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Herding and information based trading

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ABSTRACT

This paper expands on the existing literature on information asymmetry by testing if herding exists. We test herd behavior in a transparent and order-driven market using intraday data. We propose (1) a modification in the herding measure, (2) that investors tend to herd more based on fundamental analysis relative to technical analysis, and (3) that informational asymmetry can be identified by applying the informational cascade model to herding. In general, our analyses agree with the existing literature that herding tends to be more prevalent with small stocks and in economic downturns and that investors are more likely to herd when selling rather than buying stocks. Most importantly, our results reveal the existence of informational cascades, which highlights the crucial role played by so-called fashion leaders, especially when more informed investors trade with "noise".

1. Introduction

This paper tests the coexistence of two types of phenomena: herding and informational cascades. With herding, people tend to crowd together with others, making identical investment decisions. This is especially common in markets having less publicly available information. This well-known phenomenon has been widely studied over the last two decades. According to Bikhchandani et al. (1992), individuals with access to information that is less accurate tend to follow the lead of individuals that have access to information that is more accurate than their own. Ignoring their own information, such individuals tend to form herds, with the best informed individuals making their decisions first. These decision makers are known as "fashion leaders", and the phenomenon hence known as "informational cascades". In this paper, we extend the literature by determining if informational cascades do, in fact, cause part of the herding phenomenon. We start by testing if herding takes place in the market. If so, we examine if informational asymmetry exists within the herding process.

2. Methodology and sample

We start by examining the behavior of "sheeple"[1] without taking into account the net changes in the stock holdings. To see this, suppose a market participant buys 1000 shares of a stock 10 times but sells 20,000 shares once during a given period. According to Lakonishok et al. (1992), which is hereafter referred to as the LSV model, this market participant would be defined as a net seller. In this paper, we will consider this heavier than expected inclination toward one side of trading as evidence of herding. Thus, we

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[1] Sheeple, often used as a synonym of herd, is created by combining the words "sheep" and "people."

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avoid the stronger assumption that institutional investors trade because they are equally well-informed or that they trade for the same reason, as in the LSV model.[2] By modifying this model, the herding measure of stock *i* in any stock-period *t* would be

$$H_{i,t} = \left| \frac{B_{i,t}}{N_{i,t}} - E\left[\frac{B_{i,t}}{N_{i,t}}\right] \right| - E\left| \frac{B_{i,t}}{N_{i,t}} - E\left[\frac{B_{i,t}}{N_{i,t}}\right] \right| \tag{1}$$

where $B_{i,t}$ ($S_{i,t}$) is the number of buys (sells) of stock *i*, and $N_{i,t} = B_{i,t} + S_{i,t}$ is the total number of trades of stock *i* in a stock-quarter (i.e. a given stock in a given quarter). The larger the value of $H_{i,t}$, the higher is the level of herding. Furthermore, if $\lfloor B_{i,t}/N_{i,t} \rfloor$ is larger (less) than $E\lfloor B_{i,t}/N_{i,t} \rfloor$, the herding measure is classified as buy-side (sell-side).

We then examine whether investors are more likely to herd when there is a higher proportion of information based trading, thus leading to an informational cascade. Hirshleifer and Teoh (2003) note that informational cascades are associated with informed trading. We therefore expect to find that a higher probability of information based trading would cause a higher level of herding by traders with information of low precision. Given the limited amount of information available, we distinguish between informed and uninformed traders by proposing that the high probability of information based trading implies that there are more informed traders than uninformed traders. We apply the probability of informed trading (PIN) concept, which is usually calculated to study the impact on spread, to deduce information based trading. If there is a positive relationship between herding and the probability of information based trading, then, consistent with the informational cascade model, we can conclude that investors with a lower probability of information based trading cascade on those with a higher probability.

Following Easley et al. (2005), we obtain maximum likelihood estimates from

$$\begin{aligned} L\left((B_t, S_t)_{t=1}^{T} \mid \alpha, \delta, \mu, \varepsilon_b, \varepsilon_s\right) = & \sum_{t=1}^{T} \left[-\varepsilon_b - \varepsilon_s + M_t(lnx_b + lnx_s) + B_t ln(\mu + \varepsilon_b) + S_t ln(\mu + \varepsilon_s)\right] \\ & + \sum_{t=1}^{T} ln\left[\alpha(1-\delta)e^{-\mu} x_s^{S_t - M_t} x_b^{-M_t} + \alpha\delta e^{-\mu} x_b^{B_t - M_t} x_s^{-M_t} + (1-\alpha) x_s^{S_t - M_t} x_b^{B_t - M_t}\right] \end{aligned} \tag{2}$$

where $M_t = (\min(B_t, S_t) + \max(B_t, S_t))$, $x_b = \frac{\varepsilon_b}{\mu + \varepsilon_b}$, and $x_s = \frac{\varepsilon_s}{\mu + \varepsilon_s}$. We adopt the algorithm proposed by Yan and Zhang (2006) and construct 125 sets of initial values with the data on daily buys and sells of the stock from

$$\alpha^0 = \alpha_i, \delta^0 = \delta_j, \varepsilon_b^0 = \gamma_k \cdot \bar{B}, \mu^0 = \frac{\bar{B} - \varepsilon_b^0}{\alpha^0(1-\delta^0)}, \varepsilon_s^0 = \bar{S} - \alpha^0 \cdot \delta^0 \cdot \mu^0 \tag{3}$$

After eliminating the initial value sets with negative values of ε_s^0, we run the maximization procedure and choose the set of parameters that generates the highest value of the objective functions among the non-boundary solutions.

We use bid/ask quotes and trade records from the Hong Kong Stock Exchange, which is a purely order-driven market (see Ahn et al., 2001, for details). It is an extremely transparent trading system with very low transaction costs. The emphasis from O'Hara (1995) on the impact that market transparency has on trading strategies supports our choice of Hong Kong's stock market as a good sample for our study. Similar to Brockman and Chung (2000), but with a larger sample covering a different period, we study a total of 200 constituent stocks in the Hang Seng Composite Index (HSCI) from January 2003 to December 2004. This covers 90% of the market capitalization of stocks listed on the Main Board of the Hong Kong Stock Exchange. Our two-year sample period, which constitutes 523 trading days, is adequate for an intraday microstructure study. It also covers a clearly defined business cycle from the trough in the beginning of 2003 to the recovery, which started at the end of 2003.

3. Results on herding

Since our focus is on the existence of informational cascades in herding, we summarize our findings on the herding phenomenon in this section. There are a total of 96,381 positive (implying herding) and 861 negative (no apparent herding) stock-day herd measurements in the 523 trading-day sample (details are available upon request). In general, herding is stronger in 2003 than in 2004. A decrease in the measures accompanied by an increase in trading volume suggests that investors herd more often at times when market sentiment is poor. More herding takes place in the financial sector and the property and construction sector, which are Hong Kong two most important industries, than in other sectors. This is especially true in 2003. This phenomenon gives credence to the hypothesis that investor sentiment is highly reliant on dominant industries and that investors are more inclined to follow others when making trading decisions in order to play safe.

In terms of market capitalization, we adopt two data sets. First, we test SmallCap, MidCap, and LargeCap Indices within the Hong Kong Composite Index (HSHKCI). Second, we divide all of the 200 constituent stocks into market size quintiles, rebalancing them every month based on changes in market capitalization. Consistent with the existing literature, we find a monotonic reverse relationship between market capitalization and herding measures. In addition, herding in the smallest quintile is on average about 5% more than that in the largest quintile. Herding among stocks in the HSHKCI is slightly stronger than in the Mainland Composite

[2] Nor do we necessarily assume that each trade is done by an individual investor in Choe et al. (1999).

Index (HSMLCI). It is nevertheless worth noting that the HSMLCI constituents, which derive at least 50% of their sales revenue from mainland China, generally have much larger market capitalizations (equivalent to LargeCap) and should hence experience less herding. While Wermers (1999) suggests that sell-herding is much more frequent among stocks in the smallest quintile of capitalization, we find that sell-side herding is consistently larger than buy-side herding in all capitalization quintiles.[3] This pattern indicates that investors in general are more likely to herd when selling than when buying.

Finally, since trading following past returns suggests technical analysis, while trading on past P/E ratios implies fundamental analysis, we test which type of investment analysis generates the most herding. We separate stocks into quintiles according to their past returns and past P/E ratios. Similar to Lakonishok et al. (1992), Choe et al. (1999), and Voronkova and Bohl (2005), we fail to observe strong evidence to support the hypothesis that herding is more prevalent in stocks with high or low past returns. On the contrary, herding in some quarters is even most prevalent in the medium return quintile. Furthermore, we fail to find larger buy-side (sell-side) herding in the larger (smaller) past return quintiles. In other words, there is no evidence that investors "cluster" to sell stocks with lower returns and buy those with higher returns.[4] Again, sell-herding is consistently larger than buy-herding in each of the past return quintiles. Herding measures by past P/E ratios are, in fact, larger in the smallest and largest quintiles but smaller in the middle quintile. We observe that for each quarter in the sample period, herding measures decrease first and then increase. However, herding in the largest P/E quintile is consistently higher than that in the smallest P/E quintile.

Basu (1977) indicates that stocks with low P/E ratios may have higher returns because riskier firms may sell their stocks at lower prices *ceteris paribus*. Given this, the impacts of returns and P/E ratios might be correlated. We repeat the study by controlling for both effects. We form 25 groups by sorting stocks into past return quintiles and past P/E ratio quintiles. We find that while investors do not herd in general by past returns, they tend to herd more often with stocks that have lower past returns that also have high past P/E ratios. Investors thus seem more likely to herd when basing their decisions on fundamental analyses than on technical analyses. This provides very interesting insights. Investors that rely on public information tend to increase their holdings when stocks are reported as having better prospects (or higher P/E ratios). Chartists usually rely on their own forecasts and are not affected by other influences when making investment decisions. We also find similar results when we repeat the procedure with past earnings-per-share (EPS) quintiles and by trading volume quintiles.

4. Herding with fashion leaders

In this section, we test to see if informational cascades exist within markets that experience herding. We calculate the PIN for each stock on a quarterly basis using Eq. (2) with an initial value setting in Eq. (3) following the requirement that there be a minimum of 60 trading days, as proposed by Easley et al. (1993). Using a quarterly basis ensures that the estimated parameters are sufficiently robust. It also enables direct comparisons of our findings with most of the other research that has adopted the quarterly basis model. A minimum of at least 50 trading days is applied to each quarter. There are totally 1532 available sets of estimated parameters after deleting those that would generate boundary solutions and those without sufficient trading days.[5]

Table 1 depicts the herding measures across the PIN range. Panel A reveals a pronounced positive correlation between PIN and overall, buy-side, and sell-side herding. In addition, sell-side herding is larger than buy-side herding for most quarters in the sample period. However, their coexistence may be due to a common source: market capitalization. We therefore further test the relationship by forming 25 portfolios by independently placing the sample stocks into market capitalization quintiles and then into PIN quintiles. Panel B shows a positive correlation between informed trading and herding, conditional on each market capitalization quintile. In unreported results, we obtain the same finding after testing 25 portfolios grouped into trading volume quintiles and PIN quintiles.

Attempting to confirm the findings with another approach, we regress the herding measures on market capitalization (*CAP*), past returns (*RET*) and P/E ratios (represented by the inverse of the P/E ratio, or *INV_PE*, to avoid companies with zero or negative earnings) and probability of informed trading (*PIN*) according to the following panel regression:

$$HM_{i,t} = \alpha_0 + \alpha_1 CAP_{i,t} + \alpha_2 RET_{i,t} + \alpha_3 INV\_PE_{i,t} + \alpha_4 PIN_{i,t} + \alpha_5 Vol_{i,t} + \alpha_6 Std_{i,t} + \varepsilon_{i,t} \quad (4)$$

where all measures are on a quarterly basis because of the quarterly PINs. We include volume (*VOL*) because of the high correlation between trading volumes and PINs, as discussed in previous section. The volatility (*STD*) computed as the standard deviation of daily returns for a given quarter is included to consider the effect of spread and the trading behavior of institutional investors. Furthermore, herding may be more prevalent in more volatile stocks. To separate the effects of past returns and P/E ratios on the herding measure, we exclude *INV_PE* and *RET* one at a time from Eq. (4).

Table 2 presents the regression results with fixed effects, as supported by the Breusch and Pagan (1980) Lagrangian multiplier test. The dependent variables are represented as follows: herding measure in Panel A, buy-side herding measure in Panel B, and

[3] Although not reported here, we calculate the *t* statistics of the mean difference between buy- and sell-herding for each quarter. For example, sell-herding in the smallest capitalization quintile is significantly higher than buy-herding in only three out of eight quarters.

[4] In Hirshleifer and Teoh (2003), "clustering" means that "people act in a similar way owing to the parallel independent influence of a common external factor." However, "herding" depends on actual interaction between individuals.

[5] While our estimated parameters are bounded with relatively large standard deviations, our results are consistent with the findings of Easley et al. (1996) when trading volumes are considered. In particular, we group the constituent stocks into volume quintiles and found that the magnitudes of the corresponding PINs decrease as the trading volumes increase. In addition, the standard deviation in each quintile is considerably smaller than that when all stocks are pooled together. Results are available upon request.

Table 1
Herding measures by probability of information-based trading (PINs).

Panel A: Overall result

PIN quintile		2003 Q1	2003 Q2	2003 Q3	2003 Q4	2004 Q1	2004 Q2	2004 Q3	2004 Q4
1 (smallest)	Overall	9.18	8.24	6.68	6.75	6.96	6.61	8.43	8.33
	Buy	9.07	7.83	6.16	6.52	6.67	6.52	8.21	8.41
	Sell	9.31	8.48	6.92	6.89	7.28	6.81	8.94	8.25
2	Overall	10.56	10.38	8.79	8.64	8.05	7.96	8.74	9.60
	Buy	9.71	10.89	8.81	7.43	7.99	7.83	8.69	9.01
	Sell	11.02	10.29	8.78	9.29	8.25	8.04	8.80	9.98
3	Overall	12.05	11.42	10.25	10.09	9.42	10.24	10.78	11.14
	Buy	11.81	10.18	9.07	9.23	8.91	10.49	9.86	10.39
	Sell	12.29	12.09	10.96	10.96	9.796	10.14	11.74	11.65
4	Overall	15.12	13.13	11.49	12.52	10.99	13.10	14.36	13.57
	Buy	12.88	11.69	10.29	10.31	9.84	12.37	12.90	11.68
	Sell	16.13	13.83	12.20	13.60	11.64	13.42	14.80	14.34
5 (largest)	Overall	16.62	16.39	15.61	15.92	15.05	15.65	16.01	16.18
	Buy	14.35	15.03	14.10	14.10	13.66	14.04	14.51	14.76
	Sell	17.67	17.44	16.53	17.59	15.99	16.66	17.40	17.25

Panel B: Herding measures by PIN quintile and market capitalization quintile

Market capitalization quintile	PIN quintile	1 (smallest)	2	3	4	5 (largest)	t statistics Q1–Q5
1 (smallest)	Overall	11.19	12.02	13.42	15.79	16.43	−4.80*
	Buy	11.47	10.47	11.80	14.09	16.22	−4.02*
	Sell	11.15	13.63	15.60	17.18	17.71	−7.57*
2	Overall	9.95	11.87	13.24	15.08	16.22	−10.41*
	Buy	9.02	10.16	12.08	13.39	15.10	−9.62*
	Sell	10.14	12.73	13.89	16.20	17.54	−10.62*
3	Overall	8.68	9.51	11.08	12.01	15.02	−6.02*
	Buy	7.72	8.71	9.67	11.04	14.75	−5.85*
	Sell	9.33	9.97	11.94	12.62	15.13	−6.48*
4	Overall	7.58	8.26	9.61	10.74	13.28	−9.04*
	Buy	7.33	7.89	9.65	10.52	12.45	−10.58*
	Sell	7.73	8.45	9.60	10.90	13.81	−7.78*
5 (largest)	Overall	6.30	7.71	8.09	8.50	11.66	−7.36*
	Buy	6.26	7.41	7.76	8.29	10.94	−6.21*
	Sell	6.39	7.81	8.18	8.67	11.97	−9.00*
t statistics Q1–Q5	Overall	8.34*	6.59*	6.84*	8.05*	5.54*	
	Buy	7.32*	4.55*	5.94*	8.98*	4.37*	
	Sell	8.66*	8.84*	8.65*	9.12*	6.28*	

Note: '*' indicates significance at 1% level.

sell-side herding measure in Panel C. Column (1) provides estimates of Eq. (4) while Columns (3) and (5) refers to Eq. (4) with P/E ratios and past returns omitted respectively. We estimate these equations again by replacing *PIN* by relative spread (*R_Spread*, the log of the differences between the ask and bid price, divided by the price midpoint) as another proxy of informed trading (i.e. the higher the spread, the higher the proportion of informed trading).[6] The results are presented in columns (2), (4), and (6).

It is apparent that all the estimated coefficients are significant with the exception of past returns. Hence, the results are consistent with the previous section in the following ways. First, capitalization is negatively correlated with herding because of the high (low) information transparency in stocks with higher (lower) levels of capitalization. Second, investors tend to herd more often with stocks that have high P/E ratios. This may suggest that investor sentiment is affected by a firm's growth prospects regardless of its size or level of risk. On the other hand, none of the estimated coefficients of return prove significant. We can thus assume that investors tend to herd when relying on fundamental indicators but not when relying on technical analyses. Third, the significant and positive signs of the coefficients of *PIN* support the notion that informational cascades exist. This relationship remains consistent when we replace *PIN* by *R_Spread*, another proxy of informed trading. The negative coefficient of trading volume suggests that herding intensifies with stocks that are infrequently traded. Finally, less volatile stocks seem to attract more herding. This indicates that investors may share common beliefs regarding the future prospects of stocks that are less volatile. Buy-side and sell-side herding measures in Panels B and C demonstrate similar results.

In the previous section it was shown that herding measures are more frequent with financial and property stocks. We finalize the test of informational cascades in herding by considering nine industries using dummies in the regression Eq. (4), and with/

[6] See, for example, Glosten and Harris (1988) for the theoretical models of the relationship between spread and information asymmetry.

Table 2
Regression herding measures on probability of informed trading.

Herding measure						
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Panel A On all data						
Intercept	0.4751*	0.6270*	0.4683*	0.6143*	0.4761*	0.6251*
LOGCAP	−0.0119*	−0.0027*	−0.0117*	−0.0025**	−0.0120*	−0.0026**
RET	−0.0055	0.0101	−0.0099	0.0047		
INV_PE	−0.0043*	−0.0458*			−0.0434*	−0.0450*
PIN	0.1257*		0.1234*		0.1255*	
R_Spread		0.0433*		0.0430*		0.0432*
LOGVOL	−0.0081*	−0.0124*	−0.0081*	−0.0122*	−0.0081*	−0.0124*
STD	−0.4149*	−0.5519*	−0.3976*	−0.5303*	−0.4204*	−0.5285**
Panel B Buy-side herding						
Intercept	0.3886*	0.5488*	0.3852*	0.5410*	0.3882*	0.5472*
LOGCAP	−0.0076*	0.0019	−0.0075*	0.0021***	−0.0076*	0.0020***
RET	0.0026	0.0079	0.0003	0.0041		
INV_PE	−0.0275*	−0.0337**			−0.0273**	−0.0332*
PIN	0.1190*		0.1181*		0.1191*	
R_Spread		0.0448*		0.0447*		0.0447*
LOGVOL	−0.0080*	−0.0125*	−0.0081*	−0.0125*	−0.0080*	−0.0126*
STD	−0.4149*	−0.5519*	−0.3976*	−0.5303*	−0.4204*	−0.5285**
Panel C Sell-side herding						
Intercept	0.4881*	0.6023*	0.4813*	0.5936*	0.4874*	0.5983*
LOGCAP	−0.0127*	−0.0063*	−0.0125*	−0.0062*	−0.0126*	−0.0061*
RET	0.0038	0.0202	−0.0004	0.0166		
INV_PE	−0.0378*	−0.0294**			−0.0375*	−0.0281**
PIN	0.1388*		0.1367*		0.1389*	
R_Spread		0.0286*		0.0285*		0.0284*
LOGVOL	−0.0081*	−0.0119*	−0.0081*	−0.0117*	−0.0081*	−0.0119*
STD	−0.3764*	−0.4150*	−0.3674*	−0.4050*	−0.3730*	−0.3700**

Note: '*', '**' and '***' indicate significance at the 1%, 5%, and 10% level respectively.

without past returns and P/E ratios. With lengthy results omitted, we find that while all of the estimated coefficients are consistent with our previous findings, there is a significant discrepancy in the coefficients of industry dummies between the buy-side herding model and the sell-side herding model. None of the estimated coefficients of the industry dummies is significant in buy-side herding. However, herding on the sell-side takes place significantly less often with industries such as industrial goods, information technology, properties and construction, and utilities. This conclusion may not be consistent with previous findings, which show that herding is more common among the financial and property and construction industries. It therefore highlights that univariate test results presented in the previous section fail to address the impact of other control variables. A more important implication addressed here is that exogenous factors for the same industry may have a heterogenous effect on buy- and sell-herding.

Consistent with the informational cascade model proposed by BHW (1992), our empirical results suggest that when there are different levels of information precision in the market, investors with less precise information tend to herd with fashion leaders that are perceived as having better information. Hence, we can conclude that informational cascading exists, at least in the case of the Hong Kong stock market.

5. Conclusion

This paper examines the herding behavior and informational cascades of general investors in a transparent, order-driven market by applying intraday data. We conclude that herding measures differ in stocks in both geographic and industrial classification. We propose that investors in general rely more on fundamental analysis than technical analysis. We find a consistently higher frequency of herding on the sell-side than on the buy-side. We also find that exogenous factors within the same industry may have a heterogeneous effect on buy- and sell-herding. As possibly the most significant contribution of the paper, we reveal evidence of informational cascading by highlighting the crucial role that fashion leaders play when informed investors trade with "noise". Our study verifies that herding still exists and can be, to certain extent, largely the result of informational cascades, even in a transparent market in which information can be easily disseminated.

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References

Ahn, H.J., Bae, K.H., Chan, K., 2001. Limit orders, depth, and volatility: evidence from the Stock Exchange of Hong Kong. Journal of Finance 56, 767–788.
Basu, S., 1977. The investors performance of common stocks in relation to their price-earnings ratios: a test of the efficient market hypothesis. Journal of Finance 32, 663–682.
Bikhchandani, S., Hirshleifer, D., Welch, I., 1992. A theory of fads, fashion, custom and cultural change as information cascades. Journal of Political Economy 100, 992–1026.
Breusch, T.S., Pagan, A.R., 1980. The Lagrange Multiplier test and its applications to model specification in econometrics. Review of Econometric Studies 47, 239–253.
Brockman, P., Chung, D.Y., 2000. Informed and uninformed trading in an electronic, order-driven environment. The financial Review 35, 125–146.
Choe, H., Kho, B., Stulz, R.M., 1999. Do foreign investors destabilize stock markets? The Korean experience in 1997. Journal of Financial Economics 54, 227–264.
Easley, D., Kiefer, N., O′Hara, M., 1993. One day in the life of a very common stock. Working paper. Cornell University.
Easley, D., Kiefer, N., O′Hara, M., Paperman, J.B., 1996. Liquidity, information and infrequency traded stocks. Journal of Finance 51, 1405–1436.
Easley, D., Hvidkjaer, S., O′Hara, M., 2005. Factoring information into returns. Working paper. Cornell University.
Glosten, L.R., Harris, L.E., 1988. Estimating the components of the bid/ask spread. Journal of Financial Economics 21, 123–142.
Hirshleifer, D., Teoh, S.H., 2003. Herd Behavior and cascading in capital markets: a review and synthesis. European Financial Management 9, 25–66.
Lakonishok, J., Shleifer, A., Vishny, R.W., 1992. The impact of institutional trading on stock prices. Journal of Financial Economics 32, 23–43.
O′Hara, M., 1995. Market Microstructure Theory. Blackwell Publishers, Cambridge, Mass.
Voronkova, S., Bohl, M.T., 2005. Institutional traders′ behavior in an emerging stock market: empirical evidence on Polish pension fund investors. Journal of Business Finance and Accounting 32, 1537–1560.
Wermers, R., 1999. Mutual fund herding and the impact on stock prices. Journal of Finance 54, 581–622.
Yan, Y., Zhang, S., 2006. An improved estimation method and empirical properties of PIN. Working paper. University of Pennsylvania and Nanyang Technological University.