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E2008/2

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ISSN 1749-6101
January 2008

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Information-Based Trade in the Shanghai Stock Market

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October 31, 2007

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Abstract

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We show that the probability of information-based trade (PIN) played a significant role in explaining monthly returns on Shanghai A shares over the period 2001 to 2006. In particular, PIN, as approximated by order imbalance as a proportion of total transactions, appears to explain returns even after controlling for risk in the much-cited Fama and French (1992) three-factor model. However, we also find that some of the PIN effect appears to be indistinguishable from a turnover effect.

1 Introduction[1]

After several decades of studying asset pricing theories based on the idea that investors have equal access to information, the last few years have seen increasing attention devoted to models which explicitly allow for the possibility that some agents are better informed than others.[2] In particular, the branch of the literature starting with Easley and O'Hara (2004) focuses on the question of how to estimate the probability that a given trade is motivated by information, rather than liquidity or noise. Insofar as an informational asymmetry puts one side or another at a potential disadvantage in any trade, it represents an undiversifiable risk which will therefore require compensation in the form of higher return, other things being equal. Relaxing the standard homogeneous information assumption generates an equilibrium very different from the one visualised in textbook models. Instead of a world where all investors hold the same market portfolio, we accept that informed and uninformed investors hold different stocks. The uninformed hold more "bad news stocks" than the informed, and fewer "good news stocks". Although they cannot be sure of the existence or content of relevant news about a stock, they are fully aware of their informational disadvantage, insofar as they know that they have to bear the risk of dealing with better-informed traders. This is the risk which requires compensation in the return. Ex-post, therefore, the cross-section pattern of returns will reflect, over and above any of the standard established risk factors, a premium to reward investors for carrying the risk of dealing with a better informed counterparty.

This generalization of market efficiency to cover heterogeneous information, called dynamic market efficiency by Easley and O'Hara (2004), can be viewed as one response to the famous Grossman and Stiglitz (1980) paradox, in the sense that, if we accept the proposition that news is not always instantaneously incorporated into prices, then there must of necessity be some transitional stage when some traders are in possession of information not yet available to the market as a whole. Given that most relevant news is firm- or sector-specific and that it arrives

[1] The authors would like to record their gratitude for funding from the School of Management, University of Electronic Science and Technology of China

[2] See O'Hara (1995) as the ideal starting approach to this literature.

at unpredictable intervals, it follows that the best we (and the uninformed traders) can do is to assume that there is always a nonzero probability of asymmetric information in any stock market deal. Estimating the probability of information-based trade (PIN) and testing whether it is rewarded in the market is therefore a test of the generalized market efficiency model. Clearly, however, the question can only be addressed in the context of a model of asset pricing where, if the market is only dynamically efficient, PIN may well play a critical part. On this view, rectifying the omission of PIN may be expected not only to improve the explanation of returns, but might also contribute to explaining the apparent failure of some of the more conventional models. In addition to these research issues, as far as practitioners are concerned, incorporating this factor into their calculations may significantly improve the attainable risk return trade-off.

While the literature starts from tests applied to US data, the case of China is potentially more interesting, since the Chinese markets have a number of features which might be expected to provide a serious challenge to any model which has been found to fit the USA. For example, the Chinese market operates as a continuous auction during the trading day (which is in fact broken into pre- and post-lunch sessions). There are restrictions on short sales, and dealing limits. Moreover, instead of the large institutions who dominate the US market, small investors are responsible for a large proportion of trade and, if anecdotal evidence is to be believed, for most of its apparently excessive volatility. The unique structure of corporate governance and the associated fact that many firms have far lower free float than is normal in the US corporate sector are additional reasons for wondering whether the PIN model is robust enough to be applied to China. Above all, it is often suggested, or even taken for granted, that the Chinese markets are hotbeds of insider trading, where well-connected traders prey on informationally-disadvantaged small investors, a fact which should be reflected other things being equal in a higher PIN than for USA.[3]

In the following sections, we introduce our dataset, discuss PIN estimation issues, and present

[3] Note that this is certainly *not* to say that all informational asymmetry is associated with insider trading in the legal sense, or that insiders to the firm are the only or even the major source of private information. We are only saying that, given the other private news sources, more insider trading equates to higher PIN.

our results. We then go on in Section 5 to show how PIN contributes to the now-standard Fama and French (1992) factor pricing model, and indeed to the augmented model introduced more recently by Ku (2005).

2 Dataset

Our dataset consists of around half a billion real time buy/sell datapoints for the sample period January 2000 to December 2006. The data relate only to the Shanghai stock exchange (SHSE) A shares i.e shares denominated in RMB and traded by Chinese investors exclusively.[4].

Insofar as the SHSE operates in an institutional setting which stands in stark contrast to the NYSE, it provides a severe test of the robustness of the conclusions reached by Easley, Hvidkjaer and O'Hara (2002b). First, there are no market makers on the SHSE. Instead, trading is centralised, computerised and continuous, so that the market process is purely order-driven, with buy and sell orders submitted and auctioned off as they arrive. Matched orders are executed and then dispatched from the system, whereas unmatched orders remain open in the system until they are either executed or cancelled.[5] Secondly, although the market opens with a standard call auction, the SHSE then has a five minute break before the start of continuous trading. Thirdly, like most Asian markets, Shanghai takes a lunch break, so that the day is effectively broken up into three parts: the opening call auction, and the continuous morning and afternoon sessions.(Tian and Guo (2007)).

Descriptive statistics are given in Table 1A.

3 Estimation

The question of how to estimate PIN is addressed in Easley, Hvidkjaer and O'Hara (2002b) which starts from a microstructure model in which market makers observe dealing activity and draw

[4] Note that Shanghai is the bigger of the two Chinese stock markets, and it is also where most of the larger predominantly state-owned companies are listed, whereas in Shenzhen many of the smaller stocks are traded. (see e.g. Xu (2000))

[5] For further details, see Xu (2000) and Tian and Guo (2007).

inferences about the underlying true value of an asset (i.e. the firm). Each trade conveys private information which is used in Bayesian updating of their prior probability distribution, so that the next round of dealing starts from prices based on their updated beliefs. Over time, the process of trading, learning and price-setting results in prices converging to full information levels. In this sense, the market is dynamically or asymptotically efficient.

To make this model operational, we use the mid-quote and transaction price rules of Lee and Ready (1991) to calculate the number of buy and sell trades, B and S, in a single day for each firm. Easley, Hvidkjaer and O'Hara (200 show that, if the buy and sell orders originated by uninformed investors arrive in a pattern which follows a Poisson process, the likelihood function induced by this simple model of the trade process for a single trading day is:

$$\begin{aligned} L\left(\theta \mid B,S\right) = &\left(1-\alpha\right) \cdot e^{-\varepsilon_b} \frac{\varepsilon_b^B}{B!} \cdot e^{-\varepsilon_s} \frac{\varepsilon_s^S}{S!} \\ &+\alpha\delta \cdot e^{-\varepsilon_b} \frac{\varepsilon_b^B}{B!} \cdot e^{-(\mu+\varepsilon_s)} \frac{\left(\mu+\varepsilon_s\right)^S}{S!} \\ &+\alpha\left(1-\delta\right) \cdot e^{-(\mu+\varepsilon_b)} \frac{\left(\mu+\varepsilon_b\right)^B}{B!} \cdot e^{-\varepsilon_s} \frac{\varepsilon_s^S}{S!} \end{aligned} \tag{1}$$

where μ represents the daily volume of trade by informed traders, and $\varepsilon_{b,}^{B}$ $\varepsilon_{s,}^{S}$ the random component of buy and sell orders generated by noise traders. (1) is a weighted average of three components. The first line on the RHS of the equation deals with a no-news day. It is the likelihood of uninformed buyer/seller arrival weighted by the probability of a no-news day $(1-\alpha)$. The second line relates to a bad-news day, which occurs with probability $\alpha\delta$ and the last line to a good-news day, for which the probability is $\alpha(1-\delta)$. In order to estimate the parameter vector $\theta = (\alpha, \mu, \varepsilon_b, \varepsilon_s, \delta)$, Easley, Hvidkjaer and O'Hara (2002b) impose independence conditions across the I trading days which allow them to represent the likelihood function for any period as:

$$V = \left(\theta \mid M\right) = \prod_{i=1}^{I} L\left(\theta \mid B_i, S_i\right) \tag{2}$$

where B_i, S_i denote buy, sell data for period $i \in (1...I)$, and $M = \{(B_i, S_i)\}_{i=1}^{I}$ refers to the dataset. The estimator for θ computed by maximizing this likelihood function would allow us to derive the probability that the trade is information-based as follows:

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_b + \varepsilon_s} \tag{3}$$

i.e the daily volume of informed trades, $\alpha\mu$, as a proportion of the total volume of informed and uninformed trades, $\alpha\mu + \varepsilon_b + \varepsilon_s$.As Easley, Hvidkjaer and O'Hara (2002b) point out, their model amounts to assuming that market activity on any given day has a normal base-level which reflects the volume of uninformed trade. Any deviation from this level can therefore be identified with informed trade, and estimated accordingly.[6]

4 PIN Estimates

Although our data are in real time, we concentrate on the monthly PIN. Our dataset is large enough to generate 44,186 monthly PIN estimates for the firms covered[7], using an average of 8,181 buy/sell observations per estimate (see Table 1A). The estimates displayed a high degree of intertemporal stability, so we concentrate on the results for the period as a whole. The estimated PIN values are plotted as the histogram given in Figure 1. As can be seen, the overall mean probability of a trade being informed is 0.11, far lower than the 0.18 reported for USA by Easley, Hvidkjaer and O'Hara (2002b), but displaying the same sort of distribution, varying from a minimum of 0.02 to a maximum of 0.75, with most firms tightly clustered around the mean.

This result may seem somewhat surprising, given the anecdotal evidence about the nature of the Chinese stockmarkets, where access to information may be very unequal and rumours of insider trading are rife. However, the PIN is a measure of the frequency of informed *relative to uninformed trades.* Hence, the unexpectedly low PIN estimate may simply reflect the fact that informed trading is swamped by the very high level of uninformed trades.[8]

[6] We also experimented with the estimation method suggested in Easley et al (2002a) who show that PIN can be well-approximated by:

$$PIN = \frac{E(|S-B|)}{E(|S+B|)} \tag{4}$$

provided that the arrival rate of informed trades is large and that the flow of uninformed orders on to the market is balanced, in the sense that buy and sell orders are equal. Subject to these two assumptions, (4) says that PIN can be estimated from the expected order imbalance as a proportion of total trade volume. The results, which were not very different from those reported here, are available from the authors on request.

[7] The number of firms in the dataset varies over the sample period as a result of M&A activity, delistings etc.

[8] Indirect support for this view comes from the fact that, according to our estimates of the α, news only arrives

Since our concern is ultimately with PIN in the context of a pricing model, we summarise the descriptive statistics of the potential factors side-by-side in Table 1B, with the correlation matrix in Table 1C. There are a few noteworthy features of the data. First, note that the momentum returns are on average negative, albeit tiny compared to their standard deviation. The range of momentum is from -1.2% to +1.2% over one month. The beta estimates vary spectacularly from -1.15 to +2.8, as does the book-to-market ratio, BM, which again has an unremarkable mean of 0.86, but with a range from as low as 0.03 up to nearly 15! To some extent, this spread may result from the fact that the dataset covers an extremely broad range of companies from the smallest, with a market capitalization of only RMB25mn, to the largest, worth over RMB23bn, with a mean of around RMB1bn. As far as the turnover figures in Table 1B are concerned, it is not easy to make a judgement, as Chinese stocks tend to have a low level of free float compared to shares in typical European or North American markets. Relative to the actual (unobservable) number of shares freely available to trade, the turnover may actually be higher than appears in our dataset. The final two columns of Table 1B document the exceptional volatility of the Shanghai market, with the standard deviation of annualized daily log returns amounting to 38% and the bid-ask spread averaging just under one half of one percent.

As far as the cross-sectional rank correlations in Table 1C are concerned, PIN is negatively correlated with beta, book-to-market, turnover and volatility, and positively correlated with size and spread.[9] In particular, the correlation between PIN and turnover is significantly negative, indicating that the adverse-selection risk of dealing with better-informed traders is lower for high-volume stocks, as in the USA (Easley, Hvidkjaer and O'Hara (2002b)). In other respects, however, our results for China suggest a somewhat different information structure. For both the USA and Taiwan (Lu and Wong (2007)), the observed pattern is for high-PIN firms to be smaller, more volatile and lower-priced i.e PIN correlates negatively with size, positively with beta and book-

on about one in three days, with volume on the remaining two-thirds of days being one hundred percent uninformed trades. As regards the remaining of the model, the estimates reported here were generated under the constraints that $\varepsilon_b = \varepsilon_s = \varepsilon$ and $\delta = 0.5$.

[9] With the exception of some of those involving momentum, all the correlation coefficients in Table 1C are significantly different from zero.

to-market, BM. For China, this pattern seems to be reversed: high PIN is associated with larger firms, with consequently less volatility and higher market capitalizations. One other point to note in Table 1C is that turnover is lower for larger firms, which therefore exhibit lower volatility and are traded at a narrower bid-ask spread, possibly reflecting a low level of free float and/or a higher average percentage of state ownership in big companies.

One well-established approach to testing asset-pricing in this type of situation relies on examining the characteristics of portfolios sorted by potential factors. In month t, we divide the stocks in our dataset into a number of portfolios based on each of the pricing factors and examine the outcome in the succeeding month, $t+1$. In Table 2A, the first column gives the mean PIN values of ten portfolios pre-sorted from lowest PIN in the previous period (portfolio #1) to highest (#2). It can be seen that the ranking is perfectly preserved, indicating that PIN is highly stable from one month to the next. As might be expected, the same is true of all the other factors with the sole exception of one-month momentum, where the ranking is almost completely inverted, suggesting that the Shanghai market may be characterised by a high degree of mean-reversion.[10]

In order to examine the relationships between the factors, Tables 2C to 2I present the results of sorting portfolios twice on different criteria at each stage. In each case, the resulting portfolio data cover between 4500 and 5700 monthly observations on an average portfolio size of 50 to 90 stocks.

The first point to note is that returns are almost invariably increasing in PIN, even controlling for the other factors (size, book-to-market, beta, turnover, momentum, volatility, spread), providing broad confirmation that this type of risk is rewarded in the market. This is true in spite of the fact that, in most cases, beta is lower for higher-PIN stocks. As would be expected, higher-PIN stocks also tend to have a higher bid-ask spread, though the effect is surprisingly small (Table 2I), possibly because they also have lower volatility, other things being equal.

[10] Note that SIZE denotes the natural log of market capitalization.

5 Direct Tests of the Pricing Model

In testing explicit pricing models, we consider the five potential risk factors for which the correlations are given in Table 1C. Apart from CAPM beta, we entertain the possibility that Chinese returns are driven by the two extra factors identified by Fama and French (1992) for the USA and subsequently for all the other major world stockmarkets i.e size and book-to-market (BM). In addition, we test for a momentum effect, as in Ku (2005), and more specifically in work on PIN by Easley, Hvidkjaer and O'Hara (2002b) for USA and Lu and Wong (2007) for Taiwan.

The version of the Fama and French (1992) model tested here involves the following cross-section regression for R_{it}, the return on the ith stock in month t:

$$R_{it} = \gamma_{0t} + \gamma_{1t}\widehat{\beta}_p + \gamma_{2t}PIN_{it-1} + \gamma_{3t}SIZE_{it-1} + \gamma_{4t}BM_{it-1} + \gamma_{5t}MTM1_{it-1} + \gamma_{6t}TURN1_{it-1} + \eta_{it} \tag{5}$$

which is the now-standard three-factor model augmented by the previous period's PIN-value, momentum and turnover. We also consider size, volatility and spread as other possible factors. Our principal concern is with the significance and sign of the coefficient γ_{2t}.

Using the standard Fama and MacBeth (1973) methodology of averaging the coefficients, we derive the results given in Table 3. The top half of the table shows estimates of (5) using the PIN for each stock. In the bottom half, we take PIN-values averaged over the portfolio. In addition to standard t-ratios, we show t-ratios corrected along the lines suggested by Shanken (1992).

Overall, the results of testing four specifications of the model indicate that, for the Shanghai market, book-to-market, log(PIN), turnover and volatility are robust pricing factors. PIN is positive and significant in all four cases. The size of the coefficient, which is in the range from 0.6 to 1.2, suggests that, if we compare two stocks, one with a PIN of 0.1, the other with a PIN of 0.125, the latter will need to offer a return between 15% and 30% higher than the former i.e. if the return on the lower-PIN stock is 10%, the higher-PIN stock will offer something between 1.5% and 3% in return for the additional risk. Note that beta is insignificant in every case, and mostly wrongly signed. Perhaps surprisingly in view of the anecdotal evidence, value seems to play a more important role in the Chinese market than in USA (Easley, Hvidkjaer and O'Hara (2002b)) or Taiwan (Lu and Wong (2007)), with BM significant and correctly signed in all four equations estimated. On the other hand, the negative (albeit insignificant) coefficient on size suggests that investing in Chinese small-caps is compensated by higher return. The negative sign on turnover is hard to interpret. Note that Lu and Wong (2007) also found a negative effect of this variable for Taiwan, but their coeffcient was far smaller and insignificant. For China, this finding may reflect a high degree of mean reversion, with news generating excessive trading volume in one period and consequent overreaction, followed by reversal in the next. This would be consistent with our finding of a negative relationship between return and momentum.

6 Conclusions

In this paper, we estimated the PIN model to examine the question of whether information asymmetry plays a part in determining returns on stocks in the Shanghai market. Our results suggest that, as in other countries, the existence of private information, as measured by PIN, does indeed help to explain returns, and that uninformed Chinese investors are compensated for the adverse selection risk they bear. However, in a number of other respects the Shanghai market seems to be different from those in other countries, and in ways that are somewhat surprising. These features, notably the anomalous relationship between size and PIN (and beta), and the apparently robust link between book-to-market and returns, merit further investigation. It would also be interesting to know whether the same features are found in the Shenzhen stock market, where smaller capitalization stocks than in Shanghai are listed.

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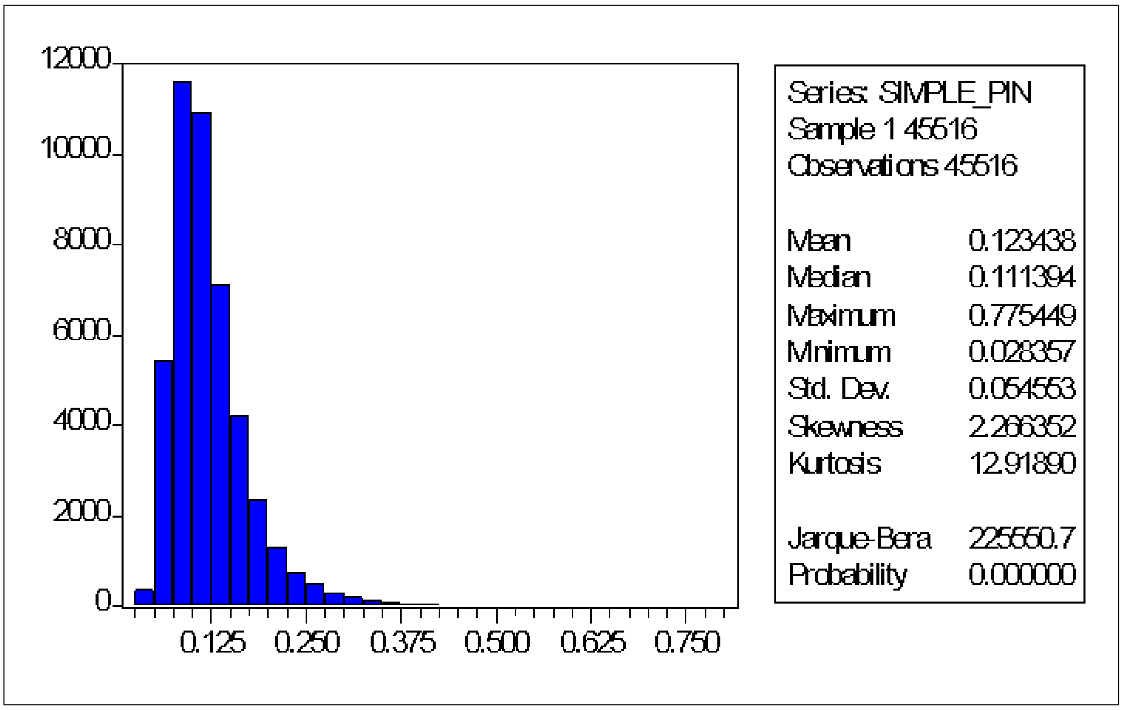

Figure 1 PIN Frequency Distribution

TABLE 1 DESCRIPTIVE STATISTICS

TABLE 1A: DATASET

# of firm-month PIN estimates	44,186
Total # of trades	428,169,264
Average # of trades used per PIN estimate	8,181
# of days used per PIN estimate	20
Average # of trades per day	431
Minimum # of trades per day	100

TABLE 1B: ASSET PRICING FACTORS

	PIN	BETA	BM	SIZE	MOMENTUM %	TURNOVER	VOLATILITY	SPREAD
Mean	0.114	0.999	0.862	1.106	-0.002	1.404	37.7%	0.475
Stdev	0.055	0.327	0.747	1.376	0.110	0.713	10.2%	0.212
Min	0.023	-1.145	0.030	0.033	-1.240	1.004	3.9%	0.062
Median	0.104	1.001	0.649	0.771	-0.003	1.228	36.7%	0.438
Max	0.747	2.791	14.696	28.600	1.205	64.293	97.3%	3.887

MTM = momentum over preceding month
SIZE = log(market capitalization in RMBbillion)
SPREAD = average bid-ask spread as proportion of price during first hour of trading over preceding 6 months
VOLATILITY = standard deviation of annualized daily log returns over preceding 6 months
TURNOVER = turnover over preceding month, defined as log of number of shares traded
divided by number of shares outstanding
BM = ratio of book to market value, with negative book values excluded

TABLE 1C: CORRELATION MATRIX

Avges of monthly cross-sectional rank correlations (t-ratios in italics)

	PIN	BETA	BM	SIZE	MOMENTUM	TURNOVER	VOLATILITY	SPREAD
PIN		-0.1559	-0.14	0.0489	0.0021	-0.273	-0.2718	0.1584
		-10.3047	*-8.553*	*4.0143*	*0.1172*	*-22.4376*	*-12.558*	*9.8904*
BETA			0.0606	-0.2509	-0.0455	0.0827	0.3834	0.1823
			4.291	*-8.7924*	*-1.5174*	*4.8643*	*19.3031*	*11.1544*
BM				-0.0076	-0.0935	-0.128	-0.078	0.0822
				-0.4814	*-5.9105*	*-8.7167*	*-5.2196*	*4.5763*
SIZE					0.0835	-0.2118	-0.2801	-0.5364
					2.9682	*-13.0749*	*-14.1839*	*-29.8088*
MOMENTUM						0.1759	-0.0368	0.001
						9.3222	*-1.3766*	*0.0508*
TURNOVER							0.4325	-0.0713
							30.3308	*-4.7684*
VOLATILITY								0.103
								6.9768

TABLE 2 PERSISTENCE

TABLE 2A: PORTFOLIO PERSISTENCE (SINGLE CRITERION)

Average values for portfolios sorted by a single criterion

	PIN	BM	SIZE	MOMENTUM	TURNOVER	BETA
1	0.080	0.288	0.276	0.080	1.199	0.441
2	0.091	0.426	0.418	0.057	1.225	0.694
3	0.098	0.521	0.514	0.127	1.259	0.806
4	0.101	0.612	0.609	0.138	1.288	0.892
5	0.105	0.713	0.714	-0.115	1.324	0.966
6	0.109	0.822	0.841	-0.297	1.364	1.036
7	0.115	0.940	1.009	-0.377	1.404	1.108
8	0.123	1.096	1.242	-0.702	1.477	1.193
9	0.137	1.325	1.675	-0.772	1.572	1.307
10	0.185	1.947	3.770	-1.289	1.886	1.554

Tables 2B to 2G give average values for portfolios sorted by two criteria
PIN based on 30-day window, ending on last day of prior month
AVERAGE RETURN = % return in excess of riskless rate (3-month deposit rate)

TABLE 2B: PORTFOLIO PERSISTENCE (DOUBLE CRITERION PIN/PIN)

Ranking by: PIN	PIN	#OBS	AVERAGE RETURN %	PIN	maxPIN	BM	BETA	SIZE
1	**1**	14729	-0.900	0.076	0.137	0.865	1.048	1.040
2	**1**	14729	-0.261	0.105	0.175	0.891	1.021	0.960
3	**1**	14728	0.035	0.162	0.747	0.830	0.927	1.320

TABLE 2C: PORTFOLIO PERSISTENCE (DOUBLE CRITERION SIZE/PIN)

Ranking by: SIZE	PIN	#OBS	AVERAGE RETURN %	PIN	maxPIN	BM	BETA	SIZE
1	1	4726	-1.026	0.078	0.136	0.882	1.133	0.420
1	2	5721	-0.535	0.105	0.175	0.871	1.102	0.410
1	3	4282	0.301	0.152	0.747	0.838	1.047	0.430
2	1	5025	-0.783	0.075	0.137	0.885	1.040	0.780
2	2	5002	-0.076	0.105	0.172	0.907	1.013	0.780
2	3	4702	-0.132	0.163	0.739	0.828	0.936	0.790
3	1	4978	-0.899	0.074	0.136	0.828	0.975	1.890
3	2	4006	-0.100	0.105	0.175	0.898	0.916	1.970
3	3	5744	-0.027	0.169	0.567	0.827	0.831	2.410

TABLE 2D: PORTFOLIO PERSISTENCE (DOUBLE CRITERION BM/PIN)

Ranking by: BM	PIN	#OBS	AVERAGE RETURN %	PIN	maxPIN	BM	BETA	SIZE
1	1	4361	-0.766	0.075	0.136	0.460	1.056	1.080
1	2	4346	-0.492	0.105	0.173	0.430	1.001	1.020
1	3	6022	-0.299	0.174	0.747	0.377	0.868	1.480
2	1	5009	-0.971	0.075	0.137	0.769	1.045	0.980
2	2	5089	-0.427	0.105	0.175	0.752	1.019	0.880
2	3	4631	0.069	0.157	0.525	0.754	0.956	1.170
3	1	5359	-0.944	0.077	0.136	1.283	1.043	1.070
3	2	5294	0.089	0.105	0.175	1.402	1.040	0.990
3	3	4075	0.491	0.151	0.474	1.588	0.981	1.260

TABLE 2E: PORTFOLIO PERSISTENCE (DOUBLE CRITERION BETA/PIN)

Ranking by: BETA	PIN	#OBS	AVERAGE RETURN %	PIN	maxPIN	BM	BETA	SIZE
1	1	4053	-0.400	0.076	0.137	0.804	0.673	1.320
1	2	4412	0.030	0.105	0.175	0.824	0.681	1.280
1	3	6264	0.221	0.172	0.747	0.762	0.630	1.780
2	1	4941	-0.939	0.076	0.136	0.889	1.000	1.000
2	2	5202	-0.104	0.105	0.174	0.933	1.002	0.860
2	3	4586	0.026	0.157	0.555	0.919	0.991	0.990
3	1	5735	-1.220	0.076	0.136	0.886	1.353	0.880
3	2	5115	-0.670	0.105	0.174	0.904	1.335	0.780
3	3	3878	-0.255	0.152	0.549	0.837	1.332	0.950

TABLE 2F: PORTFOLIO PERSISTENCE (DOUBLE CRITERION TURNOVER/PIN)

Ranking by: TNR	PIN	#OBS	AVERAGE RETURN %	TURNOVER	PIN	maxPIN	BM	BETA	SIZE
1	1	3047	-0.198	0.135	0.081	0.137	0.933	0.985	1.340
1	2	5319	0.132	0.130	0.107	0.175	0.969	0.994	1.110
1	3	6363	0.577	0.132	0.159	0.632	0.896	0.912	1.440
2	1	4606	-0.418	0.251	0.078	0.135	0.898	1.041	1.050
2	2	5263	-0.197	0.240	0.105	0.174	0.879	1.036	0.890
2	3	4860	0.104	0.232	0.162	0.747	0.826	0.942	1.260
3	1	7076	-1.516	0.544	0.072	0.137	0.813	1.079	0.910
3	2	4147	-0.845	0.482	0.103	0.175	0.804	1.038	0.850
3	3	3505	-1.045	0.442	0.169	0.636	0.717	0.935	1.170

TABLE 2G: PORTFOLIO PERSISTENCE (DOUBLE CRITERION MOMENTUM/PIN)

Ranking by: MTM	PIN	#OBS	AVERAGE RETURN %	MOMENTUM	PIN	maxPIN	BM	BETA	SIZE
1	1	4997	-0.360	-9.264	0.077	0.136	0.916	1.064	1.010
1	2	4889	0.189	-8.106	0.105	0.175	0.944	1.040	0.920
1	3	4843	0.161	-7.128	0.160	0.632	0.873	0.937	1.270
2	1	4557	-0.681	-0.425	0.077	0.136	0.879	1.029	1.010
2	2	5377	-0.093	-0.604	0.105	0.175	0.917	1.016	0.930
2	3	4795	-0.049	-0.737	0.158	0.747	0.899	0.945	1.210
3	1	5175	-1.615	9.010	0.074	0.137	0.802	1.048	1.100
3	2	4463	-0.955	8.007	0.104	0.175	0.800	1.007	1.040
3	3	5090	-0.005	7.066	0.168	0.739	0.725	0.901	1.460

TABLE 2H: PORTFOLIO PERSISTENCE (DOUBLE CRITERION VOLATILITY/PIN)

Ranking by: STD	PIN	#OBS	AVERAGE RETURN %	VOLATILITY	PIN	maxPIN	BM	BETA	SIZE
1	1	3246	-0.166	0.312	0.078	0.137	0.885	0.877	1.400
1	2	4765	0.160	0.306	0.105	0.175	0.922	0.891	1.240
1	3	6718	0.226	0.294	0.170	0.747	0.854	0.811	1.640
2	1	4716	-0.656	0.374	0.077	0.134	0.879	1.017	1.050
2	2	5303	-0.254	0.371	0.105	0.175	0.896	1.025	0.880
2	3	4710	0.334	0.372	0.156	0.555	0.850	0.988	1.050
3	1	6767	-1.422	0.462	0.074	0.136	0.845	1.151	0.870
3	2	4661	-0.698	0.454	0.104	0.174	0.852	1.150	0.760
3	3	3300	-0.781	0.453	0.155	0.541	0.756	1.078	1.040

TABLE 2I: PORTFOLIO PERSISTENCE (DOUBLE CRITERION SPREAD/PIN)

Ranking by: SPR	PIN	#OBS	AVERAGE RETURN %	SPREAD	PIN	maxPIN	BM	BETA	SIZE
1	1	6206	-0.620	0.302	0.073	0.137	0.815	0.989	1.430
1	2	4284	-0.127	0.322	0.104	0.175	0.822	0.921	1.560
1	3	4239	-0.352	0.319	0.173	0.647	0.729	0.812	2.280
2	1	4998	-1.146	0.445	0.077	0.137	0.887	1.077	0.820
2	2	5144	-0.017	0.448	0.105	0.174	0.903	1.036	0.820
2	3	4587	-0.039	0.452	0.159	0.636	0.874	0.939	1.090
3	1	3525	-1.045	0.666	0.079	0.136	0.919	1.111	0.680
3	2	5301	-0.606	0.664	0.106	0.175	0.934	1.088	0.610
3	3	5902	0.370	0.666	0.157	0.747	0.869	1.000	0.810

TABLE 3 FAMA-MACBETH REGRESSIONS

The dependent variable is the stock return in excess of the riskless rate
Shanken (1992) t-statistics

	coefficient	t-stat	Shanken t-stat	coefficient	t-stat	Shanken t-stat	coefficient	t-stat	Shanken t-stat	coefficient	t-stat	Shanken t-stat	coefficient	t-stat	Shanken t-stat	coefficient	t-stat	Shanken t-stat
log (PIN)	1.145	4.040	3.925	1.166	4.254	4.133	0.650	2.439	2.439	0.955	3.927	3.646	1.158	4.323	4.194	0.768	3.561	3.514
BETA	-0.411	-1.436	-1.396	-0.360	-1.294	-1.257	-0.303	-1.046	-1.046	0.044	0.175	0.163	-0.431	-1.511	-1.466	-0.082	-0.342	-0.338
BM	1.090	3.968	3.855	1.016	3.898	3.786	0.822	3.193	3.193	0.894	3.462	3.215	1.062	3.999	3.880	0.702	3.095	3.054
SIZE	-0.090	-0.324	-0.315	-0.026	-0.099	-0.096	-0.242	-0.852	-0.852	to	-0.633	-0.588	-0.108	-0.394	-0.383	-0.249	-0.954	-0.942
MTM1				-0.036	-2.320	-2.253										-0.022	-1.427	-1.408
TURNOVER							-1.057	-6.335	-6.334							-0.949	-5.817	-5.741
VOLATILITY										-6.457	-4.159	-3.862				-3.071	-2.023	-1.997
SPREAD													-0.058	-0.108	-0.105	-0.510	-0.957	-0.944
Average R-sq	0.089			0.104			0.102			0.101			0.094			0.130		
N	82			82			82			82			82			82		