What Does Equity Sector Orderflow Tell Us About the Economy?

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Investors rebalance their portfolios as their views about expected returns and risk change. We use empirical measures of portfolio rebalancing to back out investors' views, specifically, their views about the state of the economy. We show that aggregate portfolio rebalancing across equity sectors is consistent with sector rotation, an investment strategy that exploits perceived differences in the relative performance of sectors at different stages of the business cycle. The empirical footprint of sector rotation has predictive power for the evolution of the economy and future bond market returns, even after controlling for relative sector returns. Contrary to many theories of price formation, trading activity, therefore, contains information that is not entirely revealed by resulting relative price changes. (*JEL* E17, G11, G12)

1. Introduction

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

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

Combining these two observations—1) that asset prices help forecast business cycles; and 2) that orderflow is the mechanism by which asset prices change—raises the question of how orderflow itself is related to current and future economic conditions.

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

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

There are many different settings that could be used to investigate these questions, as there are numerous ways in which investors adjust their portfolios in response to changes in their views about economic fundamentals, e.g., investors change their stock/bond/cash allocation, their positions in real assets, such as gold or inflation-indexed Treasury securities, or their relative equity allocation within different sectors of the economy. We focus our analysis on the last case of sector rotation, which is a highly publicized investment strategy that exploits perceived differences in the relative performance of sectors at different stages of the business cycle. This setting allows us to utilize data within a single dataset and study a very common strategy that is implemented by institutional and retail traders alike. Specifically, we analyze the dynamics of orderflow across ten U.S. equity sectors in order to investigate whether sector adjustments to investor portfolios are related to the current and future state of the macroeconomy as well as to 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, as much as three months ahead, between equity sectors, according to the collective information they receive about changes in the macroeconomy. Our results show that large-sized active orderflow into the material sector forecasts an expanding economy, while large-sized active orderflow into consumer discretionary, financials, and telecommunications forecasts a contracting economy.[1] We also find that the cross-section of sector orderflow contains information that predicts the evolution of bond markets, even after controlling for relative sector returns and traditional low-frequency forecasting variables. While it is interesting that orderflow predicts the macroeconomy and bond market, what is most intriguing is that the linear combination of sector orderflow that *best* predicts the evolution of the macroeconomy also contains the bulk of the explanatory power for predicting the bond markets. Moreover, we demonstrate that our predictability results become significantly stronger after conditioning on low dispersion of orderflow *within* sectors, which indicates a true sector view, as opposed to a view on a few stocks within the sector. Together, these results suggest that the information contained in sector orderflow is different than the information contained in returns; moreover, the information contained therein has more to do with sector allocation than with stock picking.

Our results also reveal three characteristics regarding the nature of information contained in sector orderflow. First, we show that the information in sector orderflow is directly related to the release of macroeconomic fundamentals, specifically the release of the prominent nonfarm payroll figures. Second, our results show that sector orderflow movements are related to independent mutual fund flows, which suggests that market participants are making *active decisions* regarding their equity market allocations. This finding, together with

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

stronger results obtained when orderflow is constructed with large orders, indicates that the sector rotation we identify is likely to be institutional. In this sense, our article complements literature that characterizes the trading behavior of institutions (e.g., Grinblatt and Keloharju 2000; Griffin et al. 2003). Finally, sector orderflow movements are inherently defensive in nature. In 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 primarily focused on wealth preservation by investing in low-risk stocks during difficult economic times, albeit it enjoys superior risk and return properties relative to the traditional market portfolio. Thus, taken together, our results reveal that the information in aggregate sector orderflow is directly related to macroeconomic fundamentals, is consistent with deliberate reallocation strategies by market participants, and is defensive in nature.

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

2. Related Literature

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

The other strand of the orderflow literature takes a micro view by investigating whether disaggregated (by individual security or mutual fund) orderflow can be used to forecast subsequent asset returns. In particular, Albuquerque, Francisco, and Marques (2008) estimate the Easley et al. (1996) structural model on a set of stocks with international exposure in order to investigate the relation between orderflow and exchange rates. Froot and Teo (2008) analyze institutional orderflow from State Street Global Advisors in order to investigate whether orderflow movements are related to mutual-fund-style returns. They find that fund flows appear to be related to styles, and, interestingly, sector rotation is a specific investment style they were able to identify. Campbell, Ramadorai, and Schwartz (2009) 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 article is positioned between these two strands of 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 macroeconomy as well as broad markets, rather than to less aggregate series related to liquidity, volatility, or specific mutual fund returns. Our aims are 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 importantly rests in the article's focus on the connection between market participants' decisions about sector orderflow and the larger macroeconomy and capital markets.

3. Data and Variable Construction

At the center of our empirical analysis are equity orderflow data that we constructed using the Trades and Quotes (TAQ) dataset for the sample period 1993–2005. 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 procedure that follows. First, to ensure data integrity, we eliminate nonpositive spreads and depths and trade prices as well as records in which 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 five-second rule.[2] Third, we aggregate all trades that are executed at the same price and 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. Finally, each trade is assigned to a dollar-size category whose cutoffs are defined as small ($<$ \$25,000), medium (\$25,000–\$250,000), and large ($>$\$250,000).[3] The rationale for using dollar orderflow is that by summing the net dollar orderflow into sectors, we are implicitly value-weighting (this is unlike stock returns that are expressed on a homogeneous [scale-free] basis across size). This procedure results in a set of daily orderflow

[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.

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) and developed by Morgan Stanley Capital International (MSCI) and Standard & Poor's (see Appendix 1 for specific sector descriptions). We then construct sector-level net orderflow by simply summing all orderflow for the individual stocks included in each sector; net orderflow to the stock market as a whole is the analogous sum of net orderflow of each sector. Likewise, we define sector-level capitalization as the sum of the capitalizations (shares outstanding multiplied by end-of-month price) of the individual stocks in the sector. Throughout this article and in our tables, the sectors are ordered with respect to their cyclicality with the U.S. business cycle. We use, as an objective sector ordering, the MSCI/Barra partition of the ten sectors into three groups: procyclical (information technology, materials, and industrials), neutral (consumer discretionary, financials, energy, and telecommunications), and countercyclical (utilities, consumer staples, and health care).[5] As a robustness check, we also conducted our own regressions regarding each sector's degree of cyclicality; our results largely confirmed the MSCI ordering.

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, upon entering the stock market, is distributed across sectors by their weight in the market portfolio. Active net orderflow for each sector is the difference between sector-level total net orderflow and passive net orderflow, thereby measuring the excess or shortfall in orderflow relative to a market capitalization weighted distribution of total orderflow. We interpret active net orderflow as deliberate decisions/actions by market participants about their capital allocation within the equity market.

Table 1 displays our total aggregate orderflow by sector and year, expressed as a percentage of the total net orderflow for the year. While the percentage of orderflow across years remains fairly stable, there is certainly variation across years, particularly leading up to and during the economic downturn in 2000. In addition, these shifts in the shares of orderflow across sectors appear more

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4 We acknowledge that breaking up orderflow by trade size, in order 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 exclusively trade large quantities, nor do retail traders solely trade small or medium trades, as a general rule, we believe the likelihood of large trades originating from institutions remains high. In addition, we are able to provide evidence (upon request) that all our key results hold irrespective of whether we use large or all-trade orderflow.

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

Table 1
Aggregate orderflow summary statistics

Panel A: All Orders

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

Panel B: Large Orders

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

This table displays aggregate net orderflow figures by sector and year expressed as a percentage of the total dollar net orderflow expressed in millions of dollars. Sectors are ordered down the column from procyclical to neutral to countercyclical. Net orderflow is calculated by summing the buyer-initiated trades and subtracting all seller-initiated trades for all stocks within each sector.

pronounced for large orders (panel B) relative to all orders (panel A), which suggests that market participants who place 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), and nonfarm payroll expectations and announcement information. For the nonfarm 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&P 500 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 and was first developed by Stock and Watson (1999).[6] Note that an index value above (below) zero indicates economic growth above (below) the trend. In contrast to the NBER expansion and recession periods, the CFNAI index has the advantage of being a coincident indicator, i.e., 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 present in our analysis.[7]

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 in their orderflow decisions. Consequently, if we are interested in the information component of orderflow, as it relates to the macroeconomy, 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 this possibility by conducting a principal component decomposition of sector orderflow. While our untabulated results reveal one dominant factor explaining 68% of orderflow movements, which is consistent with Hasbrouck and Seppi (2001), there are at least five other significant factors that are important in explaining orderflow. Given this result, we

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

7 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 A1 (Appendix 1).

can quickly dispel the notion that aggregate equity orderflow simply blankets the equity sectors uniformly.

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

Portfolio rebalancing of sector positions is another common motive for trade. If market participants engage in a buy-and-hold strategy (thereby effectively not rebalancing their portfolios), we would expect to see no relation between aggregate sector orderflow and the previous performance of the sector, while a negative relation between sector orderflow and previous performance would be consistent with a constant mix strategy. To investigate these possibilities, we analyze the temporal relation between sector orderflow and the corresponding lagged sector returns at both a weekly and monthly frequency. We suspect that the monthly aggregation may be more appropriate, as it is better able to cancel out components that are related to liquidity and inventory yet retains 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 they were 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 the aggregate, market participants defensively rebalance their portfolios. If anything, orderflow seems to positively respond to past sector returns but only at a weekly frequency. These

Table 2
Unconditional relation between active net order flow and lagged excess returns

Panel A: Weekly

Order Size	α	β	R^2	Obs.
Small	−1.1408	749.906	0.0002	6,760
	(−0.0762)	(1.5594)		
Medium	−9.3829	6, 168.042	0.0011	6,760
	(−0.1787)	(3.0328)		
Large	−32.2700	21, 213.430	0.0050	6.760
	(−0.3836)	(4.7967)		
All Orders	−42.7918	28, 130.200	0.0033	6.760
	(−0.3134)	(4.5692)		

Panel B: Monthly

Order Size	α	β	R^2	Obs.
Small	−4.6312	730.6475	0.0001	1,550
	(−0.0057)	(0.4728)		
Medium	−31.5317	4, 974.594	0.0002	1,550
	(−0.0082)	(2.1643)		
Large	12.5099	−1, 973.620	0.0001	1,550
	(0.0025)	(−0.1285)		
All Orders	−23.6266	3, 727.440	0.0001	1,550
	(0.0025)	(0.2199)		

This table contains the results of the following unconditional regression:

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

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

findings, combined with the evidence from the principal components analysis, suggest that orderflow is driven by more than simple indiscriminant 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 macroeconomy. Our conjecture is that market participants are continually digesting news about the macroeconomy; 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.[8] This empirical specification has a number of advantages. First, our key variable reflects the orderflow that is entering a sector in excess of new funds invested into the stock market. Second, standardization by sector market capitalization enjoys the intuitive interpretation of market share and also avoids the practical difficulty of overweighting the largest sectors.[9] Recall that the construction of dollar sector orderflow is comparable to value-weighting sector returns. Finally, we are careful to control for the current level of the expansion indicator, in order to ensure that coefficients on the orderflow do not pick up any contemporaneous relation with the economy.

At the outset, we investigate whether active monthly orderflow, within each separate sector, has 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 are shown in Table 3. As a reminder, note that the sectors are ordered by their cyclicality: Procyclical sectors are at the top, neutral sectors are in the middle, and countercyclical sectors are at the bottom of the table.

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

Figure 1 provides a visual sense for these results, where we plot the CFNAI indicator together with the average *active* orderflow for sectors that are procyclical, countercyclical, or not significant (neutral), according to the signs of the coefficients shown in Table 3, panel A. It is interesting to note how procyclical sector orderflow tends to lead the economy, while the contrary is observed for countercyclical sectors.

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

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[8] We repeat all of the regressions in the article, 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.

[9] We measure the sector market capitalization using stock prices at the beginning of the month in order 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, and we obtain similar results.

Table 3
Relation between expansions and past active net orderflow

Panel A: One-Month Lead

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

(*continued*)

Table 3
Continued

Panel B: Three-Month Lead

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

This table contains the results of the following unconditional regression:

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

where CFNAI is the Chicago Fed National Activity Index and our measure of economic growth/contraction. Net $\text{Orderflow}_{\text{j,t}}$, Passive Net $\text{Orderflow}_{\text{j,t}}$, and $\text{Capsector}_{\text{j,t}}$ represent the actual net orderflow, the passive net orderflow, and 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. Orderflow is partitioned into small (<\$25,000), medium (\$25,000 to \$250,000), and large (>\$250,000) groups. Regressions are run leading the CFNAI by one month (panel A) and one quarter (panel B). Sectors are grouped in three broad groups by cyclicality, as per the MSCI ranking: procyclical, neutral, and countercyclical, moving down the sector column. t-statistics are calculated using White heteroscredastic consistent standard errors.

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

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

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

The coefficients are both statistically significant and economically significant; as an example, a one-standard-deviation shock to large orderflow in the materials sector implies a 0.14 higher expansion index one month later, and such a move is approximately 10% of the maximum value of the expansion index within our sample. While the relation between sector orderflow and

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

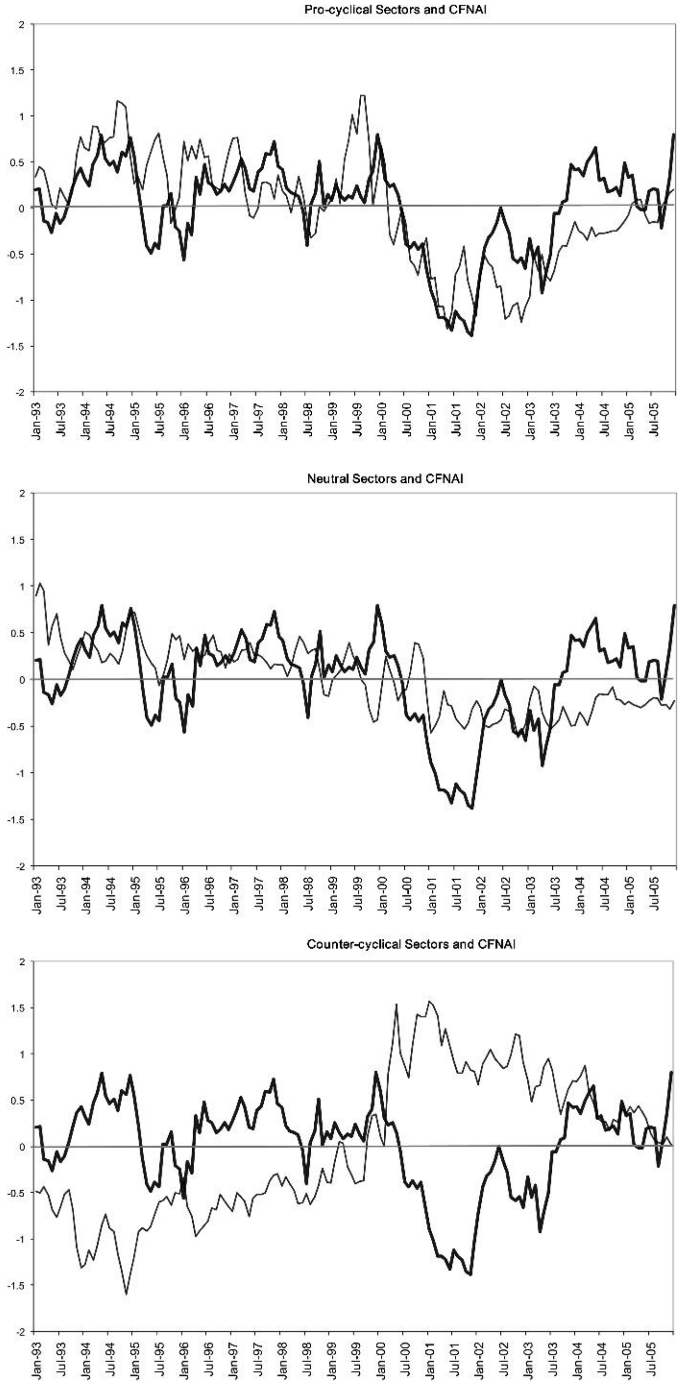

Figure 1
(Continued)

the macroeconomy is quite compelling for the large orders, the forecasting power of the medium- and small-sized orderflow is dramatically lower, with only active orderflow into utilities being consistently (negatively) associated with the expansion index. The contrast between the large and small/medium orderflow results is interesting because it suggests that the information, expectations, preferences, and risk tolerance of the market participants in each of the different-sized 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 employed.[11]

After investigating, by individual industry, the relation between the expansion index and sector orderflow, we now turn to an analysis of the cross-section of orderflow. We are specifically interested in determining the orderflow factor (i.e., the set of sector loadings) with the highest correlation to the state of the macroeconomy. As before, the numerators of the active net orderflow variables represent deviations from passive allocations; thus, their sum is equal to zero. As a result, the ten sectors have orderflow that are highly collinear, and the coefficients in the multivariate regression are difficult to interpret. Therefore, we refrain from showing the coefficients of the multivariate regression, and instead present the correlations between each sector orderflow and the best linear combination of sector orderflow estimated in the multivariate regression. Lamont (2001) encounters the same problem when using the returns of the base assets and concludes that "the portfolio weights have no particular meaning."

←

Figure 1
Chicago Fed national activity index (CFNAI) and sector orderflow
We plot 3-month moving averages of the CFNAI index (bold line) and average *active* net orderflow of large orders (continuous line) for pro-cyclical sectors, neutral nonsignificant sectors and counter-cyclical sectors, as defined by regressing the CFNAI expansion indicator on sector orderflow (see Table 3, Panel A, for details). 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.

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

Table 4 presents the cross-sectional results. Consistent with our intuition, the large orderflow results display positive coefficients for procyclical sectors that tend to negative coefficients as sectors become more countercyclical; the one exception to this is consumer staples. We are puzzled by the results for consumer discretionary and consumer staples and hypothesize that the categories are so large and heterogeneous that it is difficult to get a clear signal about pure

Table 4
Relation between expansions and past active net orderflow

Panel A: One-Month Lead

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

Panel B: Three-Month Lead

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

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

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

where Net Orderflow$_{j,t}$, Passive Net Orderflow$_{j,t}$, and Capsector$_{j,t}$ represent the actual net orderflow, the passive net orderflow, and 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. Orderflow is partitioned into small ($<$ \$25,000), medium (\$25,000 to \$250,000), and large ($>$\$250,000). Sectors are grouped in three broad groups by cyclicality, as per the MSCI ranking: procyclical, neutral, and countercyclical, moving down the sector column.

*, **, *** denote significance at the 10%, 5%, and 1% levels respectively. At the bottom of each panel, we also report the R^2 of the multivariate regression of the expansion indicator on the active orderflow in all ten sectors that we use to obtain the best linear combination.

discretionary and necessity purchases. However, the puzzle is consistent across both orderflow and return regressions, which lends credibility to a feature that is systematic across various measures within our data.

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

Fewer sectors have significant correlations at the one-month horizon, which suggests that one quarter ahead of an expansion (contraction) market participants perform a broad portfolio reallocation (three-month results), while the final adjustments that precede a turn in the economy appear to be concentrated into (out of) fewer sectors (one-month results). At the one-month horizon, the materials sector is the most aggressive sector for large orderflow, while health care and information technology are the most aggressive for medium and small orderflow, respectively. Consumer discretionary, financials, and telecommunications are the defensive sectors for large-sized orderflow, while utilities remain the one defensive sector for small- and medium-sized orderflow.

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

4.3 Sector orderflow and markets

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

Table 5
Relation between stock market and past active net orderflow

Panel A: One-Month Lead

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

(*continued*)

Table 5
Continued

Panel B: Three-Month Lead

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

This table contains the results of the following unconditional regression:

$$\mathrm{SP500_t} = \alpha + \beta \frac{\left(\text{Net Orderflow}_{j,t-1} - \mathit{Passive}\ \text{Net Orderflow}_{j,t-1}\right)}{\text{capsector}_{j,t-1}} + \varphi \mathrm{SP500}_{t-1} + \varepsilon_{j,t},$$

where SP500 is the return of the S&P 500 index portfolio and our measure of equity market performance. Net Orderflow$_{j,t}$, Passive Net Orderflow$_{j,t}$, and Capsector$_{j,t}$ represent the actual net orderflow, the passive net orderflow, and 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. Orderflow is partitioned into small (<\$25,000), medium (\$25,000 to \$250,000), and large (>\$250,000) groups. Regressions are run leading the CFNAI by one month (panel A) and one quarter (panel B). Sectors are grouped in three broad groups by cyclicality, as per the MSCI ranking: procyclical, neutral, and countercyclical, moving down the sector column. t-statistics are calculated using White heteroscedastic consistent standard errors.

Table 6
Relation between bond returns and past active net orderflow

Panel A: One-Month Lead

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

(*continued*)

Table 6
Continued

Panel B: Three-Month Lead

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

This table contains the results of the following unconditional regression:

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

where 1yBondRet is the return of the Fama-Bliss CRSP discount bond series and our measure of the performance of the bond market. Net Orderflow$_{j,t}$, Passive Net Orderflow$_{j,t}$, and Capsector$_{j,t}$ represent the actual net orderflow, the passive net orderflow, and 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. Orderflow is partitioned into small ($<$ \$25,000), medium (\$25,000 to \$250,000), and large ($>$\$250,000) groups. Regressions are run leading the CFNAI by one month (panel A) and one quarter (panel B). Sectors are grouped in three broad groups by cyclicality, as per the MSCI ranking: procyclical, neutral, and countercyclical, moving down the sector column. t-statistics are calculated using White heteroscedastic consistent standard errors.

For example, at the one-month horizon, small-sized orderflow into utilities, as well as medium- and large-sized orderflow in 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 three-month horizon, with weak and sporadic significance displayed among the sectors. Admittedly, the number of significant regressors for the stock market is in line with chance. We also compute the correlations between each sector's active orderflow and the linear combination of ten sector factor loadings that best predict the stock market, as is similar to the analysis presented in Table 4 for the macroeconomy. We find that the most aggressive sector for large-sized orderflow is information technology and the most defensive is the telecommunication sector, which is consistent with the univariate results (results not reported).

We perform the same analysis on the bond market (one-year maturity) (see Table 6). Not surprisingly, the results are stronger than were the corresponding results for the equity market, which is consistent with the received wisdom that the macroeconomy and the fixed income market may have more in common with each other than either has in common with the equity market. For the medium- and large-sized orderflow, the materials sector has a negative sign and the financials and utilities sectors have a positive sign, which is exactly the opposite result found for the expansion indicator.[12] Furthermore, these results hold at both the one- and three-month horizons. As an example of the substantial economic impact of these results, consider that a one-standard-deviation shock to orderflow into the material sector predicts a 0.0005-lower monthly bond return (0.6% lower annual return), which is about ten times the average one-year bond return in our sample. Moreover, the analysis of the correlations between each sector's active orderflow and the linear combination of ten sector factor loadings that best predict the bond market confirms that the most aggressive sector for large-sized orderflow is materials and the most defensive is the financial sector (results not reported).

4.4 Relation between orderflow information within the economy and markets

To further investigate the predictability of sector orderflow, we regress future values of the expansion indicator, the stock market return, and the bond market return on the current value of the dependent variable and a forecasting factor. The forecasting factor is a linear combination of either active orderflow or excess sector returns, where the loadings are computed as those with the maximal correlation with each of the dependent variables, respectively.

[12] Regressions were also run using the three- and five-year bond returns. The results were similar and are available upon request.

Panels A, B, and C of Table 7 display the explanatory power of the regressions for the economic expansions, stock markets, and bond markets, respectively. As one would intuit, the results show that own orderflow and own returns have predictive power across the three panels. Beyond this, Table 7 highlights four observations about the interaction among the three independent variables that reveal much about the predictability of sector orderflow. First, the orderflow factor having the maximal correlation with the expansion indicator has the ability to predict not only the expansion index but also the one-year bond return and, to a lesser extent, the stock market return (at least, at the

Table 7
Relation between orderflow information within the economy and markets

Panel A: Dependent variable CFNAI

Forecasting Factor (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&P 500

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

Panel C: Dependent variable one-year bond returns

Forecasting Factor (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***

This table shows the explanatory power of regressing one- and three-month-ahead values of the CFNAI expansion indicator, the stock market return, and the bond market return on the current value of the dependent variable and a forecasting factor of either active sector orderflow or excess sector returns. The specific forecasting factor is a linear combination of either active sector orderflows or excess sector returns, where the loadings in the linear combination produce the maximal correlation with each of the dependent variables in turn. We report only the adjusted R^2.

*, **, *** denote a significant coefficient on the factor at the 10%, 5%, and 1% levels, with White heteroscedastic consistent standard errors.

one-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 an R^2 of 32%, 2%, and 13% for the expansion index, stock markets, 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. This would be consistent with the evidence in Boyd et al. (2005), who show that unemployment news contains information on interest rates and future earnings that has conflicting effects for stocks, with the nature of the bundle depending on the state of the economy. Second, there is a high degree of reciprocity among factors; the combination of sector orderflow, which best predicts the stock market (bond market), also has predictive power over the CFNAI index, with a statistically significant R^2 of 22% (26%). Third, forecasting factors based on linear combinations of *excess returns* appear to have little explanatory power beyond their own market, which suggests that orderflow contains more cross-market information than do returns. Fourth, the sector orderflow coefficients are relatively stable across the three regressions. Thus, the reciprocity of orderflow's predictive power across the regressions, coupled with the coefficients, stability across sectors, implies the existence of a single orderflow forecasting factor, which is strongly related to macroeconomic information and has the ability to forecast performance within the economy and capital markets.

4.5 Orderflow versus returns

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

Others have investigated whether returns have incremental predictive power. Specifically, Lamont (2001) and Hong et al. (2007) show that the cross-section of *returns* across sectors predicts the economy and the stock market. Thus, when juxtaposing our orderflow results with results from the existing literature, a natural question arises as to whether orderflow contains the same information as do returns. On the one hand, returns and orderflow are related through the interaction of the demand and supply of shares (orderflow), which generates the equilibrium price (returns) and quantity (volume), and 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*.

To formalize this comparison, we predict the expansion indicator CFNAI with excess sector returns rather than orderflow, sector by sector. Table 8 displays our results; for comparison, we include the R^2 from the large-sized orderflow results in Table 3. The R^2 comparison reveals very little difference, on average, between the explanatory power of orderflow and the explanatory power of returns. However, further inspection reveals that the sector returns with predictive power are different than are those for sector orderflow.

Table 8
Relation between expansions and past excess sector returns

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

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

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

where CFNAI represents the Chicago Fed National Activity Index and our measure of economic growth/contraction. $\mathrm{Ret}_{j,t}$ represents the value-weighted return of sector j over month t, and $\mathrm{Ret}_{mkt,t}$ represents the value-weighted return on the stock market index. The excess return regressor is standardized to have zero mean and a standard deviation of one. Regressions are run leading the CFNAI by one month and one quarter. Sectors are grouped in three broad groups by cyclicality, as per the MSCI ranking: procyclical, neutral, and countercyclical, moving down the sector column. 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.

*, **, *** denote significance at the 10%, 5%, and 1% levels, with White heteroscedastic consistent standard errors.

For example, within the return regression, consumer discretionary, and consumer staples, health care, financials, and utilities are all negatively related to economic expansion, which suggests that a negative excess return in these sectors predicts an expansionary economy. In contrast, recall that the orderflow regression showed that orderflow into the materials sector and orderflow out of the financial and utility sectors are associated with an expanding economy.[13] Thus, Table 8 suggests that the information contained in orderflow and returns is, at a minimum, different.

To complement the above analysis, we run two auxiliary sets of regressions on the economic expansion index, the stock market return, and the bond market return, varying the set of independent variables among the various orderflow and return series. Table 9 displays our results, which compare the adjusted R^2 across small-, medium-, and large-sized active net orderflow predictors, along with returns, at the three-month horizon. The first item to note is that the cross-section of orderflow contains more explanatory power than do returns for future economic expansions, specifically, adding orderflow to

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

Table 9
Relation between business cycle, stock market returns, bond market returns, and past active net orderflow and returns

Regressors	CFNAI	Adjusted R^2 (3-months ahead) S&P 500 Return	1-Year Bond Return
Only Y_{t-1}	0.2461	–0.0016	0.0258
Small Active NOF	0.3216	0.0121	0.0334
Medium Active NOF	0.3844	–0.0058	0.1178
Large Active NOF	0.4250	–0.0319	0.1433
Excess Returns	0.2708	0.0178	0.0159
Large Active NOF + excessreturns	0.4396	–0.0006	0.1341

This table contains the resulting adjusted R^2 of the following unconditional regression:

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

where the dependent variable, Y_t, is either the CFNAI indicator, the S&P 500 return, or the one-year bond return, as displayed in their respective columns. Regressors are calculated as follows: Net Orderflow$_{j,t}$, Passive Net Orderflow$_{j,t}$, Capsector$_{j,t}$, and Ret$_{j,t}$ represent the actual net orderflow, the passive net orderflow, the sector capitalization, and the value-weighted return 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.

Ret$_{mkt,t}$ represents the value-weighted return on the stock market index.

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 orderflow dominates returns. Finally, like the results for the economic expansion, the large-sized orderflow dominates returns in predicting the one-year maturity bond returns. In summary, these results demonstrate that orderflow encompasses more information than is contained in returns.

While Tables 8 and 9 suggest that there appears to be more information in orderflow and that information is materially different than information contained in returns, it is possible that orderflow is merely proxying for low-frequency variables, such as the dividend yield, the default spread (BAA less AAA yields), and the term spread (ten-year less three-month), i.e., variables that the literature has already demonstrated have predictive power for the economy and other capital markets.[14] The final set of auxiliary regressions, contained in Table 10, address this concern. The regressions compare the predictive ability of nested sets of variables: Equations (1) and (2) provide the baseline regression, Equations (3) and (4) add returns and active net orderflow, respectively, and Equations (5) and (6) investigate whether active net orderflow explains the residual of the return equation (Equation (3)) and vice versa.[15] However, it is

[14] See Keim and Stambaugh (1986), Campbell and Shiller (1988), and Fama and French (1988), among others.

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

Table 10
Relation between business cycle, stock market returns, bond market returns, past large active net orderflow, past excess returns, and other predictors

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

This table contains the resulting adjusted R^2 and the number of significant regressors of the following six regression specifications:

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

$$(2)\ Y_{t+2} = \alpha_2 + \varphi_{12} Y_{t-1} + \varphi_2 2DIV_{t-1} + \varphi_{32} DEF_{t-1} + \varphi_{42} TERM_{t-1} + \varepsilon_{t+2,2}$$

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

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

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

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

where the dependent variable, Y_t, is either the CFNAI indicator, the S&P 500 return, or the one-year bond return and are displayed in their respective columns. Regressors are calculated as follows: DIV_t, DEF_t, $TERM_t$ represent the dividend yield, the default spread (difference between corporate BAA and AAA yields), and term spread (difference between Treasury ten year and three months), respectively. Net Orderflow$_{j,t}$, Passive Net Orderflow$_{j,t}$, Capsector$_{j,t}$, and Ret$_{j,t}$ represent the actual large net orderflow, the passive large net orderflow, the sector capitalization, and the value-weighted return 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. Ret$_{mkt,t}$ represents the value-weighted return on the stock market index.

difficult to interpret the individual coefficient estimates for two reasons. First, in Equations (3) and (4), there is collinearity induced by regressors expressed as deviations from a passive benchmark. Second, in Equations (5) and (6), the dependent variable is a residual and, as a result, the signs of the explanatory variables are not meaningful. For these reasons, Table 10 simply displays the number of significant regressors and the R^2 in order to provide some sense of the economic significance.

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

5. The Nature of Orderflow Information

Thus far, our results show that orderflow contains different information than do returns. What remains is to better understand the exact nature of the information contained therein.

5.1 Orderflow dispersion within sectors

We conjecture that, beyond the level of active sector orderflow, its composition may be important. Specifically, we hypothesize that the strength of the macroeconomic signal depends on whether investors increase the weight of the sector in the portfolio (strong signal) versus investors trading a small number of stocks in the sector.

In order to measure whether investors are trading the whole sector versus select stocks, we calculate the standard deviation of active orderflow for each stock as a measure of dispersion of orderflow within each sector.[16] Next, we average sector orderflow dispersion at the market level, using two different weighting schemes. The first dispersion measure (σ_1) uses weights that correspond 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 11, we present the results of forecasting the expansion indicator, the stock market, and the bond market with the sector orderflow in high and low dispersion states. In a given month, dispersion is high (low) when the aggregate standard deviation is above (below) its median in the last 12 months.[17] Our conjecture is clearly confirmed. When orderflow has low dispersion weighted by market capitalization (σ_1), the explanatory power is between 1.47 and 1.83 times higher than it is with high dispersion. If we give more weight to the

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

[17] The rolling threshold is preferred to a static threshold in order to avoid having 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).

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

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

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

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

where the dependent variable, Y_t, is either the CFNAI indicator, the S&P 500 return, or the one-year bond return, as displayed in their respective columns. Regressors are calculated as follows: Net $\text{Orderflow}_{\mathrm{j,t}}$, Passive Net $\text{Orderflow}_{\mathrm{j,t}}$, and $\text{Capsector}_{\mathrm{j,t}}$ represent the actual net orderflow, the passive net orderflow, and 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 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.

sectors that are more relevant for predicting the economy and the asset markets (σ_2), the results are even more striking; in months with low dispersion, the average explanatory power of orderflow doubles.

5.2 Orderflow and macroeconomic news

In this section, we investigate whether sector orderflow directly responds to important macroeconomic announcements, which we know are (noisy) signals 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.[18]

Our empirical design is to investigate the relation between orderflow factors having the highest correlation with the macroeconomy, stock market, and bond market with the standardized nonfarm payroll (NFP) announcement surprise, which is commonly understood to be the first and most influential macro announcement within a given month (see Andersen et al. 2007).[19] Orderflow is

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

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

measured over the week and the month following the nonfarm payroll release. If active orderflow is indeed capturing portfolio adjustments in response to changes in economic conditions, then the release of NFP news should trigger active orderflow in the sectors that are linked to the evolution of the economy. Our investigation encompasses two complementary approaches: measuring cumulative sector orderflow following nonfarm payroll releases (Figure 2) and a regression of the orderflow factors onto the nonfarm payroll surprise.

Figure 2 cumulates orderflow by sector following nonfarm payroll announcements. We distinguish sectors in three groups according to a predictive regression of the CFNAI indicator on sector orderflow (see Table 3, panel A): Financials, consumer discretionary, and telecom sectors act in a countercyclical fashion; materials and consumer staples act in a procyclical fashion; and the remainder of the sectors are not significant. The cumulative orderflow series are further partitioned by whether the announcement was a positive (panel A) or negative (panel B) surprise relative to expectations. Consistent with having a strong direct tie to macroeconomic news, the orderflow results show that the financials, consumer discretionary, and telecom sectors shed (accumulate) orderflow after positive (negative) surprises, while materials and, to a lesser extent, consumer staples sectors have the opposite pattern.

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

5.3 Orderflow and mutual fund flows

A drawback of the empirical measures of orderflow used in the literature and in our article is that the identity of the trader is unknown, and thus it is not possible to determine the category of investors primarily responsible for orderflow

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

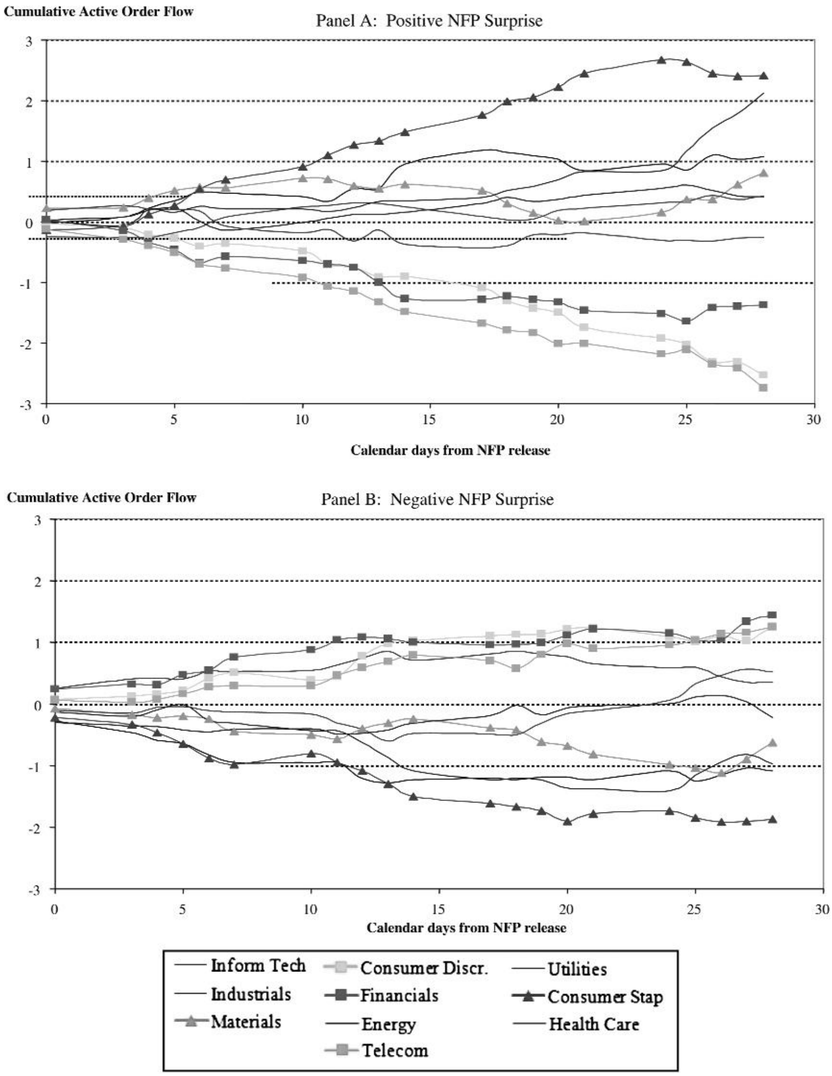

Figure 2
Cumulative active orderflow after nonfarm payroll surprises
Panels A and B of this figure show the cumulative *active* orderflow during the calendar days following the release of the nonfarm payroll data for positive and negative surprises, respectively. Triangles denote procyclical sectors, squares denote countercyclical sectors, and the remainder are nonsignificant sectors, as defined by regressing the expansion indicator on sector orderflow (see Table 3, panel A, for details).

into a group of stocks of the same sector. Mutual funds are, however, 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 are obtained from two mutual fund databases: The

Table 12
Relation between equity flows and nonfarm payroll surprises

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

This table shows the results of estimating the following regression:

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

where F is a linear combination of sector flows or returns in the period τ that follow the nonfarm payroll release at t. $\mathrm{NFP}_{ACT,t}$ is the actual NFP release, $\mathrm{NFP}_{EXP,t}$ 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 one-year bond returns. t-statistics are calculated using bootstrapped standard errors.

first database is the TFN/CDA Spectrum database, which 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, the Lipper-style data, unfortunately, begin 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 are 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 three months away from the previous reporting date. We also exclude all funds that do not exhibit positive stock holdings in all of the ten sectors used 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 article.

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, previously used 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 flow to industrial is $20 and deviations from this level constitute active allocation strategies. Similar 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 in order to match the frequency of mutual fund holding data, and we compute the correlation between the standardized active components of sector orderflow and sector mutual fund flows. We do not expect to find a significant correlation between sector orderflows and mutual fund flows in an analysis of *all* mutual funds because there would be plenty of confounding effects, like passive index mutual funds or mutual funds that are constrained to invest in only one sector. In contrast, we focus our attention on the Lipper "core" category, without distinction for size because we assume that the categories of mutual funds most likely to implement sector rotation strategies are those with an investment objective that is not constrained to a particular category of stocks.

Table 13 shows the correlation results by sector for the mutual funds with the "core" investment objective, i.e., a blend of value and growth. All ten sector flows present in core mutual funds exhibit a positive correlation with sector net orderflow of large orders. In four of the sectors, this positive correlation is statistically significant, despite the small sample (52 observations). This result is notable, given the number of confounding influences on quarterly mutual fund holdings. This is strong evidence that our active net orderflow variables are measuring the rebalancing strategies within core funds. As a benchmark, we also include the correlation of sector net orderflow with a passive replication strategy of the S&P 500 index (labeled S&P 500 in Table 13). By definition, these correlations should be unrelated to sector rotation strategies. As expected, the average correlation is close to zero, with only six of ten sectors being positive correlations and two cases of correlations that are significantly different from zero (one positive and one negative).

5.4 The orderflow mimicking portfolio

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

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

Table 13
Relation between active net orderflow and mutual fund flows

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

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

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

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

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

where Net Flow$_{j,t}$ and Passive Net Flow$_{j,t}$ represent the actual flow and the passive flow within sector j over quarter t in the mutual fund category L. We compute the passive net flow for sector j in mutual fund category L as the total flows to the category L multiplied by the weight of sector j in the market. The core investment objective represents a blend of the value and growth styles, while the S&P investment objective represents the passive style of replicating the S&P 500 index. Sectors are grouped into three broad groups by cyclicality, as per the MSCI: procyclical, neutral, and countercyclical, moving down the sector column.

*, **, *** denote significance at the 10%, 5%, and 1% levels.

nature of information that is 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 that define an orderflow-mimicking portfolio. These tilts define a marketwide portfolio that is potentially different from the traditional CAPM market portfolio that will provide an evaluation of the economic importance of the information contained in the cross-section of sector orderflow.

To implement such an orderflow portfolio, we start at the beginning of our sample with an equity portfolio, where the allocations across sectors are determined by market capitalization weights. As before, we compute the weekly net *active* orderflow of large-sized orders in different sectors as the difference between total orderflow for each sector and the *passive* orderflow, i.e., orderflow expected given the market capitalization weight of each sector the previous week. Thus, active orderflow represents the proportion of the orderflow to the aggregate stock market that deviates from the current allocation based on *current* portfolio weights. We translate dollar orderflow into percentage weight changes through a simple, normal cumulative density function transformation. Like most other asset allocation techniques, our procedure has the potential to generate extreme and unrealistic weights. For example, an extremely positive (negative) active orderflow in one sector may translate into a 100% increase (decrease) in the weight of that sector in the orderflow portfolio. Since we rebalance the portfolio weekly, we impose a reality constraint of 1% on the maximum weekly adjustment so that the largest possible change in a sector weight is 1% every week. Economically, this constraint on the sector weights might be interpreted as a transaction cost, implementation constraint, or even 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 vs. $2.50). Moreover, a closer examination of the figure reveals that the orderflow portfolio does not suffer the year 2000 downturn in the market portfolio, which is consistent with the orderflow portfolio being a largely 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 2000 recession. Furthermore, the orderflow portfolio enjoys superior risk and return metrics compared with 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 with 11.8%, 15.7%, and 0.75, respectively, for the market portfolio.[21] Finally, the sector weights are well behaved and range from a high of 30% to a low of 0%, which argues for the feasible implementation of the orderflow-mimicking portfolio.

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

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

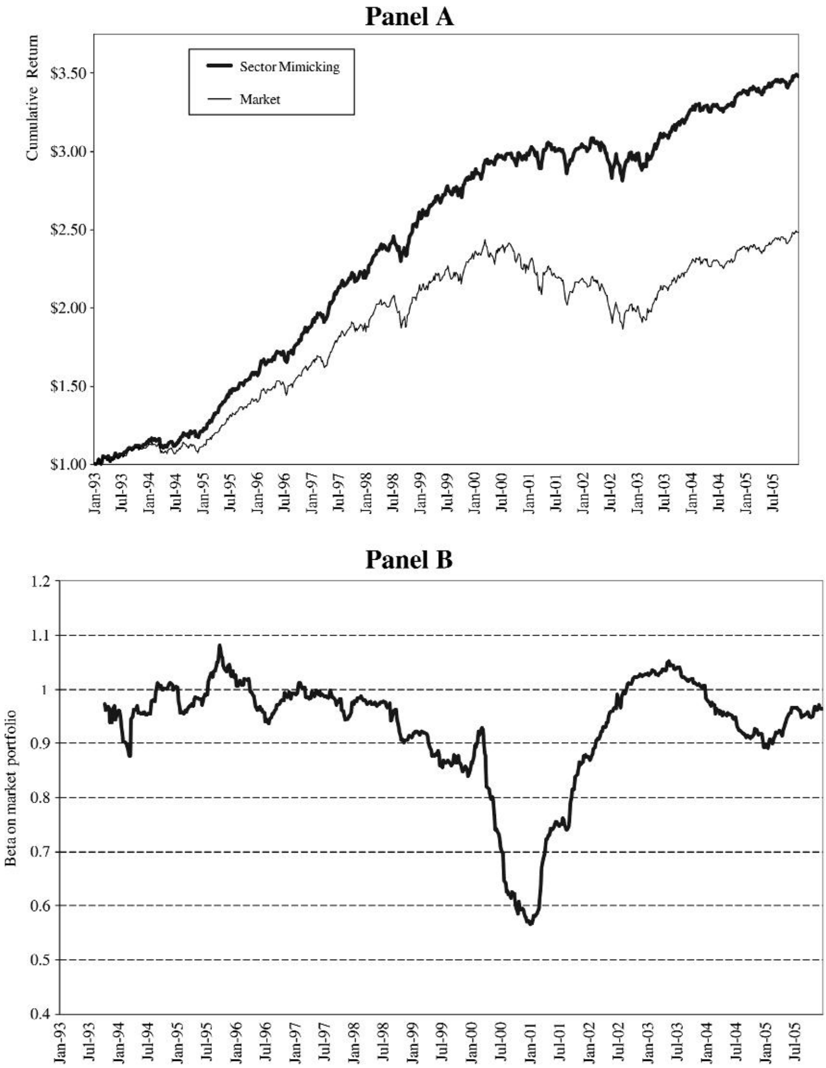

Figure 3
Characteristics of the orderflow portfolio
Panel A of this figure shows the cumulative return performance of investing $1 in the orderflow portfolio compared with the market portfolio during our sample period. The orderflow mimicking portfolio is constructed by tilting the market portfolio by movements of weekly net *active* orderflow of large-sized orders between different sectors. Active orderflow is the difference between total orderflow for each sector and the *passive* orderflow, i.e., orderflow expected given the market capitalization weight of each sector the previous week. Dollar orderflow is translated into percentage weight changes through a normal cumulative density function transformation. The maximum weekly adjustment is constrained to be 1%. Panel B displays the rolling betas of the orderflow portfolio.

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&P 500. This is just another manifestation of the Roll Critique. What is remarkable, though, is that the information contained in orderflow across sectors has striking economic implications, as reflected through our orderflow-mimicking portfolio dominating the market portfolio. Moreover, the information contained in the orderflow portfolio is directly related to the macroeconomy, tends to be defensive in nature, and goes beyond the information captured by sector excess returns.[22]

6. Conclusion

There is mounting evidence in the literature that the trade decisions of market participants incorporate their risk preferences, expectations, and actual or perceived information. Armed with this evidence, we investigate what orderflow movements among equity sectors are able to tell us about the macroeconomy 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 and the future performance of the bond markets. The comparison of the orderflow factors that predict the economic expansion, stock markets, and bond markets reveals that not only does orderflow contain more and different information compared with returns and traditional low-frequency forecasting variables but the nature of the information is common across the three markets. Furthermore, this information is explicitly linked to information about the macroeconomy, as seen through its relation to the nonfarm payroll announcement. Finally, our results are stronger when orderflow is less dispersed within sectors, which lends further support to our conjecture that the sector orderflow measures do indeed reflect the empirical footprints of broad sector rotation, rather than stock picking within particular sectors.

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 that our orderflow measures are indeed capturing institutional trader flows. Moreover, when we translate sector orderflow movements into tilts to the market portfolio, in order to produce an orderflow-mimicking portfolio, the result is that the orderflow portfolio enjoys superior risk and return properties relative to the traditional market portfolio or industry momentum portfolios.

[22] A potential concern might be that the results are proxying for other factors known to be priced. One specific concern might be the momentum factor at the industry level, which reflects 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.

Interestingly, this finding is attained because orderflow contain asymmetric information in that it is primarily defensive in nature and largely related to wealth preservation. In this article, we presented compelling evidence that orderflow, which reflects the *actions* of investors, contains information that is not entirely revealed by returns, which reflect the *consequences* of these actions. This is contrary to many theories of price formation and suggests fruitful avenues for future research.

Appendix 1

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, which we define here:

[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 services 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 and defense; construction, engineering, and 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, and 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 and apparel, and leisure equipment. The services segment includes hotels, restaurants and other leisure facilities, media production and services, and consumer retailing 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 nondurable household goods and personal products. It also includes food and drug retailing companies as well as hypermarkets and consumer supercenters.

[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.

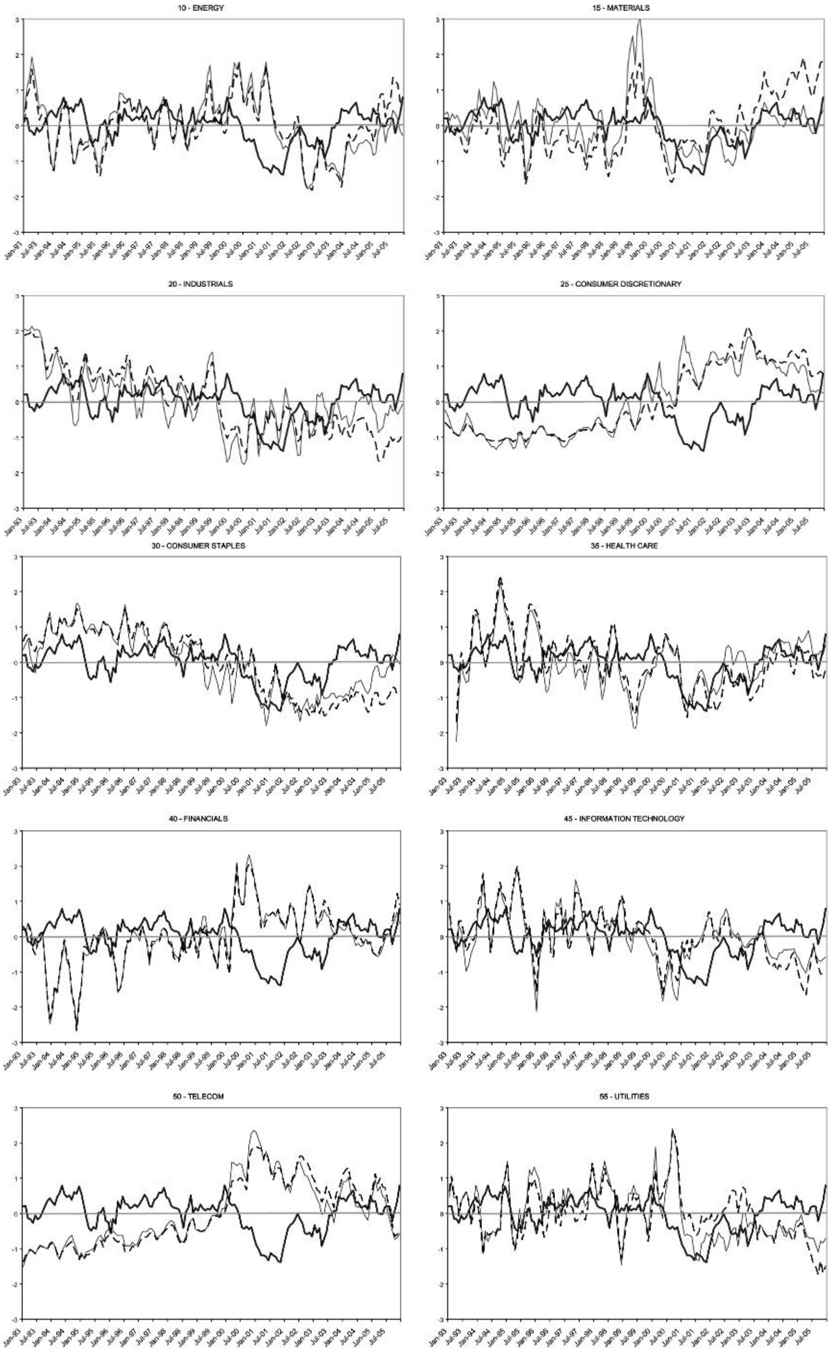

Figure A1
(continued)

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Figure A1
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.

[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, financial investment, and real estate, including REITs.

[45] Information technology sector. The GICS Information Technology Sector covers the following general areas: first, technology software and 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; second, technology hardware and equipment, including manufacturers and distributors of communications equipment, computers and peripherals, electronic equipment, and related instruments; and third, semiconductors and semiconductor equipment manufacturers.manufacturers.

[50] Telecommunications services sector. The GICS Telecommunications Services Sector contains companies that provide communication services primarily through fixed-line, cellular, wireless, high bandwidth and/or fiber optic cable network manufacturers.

[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.

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