Order flow and prices

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Practical relevance

- Order flow and prices are dynamically related
  - measuring and managing price impact is essential for execution cost management
  - strategy changes will prompt other traders to change strategies as well
  - predicting the optimal strategy requires a good understanding of these dynamics, and our paper provides new result in this regard

Order flow moves prices

- Microstructure theory provides two reason for the price impact of order flow
  - inventory effects (e.g. Garman 1976, Stoll 1978, Ho & Stoll 1981)
  - Informed trading (e.g., Kyle 1985, Glosten & Milgrom 1985)
  - the basic prediction is robust to alternative assumptions about the trading game

- Empirical evidence uniformly supports this prediction

Details of order flow-price relation are not well understood

- Theory distinguishes
  - informed traders who move prices ‘permanently’
  - uninformed traders who trade for non-information reasons and have a transient effect on prices

- Trading strategy affects the order flow-price relationship
  - impatient traders trade aggressively and typically move prices significantly
  - patient traders choose to trade passively – they supply liquidity and ‘earn the spread’
  - strategies may depend on past returns, creating the dynamic relation

- Given that traders with different informedness and patience trade contemporaneously
  - what’s the equilibrium effect of trading on prices?
  - which order flow–return dynamics characterize this equilibrium?

This paper

- We use information on trader types to distinguish
  - informed and uninformed traders
  - liquidity providers and liquidity demanders
- Using the cross-section of stocks, we draw inferences from each type's order imbalance–price relationship
- We provide new insights into trading motives and into how and why trading activity affects prices

Recent empirical work on order imbalances (OIB)

- Studies of aggregate OIB
  - e.g. Chordia et al 2002, Griffin et al. 2005, Lee et al. 2004, Lipson & Puckett 2005
- Cross-sectional studies
  - Trade-based (TAQ) OIB are positively related to current and future returns (Chordia & Subrahmanyam 2004)
- Most related: cross-sectional studies distinguishing trader types
  - Nasdaq institutional investors chase returns (Griffin et al. 2003)
    →***we use cleaner trader type classification and a broader sample***
  - Individuals are contrarians and earn excess returns (Kaniel et al. 2004)
    →***same data set but different objective***

Data

- NYSE Consolidated Audit Trail Data (CAUD) contain buy and sell side components for each trade
  - Jan 2000 – April 2004
  - data aggregated daily for each symbol by trade direction and account type
  - differentiate trading by individuals, institutions (regular, program, index arbitrage program), specialists, and non-NYSE market makers

- Additional data from CRSP, Compustat, and TAQ

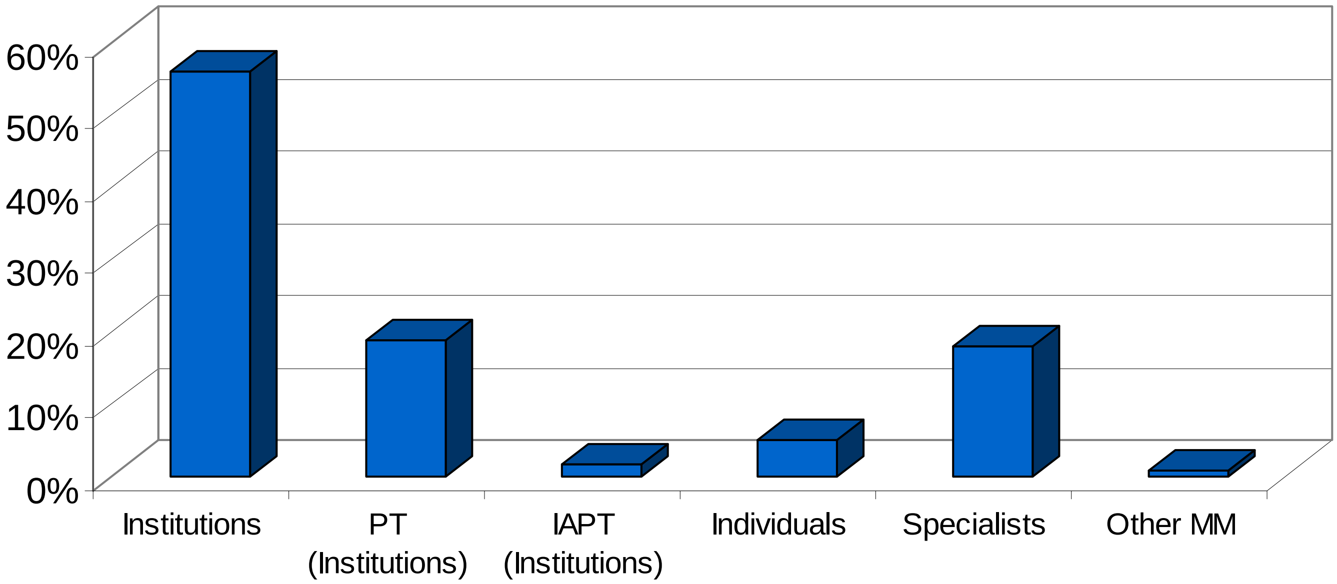
Trade-based vs CAUD-based OIB: Example

- An institution wants to buy 500,000 shares over the day
  - early in the day, it buys 300,000 shares from retail using limit orders
  - later submits market order and buys 200,000 from specialist
  - TAQ OIB (Lee & Ready) = –300,000 + 200,000 = -100,000
- We prefer actual OIB because informed traders may use both types of orders (Bloomfield et al 2005, Kaniel & Liu 2005)
  - OIB(institution) = 500,000
  - OIB(retail) = -300,000
  - OIB(specialist) = -200,000
- CAUD-based data provides richer and more accurate information based on actual OIB, compared to TAQ OIB

Sample and method

- Start with all equity securities on CRSP
  - select domestic, single-class, common stock
  - price between $1 and $999
  - at least 100 trading days
  - ➢ results in a sample of 1,300 different stocks
- Important: all security / market return measures are based on end-of-day quote midpoints
- We use three measures of OIB
  - number of trades, share volume, or dollar volume
  - all OIB measures are scaled by the corresponding total flow for that stock

Relative trading volume ($) by trader types



Empirical analysis

- We ask three main questions:
  - what determines OIB?
  - how do OIB affect prices contemporaneously?
  - do OIB predict future returns?

- Examine how results differ across trader types

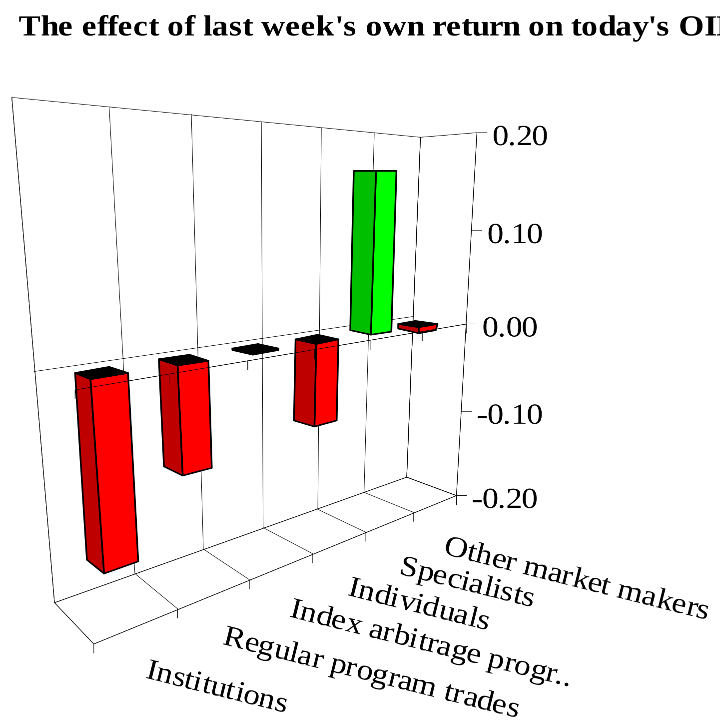
Method

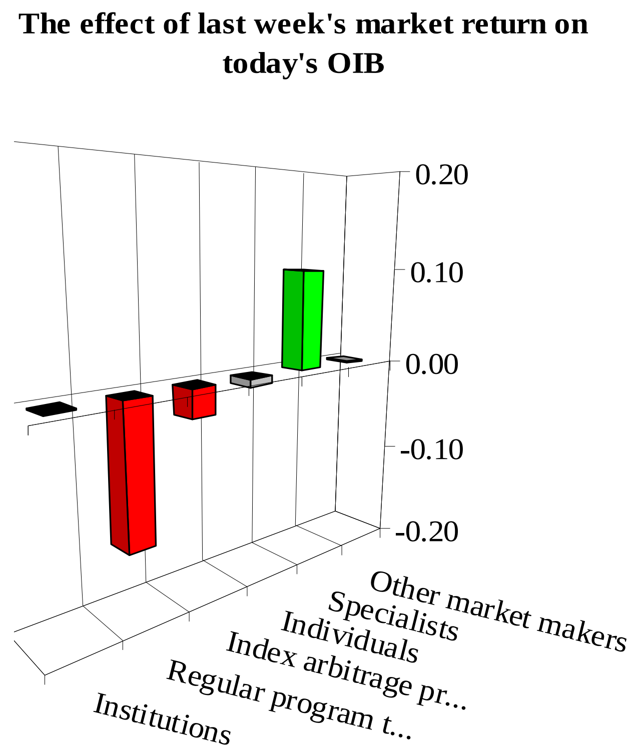
- Estimate daily time-series regressions for each stock
- Report cross-sectional mean coefficients (usually similar results for medians)
- Statistical significance measured in the cross-section of stocks (all standard errors are adjusted for cross-sectional correlations)
- Conduct a variety of robustness tests

1. What determines OIB?

- Know order flow is persistent
  - control for past OIB
- Know order flow depends on past returns
  - control for market returns Rm(t)
  - control for security returns R(t)
  - to differentiate between the effects of own and market returns, we orthogonalize R(t) w.r.t. to Rm(t)

Determinants of OIB
(mean coefficients, DV: scaled $OIB(t))





- Regression controls for past OIB, not sensitive to other specifications
- Traders are contrarians; specialist satisfies contrarian demand by others
- Market returns important for PT (non firm-level info)

Now are institutions contrarians or momentum traders?

- Griffin et al. 2003: institutions are momentum traders
  - Their sample covers Nasdaq 100 stocks during a period when market declined by 51%

- For large stocks in our broader sample, institutions trade contrarian w.r.t. R(i) but momentum w.r.t. R(m)

Regressions of OIB on past returns **Largest size quartile only** **Regular institutional trades only**	
Residual Ret (t-5, t-1)	**-0.0856**
Rm (t-5,t-1)	**0.0612**

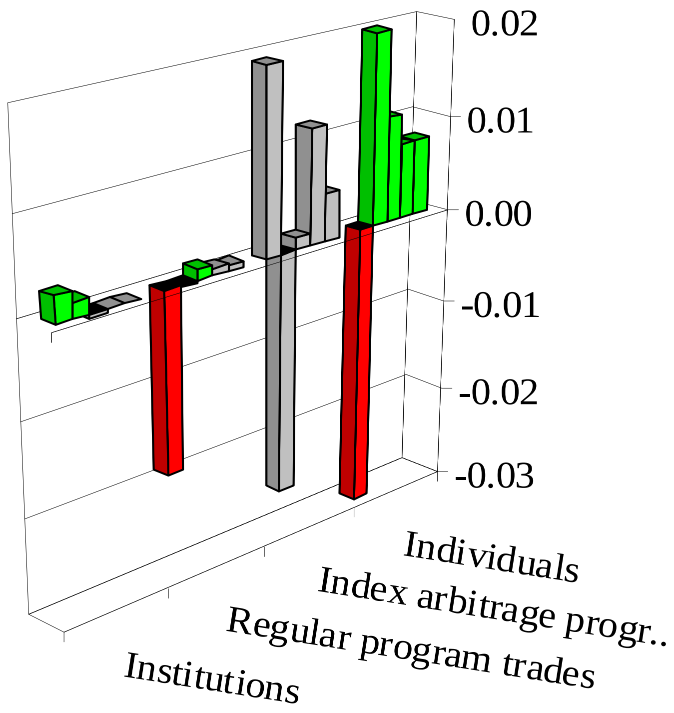
- This can explain Griffin's results if Nasdaq 100 returns are sufficiently correlated across component stocks

2. Price impact – how do OIB affect prices contemporaneously?

- Expect OIB of impatient / informed traders to be positively related to returns
- Expect OIB of patient / uninformed traders to be negatively related to returns

Price impact of scaled $OIB
(mean coefficients, DV: R(t))

The contemporaneous price impact of OIB



- Regression of R(t) on Rm(t), OIB(t) and four OIB lags
- Regular institutional OIB have positive price impact; program trades have negative coefficient
- Individual OIB have negative price impact, consistent with liquidity provision (as in Kaniel et al. 2004)
- Specialists supply liquidity as market makers (as in Hendershott & Seasholes 2006)
- Obtain almost identical results using only trading-period returns

Do institutional price impacts result from information traders have?

- If they are information effects, price impact coefficients (PICs) should be positively related to proxies for information asymmetry

- We regress institutional PICs on two sets of proxies for info asymmetry
  - intraday measures: ES = RS+0.5*PI and its components
  - accounting measures: R&D/sales, intangibles/TA

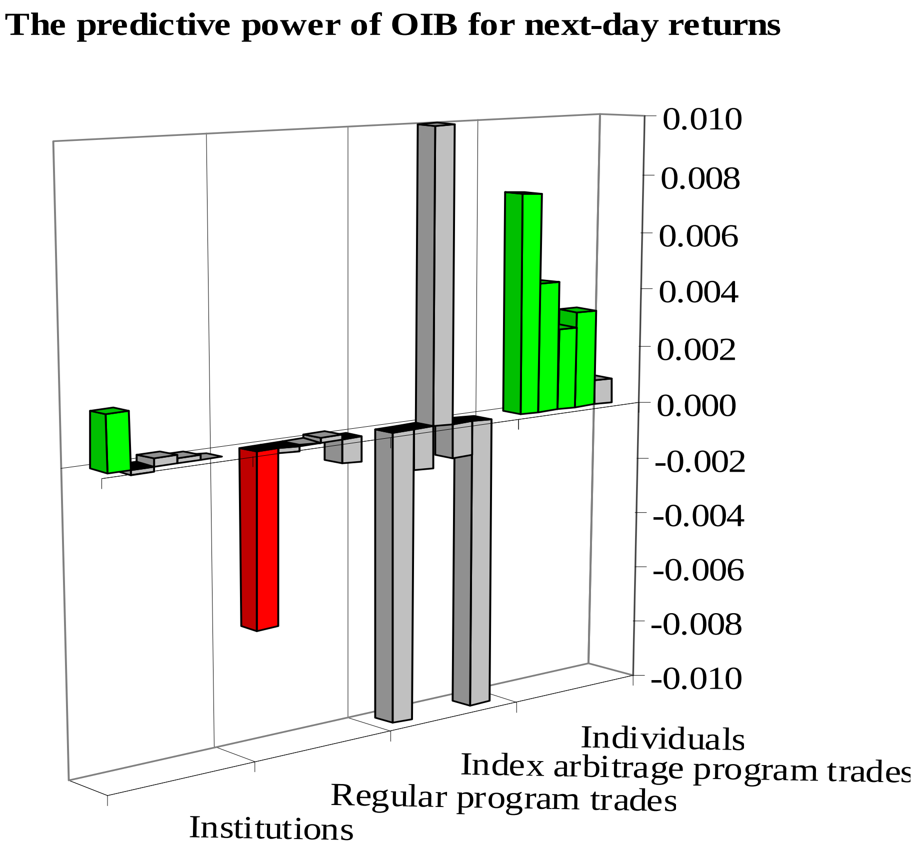
- Controlling for firm size, we find that institutional PICs
  - increase significantly with ES and in particular with its permanent component
  - increase significantly with RD/sales

- Evidence supports the argument that information drives the price impact of institutional OIB

3. Do OIB predict future returns?

- **Chordia & Subrahmanyam 2004:** aggregate OIB can predict next-day returns – which trader types can do this?
- **Kaniel et al. 2004**: retail OIB predict next week's return
- NB: trader type info is generally not observable to anyone

Return predictability
(Mean coefficients, DV: R(t))



- Regressions of R(t) on Rm(t) and five lags of OIB
- Regular institutional OIB predict returns (consistent with an information-related price impact)
- Individuals also predict returns correctly (as in Kaniel et al.)

Are retail traders as smart as institutions?

- Institutions have positive contemporaneous price impacts and predict R(t+1)
- Individuals have negative contemporanous price impact and also predict R(t+1)
- To reconcile, we divide the prediction period into a non-trading (overnight) and a trading period (am to pm on the next day)
  - only institutions predict returns during subsequent trading period
  - individuals experience a reversal overnight, consistent with a temporary effect associated with liquidity provision (as in Kaniel et al.)

More robustness checks

- OIB and returns across trader types are related
  - estimate SUR model
  - also allows us to explicitly incorporate restriction that OIB sum to zero in the aggregate
  - results are qualitatively identical for each of the three main tests

- We can view OIB and return processes as components of a VAR model
  - re-examine determinants of OIB and return predictability
  - inferences based on the VAR are consistent with the results reported in the paper

Conclusions

- Theory predicts that order flow affects prices
  - informed traders' OIB should be positively related to returns, but OIB of liquidity providers/uninformed should be negatively related to returns
- Results on trading motivation
  - institutions use regular trades when they are informed and hence move prices
  - institutions use program trades when they are not informed
  - together with individuals and market makers, program traders provide liquidity to active institutional traders
- Results on price impact
  - institutional OIB have positive price impacts, apparently resulting form information, and they predict next-day returns
  - individuals and program traders have negative price impacts, apparently resulting from liquidity provision