [15] has a negative sign and the financials [40] and utilities [55] sectors have a positive sign, which is exactly the opposite result found for the expansion indicator.[2] 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, which corresponds to a 0.6% annually, which is about ten times the average one-year bond return in our sample. Moreover, the analysis of the correlations between each sector unexpected orderflow and the linear combination of factor loadings on the ten sectors that best predict the bond market, confirms that the most aggressive sector for large flows is materials and the most defensive is the financial sector (results not reported).

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

Now that we have established that sector orderflow has predictive power to forecast the macro economy as well as returns in the equity and bond markets. The next obvious question is what is the relationship if any between the information in orderflow that predicts the macro economy, the equity market and the bond market? Is the information the same or different, if it is the same what is the nature of this information?

4.4 Orderflow versus Returns

Our empirical analysis shows that the cross-section of orderflow across sectors contains important information about the economy, the bond market and to a lesser extent the stock market. In this sense, 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. Within this context, a natural question is 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 7 displays our results for the large sized orderflow, for comparison purposes we include the R^2 from orderflow results within Table 3. The R^2 comparison shows very little difference on average between the explanatory power of flows and the explanatory power of returns. Further inspection shows that the sector returns with predictive power are different than the 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 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. We conjecture that the difference in the results between the orderflow and return series may be due to the frictions within the trading process (such as stale orders on the limit order book) that necessarily keep returns from being as extreme as they otherwise would be.

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 8 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 flows; specifically, adding flows to the current level of the index generates a twofold increase in the explanatory power, while returns alone only increase the R^2 by about 2%. For the stock market return, not only is there less predictability, but it is not clear whether flows dominate returns. At the one month horizon, flows of large orders dominate while at the three month horizon excess sector returns offer better predictability. Finally, like the results for the economic expansion, the large flows dominate returns in predicting the one-year maturity bond returns, strikingly so at the three-month horizon. These results clearly demonstrate that orderflow encompasses more information than is contained in returns.

4.5 The Nature of Orderflow Information

While our results clearly show that sector orderflow predicts changes in the macro economy as well as the stock and bond markets better than returns, a potential concern is that our results could be driven by something other than our earlier conjecture that economic news alters market participants' fundamentals, 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. Our hypothesis is that investors receive information about the economy by observing, among other things, the release of some macro-economic announcements, after which they process this information and trade. Thus, the linear combination of sector orderflows that best predicts the economy should be related with the new information released on the announcement day. A significant relation between aggregate sector orderflow and macroeconomic announcements that are known to be associated with the economy would be consistent with our hypothesis and alleviate concerns that our results are driven by other latent factors.

For this test, 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 announcement surprise, which is commonly known to be the first, and most influential, macro announcement within a given month. Standardization of the announcement involves measuring the announced figure against the median expectation and dividing by the standard deviation of the market participant estimates. Orderflow is measured over the week and the month following the Non-farm payroll release. Panel A of Table 9 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 indicative of new jobs being associated with flows into the equity market which in turn put 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 different.

As another robustness check and further investigation into the exact nature of the information contained in orderflow, we consider whether the orderflow factors which have the maximal correlation with economic expansions, the stock market and the bond market has predictive power over the other dependent variables. For example, does the maximal linear combination of sector flows which predicts economic expansions have any ability to predict the stock and bond market returns and vice versa? Specifically, Table 10 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 unexpected 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 10 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 10 highlights three observations about the interaction among the three independent variables that reveals much about the nature of the information contained in 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). Notice at the one-month horizon, the best linear combination of the cross-section of sector orderflows 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. Second, the orderflow factors which have the highest correlation with the stock and bond markets have predictive power for the expansion index. For example, the combination of sector flows best predicting the stock market (bond market) also has predictive power over the CFNAI index, with a statistically significant R^2 of 22% (26%). Third, returns appear to have little explanatory power beyond their own market. Taken together these results suggest that orderflow contains more cross market information than returns. In addition, the nature of the orderflow information is such that it is (1) strongly related to the macro economy and (2) that information has the ability to predict the future performance in the economy as well as the stock and bond markets. These observations are consistent with the existence of a single orderflow factor which contains macroeconomic information and has the ability to forecast performance within the capital markets. Figure 1 summarizes these results by displaying the orderflow coefficients across select sectors. The stability of the coefficients across sectors provides a graphical representation for the intuition behind the existence of a single orderflow forecasting factor.

Thus, the results are consistent with (1) our conjecture that both the macroeconomic and bond market orderflow factors are related to one of the most influential macro announcements, and (2) the same macroeconomic information is likely to be contained in both of these orderflow factors.

4.6 Conditioning on Orderflow Dispersion Within Sectors

We find that sector orderflow predicts changes in the macro economy as well as the stock and bond markets. Our results hinge on the conjecture that the expected economic conditions, returns, and risk, induce trade in more or less cyclical sectors. We show in Section 3 that sector net orderflow is the sum of all orderflow for the individual stocks included in that sector. A large net ordeflow in one sector could thus be the result of investors increasing the weight of that sector in their portfolios, but 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 conjecture is correct, our results should be stronger whenever orderflow within one sector is more homogeneous across stocks.

We thus compute a measure of dispersion of orderflow within each sector as an indication of investors trading the whole sector or just selected stocks. The orderflow sector dispersion at the monthly frequency is the standard deviation of unexpected flows for each stock, where unexpected flows are equal to the difference between total flows and expected flows (total sector flows multiplied by the relative market capitalization of the stock within the sector) for each stock.[3]

We then aggregate sector orderflow dispersion at the market level using a weighted average with two methods. First, we use weights corresponding to the monthly market capitalization of each sector. This method gives more importance to the dispersion of orderflow

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

within large sectors. We label this dispersion measure σ_1. Second, we give more importance to the dispersion of orderflow within the sectors that matter more for predicting the economy and we label this measure σ_2. Specifically, we weight orderflow dispersion by the absolute value of the correlations reported in Table 4, normalized to sum up to one.

In Table 11, we present the results of forecasting the expansion indicator, the stock market and the bond market with the cross-section of 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.[4] Our conjecture is clearly confirmed. When orderflow has low dispersion 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, the results are even more striking: in months with low dispersion σ_2 the average explanatory power of flows doubles.

In summary, we find much stronger empirical results when we condition on low dispersion of orderflow within sectors. This is true using different methodologies and predicting three different underlyings, demonstrating that our sector measures of flows reflect indeed the empirical foot-prints of sector rotation. Other potential explanations (e.g., liquidity trading, stock picking) would be more consistent with stronger results when flows have high dispersion.

5. The Orderflow Mimicking Portfolio

Thus far, our results have demonstrated that the cross-section of sector orderflow has strong predictive power for the evolution of the economy, the stock market, and the bond market even after conditioning on returns. Moreover, the nature of the information contained therein is

[4] 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).

strongly related to the state of the macro economy. 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. Following this line of reasoning within an asset pricing context, if consistent with our findings, market-wide sector orderflow reflects the aggregate preferences and expectations within the market and aggregate trading does not simply reflect portfolio rebalancing, then market participants must necessarily hold portfolios that are different than the market portfolio. Therefore, as a capstone to our analysis we investigate the information contained in the movement of orderflow across sectors in the context of the Capital Asset Pricing Model (CAPM).

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 orders. The general intuition behind this exercise is that movements of orderflow across the various sectors represent "tilts" to the market portfolio which define an orderflow portfolio, i.e. a market-wide portfolio that is potentially different from the traditional CAPM market portfolio.

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. For each week, we compute the net *excess* orderflow of large orders in different sectors as the difference between total orderflow for each sector and the *expected* orderflow, that is, orderflow expected given the market capitalization weight of each sector in the orderflow portfolio the previous week. The *excess* 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.[5] Like most other asset allocation techniques, our procedure has the potential to generate extreme and unrealistic weights. For example, an extremely positive (negative) unexpected 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 or implementation constraint or even a risk management technique.

The orderflow 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 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 doesn't suffer the 1999-2000 down-turn in the market portfolio which is consistent with the orderflow portfolio being largely a defensive allocation vehicle. Panel B of Figure 3 confirms this intuition as the ordeflow portfolio loads heavily on low beta stocks over the course of the 1999-2000 recession period. 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.[6] Lastly, Panel C in Figure 3 shows

[5] We have also relaxed this transformation of the data and the results are quantitatively and qualitatively similar.
[6] 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

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 portfolio.

We acknowledge that a number of assumptions were made to generate the orderflow portfolio 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 should be surprising is that following the movement of publically available orderflow across sectors defines an objective orderflow portfolio that dominates the market portfolio. Moreover, the information contained in the orderflow portfolio is directly related to the macro economy and tends to be defensive in nature.[7]

6. Conclusion

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

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with previous results, the Sharpe ratio of the low dispersion strategy is higher than in the case of the high dispersion strategy.

[7] 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. However, our results show that the orderflow portfolio is different from the momentum portfolio which has an annual return, standard deviation and Sharpe ratio of 22.4%, 25.1% and 0.89 respectively. Therefore, even though the momentum factor has superior returns, on a risk adjusted basis the orderflow portfolio produces superior performance and must therefore contain different information than merely momentum.

We find that sector orderflow movements predict changes in the expansion/contraction index, the future performance of the bond markets and to a less extent the equity markets. In comparing the various orderflow factors which predict the economic expansion, stock and bond markets, we find that not only does orderflow contain more and different information compared to returns, but the nature of the information is common across the three 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 reflect indeed the empirical foot-prints of sector rotation. Finally, we investigate the macroeconomic information contained in sector orderflow movements in the context of the CAPM market portfolio. We translate sector orderflow movements into “tilts” to the market portfolio produce an orderflow portfolio. This orderflow portfolio enjoys superior risk and return properties relative to the traditional market portfolio. Furthermore, like the previous sector results, the orderflow portfolio tends to be defensive in that it dominates the market portfolio during times of economic contractions.

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.

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Appendix

Sector definitions

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

[10] 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] 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] 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] 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] 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] 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] 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] 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] 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] 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

3-Month Moving Average of the Chicago Fed National Activity Index (CFNAI)

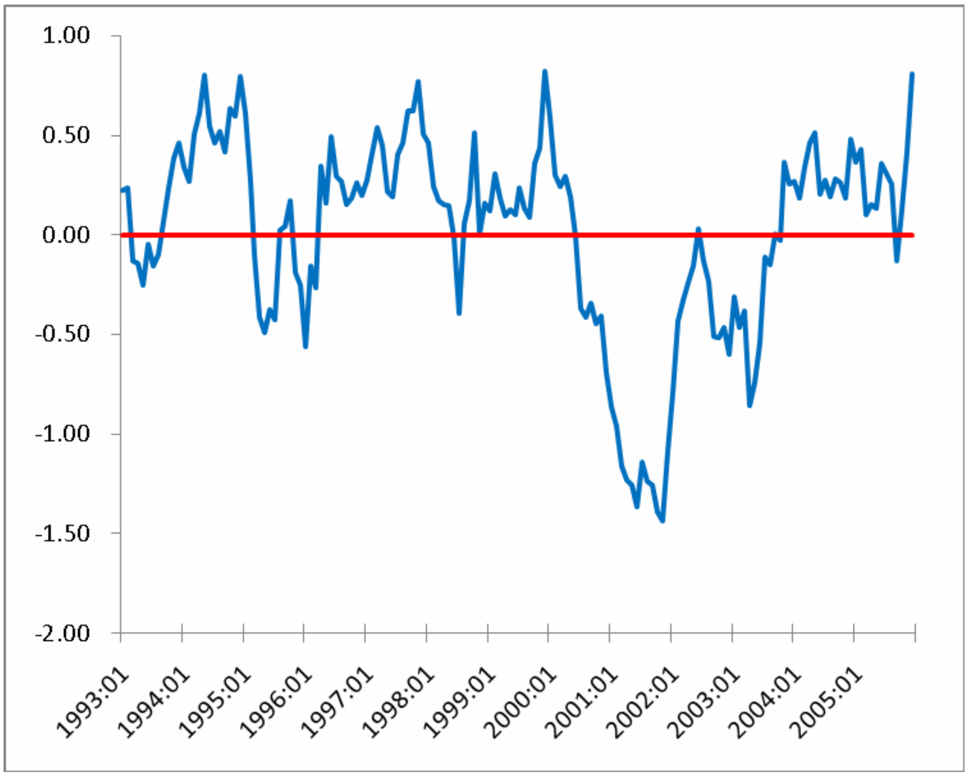
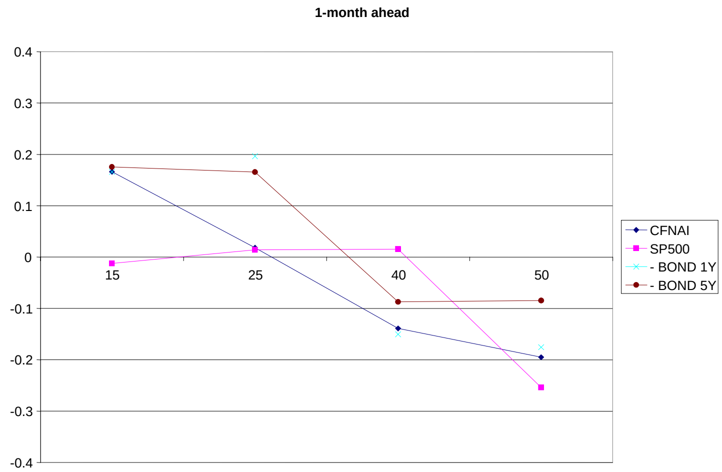


Figure 2

Sector Coefficients from the Restricted Regressions

This figure shows the coefficients on the orderflow of the four most significant sectors, materials (gics15), consumer discretionary (gics25), financials (gics40), telecom (gics50), predicting the expansion indicator (CFNAI), the stock market, and bond returns at 1-year and 5-year multiplied by -1, for the one and three month horizons.



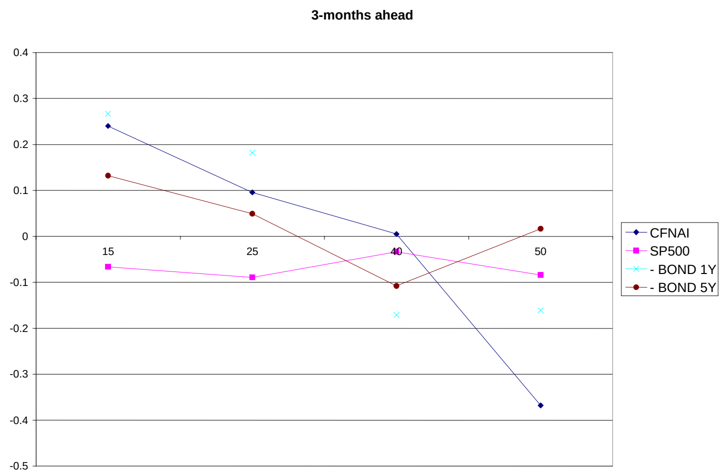
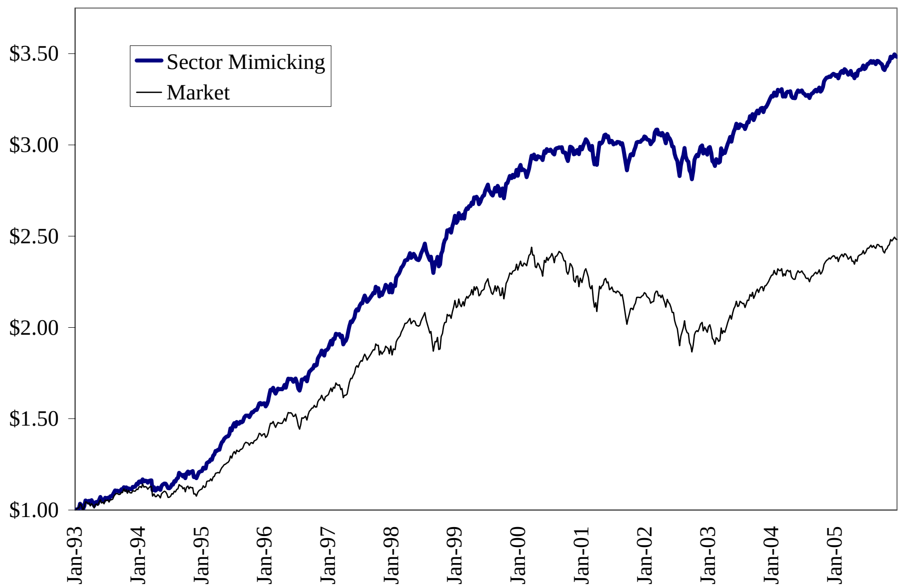


Figure 3

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

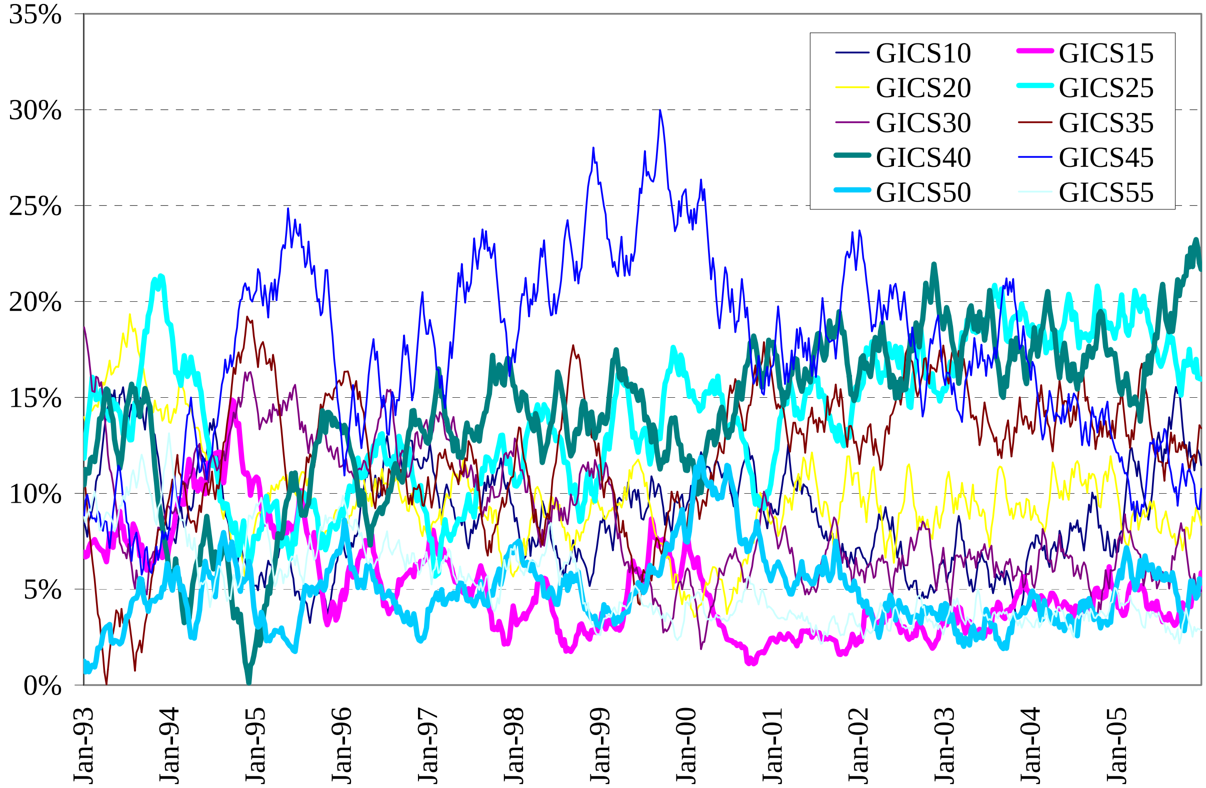


Table 1
Aggregate Orderflow Summary Statistics

The following table provides aggregate net orderflow figures by sector and year expressed as a percentage of the total dollar net orderflow.

Panel A: All Orders

Sector	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
10	12%	7%	6%	10%	9%	7%	9%	10%	9%	7%	7%	9%	14%
15	9%	12%	6%	7%	5%	4%	6%	3%	3%	4%	5%	6%	6%
20	15%	9%	11%	10%	9%	9%	8%	7%	10%	9%	9%	10%	9%
25	20%	11%	11%	13%	11%	13%	15%	12%	16%	18%	19%	19%	18%
30	4%	11%	11%	12%	10%	9%	5%	7%	6%	6%	6%	6%	6%
35	3%	14%	13%	11%	11%	13%	7%	15%	12%	13%	13%	13%	11%
40	11%	4%	13%	12%	15%	13%	14%	16%	16%	18%	18%	17%	18%
45	11%	23%	19%	17%	20%	24%	27%	20%	21%	18%	17%	14%	12%
50	5%	4%	4%	3%	5%	4%	6%	7%	5%	3%	3%	3%	4%
55	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	15%	8%	7%	11%	9%	7%	10%	10%	9%	6%	6%	8%	12%
15	8%	12%	6%	7%	5%	3%	7%	2%	2%	3%	4%	4%	4%
20	16%	8%	10%	9%	8%	9%	8%	7%	10%	9%	10%	10%	8%
25	22%	8%	9%	11%	10%	12%	16%	12%	15%	16%	19%	18%	18%
30	3%	14%	13%	13%	11%	10%	5%	7%	6%	7%	6%	6%	6%
35	0%	16%	14%	10%	11%	13%	7%	16%	13%	15%	14%	14%	13%
40	10%	3%	12%	10%	15%	13%	14%	17%	16%	18%	18%	17%	19%
45	8%	20%	17%	18%	20%	23%	24%	15%	20%	19%	17%	14%	10%
50	5%	5%	5%	4%	5%	5%	6%	9%	6%	4%	3%	4%	6%
55	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 Unexpected Net Order Flow and Lagged Excess Returns

This table contains the results of the following unconditional regression:

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

Net $\text{Orderflow}_{j,t}$, Expected Net $\text{Orderflow}_{j,t}$, $\text{Ret}_{j,t}$ represent the actual net orderflow, the expected 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 expected 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	21213.43***	0.0050	6760
	(84.1257)	(4422.542)		
All Orders	-42.7918	28130.20***	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	-1973.62	0.0001	1550
	(5010.902)	(15356.10)		
All Orders	-23.6266	3727.44	0.0001	1550
	(9552.792)	(16945.52)		

Table 3

Relation between Expansions and past Unexpected Net Orderflow

This table contains the results of the following unconditional regression:

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

where Net $\text{Orderflow}_{j,t}$, Expected Net $\text{Orderflow}_{j,t}$, $\text{Capsector}_{j,t}$ represent the actual net orderflow, the expected net orderflow, the capitalization of sector *j* over month *t*. We compute the expected 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

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

Panel B: Three-Month Lead

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

Table 4

Relation between Expansions and past Unexpected Net Orderflow

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

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

where Net $\text{Orderflow}_{j,t}$, Expected Net $\text{Orderflow}_{j,t}$, $\text{Capsector}_{j,t}$ represent the actual net orderflow, the expected net orderflow, the capitalization of sector *j* over month *t*. We compute the expected 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 unexpected orderflow in all ten sectors that we use to obtain the best linear combination.

Panel A: One-Month Lead

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

Panel B: Three-Month Lead

	Small	Medium	Large
Sector			Correlation
10	0.0380	0.0863	-0.1777**
15	0.2305***	0.1454**	0.6232***
20	-0.4256***	0.2970***	0.2417***
25	0.2807***	-0.1111	-0.3583***
30	-0.3541***	0.1005	0.3833***
35	-0.095	0.2476***	0.1066
40	-0.0494	-0.1246*	-0.4274***
45	0.2682***	-0.1882**	0.0974
50	0.3148***	-0.4473***	-0.7255***
55	-0.6879***	-0.7697***	-0.0584
R^2	0.3707	0.4289	0.4666

Table 5

Relation between Stock Market and past Unexpected Net Orderflow

This table contains the results of the following unconditional regression:

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

where Net $\text{Orderflow}_{j,t}$, Expected Net $\text{Orderflow}_{j,t}$, $\text{Capsector}_{j,t}$ represent the actual net orderflow, the expected net orderflow, the capitalization of sector *j* over month *t*. We compute the expected 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

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

Panel B: Three-Month Lead

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

Table 6
Relation between Bond returns and past Unexpected Net Orderflow

This table contains the results of the following unconditional regression:

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

where Net $\text{Orderflow}_{j,t}$, Expected Net $\text{Orderflow}_{j,t}$, $\text{Capsector}_{j,t}$ represent the actual net orderflow, the expected net orderflow, the capitalization of sector *j* over month *t*. We compute the expected 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

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

Panel B: Three-Month Lead

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

Table 7
Relation between Expansions and past excess sector returns

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

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

where $\mathrm{Ret}_{j,t}$ represent the value-weighted return of sector *j* over month *t*, $\mathrm{Ret}_{mkt,t}$ represents the value-weighted return on the stock market index, and CFNAI is the expansion indicator.
We report the R^2 of the regressions together with R^2ofl, which is the R^2 of the large orderflow regressions reported in Table 3. The excess return regressor is standardized.
*, **, *** denote significance at the 10%, 5%, and 1% level with White heteroschedastic consistent standard errors.

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

Table 8
Relation between Business Cycle, Stock Market Returns, Bond Market Returns and past Unexpected Net Orderflow and returns

This table contains the results of the following unconditional regression:

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

where Net $\text{Orderflow}_{j,t}$, Expected Net $\text{Orderflow}_{j,t}$, $\text{Capsector}_{j,t}$, $\text{Ret}_{j,t}$ represent the actual net orderflow, the expected net orderflow, the capitalization, the value-weighted return, of sector *j* over month *t*. $\text{Ret}_{mkt,t}$ represents the value-weighted return on the stock market index. We compute the expected 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 Unexpected NOF	0.2843	0.3216
Medium Unexpected NOF	0.3237	0.3844
Large Unexpected NOF	0.2789	0.4250
Excess Returns	0.2473	0.2708
Large Unexpected NOF + excess returns	0.3329	0.4396
Panel B: S&P500 return		
Small Unexpected NOF	0.0034	0.0121
Medium Unexpected NOF	0.0023	-0.0058
Large Unexpected NOF	0.0160	-0.0319
Excess Returns	-0.0087	0.0178
Large Unexpected NOF + excess returns	-0.0092	-0.0006
Panel C: 1-year Bond return		
Small Unexpected NOF	0.1294	0.0334
Medium Unexpected NOF	0.1694	0.1178
Large Unexpected NOF	0.1284	0.1433
Excess Returns	0.0962	0.0159
Large Unexpected NOF + excess returns	0.1562	0.1341

Table 9

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 10
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 unexpected 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***
Unexpected 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 S&P500		-0.01	0.00
Unexpected 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 1-y Bond		0.08***	0.03***
Unexpected 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 11

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

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

$$\mathrm{Y}_t = \alpha + \sum_{j=1}^{10} \beta_j \frac{\left(\text{Net Orderflow}_{j,t-1} - \text{Expected Net Orderflow}_{j,t-1}\right)}{\text{Capsector}_{j,t}} + \phi Y_{t-1} + \varepsilon_{j,t}$$

where Y_t is either the CFNAI indicator, stock market returns, or bond market returns. Net $\text{Orderflow}_{j,t}$, Expected Net $\text{Orderflow}_{j,t}$, $\text{Capsector}_{j,t}$ represent the actual net orderflow, the expected net orderflow, the capitalization of sector *j* over month *t*. We compute the expected 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 unexpected flows within each sector. We aggregate dispersion at the market level using either the market capitalization of each sector (σ_1) or the absolute value of the correlations reported in Table 4 and normalized to sum up to one (σ_2). In a given month, dispersion is high (low) when the standard deviation is above (below) its median in the last 12 months.

		CFNAI	Stock Market	Bond Market 1y
Low dispersion σ_1	R^2	0.54	0.22	0.28
High dispersion σ_1	R^2	0.34	0.12	0.19
Ratio		1.59	1.83	1.47
Low dispersion σ_2	R^2	0.47	0.20	0.31
High dispersion σ_2	R^2	0.28	0.08	0.16
Ratio		1.68	2.50	1.94