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Abstract

This paper focuses on the time series properties of the level of underpricing of IPO shares and volume of initial selling in Hong Kong equity market. Strong autocorrelation among the level of underpricing has been identified. Evidence suggests that the initial selling volume plays an important role in the relationship. The links between underpricing and clustering of IPOs within different industries are weak, suggesting the reasons for underpricing are rather related to the market liquidity than industry specific risk characteristics.

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1 Introduction

IPO underpricing is a well documented fact in many empirical studies in financial markets all over the world. During the period from 1990 to 1998, more than $27 billion were left on the table in U.S. by IPO underpricing (Loughran, Ritter, 2002). Although great effort has been made to verify the existence of IPO underpricing and other IPO related puzzles, such as long term under performances, it is surprising that there is relatively few works on the degrees of IPO underpricing and the reasons for the differences in the level of underpricing.

Meanwhile, clustering, another IPO related question, is less noticed. In a few existing works related to IPO clustering (Hoffmann-Burchardi, 2001, Yung et al., 2006, Alti, 2005), underpricing is always claimed as the result of clustering, in the name of information externality and investor sentiment.

1.1 IPO Underpricing

An asymmetric information story is a natural first thought that investigator would have when it comes to explaining IPO-related phenomena. As in the Akerlof's "Lemon market", in a market for newly offered shares the public may know little about the firm and its shares. IPO firms may face a consistently pessimistic public who on average tend to undervalue the shares. Through the initial public offering, better informed investors may take advantage of these pessimistic public by trading the IPO shares. At the end, their inside information becomes public, appearing in the trading price of the shares in secondary market.

Another interpretation of the information asymmetric theory is avoidance of the "winner's curse" (Rock, 1986). The best informed investors are not usually the successful bidders. The best informed investors do not want to bid for shares because the fair price according to their information is lower than the trading price. As a result, the successful but uninformed bidders are cursed by paying an extra amount of money for some goods which are not worthy. The consequence of "winner's curse" is that the uninformed investors will only win when the shares are not so good.

Since the IPO firms are usually young with relatively opaque information, irrational investor story claims that the irrational investors might misperceive the value of information and market momentum. Ljungqvist, Nanda and Singh (2004) first model the sentiment investors in IPO market. Intuitively, this kind of sentiment or irrational investors should die out in financial market and in the long run only rational investors will survive. However, existing research (Yan, 2005) presents evidences that in a limited arbitrage world, the irrational investors might be able to survive long enough to drive prices to an "unreasonable" level for a considerable period ("bubbles").

The agreement theory is based on the assumption that the issuer wants some target investors. The underpricing is purposeful as it serves to attract more investors and select the most desirable one. The intentions could be either to attract investors who can aid in acquisitions that are being financed by the IPO (Brennan and Franks, 1997) or to attract investors who are more likely to be favorably disposed to the firm's business or methods of management (Stoughton and Zechner, 1997). In both cases, the target investor selection will increase the value of the firm. Unlike the information asymmetry and sentimental theories, this kind of underpricing is artificial one and the degree of underpricing is controlled by the issuer.

There are many other interpretations for the IPO puzzles, such as legal problems, price stabilization strategy, and tax issues. However, none of them alone could explain the underpricing puzzle. Moreover, most of theoretical works which aim to shed light to IPO's underpricing assume that the IPOs are independent in time so that the level of underpricing should not show any pattern in time series. As we will see it is not the case and the level of underpricing exhibits strong auto-correlation. After all, the question is still remaining: Why are IPO shares underpriced?

1.2 IPO Clustering

Traditionally the reason for IPO clustering has been always related with the industry specific information or investor sentiment.

Mauer and Senbet (1992) argue that the price exhibited in secondary market of an IPO firms can reduce the uncertainty of the following firms going public. Booth and Chua (1996) argue that the marginal cost of information can be reduced for firms going public at the same time.

Along the line of the information spillover, Hoffmann-Burchardi (2001) focuses on the revelation of a common-value component in the process of price determination, and lays emphasis on the importance of information externalities. The price of the IPO shares of one firm from a particular industry serves as an indicator of the common positive information about the followers in the same industry.

From the entrepreneur's perspective, Hoffmann-Burchardi claims that a firm with utility-maximizing risk-averse characteristic will go public if and only if the entrepreneur gains less from the risky cash flow from the firm than selling it to the public risk-neutral investors. In his model where firms go public sequentially, one after another, the value of the firm is decided by two factors: firm specific factor and industry specific factor. There is asymmetric information between the entrepreneurs and investors. The entrepreneur does not know much about industry specific factors, while he may be better informed about the firm specific factor. On the other side the investors in the market may posses more information about the industry specific factor than the issuer. Once the issuer believes the market value is much greater than he estimates, which indicate the market is hot, he will sell shares to the market. This paper concludes that this story also explains why hot market often coincides with greater underpricing. In the market where trading price is greater than that expected by issuer the underpricing is more severe for sure.

Meanwhile, some researches show that time-varying adverse selection, the result of information asymmetry, plays a greater role in IPO clustering.

Benninga, Helmantel, and Sarig (2005) argue that IPO clustering in a particular industry is triggered by the firm with the highest cash flow in this industry going public, which in turn produces the information of both the firm's value and the investment opportunities in this industry. The valuable information about the industry prospect being perceived by both investors and private firms serves now as a focal point for another agents and leads to clustering. The cluster dies out with the end of market optimism. Additionally, Jain and Kini (2005) believe that lower information asymmetry between issuers and investors together with an increase in investor optimism are also important factors to trigger the IPO cluster. Meanwhile, they claim that the downside of the IPO clustering is because of the over investment in the industry, which results in a long term under performance.

Up to my knowledge, the closest research to this paper is one made by Lowry and Schwert (2002). This paper directly tests the relation between clustering and underpricing level. By examining the sample of IPOs during the period from 1960 to 1997, they find that the IPO volume and average underpricing are highly auto-correlated, and that the greater number companies tend to go public after periods of high IPO underpricing. They conclude that similar types of firms choose going public at the same time. More importantly, the offering registration information has an effect on the offering price and going public decisions. In their analysis they use the average underpricing data for each month instead of the underpricing level of each IPO share as we do. Also they do not differentiate between different industry sectors except for high tech firms which are insufficient to justify any arguments related to the industry specific factor. Their conclusion that "similar" firms choose the same time of being public seems to be a premature one. Further more, failing to control the influence of initial selling on the initial return leave us with another unanswered question: Is the cluster just a gathering of firms or an increase demand for capital?

1.3 Structure of the Paper

In this paper, we test our hypothesis in Hong Kong equity market. On one hand, overwhelming research has been done in mature financial market, such as United States and United Kingdom. However, Hong Kong market is seldom mentioned in the existing literatures. It is reasonable to believe that by using the data from Hong Kong market, the research could provide new data to extend the existing research. On the other hand, it is arguably that the rules for financial market are incomplete and changing over time. Applying the data sample from emerging market, such as India and Mainland China, the research may be less convincing when we compare the result with the existing literatures.

This paper examines the empirical data to answer the above posed questions. Also, it simulates a shock on the underpricing to demonstrate the relationship between liquidity and underpricing level. The simulation result suggests that the competition among IPO shares and the effect of liquidity shock is determined by some exogenous parameters, but not by the shocks *per se*. Furthermore, this paper focuses on the liquidity shock, and also demonstrates that the clustering is neither the reason for nor the result of the severe underpricing. The reasons for the clustering may vary, and further investigation is needed but beyond this paper.

The paper is organized as follows. Section 2 describes the data set. Section 3 shows the result of the empirical analysis. In section 4 discusses results and simulates a shock to demonstrate their robustness. Section 5 concludes.

2 Data

The data used in this paper is from Investment Service Centre of Hong Kong Exchange and Clearing Limited (http://www.hkex.com.hk/invest/isc.htm) for initial public offerings from the November, 1999 to the end of 2005. The offer price, number of shares offered and the date of the first trading day of the IPO shares are collected from their prospectus in Hong Kong Exchange's public document database. First day open price and trading volume are collected from both Datastream Advanced® (DA) and Yahoo! Finance (Hong Kong) (hk.finance.yahoo.com), since some trading prices are missing from either DA or Yahoo! database. A few trading information are still missing from both of them. The information about the industry sector categorization is also collected from Datastream Advanced®. Except for internet bubble, none other significant bubble was recorded in Hong Kong market and worldwide as well during this period. Internet bubble is significantly influential in U.S. financial market, but much more moderate in Hong Kong. By considering other industries were not significantly influenced by the internet bubble and the availability of the data, the data from year of 1999, 2000 and 2001 is included.

The IPO prospectus before November 1999 is not available on the Hong Kong exchange web page. The IPOs after 2005 are not included in this research because of blooming of IPOs in both China Mainland and Hong Kong since the beginning of 2006.

The interest rate is used as the risk free rate in this paper. The information of interested rate are separately collected from The People's Bank of China (www.pbc.gov.cn), China's central bank, for one year fixed rate for Yuan (RMB) and

Hong Kong Census and Statistic Department (www.censtatd.gov.hk) for Hong Kong dollar's "best lending rate". This paper does not take the exchange rates as a risk factor, since the exchange rate is almost fixed for both currencies. RMB kept its exchange rate to US dollar at the level of 8.27 during the period and Hong Kong dollar was kept at the level between 7.758 and 7.799.

The underpricing level UP_i is defined as the ratio between the difference between first day open price $OPEN_i$ and offering price $OFFER_i$. The market initial selling CAP_i is defined as the product between the shares offered $NSHARE_i$ and the open price $OPEN_i$.

$$UP_i = \frac{OPEN_i - OFFER_i}{OFFER_i} \tag{1}$$

$$CAP_i = NSHARE_i \times OPEN_i \tag{2}$$

I use log market capitalization based on e $LNCAP_i$ to represent market capitalization. The number of IPOs N_t , total initial selling volume $LN(CAP_t)$ in every month are used to describe the trend of the IPO market. There are 34 industry sectors $INDSECT_i$ with 440 in total plus "unclassified sector" which consists of 50 firms.

Table 5.1 provides the descriptive information about the variables used in this paper. In the sample period, the average underpricing level is 34.9%. In only one extreme case with stock code 8036, "36.com Holding Limited", the underpricing is 399.0, which is excluded from the descriptive statistics. Some of the data are not available, so the number of data is not the same for different variables as it is shown in Table 5.1.

Table 1 Descriptive Statistics for IPO sample

Panel A: Basic Information

	Min	Max	Mean	Std Dev	N
UP	-0.96	21.00	0.35	1.94	454
LN(CAP)	12.90	24.85	18.84	1.70	455
OFFER	0.10	84.00	1.78	4.46	490
VLM	14378	3637142272	109492411.9	251435461.2	455
N_SHARE	4002005	26485944000	423497776.4	1761543296	490

Panel B: Number of IPOs

Time Window	Total No. of IPOs	Avg No. of IPOs per Month	Std Var of No. of IPOs per Month
1999 Nov to 1999 End	15	7.00	0.50
Year 2000	85	7.08	13.36
Year 2001	88	7.33	17.88
Year 2002	108	9.00	13.45
Year 2003	64	5.33	8.97
Year 2004	66	5.50	12.09
Year 2005	64	5.33	20.79

The statistic information about the underpricing level and capitalization in different industries are listed in Table 5.2. By the sector information provided in Datastream, the IPO firms are distributed among 34 industries. The "Unclassified cases" are labeled to the firms without sector information in Datastream.

Among all classified industries, the mean of underpricing level for a particular industry is minimal for the industry labeled by "Oil and Gas Producers" and maximal for "Travel & Leisure". The greatest averaged underpricing level is in unclassified group. Only one firm is in the "Mobile Telecommunications" industry and it has the greatest average market capitalization, while the "Chemicals" industry has the lowest average capitalization. "Personal Goods" is the largest industry group in our sample, except the "Unclassified Cases" group. The numbers of samples vary across different industries.

Table 2 Statistic Information across Industries

Industry Sectors	UP				CAP (million HKD)				N
	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev	Valid Cases

Electronic, Electrical Equip.	-0.55	0.98	0.03	0.30	146.42	1,456.00	228.00	361.25	17
General Retailers	-0.79	0.28	-0.07	0.37	12.80	1,920.96	456.75	702.81	9
Leisure Goods	-0.03	0.26	0.05	0.09	7.35	1,320.00	397.97	509.57	7
Household Goods	-0.66	4.71	0.33	1.20	27.00	1,952.70	236.96	491.38	16
Mobile Telecommunications	0.10	0.10	0.10	NA	43,895.41	43,895.41	43,895.41	N.A.	1
Software & Computer Services	-0.90	19.59	1.04	3.48	4.48	5,100.00	394.28	905.03	34
General Industrials	-0.20	0.04	-0.02	0.11	51.00	196.00	103.33	64.89	4
Personal Goods	-0.07	0.32	0.06	0.08	21.06	2,272.91	235.30	418.93	37
Technology Hardware & Equip.	-0.10	4.81	0.24	0.85	27.97	12,466.67	720.79	2,241.45	24
General Financial	-0.71	0.90	0.09	0.38	20.30	315.00	85.66	80.42	11
Real Estate	-0.12	0.55	0.13	0.23	0.00	3,820.28	845.78	1,340.05	7
Travel & Leisure	-0.04	9.65	2.47	3.82	51.50	18,400.00	4,655.07	7,573.99	6
Industrial Metals	-0.20	0.27	0.00	0.20	44.00	3,928.94	1,666.49	1,861.13	4
Pharmaceuticals, Biotechnology	-0.02	1.14	0.22	0.33	0.00	2,875.40	285.68	657.71	15
Construction & Materials	-0.69	0.42	0.02	0.22	15.50	600.60	135.92	178.72	14
Industrial Transportation	-0.09	0.10	0.01	0.05	22.00	7,671.40	1,947.08	2,428.96	10
Oil Equipment & Services	0.04	0.88	0.27	0.35	57.60	2,402.37	578.45	1,020.66	4
Food & Drug Retailers	0.05	0.08	0.06	0.02	65.75	607.50	290.52	282.40	3
Support Services	-0.05	3.26	0.32	0.89	39.37	5,120.00	501.92	1,390.44	11
Healthcare Equipment, Services	0.02	1.00	0.33	0.41	74.88	209.30	125.93	52.16	5
Industrial Engineering	0.00	0.65	0.12	0.20	50.40	5,083.68	765.42	1,440.85	13
Automobiles & Parts	0.00	0.37	0.12	0.14	41.86	4,047.70	1,020.93	1,418.04	8
Banks	0.00	0.12	0.03	0.05	2,302.30	62,241.97	21,992.48	24,660.02	5
Media	-0.08	0.51	0.11	0.14	13.67	4,500.00	376.59	887.97	22
Chemicals	-0.94	9.00	1.08	3.52	3.00	103.54	46.50	33.15	5
Food Producers	-0.14	0.41	0.10	0.13	52.20	1,685.17	467.64	547.18	13
Equity Investment Instruments	-0.96	0.52	-0.17	0.45	0.40	326.35	73.91	105.36	11
Mining	0.01	0.42	0.22	0.30	163.70	23,129.42	11,646.56	16,239.22	2
Forestry & Paper	0.27	0.27	0.27	NA	151.20	151.20	151.20	N.A.	1
Beverages	-0.78	0.30	-0.19	0.54	31.54	876.00	378.90	441.69	3
Nonlife Insurance	0.34	0.40	0.37	0.04	594.42	7,272.58	3,933.50	4,722.18	2
Life Insurance	0.02	0.27	0.14	0.18	14,572.87	29,441.18	22,007.02	10,513.48	2
Fixed Line Telecommunications	-0.01	0.13	0.06	0.06	23.26	10,503.40	4,160.63	5,490.69	4
Electricity	0.07	0.14	0.10	0.05	2,760.00	2,851.20	2,805.60	64.49	2
Oil & Gas Producers	-0.65	0.06	-0.19	0.40	10,864.65	28,191.22	20,520.45	8,832.20	2
Unclassified Cases	-0.79	399.00	6.30	47.39	12.10	40,320.00	889.26	4,802.35	59

3 Empirical Finding

3.1 Underpricing autocorrelation and capitalization impact

Since the trading price is immediately effective in the secondary market, the issuer will always suffer a loss from selling its shares at price lower than the market price with the discount rate equal to the underpricing level. Thus the underpricing level is also regarded as the measure for the cost of capital for the issuers. If the issuer hopes to sell their shares successfully, the underpricing level must be competitive. Examining the aggregated underpricing data series by unit root assumption (Phillips-Perron test), I find that the stochastic trend exists in the time series of data and this trend should be removed from the underpricing series. Instead of the variable UP_i, I used the difference in two nearest underpricing level $diff(UP)_i$ as the dependent variable. The same unit root test has been performed on this data set and no significant trend is found. Moreover, the initial selling CAP_i of the IPO *per se* will also influent the underpricing level when the liquidity in the market is limited. The time series equation I test is as follow.

$$diff_i = \sum_{j=1}^{J} k_j diff_{i-j} + k_0 \ln(CAP_i) + p_1 i_{hk} + c + \varepsilon_i \qquad (3)$$

The test results for various choices of *J* are shown in Panel A of Table 5.3. The results suggest that the influence of *J=7* periods backward is significant, and also that the CAP_i significantly influents the difference in the underpricing level. The dummy variables Y99, Y00, Y01, Y02, Y03, Y04, and Y05 are used to represent the market wide factors in different years. For example, if the IPO takes place in the year 1999, Y99 is 1. Otherwise, Y99 is 0. As shown in Table 5.3, none of the year dummy variable is significantly influential to the regression.

It's interesting that the initial selling positively influents the difference of underpricing level, but not the underpricing itself (the last is confirmed by performing corresponding test). Supposing that the capitalization is constant and equal to its average level, we could expect that $diff_i$ will be zero. So the average underpricing in period *i* will remain the same as the previous one. This result suggests that if the selling of IPO shares is continuous without huge jumps the underpricing will remain at the same level. The R square in this testing is 0.44 in this regression, suggesting the liquidity shock caused by the initial selling and the auto-regression part explain considerable part of the change of underpricing. Other factors, such as risk free rates (Hong Kong interest rate i_{hk} and Mainland China interest rate i_{cn}, are not significant in this regression.

Time should be another factor in measuring market liquidity. Define t_i as the time distance between IPO *i* and *i-1*. Another regression test is done on the following equation:

$$diff_i = \sum_{j=1}^{J} k_j diff_{i-j} e^{-t_{i-j}} + k_0 \ln(CAP_i) + c + \varepsilon_i \tag{4}$$

However, the regression is not significant, and cannot rule out the hypothesis that all k_j are statistically zero. This result suggests that the liquidity shock does not exist on time scale, but on the scale of sequential IPOs. This finding is interesting as well. If the large scale initial selling is regarded as the liquidity shock on the market, issues of liquidity should rather be considered on the scale of IPOs' sequences than on the natural calendar time scale. The additional argument could be that investors prefer IPOs shares over common ones which are available at any point of time.

Insignificant influence of interest rate and none existence of time factor in underpricing auto-regression together imply that the liquidity here is not the usual market liquidity, but rather the capital liquidity for IPO shares.

Traditionally industry cycles and industry specific risk have been used to explain the underpricing and clustering. A similar analysis has been performed within different industry sectors to verify the influence of liquidity shocks. The result of this testing is shown in Panel B of Table 5.3. Since the analysis is limited by the number of samples available in different industry sectors, only four industry sectors with significant number of firms are available for performing such regression: "Electronic, Electronic Equip.", "Software & Computer Services", "Personal Goods" and "Media".

No significant relationship is shown among $\ln(CAP_i)$ and $diff_i$ variables in any of these sectors as we found earlier. This again verifies the finding that the change in underpricing is not caused by the business cycles in different industries, change of risk factors, or investors' optimistic or pessimistic views about different industries, but due to the liquidity shocks. Basically, the IPO shares are chasing the capital by changing the underpricing level, regardless their industry sectors.

Based on the negative coefficients in the auto regression, I found that the underpricing level trends to be stable except when great liquidity shock comes. Since the calendar time is not involved in this regression, the result does not imply that the underpricing will be clustering in time. But the clustering will happen when the IPOs come more frequently with greater initial selling.

Table 3 Auto-regression of Underpricing Level

Panel A: Aggregate Level Data

Dependent Variable: UP

	1	2	3	4	5	6	7	8	9[a]
Const	-51.675 **	-51.760 **	-52.304 **	-53.179**	-51.800 *	-52.245 **	-53.10*	-54.652*	-51.62*
	(15.288)	(15.282)	(15.408)	(15.602)	(15.323)	(15.364)	(15.435	(15.810)	(15.2)
Δf_{t-1}	-0.852 **	-0.852 **	-0.852 **	-0.852 **	-0.852 *	-0.85 **	-0.852*	-0.853 *	-0.852*
	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.056)
Δf_{t-2}	-0.733 **	-0.733 **	-0.733 **	-0.733 **	-0.733 *	-0.73 **	-0.73*	-0.734 *	-0.733*
	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.073)	(0.072)
Δf_{t-3}	-0.613 **	-0.613 **	-0.614 **	-0.614 **	-0.613 *	-0.61 **	-0.61*	-0.615 *	-0.613*
	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)	(0.081)	(0.080)
Δf_{t-4}	-0.495 **	-0.495 **	-0.496 **	-0.496 **	-0.495 *	-0.50 **	-0.50*	-0.497 *	-0.495*
	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)	(0.084)	(0.083)
Δf_{t-5}	-0.381 **	-0.381 **	-0.381 **	-0.381 **	-0.381 *	-0.38 **	-0.38*	-0.382 *	-0.381*
	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)	(0.080)
Δf_{t-6}	-0.256 **	-0.256 **	-0.256 **	-0.256 **	-0.256 *	-0.26 **	-0.26*	-0.257 *	-0.256*
	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.073)	(0.072)
Δf_{t-7}	-0.135*	-0.135 *	-0.135 *	-0.135 *	-0.135 *	-0.14 *	-0.14*	-0.136 *	-0.135*
	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.057)	(0.056)
$Ln(CAP)_t$	2.761 **	2.779 **	2.786 **	2.820 **	2.765 *	2.800**	2.85*	2.981 *	2.760*
	(0.814)	(0.817)	(0.817)	(0.823)	(0.814)	(0.821)	(0.825)	(0.852)	(0.812)
Y99	1.096							0.087	
	(13.947)							(14.200)	
Y00		-0.870						-1.788	
		(3.070)						(3.698)	
Y01			1.301					0.078	
			(3.891)					(4.417)	
Y02				1.474				[b]	
				(3.040)					
Y03					0.588			-0.556	
					(4.075)			(4.601)	
Y04						-1.907		-3.009	
						(5.152)		(5.648)	
Y05							-3.417	-4.405	
							(5.283)	(5.781)	
R Square	0.435	0.435	0.435	0.435	0.435	0.435	0.435	0.436	0.435

Panel B: Auto-regression within industries

Industry	Electronic, Electrical Equip.		Software & Computer Services		Personal Goods		Media	
	Coef	StdError	Coef	StdError	Coef	StdError	Coef	StdError
Const	0.06	0.12	-38.15**	10.45	-0.06	0.32	-1.81	0.79
Δf_{t-1}	-1.11	0.57	-0.89**	0.17	-0.74**	0.22	-1.23	0.31
Δf_{t-2}	-0.48	0.72	-0.70**	0.22	-0.74**	0.28	-1.16	0.35

Δf_{t-3}	-0.11	0.57	-0.56	0.24	-0.72**	0.29	-0.27	0.66
Δf_{t-4}	-0.22	0.29	-0.40	0.23	-0.63*	0.30	-0.65	0.29
Δf_{t-5}	-0.22	0.21	-0.23	0.22	-0.64*	0.30	-0.47	0.24
Δf_{t-6}	-0.15	0.15	-0.28	0.20	-0.12	0.29	-0.74	0.27
Δf_{t-7}	-0.02	0.12	-0.07	0.15	-0.09	0.24	-0.55	0.29
$Ln(CAP)_t$	0.00	0.01	2.07**	0.57	0.00	0.02	0.10	0.04
R Square	0.75		0.44		0.49		0.97	

** Significant at 5% level

* Significant at 10% level

a The model 1,2,3,4,5, 6 and 7 uses dummy variable of year Y99, Y00, Y01, Y02, Y03, Y04 and Y05 respectively. Model 8 uses the whole group of dummy variables, while model 9 uses none.

b Variable Y02 is excluded because the dummy variable matrix is near singular matrix.

3.2 Clustering of Capitalization, Number of IPOs

Since the severe underpricing level is caused by liquidity shock, the initial selling waves (peaks) are crucial to understand the changes in underpricing.

Table 4 Auto-regression of Capitalization

	Coef		Std Error
$\Delta(cap)_{-1}$	-0.66	**	0.06
$\Delta(cap)_{-2}$	-0.57	**	0.08
$\Delta(cap)_{-3}$	-0.49	**	0.09
$\Delta(cap)_{-4}$	-0.29	**	0.06
$\Delta(cap)_{-5}$	-0.16	**	0.06
R Square			0.27

** Significant at 1% level

The clustering can be discovered in the frequencies of IPOs and the average initial selling in a longer period. With time window of one month, the number of IPOs (N_t) is used to represent the frequency and total initial selling $TCAP_t$ of each month and thus get the average initial selling of IPO shares $ACAP_t$. The number of IPOs in every month is illustrated in Figure 5.1, and the average initial selling in every month is presented in Figure 5.2.

It is interesting that the auto-regression results show that only previous 5 periods have significantly influence on the initial selling now, whereas the auto-regression result of underpricing shows that previous 7 periods matters. This difference in time series indicates that the underpricing have different cycles from initial selling.

Figure 1 N of IPOs

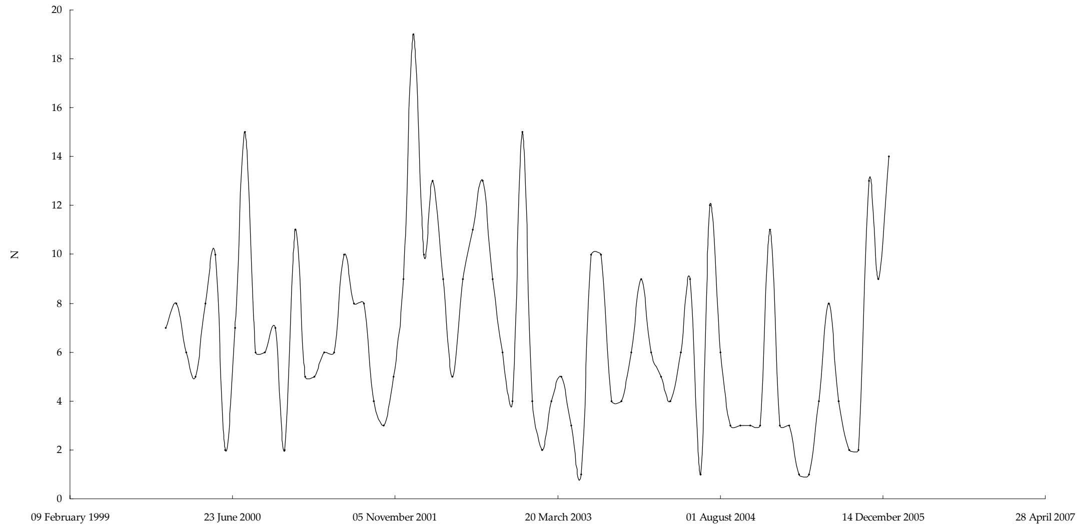
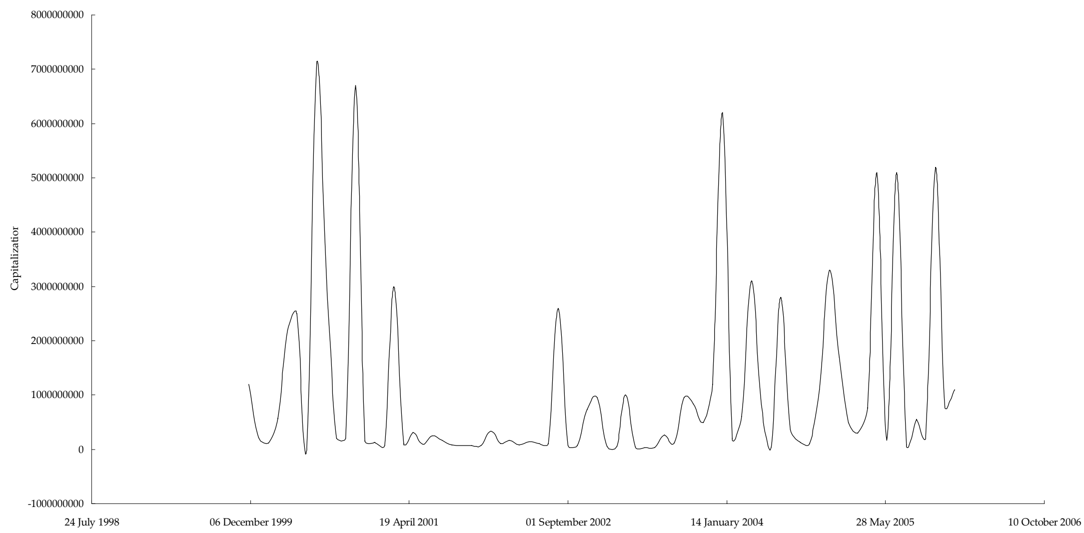


Figure 2 Average IPO Capitalization



A Spearman correlation test among frequencies, average underpricing and aggregated initial selling is crucial to find out the relation between clustering and underpricing. The result of the correlation test is shown in Table 5.5. This result shows that the clustering measured by the number of IPOs, N, is not correlated with the average underpricing level, AUP. The average initial selling of IPO shares of every month, $\ln ACAP_t$, is not correlated with average underpricing of that month, either.

This evidence is contrary to the predictions of many theoretical papers which claim the severe underpricing is either the result of a bubble, or the reason of a bubble.

In some cases, more severe underpricing is observed in the period of IPO clustering and seemingly they are related. Especially in 1999, during the "dot-com bubble", the average underpricing was 69%. However, the relationship between these two variables is not statistically significant in our sample. And thus it is reasonable to believe that a severe underpricing is not a necessary consequence of clustering.

Table 5 Correlation Test: Clustering and Underpricing

		N	ln(ACAP)	AUP
N	Spearman's rho	1.000	-0.991**	0.249
	Sig. (2-tailed)		0.000	0.306
	N	74	74	74
ln(ACAP)	Spearman's rho	-0.991**	1.000	-0.208
	Sig. (2-tailed)	0.000		0.075
	N	74	74	74
AUP	Spearman's rho	0.249	-0.208	1.000
	Sig. (2-tailed)	0.306	0.075	
	N	74	74	74

**Correlation is significant at the 0.01 level (2-tailed).

3.3 Remarks

Based on the regression result of underpricing, I simulate the time series process by injecting a shock of initial selling volume, which is much greater than normal initial selling volume. The result is shown in Figure 5.3. The following equations are used for this simulation:

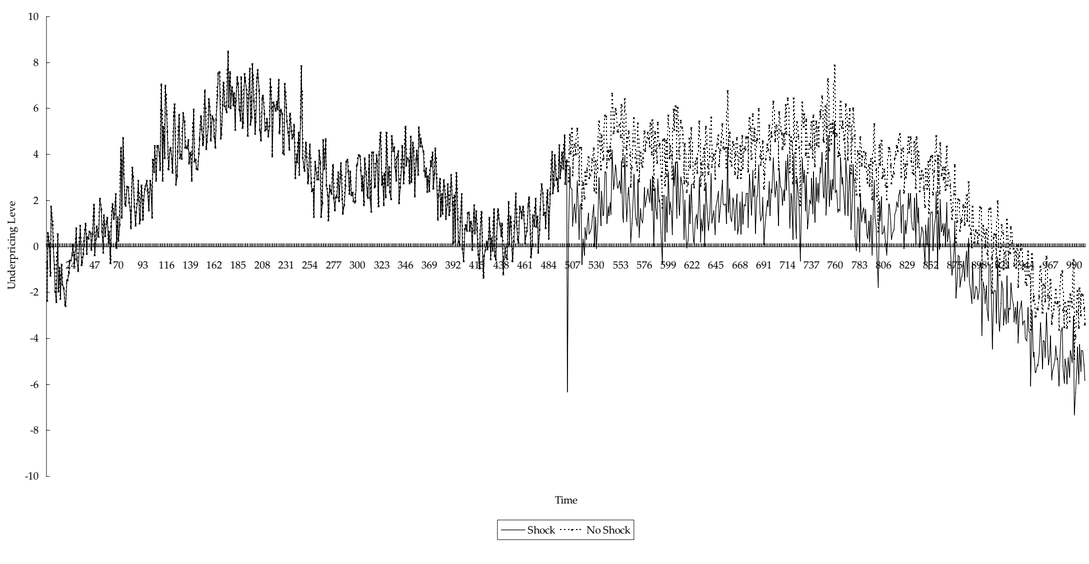
$$up_i = up_{i-1} + diff_i \tag{5}$$

$$diff_i = \sum_{j=1}^{7} k_j diff_{i-j} + \varepsilon_i \tag{6}$$

I used for k_j the numbers in Panel A (Table 5.3) and injected one liquidity shock of the size -10[3] at the step i=500. There are in total 1000 steps (periods) in the simulation, and we take $\varepsilon_i = N(0,1)$. To keep things simple, I initialize the first 7 period up_i by the first 7 realizations of ε_i and eliminate the constant in the first order difference equation (3) assuming that the majority of IPO initial sellings are at the average level.

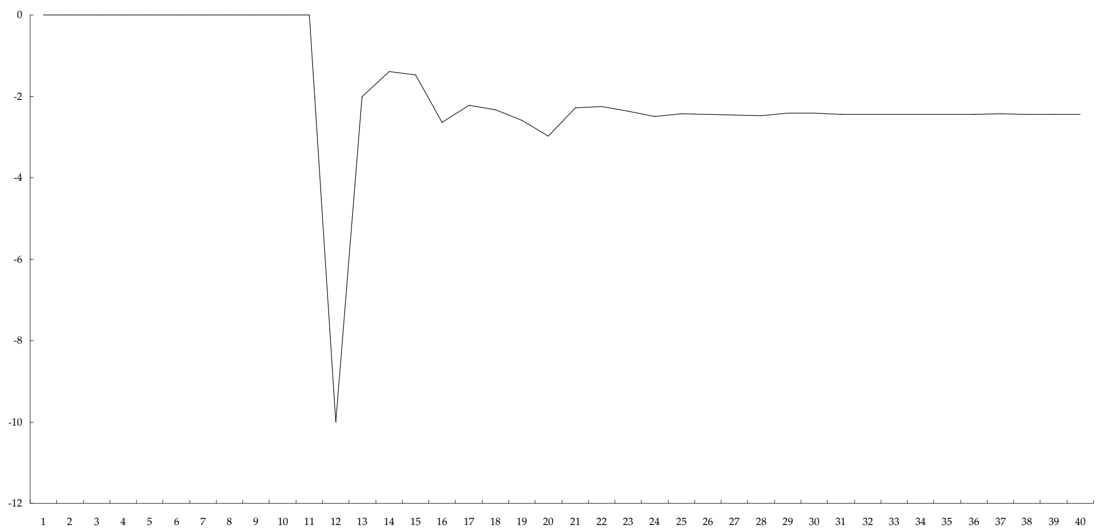
The dotted line in Figure 5.3 is the simulated underpricing level without shock, and the continuous line is with shock. The enlarged shock effect can be seen in Figure 5.4. The first impression is that the shock causes volatility of underpricing level to increase, and also moves the underpricing out of its equilibrium level.

Figure 3 Simulation of a Shock in IPO Market



[3] The particular size of the shock does not change essentially transition path represented in Figure 5.4.

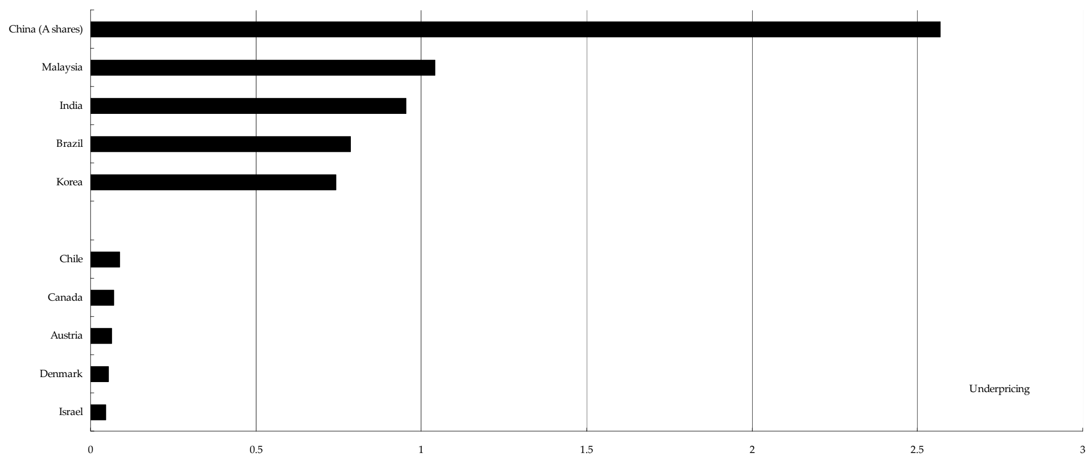
Figure 4 Shock Effect: Offsetting Underpricing Level



Noteworthy, the volatility effect of the shock in this simulation will be lasting for 21 periods after the shock until the volatility reduced to less than 1% of the shock, and the length of the period is solely decided by the k_j, neither change after the variance of ε_i, nor the size of the shock. The percentage of change as the consequence of the shock remains the same when I changed the variance of ε_i to 100, or the shock to 1 and 600. The underpricing level changed by the shock related with the size of the shock, but the ratio of the changed level over the size of the shock depends solely on k_j.

k_j and the constant in the regression should be varying and intrinsic in different market. Recorded by J. Ritter by collecting average initial returns (underpricing) in 39 countries and areas, Figure 5.5 shows the 5 countries with highest average initial return and 5 countries with lowest average initial return. Although the time period varies in the average initial return date in different countries, the difference between the two groups is clearly shown. The average underpricing level in the 5 lowest countries are 8.40%, while 121.84% in the 5 highest countries. And the countries with highest underpricing level are usually those with immature financial market and strict capital control, which implies limited capital liquidity and investors' limited ability to arbitrage because of capital control.

Figure 5 Average Underpricing Level across Countries



Data Source: Jay Ritter, IPO Data, http://bear.cba.ufl.edu/ritter/ipodata.htm,2007

4 Concluding Discussion

This paper investigates the IPO underpricing from the perspective of integrated primary and secondary market, and documents that the IPO underpricing is determined by the previous IPOs' underpricing level for the first time. It implies that there is a competition among IPO shares. Note that other outstanding stocks are excluded from this competition.

By analyzing the distinctive feature of IPO cases in Hong Kong from November in 1999 to the end of 2005, this paper documents the fact that apart from underpricing, there was significant clustering of IPOs over time. Moreover, the level of underpricing is closely related to the underpricing level of previous IPOs. This finding suggests that the underpricing is strategically arranged by underwriter's syndicate to favor the investors. This investigation also reveals that the initial selling volume of IPOs is strongly auto-correlated. Together with IPOs' clustering, evidences also suggest that the issuers tend to choose the specific time to go public, and an increase in initial selling volume leads to more severe underpricing. It could be interpreted as the compensation for the liquidity shock caused by supplying a huge amount of shares in the market.

This underpricing competition implies the specific characteristic of IPO shares per se, which could be interpreted as a specific risk premium. This characteristic might also help us to understand the reason for IPO underpricing within the framework of rational investor paradigm in the future research.

The predictability of IPO underpricing by previous IPO underpricing clearly should not be result of investors' sentiment, but rather a reflection of the risk, such as coordination problem in IPO and the compensation of the liquidity shock. The coordination risk comes from the asymmetric information, because IPO per se is a process of information creating, "information cascade" (Welch, 1992). The "information cascades" story claims that investors make their investment decisions sequentially. Successful initial sales encourage following investors to revise their own information about the share and to invest, and vice versa, unsuccessful initial sales discourage the investors. IPO underpricing competition prevents public from continuous pessimism. Further investigations are needed to discover the nature of the risk associated with IPO shares within the framework of efficient market hypothesis (EMH).

This liquidity shock and IPOs' competition can also explain the severe underpricing during the internet bubble period around 1999. Documented by Ljungqvist and Wilhelm (2003), the IPO underpricing is 69% in the year of 1999 averagely and 56% in 2000, whereas the underpricing in 1996 is only 17% averagely. The initial selling of the IPOs is averagely $65.3 million and $124.1 million in 1999 and 2000, significantly greater than the previous years. In 1996, 1997, 1998, the initial selling of IPO shares are $35.3 million, $32.6 million and $51.3 million. From the perspective of liquidity, this is exactly the result of the liquidity shock of IPO shares.

Interestingly, the influence of previous IPOs underpricing level on the following one is not subject to the time interval between IPOs. In the regression, the underpricing level is not significantly related to the previous one when the time is added as a factor.

The investigation among different industries reveals that the IPO underpricing auto-correlation is not statistically significant at the industry level. Clearly the changes in IPO underpricing levels are not related with industry specific factors (specific risks), but the market factors (market risk), such as market liquidity. The analysis on the initial selling reveals that in the short run, initial selling volume is influenced by the previous IPO initial selling volumes. This fact indicates that despite the specific industry cycle, issue choose the time to go public mainly relying on information related to a few previous IPOs.

The evidences presented in this paper suggest that the IPO underpricing is predictable and the liquidity shocks caused by IPO shares at least partially explain the level of underpricing. Further promising investigation should focus on the specific risk factors associated with IPO shares.

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