Some Introductory Comments on Liquidity and Trading Costs

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Liquidity and Trading Costs

- Useful to step back and employ a wider perspective by organizing our thinking under the umbrella of ***market microstructure***

  → The process by which investors' latent demands for securities are translated into transactions (the "*black box*")

- In his excellent survey, Madhavan breaks down the research and ideas underlying market microstructure into four broad categories:

  1. Price Formation

  2. Market structure and design

  3. Information and Disclosure

  4. Interface between microstructure and traditional finance

- I begin by briefly discussing each of these areas and placing the conference papers on liquidity and trading within the context of the research represented in each category.

- I will then discuss some recent (unpublished) research of mine relating to the behavior of momentum traders, their costs, and the effects of their trading on observed stock returns.

(1) Price Formation

• The process by which information motivating trade is impounded into security prices.

→ Looks inside the black box and models the interplay between market participants (traders who demand liquidity, market makers who supply liquidity).

• Research in this area is concerned with:

(a) Behavior of Traders; Trade Strategies
(*Kyle(1985); Admati & Pfleiderer (1988)*; many, many more)

(b) Costs of Trading
(models of the spread, etc.)

(c) Price Impacts of trades generated by these strategies
(block trade literature, institutional trade impacts, etc.)

(1) Price Formation (cont.)

- ***"Market Impact Costs of Institutional Equity Trades" by Bikker, Spierdijk & van der Sluis*** is a nice example of research in category (c).

  ♦ Measure the price impacts of the trades of largest Dutch pension fund (ABN) during 1st quarter 2002 (as such, a case study).

  ♦ Distinguish between principal and agency trades.
  Examine trades executed in diverse investment styles and many markets worldwide.

  → interesting cross-sectional variation

  ♦ Analyze the determinants of price impacts using a wide array of trade-, stock-, and exchange-specific characteristics.

  → results are similar to those found in earlier studies

  ♦ Examine determinants of *volatility* of the price impacts.

(2) Market Structure and Design

- How the rules that define the architecture of a market affect trader behavior, and how the specific features of a market affect trading and the associated costs.

  → How do market-specific rules affect the black box and, thus, liquidity

  (e.g., continuity of trading; auction vs. dealer market; degree of automation; types of orders available to traders)

- Examples of research in this area are:

  (a) Dealer vs LOB Markets (much interest; much ongoing research)

  (b) Decimalization and Discreteness

  (c) Effects of Market Fragmentation on Price Determination

  (e.g., multiple competing venues for trading same asset, off-exchange (upstairs) trading)

(2) Market Structure and Design (cont.)

- ***"Competition for Order Flow and Smart Order Routing Systems" by Foucault & Menkveld*** contributes to strand (c) of this literature.

  ♦ Develop a model of competing LOB markets that examines the effect of
    (a) relative efficiency of order routing and
    (b) differential fees for market and limit orders
  on the relative liquidity of the rival markets.

  ♦ Test the predictions of the model with a very interesting natural experiment
    – introduction of trading of Dutch stocks on EuroSETS (est. by London Stock Exchange) in May 2004 in parallel with ongoing trading on NSC (operated by Euronext.)

  ♦ Consistent with prediction of model, liquidity is enhanced with introduction of new mkt.

    – Consolidated depth is larger after entry of EuroSETS

    – The relative liquidity of EuroSETS (e.g., share of total depth) is positively related to the proportion of smart routers.

(3) Information Disclosure (Market Transparency)

• How visible to market participants is information about the trading process, both *pre*-trade (quotes, depth) and *post*-trade (price, volume, time of trade, trader identification)?

→ market transparency is concerned with the revelation of the workings of the black box, and the associated effects on traders and their strategies.

• Research in this area has dealt with:

(a) How much information to reveal, and how quickly?
→ does increased transparency necessarily increase liquidity?

(b) Sunshine trading – pre-announced intentions and the effects on trade costs

(e.g., *Admati & Pfleiderer (1991), Madhavan (1996)*)

(c) Empirical measurement of benefits/costs of added transparency

Pre-trade (*Porter and Weaver (1998)* – Toronto)
Post-trade (*Gemmill (1996)* – London)

(4) Interface between Microstructure and Asset Pricing

- Models of the black box might influence our thinking about, and yield new insights into, the more traditional models in finance.

  → Of most relevance here is the interface between microstructure and asset pricing models.

- Much recent research has been interested in the influence of liquidity and liquidity risk on security prices and returns.

  (a) Studies are in the spirit of cross-sectional tests of asset pricing models using methods similar to *Fama and MacBeth (1973)*

  (b) Liquidity as a security characteristic (e.g., bid-ask spread), and its ability to explain the cross section of returns

  (e.g., *Amihud and Mendelsohn (1986)*, *Brennan & Subrahmanyam (1996)*)

  (c) Measure security's exposure ("beta") to a market-wide liquidity factor, and the ability of these liquidity betas to explain the cross section of returns.

  (e.g., *Pastor & Stambaugh (2003), Acharya & Pedersen (2004)*)

(4) Interface between Microstructure and Asset Pricing (cont.)

- ***"Liquidity Risk in Corporate Bond Markets," by de Jong and Driessen****,* extends this type of analysis to U.S. corporate bonds.

  - ♦ Construct a liquidity factor based on Amihud's (2002) illiquidity measure computed for a sample of 1500 U.S. stocks and aggregated to the market level.

  - ♦ Estimate bond portfolio sensitivities to the liquidity factor for the period 1993 to 2002.

  - ♦ Estimate a significant cross-sectional relation between returns and liquidity betas for the bond portfolios (which are constructed on the basis of maturity and credit rating).

  - ♦ Find liquidity exposure, and the premium associated with it, is related to credit quality.

    → may help in understanding the credit spread in corporate bonds.

  - ♦ Validate the results on a sample of European corporate bonds.

(5) Optimal Portfolios and Portfolio Strategies

Finally, we have two papers that are on the periphery of liquidity and trading costs (according to my taxonomy).

Persistence, Predictability and Portfolio Planning, by Michael Brennan & Yihong Xia.

♦ Focus on optimal dynamic portfolio strategies that exploit time variation in expected returns.

♦ Show that even though long-run return predictability may be hard to detect from short-run returns, this predictability is economically valuable to investors with long horizons and should be incorporated into their dynamic portfolio strategies.

Robust Portfolio Optimization with Multiple Experts, by Frank Lutgens & Peter Schotman.

♦ Focus on optimal portfolio choice (i.e., Markowitz MV analysis) when there is both *model uncertainty* and *estimation uncertainty*.

♦ Develop framework where the return model is an endogenously-determined combination of alternative models (e.g., CAPM, Fama-French 3-factor model)

♦ Examine the cost of deviations from optimal (“expected loss”) due to model uncertainty and/or estimation uncertainty using equity returns from nine world-wide markets.

Trading Styles and Price Impacts: Implications for Stock Returns

- I examine the claim of profitability of *simulated* momentum strategies by documenting the price impacts associated with implementing *actual* momentum strategies.

- The behavior of momentum traders is interesting because of

  (1) the *urgency* and *size* of their trades, and

  (2) their desire to *buy in rising markets* and *sell in falling markets*.

  → These aspects of their trade behavior distinguish them from other traders.

  ⇒ The actual costs of momentum traders are likely to be large and very different from the "unconditional" estimates used as trade cost benchmarks in the simulated momentum experiments.

  ⇒ The potentially large price impacts resulting from momentum trades might noticeably impact stock return distributions.

- Using a database of institutional asset manager trades, I contrast the behavior (and costs) of momentum traders with other traders who do not explicitly pursue price trends and assess the effect of their trades on stock returns.

• I focus on three questions:

(1) Are institutional trades conditioned on prior price moves?

(2) Can the "paper" profits generated by *simulated* momentum strategies be realized in *actual* portfolios, after accounting for implementation costs?

(2) Do the trades of momentum managers significantly affect stock return distributions?

Investment Style and Motivation for Trade

- Investment strategy, or style, of an institution provides important information regarding motivation for trade (e.g., Keim and Madhavan (1997)).

- Three types of investment style are identified by Plexus:

  Momentum – trend chasers who buy stocks in rising markets and sell stocks in falling markets.

  Value – investment decisions are dependent on long-term fundamentals;

  buy stocks when they are "undervalued" relative to some benchmark valuation metric (e.g., low P/E, low P/B) and sell when "overvalued."

  Diversified/Index – objective is to maintain a well-diversified "balanced" portfolio, or to minimize tracking error relative to an index;

  trades are "liquidity motivated" rather than information motivated.

→ Expectation is that only the momentum traders explicitly condition trades on recent stock price movements.

The Data

- The transaction history of the U.S. equity trades of 33 institutional traders (provided by the Plexus Group)
  - Time periods: April 1996 to March 1997 (“96-97’) and January 2000 to December 2000 (“2000”)
  - Contains more than 153,000 orders (about 350,000 individual trades) with total value of almost $240 billion (U.S.)

- The unit of observation for the analysis is the *trade order*, which is composed of one or (typically) more trades

- The data include:

(i) the identity of the stock to be traded and the date when the trading decision was made;
(ii) an indication as to whether the trade is buyer- or seller-initiated;
(iii) the closing stock prices for the fifteen trade days before the decision to trade is made, and for fifteen trade days after the order is completed;
(iv) the dates and the individual components of the order released to the broker;
(v) the trade price, number of shares traded, and date(s) associated with the trade(s) executed by the broker within a specific order; and
(vi) commissions and other explicit trade fees.

Evidence on Trend Chasing (I)

Allocating traded stocks to Jegadeesh and Titman (JT) Deciles

- Academic research that simulates momentum strategies typically conditions on price movements over past 3, 6, 9 or 12 months. Most follow Jegadeesh and Titman (1992) and create JT deciles based on prior (say, 12 month) returns and combine stocks into portfolios based on these deciles.

  → Portfolios range from extreme winner portfolio (decile 10) to extreme loser portfolio (decile 1)

  Question: Are the institutional momentum traders in my sample pursuing strategies like those described in JT?

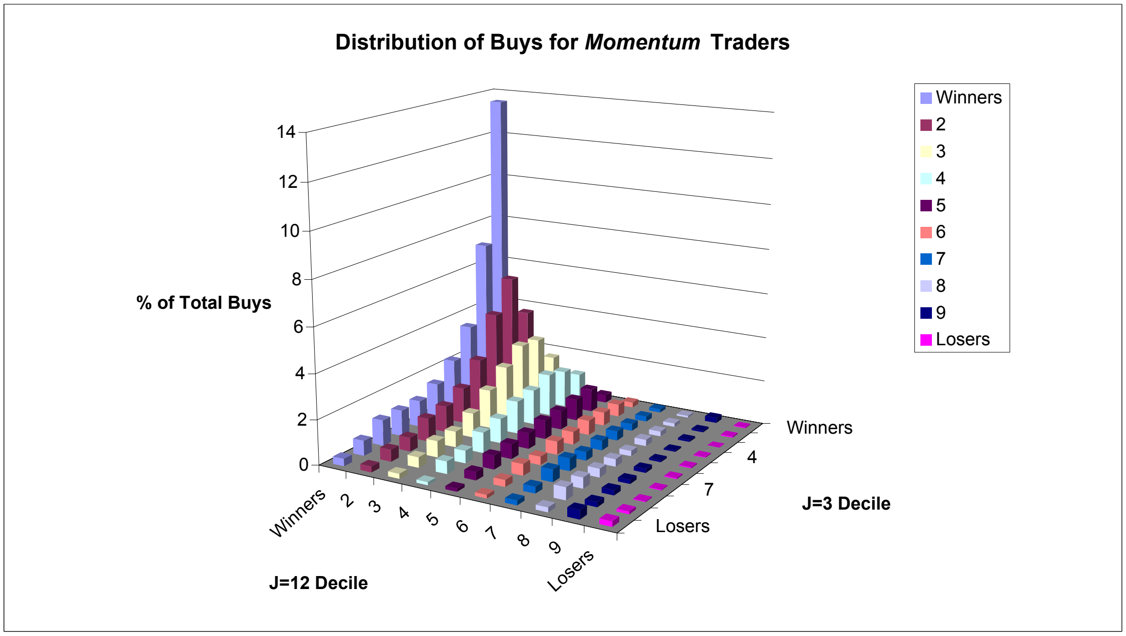
- To answer the question, I assign the trades of the sample institutions to the JT momentum deciles in which the traded stock was a member at the time of the trade

  → Momentum deciles used here are based on **prior 3-month** and **prior 12-month** returns

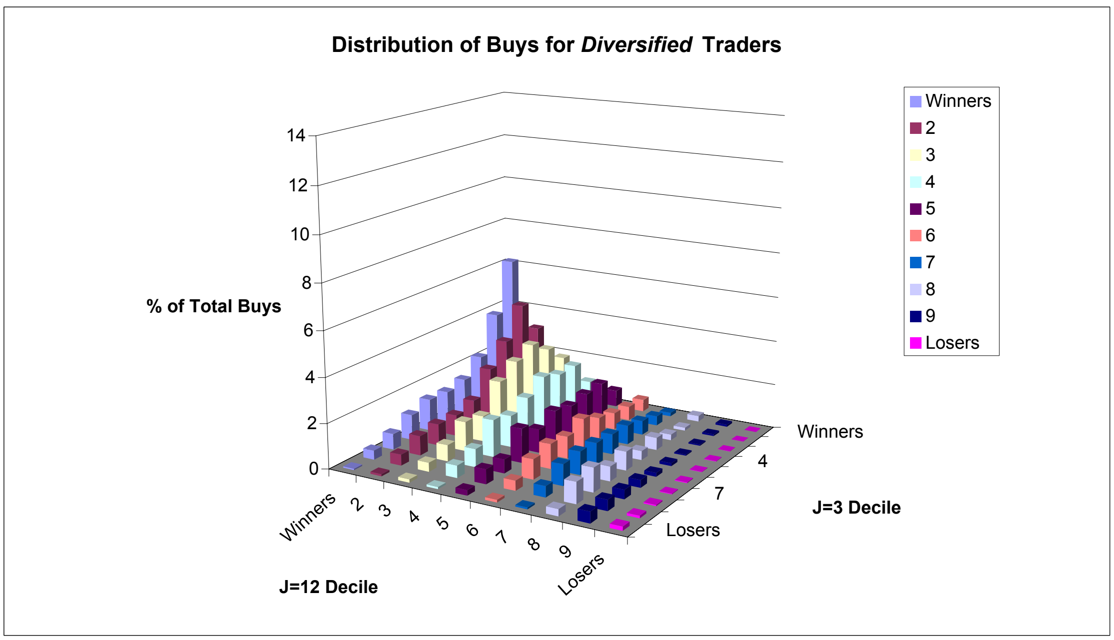
- Hypotheses:

  (1) *If the strategies of the actual momentum managers mirror the simulated strategies, their buys (sells) will be concentrated in the winner (loser) end of the JT prior-return deciles.*

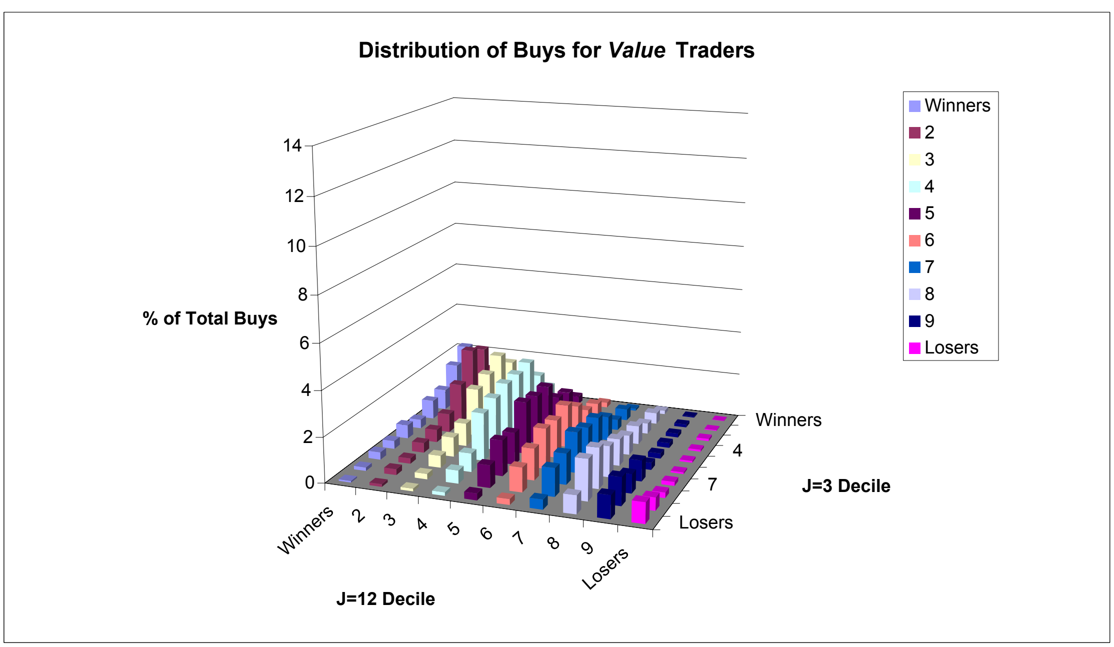
  (2) *The trades of the value and diversified managers will be more evenly distributed over the prior return deciles because they are not explicitly conditioning on past price movements.*



Distribution of Buys for *Momentum* Traders
% of Total Buys
14
12
10
8
6
4
2
0
Winners
2
3
4
5
6
7
8
9
Losers
J=12 Decile
Winners
4
7
Losers
J=3 Decile
Winners
2
3
4
5
6
7
8
9
Losers



Distribution of Buys for *Diversified* Traders
% of Total Buys
14
12
10
8
6
4
2
0
Winners
2
3
4
5
6
7
8
9
Losers
J=12 Decile
Winners
4
7
Losers
J=3 Decile
Winners
2
3
4
5
6
7
8
9
Losers



Distribution of Buys for *Value* Traders
% of Total Buys
14
12
10
8
6
4
2
0
Winners
2
3
4
5
6
7
8
9
Losers
J=12 Decile
Winners
4
7
Losers
J=3 Decile
Winners
2
3
4
5
6
7
8
9
Losers

Evidence on Trend Chasing (II)

Are Institutional Trades Conditioned on Recent (3-week) Prior Price Movements?

The table reports average 3-week excess returns prior to institutional trade packages and estimates of a logistic regression model for these buy and sell packages. The average excess returns are measured over the *15 trading days prior to the commencement of a trade* . The 3-week pre-trade excess return for security *i* , $PriorXRet_i$, is defined as the return for security *i* for the 15 trading days preceding the trade minus the return (for the same period) for the market in which the stock is traded. The dependent variable in the logit model is a dummy variable that takes the value 1 if the package is a buy, and 0 otherwise. $PriorXRet_i$ is the independent variable in the model. Maximum liklihood estimates of the model are reported, with asymptotic standard errors in parentheses. Results are reported for the 33 institutions in the U.S. equity markets for the pooled 96-97 and 2000 sample periods.

	Mean 3-week excess price change (%) (*PriorXRet*) prior to:			**Logit Model Coefficient Estimates**	
	Buys	**Sells**	**t(Buys-Sells)**	**intercept**	***PriorXRet***
All Institutions	1.046	0.256	11.52	**-0.1460**	**0.0049**
				(-0.0054)	(0.0004)
Diversified Institutions	0.530	0.340	1.42	**-0.2760**	0.0011
				(0.0102)	(0.0008)
Value Institutions	-0.318	0.819	-10.61	**0.0304**	**-0.0089**
				(0.0094)	(0.0008)
Momentum Institutions	2.469	-0.345	24.36	**-0.1933**	**0.0164**
				(0.0088)	(0.0007)

Bold indicates significance at the 5% level.

• Trade size is larger for momentum traders than for other traders

Number shares traded (in the institutional order) as a percent of total volume for that stock on day(s) of the trade. Results are reported for trades executed on U.S. exchanges during the periods April 1996 - March 1997 and calendar year 2000.

	Min	1%	5%	10%	25%	Median	75%	90%	95%	99%	Max
Buys											
Diversified	0.0002	0.0008	0.0023	0.0047	0.0182	0.1104	1.0753	5.3648	10.6655	26.3158	100.000
Value	0.0001	0.0012	0.0040	0.0089	0.0397	0.2307	1.4663	7.0721	15.5045	46.4286	100.000
Momentum	0.0002	0.0030	0.0125	0.0339	0.2012	1.2826	**6.0867**	**18.8324**	31.3646	**67.0412**	100.000
Sells											
Diversified	0.0001	0.0008	0.0023	0.0048	0.0208	0.1296	1.0309	5.5521	11.2360	28.7165	99.530
Value	0.0002	0.0015	0.0060	0.0135	0.0526	0.2804	1.4321	6.1174	13.5728	48.8762	100.000
Momentum	0.0004	0.0031	0.0139	0.0348	0.1967	1.2403	6.0729	19.4096	34.2466	69.7318	100.000

For momentum traders:

- 1% of their *buy* trades represent at least 67% of total trade volume for that day.
- 10% of their *buy* trades represent at least 19% of total trade volume for that day.
- 25% of their *buy* trades represent at least 6% of total trade volume for that day.

Price Impacts – Some Preliminaries

- Price impact for an order containing the individual trades of stock *i* is defined as

$$[(\text{Trade Price}(i) / \text{Pre-Trade Price}(i)) - 1.0] - R_m$$

where:

Trade Price(i) = volume-weighted avg. trade price for the order;
Pre-Trade Price(i) = closing price for stock *i* on the day before the order is initiated;
R_m = local market index return during trade interval.

- The 96-97 and 2000 periods represent very different market environments:

	96-97	2000
Value Weighted CRSP	1.27%	-0.86%

- Price impacts measured in 96-97 and 2000 do not display important differences and the results of tests in the paper are similar when estimated separately in the two subperiods.

→ I pool results from the two subperiods for the remaining analysis

• Trend Chasing and Price Impacts

Average price impacts conditioned on upward- or downward-trending markets

Prior excess stock return (*PriorXRet*) is defined as the return on the traded stock, measured over the three weeks prior to the initiation of trade, less the market return over the same period. Price impact is the ratio of the average trade price to the closing stock price on the day before the order was initiated, minus 1.0, in excess of the market return over the interval of the trade. Price impacts for sells are multiplied by negative one so that they can be interpreted as costs and easily compared to the impacts for buys. T-values of the difference in average impact in upward- and downward-trending markets is to the right of these values. Agregate investment flow is the sum of the dollar value of all trades in the respective category, reported in billions of dollars. Number of orders is in parentheses. Results are reported for the 1996-97 and 2000 periods

	A. Buys			**B. Sells**		
	(A) ***PriorXRet*** **<0**	**(B)** ***PriorXRet*** **> 0**	**t (B-A)**	**(C)** ***PriorXRet*** **<0**	**(D)** ***PriorXRet*** **> 0**	**t (D-C)**
Diversified	-0.197	0.908	16.39	1.413	-0.494	-23.08
	\$9.44	\$10.91		\$8.81	\$9.18	
	(11842)	(12803)		(9316)	(9921)	
Value	-0.155	0.851	14.23	0.889	-0.366	-19.09
	\$32.31	\$24.77		\$23.03	\$34.82	
	(13231)	(12301)		(12454)	(13598)	
Momentum	0.494	1.892	20.55	2.238	0.319	-24.44
	\$14.19	\$30.08		\$23.93	\$17.10	
	(14159)	(17959)		(13557)	(12218)	

Do Institutional Trades impact stock returns?

Mean Daily Returns (%) in Excess of the CRSP Value-Weighted Stock Market Index for Stocks Traded by the Sample Institutions

	(A) Average Daily Excess Return for 12 months prior to trade	Average Price Impact in excess of VW CRSP	**(B)** Average Daily Excess Return During Trade Interval	**(B) - (A)** (t-value)
A. Buy Trades				
All	0.1304	0.6112	0.3536	0.2232 (17.43)
Diversified	0.1407	0.3751	0.3394	0.1987 (7.64)
Value	0.0321	0.2261	0.1808	0.1487 (7.39)
Momentum	0.1953	1.0754	0.4924	0.2971 (14.63)
B. Sell Trades				
All	0.0904	-0.6555	-0.2212	-0.3116 (-21.80)
Diversified	0.0815	-0.3778	-0.2632	-0.3448 (-10.78)
Value	0.0257	-0.2584	-0.0181	-0.0438 (-2.23)
Momentum	0.1573	-1.2236	-0.3825	-0.5398 (-22.53)