

CHAPTER 1: EVIDENCE ON INSTITUTIONAL TRADING PRACTICES

Moderator – Lin Peng, Zicklin School of Business, Baruch College
Assistant Professor

Asani Sarkar, Federal Reserve Bank of New York
Economist

Robert Schwartz, Zicklin School of Business, Baruch College
Marvin M. Speiser Professor of Finance and University Distinguished Professor

Wayne Wagner, Plexus Group
Co-Founder & Chairman

Avner Wolf, Zicklin School of Business, Baruch College
*Executive Director, University International Programs*²

LIN PENG: It is a great pleasure to moderate this panel today. Wayne Wagner could not be with us today. John Phinney from JP Morgan is here, and John we thank you for filling in.³

JOHN PHINNEY: I will do my best to convey the essence of the research that we recently completed on the cost dynamics associated with institutional order flow.⁴

To a retail investor, the stock exchanges look like a vending machine. An order is placed, the delivery is made and the execution comes back. The broker has completed his or her job, often within seconds. But this is not the case for the institutional trader. As we know, the order size – the ‘peg’ of

² At the time of the conference, Avner Wolf was Chairman of the Economics & Finance Department.

³ The presentation was prepared by Wayne Wagner with the help of John Phinney, who made the presentation. At the time of the conference, John Phinney was at JP Morgan.

⁴ The analysis is based on data supplied by investment management clients of the Plexus Group. Ali Jahansouz of Plexus Group conducted most of the internal research. Meei Tsern Jeng of the University of California Financial Engineering Program also provided research.

institutional trading interest – is much larger than the ‘hole’ size of the exchange process.

One perspective that is shared by many is that, with all the steps between the asset managers and the specialist post, the managers can’t execute efficiently. In 1994, specialists were involved in 8% of the trades. This year that number is expected to double, to almost 15% of trading.

We can illustrate the nature of a large trade. A client provided us with the complete trading records for a trade in Oracle on August 15, 2002. A momentum manager had sent a 1.8 million share buy order to his trading desk. The process unfolded as follows. The order was fed to an automated trading system. Trading began at 9:53 in the morning and the order was completely executed within 51 minutes. It required over 1,000 separate executions to complete that order. The average execution size was 1,700 shares. The single largest execution was 64,000 shares. That large trade occurred in a cluster of rapid executions when almost 190,000 shares were executed in less than one minute. The smallest execution in the block was for 13 shares. Seventeen percent of the executions were for 100 shares or less, and 44% of the total order was executed in pieces of less than 1,000 shares. There were up to 153 executions per minute.

To put this trade into context, let’s examine Oracle trading on that day. The total share volume was 59,000,000 shares. Thus this particular trade represented less than 3% of total volume. After the trading was completed for the block, the price of Oracle rose to \$11.46 from \$10.86 when the trade was started. In trading parlance, this would be referred to as a ‘DFT,’ otherwise known as a ‘Damn Fine Trade.’

Now let us take a peek at exactly why it was a DFT. First, the *delay cost*, computed as the difference between the opening price and the price of the first trade done, was 8 cents. The *market impact*, computed as the average execution price less the first trade price was only 7 cents per share. The *captured value* for that particular trade for that day of almost 45 cents represents the difference between the closing price and the average execution price. Thus, over the very short term, it looks like a most successful trade in terms of captured value versus cost of acquiring. It was a success from the perspective of the broker, the trade desk and especially the portfolio manager.

What does this example tell us about the nature of institutional trading? First, it shows that it is possible today to complete large liquid trades in both the central and the peripheral markets. But think about the process that it took to make that happen. It required a thousand-to-one reduction of the

manager's intent, to get trade pieces small enough to be digestible by the market. It took a significant amount of technology to automate that. The order had to be cut up to fit the average size of the hole: the exchange's – in this instance an ECN's – capability. Curiously, the 1,700 share average print in this case happens to be nearly the same as the average trade size on both the NYSE and Nasdaq.

In contrast, alternative institutional markets like Liquidnet and Harborside+ show significant size taking place, in the range of 44,000 shares for Liquidnet, and 70,000 shares for Harborside+. The issue on the table today is whether this meat grinder approach to trading institutional orders is *natural*, deriving from the desires and habits of the big investors, or whether it is *structural*, deriving from the nature of the exchange. Is it an artifact of the essentially retail nature of the exchange? That is the question that we addressed in our research project.

All too often institutional trades must be broken down and jammed through the retail sized trading window of the exchanges. This raises some questions:

- Does the breaking down of institutional trades encourage unnecessary dealer inter-positioning during the process?
- What information value is conveyed to the market as a result of this extended trading period?
- What do these search delays cost the investment professional?
- Does this structural issue, either exogenous or endogenous, impact trading costs?
- To what degree do they result in the leaking of overall performance?
- Do investors unintentionally leak performance to market middlemen?

The only way to get a very large trade-through a constricted hole is to stretch it out in time. Thus squeezing these very large trades through very small market windows results in significant delays in transmission, strategy and, of course, execution. Implementation cycles become extremely long, measured in days for many large or liquid institutional orders.

These are important issues. Do the investment managers truly understand the cost of implementing their investment ideas? Probably not. If they did, would the dynamics of trading institutional order flow change? Would the orders from the portfolio manager at the desk actually change?

Money managers need to understand the frictional costs and how they affect their ability to accumulate assets and performance returns over time.

Certainly the market places need to understand and to assess their ability to provide the facilities that are efficient, deep, liquid, and fair. Against the backdrop of the AIMR Trade Management Guidelines, trading costs really must be assessed relative to the value of trading itself.

We can serve up a bowl of statistics. We looked at the complete set of Plexus manager-supplied data for a six-month period, the fourth quarter of 2001 through the first quarter of 2002. There were almost 870,000 unique orders that were in this main rising-market sample. The follow-up sample consisted of 432,000 orders from the subsequent declining market quarter.

Included are data from 93 managers of all sizes, shapes, and styles. The data contain a high quality level of information linked together from the managers' accounting systems and order management systems.

There is a tremendous range of trade size in this universe. To avoid having our attention overwhelmed by the hundreds of thousands of small trades, or by the gigantic trades on the other end of the spectrum, we formed five trade groups. The first group contained the smallest trades. It was constructed so that one fifth of the trading dollars involved in the universe fell into this quintile. Four other quintiles of equal trading dollars were constructed, with the fifth quintile representing the largest trades in the universe. Each group should be of equal interest to investors because they each contain the same amount of trading dollars.

We want our cost assessment to show the real impact of interacting in the marketplace. We exclude from our cost analysis commissions and costs due to missed trades. We focus on (1) impact or market presence effects, and (2) trader delays (which are both tactical and liquidity seeking in nature), and (3) trading delays that occur during the search for liquidity. Using the implementation shortfall approach, we define total trading cost as execution price minus decision price. Decision price in our sample might be based on multiple orders from multiple managers within the organization at different release times. Exhibit 1 presents an interesting picture of the relationship between trade size and trading costs. The chart is fairly busy, but let me point out the extremes.

Trade Size	Trade Count		Shares (000)		Dollars (Mil)		% Avg Daily Volume		Cost (bp)	
Quintile			(Median)		(Median)		(Median)		(Median)	
	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
1(small)	444,485	356,053	2	2	0.05	0.06	0.4	0.3	11	6
2	22,906	18,988	154	176	4.82	5.79	10.8	11.1	47	36
3	8,340	7,217	393	430	13.74	15.61	18.3	18.2	64	47
4	3,527	3,199	851	923	31.86	35.24	28.1	30.8	81	69
5(Large)	1,303	1,209	2,014	2,105	75.62	80.91	52.6	53.8	90	127

• Cost per dollar traded rises from 0.11% to 0.90% with size of trade.

Is this a liquidity cost (proportional to trade size) or a frictional cost (proportional to time to execute)?

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Exhibit 1. Equal Dollar Quintiles / Rising Market

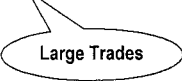
The first quintile, which contains the smallest trades, represents 90% of the total number of trades. At the other extreme are the largest trades. These are very small in number, less than one quarter of one percent of our sample. If you move to the median cost in basis points, you see that the smallest trade orders are handled efficiently at minimal cost. As we move to larger orders, trading gets dramatically more expensive – almost eight times as expensive for buys. Selling is almost always cheaper, unless you move into the fifth quintile, the largest trades.⁵ This represents what we call a ‘fire sale condition’ that results from selling large blocks of stock under panic conditions. To repeat, the distribution of the trade size is extremely wide. The median trade size in the smallest quintile is only \$53,000, while the

⁵ Most of the activity is driven by the buy decision, which in turn is driven by improving prospects or other good news. Most selling, in contrast, is more liquidity driven than information driven.


median trade size in the largest quintile is \$77,000,000.⁶ Shares, dollars, and percent of daily volume, all rise correspondingly. As I mentioned earlier, selling in this rising market was cheaper than buying, except at extreme size.

To observe the range of costs, we determined the 5th percentile cost of executions through what we would call the more challenged executions, the 95th percentile of cost. The results are shown in Exhibit 2.


		← Percentiles of Cost Distribution →				
	Sample	5th	25th	50th	75th	95th
Quintile 1	444,485	-369	-82	-11	29	240
Quintile 2	22,906	-689	-185	-47	29	376
Quintile 3	8,340	-732	-218	-64	29	443
Quintile 4	3,527	-842	-266	-81	41	588
Quintile 5	1,303	-979	-328	-90	107	934



Large Trades



Adverse Momentum



Favorable momentum

Large trades are much more costly than small trades; by a factor of 8 in the median cost

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Exhibit 2. Cost Range of Institutional Buying; Equal Dollar Quintiles / Rising Market

You can see that in almost every quintile, the most costly trade executions are dramatically different from the least costly executions. If anyone wonders whether best execution and excellent trading desks add value, this particular slide answers the question. The largest trades are far more costly than smaller trades. The range of costs within quintile is very

⁶ These numbers are the averages of the two-dollar figures (buys and sells).

wide, from 6% for the small order quintile to 19% for the large order quintile. The range separates those traders who demand liquidity and are willing to pay for it from those who supply that liquidity to them. To the right of the table are the traders who supply liquidity. To the left of the table are the orders of managers who are willing to pay large amounts to acquire liquidity. Suppliers and demanders of liquidity do not offset in this table; the gains from the natural liquidity providers are significantly lower than the corresponding costs on the other end of the distribution. The difference is in a rough sense the frictional cost of implementing investment ideas.

We next created a side-by-side comparison between the size distribution of our institutional trading population and the distribution of NYSE trades as reported in the 2002 New York Stock Exchange Fact Book.

Shares (<i>l</i>)	less than 2100	2100 - 5K	5k - 10K	10K - 25K	25K - 100K	100k - 250K	250 K +
	Percentage of Orders						
Managers	46.2	13.7	9.5	10.3	11.2	5.6	4.1
NYSE *	84.9	7.6	3.9	2.6	0.9	0.8	0.02
	Percentage of Dollars Traded						
Managers	1.1	1.2	17.6	4.4	18.6	21.6	35.4
NYSE *	12.9	4.2	44.5	6.9	9.2	21.3	1.1

* Source: 2002 NYSE Factbook

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Exhibit 3. Comparison of Institutional Order Size to Exchange Trade Size (Percentage of Orders)

At the upper end of trade sizes, greater than 25,000 shares, you can see

what Bob Schwartz referred to as *latent demand*. We also call it *big block demand*. It is very significant: 22% of total institutional orders were in the big block range. Yet less than 2% of all NYSE executions fall into that size category. With respect to dollars, the differential is similar though not as egregious. Seventy six percent of the total institutional dollars are represented by that 100,000 share-and-up category, while only 31% of the dollars traded on the exchange represent that type of size. This notion of structural dissonance becomes clearer as we delve deeper into the data.

Why do managers trade in such large sizes when we all know that trading in size is costly? To approach this question, we look at what we will call ‘the success of the decisions themselves.’ Consider the six-month performance, which is perhaps a classic value orientation of six months or longer.

Trade Size	5 days		1 day		5 days		6 weeks		6 months	
Quintile	Pre-trade		Pre-trade		Post-trade		Post-trade		Post-trade	
	Buys	Sells	Buys	Sells	Buys	Sells	Buys	Sells	Buys	Sells
1(smallest)	0.50	0.65	0.09	0.16	0.86	0.57	3.73	3.20	-3.71	-4.12
2	0.58	0.24	0.24	-0.13	1.22	-0.16	3.26	2.01	-8.87	-9.18
3	0.39	0.03	0.29	-0.19	1.38	-0.18	3.34	1.86	-9.22	-9.70
4	0.46	-0.24	0.32	-0.44	1.47	-0.32	2.91	1.59	-10.59	-11.18
5(Largest)	0.42	-0.79	0.27	-0.34	1.16	-1.05	2.32	0.00	-11.64	-13.19
					2.21		2.32		1.55	

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Exhibit 4. Median Buying / Selling Price Changes Equal Dollar Quintiles / Rising Market⁷

⁷ The good news in this table is that the median price performance on the buy orders exceeds that of the sells. All the net gain differences are positive. Within the largest-order fifth quintile, a net difference of 2.42% opens up within a week, sustains for at least six weeks, and then declines to 1.25% within six months. That is, the managers who made these buys

You can see that, in almost every case, in every quintile, the decision value is not large enough to support the costs incurred to implement these decisions over a period of six months. And remember that these results occurred in a rising market. The differential decision value is even more egregious as you go up in size.

It is tempting to think of the large trades as the ones that are most important to the managers because they are ‘dripping’ with informational content. However, the data do not support this view. On the basis of return capture, it seems more likely that these giant trades fall more into the category of portfolio diversifiers and longer term strategic bets. The results suggest that a penalty is incurred: the portfolio becomes unwieldy having such a large sum to manage. Based on the success of the decisions, one wonders if these trades are really necessary. Are they an inexorable part of the overhead cost of managing a very large fund?

The good news is that there is value in the security selection process. As we noted above, buys always outperform the sells,⁸ except for the smallest trades over the shortest time frames. As I said before, the buy-sell differential increases with the size of the trade. For the largest trades, a 2% to 2.5% buy-sell differential establishes itself in a week and sustains itself for at least six months. That might be considered the good news. But do large trades outperform small trades after the costs of implementing the decisions? No, they do not.

The larger the trade, the worse the return across the entire distribution (Exhibit 5).

in toto and financed the purchase with the proceeds of the sells in toto would have added value to the portfolios, excluding transaction costs. With few exceptions, the higher the quintile, the greater the differential, suggesting that the large trades are the most profitable. The not-so-good-news, however is that as the horizon lengthens out to six weeks and six months, the value of the buy decisions in the higher quintiles dissipates strongly, so that the smaller buy decisions appear to be much better decisions six months out.

⁸ There are two possible reasons for this. Managers are reacting correctly to changing prospects in the companies they are buying and selling. Alternatively, institutional buying pushes stock prices up while institutional selling pushes prices down.

		← Percentiles of Return Distribution →				
	Sample	5th	25th	50th	75th	95th
Quintile 1	444,485	-22.9	-4.3	3.7	11.8	31.0
Quintile 2	22,906	-24.0	-5.0	3.3	11.8	30.5
Quintile 3	8,340	-23.1	-4.6	3.3	11.0	28.0
Quintile 4	3,527	-23.2	-4.9	2.9	10.0	25.3
Quintile 5	1,303	-24.2	-5.2	2.3	10.1	25.2

**The larger the trade, the worse the return --
across the whole distribution.**

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Exhibit 5. Range of 30-Day Institutional Buy Returns (Equal Dollar Quintile Medians)

Something about decision value and the ability to implement good investment ideas emerges from our data. It challenges the need for the large block trading that is taking place. It suggests that portfolios can become too large to maneuver in today's shallow markets.

To summarize, we do not see much decision value differentiation by trade size. At the fifth percentile of returns, large decisions do worse. For median returns, the large decisions do worse. And for the 95 percentile of returns, the large decisions were much worse at decision capture. Managers pay a lot more to execute these big trades, and the information value does not appear to justify the cost. The alpha appears to be 'paid away.'

We need to ask if there is something systemically wrong with the process of capturing an information edge. As large trades are forced to stretch out over time, do middlemen and other prying eyes take away some of the alpha advantage that comes from quality research? If the large decisions are not particularly driven by information, do market makers really suffer from informed trader risk? The data indicate that the information disadvantage is

not stronger for large trades than for small trades.

We next tackled the question, ‘Over what time horizon, post decision, is my information edge most effective?’ The results are shown in Exhibit 6.

Center cell (0.45): Median Buy Return (1.38) *less* Median Sell Return (-0.18)
Less Median Buy Cost (-.64) *Less* Median Sell Cost -.47)

	1 Day	5 Days	30 Days	125 Days
1 (small)	0.03	0.12	0.36	0.25
2	0.23	0.54	0.42	-0.53
3	-0.02	0.45	0.37	-0.64
4	-0.25	0.28	-0.19	-0.92
5 (large)	-0.75	0.04	0.15	-0.62

- **Caveat:** The sum of medians is not equal to the median of the sums!
 (It could be worse: doing arithmetic on quartiles!)
- **Nonetheless:** hints that:
 - Small to medium trade sizes perform best.
 - Net value of decision peaks early; turnover implications.

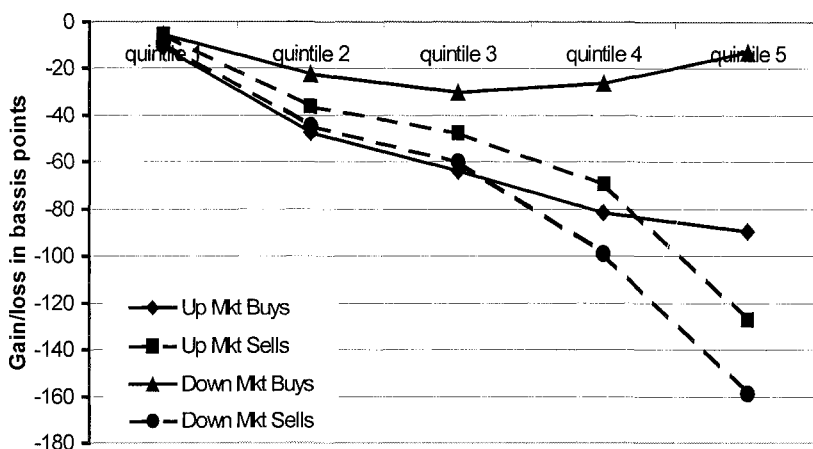
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Exhibit 6. A Suspect Computation! Median % Return Differentials Less Median Round Trip Costs

The data suggest that decision value peaks very quickly: within five days of our particular sample set. Within 125 days, with our sample set, net decision value is negative in all cases with the exception of the smallest trading quintile.

Our theory is that total transaction costs are determined by the perceived value of the research triggering the decision. Investors will continue to trade until the price approaches fair value within an amount less than the total transaction cost of the most efficient trader.

Finally, we turn to Exhibit 7, which contrasts results for the up and down market samples.



**Managers who buy big in falling markets
get paid for providing liquidity.**

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Exhibit 7. Cost of Trading. Up & Down Market Contrast

Many of you may have suspected this already, but in up markets, buying costs increase. In down markets, selling costs increase, and they are dramatically linked to trade size. Our observation is that managers who buy big in falling markets get paid significantly for the provision of liquidity.

Let's return to the original question about exogenous versus endogenous factors. Is this meat grinder approach to trading institutional orders natural (exogenous, deriving from the desires and habits of the investors), or is it structural (endogenous, deriving from the nature of the exchange)? Alternatively phrased, is it an artifact of the essentially retail nature of the exchange?

The meat grinder appears clearly in all of our data sampling. Trading costs seem to be much more related to endogenous market factors, structure, and process, than to exogenous factors derived from investor behavior. Trades get done, obviously. The question is whether what you are required to pay can be justified by the value received. Cost is inevitable. Cost represents a necessary discipline on the market. Yet do we, as investment

professionals, really understand what it costs us to implement our investment ideas?

While costs may be inevitable and unavoidable, the consequences of liquidity demand during high information moments appears to be poorly understood by professionals. Managers seem to pay up for size even though the information value may not be there, even though it may not appear to support investment returns over time. Our data hint at evidence of ‘lucrative friction,’ which we define as unnecessary inter-positioning, leakage to prying eyes, and the resulting increase in delay and impact costs.

Take a peek at a simple statistic. In 1982, there were about 1,000 investment managers servicing the market. Today there are over 8,300. Those are a lot of pairs of eyes watching trading action. Bob Schwartz noted this earlier. Everyone wants to play poker, and everyone is trying to out-bluff everyone else. Traders on the buy-side want to see, but they do not want to be seen. Yet advertising the desire to trade is a necessary requirement to draw out the liquidity that allows the trade to be completed. Electronic trading, ATSS and ECNs are a partial solution, but they are not the full answer. We need a trustworthy human intelligence factor at the core of the market.

We have one last point to make. John Phelan is alleged to have said, ‘Technology and communication bring efficiency. Unfortunately, money is made in inefficiency.’ It was a lighthearted comment. We hope that he was joking. Thank you everybody.

DOREEN MOGAVERO⁹ [From the Floor]: On your first slide you showed an execution and a chart with that execution. You classified that execution as a damn fine execution. If I had had that order in its entirety as a not held order throughout the day, my customer would not have classified that as a damn fine execution to me. It would seem to me it would have been mediocre at best, as it was done in the middle of the day at a medium price on the chart. Can you tell me what you think the difference in mindset is for a human execution versus an electronic execution?

PHINNEY: The difference in perspective between your client’s view and the representation made by the trader?

MOGAVERO [From the Floor]: That would be one way of looking at it (laughter).

PHINNEY: I think that is the answer. The communication of best

⁹ Doreen Mogavero is President & CEO at Mogavero, Lee & Company.

execution is sometimes an art form. When we use the term DFT with a particular trade, we are judging it from the perspective of the money owner, and his prime agent, the portfolio manager. I think it is in who is conveying what to whom at the end of the day.

HENRY WAELBROEK¹⁰ [From the Floor]: You made the point that there is really no statistically significant trader information risk in the larger block trades than in the smaller ones. I think that is a very important point for those of us who worry about creating systems that enable people to execute very large trades. We know that institutional traders are instinctively fearful of larger orders. Is this fear a product of the market structure itself? Do defects in the market structure cause larger orders to create excessive market impact because of the essentially parasitic activities of traders who front run and penny jump ahead of the institutional orders, once the orders are detected?

PHINNEY: A suggested substitution for the entire paragraph: Dealer risk is measured in principal risk to his capital. The larger the trade, the more significant the capital risk. Thus dealers would be disinclined to taking on large positions, especially when they fear more orders may lie behind it. However, our data consistently show that, on average, the search for liquidity in very large transactions consumes most of the decision value. Perhaps these large orders are not as much information-laden as they are liquidity-consumers.

PENG: Next, Avner Wolf, Asani Sarkar and Bob Schwartz will share their recent research with us.

AVNER WOLF: This presentation is on institutional order flow and market quality. In it we identify three objectives with respect to market quality: efficient price and quantity discovery, acceptable price volatility, and reasonable trading costs. We underscore two problems with respect to institutions' interaction with price and quantity discovery. First, institutions avoid active price discovery, mainly because large traders know that their orders can impact market prices. Second, buy and sell orders that could ideally meet, lie unexecuted in traders' pockets. The unrevealed institutional orders can represent a huge latent demand to trade. This second issue will be addressed shortly by my co-authors.

Market structure is not working for institutional investors. Their orders (the pegs) are large and their opportunities to trade (the holes) are tiny. The

¹⁰ Henry Waelbroek is Director of Research at Pipeline Trading Systems, LLC. At the time of the conference, he was with e-Xchange Advantage.

institutions slice, dice, and shred their orders. The result is high transaction costs, high volatility, and high latent demand.

To study these issues, we have considered trades of less than 5,000 shares to be retail trades, and trades of 5,000 shares and more to be institutional trades. We found half-hour volatility to be high, and that the high volatility is attributable mainly to the institutional orders, not the retail orders. We have also found that institutional order flow is two-sided (not one-sided), and that institutional trades tend to bunch in half-hour intervals.

We have measured volatility as a stock's high-low price range over a half-hour interval. We have half-hour intervals for 100 stocks (50 large cap Nasdaq stocks and 50 large cap NYSE stocks), for 20 days (in June 2001), for 13 half-hour periods a day. This gives us $100 \times 20 \times 13 = 26,000$ observations. These observations were used to run a regression in which the dependent variable is a stock's high-low price range in a half-hour interval. Our four independent variables are:

1. A stock's market value
2. A stock's close-to-open return (the price change from the previous day's close to the current day's open)
3. The number of trades less than 5000 shares in the half-hour interval (the retail-size trades)
4. The number of trades equal to or greater than 5000 shares in a half-hour interval (the institutional-size trades)

Summary statistics for the Nasdaq stocks are shown in Exhibit 8.

	All ½ Hrs		First ½ Hr	
	<u>Mean</u>	<u>Median</u>	<u>Mean</u>	<u>Median</u>
Hi/Lo %	2.24	1.50	3.61	2.87
 Cl to Op Ret %	1.66	.89	1.66	.89
# Trades < 5K	239.0	148	485.6	143
# Trades ≥ 5K	6.2	2.0	10.4	2.0
Ave Size < 5K	488	425	465	411
Ave Size ≥ 5K	11,837	9,600	11,041	9,446

Exhibit 8. Nasdaq Stocks

The mean percentage high-low range for all half-hours is 2.24. For the first half-hour it is 3.61. Note the relative amount of activity in the first half-hour compared to all half-hours. Look at the amount of volatility as reflected in the high-low ranges. Yesterday I spoke to Bob. I looked at the number and said, 'this is a huge number.' I asked Bob to give me a number for the volatility for the day. He picked 5%. Look at this number. Those of you who think that this is high volatility raise your hand. Be brave. Many hands are raised. Thank you.

ROBERT SCHWARTZ: How many don't think the number is high?

WOLF: Yeah, how many don't think that it is high? Very few.

Let me give you some intuitive feeling for this. If this number that we see in Exhibit 8, or the 5 % number that Bob gave me, were to translate to an annual volatility, it would be about 80%. David Krell is here, he may comment on this volatility. This means that, if a stock's price right now is

\$20, it would, with fairly high probability, fluctuate between \$5 and \$65 within one year. This is huge. Clearly this is something that we want to look at, analyze, and understand. We found similar results for the NYSE (Exhibit 9).

	All ½ Hrs		First ½ Hr	
	Mean	Median	Mean	Median
Hi/Lo %	0.67	0.51	1.18	0.98
 CI to Op Ret %	0.70	0.40	0.67	0.40
# Trades < 5K	42.4	30	49.0	36
# Trades ≥ 5K	4.2	1	6.4	2
Ave Size < 5K	719	682	823	806
Ave Size ≥ 5K	13,689	10,044	15,716	12,014

Exhibit 9. NYSE Statistics

Volatility is lower, but basically the results are the same. There is more activity in the first half-hour compared to all half-hours.

As to our four independent variables, we found the following. First, the Nasdaq stocks. Look at Exhibit 10.

	a	Mkt Value	Close to Open Ret	# Trades < 5,000	# Trades ≥ 5,000	\bar{R}^2
All 1/2 Hrs						
Parameter	0.192	-.0084	+0.189	+1.01e-06	+ .0005	
t statistic	14.32	-13.64	+3.19	+ 6.73	+ 4.49	0.438
(13,000 obs)						
First 1/2 Hr						
Parameter	0.228	-.0096	+0.250	+7.43e-06	+ .0004	0.419
t statistic	5.59	-5.087	+2.035	+2.64	+1.81	
(1,000 obs)						

Exhibit 10. Half-Hour High-Low Regression Results: 50 Nasdaq Stocks

For market value, as expected we got a negative coefficient. In the two cases (all half-hours and the first half-hours), market value is statistically significant. For the close-to-open return, as expected we got a statistically significant positive coefficient. For retail trades (less than 5000 shares), we got results that are positive and statistically significant, but the coefficients are tiny, they are very small compared to the coefficient for the number of trades greater than 5000. Here it is statistically significant. Most important, the adjusted R^2 s are very high. This means that these regressions are meaningful. We should pay attention to them – especially to the number of trades greater than 5000.

The results for the NYSE stocks are quite similar (Exhibit 11).

	a	Mkt Value	Close to Open Ret	# Trades < 5,000	# Trades ≥ 5,000	\bar{R}^2
All 1/2 Hrs						
Parameter	0.063	-.0027	+0.040	+6.40e-05	+ .0002	
t statistic	19.07	-17.91	+2.49	+16.56	+ 10.96	0.361
(13,000 obs)						
First 1/2 Hr						
Parameter	0.094	-0.004	+0.103	+9.46e-05	+0.0003	0.373
t statistic	9.95	-9.23	+2.16	+5.91	+4.55	
(1,000 obs)						

Exhibit 11. Half-Hour High-Low Regression Results: 50 NYSE Stocks

Again, market value is negative and statistically significant. Close-to-open returns are positive and statistically significant. Trades less than 5000, is positive, tiny, but statistically significant. Trades greater than 5000 is positive, statistically significant, and clearly more important than trades less than 5000 (even though there are many fewer of these trades). Once gain, the R^2 's are all reasonably high. Once more, we find that this regression is very meaningful.

We must focus on these volatilities. The traders among you will know that they are high. We need to look at them and to explain them. Hey Asani, what explains this? Take the baton and run with it.

ASANI SARKAR: Avner showed that the large trades produce substantially more volatility than the smaller trades. I will talk about the source of this volatility. One obvious potential source is news. News would

cause markets to be one-sided (buy orders only or sell orders only). But we find that markets tend to be two-sided – namely, there are both buy-triggered and sell-triggered trades occurring jointly in half-hour intervals. Thus, news does not appear to be the main source of this volatility.

To analyze this, we have classified trades in the usual way. Buy-triggered trades are the ones that hit the offer, and sell-triggered trades are the ones that hit the bid. With the trades classified, we count the number of large buy-triggered trades and the number of large sell-triggered trades in each half-hour interval. We then look at every possible combination of large buy and large sell trades, and count the percentage of half-hour intervals that have each specific combination.

To illustrate, let’s take one specific combination – two large buy-triggered trades and one large sell-triggered trade. We count how many half-hour intervals have that specific combination. Lets suppose that X% of the half-hour intervals have this combination. We create a matrix and put this X% number in the 2,1 cell (Exhibit 12).


Percentage of Total Arrivals in the 1/2 Hr Windows

Number BUY – Triggered	Number SELL – Triggered							
	0	1	2	3	4	5	>=6	
0								
1								
2		X%						
3								
4								
5								
>=6								
								100%

Exhibit 12. Combinations in Matrix Formation

The total of the percentages in all of the cells in the matrix will add up to 100%.

Suppose markets are one sided. What would this matrix look like? First, assume that there is good news and only buy-triggered trades. In such a case, all of the trades would be concentrated in the first column (Exhibit 13).

 = Buyer(s)








Number BUY – Triggered	Number SELL – Triggered							
	0	1	2	3	4	5	>=6	
0								
1								
2								
3		Good News!!! Buyers Arrive						
4								
5								
>=6								
	100%							

Exhibit 13. If Good News and Buyers Only

Alternatively, if the news is bad, there will only be sell-triggered trades. In this case, all the large trades would be concentrated in the first row (Exhibit 14).

 = Seller (s)







Number BUY – Triggered	Number SELL – Triggered							
	0	1	2	3	4	5	>=6	
0								100%
1								
2								
3								
4								
5								
>=6								

Exhibit 14. If Bad News and Sellers Only

More generally, with good news and bad news alternately arriving in different half-hour windows, the observations would be on the borders – the first row and the first column (Exhibit 15).



Exhibit 15. If News is Good in Some ½ Hrs and Bad in Others

What would happen if, instead of being one-sided, the orders are two-sided? In this case, we would find that many of the observations would be on and near the diagonal rather than on the borders (Exhibit 16).

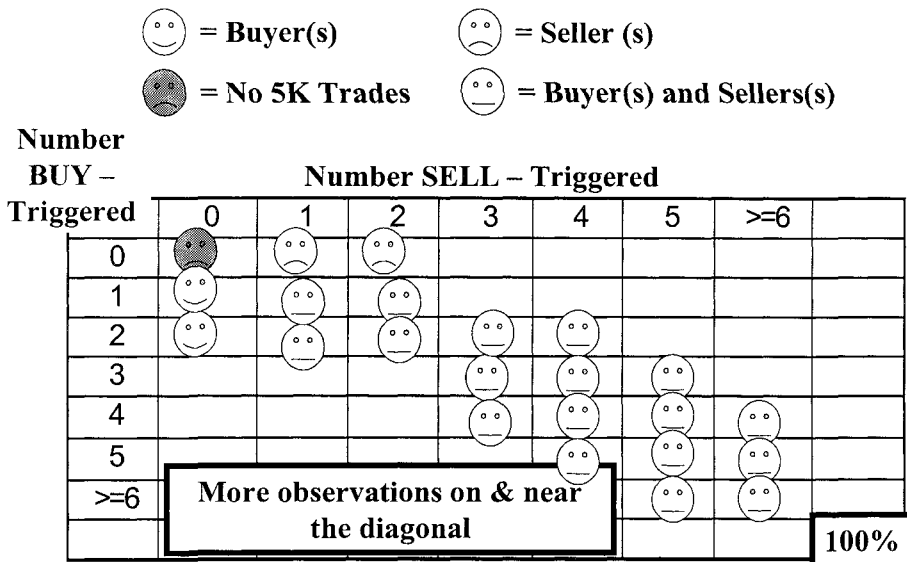


Exhibit 16. If Markets are Predominantly 2-Sided

Further, if the markets are two-sided and there is clustering, we would find that a lot of these observations would be bunched in the upper left hand corner (the 0,0 cell) and in the lower right hand corner (Exhibit 17).

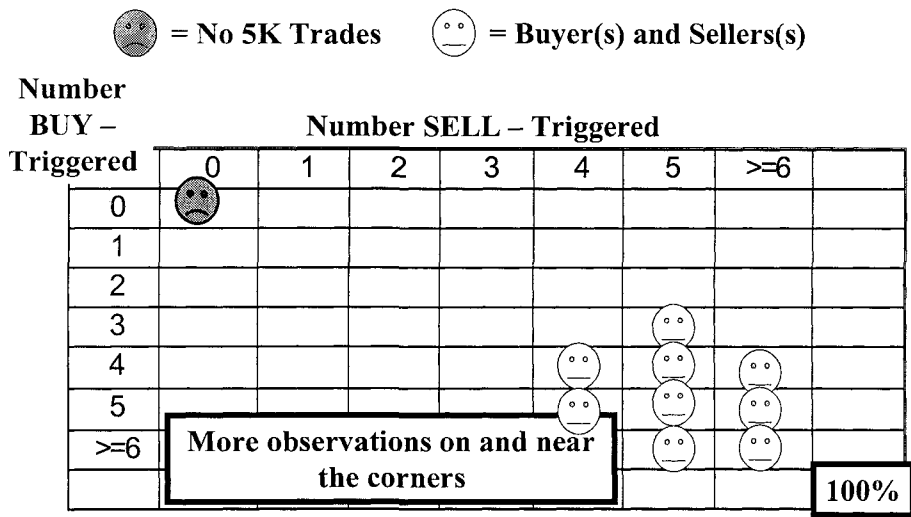


Exhibit 17. Strong Clustering

In other words, if nobody is trading, then nobody else will be trading. Alternatively, if people are trading a lot, then more people are attracted to trade.

We have these three patterns (Exhibit 18).

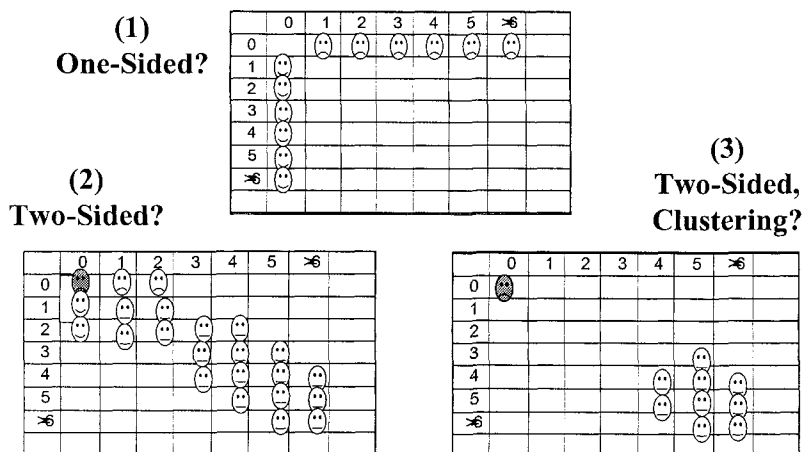


Exhibit 18. Which Pattern Did We Find?

One possibility is one-sided – how many people in the audience think that one-sided patterns predominate? Almost nobody. How about two-sided (observations on the diagonal)? How many people think that two-sided markets predominate? Only a small number as well. How about the final possibility – two-sided with clustering (observations in the 0,0 cell and in the lower right corner)? OK, more of you think it is this one. Which did we find?

The results for Nasdaq are shown in Exhibit 19.

Number BUY – Triggered	Number SELL – Triggered							
	0	1	2	3	4	5	≥6	
0	37.62%	6.52%	2.70%	1.08%	0.50%	0.23%	0.47%	49.09%
37.62% of ½ hour periods had no trade ≥ 5000 shares						0.42%	0.84%	1.15%
						0.33%	0.90%	7.88%
3	0.90%	1.19%	0.92%	0.64%	0.44%	0.34%	1.08%	5.44%
4	0.41%	0.63%	0.50%	0.58%	0.44%	0.28%	0.92%	3.77%
5	0.29%	0.39%	0.48%	0.42%	0.34%	0.29%	1.10%	3.27%
≥6	0.34%	0.60%	0.92%	1.17%	1.00%	0.96%	1.41%	15.40%
	48.80%	12.21%						
10.41% of ½ hour periods had 6 or more buy-triggered trades and 6 or more sell-triggered trades								

Exhibit 19. Nasdaq All Day (Actual Arrivals)

This is for all of the half-hour intervals throughout the day. This is the matrix that I was talking about. Each cell of the matrix is filled in. What we find is that the entry for the 0,0 cell (no large buy or sell trades) is 38%. The entry for the lower right-hand corner of the matrix (the 6+, 6+ cell) is close to 11%.¹¹ These are the two largest numbers in the matrix.

Those were the actual trades. Suppose that trades are in fact independent and unclustered. What would the expected arrival of trades then be? Hypothetically, what would the matrix then look like? The entry for the 0,0 cell would be less than 1%, and the entry for the 6+,6+ cell would be even smaller (Exhibit 20).

¹¹ By 6+ we mean six trades or more in a half-hour period.

Number

BUY –

Triggered

Number SELL – Triggered

	0	1	2	3	4	5	≥6	
0	0.61%	15%	19%	16%	10%	05%	03%	77%
1	15%	39%	50%	42%	27%	13%	08%	97%
2	19%	50%	64%	54%	34%	17%	11%	253%
3	17%	43%	54%	46%	29%	15%	09%	216%
4	10%	27%	35%	29%	19%	09%	06%	138%
5	05%	14%	18%	15%	09%	05%	03%	70%
≥6	03%	09%	11%	10%	06%	03%	0.21%	46%
	78%	99%	254%	215%	172%	69%	45%	1000%

Exhibit 20. Expected Arrivals if Trades are Independent (unclustered)

We subtract the expected values from the actual values in the matrix to get the unexpected trading frequency. The results are shown in Exhibit 21.

Average trade arrival per 1/2 hour Buyers = 3.02, Sellers = 3.02								
Number BUY – Triggered	Number SELL – Triggered							
	0	1	2	3	4	5	6+	
	37.01%	4.98%	0.74%	-0.62%	-0.53%	-0.31%	0.12%	41.34%
	54.2%	-0.54%	-3.23%	-3.18%	-2.11%	-0.98%	-5.00%	-4.63%
The Winner ! (3) Two-Sided, Clustering								
		-3.54%	-5.18%	-4.54%	-2.81%	-1.44%	-0.24%	-1.74%
		-3.18%	-4.57%	-4.02%	-2.53%	-1.11%	0.07%	-1.18%
			-2.90%	-2.47%	-1.40%	-0.69%	0.30%	-1.10%
				-1.32%	-1.11%	-0.63%	-0.21%	-3.82%
				-0.25%	0.11%	0.37%	0.6	1.78%
					-1.77%	-1.74%	-9.72%	-4.18%
							11.8%	0.00%

Exhibit 21. Nasdaq All Day (Actual Minus Expected)

For Nasdaq, the difference between the actual and the expected value is 37% for the 0,0 cell, and 10% for the 6+, 6+ cell. This pattern is consistent with a market where trades are two-sided with clustering. Essentially, if nobody is trading, then nobody else will trade. It is like an empty restaurant – if no one else is in it, you do not go there yourself. Alternatively, you could have the 6+,6+ cell where there is a lot of trading. This is like a good party – everybody wants to go there.

We have repeated this analysis for the first half-hour intervals only (Exhibit 22).

Average trade arrival per 1/2 hour Buyers = 5.08, Sellers = 5.1											
Number BUY – Triggered		Number SELL – Triggered									
		2	3	4	5	6	7	8	9	>=10	
0	34.92%	2.8%	1.2%	0.4%	0.2%	-0.0%	0.0%	0.0%	0.0%	0.2%	44.82%
1	6.0%	2.8%	0.9%	0.6%	0.0%	0.0%	0.0%	-0.1%	0.2%	0.2%	1.64%
2	2.2%	0.8%	0.6%	0.0%	0.0%	-0.7%	-0.5%	-0.4%	0.0%	-0.0%	1.7%
3	1.0%	0.1%	-0.2%	-0.6%	-1.0%	-0.8%	-1.0%	-1.0%	-0.3%	0.2%	-4.8%
4	0.1%	0.4%	-0.3%	-1.3%	-1.7%	-2.0%	-2.0%	-1.4%	-0.8%	-0.1%	-1.4%
5	0.3%	-0.2%	-0.5%	-1.4%	-2.3%	-2.6%	-2.4%	-1.5%	-0.8%	-0.0%	-2.5%
6	-0.1%	-0.3%	-1.0%	-1.9%	-2.5%	-2.8%	-2.8%	-1.7%	-1.1%	-0.2%	-3.8%
7	0.0%	-0.1%	-0.8%	-1.8%	-1.9%	-2.2%	-1.7%	-1.4%	-0.9%	-0.5%	-1.4%
8	-0.0%	-0.3%	-0.6%	-1.0%	-1.5%	-1.5%	-0.9%	-0.4%	-0.4%	-0.3%	-7.2%
9	-0.4%	-0.1%	-0.4%	-0.8%	-1.0%	-0.8%	-0.8%	-0.3%	-0.2%	-0.4%	5.8%
>=10	-0.4%	-0.2%	-0.5%	-0.7%	-0.8%	-0.5%	-0.1%	-0.2%	0.0%	0.1%	11.08%
	44.5%	8.0%	-1.0%	-7.7%	-16.2%	-14.0%	-11.1%	-9.3%	-4.9%	-2.3%	0.0%

Exhibit 22. Nasdaq First Half-Hour (Actual Minus Expected)

The results are very similar. There are many observations in the 0,0 cell (no trades at all), and many more observations than expect are clustered in the 10+, 10+ cell.¹²

Lets look at the NYSE (Exhibit 23).

¹² By 10+ we mean ten trades or more in a half-hour period.

Average trade arrival per 1/2 hour

Buyers = 2.31, Sellers = 1.70

Number BUY – Triggered

Number SELL – Triggered

	1	2	3	4	5	6	7	8	9	>=10	
0	38.26%	-039%	-064%	-027%	-002%	003%	003%	002%	002%	002%	463%
1	389%	-357%	-423%	-248%	-092%	-013%	003%	007%	003%	002%	-721%
2	-100%	-007%	-563%	-311%	-113%	-023%	003%	004%	004%	004%	-1738%
3	-244%	-503%	-437%	-237%	-090%	-009%	004%	004%	003%	003%	-513%
4	-149%	-297%	-233%	-122%	-044%	004%	013%	007%	013%	003%	-732%
5	-053%	-123%	-093%	-033%	003%	013%	014%	013%	004%	003%	-253%
6	-020%	-039%	-022%	003%	013%	013%	013%	009%	013%	013%	013%
7	003%	003%	003%	011%	013%	013%	007%	003%	007%	003%	097%
8	013%	003%	013%	014%	022%	012%	012%	013%	003%	007%	143%
9	003%	007%	003%	013%	013%	013%	003%	003%	003%	003%	173%
>=10	011%	023%	037%	037%	033%	057%	044%	042%	042%	034%	2.23%
	3613%	-539%	-1743%	-963%	-253%	082%	123%	130%	112%	083%	333%

Exhibit 23. NYSE All Day (Actual Minus Expected)

We find very similar results. For the NYSE all day tests, there are many more observations than expected in the 0,0 cell and in the 10+, 10+ cell. The results for the NYSE first half-hour only tests are the same (Exhibit 24).

Average trade arrival per 1/2 hour

Buyers = 3.54, Sellers = 2.64

Number BUY – Triggered		Number SELL – Triggered										
		1	2	3	4	5	6	7	8	9	>9	
0	30.39%	06%	-00%	-00%	-02%	-00%	-01%	-00%	00%	00%	00%	389%
1	25%	18%	-10%	-15%	-07%	-03%	-02%	-00%	00%	-00%	00%	54%
2	18%	-16%	-31%	-33%	-17%	-06%	-05%	-01%	-00%	-00%	00%	92%
3	03%	20%	40%	45%	-23%	-12%	-06%	-00%	-00%	00%	00%	-15%
4	-05%	-29%	-39%	-36%	-25%	-14%	-05%	-01%	03%	-00%	01%	-19%
5	-06%	-19%	-29%	-24%	-14%	-03%	00%	-00%	02%	00%	01%	91%
6	-05%	-14%	-15%	-12%	-08%	-03%	-01%	02%	-00%	01%	01%	-56%
7	00%	-01%	-05%	-06%	01%	-02%	-00%	02%	00%	01%	03%	-07%
8	-01%	-00%	-03%	-03%	01%	01%	00%	-00%	-00%	00%	02%	-03%
9	-00%	00%	00%	00%	00%	00%	00%	00%	01%	01%	06%	11%
>9	-00%	-00%	05%	07%	03%	14%	05%	06%	04%	08%	5.47%	
	373%	-04%	-17%	-11%	-92%	-25%	-15%	06%	11%	12%	72%	00%

Exhibit 24. NYSE First Half-Hour (Actual Minus Expected)

So, our findings of clustering are consistent for both the NYSE and Nasdaq, and for both the first half-hour and for all day. Bob will now explain what we can make of this.

SCHWARTZ: One thing that we can make of it is that the arrival of trades is not the result of news per se. Neither is it the result of a coin flip. Rather, it is caused by something inherent in the trading process. Markets are commonly two-sided. There are both buyers and sellers triggering trades. John Phinney, as you were talking, I was thinking about some of your results in this context. At a time when two large participants are trading, but not with each other, and neither may turn out to be a winner. That has implications for market structure.

We have some observations on the borders (the top row and the left hand column). To some extent, this is the result of big orders being sliced and diced. Because of slicing and dicing, I would say that our findings may be conservative. Our results, though conservative, suggest that large trades attract additional large trades. When there is action, there is indeed action!

Doreen Mogovero, I promise you that, in two panels, I will ask you about this.

Isn't it funny to be talking about a 5000 share institutional order when you guys want to trade 300,000, 500,000, or more? The big orders are much larger, but the pieces they are broken into aren't. You might ask why we took 5000 shares as the dividing line between big and small trades. It is because, if we had taken a 10,000-share cut, we would have had hardly any observations. We wouldn't have had a study. Further, not many retail customers submit orders larger than 5,000 shares.

Assume that a stock's price is 50 and that good news comes out. Large trades come in and price goes to 53. This could give us a three-point high-low range. Similarly, if it is bad news, a three-dollar price drop could result in a three-point high-low range. News certainly could explain it. But should we get this large high-low range with a two-sided market? Possibly, but if buyers and sellers both trigger trades in the same half-hour interval, we suggest that a large high-low range is attributable, not to news, but to how the orders are handled. This is the thinking that led us to our study.

The markets could be a whole lot more efficient. The big orders are not meeting each other efficiently. For a moment, let's step back from market structure per se and talk about how a buy-side trading practice may also be accounting for this. I want to give you some results from a study that I did with Benn Steil.¹³ Benn and I surveyed 72 chief investment officers at major asset management firms in North America, Europe and Australia.

We asked the chief investment officers what they believe the liquidity of a market is attributable to (Exhibit 25).

¹³ Reprinted with permission from Institutional Investor, Inc. 'Controlling Institutional Trading Costs: We Have Met the Enemy, and it is Us,' Robert A. Schwartz and Benn Steil, *The Journal of Portfolio Management*, Volume 28 Number 3, Spring 2002, pp. 39-49.

scale: 5 ("very frequently," or 75-100 percent of the time) to 1 ("never")

Because buyers and sellers:

Receive similar information but disagree in their interpretations	3.97
Have different portfolio objectives	3.65
Have different cash flows at a given point in time	3.31
Receive different information about stocks	2.79


Three cheers for two-sided markets!

Exhibit 25. Why CIOs Believe That 'Markets Are Liquid'

The number one reason that they pointed to is that participants receive similar information but disagree in their interpretations of the information. *Disagreement* in the interpretation of news underlies a lot of what drives trading. The lack of agreement amongst participants on the fundamental determinants of share value is one of the relatively unstudied aspects of market structure. But by gosh, that is why we have trading. It is disagreement that leads to two-sided markets and trading.

What do the CIOs look at when they judge the quality of the executions that they get? Look at Exhibit 26.

scale: 1 ("not at all important") to 5 ("very important," or 75-100 percent of the time)



Little or no market impact	3.95
Speed	3.42
Not revealing the full size of order to market	3.40
Not revealing the identity of company or fund	3.21
Within the current market inside spread	3.06
Price better than the VWAP	2.93
Low or no commission	2.29

Exhibit 26. Factors Important to CIOs on Judging the Quality of Execution for Large Orders

The most important consideration is that their orders have little or no market impact. Market impact should be first. The second most important consideration is speed. Why speed? Is it demanded for endogenous reasons or for exogenous reasons? An endogenous demand would mean that portfolio managers have their own internal reasons for wanting to trade quickly. An exogenous demand would mean that the portfolio managers would be willing to trade at a different time, but that market structure induces the demand for immediacy. Why might market structure do this? Because of information leakage and front running.

Let's turn to three more questions from the survey that focus on time. First, in their purchase decisions, what weight do the portfolio managers give to their expectations of what price will be one day into the future, one week into the future, or up to two years or more into the future? The responses to this question are shown in Exhibit 27.

scale: 5 ("very great") to 1 ("none")

	5	3	1	Mean
One day	0.0%	12.1%	65.1%	1.53
One wk	0.0%	20.0%	53.8%	1.72
One mth	0.0%	32.3%	33.9%	2.20
One qtr	6.2%	29.2%	23.0%	2.80
One yr	34.3%	20.8%	11.9%	3.69
Two yrs or more	53.7%	11.9%	11.9%	3.94

Exhibit 27. In Stock Purchase Decisions, Weight Given to Estimate of Share Price in...

The predominant answer was not 'one day' or 'one week.' Rather, it was 'one year' or 'two years.'

Second, how much time do the portfolio managers typically take to make a buy decision? The survey responses are shown in Exhibit 28.

scale: 5 ("very frequently," or 75-100 percent of the time) to 1 ("never")

	5	3	1	Mean
Less than one hour	3.1%	13.8%	30.8%	2.05
One hour to one day	7.7%	41.6%	17.0%	2.66
Over day to one week	10.7%	27.7%	9.2%	3.15
One week to one month	7.5%	21.2%	12.1%	3.14
Over one month	15.2%	19.7%	18.2%	2.92

Exhibit 28. Time Typically Taken to Make a Buy Decision

Clearly, the PMs do not make snap decisions. The categories 'less than one hour' and 'one hour to one day' did not get many votes, not compared to the categories at the longer end of the spectrum. Look at 'a week to one month,' and at 'over one month.' 15% of the respondents checked 'very frequently' for 'over one month.' It appears that the time clock does not tick so fast for the PMs.

Third, if you believe that a stock is mispriced, what is the time expected for a price correction to occur? The responses are shown in Exhibit 29.

scale: 5 ("very frequently," or 75-100 percent of the time) to 1 ("never")

	5	3	1	Mean
less than one hr	1.6%	9.5%	60.3%	1.60
One hr – one day	3.2%	7.9%	52.3%	1.75
One day – one week	4.8%	17.5%	25.4%	2.29
One week – one mth	1.6%	32.3%	14.5%	2.81
One mth – one yr	15.9%	36.5%	6.4%	3.51
Over one year	19.7%	16.4%	9.8%	3.28

Exhibit 29. If a Stock is Believed to Be Mispriced, Time Expected for the Price Correction to Occur

The categories range from less than an hour up to over one year. On what end of the spectrum do you think the answers lie? The responses surprised me. Only 1.6% of the respondents checked 'very frequently' for 'less than one hour,' and only 3.2% had this response for 'one hour to one day.' In contrast, 19.9% checked 'very frequently' for 'one month to one year,' and 19.7% had this answer for 'over one year.' Apparently, the PMs expect corrections to be made over an extended period of time.

So, why is immediacy demanded? We suggest that the demand is exogenous, that it is a product of our trading systems. That is what we are here today talking about and thinking about. We have seen that the institutional part of the market is two-sided, and that it is common for big trades to cluster in time. The clustering of trades strongly suggests that institutional orders are portable in time.

The portability of orders, in turn, strongly suggests that, at any moment

in time, the institutions have a sizable latent demand to trade. A PM's demand to trade is latent because the order is in the trader's pocket rather than being out there in the marketplace where others can see it and interact with it. Avner, Asani and I suggest that a major market structure objective should be to bring latent demand in from the cold. We got that line from the novelist, Le Carré. Remember his book, *The Spy Who Came In From The Cold*? It was a thriller. Can we do it with latent demand? Latent demand is latent liquidity. There is a lot of potential power out there. We should bring it in from the cold.

LIN: We have a few minutes for questions.

MICHAEL SCOTTI¹⁴ [From the Floor]: We had done that survey together when I was at Trader Forum.

SCHWARTZ: Yes.

SCOTTI [From the Floor]: It was run during a rising market. That might have some influence on why portfolio managers needed to get their trades done right away. It was a growth market. That might have been a factor. I do not know if their thoughts would be different if you interviewed them today. Maybe the traders can tell you otherwise on the buy-side, but at the time that was definitely a strong growth market. That definitely had an influence. The survey was done in 1998 and 1999. That was definitely a bubble period.

SCHWARTZ: Yes, it could be, Michael. Larry Harris?

LAWRENCE HARRIS¹⁵ [From the Floor]: To what extent is the clustering in your matrix due to the construction of the experiment? I believe that you pooled results across all the stocks. Some of the stocks are more actively traded and some are less actively traded. The more actively traded stocks would tend to pool in the lower right corner, and the less actively traded stocks would tend to pool in the upper left corner. This could give us the clustering, but not clustering within a given stock. Rather, it could be clustering across stocks.

SARKAR: I think our sample is all large cap stocks, so pretty much all of these stocks are trading frequently. But it is a good suggestion to make the study stock specific. We could do it stock-by-stock and see if there is a cross-sectional difference between the stocks.

SCHWARTZ: Could I add to that answer? That is a well-taken point

¹⁴ Michael Scotti is Director, Client Relations at KV Execution Services.

¹⁵ Larry Harris is currently a Professor at the University of Southern California. At the time of the conference, he was Chief Economist at the U.S. Securities and Exchange Commission.

Larry. The implication of trading attracting trading has a cross-sectional application. I ought to add that we are probably closer to the beginning of this study than to the end. But the idea that trading attracts trading can also explain why there is more trading in bigger stocks. The basic point that we are making holds in both the intra-stock and inter-stock dimensions, but we should disentangle the two.¹⁶ Thanks for the observation.

PENG: Thank you for an excellent panel.

¹⁶ Additional work that we have done since the conference confirms that clustering does occur on the individual firm level. The results are presented in Sarkar, Schwartz and Wolf, 'Inter-temporal Trade Clustering in Two-Sided Markets: An Intra-Day Analysis, Baruch College working paper, 2004.



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