て，わが国においても，マネージャー・スキルにはある程度の持続性が存在することが明らかとなった．ただし確認された持続性は，過去 2 年程度のトラックレコードを用いて計測したアルファが，その後 2 年程度に再現されることが期待できるというものである．この点でマネージャー・スキル評価信頼性を確保するためには，現在の実務界で要求されているのと同程度の期間のトラックレコードを使用することが合理的であるし，また単年度のパフォーマンス評価に基づいてマネージャー構造を変更することは適切ではないと言える．

もし単年度，あるいは 1 年以内のさらに短期での投資成果を重視するという基本方針が存在する場合，あるいはスタイルローテーション戦略が明示的に許容される場合には，対ベンチマーク超過リターン，あるいは CAPM のもとでのパフォーマンス評価を行うことが，短期の持続性が期待できるという意味で，経済的合理性を持つ．ただし年金基金の資産運用は，長期的視点で管理されるべきであるし，またスタイルローテーション戦略も本来認めるべきではない．したがって，マネージャー構造の決定におけるスタイルエクスポージャーの管理は必須であり，パフォーマンス評価は投資スタイルに起因するリスク調整後のリターンをもって行われるべきである．

参考文献:

Berk, J. and R. Green (2004), "Mutual fund flows and performance in rational markets," *Journal of Political Economy*, 112, 1269-1295.

Brown, S. and W. Goetzmann (1995), "Performance persistence," *Journal of Finance*, 50,679-698.

Carhart, M. (1997), "On persistence in mutual fund performance," *Journal of Finance*, 52, 57-82.

Cohen, R, J. Coval and L. Pastor (2005), "Judging fund managers by the companies they keep," *Journal of Finance*, 60, 1057-1096.

Elton, E., M. Gruber and C. Blake (1996), "The persistence of risk-adjusted mutual fund performance," *Journal of Business*, 69, 133-157.

Fama, E. F. and K. R. French (1993), "Common risk factors in the returns on stock and bonds," *Journal of Financial Economics* 33, 3-56.

Grinblatt M., and S. Titman (1992), "The persistence of mutual fund performance," *Journal of Finance*, 47, 1977-1984.

Jagadeesh, N. and S. Titman (1993) "Returns to buying winners and selling losers: Implications for stock market efficiency," *Journal of Finance*, 48, 65 - 91.

Jensen, M. (1968), "The performance of mutual funds in the period 1945-1968," *Journal of Finance*, 23, 389-416.

Kubota, K. and H. Takehara (2010), "Expected Return, Liquidity Risk, and Contrarian Strategy: Evidence from Tokyo Stock Exchange Firms," *Managerial Finance*, 36, 655-679.

Malkiel, B. (1995), "Returns from investing in equity mutual funds 1971 to 1991," *Journal of Finance*, 50, 549-572.

Sharpe, W., (1966), "Mutual fund performance," *Journal of Business*, 39, 119-138.

Treynor, J. and F. Black (1973), "How to use security analysis to improve portfolio selection," *Journal of Business*, 46, 66-86.

久保田敬一,竹原均 (2007),「Fama-French ファクターモデルの有効性の再検証」,『現代ファイナンス』, 22, 3-23.

表 1. Fama-French ファクター, UMD ファクターに関する記述統計量

EVW は東証全上場企業加重平均インデックスの配当修正後超過リターン, SMB は Small-Minus-Big ファクター, HML は High-Minus-Low ファクター, UMD は Upward-Minus-Downward ファクター. 分析期間は 2000 年 1 月～2010 年 12 月.

	EVW	SMB	HML	UMD
Mean	-0.209	0.278	0.957	-1.264
S.D.	5.031	2.542	2.856	4.026
Correlation Matrix				
	EVW	SMB	HML	UMD
EVW	1.000	-0.077	-0.102	-0.180
SMB	-0.077	1.000	0.002	0.039
HML	-0.102	0.002	1.000	-0.431
UMD	-0.180	0.039	-0.431	1.000

表 2. 分析対象ファンド数, 純資産額の推移

Year	分析対象ファンド数	(うちリターンが36ヶ月以上計算可能)	運用会社数	純資産(総額)	純資産額(1ファンド当たり)
2000	375	168	44	7985	21293
2001	443	210	47	6466	14596
2002	481	273	48	5054	10508
2003	512	375	49	5862	11449
2004	543	446	49	6514	11996
2005	595	483	50	9312	15650
2006	669	512	51	10369	15499
2007	715	543	54	8064	11278
2008	726	568	55	4750	6543
2009	699	574	55	5044	7216
2010	682	586	56	4699	6890

表 3. パフォーマンス測定結果の分布，平均，および標準偏差

各評価手法に基づくアルファの 5, 25, 50, 75 ,95 パーセンタイルと平均，標準偏差. (単位 %)

	Tracking Error	CAPM	Fama-French	FF3+UMD
5%ile	-0.453	-0.423	-0.350	-0.379
25%ile	-0.170	-0.161	-0.096	-0.082
Median	-0.030	-0.028	0.000	0.010
75%ile	0.126	0.135	0.155	0.139
95%ile	0.645	0.602	0.441	0.470
Mean	0.010	0.008	0.019	0.021
S.D.	0.335	0.327	0.253	0.277

表 4. パフォーマンス評価値間の相関構造

下三角行列にピアソン相関係数，上三角行列にスピアマン順位相関係数を示す.

	T. E.	CAPM	Fama-French	FF3+UMD
T. E.	1.000	0.971	0.616	0.450
CAPM	0.982	1.000	0.674	0.508
Fama-French	0.641	0.675	1.000	0.875
FF3+UMD	0.521	0.562	0.907	1.000

表 5. トラッキングエラー平均値を評価尺度とした場合の推移確率行列

各パネルの縦軸 B1(最上位 20%)～B6(最下位 20%)が評価前アルファの順位, 横軸 A1(最上位 20%)～A5(最下位 20%)が評価後アルファの順位. 数字 J は評価前アルファの測定に用いたデータ年数, K は評価後アルファの測定に用いたデータ年数. セル(Bn, Am)の値は, 評価前アルファがグループ Bn に属していたファンドが, 評価後アルファにおいて Am グループに属している確率を示している. (単位は%.)

		K=1						K=2						K=3				
		A1	A2	A3	A4	A5		A1	A2	A3	A4	A5		A1	A2	A3	A4	A5
J=1	B1	31.77	19.91	9.88	15.04	23.66	B1	29.64	23.05	12.90	11.19	23.53	B1	35.24	18.15	10.67	11.72	24.43
	B2	20.74	22.18	17.93	21.37	17.55	B2	19.19	22.28	19.83	22.68	15.88	B2	18.93	21.33	21.89	20.20	17.49
	B3	10.17	24.02	29.00	24.00	12.88	B3	11.30	19.11	29.78	25.76	13.96	B3	9.22	17.23	34.01	25.35	14.13
	B4	15.88	15.01	27.66	23.70	17.49	B4	16.51	18.30	24.19	21.50	19.28	B4	13.15	25.42	22.58	21.30	17.34
	B5	21.43	18.89	15.54	15.88	28.42	B5	23.36	17.26	13.29	18.88	27.35	B5	23.45	17.86	10.85	21.43	26.61
J=2	B1	29.91	19.69	11.86	15.50	23.37	B1	29.27	15.11	13.22	15.08	27.63	B1	26.99	17.14	12.62	15.31	28.24
	B2	22.10	24.14	16.53	20.29	16.69	B2	18.59	24.49	19.97	22.49	14.23	B2	22.90	19.95	20.01	19.17	17.77
	B3	10.42	21.13	31.51	24.25	12.82	B3	11.34	25.50	29.48	18.78	15.13	B3	13.76	22.33	31.76	17.46	14.91
	B4	15.75	17.91	24.13	22.85	19.04	B4	17.43	17.76	24.34	22.80	17.25	B4	14.87	21.26	21.81	26.84	15.06
	B5	21.82	17.13	15.98	17.11	28.08	B5	23.37	17.14	12.99	20.86	25.76	B5	21.48	19.32	13.80	21.23	24.02
J=3	B1	34.52	11.90	10.30	14.14	29.49	B1	24.82	16.20	11.46	16.25	31.56	B1	22.38	14.19	13.13	15.68	35.19
	B2	15.97	22.93	20.82	24.88	15.15	B2	21.18	18.06	19.23	27.29	14.08	B2	22.27	20.09	16.40	23.40	17.57
	B3	8.35	28.31	35.64	16.36	11.37	B3	11.29	28.83	34.80	13.94	11.17	B3	12.55	22.57	35.62	18.27	10.94
	B4	18.89	18.79	16.67	25.37	20.00	B4	18.91	19.93	19.21	21.76	20.02	B4	22.58	21.34	20.81	19.10	15.79
	B5	22.27	18.06	16.57	19.24	23.98	B5	23.79	16.99	15.31	20.75	23.16	B5	20.23	21.81	14.04	23.56	20.52

表 6.　CAPM のもとでのジェンセン・アルファを評価尺度とした場合の推移確率行列

各パネルの縦軸 B1(最上位 20%)～B6(最下位 20%)が評価前アルファの順位，横軸 A1(最上位 20%)～A5(最下位 20%)が評価後アルファの順位. 数字 J は評価前アルファの測定に用いたデータ年数, K は評価後アルファの測定に用いたデータ年数. セル(Bn, Am)の値は，評価前アルファがグループ Bn に属していたファンドが，評価後アルファにおいて Am グループに属している確率を示している. (単位は%.)

		K=1						K=2						K=3				
		A1	A2	A3	A4	A5		A1	A2	A3	A4	A5		A1	A2	A3	A4	A5
J=1	B1	32.74	17.38	11.23	14.79	24.05	B1	35.17	25.01	9.31	8.84	21.93	B1	34.19	18.17	9.66	11.46	26.80
	B2	15.66	21.77	19.56	26.63	16.20	B2	16.19	22.14	19.28	27.32	14.91	B2	19.39	18.12	20.98	21.53	19.74
	B3	14.89	25.97	28.16	19.54	11.46	B3	13.20	19.07	33.89	22.39	11.38	B3	12.81	18.88	35.42	21.50	11.38
	B4	12.31	22.98	24.15	18.54	21.80	B4	13.09	18.66	23.98	23.27	20.83	B4	10.54	26.90	21.03	23.85	17.50
	B5	24.40	11.90	16.90	20.50	26.49	B5	22.34	15.13	13.54	18.17	30.96	B5	23.09	17.93	12.92	21.66	24.59
J=2	B1	40.43	18.42	7.66	14.01	19.79	B1	33.26	23.55	11.18	10.54	21.80	B1	34.74	17.69	8.64	12.86	26.35
	B2	18.13	26.15	20.48	20.13	14.85	B2	24.47	20.56	19.63	21.33	13.70	B2	21.76	22.31	17.89	21.84	16.02
	B3	8.00	22.11	29.72	26.23	13.97	B3	8.40	17.39	31.73	25.97	16.55	B3	8.11	17.01	36.21	22.87	15.86
	B4	15.15	16.07	25.77	20.01	22.79	B4	13.50	19.07	24.21	21.52	21.46	B4	16.98	22.86	21.52	19.66	18.85
	B5	18.29	17.24	16.37	19.62	28.60	B5	20.37	19.43	13.26	20.63	26.48	B5	18.41	20.13	15.74	22.77	22.93
J=3	B1	37.08	16.38	9.09	15.04	22.71	B1	28.47	25.21	10.19	12.26	24.13	B1	26.95	17.56	10.51	12.22	33.25
	B2	23.05	24.97	14.88	21.60	15.19	B2	22.26	19.89	18.56	23.88	15.27	B2	22.98	19.44	16.99	23.27	16.99
	B3	7.62	27.04	34.65	18.19	12.58	B3	16.09	17.65	37.25	18.84	10.15	B3	17.20	22.07	34.79	17.39	8.51
	B4	11.97	16.73	23.31	23.44	24.33	B4	13.32	20.03	20.39	22.48	23.64	B4	16.00	21.88	20.62	24.02	17.19
	B5	20.27	14.88	18.07	21.74	25.20	B5	19.87	17.22	13.61	22.54	26.81	B5	16.87	19.05	17.10	23.10	24.06

表 7. Fama-French(1993) 3 ファクターモデルのもとでのジェンセン・アルファを評価尺度とした場合の推移確率行列

各パネルの縦軸 B1(最上位 20%)～B6(最下位 20%)が評価前アルファの順位，横軸 A1(最上位 20%)～A5(最下位 20%)が評価後アルファの順位．数字 J は評価前アルファの測定に用いたデータ年数，K は評価後アルファの測定に用いたデータ年数．セル(Bn, Am)の値は，評価前アルファがグループ Bn に属していたファンドが，評価後アルファにおいて Am グループに属している確率を示している．(単位は%.)

	K=1						K=2						K=3					
		A1	A2	A3	A4	A5		A1	A2	A3	A4	A5		A1	A2	A3	A4	A5
J=1	B1	20.25	20.58	15.03	15.54	28.86	B1	29.50	24.08	14.55	13.39	18.82	B1	27.23	19.02	20.46	13.31	20.32
	B2	22.02	18.82	21.11	22.28	15.59	B2	19.82	30.80	17.57	17.97	13.65	B2	22.02	22.38	20.59	19.77	15.03
	B3	19.77	24.65	17.57	23.56	14.41	B3	12.16	16.46	33.59	21.11	16.52	B3	12.15	24.92	22.38	24.46	15.98
	B4	13.87	19.64	30.71	21.63	13.97	B4	19.16	15.55	17.22	29.91	18.04	B4	16.79	16.21	24.18	27.44	15.22
	B5	24.09	16.30	15.59	16.99	27.17	B5	19.36	13.11	17.07	17.61	32.98	B5	21.81	17.46	12.39	15.02	33.45
J=2	B1	30.07	25.54	12.06	13.12	19.63	B1	35.35	20.18	13.60	12.40	18.83	B1	32.63	22.66	12.78	16.40	15.80
	B2	22.91	19.87	20.39	19.15	17.42	B2	17.03	35.80	19.18	15.27	12.44	B2	20.56	21.65	25.00	18.21	14.38
	B3	17.18	21.54	25.02	23.14	13.04	B3	18.90	16.98	28.25	18.10	17.82	B3	22.70	23.38	18.87	17.38	17.67
	B4	12.34	19.41	28.74	25.32	13.99	B4	9.88	14.58	27.14	30.96	17.21	B4	7.92	16.17	30.06	29.06	16.68
	B5	17.50	13.63	13.78	19.27	35.92	B5	18.84	12.46	11.82	23.28	33.69	B5	16.18	16.14	13.28	18.95	35.47
J=3	B1	28.96	22.04	12.11	14.11	23.15	B1	31.81	19.32	10.54	12.32	26.28	B1	30.33	17.57	11.75	15.16	25.65
	B2	19.39	23.74	14.59	22.32	19.72	B2	21.70	34.91	19.29	12.38	11.57	B2	26.68	18.95	24.41	16.03	13.56
	B3	21.48	21.14	24.10	21.58	11.71	B3	17.20	16.56	29.36	22.44	14.46	B3	20.80	28.38	18.11	17.67	14.94
	B4	12.76	18.47	31.29	23.82	13.42	B4	11.88	15.02	27.84	29.92	15.20	B4	8.19	16.99	29.68	30.57	14.42
	B5	17.40	14.62	17.91	18.17	32.01	B5	17.41	14.19	12.96	22.95	32.50	B5	14.00	18.11	16.05	20.57	31.43

表 8. Carhart(1997) 4 ファクターモデルのもとでのジェンセン・アルファを評価尺度とした場合の推移確率行列

各パネルの縦軸 B1(最上位 20%)～B6(最下位 20%)が評価前アルファの順位, 横軸 A1(最上位 20%)～A5(最下位 20%)が評価後アルファの順位. 数字 J は評価前アルファの測定に用いたデータ年数, K は評価後アルファの測定に用いたデータ年数. セル(Bn, Am)の値は, 評価前アルファがグループ Bn に属していたファンドが, 評価後アルファにおいて Am グループに属している確率を示している. (単位は%.)

		K=1						K=2						K=3				
		A1	A2	A3	A4	A5		A1	A2	A3	A4	A5		A1	A2	A3	A4	A5
	B1	22.60	19.03	13.44	14.19	30.95	B1	28.91	21.14	16.91	14.01	19.37	B1	27.40	23.92	16.97	13.36	18.66
	B2	21.12	19.40	21.79	20.75	16.80	B2	20.27	26.50	18.40	20.13	14.53	B2	18.32	23.26	25.07	15.98	17.19
J=1	B3	18.79	25.78	14.84	25.01	15.54	B3	10.62	24.42	25.46	20.94	18.40	B3	14.53	23.21	23.70	20.57	17.92
	B4	12.57	19.22	31.93	22.70	13.40	B4	19.25	12.60	19.49	29.29	19.23	B4	16.20	14.42	19.55	34.57	15.08
	B5	24.92	16.57	18.00	17.34	23.32	B5	20.95	15.35	19.74	15.62	28.47	B5	23.55	15.19	14.72	15.53	31.14
	B1	33.79	22.94	13.85	11.31	18.52	B1	33.30	19.30	14.11	14.24	19.40	B1	35.44	21.83	13.31	11.84	17.83
	B2	16.85	22.24	20.29	21.48	18.94	B2	17.09	30.66	21.81	14.63	15.55	B2	20.91	24.48	27.50	12.61	14.31
J=2	B3	21.37	17.01	24.09	23.17	14.23	B3	16.94	23.93	27.08	17.46	14.66	B3	18.68	24.85	20.88	20.95	14.67
	B4	13.04	21.31	26.41	24.62	14.42	B4	14.05	12.63	22.79	32.88	17.41	B4	9.52	13.50	25.39	33.40	18.06
	B5	14.94	16.50	15.36	19.43	33.89	B5	18.63	13.47	14.22	20.80	32.98	B5	15.44	15.33	12.93	21.20	35.13
	B1	32.05	20.58	13.32	12.26	22.14	B1	33.34	16.49	13.08	12.34	25.01	B1	32.76	17.52	13.01	13.07	24.10
	B2	19.76	23.80	16.92	21.27	17.99	B2	22.39	32.13	19.02	11.49	14.82	B2	27.17	20.12	21.59	14.34	16.42
J=3	B3	20.23	17.48	24.98	22.32	15.01	B3	16.33	21.47	29.53	19.52	13.15	B3	17.69	32.00	19.79	15.29	15.17
	B4	12.51	20.57	29.60	24.49	12.59	B4	11.81	15.63	24.55	33.75	14.13	B4	8.24	15.23	25.92	38.24	12.18
	B5	15.45	17.58	15.18	19.66	32.27	B5	16.14	14.27	13.82	22.90	32.89	B5	14.14	15.14	19.69	19.05	32.13

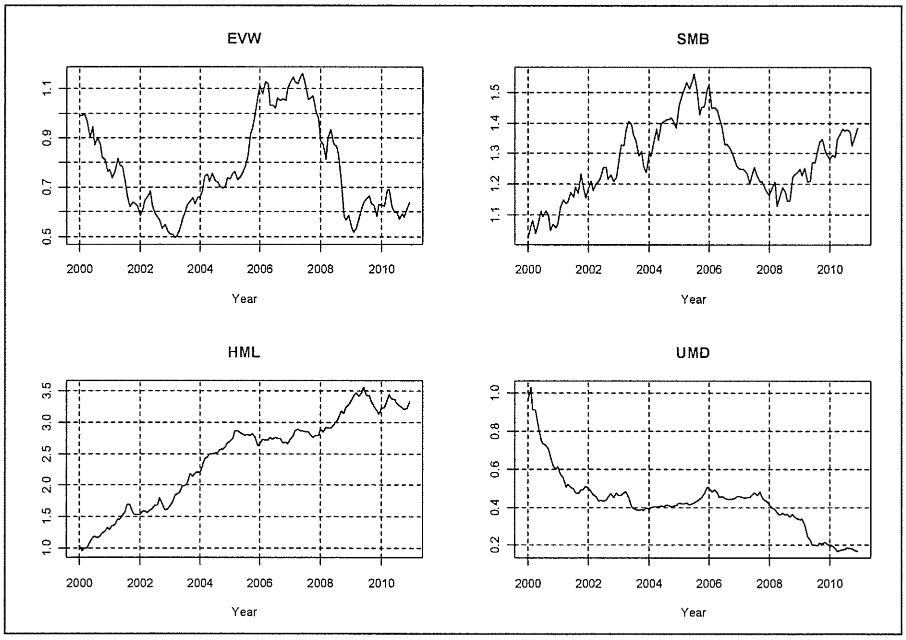

図 1. Fama-French ファクター, UMD ファクターの時系列推移

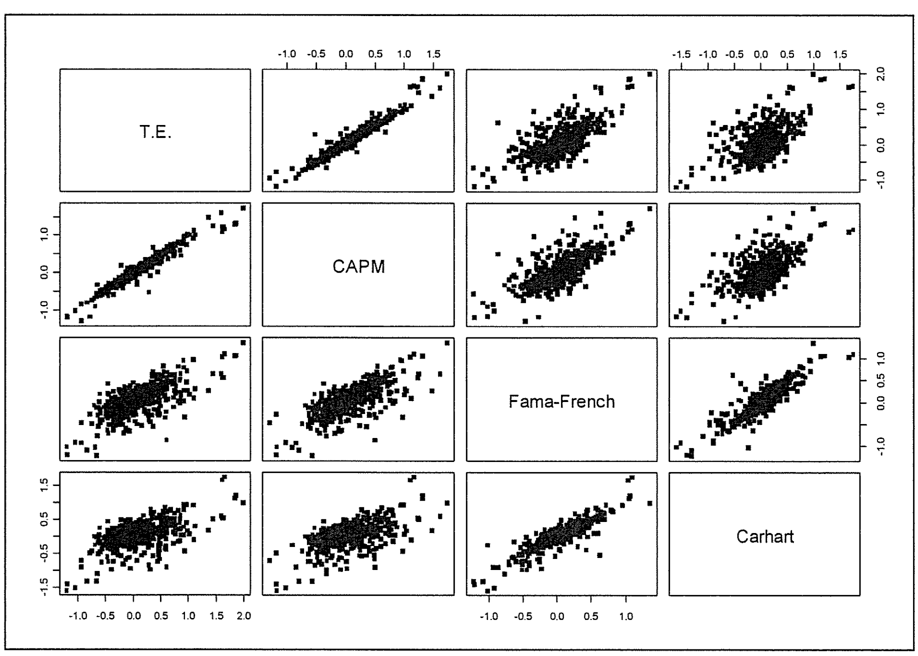

図 2. パフォーマンス評価結果の対散布図

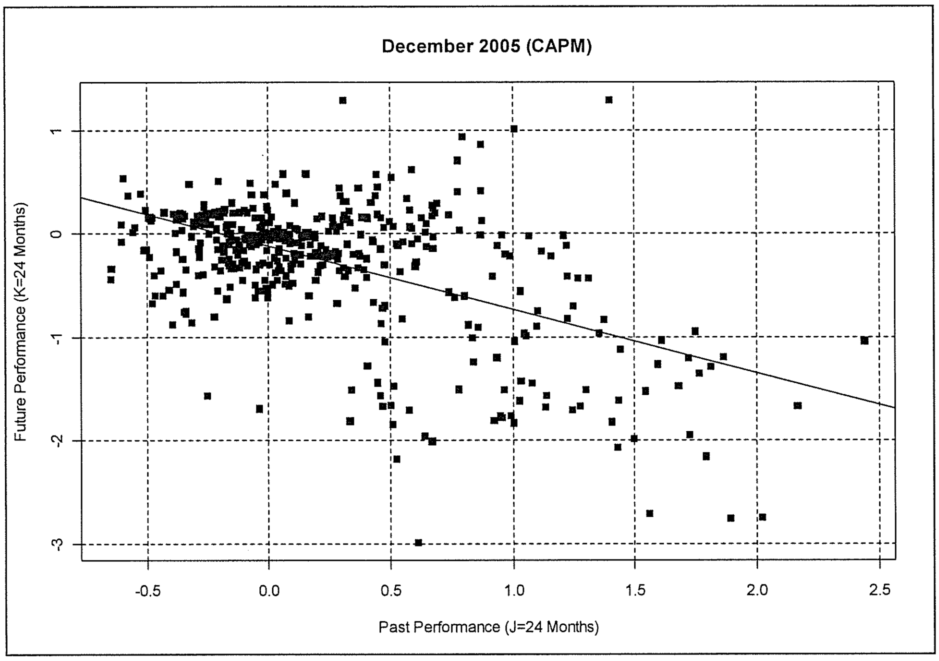

図 3. 事前と事後のアルファの関係: 2005 年 12 月, CAPM の場合

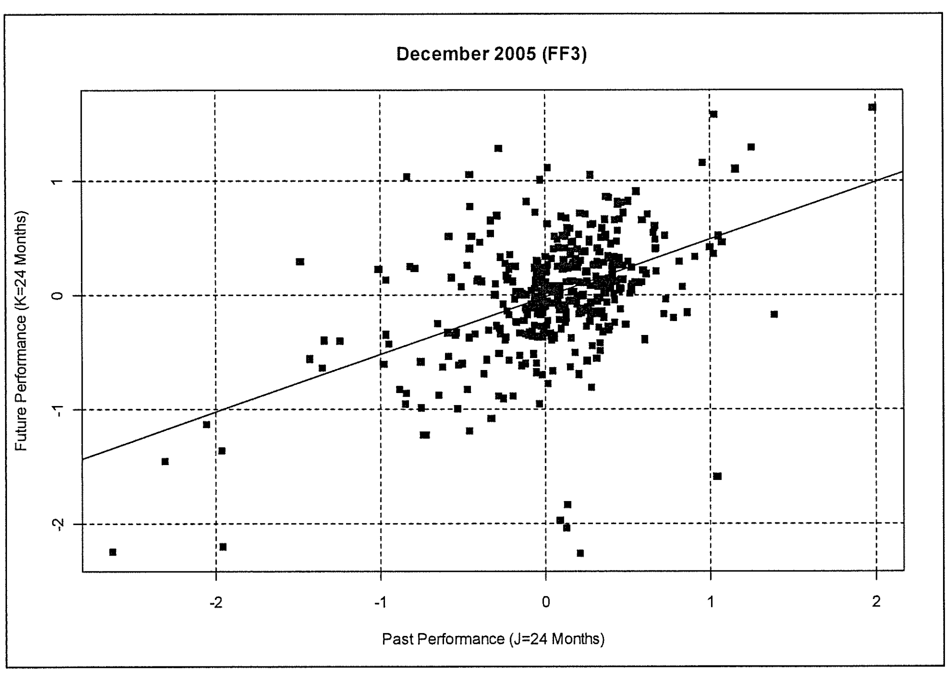

図 4. 事前と事後のアルファの関係: 2005 年 12 月, Fama-French model の場合

Speed of Trade and Liquidity

Jun Uno, Waseda University
Mai Shibata, Rikkyo University

Abstract

We investigate whether increasing the speed of order execution affects investor trading strategy and market liquidity. With the new trading platform Arrowhead, the Tokyo Stock Exchange has eliminated the three-second matching cycle, executes orders immediately, and instantaneously updates the limit order book, rendering computerized trading strategies more powerful. Since Arrowhead's introduction, there have been an increase in execution frequency and a reduction in trade size, leading to declines in effective spread and increases in adverse selection costs. Among trade intensity variables we examine, persistency of runs affects adverse selection cost more than share imbalance. High-speed quote revisions improve market depth.

JEL Classification: G10,G12,G14
Keywords: Liquidity Provision, High Frequency Trading, Matching Interval, Bid Ask Spread,

1. Introduction

This paper investigates whether increasing the speed of order execution affects trading strategy and liquidity. Recently, global stock exchanges have been competing in how quickly information on quotes and trades can be transmitted. This competition is now in the millisecond to microsecond range as a result of strong demand from investors who take advantage of technological innovations such as algorithmic trading.

In January 2010, the Tokyo Stock Exchange (TSE) upgraded its trading platform by introducing the Arrowhead system. Many changes were brought about by the new system, a particularly important one involving the matching cycle[1]. The matching interval had been three seconds before the introduction of the new system; now, when a market and/or limit order is entered, it is processed immediately. The order is then executed immediately and the limit order book updated instantaneously. This change has made computerized trading strategies more powerful, because computers can place and cancel orders faster than human traders. Although algorithmic trading was used in the TSE before 2010, the three-second interval in the matching process prevented quick trading strategies. Trading volume is expected to increase due to the introduction and expanded use of trading algorithms.

Algorithms typically determine the timing, price, and quantity of trades by dynamically monitoring market conditions across different securities, reducing market impact by optimally and sometimes randomly breaking large orders into smaller pieces, and closely tracking benchmarks such as the volume-weighted average price (VWAP)[2] over the execution interval.

Faster execution allows liquidity demanders to monitor the market more closely for temporary mispricings or stale quotes, which can raise adverse selection costs (Foucault et al. 2003). Faster execution attracts more informed trading (Barclay et al. 2003). The resulting higher adverse selection can raise the cost of immediacy for liquidity demanders. If investors rely on the same or similar algorithms for their trading decisions, however, this can increase herding behavior among sophisticated investors (positive feedback effects). The order flow imbalance thus results in a higher transaction cost for liquidity demanders.

Menkveld(2011) focus on a type of trader referred to as high frequency trading(HFT). The HFT only engages in proprietary trading, it starts and ends most trading days with a zero net position. This definition accords to other studies such as Brogaard(2011) and Kirilenko et al.(2011). Their strategy can be viewed as computerized market-making. Fast trading capability enhances skills of position risk management and quote setting. They utilize co-location service[3] newly provided by the TSE to maximize transmission speed of order submitting/revising/canceling strategy. Orders via co-location servers started at 10% of total orders

[1] TSE has revised the rules for maximum price change between trades and conditions for opening and closing auction. See TSE(2010) for further details.

[2] VWAP is used frequently by institutional investors to execute large orders. VWAP target order is referring to the order submission strategy in which a brokers slices large institutional orders into small pieces and execute them throughout a day.

[3] An exchange allows customers' computer server to locate on the same floor of the exchange's matching server.

on January 2010 and it exceeds 30% after May 2010 according to the TSE. New entrance of HFTs in the TSE can help improve liquidity of stocks.

The introduction of Arrowhead in the TSE can provide insights into the tradeoff between the concentration of orders from liquidity demanders and competition in liquidity providers. Since the change at the TSE, we have observed the following: There are an increase in execution frequency and a reduction in trade size, but no significant volume increases. The shift to HFT has been pronounced for larger stocks. We estimate a model that captures the relation between quote revisions and trading measures, which we quantify as HFT effects on quotes message traffic (MT) from the new system for individual stocks. Immediate matching promotes competition among liquidity providers, and HFT reduces compensation for liquidity provision while it increases adverse selection costs. Both trends are more pronounced for stocks characterized by heavy HFT, where quote revisions have increased substantially relative to the number of trades since January 2010.

Decomposing liquidity measures into two factors such as order flow intensity and market-making activity, we select four proxies for multiple regression analysis. A proxy for market-making is frequency of quote updates, and three order flow proxies are size of trade(number of trade), order imbalance and persistency of runs.

Quote updates are negatively associated with effective spread, realized spreads as well as adverse selection. It means that severe competition among liquidity providers reduces all spread measures. Size of trades is positively correlated with effective spread, realized spread and adverse selection cost. Order (share) imbalance is positively correlated with effective spread and adverse selection, but negatively correlated with realized spread. Persistency of runs are negatively correlated with effective spread and realized spread, but positively correlated with adverse selection. When effective spreads are low, then sequence of one side of trade prolonged. These variables indicate the increase in position risk. Quote revisions and trade intensity proxies except persistency of runs show positive relation with depth. Spread cost decomposition analysis for additional three month on 2010 show that price pressure factors and market-making factor seem to influence more compared to January 2010.

The remainder of this paper is organized as follows. Chapter 2 explains the TSE's new trading system and briefly surveys related research. Chapter 3 describes our hypotheses and the design of this empirical study. Chapter 4 presents our results and determinants of the spread changes brought about by Arrowhead. Chapter 5 gives our conclusions.

2. The new trading platform

On January 4, 2010, the TSE launched the new trading system Arrowhead. The main features of this system are accelerated computer processing speeds, a colocation service that reduces the physical distance between market participants (investors as well as brokerage firms) and the exchange, and a revision of the tick size. Prior to 2010, TSE implemented a series of computerizations in the trading process to replace human-based order handling. However, Arrowhead has the potential to incur a major paradigm shift in trading by changing the balance among market participants.

Increasing number of papers begins to address high frequency trading as well as algorithmic trading. Hendershott and Moulton (2009) study the 2007 introduction of Hybrid Market on the New York Stock Exchange (NYSE). The system expands the use of automated electronic execution and decreases execution times for market orders from over 10 seconds to less than one second. From the month prior to each stock's Hybrid Market activation date to the month after, NYSE's effective spreads increased from 5.6 to 5.9 basis points due to an increase in adverse selection. Hendershott et al. (2010) cite NYSE's 2003 switch to automated quote dissemination to show that algorithmic trading improves liquidity and, equivalently, decreases the speed of price discovery associated with trades. Chordia et al. (2011) note that rapid increases in turnover ratio, a striking increase in the number of trades, and consistent reductions in trade size are characteristic of current US stock markets. These findings reflect the increasing influence of HFT.

High-speed order flow may increase order imbalance for short-time period, such as one minute. Chordia and Subrahmanyam (2004) analyze daily order imbalance and their results indicate that order imbalances can be one of the most important factors to increase risk of market making in high frequency trading environment. They said that a high absolute order imbalance can alter returns as market makers struggle to re-adjust their inventory. In addition, order imbalances can signal excessive investor interest in a stock, and if this interest is auto-correlated, then order imbalances could be related to adverse section cost for liquidity providers.

Auto-correlated order flow can be analyzed by runs test. Runs test has been used the test of random walk hypothesis for price movements (Fama 1965, McInish and Puglisi 1982). Li(2005) estimates the hazard ratio of runs for directional movement of stock index returns. We apply the runs test for order flow data where buyer-initiated trade is assigned +1 and seller-initiated trade assigned -1. We believe this method has potentiality to capture persistency of order flow and associated risk for liquidity providers.

3. Empirical study design

3.1. Hypotheses

Faster execution allows all market participants to monitor the market conditions more closely and submit orders more quickly. Thus faster execution attracts more informed investors. The resulting higher adverse selection risk can raise the cost of immediacy for liquidity providers.

> Hypothesis 1: HFT increases adverse selection costs due to more informed and positive feedback traders and faster price discovery.

As trading became more computerised, it became easier and cheaper to replace the floor traders who played the role of liquidity provider with a computer program. High frequency liquidity suppliers who monitor market conditions across different securities can quickly notice an abnormally wide bid–ask spread and provide liquidity accordingly via a limit order.

> Hypothesis 2: Due to increased competition between liquidity providers, HFT reduces costs of immediacy.

The TSE's introduction of Arrowhead can provide insights into the tradeoff between liquidity demanders' increasing adverse selection and increasing competition among liquidity suppliers.

3.2. Samples

With the TSE's introduction of Arrowhead, the liquidity and price formation of listed stocks may be influenced by two major changes: the matching process cycle and tick size reduction. The former impacts all stocks, while the latter affects only stocks traded within a specific price range, such as ¥2,000–5,000 as you see in figure 1 for effective spread and figure2 for depth in the best ask and bid book. Since our empirical study focuses on the effect of trading speed, we separate the stocks according to whether or not they are affected by the tick size change.

Boosting the speed of trade through Arrowhead is an exogenous change that affects all the stocks listed on the TSE. We collect stocks from the first section of the TSE[4] and separate them into two groups, no change group unaffected by tick size changes and changed group affected by tick size changes. The sample period is from one month before the introduction of Arrowhead to one month after. We exclude the last week of December 2009 and the first week of January 2010 based upon our conversations with institutional investors who voiced their reluctance to trade in the brand new system. We exclude stocks that move into and out of different tick size and traded for fewer than five days in any month or below ¥100. Table 1 shows a number of stocks in each group and price ranges. Figure 1 shows daily movement of effective spread and figure 2 shows that the changes in depth for stocks in different price range.

(insert Table 1, Figure 1&2 here)

[4] Tokyo Stock Exchange has two sections. Listing requirements for the first section stocks such as number of shares outstanding and shareholders are higher than those for the second section..

4. Arrowhead's impact

4.1. Trading activities

Table 2 summarizes the trading activities for the two groups of stocks, affected by tick size change and not. After Arrowhead's introduction in the TSE, a shift toward high-frequency, small orders were observed in investors' order execution patterns. Of the four trading-related measures selected here, the number of quote revisions shows the largest percentage of change from December 2009 to January 2010. The average number of quote revisions in a five-minute period for no change (changed) group increased from 18.2 (25.6) to 37.1 (73.4). The average number of trades in the five-minute period increased from 5.7 (7.7) to 7.9 (16.6). The average size of trades in the five-minute period decreased from 6.9 (8.8) units to 5.7 (6.6) units. The changes for both groups are statistically significant at the 1% confidence level. The total volume in the five-minute period did not increase for either group.

It should be noted that the transition to HFT is more pronounced for large-cap stocks, and changes in quote revisions, the number of trades, as well as the size of trades are larger. For large-cap stocks, quote revisions in a five-minute period almost triple, from 45.5 (40.3) to 110.8 (125.1) for no change (changed) stocks. The average number of trades in the five-minute period increases from 15.0 (12.1) to 23.9 (28.9), and the average size of trades decreases from 22.8 (15.4) units to 16.4 (11.5) units.

An examination of trading-related measures reveals that the changes following Arrowhead's introduction do not occur across the stocks listed in the TSE. Significant changes appear to be concentrated around large-cap stocks. The next section investigates this issue.

(insert Table 2 here)

4.2. Event study on impact of HFT

Arrowhead's introduction has been characterized by a high frequency of trades and quote revisions. In particular, of the four measures in Table 2, the frequency of quote revisions increases the most. This change is consistent with Hasbrouck and Saar (2009) and Hendershott and Moulton (2009). The change relates to the behavior of high frequency market making. High speed transmission improves liquidity providers' ability to change their limit order conditions according to varying market. In the case of the TSE, elimination of the three-second matching cycle also influence trades and quotes message traffic (MT). Under the three-second matching cycle, market and limit orders that came to market in between were batched and reported cumulatively. Under the Arrowhead system, these orders are executed and reported individually. As a result, the numbers of orders and quotes have increased for high-volume stocks. In addition, investors can enter, change, and cancel orders faster than before the introduction of the new system, thereby affecting their order submission behavior.

In order to conduct an event study, we quantify these changes by modeling the quote frequency with trade-related variables. An important issue is the normalization of the quote frequency numbers. Hendershott and Moulton (2009) use the number of electronic messages per US$100 of trading volume as a proxy for algorithmic trading instead of raw MT numbers. We model MT numbers that are influenced by not only the number of trades but also the depth and width of the spread. To estimate the relation for all stocks listed in the TSE, we use four explanatory variables: the *number of trades, depth, tick spread,* and the *log of the market cap*. The dependent variable is the number of quote revisions, which is equivalent to MT in Hendershott and Moulton (2009).

First, we estimate the following regression model using daily data from December 2009:

$$MT_{jt} = a + b \cdot \# ofTrade_{jt-1} + cDepth_{jt-1} + dTick\_spread_{jt-1} + e\log(CapSize'_{j0}) + f_{jt} \quad (1)$$

The result in Table3 shows that all variables in the equation (3) except tick spread are highly significant and the adjusted R-squire is 0.88. Using the estimated parameters, we compute the predicted MT for January 2010 and the difference between the predicted and the actual MT (i.e., the prediction error). We assume that the difference indicates the degree of change brought about by the HFT, which we call the "HFT effect" hereafter. We use the model prediction error as a proxy for the HFT effect, which reflects sliced order submissions, changing limit prices as well as quantities, and cancellations. The speedup of a few seconds provides critical new information to high-frequency traders but is unlikely to affect the trading behavior of humans. Elimination of the three-second matching interval allows algorithmic liquidity suppliers to quickly notice abnormally wide inside quotes and provide liquidity accordingly via limit orders. Algorithmic liquidity demanders can quickly access these orders via conventional market or marketable limit orders.

(insert Table 3 & 4 around here)

We form portfolios and sort them into five groups according to HFT effects. In Table 4, the heavy HFT quintile with no tick change (with tick change) stocks shows that the average deviation of the number of quote revisions during five minutes is 56.4 (83.6) from that of the previous month. The smallest HFT quintile shows that the average deviation of the number of quote revisions is slightly negative, -1.2 (-1.4), which is statistically significantly different from zero. It seems that MT patterns for stocks in lower HFT quintiles do not deviate from those in December 2009. As in Hendershott and Moulton (2009), the results are consistent with the conventional wisdom that algorithmic trading was more prevalent at the time for active, liquid stocks.

4.3. Cost of immediacy

We now examine the effects of Arrowhead's introduction on liquidity. This section focuses on spread measures such as effective spread, realized spread, and adverse selection (market impact) costs. The effective spread is the cost of immediate execution paid to the market by liquidity demanders. The wider the effective spread, the less liquid the stock. For our sample TSE stocks, effective spreads are almost always identical to quoted spreads because the TSE uses a pure order-driven mechanism.

For the tth trade in stock j, the proportional effective half-spread, *ESPRD*, is defined as

$$EffectiveSpread(ESPRD)_{jt} = q_{jt}\,(p_{jt} - m_{jt})/m_{jt}, \tag{2}$$

where q_{jt} is an indicator variable that equals +1 for buyer-initiated trades and −1 for seller-initiated trades, p_{jt} is the trade price, and mjt is the quote midpoint prevailing at the time of the trade. For stock j, each month we calculate the simple average across days and then average it across the month.

Narrower effective spreads imply less revenue per trade for liquidity providers. We decompose effective spreads into a realized spread component(*RSPRD*) and an adverse selection or price impact component(*MI*), to understand the source of the improvement in liquidity under Arrowhead's implementation:

$$\begin{aligned} ESPRD\,jt &= RSPRDjt + MIjt \\ &= (q_{jt}\,(p_{jt} - m_{j,t+5\min})/m_{jt}) + (q_{jt}\,(m_{j,t+5\min} - m_{jt})/m_{jt}), \end{aligned} \tag{3}$$

where p_{jt} is the trade price, q_{jt} is the buy–sell indicator (+1 for buys, −1 for sells), m_{jt} is the midpoint prevailing at the time of the t-th trade, and $m_{j,t+5\min}$ is the quote midpoint five minutes after the t-th trade. We estimate the revenue to liquidity providers using the five-minute realized spread, which assumes the liquidity provider is able to close his or her position at the quote midpoint five minutes after the trade. We measure gross losses to liquidity demanders due to adverse selection using the five-minute market impact of a trade.

Table 5 compares these measures between December 2009 and January 2010. Overall changes in effective spreads are negative for all quintiles. Stocks in the largest HFT quintile show the smallest decline (-0.006%), and those in the two lighter quintiles show a larger decline (-0.031%, -0.039%). The heavier the HFT effect, the smaller the reduction of the cost of immediacy. It seems that high-speed transactions somewhat prevent the reduction of the cost of immediacy.

Decomposing the effective spread into liquidity provider revenues—the realized spread—and adverse selection—permanent market impact—we find effects in two opposite directions. For stocks in a heavy HFT quintile, the realized spread shows a statistically significant decline (-0.014%) and market impact shows a statistically significant increase (0.008%), but for stocks in a light HFT quintile, the realized spread significantly increases (0.017%) and market impact significantly declines (-0.048%). From the results above, compensation for liquidity providers is reduced in the five-minute period due to positive market impact. This finding contradicts the results of Hendershott et al. (2010) in the US market, where both the effective spread and market impact declined. For stocks in smaller HFT quintiles, however, the source is the reduction of permanent market impact costs, similar to US stocks.

(insert Table 5 and Figure 3 around here)

4.4. Determinants of execution costs

We have observed a reduction in the cost of immediacy and compensation for liquidity provision. We now investigate the determinants of these changes. Candidate variables are the HFT effect, the cumulative yen volume, the number of trades, and the size of trades. The natural way to test these variables is by regressing the various liquidity measures, Li, on *HFT*, *Vol*, *#Trade*, and *TradeSize* and controlling variables Xi:

$$\Delta L_i = \alpha + \beta_1 HFT_i + \beta_2 \frac{Vol_{i,Jan}}{Vol_{i,Dec}} + \beta_3 \frac{\# Trade_{i,Jan}}{\# Trade_{i,Dec}} + \beta_4 \frac{TradeSize_{i,Jan}}{TradeSize_{i,Dec}} + \gamma \Delta X_j + \varepsilon_i, \quad (4)$$

where △Li is $\Delta ESPRD_i = ESPRD_{i,Jan} - ESPRD_{i,Dec}$, differences in the effective spread between December 2009 and January 2010; similarly, *△RSPRD*i is the realized spread and *△MI*i the market impact; *HFT*i is a prediction error of equation (1); $\frac{Vol_{i,Jan}}{Vol_{i,Dec}}$ is the ratio of the yen volume on January 2010 to that on December 2009; similarly, $\frac{\# Trade_{i,Jan}}{\# Trade_{i,Dec}}$ is the ratio of the numbers of trades, $\frac{\# TradeSize_{i,Jan}}{\# TradeSIze_{i,Dec}}$ is the ratio of trade sizes, and the Xi are stock-level control variables, including *△tickspread*, the difference in tick spread, and *△tickspread* x *tick size change dummy,* which is the difference in tick spread for stocks affected by tick size change, and zero otherwise.

Table 6 presents the coefficients for variants of equation (4). When the dependent variable Li is *△ESPRD* for stock *i*, the coefficients of HFTi are positive and marginally significant at the 10% level. This means that the larger the HFT effect, the larger the increase in effective spread. The variables of the ratios of *#Trad*e and *TradeSize* show significant negative relations with effective spread change. This means that the larger the increase in the number of trades or in the size of the trades, the larger the reduction in effective spread. It is interesting that the ratio of *Vol* has a significant, positive coefficient with effective spread change. Here *Vol* is a product of the number of trades and their size, so increasing volume widens the effective spread due to adverse selection risk. The results indicate that the changes in effective spread is more strongly related with the number of trade and trade size than the HFT effects.

When the dependent variable Li is *△RSPRDi* for stock *i*, the coefficients of *HFT* are negative and significant at the 1% level. The variables *△#Trade* and *△SizeTrade* do not have significant coefficients. This means that the larger the HFT effect, the greater the reduction of the compensation for liquidity providers.

When the dependent variable Li is ⊿*MI*i for stock *i*, the coefficient of *HFT* is positive and significant at the 1% level. Frequent quote revisions are related to a permanent price impact after the trade. Here ⊿*#Trade* and ⊿*SizeTrade* have a significant negative relation, which means that the larger the HFT effect, the greater the market impact. The negative relations of ⊿*#Trade* and ⊿*SizeTrade* imply that the frequency and size of trades indicate high liquidity.

From the results in Table 6, we conclude that the overall reduction in effective spread is due to the increased number of trades as well as the size of trades. Increased MT intensifies adverse selection risks and creates a permanent market impact after the trade.

(insert Table 6 around here)

5. Extended sample periods and robustness check

In order to perform robustness check, we extend the sample period by including October, November and December 2010. In the event study at the previous section, January 2010 represents a month of the TSE's new trading platform, however, participants may need time for adjustment of their trading parameters. High frequency traders rely on computerized trading strategies and they want testing performance of their strategies with historical data under new environment before they start trading at the TSE. According to TSE, orders via collocation servers started at about 10% level of total orders on January 2010 and it has exceeded 30% as of May 2010. It indicates more high-speed participants become ready for trading after May 2010. In addition, the share of off-exchange markets begins to increases after October 2010. It is said that high frequency market makers trade multiple trading venues (Menkvelt 2011, Broggard 2011). It seems additional three months data provide us more reliable results after the high speed trading arena.

5.1 A summary statistics for liquidity measures

Table.7 summarizes four A summary statistics for spreads and depth measures for five months period. Effective spread gradually declines toward December 2010. As of December 2009 an average effective spread is 0.20%, it does not change much until November 2010. As of December 2010 an average effective spread 0.16% which is almost 20% reduction. Realized spread for December 2010 is 0.060% which is slightly higher than that for December 2009 and January 2010 (0.052%, 0.52%, respectively). Adverse selection cost for December 2010 is 0.10% which is smaller than that for December 2009 and January 2010 (0.16%, 0.14%, respectively). Average depth at the best ask and bid book for December 2010 is 99,235 shares which is almost double compared to that for December 2009 and January 2010 (51,386, 55,262, respectively). In summary, participants have adapted new trading environment. They mitigate market impact cost which is equivalent to adverse selection in our definition and it results in smaller cost of