

# **Caught On Tape: Predicting Institutional Ownership With Order Flow**

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# Broad Research Agenda:

## Equity Flows of Institutional Investors

- Do institutional investors respond differently to information than individuals?
- Do institutions take liquidity or provide it? Do they stabilize or destabilize prices?
- Need information on returns, high frequency institutional equity flows, and high frequency cash- flow relevant information.
- But high frequency institutional equity flows are not readily available! (Few sources such as Plexus, TORQ, NYSE Audit Trail: limited coverage)
- Need to construct...

# Existing Studies on Institutional Trading

- At quarterly frequency, institutional holdings are readily measured from 13-F filings (Spectrum data)
- Intriguing results:
  - Stock returns and institutional flows are contemporaneously correlated (Grinblatt, Titman, and Wermers 1995, Wermers 1999, 2000, Nofsinger and Sias 1999)
  - Institutional investors buy shares from individuals in response to good cash-flow news (Cohen, Gompers and Vuolteenaho 2002)
- We would like to know if these results hold up at higher frequency

# Existing Studies on Institutional Trading

- High-frequency proprietary data
  - State Street custodial data (Froot, O’Connell, Seasholes 2001, Froot and Ramadorai 2005a, Froot and Teo 2005)
  - NYSE Audit Trail (Kaniel, Saar, and Titman 2005, Jones and Lipson 2003)
  - Plexus (Barber and Odean 2005, Jones and Lipson 2001)
  - Discount brokerage data on individuals (Odean 1998, 1999, Barber and Odean 2000, 2001, 2005)
  - Finnish data (Grinblatt and Keloharju 2000a, b)
  - Currency trading data (Evans and Lyons 2005, Froot and Ramadorai 2005b)

# Existing Studies on Institutional Trading

- Proprietary data tend to have limited cross-sectional and time-series coverage
- Alternative is to use TAQ transactions data:
  - Classify buys and sells using Lee-Ready (1991) algorithm
  - Classify institutional trades using cutoff rule (Lee-Radhakrishna 2000)
  - Bennett-Sias (2001), Kim (2001) take this approach
- Our idea:
  - combine Spectrum with TAQ
  - find the best way to infer high-frequency institutional behavior from the transactions recorded in TAQ

# Methodology

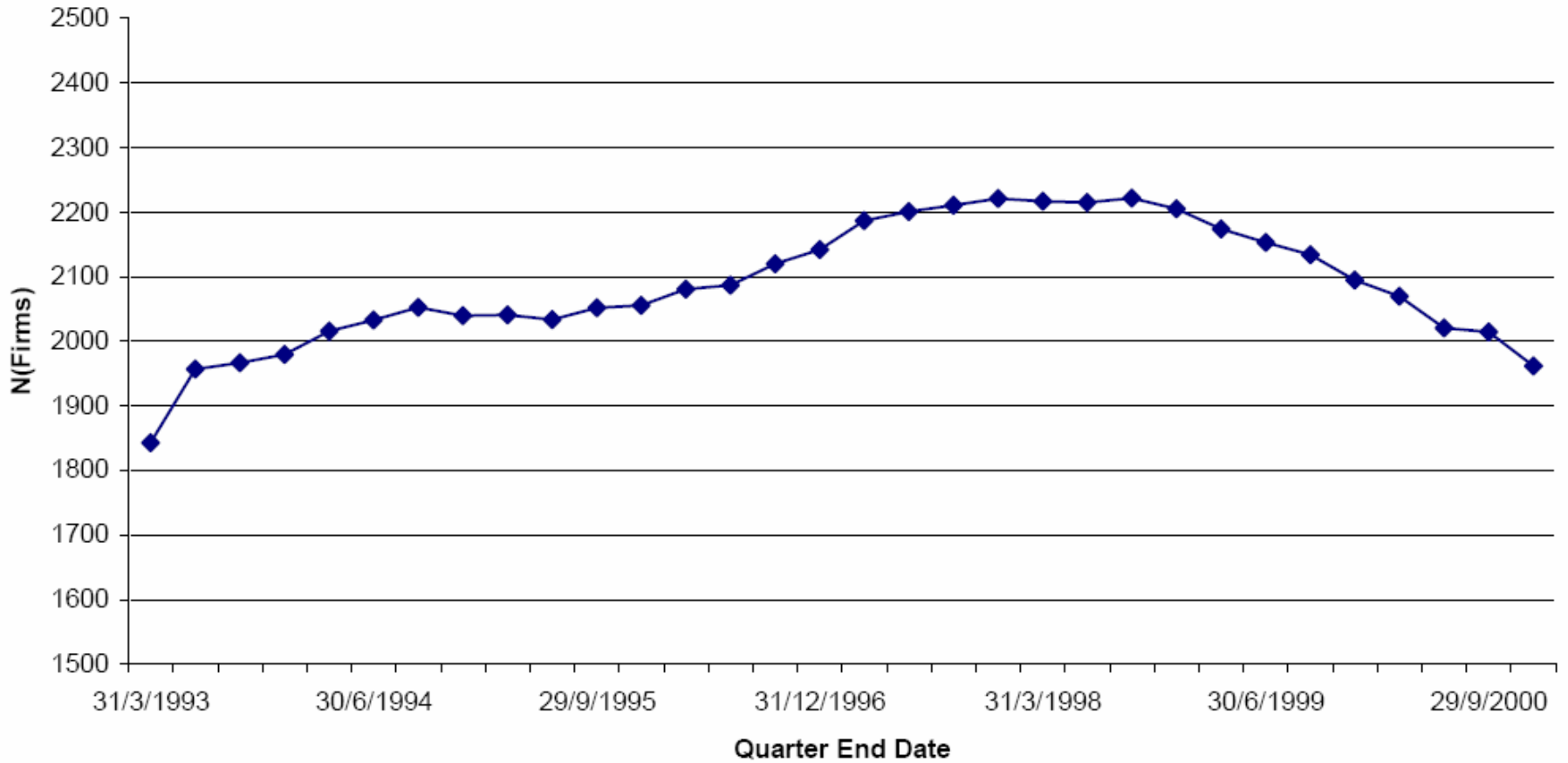
- **Goal:** To predict overall changes in institutional ownership from the general patterns of trading on a particular day.
- Find the best function mapping trade size to institutional behavior. This is distinct from a trade classification system.
- Regress changes in Spectrum ownership on cumulative quarterly trades of different sizes – from the ‘tape’.
- Regression function can be used to track institutional trading on a daily or intra-daily basis.
- How does institutional trading vary with characteristics of the stock (size, institutional ownership) and general market conditions (returns, volume, volatility)?

# Data

- Institutional Ownership: (SPECTRUM)
  - 13-F filings of U.S. institutional investors. Required by SEC.
  - Institutions managing > US\$ 1MM, in positions > 10,000 shares or US\$ 200K, report quarterly holdings.
- ‘Tape’: (Transactions and Quotes (TAQ))
  - All trades and quotes on NYSE/AMEX since 1993. Sample ends December 2000.
  - Buy-Sell classification using Lee and Ready [1991] algorithm. ‘Active’ side of trade.
  - Trade size ‘bins’ using dollar cutoffs (0-2000, 2000-3000, ..., 900,000-1MM, >1MM).
  - Summed to quarterly frequency.
- CRSP:
  - Shares outstanding, permanent company numbers, market capitalization.

# Summary Statistics

Evolution of Firms Over Time



# Summary Statistics: Annualized Percent of Firm Size

	All	Small	Q2	Q3	Q4	Large
<b>Mean</b>						
<i>TAQ Total Buys</i>	31.83	20.88	27.42	33.56	39.20	38.04
<i>TAQ Total Sells</i>	30.99	23.13	28.58	33.00	36.45	33.75
<i>TAQ Unclassifiable</i>	15.39	9.66	13.21	15.94	18.85	19.29
<i>TAQ Total Volume</i>	78.31	53.82	69.28	82.62	94.61	91.14
<i>TAQ Net Imbalance</i>	0.96	-2.13	-1.08	0.63	2.87	4.49
<i>Spectrum Change</i>	0.60	-1.31	0.29	1.73	1.49	0.77
<b>Median</b>						
<i>TAQ Total Buys</i>	23.84	13.72	18.76	24.85	31.40	30.58
<i>TAQ Total Sells</i>	23.90	15.80	20.63	25.58	29.90	27.41
<i>TAQ Unclassifiable</i>	11.57	5.70	8.73	11.47	15.04	15.81
<i>TAQ Total Volume</i>	60.42	36.43	49.26	63.03	77.00	74.35
<i>TAQ Net Imbalance</i>	0.55	-1.22	-0.62	0.15	1.62	3.09
<i>Spectrum Change</i>	0.43	-0.03	0.41	1.65	1.35	0.98
<b>Standard Deviation</b>						
<i>TAQ Total Buys</i>	13.48	11.00	13.04	13.84	14.23	12.82
<i>TAQ Total Sells</i>	12.40	11.32	12.55	12.81	12.83	11.30
<i>TAQ Unclassifiable</i>	6.79	5.69	6.69	7.00	7.03	6.21
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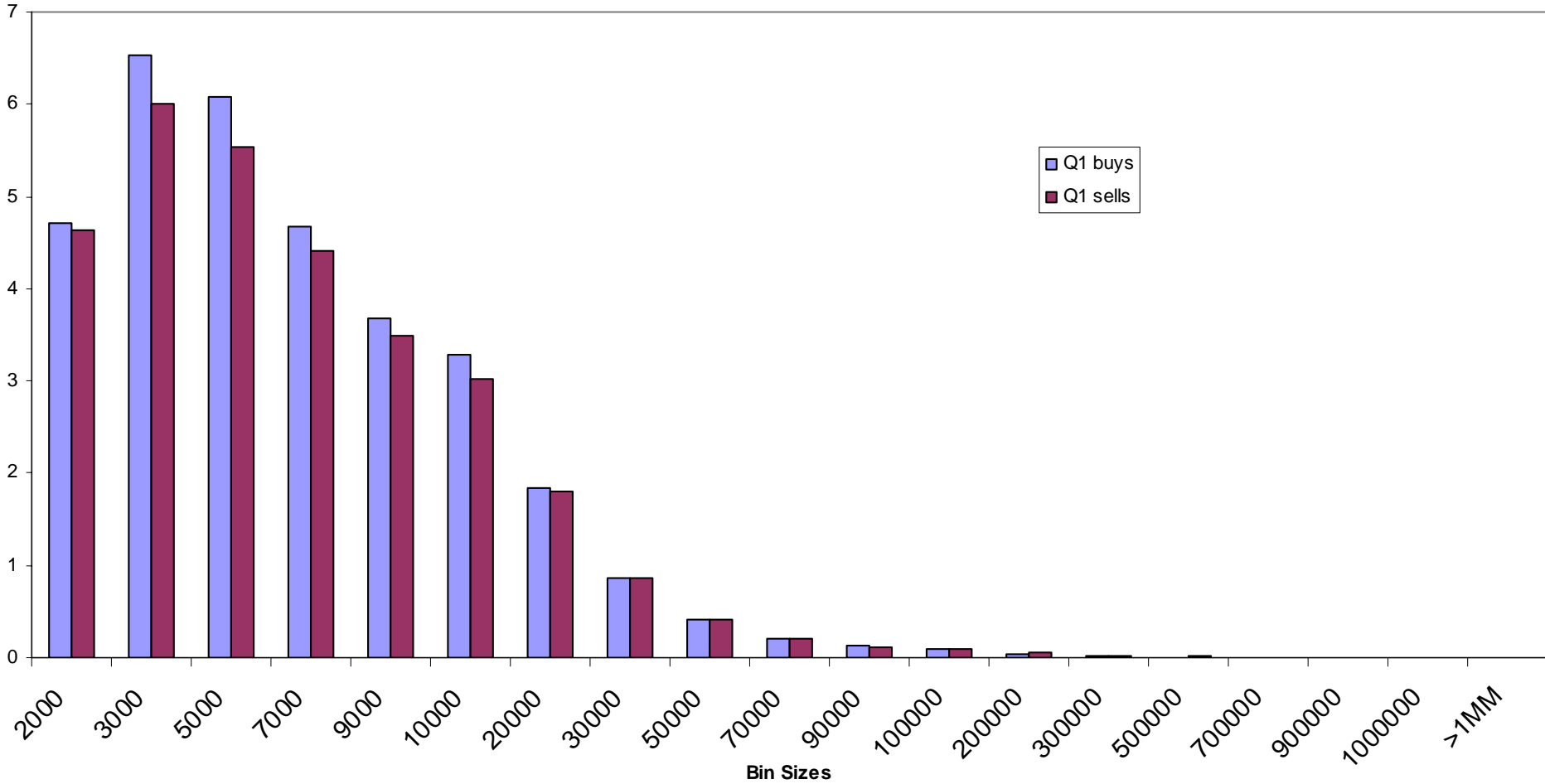
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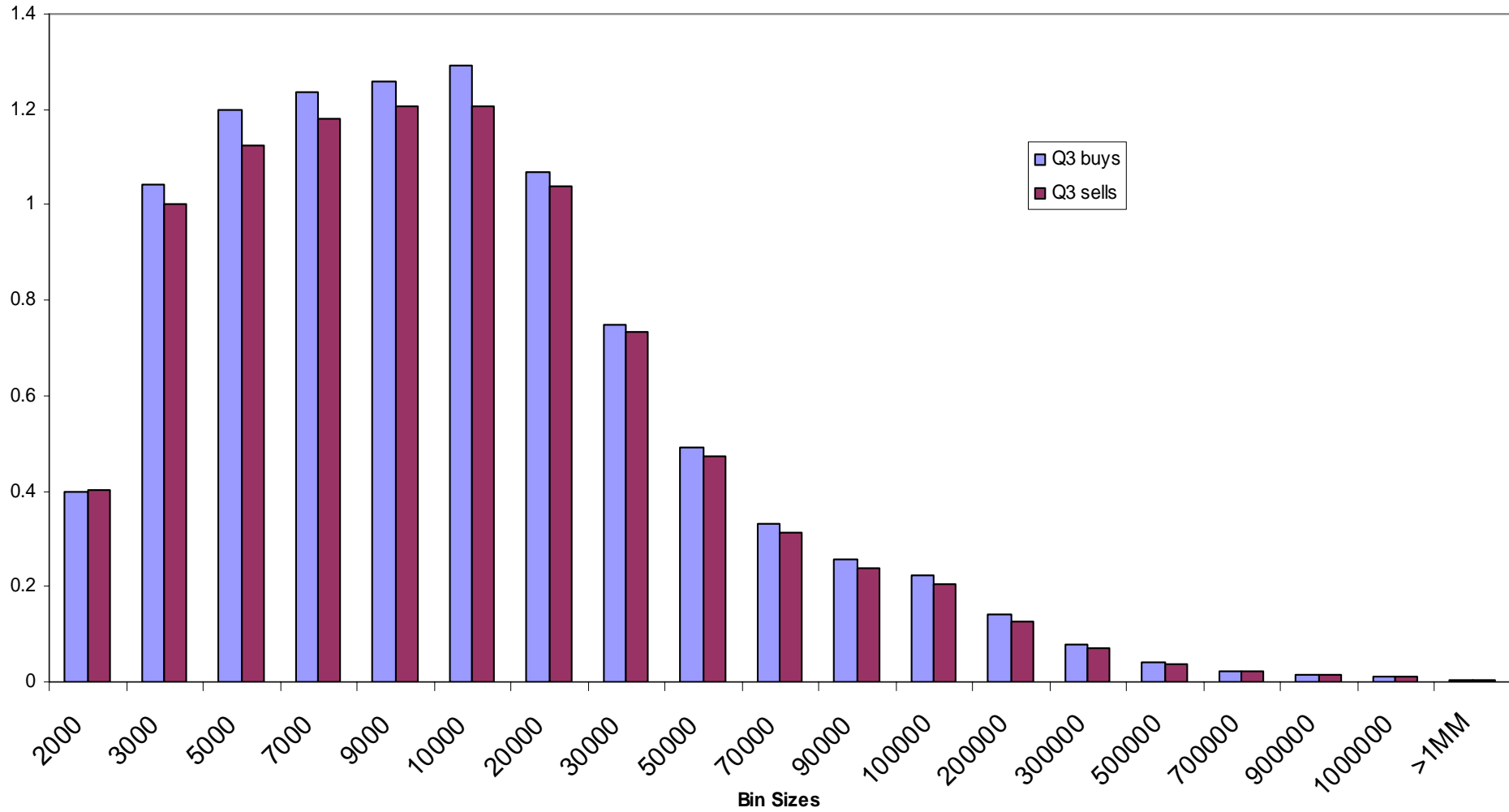
# Histogram of Trade Intensities – Small Firms

Histogram of Trade Intensities - Q1 Firms



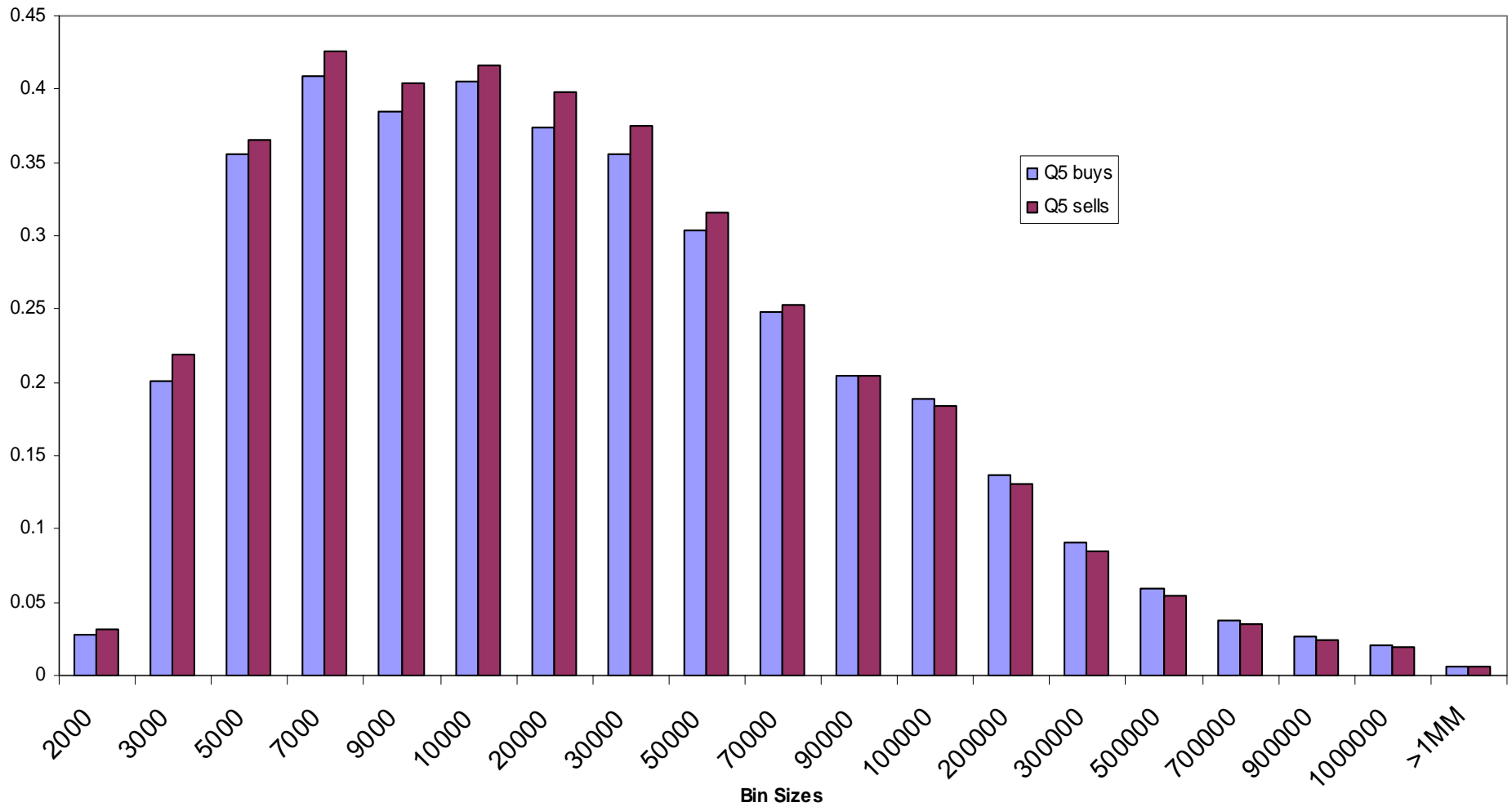
# Histogram of Trade Intensities – Mid Cap Firms

## Histogram of Trade Intensities - Q3 Firms



# Histogram of Trade Intensities – Large Firms

## Histogram of Trade Intensities - Q5 Firms



# Regression Specifications – Total Flows

$$\underbrace{\Delta Y_{it}} = \alpha + \underbrace{\phi Y_{i,t-1}} + \underbrace{\beta_U U_{it}} + \underbrace{\beta_B B_{it}} + \underbrace{\beta_S S_{it}} + \varepsilon_{it}.$$

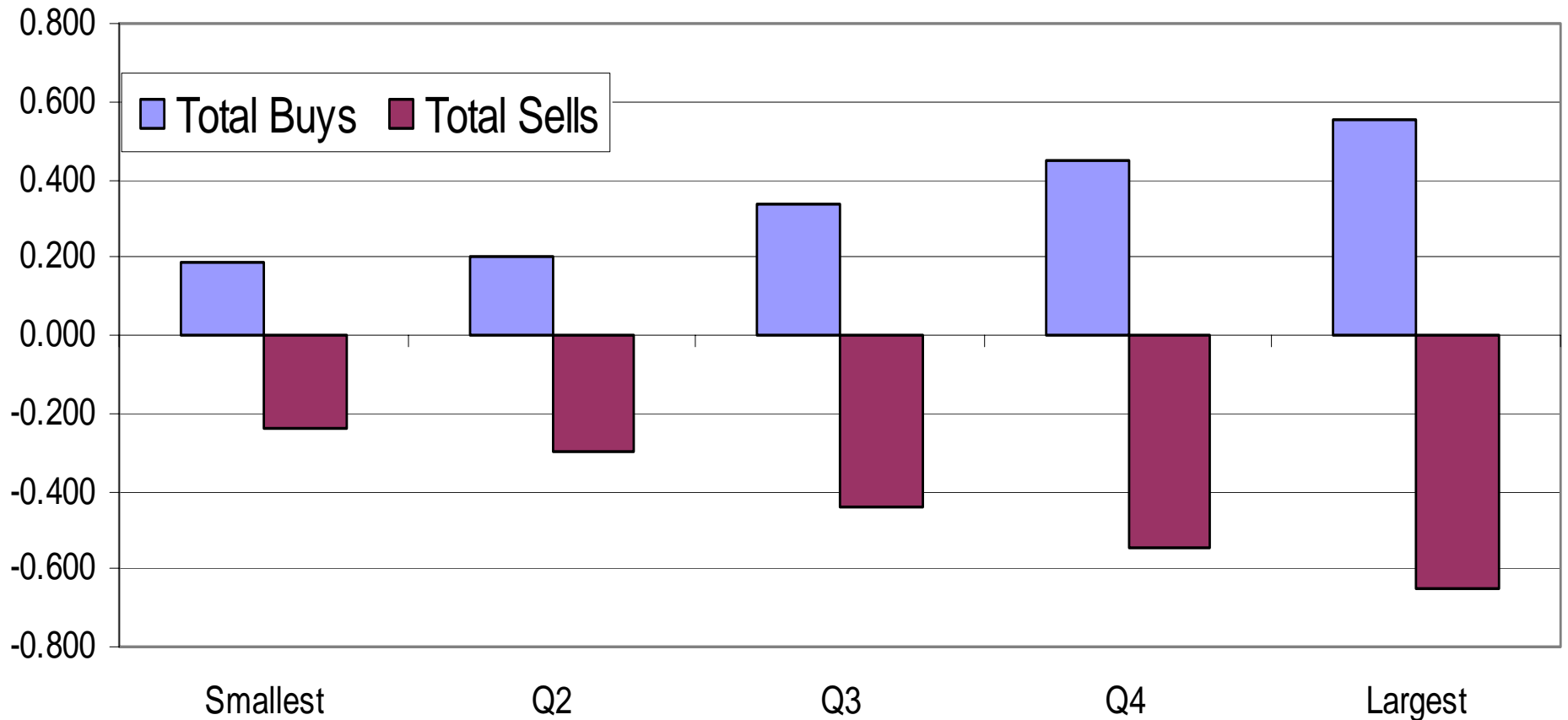
Lagged                  Unclassifiable                  Total                  Total  
Level                          Volume                          Buys                          Sells

$$\Delta Y_{it} = \alpha + \phi Y_{i,t-1} + \beta_U U_{it} + \underbrace{\beta_F F_{it}} + \varepsilon_{it}.$$

Total Net  
Flows

$$F_{it} = B_{it} - S_{it}$$

# Total Flow Coefficients Across Size Quintiles

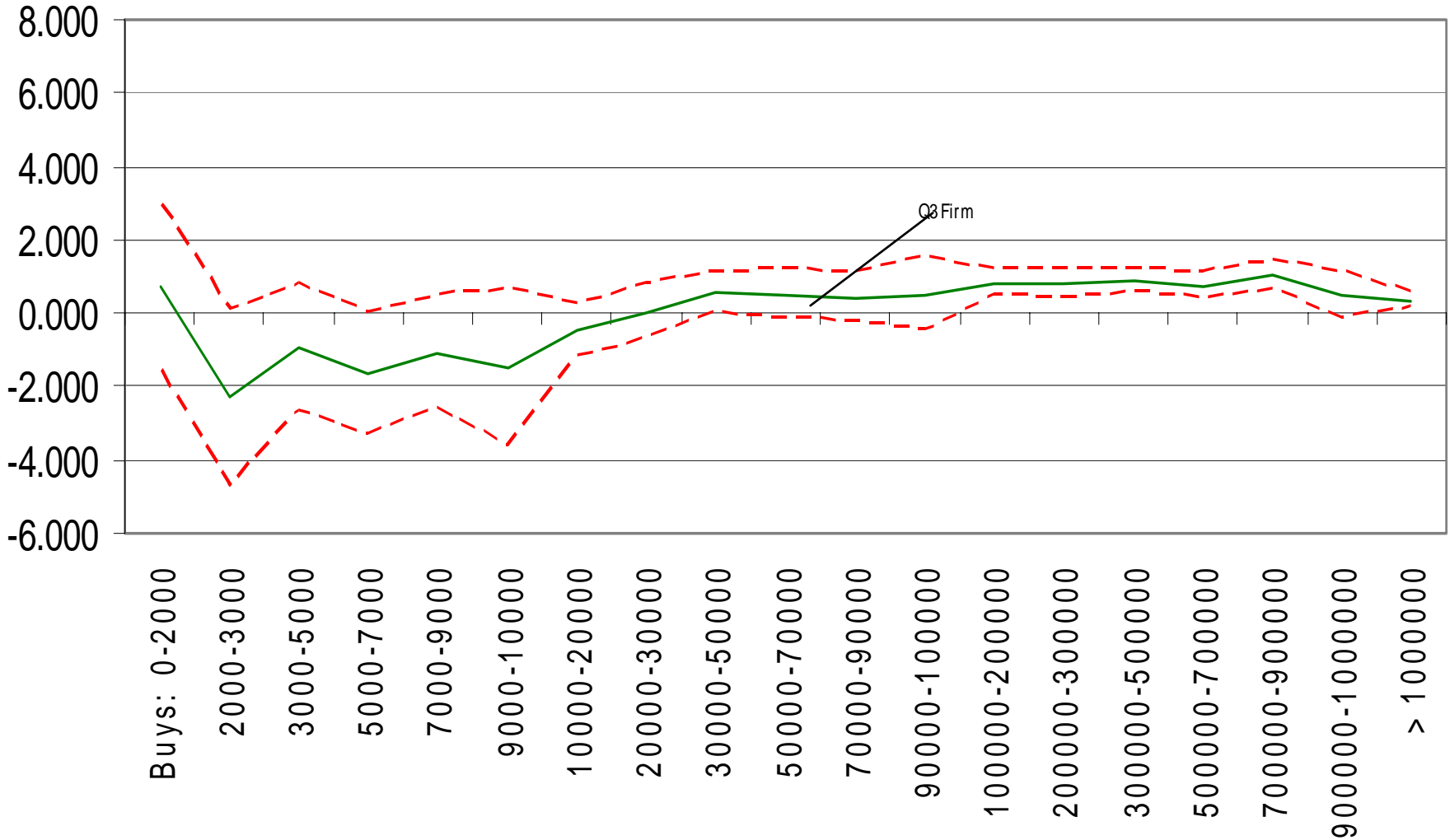


# The Information in Trade Size

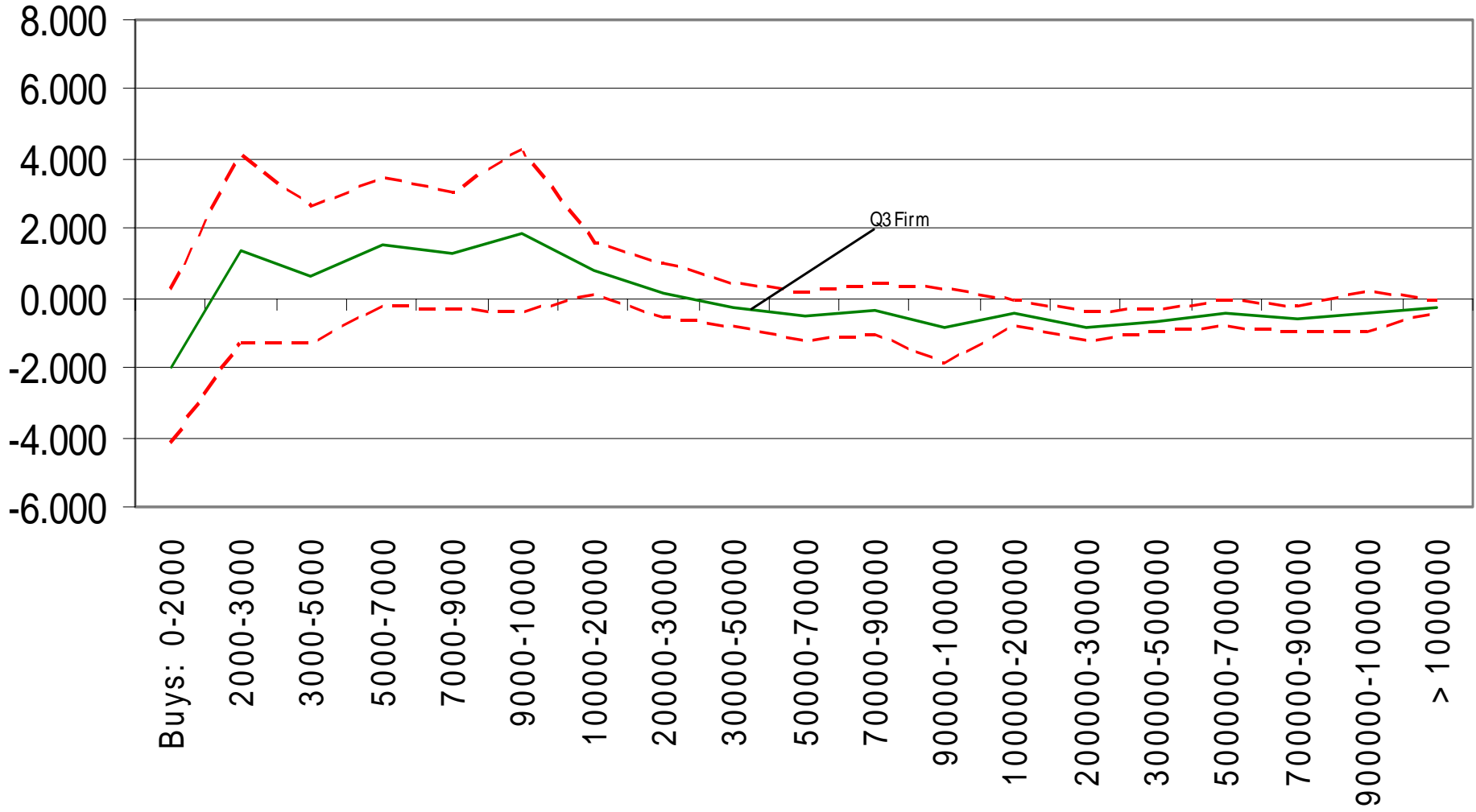
$$\Delta Y_{it} = \alpha + \phi Y_{i,t-1} + \beta_U U_{it} + \underbrace{\sum_Z \beta_{BZ} B_{Zit}}_{\text{Bin Specific Buys}} + \underbrace{\sum_Z \beta_{SZ} S_{Zit}}_{\text{Bin Specific Sells}} + \varepsilon_{it}$$

$$\Delta Y_{it} = \alpha + \phi Y_{i,t-1} + \beta_U U_{it} + \underbrace{\sum_Z \beta_{FZ} F_{Zit}}_{\text{Bin Specific Net Flows}} + \varepsilon_{it}$$

### Standardized Buy Coefficients For Different Trade Sizes



### Standardized Sell Coefficients For Different Trade Sizes



# The Story So Far:

- Total buy (sell) volume predicts increasing (decreasing) institutional ownership
  - Institutions tend to buy at the ask and sell at the bid
  - Suggests that institutions demand liquidity rather than provide it.
- Buy volume in sizes between \$2,000 and \$30,000 is associated with decreasing institutional ownership
- Buy volume in larger sizes predicts increasing institutional ownership.
- Extremely small buys below \$2,000 also predict increasing institutional ownership.
  - Scrum trades?
- All patterns are amplified as firm size increases (also as institutional ownership increases)

## Smoothing the Effects of Trade Size

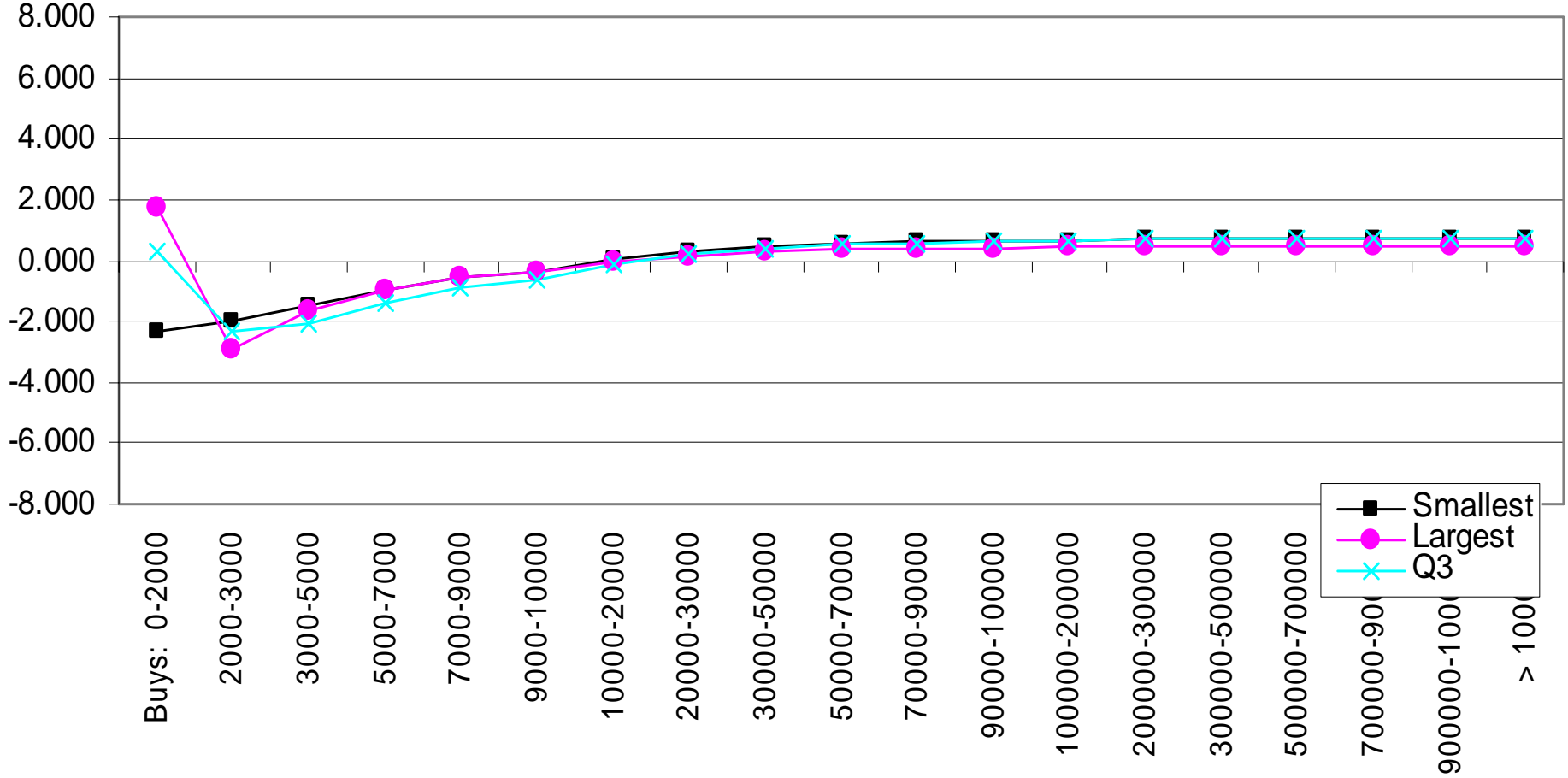
- Refine specification for a more accurate cutoff rule.
- Use Nelson and Siegel's [1987] nonlinear function (originally used for parsimonious yield-curve modeling).
- Reduces the number of parameters to estimate (weighting by bin midpoints).

$$\beta(Z) = b_0 + \underbrace{(b_1 + b_2)}_{\text{Negative exponential function: can capture a range of shapes}} \left[ \frac{1 - e^{-Z/\tau}}{Z} \right]^\tau - b_2 e^{-Z/\tau}$$

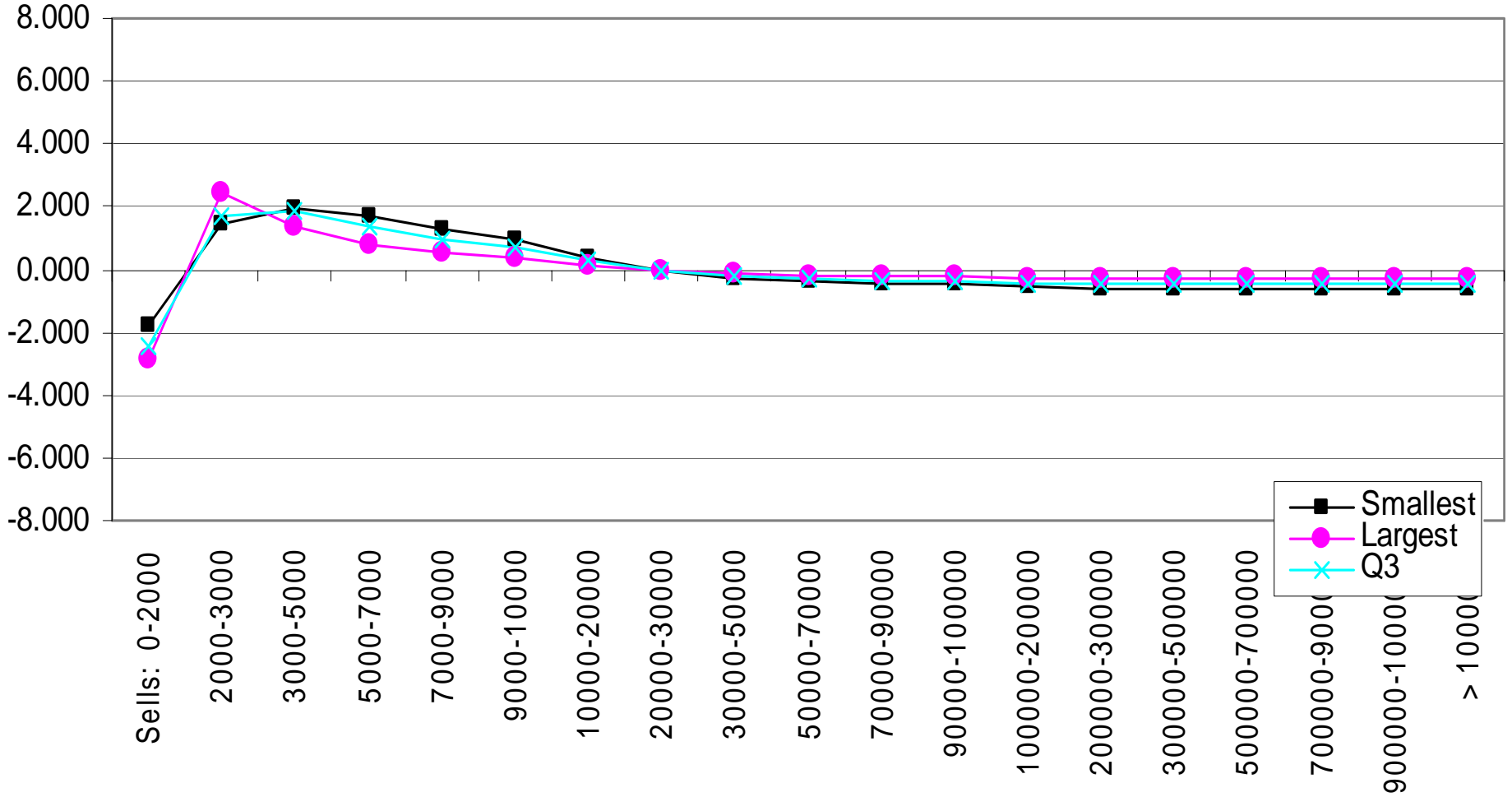
Coefficient for  
bin Z

Negative exponential function: can capture a  
range of shapes

Standardized Buy Coefficients For Different Trade Sizes



Standardized Sell Coefficients For Different Trade Sizes



# But How Good is the Method?

$R^2$	Small	Q2	Q3	Q4	Large
<b>Matched Pairs of Cutoffs</b>					
<i>Lower: 2,000, Upper: 5,000</i>	-0.080	-0.086	-0.033	0.010	0.068
<i>Lower: 3,000, Upper: 10,000</i>	-0.049	-0.062	-0.011	0.021	0.075
<i>Lower: 3,000, Upper: 20,000</i>	-0.021	-0.037	0.010	0.033	0.083
<i>Lower: 3,000, Upper: 50,000</i>	0.005	-0.014	0.032	0.046	0.091
<i>Lower: 5,000, Upper: 100,000</i>	0.004	-0.002	0.048	0.054	0.098
<b>CRV Out of Sample</b>					
<i>Q1 1997: Q4 2000</i>	0.073	0.061	0.072	0.080	0.116
<i>Rolling One Period Ahead</i>	0.077	0.072	0.092	0.089	0.117
<i>N</i>	12516	12609	12621	12732	12925
<i>N(Firms)</i>	1131	1357	1319	1161	735

# Using the Method

- Current research (ongoing revision of the paper) constructs implied daily institutional flows and relates them to returns
- Estimate a VAR, with coefficient restrictions for parsimony, to characterize the joint dynamics of institutional net flows and returns
- Main results:
  - Net flows are positively autocorrelated
  - Returns predict net flows positively
  - Returns are negatively autocorrelated, particularly in small stocks
  - Net flows predict returns negatively in larger stocks (Q2-5)
  - The pattern in larger stocks is driven by sales rather than purchases: stocks that institutions purchase have a weak tendency to go up, but stocks that institutions sell have a strong tendency to rebound
  - Suggests that institutions take liquidity when they sell

# The Basic VAR System

$$\begin{pmatrix} f_{i,t} \\ r_{i,t} \end{pmatrix} = \begin{pmatrix} \alpha_f \\ \alpha_r \end{pmatrix} + \begin{pmatrix} \phi_f & \phi_r \\ \rho_f & \rho_r \end{pmatrix} \begin{pmatrix} (1 - \chi_f) \sum_{j=1}^{t-1} \chi_f^j f_{i,t-j} & (1 - \lambda_f) \sum_{j=1}^{t-1} \lambda_f^j f_{i,t-j} \\ (1 - \chi_r) \sum_{j=1}^{t-1} \chi_r^j r_{i,t-j} & (1 - \lambda_r) \sum_{j=1}^{t-1} \lambda_r^j r_{i,t-j} \end{pmatrix} + \begin{pmatrix} u_{i,t}^f \\ u_{i,t}^r \end{pmatrix}$$

# Basic VAR Results

	Small	Q2	Q3	Q4	Large	All
	$f_{i,t}$	$f_{i,t}$	$f_{i,t}$	$f_{i,t}$	$f_{i,t}$	$f_{i,t}$
$\chi_f$	<b>0.90</b>	<b>0.90</b>	<b>0.90</b>	<b>0.90</b>	<b>0.90</b>	<b>0.90</b>
$\phi_f$	0.664	0.636	0.633	0.681	0.691	0.671
	101.820	108.652	121.177	153.230	170.689	294.700
$\chi_r$	<b>0.75</b>	<b>0.90</b>	<b>0.75</b>	<b>0.50</b>	<b>0.50</b>	<b>0.75</b>
$\phi_r$	0.0007	0.0050	0.0060	0.0048	0.0056	0.0033
	18.276	23.256	35.772	42.009	64.667	65.482
$R^2$	0.0691	0.0629	0.0687	0.0872	0.1085	0.0782
	$r_{i,t}$	$r_{i,t}$	$r_{i,t}$	$r_{i,t}$	$r_{i,t}$	$r_{i,t}$
$\lambda_f$	<b>0.98</b>	<b>0.00</b>	<b>0.00</b>	<b>0.90</b>	<b>0.90</b>	<b>0.90</b>
$\rho_f$	1.420	-0.836	-0.379	-0.493	-0.736	-0.472
	1.671	-8.260	-6.740	-3.900	-5.288	-5.117
$\lambda_r$	<b>0.50</b>	<b>0.75</b>	<b>0.00</b>	<b>0.75</b>	<b>0.75</b>	<b>0.50</b>
$\rho_r$	-0.322	-0.076	0.018	-0.035	-0.051	-0.155
	-28.938	-6.390	5.635	-5.179	-7.945	-30.994
$R^2$	0.0284	0.0010	0.0004	0.0002	0.0005	0.0073
$N$	549,979	578,707	592,630	621,557	668,413	3,015,050

# Asymmetric Return Equation

A refinement allows for different effects of positive and negative net flows:

$$r_{i,t} = \alpha_r + \rho_f^b \left| \left( (1 - \lambda_f) \sum_{j=1}^{t-1} \lambda_f^j f_{i,t-j} \right) \right|_{>0} + \rho_f^s \left| \left( (1 - \lambda_f) \sum_{j=1}^{t-1} \lambda_f^j f_{i,t-j} \right) \right|_{<0} + \rho_r (1 - \lambda_r) \sum_{j=1}^{t-1} \lambda_r^j r_{i,t-j} + u_{i,t}^r$$

# Asymmetric Return Results

	Small	Q2	Q3	Q4	Large	All
	$r_{i,t}$	$r_{i,t}$	$r_{i,t}$	$r_{i,t}$	$r_{i,t}$	$r_{i,t}$
$\lambda_f$	<b>0.98</b>	<b>0.00</b>	<b>0.00</b>	<b>0.90</b>	<b>0.90</b>	<b>0.90</b>
$\rho_f^b$	-2.344	1.238	0.498	0.285	0.795	1.363
	-1.447	7.755	5.111	1.174	3.405	6.504
$\rho_f^s$	-3.547	2.297	0.945	1.065	2.184	3.282
	-3.071	14.981	11.698	5.564	9.276	4.346
$\lambda_r$	<b>0.50</b>	<b>0.75</b>	<b>0.00</b>	<b>0.75</b>	<b>0.75</b>	<b>0.50</b>
$\rho_r$	-0.322	-0.076	0.017	-0.036	-0.052	-0.156
	-28.937	-6.470	5.436	-5.308	-8.143	-31.067
$R^2$	0.0284	0.0017	0.0007	0.0003	0.0007	0.0073
$N$	549,979	578,707	592,630	621,557	668,413	3,015,050

# Interaction with Market Conditions

- How does institutional trading vary with movements in returns, volume, volatility and depth?
- Could we improve our method by re-specifying bins in different units (e.g. percent of daily volume or quoted depth)?
- We consider one interaction variable at a time.
- Nelson-Siegel parameters at the daily level are modeled as a linear function of the interaction variable.

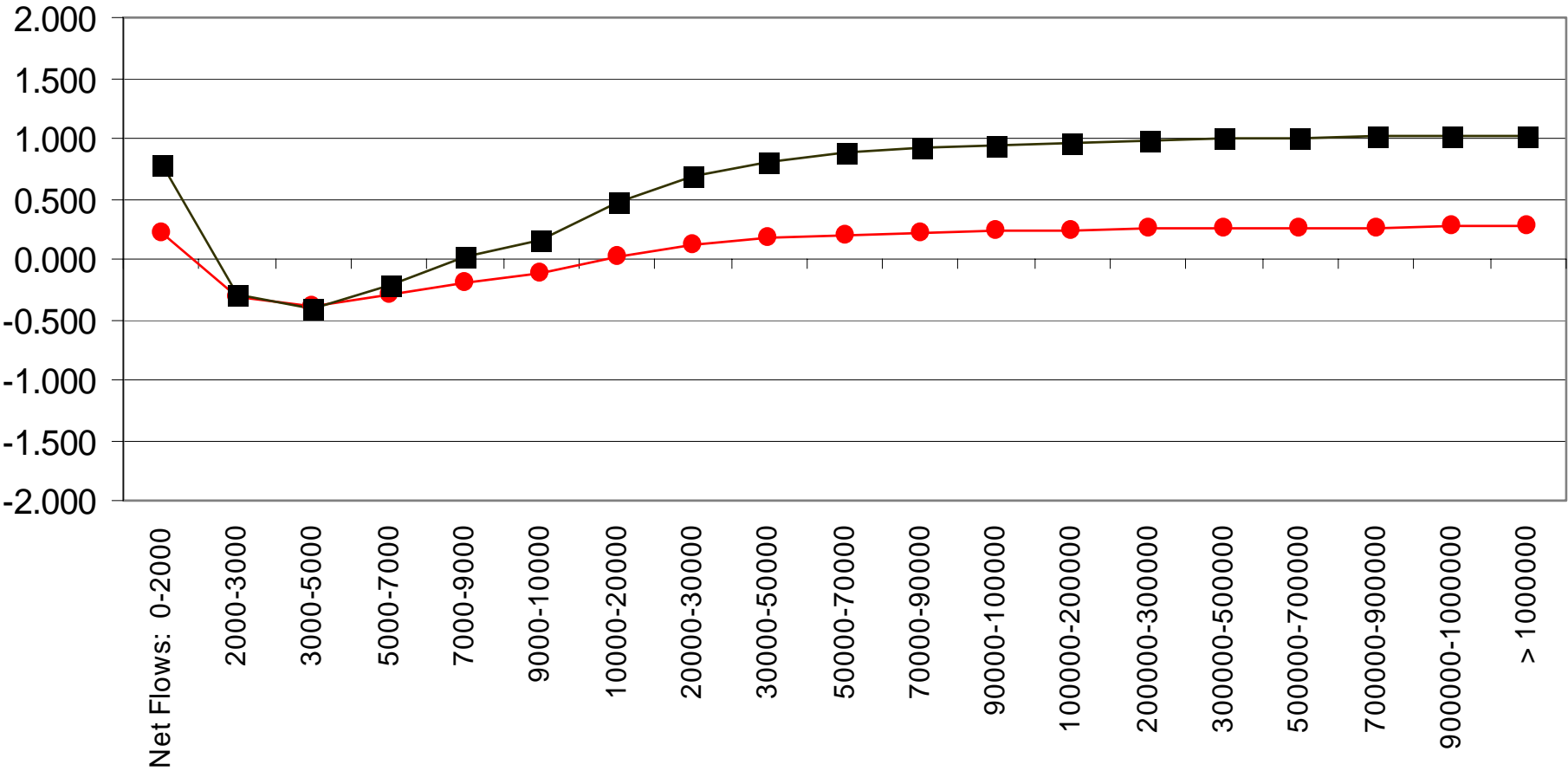
$$\begin{aligned}\beta(Z, v_{id}) = & b_{01} + b_{02}v_{id} \\ & + (b_{11} + b_{12}v_{id} + b_{21} + b_{22}v_{id})[1 - e^{-Z/\tau}] \frac{\tau}{Z} \\ & - (b_{21} + b_{22}v_{id})e^{-Z/\tau}\end{aligned}$$

# Interaction with Market Conditions

- Aggregation of the daily function to the quarterly level requires the assumption that unexplained net flows are uncorrelated with daily leads and lags of the regressors.
- More plausible for interactions that change the shape of the Nelson-Siegel function rather than its level.
- Less plausible for return interaction.

# Volatility

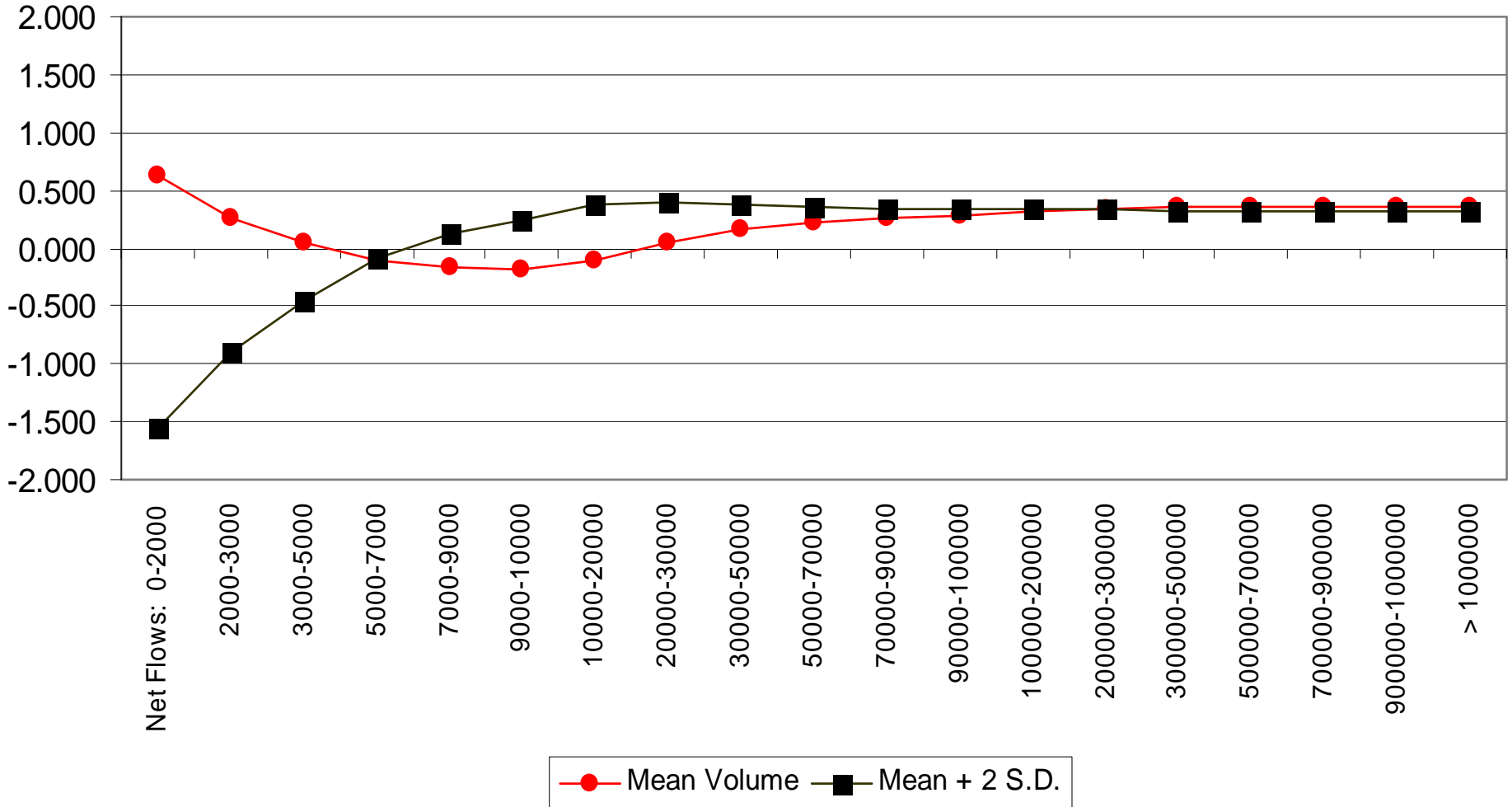
Raw Net Flow Coefficients Q1 Firms



● Mean Absolute Returns    ■ Mean + 2 S.D.

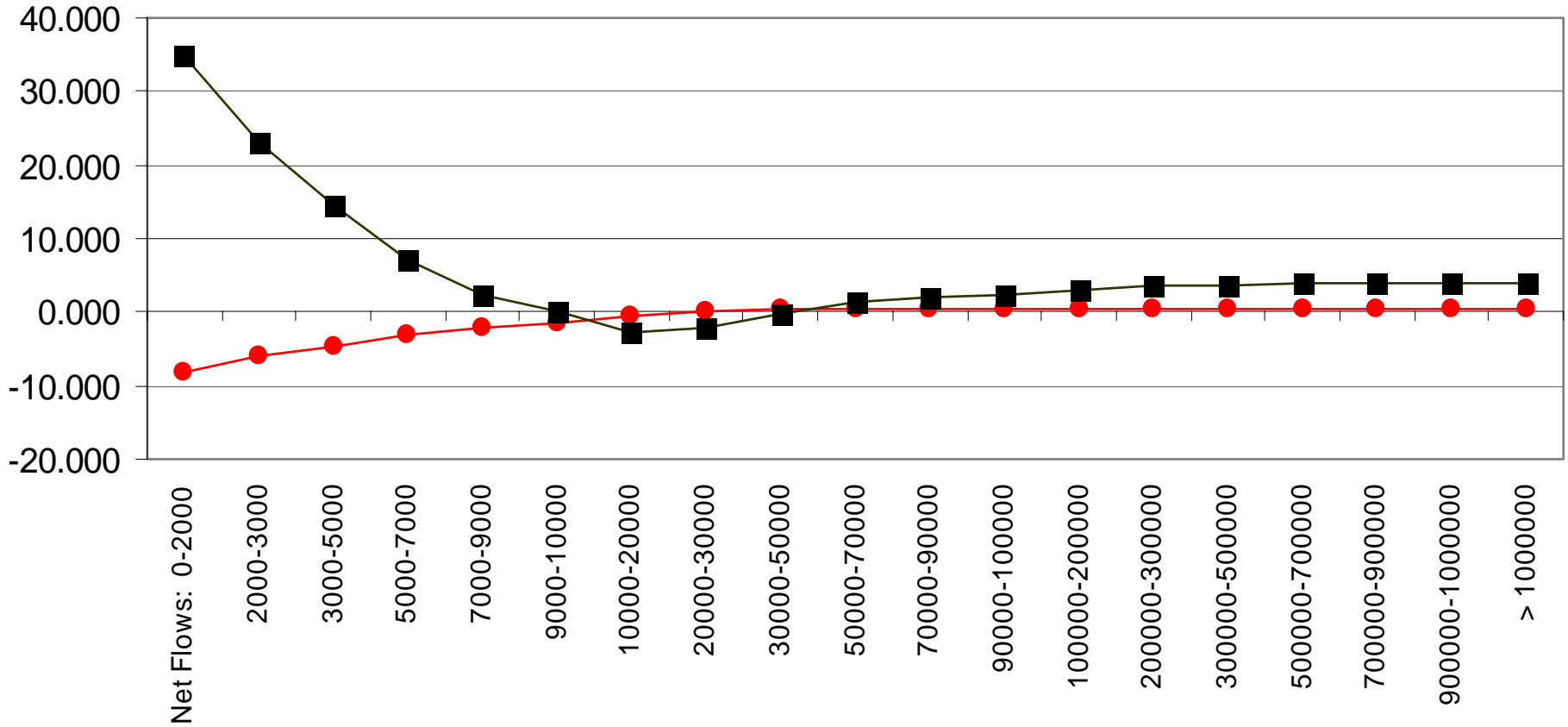
# Volume

Raw Net Flow Coefficients Q1 Firms



# Depth

Raw Net Flow Coefficients Q5 Firms



● Mean Average Quoted Depth    ■ Mean + 2 S.D.

# Interaction With Market Conditions

- High volatility increases institutional trading intensity in the large bins: high demand for liquidity?
- High volume increases institutional trading in the medium-size bins: greater opportunity for stealth trading?
- High depth increases institutional trading in the small bins: greater opportunity to exploit the market-maker's quotes?

# Next Steps and Current Research

- We are currently investigating the relationship between daily TAQ flows generated using our method and daily stock returns.
- Our next project will explore whether institutional trading is different around earnings announcements, using the Nelson-Siegel function.
- We can measure institutional trading around earnings announcements and corporate actions. Do institutions ‘arbitrage’ individual underreaction to cashflow news?
- We can use the method to investigate institutional investor responses to a wide variety of corporate actions.