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The cross-market information content of stock and bond order flow

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Abstract

In this paper I test the hypothesis that trading activity in the stock and bond markets contains important marketwide pricing information. Using a large sample of actively traded stocks and U.S. Treasury securities, I find that aggregate order imbalances play a strong role in explaining cross-market returns. I interpret this as evidence that aggregate order flow reveals information about the risk preferences, beliefs, and endowments of the investor population that is relevant for pricing securities in both markets. I also find evidence that cross-market hedging is an important source of linkages across the two markets, especially during periods of elevated equity volatility.

JEL classification: G14; G19

Keywords: Cross-markets; Stock–bond relationship; Order flow

1. Introduction

Many trading strategies allocate assets to both risky equities and riskless fixed income securities. As such, movements into and out of both asset classes can reveal important characteristics of the investor population such as beliefs, risk preferences, or endowments. The notion that aggregate signed order flows convey such information is well established in the foreign exchange and fixed income markets. Evans and Lyons (2002) show in a simultaneous trade model of interdealer foreign exchange trading that shifts in marketwide demand for currencies due to changing risk preferences or endowments can lead to changes in exchange rates; thus, order flow in the currency market can explain returns even though

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there is no asymmetric information concerning the "payoffs" of individual currencies. Evans (2002) and Evans and Lyons (2002) provide empirical evidence that order flow explains price movements in several different currency pairs. Brandt and Kavajecz (2004), Green (2004), and Pasquariello and Vega (2007) also find evidence that trades are informative in the U.S. Treasury market, with a similar interpretation of the results. In the equity markets, however, there has been much less focus on the information content of aggregate order flow. Some recent exceptions include Hasbrouck and Seppi (2001), Chordia et al. (2002), and Harford and Kaul (2005). These papers all show that aggregate order imbalances in the equity market play a significant role in explaining the returns on large portfolios of stocks.

Given the close linkages between the stock and bond market, an important question that remains unanswered is whether aggregate order flows in the two markets convey important information *across* markets. In this paper I test the hypothesis that net buying and selling pressure in the stock and bond markets contains information about cross-market returns. My results provide evidence consistent with the notion that market participants take cross-market trading activity into account in setting prices. Using a large sample of stocks and U.S. Treasury notes, I find that aggregate Treasury order flow plays a significant role in explaining contemporaneous returns on equities at an intraday frequency. This result holds even after controlling for the explanatory power of equity order flow and Treasury returns. When I examine the cross-market information content of equity order flow, I find that order flow in S&P 500 stocks also plays a role in explaining Treasury returns; however, the result is not as consistent and robust as that found for Treasury order flow. These empirical findings are the central contribution of this paper, and suggest that aggregate order imbalances in the stock and bond markets contain the type of "private" information about securities prices suggested by Ito et al. (1998).[1]

I then test whether the cross-market order flow relationship changes based on equity market uncertainty. Connolly et al. (2005) show that the correlation between daily stock and bond returns changes based on the level of the CBOE volatility index (VIX).[2] My results show that the cross-market importance of order flow does vary in a way that is related to equity market uncertainty. Treasury order flow takes on the most importance in a cross-market sense when uncertainty is low. Meanwhile, equity order flow is most important when uncertainty is high. The strength of the results across subsamples, especially for Treasury order flow, indicates that cross-market order imbalances are informative not only during episodes of "flight to quality", but also in more general settings. Thus the results presented in this paper make an important contribution relative to Connolly et al. (2005). Specifically, I show that these order flows actually contain incremental information that is relevant for the cross-market return series.

If the information being conveyed by order flow is about the risk-preferences, beliefs, endowments, etc., of the investor population, then knowing which types of traders are the marginal investors is important in understanding the pricing implications of buying and selling pressure in the equity markets. I test for cross-sectional differences based on trader type by separating equity trades into those likely initiated by individuals and those likely

[1] Ito et al. (1998) define private information as anything that (1) is not common knowledge and (2) is price relevant.

[2] VIX is commonly known as the "investor fear gauge". For the sample period used in this study, the CBOE constructed VIX by averaging the implied volatilities of eight near-the-money S&P 100 index options.

initiated by institutions. The results show that institutional trades are generally the most informative about Treasury returns. Chakravarty (2001) shows that trades initiated by institutions are the primary source of firm-specific information in the equity market. My results show that while institutional trades generally convey the most information about economywide news, trades initiated by individuals are also important, and contain information that is distinct from that contained in institutional trades. Thus the aggregation of trading activity across both individuals and institutions brings together important pieces of dispersed information about the investor population.

Besides knowing which *traders* are important in a cross-market setting, understanding which *stocks* contain the most informative trading activity is also an important component of understanding the joint nature of stock and bond pricing. To test for cross-sectional variation in the informativeness of trading activity, I divide the sample into value and growth stocks. Campbell and Vuolteenaho (2004) show that a stock's beta can be broken down into two components: a cash-flow, or "bad" beta, and a discount rate, or "good" beta. In the 1963–2001 period, growth stocks tend to have higher discount rate betas than value stocks, while value stocks tend to have higher cash flow betas than growth stocks. I find that the role for value and growth order flow varies based on the level of equity uncertainty. Order imbalances in growth stocks become more informative when uncertainty is high, suggesting that trading in discount rate sensitive securities is most informative when uncertainty about risk premia dominates. This is consistent with the popular notion of a "flight-to-quality"/"flight-from-quality", where traders are frequently revising their assessment of the riskiness of stocks.

Such a flight-to-quality, or more generally cross-market hedging, has been suggested as motivation for trading stocks and bonds with important pricing implications. Fleming et al. (1998) find evidence of strong volatility linkages between the stock and bond markets, and attribute a portion of this to cross-market hedging. Chordia et al. (2005) show that innovations to liquidity and volatility are correlated across the two markets, and suggest that this may be related to strategies which shift wealth between the two markets. And Connolly et al. (2005) document extended periods of negative correlations between stock and bond returns, finding that such periods most often occur when equity market uncertainty (proxied for by the CBOE VIX) is high. They conjecture that cross-market hedging is the driver for this pattern in returns. My results provide empirical evidence of cross-market hedging consistent with the prior literature: signed order flows in the stock and bond markets are significantly negatively correlated in periods of elevated equity volatility. In periods of lower volatility, the correlation is significantly positive.

The rest of the paper is as follows. Section 2 provides a brief review of recent work in the stock–bond area. Section 3 describes the datasets involved and the methodology employed in the study. Section 4 presents the empirical results, and Section 5 concludes.

2. Literature review

The literature on the stock–bond return relation is vast,[3] but my paper is especially closely related to several papers in recent years. In this section I briefly review these papers and highlight the contributions I make relative to these studies.

[3]See, for example, Shiller and Beltratti (1992), Campbell and Ammer (1993), Keim and Stambaugh (1986), and Barsky (1989).

Fleming et al. (1998) examine the role of information in creating volatility linkages between the stock and bond markets. Their model incorporates cross-market hedging and suggests that the linkages between the two markets are much stronger than would be implied by simple return correlations. For example, while the correlation between S&P 500 returns and T-bill returns during their sample period is 13%, the model-implied estimate of the information flow correlation between the two markets is 67%. While the authors do not directly consider order flow data, their results strongly suggest that there may be information in trading activity that would be relevant across markets.

Chordia et al. (2005) study the cross-market dynamics of liquidity in the stock and Treasury bond markets. Using a vector autoregressive framework, they analyze the impact of innovations in liquidity, volatility, and order imbalances across markets at the daily frequency. They find that shocks to liquidity and volatility in the stock and bond markets are correlated, suggesting that a common set of factors drives these characteristics of the two markets. While they do consider the role of order imbalances and their effects on liquidity across markets, they find little evidence that shocks to order flow in one market affect liquidity in the other market. In addition, they do not explore the possible informational role of order imbalances in explaining returns across markets.

Finally, Connolly et al. (2005) document the time-varying correlation between daily stock and bond returns, and show that the variation is related to equity market uncertainty, as measured by the CBOE VIX index. They find, for example, that when VIX is below 20%, there is a 6.1% chance of observing a negative stock–bond correlation over the next month. But when VIX is above 25%, there is a 36.5% chance of observing a negative correlation between stocks and bonds over the next month. Their findings suggest that stock market uncertainty has important cross-market pricing influences and should be taken into consideration when setting optimal portfolio allocations. The role that trading activity plays in bringing about these cross-market pricing influences is an important question, and is the main focus of my paper.

3. Methodology and data

3.1. Methodology

To test the hypothesis that order imbalances in the stock and bond markets have cross-market information content, I consider whether aggregate order flows in one market are able to explain returns in another market, after controlling for order flows in that market. In addition, since traders likely also observe the return series in the other market, the cross-market return should also be included as an explanatory variable. However, failing to account for the endogenous nature of this return would result in inconsistent and biased estimates of the explanatory power of cross-market order flow. To address this issue, I use a simultaneous equations system to test for the cross-market information content of order imbalances. Specifically, I consider the following system:

$$R_{\mathrm{On},t} = \beta_0 + \beta_1 R_{\mathrm{S\&P},t} + \beta_2 OF_{\mathrm{On},t} + \beta_3 OF_{\mathrm{Off},t} + \beta_4 OF_{\mathrm{S\&P},t} + \varepsilon_t \tag{1}$$

$$R_{\mathrm{S\&P},t} = \gamma_0 + \gamma_1 R_{\mathrm{On},t} + \gamma_2 OF_{\mathrm{S\&P},t} + \gamma_3 OF_{\mathrm{Non},t} + \gamma_4 OF_{\mathrm{On},t} + \nu_t \tag{2}$$

where $R_{\mathrm{On},t}$ is the return on an equally weighted portfolio of on-the-run Treasuries, $OF_{\mathrm{On},t}$ represents net order flow in the on-the-run Treasuries, and $OF_{\mathrm{Off},t}$ is order flow in off-the-run Treasuries. $R_{S\&P,t}$ is the return on an equal-weighted portfolio of S&P 500 stocks, $OF_{S\&P,t}$ is the order flow in the S&P 500 stocks, and $OF_{Non,t}$ is the net order flow in a sample of non-S&P 500 stocks. In order for the system to be identified, at least one exogenous variable must be excluded from each equation. I exclude off-the-run Treasury order flow from the S&P return equation, and non-S&P 500 order flow from the Treasury return equation, given that these securities are less liquid and less likely to be the focus of traders shifting money back and forth between the two markets. In alternate specifications discussed below, I consider the cross-market role of these variables.[4] Since each equation includes one endogenous variable as a regressor and excludes one exogenous variable, each is just identified. I estimate the model by two stage least squares (2SLS), although since both equations are just identified this is equivalent to system-based methods such as three stage least squares (3SLS).

3.2. Data

The data used in this study come from the period January 1993 through December 31, 2000. These cutoff dates are based on the availability of the necessary datasets. While the GovPX Treasury dataset is available beginning in 1991, the NYSE TAQ database begins in January 1993, providing the starting point for the analysis. The sample ends in December 2000 because GovPX stopped collecting aggregate volume for each security in early 2001. This variable was incremented each time a trade occurred, and without it one is unable to identify unique trades in the GovPX database.

3.2.1. Stock data

The equity market data for the analysis are pulled from the NYSE TAQ database. As I am interested in both (a) large scale shifts in investor portfolios and (b) the information content of those shifts, I choose a large sample of stocks where such flows may be present. I collect data for two main equity samples: the firms which are members of the Standard and Poor's 500 Index, and a large sample of actively traded firms which are not members of the index. In both cases I require the stocks to be traded on either NYSE or AMEX.[5] The non-S&P 500 stocks are included as additional instruments to aid in the identification of the system, and also because they are less likely to be influenced by the activity of index funds. While flows in and out of index funds are certainly reflective of changes in investor characteristics, they could also contain a systematic component (e.g., monthly retirement account contributions) that might overshadow the component related to changing investor beliefs and preferences. For the non-S&P 500 sample, I rank stocks according to their market capitalization in each month. I then retain the 500 largest stocks in each month which are not members of the S&P 500 during that month.

For each individual stock in the sample, all trades and quotes from the NYSE TAQ database are collected for the entire period. Data are filtered following the appropriate rules in Huang and Stoll (1996) and Weston (2000). Following Hasbrouck and

[4]I also consider another variation of the system with three equations, in which the return on non-S&P 500 stocks is also included as an endogenous variable. (The return on off-the-run Treasuries is not included, as many of these bonds go extended periods without trading.) The basic conclusions concerning the cross-market information content of order flow hold, so I elect to present results for the more parsimonious model shown above.

[5]Including NASDAQ stocks does not significantly alter the results qualitatively or quantitatively.

Seppi (2001) and Harford and Kaul (2005), each trading day is divided into 15-min intervals. The choice of interval length represents a compromise; using shorter intervals reduces the possibility of feedback trading contaminating the results, while using longer intervals reduces the number of intervals in which no trades occur. Hasbrouck and Seppi (2001) present a nice summary of the arguments in favor of using 15-min intervals.

It should be noted that while regular equity trading hours are 9:30–4:00 Eastern time, the Treasury market has no fixed trading hours.[6] Since I am only interested in periods when traders can actively participate in both markets, I limit the analysis to trading in the 9:30–4:00 time frame. Furthermore, to eliminate issues related to the opening of trading, as well as to reduce the effect of news-related shocks which are impounded into prices overnight, I eliminate the 9:30–9:45 interval from the analysis. This results in a total of 25 15-min intervals per trading day.[7]

For each stock, net order flow is calculated as the net number of trades over the 15-min period.[8] To calculate net order flow, trades are first signed as buyer or seller initiated using the Lee and Ready (1991) algorithm. The number of seller-initiated trades is then subtracted from the number of buyer-initiated trades for each 15-min interval. To facilitate comparison across stocks with potentially different levels of trading activity, this net number of trades is scaled by the total trades in the interval. This scaled net number of trades is summed across all stocks in each sample (S&P 500 and non-S&P 500) to find aggregate order flow. Finally, to remove the strong autocorrelation in the order flow series, I calculate the innovations to order flow as the residual from regressing order flow on its first five lags, as well as the first five lags of aggregate stock and bond returns. In addition to removing the autocorrelation, the order flow variable constructed from these residuals is unrelated to the past series of returns in both markets. This ensures that regression estimates of the order flow coefficient are not picking up any effects related to lagged returns, but rather the true unanticipated component of trading as suggested by Hasbrouck (1991).[9] Returns are calculated for each stock based on the midpoint of the last outstanding bid–ask quote in each 15-min interval. Portfolio returns are then calculated for each portfolio (S&P 500, non-S&P 500) as an equally weighted average of the returns on the individual securities.

As a final step, these aggregate order flow and return measures are standardized to remove any time of day effects as in Hasbrouck and Seppi (2001). McInish and Wood (1992) find evidence of intraday patterns in spreads, Foster and Viswanathan (1993) document intraday patterns in volume, trading costs, and volatility, and Hasbrouck and Seppi (2001) find evidence of intraday patterns in order flows. I standardize all of the return and order flow measures as follows:

$$x_t^* = \frac{x_t - \mu_i}{\sigma_i} \tag{3}$$

[6] Fleming (2003) shows that 95% of Treasury trading occurs between 7:30 and 5:00.

[7] In addition, I eliminate periods when the equity market is open but the bond market is closed, such as the afternoon before holidays.

[8] I also calculate net order flow using net dollar volume. The results are qualitatively similar.

[9] Five lags are sufficient to remove the serial correlation from the order flow series. The general results are insensitive to the choice of lag length for constructing the order flow innovations.

where x_t is the observation for variable x in a given 15-min interval t, μ_i is the average value of x for the given 15-min interval during month i, and σ_i is the standard deviation of x for that interval during month i.

3.2.2. Bond data

The data for the U.S. Treasury market are obtained from the GovPX dataset. GovPX maintains tick-by-tick trading data for all interdealer activity involving five of the top six interdealer brokers. From GovPX I retain all trading data for on-the-run and off-the-run 2-year, 5-year, and 10-year Treasury securities for the entire sample. "On-the-run" indicates that a security is newly auctioned and is the most recently issued security in a given maturity class. On-the-run Treasuries are very actively traded and the market is extremely liquid (Fleming, 2003). While off-the-run Treasuries are more difficult to trade (see, for example, Barclay et al., 2006), they still account for a non-trivial portion of interdealer trading (see Fabozzi, 2001) and so may reveal important information about marketwide factors. Fleming (2003) shows that the 2-, 5-, and 10-year notes are the most actively traded securities in the short to medium portion of the curve. The 30-year bond is excluded due to GovPx's sparse coverage of the long end of the curve.

For each Treasury security, I collect the same information as was collected for equities: the quote midpoint return over the 15-min interval, and the net order flow as measured by the net number of trades.[10] Of note here is the fact that trades do not have to be signed for bonds as was done with equities. The GovPX dataset clearly indicates whether each trade is a "hit"(sell) or a "take" (buy). The data are filtered for erroneous entries using the screens detailed in the appendix of Fleming (2003), and returns and order flows in the Treasury market are calculated as for equities. The same process is used to calculate innovations to Treasury market order flow for each security, as well as to standardize the variables.

3.3. Summary statistics

Summary statistics for the raw data are presented in Table 1. Net order flow, both in number of trades and in dollar terms, is on average positive for both the S&P 500 and non-S&P 500 samples of stocks. This is consistent with the findings of Hasbrouck and Seppi (2001) and Harford and Kaul (2005). As might be expected, trading frequency is higher for the S&P 500 subsample. The S&P 500 sample averages about 8500 trades per 15-min interval, while the non-S&P 500 sample averages about 2600 trades per interval. The average dollar volume reflects similar differences between the two samples. Returns (shown in percent) average close to zero for both samples. The raw net order flow series both exhibit significant first order autocorrelation, but this is effectively eliminated through the procedure outlined above.

Summary statistics for the Treasury securities are presented in the bottom half of Table 1. Net order flow is again positive on average, and the on-the-run Treasuries average about 43 trades per 15-min interval. One notable difference relative to the equity sample is the much lower autocorrelation in the Treasury order flow series, at least for the on-the-run Treasuries. As expected, returns average close to zero for the Treasuries as well.

[10] I do not track returns for off-the-run Treasuries, as many of the off-the run bonds go extended periods with no trading.

Table 1
Summary statistics

	S&P 500 stocks			Non-S&P 500 stocks		
	Mean	Std. dev.	ρ_1	Mean	Std. dev.	ρ_1
Net # trades	429.5	1282	0.320	151.7	413.9	0.278
Number of trades	8524	5796	0.932	2599	1524	0.940
Net order flow ($)	63.82	223.8	0.152	11.51	35.32	0.202
Dollar volume	685.2	529.3	0.823	139.1	83.47	0.874
Returns	0.036	0.526	0.022	0.031	0.270	0.176
	On-the-run Treasury			**Off-the-run Treasury**		
	Mean	Std. dev.	ρ_1	Mean	Std. dev.	ρ_1
Net # trades	2.461	15.77	0.021	12.60	89.73	0.701
Number of trades	42.98	23.87	0.709	216.3	106.9	0.686
Net order flow ($)	15.68	171.6	0.032	110.0	670.9	0.589
Dollar volume	361.8	242.4	0.612	1388	829.8	0.621
Returns	0.000022	0.044	0.002	–	–	–

This table presents means, standard deviations, and first order autocorrelations for 15-min intervals for the following variables: net number of trades (# buys–# sells), total number of trades, net dollar order flow (in $ millions), total dollar volume (in $ millions), and returns (in %). The sample period is 1/1/93–12/31/00.

4. Results

I take as a starting point for my analysis the results of Connolly et al. (2005). The authors find that the daily correlation between stock and bond returns is almost always positive in periods when the CBOE VIX is low (<20), while the correlation is very often negative when VIX is high (>25). Fig. 1 plots the average VIX level by month, as well as the monthly correlation between 15-min returns on the portfolio of S&P 500 stocks and the portfolio of on-the-run Treasuries. The figure shows that the basic Connolly et al. (2005) result using daily data holds using my sample of intraday returns from 1993 to 2000. Periods with lower levels of market uncertainty tend to have positive correlations, while the correlation tends to be negative later in the sample when uncertainty peaks. I thus divide the sample period into three subsamples: $\text{VIX}\leqslant 20$ (low stock market uncertainty), $20<\text{VIX}<25$ (average stock market uncertainty), and $\text{VIX}\geqslant 25$ (high stock market uncertainty). The low uncertainty period, which generally represents the first four years of the sample, includes 26,360 observations. The average uncertainty period is spread through the 1997–2000 portion of the sample and includes 13,620 15-min intervals. The high uncertainty period is also spread over the 1997–2000 period and contains 10,966 observations.

Connolly et al. (2005) argue that the negative stock–bond return correlations observed in periods of higher uncertainty may be due to cross-market hedging, as in Fleming et al. (1998). If this is true, then one should observe a similar negative correlation in signed order flows across the two markets. Table 2 confirms that order flows in the stock and bond markets exhibit behavior consistent with cross-market hedging. In periods of low uncertainty, the correlation between net order flow in S&P 500 stocks and Treasuries is positive and significant, with magnitudes ranging from 0.18 (off-the-run) to 0.225

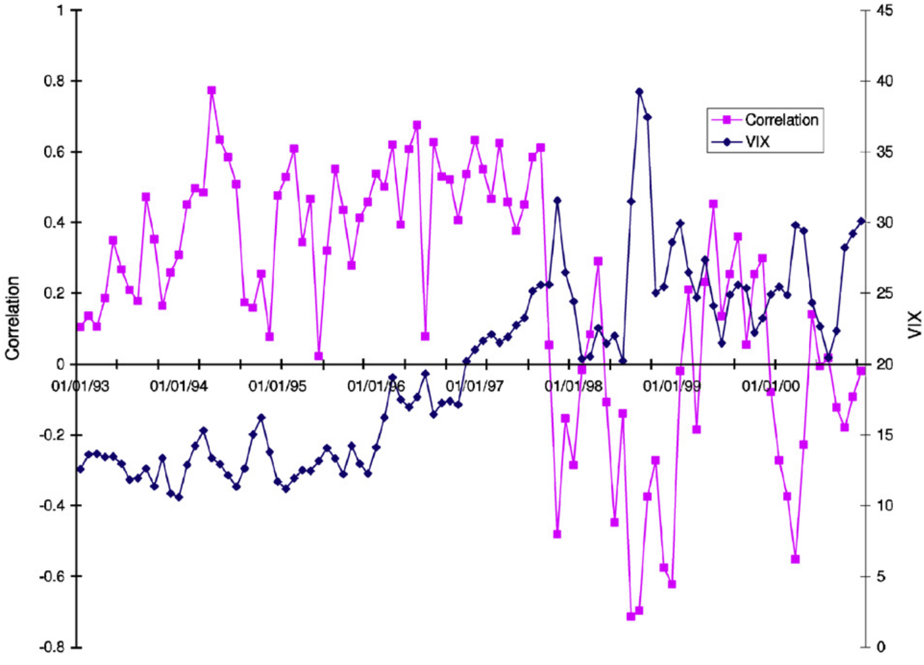

Fig. 1. Stock–Bond return correlation, VIX. This figure shows the average monthly value of the CBOE VIX index and the monthly correlation between 15-min returns on the S&P 500 stocks and an equally weighted portfolio of the 2-year, 5-year, and 10-year Treasury notes.

(on-the-run). This is in sharp contrast to the correlations in the high uncertainty period, where VIX is above 25. Here the cross-market correlations are all negative and significant, and similar in absolute value to the positive correlations in the low uncertainty period. S&P 500 order flow exhibits the strongest correlation with the on-the-run Treasuries (-0.213) while the correlation with the off-the-run Treasuries is -0.088. In periods of moderate uncertainty, the correlation between stock and bond order flows is positive and also significantly different from 0. These results support the notion that investors do practice cross-market hedging in the sense of Connolly et al. (2005) and Fleming et al. (1998).

4.1. The information content of order flow

Having established the order flow patterns documented in the previous section, I now test whether order flow conveys information that is relevant in explaining returns across markets. If, for example, a fixed income trader is in communication with his firm's equity trading desk, then it is likely that he gleans useful information from equity order flow about changing preferences of the aggregate investor population that is helpful in pricing Treasuries. This does not depend on his observing a perfect signal of cross-market order flow, only on his observing some aspect of trading activity that is relevant in a macroeconomic sense. For example, heavy selling of equities could signal that either (a) the aggregate risk aversion of the investor population is increasing or (b) investors' perception of the riskiness of equities is increasing.

Table 2
Order flow correlations

	Non-S&P 500	On-the-run Treasury	Off-the-run Treasury
Panel A: $VIX \leqslant 20$			
S&P 500	0.457	0.225	0.180
	(0.000)	(0.000)	(0.000)
Non-S&P 500		0.135	0.133
		(0.000)	(0.000)
On-the-run Treasury			0.469
			(0.000)
Panel B: $20 < VIX < 25$			
S&P 500	0.573	0.080	0.076
	(0.000)	(0.000)	(0.000)
Non-S&P 500		0.047	0.038
		(0.000)	(0.000)
On-the-run Treasury			0.289
			(0.000)
Panel C: $VIX \geqslant 25$			
S&P 500	0.577	−0.213	−0.088
	(0.000)	(0.000)	(0.000)
Non-S&P 500		−0.180	−0.118
		(0.000)	(0.000)
On-the-run Treasury			0.292
			(0.000)

This table presents correlations between order flows for the S&P 500, non-S&P 500 stocks, On-the-run Treasuries, and Off-the-run Treasuries. *P*-values for the test of $H_0 : \rho = 0$ are given in parentheses.

Table 3 presents results by subsample (high, moderate, or low VIX). Across the board, there is a very strong contemporaneous relation between own-market order flow and returns. The coefficient for on-the-run order flow in the Treasury return equation is always between 0.60 and 0.63 and highly significant across all three volatility regimes. For the S&P 500 return equation, S&P 500 order flow is also shown to be important, with coefficient estimates ranging from 0.47 to 0.61, and again highly significant T-statistics. These results for aggregate own-market order flow are consistent with Fleming (2003) and Brandt and Kavajecz (2004) from the Treasury market, and Chordia et al. (2002) for the equity market. Turning to other own-market order flow, we see that off-the-run Treasury order flow plays a non-trivial role in explaining on-the-run returns. While the coefficient estimate is about 20% of the on-the-run coefficient estimate, the variable is highly significant across volatility regimes. Thus while it is true that on-the-run order flow dominates off-the-run order flow in explaining off-the-run returns (see Brandt and Kavajecz, 2004), it is also true that off-the-run order flow plays a significant role in explaining the returns of on-the-run securities. In addition, the S&P 500 return regressions show that non-S&P 500 order imbalances help to explain S&P 500 returns, with positive and significant coefficient estimates. This result is also consistent with Harford and Kaul (2005), who find a large role for non-S&P 500 trading in explaining returns of individual S&P stocks. All of these results are consistent across uncertainty regimes, indicating that aggregate trading activity in both markets does contribute to own-market price discovery throughout the sample.

Table 3
Baseline system of equations

Dependent variable	Intercept	R_{On}	$R_{\text{S\&P}}$	OF_{On}	OF_{Off}	$OF_{\text{S\&P}}$	OF_{Non}	Adj. R^2
				Panel A: $VIX \leqslant 20$				
Treasury return	−0.001		0.150	0.601	0.136	0.032		0.535
	(−0.270)		(4.106)	(115.9)	(24.16)	(1.469)		
S&P 500 return	0.001	0.510		−0.259		0.472	0.120	0.372
	(0.299)	(13.06)		(−9.65)		(63.07)	(20.65)	
				Panel B: $20 < VIX < 25$				
Treasury return	−0.002		0.062	0.622	0.116	0.026		0.468
	(−0.280)		(1.345)	(94.07)	(17.25)	(0.792)		
S&P 500 return	−0.007	0.167		−0.086		0.601	0.166	0.542
	(−1.29)	(3.222)		(−2.48)		(75.27)	(23.39)	
				Panel C: $VIX \geqslant 25$				
Treasury return	−0.000		−0.236	0.631	0.119	0.068		0.468
	(−0.005)		(−5.12)	(76.46)	(15.27)	(2.033)		
S&P 500 return	0.008	0.119		−0.115		0.607	0.199	0.501
	(1.185)	(1.796)		(−2.54)		(60.34)	(20.95)	

This table presents two stage least squares (2SLS) estimation results for the following system:

$$R_{\text{On},t} = \beta_0 + \beta_1 R_{\text{S\&P},t} + \beta_2 OF_{\text{On},t} + \beta_3 OF_{\text{Off},t} + \beta_4 OF_{\text{S\&P},t} + \varepsilon_t$$

$$R_{\text{S\&P},t} = \gamma_0 + \gamma_1 R_{\text{On},t} + \gamma_2 OF_{\text{S\&P},t} + \gamma_3 OF_{\text{Non},t} + \gamma_4 OF_{\text{On},t} + v_t$$

where $R_{\text{On},t}$ is the equally weighted return on a portfolio of the three on-the-run Treasuries, $OF_{\text{On},t}$ represents net order flow in those on-the-run Treasuries, $OF_{\text{Off},t}$ is order flow in the off-the-run Treasuries, $R_{\text{S\&P},t}$ is the return on the equal-weighted portfolio of S&P 500 stocks, $OF_{\text{S\&P},t}$ is the order flow in the S&P 500 stocks, and $OF_{\text{Non},t}$ is the net order flow in the non-S&P 500 stocks. T-statistics are given in parentheses.

I next examine the role for cross-market variables, testing the basic hypothesis that *any* information from across markets is useful for explaining returns once we account for own-market order flow. While we know from the correlation results that returns in the two markets are correlated, it is less clear whether these cross-market returns actually contain any meaningful information beyond that contained in own-market order flow. The results show that cross-market returns are indeed important. First, looking at the Treasury return equation, in two of the three volatility regimes the coefficient on S&P 500 returns is statistically significant at the 1% level. Not surprisingly, the sign of the relation changes depending on market uncertainty levels. Panels A and B show that when VIX is less than 25, equity returns are positively related to Treasury returns, while when VIX is greater than 25, the relation is negative. Furthermore, the magnitude of the relation, both in terms of coefficient size and statistical significance, is greatest at the two extremes. Turning to the S&P 500 return equation, the results are similar in nature, but without the change in sign. After controlling for the endogeneity of Treasury returns, the coefficient estimate for Treasury returns is positive in all three cases, although it is only significant in the low and medium VIX subsamples.

Given that cross-market equity returns are informative about Treasury returns in the presence of Treasury order flows, I now turn to the central question of the paper: does aggregate order flow provide useful information about returns in another market, even in the presence of cross-market returns? Examining the Treasury return equations, it appears that S&P 500 order flow is positively related to Treasury returns in all three samples, although the coefficient estimate is only significant in the high-VIX subsample. Furthermore, the magnitude of the coefficients is rather small, ranging from 0.026 to 0.068. This suggests that a one standard deviation shock to S&P order flow is related to at most a 0.068 standard deviation change in Treasury returns, after controlling for the effect of Treasury order flow and S&P returns. The results for the cross-market information content of on-the-run Treasury order flow are quite different. In all three cases, Treasury order flow is significantly related to S&P 500 returns, with a negative sign. The coefficient estimates range from -0.086 (medium VIX) to -0.259 (low volatility), indicating that money flowing out of Treasuries is related to higher S&P returns, after controlling for equity order flow and Treasury returns.

These results indicate that buying and selling pressure in the Treasury market is informative about equity returns across regimes, while equity order flow exhibits a much weaker relation with Treasury returns. Note that the net effect of cross-market returns and cross-market order flows generally follows the pattern that we see in the order flow correlations in Table 2. When the coefficients on S&P returns and order flows in the Treasury return equations are summed, the total is positive in the low volatility period and negative in the high volatility sample. A similar result holds for the S&P return equations, where the net effect of Treasury returns and order flow are positive in the low VIX sample and close to zero in the high VIX sample. But importantly, the results show that Treasury order flow is consistently negatively related to S&P 500 returns. Money flowing into Treasuries may suggest a marginal flight to quality, and hence lower valuations for stocks. The positive coefficient on S&P order flow in the Treasury return equation is only marginally significant in the high VIX subsample, and suggests that money flowing into equities may be, after controlling for other factors, suggestive of increased levels of flows into both markets.[11]

Connolly et al. (2005) also show that *changes* in VIX are useful in explaining the correlation between stock and bond returns. Intuitively, when equity market uncertainty increases, many investors move assets from riskier stocks to Treasury bonds, leading to the observed negative correlation. If market participants are gathering information about marketwide risk preferences from trading in the other market, then periods of sharply increasing equity uncertainty should be associated with an increase in the importance of cross-market order flow. Furthermore, this would suggest that on such days cross-market order flow would be more negatively related to returns. To test this hypothesis, I repeat the estimation of Table 3, this time including an interaction term associated with days when VIX changes by 10% or more.[12] This corresponds to days which fall above the 95th percentile in the distribution of VIX changes during the sample. The equation

[11]In separate results, not reported, I consider the cross-market roles of order imbalances in (a) non-S&P 500 stocks and (b) off-the-run Treasuries. Here I reestimate the system of equations, but in the Treasury equation I exclude S&P 500 order flow, and in the equity return equation I exclude on-the-run Treasury order flow. In both cases, the coefficient estimates for the cross-market order flow variables are much smaller than those presented in Table 3, although in some cases the coefficients are still significant. For the remainder of the analysis, I will focus on S&P 500 stocks and on-the-run Treasuries as the primary carriers of cross-market information.

[12]Here, a 10% increase means, for example, an increase from 15% to 16.50% in the level of VIX.

system becomes

$$R_{\mathrm{On},t} = \beta_0 + \beta_1 R_{\mathrm{S\&P},t} + (\beta_2 + \beta_2^* D)OF_{\mathrm{On},t} + (\beta_3 + \beta_3^* D)OF_{\mathrm{Off},t} + (\beta_4 + \beta_4^* D)OF_{\mathrm{S\&P},t} + \varepsilon_t \quad (4)$$

$$R_{\mathrm{S\&P},t} = \gamma_0 + \gamma_1 R_{\mathrm{On},t} + (\gamma_2 + \gamma_2^* D)OF_{\mathrm{S\&P},t} + (\gamma_3 + \gamma_3^* D)OF_{\mathrm{Non},t} + (\gamma_4 + \gamma_4^* D)OF_{\mathrm{On},t} + v_t \quad (5)$$

where D represents a dummy equal to 1 whenever the change in VIX from the previous day is greater than 10%. Table 4 shows the results. In periods of low and high volatility, the interaction term on the cross-market order flow variable is negative and significant in all four cases; i.e., cross-market order imbalances on days with large increases in VIX are more negatively related to returns than on other days. For example, in the equity return equation in the low volatility subperiod, the overall size of the Treasury order flow coefficients when there is a spike in volatility jumps to −0.361 (−0.257−0.104). In the high volatility subperiod, the magnitude of the Treasury order flow coefficients nearly doubles, to −0.197 (−0.107−0.090). Similar results hold for the cross-market importance of S&P 500 order flow. Notably, in the high volatility subperiod the net coefficient actually becomes negative on days of large changes in VIX, with the coefficient estimate on S&P order flow being −0.06 (0.079−0.139). These results indicate that both equity and Treasury order flow become much more important in a cross-market setting when equity uncertainty jumps sharply. When the risk aversion of equity investors increases sharply, or when equity investors revise upward their assessment of the riskiness of stocks, order flow is more informative about market discount rates. This is consistent with a flight to quality scenario where equity trading activity is particularly informative about such beliefs and preferences of investors (see, for example, Vayanos, 2004).

4.2. *Cross-sectional differences in information content*

Given that cross-market order imbalances contain important market-level information, I now look to refine our understanding of which trades are the most informative. This can provide important clues about the nature of the information being revealed by trading in the two markets. In this section I separate equity trading into categories based on (a) trader type and (b) sensitivity of the equity to discount rates. I then separate Treasury trading activity by maturity.

4.2.1. *Trader type*

If aggregate order imbalances are bringing together dispersed bits of information about the characteristics of the investor population, then there may be a distinct difference between the information revealed by the trading of individuals versus that of institutions. It could be the case that institutional order flow contains a systematic component that reduces its usefulness in revealing such information. Alternatively, it could be the case that institutional trading actually reveals such information more quickly since institutions are rapidly aggregating information about their customer population.

While one cannot perfectly identify the originator of trades using the TAQ database, Lee and Radhakrishna (2000) use the TORQ database to provide useful guidelines on classifying TAQ trades as being initiated by either individuals or institutions. Since the firms in my sample are all large in size, I consider all trades below $10,000 (in 1991 dollars)

Table 4
Baseline system of equations with interaction term

Dependent variable	Intercept	R_{On}	$R_{\text{S\&P}}$	OF_{On}	$D*OF_{\text{On}}$	OF_{Off}	$D*OF_{\text{Off}}$	$OF_{\text{S\&P}}$	$D*OF_{\text{S\&P}}$	OF_{Non}	$D*OF_{\text{Non}}$	Adj. R^2
					Panel A: $VIX \leqslant 20$							
Treasury return	−0.001		0.154	0.597	0.155	0.136	−0.014	0.032	−0.048			0.536
	(−0.289)		(4.183)	(113.6)	(5.051)	(23.81)	(−0.465)	(1.472)	(−2.23)			
S&P 500 return	0.002	0.511		−0.257	−0.104			0.469	0.061	0.119	0.006	0.372
	(0.356)	(13.09)		(−9.62)	(−3.15)			(61.79)	(1.934)	(20.09)	(0.207)	
					Panel B: $20 < VIX < 25$							
Treasury return	−0.002		0.063	0.622	−0.002	0.114	0.042	0.027	−0.008			0.468
	(−0.276)		(1.345)	(91.97)	(−0.057)	(16.46)	(1.323)	(0.804)	(−0.285)			
S&P 500 return	−0.006	0.158		−0.079	−0.008			0.599	0.059	0.162	0.057	0.543
	(−1.06)	(3.069)		(−2.31)	(−0.307)			(73.85)	(1.713)	(22.26)	(1.787)	
					Panel C: $VIX \geqslant 25$							
Treasury return	−0.004		−0.224	0.619	0.099	0.117	0.005	0.079	−0.139			0.474
	(−0.521)		(−4.84)	(72.69)	(3.685)	(14.30)	(0.206)	(2.380)	(−5.98)			
S&P 500 return	0.011	0.124		−0.107	−0.090			0.601	0.039	0.190	0.049	0.502
	(1.563)	(1.848)		(−2.40)	(−3.39)			(59.28)	(1.341)	(19.43)	(1.841)	

This table presents two stage least squares (2SLS) estimation results for the following system:

$$R_{\text{On},t} = \beta_0 + \beta_1 R_{\text{S\&P},t} + (\beta_2 + \beta_2^* D)OF_{\text{On},t} + (\beta_3 + \beta_3^* D)OF_{\text{Off},t} + (\beta_4 + \beta_4^* D)OF_{\text{S\&P},t} + \varepsilon_t$$

$$R_{\text{S\&P},t} = \gamma_0 + \gamma_1 R_{\text{On},t} + (\gamma_2 + \gamma_2^* D)OF_{\text{S\&P},t} + (\gamma_3 + \gamma_3^* D)OF_{\text{Non},t} + (\gamma_4 + \gamma_4^* D)OF_{\text{On},t} + v_t$$

where $R_{\text{On},t}$ is the equally weighted return on a portfolio of the three on-the-run Treasuries, $OF_{\text{On},t}$ represents net order flow in those on-the-run Treasuries, $OF_{\text{Off},t}$ is order flow in the off-the-run Treasuries, $R_{\text{S\&P},t}$ is the return on the equal-weighted portfolio of S&P 500 stocks, $OF_{\text{S\&P},t}$ is the order flow in the S&P 500 stocks, and $OF_{\text{Non},t}$ is the net order flow in the non-S&P 500 stocks. D is a dummy equal to one if the change in the VIX index that day is in the upper 5% of VIX changes during the sample period. T-statistics are given in parentheses.

Table 5
Varying equity trade size

Dependent variable	Intercept	R_{On}	$R_{\text{S\&P}}$	OF_{On}	OF_{Off}	$OF_{\text{S\&P}}$		OF_{Non}		Adj. R^2
						Ind.	Inst.	Ind.	Inst.	
					Panel A: $VIX \leqslant 20$					
Treasury return	−0.001		0.060	0.606	0.141	0.031	0.065			0.538
	(−0.222)		(1.134)	(116.8)	(24.99)	(4.073)	(2.010)			
S&P 500 return	0.002	0.376		−0.190		0.096	0.520	0.015	0.085	0.459
	(0.386)	(10.39)		(−7.68)		(17.81)	(72.05)	(3.077)	(15.65)	
					Panel B: $20 < VIX < 25$					
Treasury return	−0.002		0.073	0.622	0.115	−0.005	0.021			0.468
	(−0.294)		(1.148)	(93.26)	(17.21)	(−0.332)	(0.505)			
S&P 500 return	−0.015	0.111		−0.050		0.165	0.554	0.022	0.112	0.588
	(−2.78)	(2.248)		(−1.52)		(23.75)	(65.44)	(3.581)	(16.42)	
					Panel C: $VIX \geqslant 25$					
Treasury return	0.002		−0.373	0.627	0.120	0.052	0.136			0.453
	(0.315)		(−4.13)	(71.22)	(14.94)	(2.461)	(2.510)			
S&P 500 return	0.015	0.132		−0.118		0.210	0.535	0.029	0.095	0.531
	(2.102)	(2.036)		(−2.66)		(22.27)	(46.92)	(3.437)	(10.41)	

This table presents two stage least squares (2SLS) estimation results for the following system:

$$R_{\text{On},t} = \beta_0 + \beta_1 R_{\text{S\&P},t} + \beta_2 OF_{\text{On},t} + \beta_3 OF_{\text{Off},t} + \beta_4 OF_{\text{S\&P(Ind.)},t} + \beta_5 OF_{\text{S\&P(Inst.)},t} + \varepsilon_t$$

$$R_{\text{S\&P},t} = \gamma_0 + \gamma_1 R_{\text{On},t} + \gamma_2 OF_{\text{S\&P(Ind.)},t} + \gamma_3 OF_{\text{S\&P(Inst.)},t} + \gamma_4 OF_{\text{Non(Ind.)},t} + \gamma_5 OF_{\text{Non(Inst.)},t} + \gamma_6 OF_{\text{On},t} + v_t$$

where $R_{\text{On},t}$ is the equally weighted return on a portfolio of the three on-the-run Treasuries, $OF_{\text{On},t}$ represents net order flow in those on-the-run Treasuries, $OF_{\text{Off},t}$ is order flow in the off-the-run Treasuries, $R_{\text{S\&P},t}$ is the return on the equal-weighted portfolio of S&P 500 stocks, $OF_{\text{S\&P},t}$ (Ind., Inst.) is the order flow in the S&P 500 stocks for trades likely initiated by individuals or institutions, and $OF_{\text{Non},t}$ (Ind., Inst.) is the net order flow in the non-S&P 500 stocks likely initiated by individuals or institutions. Individual trades are those smaller than \$10,000 in 1991 dollars, while institutional trades are those larger than \$50,000 in 1991 dollars. *T*-statistics are given in parentheses.

to be initiated by individuals, and all trades above \$50,000 (in 1991 dollars) to be initiated by institutions. Lee and Radhakrishna (2000) show that using an individual cutoff of \$10,000 results in 16% of institutional trades being misclassified as individual for large firms. The cutoff of \$50,000 results in 3% of individual trades being misclassified as institutional. Using more stringent cutoffs on either group would obviously reduce the number of misclassifications, but it would also sharply reduce the number of trades correctly classified.[13]

To test for differences related to the parties behind the trades, I repeat the estimation of the system shown in Eqs. (1) and (2), but now split equity order flow into individual and institutional trades. The results are displayed in Table 5, and show that there are large differences in the cross-market information content of individual and institutional trades. While both trade-size groups have significant coefficient estimates in the low and high volatility subsamples, the estimates for institutional trades are generally at least twice as large as those

[13]This is especially true if one reduces the individual cutoff from \$10,000 to \$5,000, as the fraction of individual-initiated trades captured falls from 61% to 31%.

for trades initiated by individuals. Tests of the null hypothesis that the coefficients are equal are rejected at the 1% level in both cases. Thus the results here indicate that institutional trades are the most closely related to Treasury returns. However, the coefficient estimates for small trades are still significant in two of three cases, indicating that trades likely initiated by individuals do contain information distinct from that in institutional trades.

4.2.2. Sensitivity to discount rates

Campbell and Vuolteenaho (2004) decompose stock betas into two components: one which measures a stock's sensitivity to the market's cash flows, and one which measures the stock's sensitivity to market discount rates. They call the cash flow beta a "bad" beta and the discount rate beta a "good" beta, since the cash flow beta commands a higher premium. The authors find that small and value stocks have higher cash-flow betas, thus potentially explaining the poor performance of the CAPM.

If fixed income traders are indeed learning about discount rates from trading activity in the equity market, then it should be the case that Treasury returns are more strongly related to trading in stocks with high discount rate betas. To test for this, I break the stocks into quintiles based on their book-to-market ratios for the previous year. Firms in the highest book-to-market quintile are considered a "value" portfolio, while firms in the lowest quintile make up a "growth" portfolio.[14] The tests are similar in nature to those in the previous section, except that now rather than varying the equity order flows based on trade size, here the equity order flows are based on the value versus growth portfolios.

Table 6 presents results of these regressions. In the low and medium VIX subperiods, it appears that order imbalances in value stocks are slightly more informative than in growth stocks. For example, the cross-market coefficient estimate for growth stock order imbalances in Panel A is 0.020, while the coefficient estimate for value stock order flow is 0.027, although the difference between these two coefficients is not significant. In the high VIX subperiod, the relationship changes: here growth stock trading appears to convey more information about Treasury returns than value stock trading. However, once again the difference in coefficients is not statistically significant.

While the results in Table 6 do not provide strong evidence about which stocks convey the most information, recall that Table 5 showed that institutional trades are much more strongly related to Treasury returns than are individual trades. I thus repeat the analysis of Table 6, but this time only include order flows from large equity trades. The results are presented in Table 7. Here the results paint a somewhat different picture. In both low and high VIX periods, growth stock trading is more informative than value stock trading. In the high VIX subsample, the difference between the coefficients is significant at the 5% level. Thus when one considers only the most informative trades likely initiated by institutions, there does appear to be more of a difference in the cross-market information content of order imbalances in growth and value stocks.

Overall, these results provide interesting evidence on the varying information content of equity order flow. There is clearly variation in the relative role of growth and value order imbalances that is related to equity uncertainty. In both the overall and large trade analyses, growth stock order flow becomes more informative in a cross-market sense as VIX increases. In some aspects this is consistent with a standard "flight-to-quality" story

[14] Since the firms in this sample are all in the universe of large firms, forming portfolios based on size is not likely to produce a meaningful difference in cross-market informativeness.

Table 6
Varying market-to-book ratio

Dependent variable	Intercept	R_{Treas}	$R_{\text{S\&P}}$	OF_{On}	OF_{Off}	$OF_{\text{S\&P}}$		OF_{Non}		Adj. R^2
						Growth	Value	Growth	Value	
Panel A: $VIX \leqslant 20$										
Treasury return	−0.001		0.113	0.607	0.140	0.020	0.027			0.535
	(−0.240)		(3.787)	(115.4)	(25.91)	(1.862)	(2.389)			
S&P 500 return	0.002	0.526		−0.252		0.275	0.283	0.116	0.062	0.373
	(0.333)	(13.70)		(−9.43)		(43.48)	(43.82)	(21.72)	(11.65)	
Panel B: $20 < VIX < 25$										
Treasury return	−0.003		−0.018	0.625	0.117	0.035	0.052			0.467
	(−0.421)		(−0.275)	(92.40)	(17.36)	(1.076)	(2.219)			
S&P 500 return	−0.011	0.156		−0.073		0.434	0.303	0.076	0.063	0.578
	(−2.07)	(3.139)		(−2.21)		(55.44)	(38.48)	(12.54)	(10.25)	
Panel C: $VIX \geqslant 25$										
Treasury return	0.001		−0.370	0.626	0.121	0.100	0.074			0.454
	(0.171)		(−4.43)	(72.87)	(14.94)	(2.471)	(2.486)			
S&P 500 return	0.011	0.175		−0.136		0.430	0.327	0.081	0.059	0.540
	(1.538)	(2.691)		(−3.09)		(38.69)	(31.88)	(9.863)	(7.012)	

This table presents two stage least squares (2SLS) estimation results for the following system:

$$R_{\text{On},t} = \beta_0 + \beta_1 R_{\text{S\&P},t} + \beta_2 OF_{\text{On},t} + \beta_3 OF_{\text{Off},t} + \beta_4 OF_{\text{S\&P(Growth)},t} + \beta_5 OF_{\text{S\&P(Value)},t} + \varepsilon_t$$

$$R_{\text{S\&P},t} = \gamma_0 + \gamma_1 R_{\text{On},t} + \gamma_2 OF_{\text{S\&P(Growth)},t} + \gamma_3 OF_{\text{S\&P(Value)},t} + \gamma_4 OF_{\text{Non(Growth)},t} + \gamma_5 OF_{\text{Non(Value)},t} + \gamma_6 OF_{\text{On},t} + v_t$$

where $R_{\text{On},t}$ is the equally weighted return on a portfolio of the three on-the-run Treasuries, $OF_{\text{On},t}$ represents net order flow in those on-the-run Treasuries, and $OF_{\text{Off},t}$ is order flow in the off-the-run Treasuries. $R_{\text{S\&P},t}$ is the return on the equal-weighted portfolio of S&P 500 stocks, $OF_{\text{S\&P(Growth)},t}$ is the order flow in the S&P 500 stocks in the top quintile when ranked by market to book ratios, and $OF_{\text{S\&P(Value)},t}$ is the order flow in the S&P 500 stocks in the bottom quintile when ranked by market to book ratios. $OF_{\text{Non(Growth)},t}$ is the net order flow in the non-S&P 500 stocks in the top market to book quintile, and $OF_{\text{Non(Value)},t}$ is the net order flow in the bottom market to book quintile. *T*-statistics are given in parentheses.

as in Beber et al. (2007): when the uncertainty about equity risk is highest, order flows in risky growth stocks are particularly informative about Treasury returns. However, the sign on the order flow coefficient is positive, suggesting that once one controls for the endogeneity of equity returns, money flowing into growth stocks is actually related to higher returns for Treasuries.

4.2.3. Varying treasury maturity

As a final step in better understanding the cross-market information content of order imbalances, I return to Treasury order flow. The results in Table 3 show that Treasury trading exhibits a strong and consistent relationship with equity returns. Here I ask whether a certain area of the yield curve is more closely related to stock returns than others.

Brandt and Kavajecz (2004) show that order flow in the 2–5 year range of the yield curve dominates in terms of price discovery within the Treasury market. I test whether this is true in a cross-market sense as well by separating the Treasury order flow into two, five, and ten

Table 7
Varying market-to-book ratio for institutional trades

Dependent variable	Intercept	R_{On}	$R_{S\&P}$	OF_{On}	OF_{Off}	$OF_{S\&P}$		OF_{Non}		Adj. R^2
						Growth	Value	Growth	Value	
				Panel A: $VIX \leqslant 20$						
Treasury return	−0.001		0.105	0.607	0.141	0.030	0.020			0.534
	(−0.233)		(3.060)	(113.6)	(25.65)	(2.040)	(2.009)			
S&P 500 return	0.002	0.498		−0.238		0.348	0.213	0.080	0.080	0.352
	(0.429)	(12.79)		(−8.78)		(53.91)	(35.43)	(15.30)	(15.16)	
				Panel B: $20 < VIX < 25$						
Treasury return	−0.001		0.095	0.622	0.115	−0.002	0.006			0.467
	(−0.224)		(1.704)	(93.53)	(17.00)	(−0.075)	(0.397)			
S&P 500 return	−0.017	0.167		−0.086		0.486	0.223	0.073	0.084	0.510
	(−2.86)	(3.123)		(−2.42)		(62.09)	(29.93)	(11.51)	(13.25)	
				Panel C: $VIX \geqslant 25$						
Treasury return	0.001		−0.221	0.633	0.119	0.063	0.004			0.469
	(0.119)		(−2.89)	(72.25)	(15.38)	(1.494)	(0.194)			
S&P 500 return	0.018	0.118		−0.120		0.516	0.235	0.075	0.062	0.481
	(2.450)	(1.750)		(−2.60)		(52.66)	(24.62)	(9.407)	(7.612)	

This table presents two stage least squares (2SLS) estimation results for the following system:

$$R_{On,t} = \beta_0 + \beta_1 R_{S\&P,t} + \beta_2 OF_{On,t} + \beta_3 OF_{Off,t} + \beta_4 OF_{S\&P(Growth),t} + \beta_5 OF_{S\&P(Value),t} + \varepsilon_t$$

$$R_{S\&P,t} = \gamma_0 + \gamma_1 R_{On,t} + \gamma_2 OF_{S\&P(Growth),t} + \gamma_3 OF_{S\&P(Value),t} + \gamma_4 OF_{Non(Growth),t} + \gamma_5 OF_{Non(Value),t} + \gamma_6 OF_{On,t} + v_t$$

where $R_{On,t}$ is the equally weighted return on a portfolio of the three on-the-run Treasuries, $OF_{On,t}$ represents net order flow in those on-the-run Treasuries, and $OF_{Off,t}$ is order flow in the off-the-run Treasuries. $R_{S\&P,t}$ is the return on the equal-weighted portfolio of S&P 500 stocks, $OF_{S\&P(Growth),t}$ is the order flow in the S&P 500 stocks in the top quintile when ranked by market to book ratios, and $OF_{S\&P(Value),t}$ is the order flow in the S&P 500 stocks in the bottom quintile when ranked by market to book ratios. $OF_{Non(Growth),t}$ is the net order flow in the non-S&P 500 stocks in the top market to book quintile, and $OF_{Non(Value),t}$ is the net order flow in the bottom market to book quintile. For the analysis in this table, only large equity trades (those greater than \$50,000 in 1991 dollars) are considered in calculating equity order flow. T-statistics are given in parentheses.

year note order flow. The results are presented in Table 8. Across all three VIX regimes, the same general result holds: order imbalances in the five year note are most strongly related to S&P 500 returns. In the low and medium volatility regimes, the coefficient estimate for 5-year order flow is significantly different from both the 2-year and 10-year coefficient. Given also that this portion of the curve is most liquid (see Fleming, 2003), it is not surprising that trading in this area of the curve is most revealing about marketwide factors affecting values in both markets. Traders who are rebalancing portfolios between stocks and bonds are more likely to trade the 5-year note due to its deep liquidity. In addition, money flowing into bond portfolios which track the aggregate bond market would likely trade the 5-year note, since the effective duration of the Lehman Brothers aggregate bond index is typically between 4 and 5 years.

Taken together, the results in this section point to important cross-sectional differences in the stock–bond relation that help us better understand how dispersed, macro-level information is incorporated into stock and bond prices. While institutional trades in the

Table 8
Varying treasury maturity

Dependent variable	Intercept	R_{On}	$R_{\text{S\&P}}$	OF_{On}			OF_{Off}			$OF_{\text{S\&P}}$	OF_{Non}	Adj. R^2
				2-year	5-year	10-year	2-year	5-year	10-year			
					Panel A: $VIX \leqslant 20$							
Treasury return	−0.001		0.142	0.200	0.312	0.233	0.084	0.074	0.032	0.031		0.546
	(−0.271)		(3.884)	(39.29)	(57.92)	(46.24)	(16.35)	(15.47)	(7.176)	(1.422)		
S&P 500 return	0.001	0.554		−0.091	−0.155	−0.113				0.469	0.119	0.367
	(0.295)	(14.15)		(−8.14)	(−10.2)	(−9.75)				(63.26)	(20.21)	
					Panel B: $20 < VIX < 25$							
Treasury return	−0.002		0.050	0.221	0.319	0.235	0.115	0.055	0.022	0.027		0.481
	(−0.356)		(1.101)	(30.80)	(42.38)	(32.70)	(16.93)	(8.352)	(3.440)	(0.822)		
S&P 500 return	−0.007	0.201		−0.034	−0.071	−0.032				0.599	0.166	0.540
	(−1.26)	(4.644)		(−2.71)	(−4.34)	(−2.53)				(77.83)	(23.34)	
					Panel C: $VIX \geqslant 25$							
Treasury return	0.001		−0.225	0.264	0.319	0.210	0.104	0.063	0.017	0.064		0.478
	(0.076)		(−4.93)	(30.14)	(36.08)	(24.89)	(13.04)	(8.075)	(2.216)	(1.926)		
S&P 500 return	0.008	0.071		−0.030	−0.041	−0.038				0.603	0.196	0.505
	(1.163)	(1.236)		(−1.57)	(−1.93)	(−2.44)				(62.59)	(21.12)	

This table presents two stage least squares (2SLS) estimation results for the following system:

$$R_{\text{On},t} = \beta_0 + \beta_1 R_{\text{S\&P},t} + \beta_2 OF_{\text{On(2)},t} + \beta_3 OF_{\text{On(5)},t} + \beta_4 OF_{\text{On(10)},t} + \beta_5 OF_{\text{Off(2)},t} + \beta_6 OF_{\text{Off(5)},t} + \beta_7 OF_{\text{Off(10)},t} + \beta_8 OF_{\text{S\&P},t} + \varepsilon_t$$

$$R_{\text{S\&P},t} = \gamma_0 + \gamma_1 R_{\text{On},t} + \gamma_2 OF_{\text{S\&P},t} + \gamma_3 OF_{\text{Non},t} + \gamma_4 OF_{\text{On(2)},t} + \gamma_5 OF_{\text{On(5)},t} + \gamma_6 OF_{\text{On(10)},t} + v_t$$

where $R_{\text{On},t}$ is the equally weighted return on a portfolio of the three on-the-run Treasuries, $OF_{\text{On},t}$ (2,5,10) represents net order flow in the three separate on-the-run Treasuries, and $OF_{\text{Off},t}$ (2,5,10) is order flow in the off-the-run Treasuries. $R_{\text{S\&P},t}$ is the return on the equal-weighted portfolio of S&P 500 stocks, $OF_{\text{S\&P},t}$ is the order flow in the S&P 500 stocks, and $OF_{\text{Non},t}$ is the net order flow in the non-S&P 500 stocks. T-statistics are given in parentheses.

equity market are most strongly related to Treasury returns, individual trades also reveal unique information about the changing risk preferences or beliefs of the overall investor population. The time-varying nature of the relative roles of value and growth stock order flow suggests that trading in different types of stocks has different implications depending on the level of equity market uncertainty. Finally, trading in the intermediate portion of the yield curve is most informative about returns on S&P 500 stocks.

4.3. Robustness to end-of-day effects

Harford and Kaul (2005) find that order flow commonality in S&P 500 stocks is much more pronounced during the last hour of trading. For example, they report that the first principal component of order flow in S&P stocks explains 12% of variation from 9:30 to 3:00, but 18% in the 3:00–4:00 h. This increase in commonality is attributed to the tendency of mutual funds, especially index funds, to execute trades near the end of the day. To test whether the cross-market relations that I find in this paper are driven by end of day trading activity, I repeat the analysis of Table 3 with all intervals from 3:00 to 4:00 pm excluded. The results, available on request, suggest that end of day trading does have an impact on the findings. Equity order flow diminishes in cross-market importance when the last hour of trading is excluded. All of the cross-market coefficients are smaller in size, and the coefficient in the high VIX sample is no longer significant. At the same time, Treasury order flow is more strongly related to equity returns when the last hour of trading is excluded. The cross-market coefficient estimates for on-the-run order flow all become more negative, and increase in statistical significance. These results indicate that Treasury order flow is strongly related to equity returns throughout the day, while some of the cross-market importance of equity order flow can be attributed to trading in the last hour.

5. Conclusion

In this paper I investigate the informational content of aggregate order flows in the U.S. equity and Treasury markets. Aggregate Treasury order imbalances are strongly related to intraday equity returns, with the effect being most pronounced when equity market uncertainty is relatively low or high. The results also show that during high VIX periods, days of large increases in VIX are associated with a stronger relation between buying and selling pressure in Treasuries and returns on equities. Equity order flow, while statistically significant in some cases, plays a smaller role in explaining returns on Treasuries. These general findings are robust to controlling for the endogenously determined cross-market returns, indicating that aggregate order flow contains information that is distinct from that reflected in the return series. All of this suggests that aggregate trading activity in the stock and bond markets does contain the type of "private" information about macroeconomic factors suggested by Ito et al. (1998). It is important to note, however, that the results presented in this paper do not necessarily imply a causality running from cross-market order flow to returns. The results could merely reflect a strong correlation between order flow and returns in the two markets, and suggest that trading activity is correlated with some unobserved variable which influences price formation. But the results do lend some support to multi-security models of price formation such as Caballe and Krishnan (1994), which assume that the market maker observes order flows in all assets in the market and takes these flows into account in setting prices.

Cross-sectional evidence shows that trades initiated by institutions have the most cross-market information content. Thus institutional trades are not only the most informative at the firm level, but also at the market level. But the results also suggest that small trades—likely initiated by individual investors—provide an important signal of changing investor characteristics. I also find that interest rate sensitive growth stocks are generally more strongly related to Treasuries than are value stocks in periods of high uncertainty. Finally, I show that trading activity in the 5-year note is more closely related to equity returns than trading in the 2-year or 10-year notes.

My results also shed light on the role of cross-market hedging in the stock and bond markets. Connolly et al. (2005) suggest that ''times of high stock uncertainty are also times with more frequent revisions in investors' assessments of both stock risk and the relative attractiveness of stocks and bonds.'' They suggest that the resulting cross-market hedging leads to the prolonged periods of negative stock–bond correlation found in their study. I find evidence consistent with such cross-market hedging in intraday order flow data. Signed trades in a large sample of equities and on-the-run Treasuries are strongly negatively correlated in periods of higher uncertainty. This is in contrast to the positive correlation in periods of lower uncertainty.

Taken as a whole, these results provide important new evidence on the nature of joint stock–bond price formation and the information content of trading activity. Cross-market hedging is an important source of linkages between the stock and bond markets, and the resulting order imbalances in one market can have important pricing implications for securities across the two markets. But my results also show that the information content of aggregate order flows is substantial even during periods when cross-market hedging is not thought to be of first-order importance.

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