IPO Waves in China and Hong Kong*

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Abstract

We analyze the anatomy of IPO waves in China and Hong Kong and draw comparisons with the US IPO cycles. The lead-lag relationship between IPO initial returns and IPO volume observed in the US is absent in these two Asian markets. Similar to the US, IPO volume in Hong Kong is sensitive to changes in market conditions and exhibits seasonal variations. In sharp contrast, however, Chinese IPO activity is much less responsive to past market returns and volatility. Surprisingly, hot markets still emerge in China, not because of market forces as in the US and Hong Kong, but due to regulatory choices.

JEL classification: E32; G30; G32

Keywords: IPO cycles; initial returns; China; Hong Kong

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1 Introduction

The center of gravity of initial public offering (IPO) activity has substantially shifted toward Asia in the past two decades owing to a dramatic growth of Asian IPO markets. Exchanges in China and Hong Kong have been instrumental in fuelling IPO markets in this region. In 1990, the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE) were just being launched, whereas the Hong Kong Stock Exchange (HKSE) was a small market with only a couple of hundred firms listed. In a matter of twenty years, these three exchanges grew to become major hives of IPO activity. In 2010, in terms of capital raised via IPOs, the HKSE, the Small and Medium Enterprise (SME) Board of the SZSE, and the SSE were globally ranked the first, third, and fourth respectively; and, in the same year, the SME Board and ChiNext Board of the SZSE were the top two IPO markets in the world in terms of the number of IPOs (Ernst & Young, 2011).

Notwithstanding the increasing significance of IPO activity in Asian markets, the literature on IPO waves in Asia is much limited compared to the research that focuses on IPO activity in the US and Europe. A deeper understanding of IPO activity in major Asian markets is not only valuable in its own right but also relevant for the entrepreneurial finance literature. This is because a country's IPO market imposes externalities on its small businesses and its venture capital industry. According to Black and Gilson (1998), a healthy IPO market is key to the vitality of venture capital. Furthermore, successful IPOs help venture capitalists raise capital for new funds (Gompers, 1996) who can then invest in new small businesses. Therefore, studying IPO cycles in China and Hong Kong has broader implications for the strands of literature that focus on entrepreneurship, venture capital industry, and IPO regulations in these markets (see e.g., Cressy and Farag, 2014, Gannon and Zhou, 2008, and Jiang et al., 2014).

This paper fills a gap in the literature by studying the anatomy of IPO waves in China and Hong Kong, the two leading IPO markets in Asia.[1] Given institutional and cultural

[1]We note that there is a separate and well-developed body of literature that studies IPO underpricing and long-run performance in China (see e.g., Chan et al., 2004, Guo and Brooks, 2008, Tian, 2011, Lin and Tian, 2012, Fan et al., 2007, and Su and Brookfield, 2013) and Hong Kong (see e.g., Cheng et al., 2006, Dawson, 1987,

differences between Asian and Western markets, it is far from obvious whether or not IPO wave patterns observed in Western markets will be present in China and Hong Kong as well. Furthermore, if IPO waves in China and Hong Kong share some similar characteristics with IPO waves in the US, this suggests that certain features of IPO cycles are robust to significant variation in institutional and cultural differences. Finally, due to strong historical ties between Hong Kong and the West (UK in particular), there are hypothesized differences between IPO waves in Hong Kong and China despite the geographical and cultural proximities of these two markets.

Our main findings can be summarized as follows. Lowry and Schwert (2002) find that an increase in the current level of IPO initial returns leads to an increase in future IPO volume (number of firms going public). We hypothesize that such a lead-lag relationship cannot be observed in China due to a distinct regulatory regime. Indeed, we find no evidence of the lead-lag relationship in China (even after controlling for IPO market shutdowns). Surprisingly, such a relationship is absent in Hong Kong as well. This suggests that the lead-lag relationship between IPO initial returns and IPO volume is not robust to institutional differences in IPO markets. Theory predicts that IPO volume is sensitive to changes in market conditions (Pástor and Veronesi, 2005, Benninga et al., 2005, Yung et al., 2008), investor sentiment (Ljungqvist et al., 2006), or both (Bustamante, 2012). However, in China, regulators exert substantial control on IPO timing, which leads us to believe that IPO volume will not be as responsive to changes in market conditions or sentiment as in the US or Hong Kong. Consistent with this belief, there is no significant relationship between IPO volume and past market returns, volatility, and valuations in China. The Hong Kong IPO market behaves very much like the US IPO market, such that the IPO volume is related to past and future market returns (not as strongly as in the US though), past changes in market volatility, and exhibits strong seasonality (more so than the US). We also observe that while there was a significant drop in US IPO volume following the Global Financial Crisis, IPO activity in China and Hong Kong remained strong in 2009. Finally, we find that hot IPO markets emerge both in China

Leung and Menyah, 2006, McGuinness, 1992, and Yu and Zheng, 2012). However, this strand of literature does not examine cyclicality of IPO activity in these two markets.

and in Hong Kong. However, Chinese hot markets are mostly artifacts of regulatory decision making, whereas those in Hong Kong tend to emerge following significant market run ups. In China, firms that go public during hot markets raise substantially more proceeds than the remaining IPO firms, which is consistent with the US evidence (Alti, 2006). Interestingly, hot market IPOs in Hong Kong do not raise significantly more proceeds than other IPOs once growth opportunities and industry effects are controlled for. This suggests that hot markets in Hong Kong are more likely to be driven by improvements in growth opportunities and a need for capital to invest in those opportunities, rather than market timing attempts (see e.g., Helwege and Liang, 2004, Lowry, 2003, and Pagano et al., 1998).

A few other studies explore hot IPOs or hot IPO markets in China or Hong Kong. Cheung et al. (2009) and Agarwal et al. (2008) study IPO underpricing in China and Hong Kong respectively. Both studies investigate whether or not IPO underpricing is related to how hot the IPO is, which is proxied by the subscription rate for IPO shares. Agarwal et al. (2008) report a strong relationship between initial returns and the level of oversubscription in Hong Kong. Cheung et al. (2009), who control for pre-IPO market returns, find that the relationship is strong in China during a particular period but is less strong outside that period. In comparison to these two studies that focus on IPO underpricing at the firm level, we investigate time-variation in average IPO underpricing at the market level. Clearly, the correlation between subscription rates and initial returns suggests that the changes in the average subscription rate over time are expected to exhibit a pattern that is similar to the time pattern in initial returns documented in this study. Guo et al. (2010) use a Markov regime switching model to search for hot and cold cycles in China. Our sample period only partially overlaps with theirs, but, there is agreement within that overlapping period, such that both studies identify a single hot market. It lasts from April to June 2004 in our study and from April to August 2004 in theirs. Furthermore, Guo et al. (2010, p. 209) note that a hot market between April 2000 and February 2001 "is triggered by encouraging regulations", which is consistent with our finding that hot markets are often triggered by regulatory actions in China. A key difference between this study and Guo et al. (2010) is that we not only detect hot markets but also formally investigate the dynamic relationships between IPO volume, underpricing, and market conditions.

The present paper contributes to the literature in a number of ways. To our knowledge, it is the first to offer a systematic study of IPO waves in China and Hong Kong and to draw comparisons with the US IPO cycles. Apart from shedding light on the characteristics of IPO waves in two leading Asian markets, the paper shows that some of the stylized facts about US IPO waves can be eradicated due to variations in the institutional framework. For example, the lead-lag relationship between IPO initial returns and IPO volume does not survive when we move from Western IPO markets to Asian ones. The paper also draws attention to the fact that IPO volume on a global scale is more stable when changes in IPO volume are less correlated between the US and Asian markets such as China and Hong Kong. Finally, the paper highlights the impact of regulation on the nature of IPO activity and demonstrates how IPO cycles are transformed when the regulatory regime changes. In particular, the weak relationship between IPO volume and market conditions and the ongoing risk of IPO market shutdowns jointly imply that a timely exit via an IPO continues to be a problem in China, which extends the results in prior literature that deals with China's venture capital industry (Bruton and Ahlstrom, 2003, White et al., 2005).

The remainder of the paper proceeds as follows. We discuss the theory on IPO cycles and develop testable hypotheses in Section 2. Empirical results are presented in Section 3. Section 4 concludes.

2 Theoretical background and hypotheses development

The cyclical nature of IPO activity is a well-established empirical regularity that is documented by Ibbotson and Jaffe (1975), Ritter (1984), Lowry and Schwert (2002), Lowry (2003), and others. It is theoretically well founded as well. Pástor and Veronesi (2005) present a theory for the formation of IPO waves. In their model, IPO waves emerge when market conditions improve and many private firms exercise their real option to go public around the same time. Yung et al. (2008) develop a model in which time-varying adverse selection leads to cycles in

IPO initial returns. According to the IPO timing model of Benninga et al. (2005), going public entails diversification benefits for entrepreneurs, but this comes at the expense of private benefits of control that are lost after the IPO. Going public becomes optimal when cash flows improve sufficiently, and IPOs cluster in time, since improvements in market conditions are likely to boost cash flows of many private firms simultaneously. Furthermore, IPO waves are more likely to be industry specific, since the correlation between the cash flows of two different firms are likely to be higher when those two firms are in the same industry. Industry-specific IPO waves are also predicted by Benveniste et al. (2002). On the other hand, Ljungqvist et al. (2006) contend that hot IPO markets (periods with unusually high number of firms going public) can also emerge as a result of investor overoptimism. Their model predicts positive initial returns during hot markets. According to the IPO timing model of Bustamante (2012), hot markets can emerge when expected profitability or investor optimism is high. Finally, Lowry and Schwert (2002) show that the current level of IPO initial returns have predictive power on the future level of IPO volume, but not vice versa. Such a relationship is likely to be observed when positive information about IPO firms is only partially incorporated into offer prices (Loughran and Ritter, 2002, Hanley, 1993) or when there are information spillovers (Alti, 2005).

There is a common feature that underlies these theoretical models: IPO volume responds to changes in market conditions, investor sentiment, or both. These predictions are empirically supported in Western markets such as the US and UK. We anticipate that they will be supported in Hong Kong as well, since the institutional setup of the Hong Kong IPO market is heavily influenced by the UK IPO market. The methods of selling and allocating shares are similar, such that Hong Kong IPOs often feature a placement tranche for institutional investors and a fixed-price subscription tranche for retail investors. Overall, the level of IPO activity is mainly driven by market forces; and, thus, we expect IPO waves and hot markets in Hong Kong to resemble those in Western markets. However, we cannot expect the same in China due to a highly distinct IPO process.

The key distinguishing feature of the Chinese IPO market from Hong Kong and the US is the level of regulatory interference. This stylized fact has been highlighted in the prior literature (see e.g., Chan et al., 2004, Tian, 2011, and Lin and Tian, 2012, Liu et al., 2013). Especially in 1990s, the China Securities Regulatory Commission (CSRC) exerted full control on the IPO activity. For example, IPO volume was regulated under a quota system, such that the CSRC decided the total number of new shares to be issued annually, which was then allocated to regions in China. Furthermore, offer prices were set according to strict formulas based on earnings multiples and were typically too low as the price-to-earnings multiplier was artificially capped. Pricing caps on IPO shares, coupled with retail investor enthusiasm for IPO shares led to astronomical levels of initial returns in 1990s. Starting from around the year 2000, the regulator gradually and partially loosened its control. The quota system was abolished and underwriters were allowed to recommend firms that desire an IPO to the CSRC. Bookbuilding mechanism was introduced to facilitate price discovery and to allow for more flexibility in setting offer prices.

Nonetheless, the CSRC still plays a major role in shaping both the level and nature of IPO activity in China. A firm cannot go public without approval from the CSRC, even if it satisfies the listing requirements. The review process undertaken by the CSRC is long and can be subject to political biases.[2] A clear manifestation of the CSRC's continuing strong hold on the IPO activity is market closures. Within the sample period of this paper, the Chinese IPO market was shut down by the CSRC on several occasions. For example, following a period of poor stock market performance, the CSRC intervened and closed the IPO market in September 2008 for approximately 10 months. More recently the IPO market was closed during the last quarter of 2012 and an IPO hiatus ensued throughout 2013. The CSRC's close involvement with the Chinese IPO market leads us to the following two hypotheses.

Hypothesis 1: There is no lead-lag relationship between IPO initial returns and

[2] When the CSRC published for the first time the list of firms waiting for an IPO approval, the list exceeded 500 firms ("China publishes full list of IPO applicants for 1st time", Reuters News, February 2, 2012). There are suggestions that the waiting period is substantially longer for private firms compared to state-controlled ones ("Beijing Plans to Loosen Control Over IPO System", Wall Street Journal Online, November 17, 2013); and some studies suggest that foreign VC-backed issuers are at a disadvantage compared to issuers backed by domestic VCs that are politically better connected (Bruton and Ahlstrom, 2003, Humphery-Jenner and Suchard, 2013, and White et al., 2005)

IPO volume in China.

Hypothesis 2: IPO volume is less sensitive to changes in market conditions in China than in the US and in Hong Kong.

The motivation behind Hypothesis 1 is as follows. Lowry and Schwert (2002) argue that releases of positive information about IPO firms (i) result in an increase in the current level of initial returns, and (ii) cause more private firms to file for an IPO, which leads to an increase in the number of future IPOs. In China, this is unlikely to happen, due to the uncertainty over the length of the IPO process. Once a firm decides to go public, the time it takes until the firm finally conducts its IPO is highly uncertain. The firm joins a long queue of firms waiting to go public. The review process is long and the firm may not obtain the CSRC's approval at the end (see Footnote 2). Furthermore, even if the firm's application is approved, there is some risk that the IPO could be delayed further if the CSRC decides to suspend IPO activity.

The uncertainties over approval and timing motivate Hypothesis 2 as well. Theory predicts a higher IPO volume following improvements in market conditions (see e.g., Pástor and Veronesi, 2005). However, in China, an improvement in market conditions would result in (i) a longer queue of firms waiting for an approval to go public, and (ii) only a fraction of firms obtaining the approval. Both of these factors are likely to severe the link between IPO volume and market conditions in China.

Hot markets commonly emerge in the US (see e.g., Ritter, 1984 and Helwege and Liang, 2004). Given that IPO activity in Hong Kong is driven by market movements, we expect to observe hot markets there as well. However, it is not obvious whether or not hot markets are likely to emerge in China. On one hand, the CSRC ensures that IPOs come to the market at regular intervals, which effectively smooths out IPO volume. On the other hand, it suspends IPO activity time to time, which can lead to a burst of IPOs when the market reopens. Furthermore, the launches of the SME Board and ChiNext fall within our sample period. These events are likely to cause an unusual hike in IPO volume, which can be significant enough to result in the formation of hot markets. Therefore, our final hypotheses are stated as follows.

> Hypothesis 3a: Hot IPO markets do not emerge in China as the IPO volume is smoothed out by regulatory actions.

> Hypothesis 3b: Hot IPO markets emerge in China due to IPO market closures and to launches of new segments.

In the following section, we describe the data and test the hypotheses developed in this section.

3 Tests

3.1 Data

We form a list of newly-listed firms in China and Hong Kong from official factbooks annually published by the SSE, SZSE, and HKSE. The list includes all new listings between 1999 and 2013. From this list, we drop cross listings, introductions, and transfers, ending up with 2,706 IPOs, which constitute the final sample. The list also excludes investment companies (unit trusts, closed-end funds, REITs) and is based on operating firms. Factbooks provide the name, ticker, listing date, offer price, number of shares issued, and amount of proceeds raised for each IPO firm. Furthermore, factbooks published by the SSE and SZSE provide the issuing date and closing price on the first day of trading as well. For Hong Kong IPOs, we obtain the first-day closing price from Datastream and the prospectus date from Perfect Information.

We also collect data on IPO activity in the US to draw comparisons with China and Hong Kong. In particular, we obtain the monthly time series of (net) IPO volume and IPO initial returns in the US from Jay Ritter's website.[3] Both time series are based on a sample of IPOs that exclude investment companies. Therefore, IPOs in the US sample are comparable to those in the Chinese and Hong Kong samples.

[3] http://bear.warrington.ufl.edu/ritter/ipoisr.htm

Table 1 provides a breakdown of our sample by year and by market. The SZSE consists of three segments: (i) Main Board, (ii) the SME Board (launched in 2004), and (iii) ChiNext (launched in 2009). The HKSE contains two segments: (i) Main Board, and (ii) Growth Enterprise Market (GEM) (launched in 1999). Both ChiNext and GEM aim to attract smaller businesses that are typically in a high-technology industry. There is substantial time variation in IPO volume in all markets. The level of IPO initial returns in Hong Kong is not too different than in the US. On the other hand, Chinese IPOs yield much higher initial returns, which is a stylized fact that is well documented in the literature (see e.g., Chan et al., 2004). However, panel B of Table 1 reveals a clear time pattern in China. Initial returns are much lower in recent years (starting from 2009) compared to the earlier years of the sample period. It suggests that as market forces start to play a bigger role in the determination of IPO prices, initial returns are converging to levels observed in the more mature IPO markets such as the US.

[Please insert Table 1 about here]

3.2 Relationship between IPO volume and IPO initial returns

Previous academic studies document a lead-lag relationship between IPO initial returns and IPO volume in the US (Lowry and Schwert, 2002) and UK (Banerjee et al., 2013). Such a relationship is expected if positive information about IPOs is partially incorporated into offer prices (Loughran and Ritter, 2002, Hanley, 1993). The partial adjustment causes an increase in the *current* level of IPO initial returns, whereas the positive information causes more private firms to decide to go public and leads to an increase in the *future* level of IPO volume, hence the lead-lag relationship between initial returns and volume.

The lead-lag relationship is unlikely to emerge in the Chinese IPO market. Once a Chinese private firm decides to go public, it joins a long queue of firms waiting to conduct an IPO. Given the uncertainties over the length of the review process and the approval decision, it is unlikely that high initial returns will be followed by high volume. In contrast, we have no reason why the lead-lag relationship would not emerge in Hong Kong.

In order to investigate the existence of a lead-lag relationship between initial returns and volume in China and Hong Kong, we conduct Granger causality tests similar to those in Lowry and Schwert (2002). For the Chinese data, monthly IPO volume observations are set to missing rather than zero during IPO market shutdowns. This is to ensure that the results of tests for the existence (or lack thereof) of the lead-lag relationship are not driven by suspensions of IPO activity. The findings are reported in Table 2. We begin by regressing monthly IPO volume on its lagged values (Model (1)). In all three markets, we observe persistence in IPO volume such that at least two of the three lags have positive coefficients that are significant at the 10% level or lower, which is in line with Ibbotson and Jaffe (1975). Next, we regress monthly IPO volume on lagged values of monthly average IPO initial return (Model (2)). As pointed out by Ibbotson and Jaffe (1975), an OLS specification leads to error terms with substantial serial correlation. Therefore, we run a Cochrane-Orcutt model that explicitly corrects for autocorrelation in residuals.[4] In Hong Kong and the US, all three lags of IPO initial return have positive coefficients and in both markets one of these coefficients is statistically significant at the 5% level or lower. In contrast, in China, only one of the coefficients is positive and furthermore the positive coefficient is not statistically significant at a conventional level. Model (3) combines the covariates in Models (1) and (2). We are particularly interested in the incremental explanatory power of lags of initial returns on volume after controlling for lags of volume. In the US, the positive coefficient of R_{-1} remains statistically significant at the 10% level and a Granger F-test rejects the null hypothesis that lags of initial returns jointly have no power to predict volume. In China and Hong Kong, we fail to reject the null at the 10% level of significance. Therefore, the evidence suggests that periods of high initial returns lead to periods of high volume in the US, but not in China and Hong Kong. In Model (4), we reach the same conclusion after controlling for any potential seasonality in volume.[5] In Models (5)-(8), the dependent variable is initial returns. In Model

[4]For example, in the case of China, the OLS specification results in a Durbin-Watson d-statistic of 0.73, which is substantially lower than the no-autocorrelation value of 2. Running the Cochrane-Orcutt model leads to a large improvement, such that the transformed d-statistic takes a value of 2.37, which is much closer to the value of 2.

[5]Helwege and Liang (2004) note that US IPO volume is seasonally low during January and September. Yung et al. (2008) find that the US IPO market is a lot more active in the fourth quarter compared to the first

(5), we regress monthly average IPO initial return on its lagged values. In all markets the coefficients of lags are positive and some coefficients are statistically significant at the 1% level, which is again consistent with Ibbotson and Jaffe (1975). In Model (6), a Cochrane-Orcutt model is run (for the same reason as in Model (2)) by regressing initial returns on lags of volume. The coefficients tend to have negative signs and none of them are significant at the 5% level. Model (7) combines the covariates in Models (5) and (6). We test for the joint predictive power of lags of volume on initial returns. In none of the markets, the null hypothesis of no power is rejected at a conventional level. This conclusion stays the same after controlling for any potential seasonality in initial returns (Model (8)).

[Please insert Table 2 about here]

Overall, our findings indicate that past levels of IPO volume are not helpful in forecasting future levels of average IPO initial return. However, in the US, past levels of average IPO initial returns are useful in forecasting future levels of IPO volume. This is the lead-lag relationship between initial returns and volume first documented by Lowry and Schwert (2002). In contrast, we find no evidence of such a relationship in China and Hong Kong. In Hong Kong, there is a positive relationship between current volume and past initial returns (Model (2)), but the relationship loses its significance once past volume is controlled for (Models (3) and (4)). Similarly, in China, no significant relationship between current volume and past initial returns remains once past volume is controlled for. The absence of the lead-lag relationship in China is consistent with Hypothesis 1, but its absence in Hong Kong is surprising. This suggests that the lead-lag relationship is not an inherent feature of IPO markets, but is sensitive to the institutional framework and market environment.

3.3 Relationship between IPO volume and market conditions

There is ample evidence in the literature that IPO volume fluctuates substantially over time. Rational explanations of swings in IPO volume include time variation in market conditions (Pástor and Veronesi, 2005) and in adverse selection (Yung et al., 2008). On the other hand,

quarter. Similarly, Banerjee et al. (2013) find that UK IPO volume is lower in the first and third quarters.

some studies suggest that IPO volume rises (and hot markets emerge) when private firms time the market to issue cheap equity (see e.g., Pagano et al., 1998, Helwege and Liang, 2004, and Alti, 2006).

While the link between IPO volume and market conditions is well documented for Western markets such as the US (see e.g., Pástor and Veronesi, 2005), UK (Banerjee et al., 2013), Italy (Pagano et al., 1998), and France (Derrien, 2005), Asian markets have so far received less attention. Therefore, we investigate whether or not IPO volume is sensitive to changes in market conditions in two major Asian IPO markets. We expect a strong link in Hong Kong, since its institutional setup is similar to the UK IPO market and since IPO activity is mainly driven by market factors. In contrast, given that regulatory actions play an important part in determining IPO volume in China, we anticipate that the link will be weaker there.

Pástor and Veronesi (2005) model the optimal time for a private firm to exercise its option to go public and argue that, given a cohort of private firms waiting to go public, many private firms will exercise their option around the same time, which results in the creation of an IPO wave. In particular, their model predicts that IPO volume will be (i) positively related to prior market returns, (ii) negatively related to subsequent market returns, and (iii) negatively related to current and past changes in market volatility. On the other hand, if changes in IPO volume are driven by market timing attempts, we expect to see more firms going public following higher valuations in the market as argued by Pagano et al. (1998) and others. Pástor and Veronesi (2005) provide evidence that while there is a positive relationship between IPO volume and the lagged level of market valuations, which can proxy for either growth opportunities or sentiment, the relationship disappears when lagged market returns are controlled for. This is consistent with their model in the sense that IPO volume is more sensitive to changes in market conditions, rather than levels.

In order to test whether IPO volume is sensitive to market conditions, we make use of market indices constructed by Datastream (TOTMKCA for China, TOTMKHK for Hong Kong, and TOTMKUS for the US). Datastream offers a total return index (symbol: RI) for each market. We define RM as the monthly market return and calculate it as the difference between the levels of the total return index at the end of the current month and the previous month divided by the level at the end of the previous month. σ is defined as the standard deviation of daily market returns in a month. $\Delta\sigma$ is the change in the level of σ between the current month and the previous one. P/B is the price-to-book value of the market index in a particular month.

We examine the relationship between IPO volume and market conditions in a regression framework. In particular, we run a series of negative binomial regressions that account for the fact that IPO volume is count data. Moreover, like in Section 3.2, we control for IPO moratoriums in China, such that months during which the Chinese IPO market was closed are excluded from the analysis. Table 3 reports our findings. In Model (1), IPO volume is regressed on past market returns. In the US, all three lags have positive coefficients and two of them are statistically significant at the 5% level or lower. In contrast, none of the lags is statistically significant at a conventional level in China. In fact, a Wald χ^2 test fails to reject the null hypothesis that regression coefficients are simultaneously equal to zero at a meaningful level of significance. Hong Kong is in between China and the US, such that two of the coefficients are statistically significant at 10% level, but with opposite signs. We add control variables in Model (2) and contemporaneous and lead values of RM in Model (3). In the US, the coefficients of past market returns remain significant in Models (2) and (3). Furthermore, RM_{+2} has a negative coefficient that is significant at the 5% level, which is consistent with Pástor and Veronesi (2005). In Hong Kong, there is a similar but weaker pattern. The coefficient of RM_{-2} is positive and significant at the 1% level and the coefficient of RM_{+2} is negative and significant at the 5% level. In China, none of the leads or lags of RM are significant at the 5% level. In Model (4), as previously documented by Pástor and Veronesi (2005), we observe a negative relationship between changes in the level of volatility and subsequent IPO volume in the US. We find that the same relationship is also present in Hong Kong, but not in China. In Hong Kong, the coefficients of the contemporaneous and lagged values of $\Delta\sigma$ are all negative and two of the coefficients are significant at the 10% level or lower. In China, some of the corresponding coefficients actually have a positive sign and all but one are not statistically significant at a conventional level. Finally, we test whether IPO volume is related to the lagged level of the price-to-book value of the market index (Models (5) and (6)). In the US, the lagged value of P/B has strong explanatory power on IPO volume in the absence of competition from other covariates (Model (5)), but the relationship vanishes once we add leads and lags of market returns and other controls (Model (6)). In Hong Kong, there is no relationship even in the absence of other covariates (Model (5)). In China, there is a negative relationship (Model (5)) that disappears in the full model (Model (6)).

[Please insert Table 3 about here]

The negative binomial models in Table 3 are appropriate models only if the count data on IPO volume is overdispersed (i.e., the variance is greater than the mean). In the absence of overdispersion, a Poisson model, which assumes that the variance is equal to the mean is more appropriate. We conduct a standard likelihood-ratio test to investigate overdispersion. In particular, the overdispersion parameter α must be equal to zero in the absence of overdispersion. The tests firmly reject the null that $\alpha = 0$ at the 1% significance level in all models and in all three markets (see the last two rows in each panel of Table 3). Therefore, we conclude that IPO volume is overdispersed, and it is appropriate to prefer negative binomial models over Poisson ones.

In summary, the way IPO volume responds to changes in market conditions is similar in Hong Kong and the US. As predicted by Hypothesis 2, we find no significant relationship between IPO volume and changes in market conditions in China. Moreover, in both the US and Hong Kong, there is strong evidence of seasonality, such that IPO volume is significantly lower in the first and third quarters. In China, there is no evidence of lower IPO volume in the third quarter and only weak evidence of a drop in IPO volume in the first quarter. This is consistent with the idea that the CSRC smooths out IPO volume during a year and provides additional support for Hypothesis 2. Finally, it is interesting to compare IPO volume in 2009 across the markets. The dummy variable $Y2009$ takes the value of one (zero) if the monthly observation is (not) in the year 2009. Following the Global Financial Crisis that reached a peak in 2008, there is a significant contraction in US IPO volume in 2009. In contrast, there is no significant change in IPO volume in Hong Kong during the same year. Most strikingly, IPO volume is significantly higher in China in 2009, owing to the launch of ChiNext in that year. Clearly, the strong performance of two major Asian IPO markets in 2009 mitigated the drop in global IPO activity in that year. This is helpful for the resilience of IPO activity on a global scale to the extent that shocks to Western and Asian IPO markets continue to have a low correlation in the future.

3.4 Hot IPO markets in China and Hong Kong

Swings in time series of IPO volume and IPO initial returns create peaks of IPO activity, which are known as hot IPO markets, or simply as hot markets. During a hot market, the number of firms that go public exceeds normal levels. According to a stream of literature, there are temporary windows of opportunity during which firms can raise equity cheaply (see e.g., Baker and Wurgler, 2002). Many private firms conduct their IPOs during such periods when investors are overoptimistic; IPO volume soars; and hot markets emerge as a result (Loughran et al., 1994 Helwege and Liang, 2004, Alti, 2006, Ljungqvist et al., 2006). Explanations of hot markets other than investor sentiment include industry clustering due to bundling by investment banks (Benveniste et al., 2002), procyclical adverse selection (Yung et al., 2008), many private firms exercising their real option to go public around the same time (Pástor and Veronesi, 2005), and cycles in aggregate demand for equity capital (Lowry, 2003).

The method used to detect hot markets differs across studies, but the general approach is as follows. First, the sample period is split into regular intervals such as months (Helwege and Liang, 2004, Pástor and Veronesi, 2005, Alti, 2006), quarters (Yung et al., 2008, Banerjee et al., 2013), or years (Bustamante, 2012). Then, the intervals are sorted on the basis of number of IPOs. Finally, those intervals that are above a prespecified cutoff point (top 25% of the distribution in Helwege and Liang, 2004 and Pástor and Veronesi, 2005, top 30% in Bustamante, 2012, and top 50% in Alti, 2006) or that (substantially) exceed either the historical average (Yung et al., 2008) or a moving average (Banerjee et al., 2013) are classified as hot. Some papers deflate IPO volume to alleviate concerns about nonstationarity raised by Lowry (2003), but Helwege and Liang (2004) show that the deflated time series is practically the same with the original time series and the tests conducted by Ivanov and Lewis (2008) provide no evidence of nonstationarity. Furthermore, some papers smooth the time series of IPO volume (over three months in Helwege and Liang, 2004, Pástor and Veronesi, 2005, Alti, 2006 and four quarters in Yung et al., 2008) to address seasonality.

All of these methods with the exception of those employed by Yung et al. (2008) and Banerjee et al. (2013) identify hot markets ex post and, therefore, are subject to a "look-ahead bias". Yung et al. (2008) address this issue by comparing IPO volume in each quarter with IPO volume in past quarters only. While their method is powerful in terms of spotting quarters that are "globally" hot compared to all past quarters, it lacks power to detect quarters that are "locally" hot compared to more recent quarters. Banerjee et al. (2013) resolve this issue by comparing IPO volume in each quarter with the IPO activity in the past five years. In particular, they focus on the moving average of IPO volume in the past 20 quarters.

In this paper, we adopt an approach similar to those used by Yung et al. (2008) and Banerjee et al. (2013). We divide our sample period into quarters and compare IPO activity in each quarter with the activity in previous quarters. More specifically, we classify a quarter as hot if the quarter's IPO volume is greater than or equal to the maximum IPO volume of the same quarters of the previous five years. This approach avoids a look-ahead bias and is powerful to detect locally hot periods. Furthermore, it addresses the issue of seasonality, since the first quarter of a year is compared only with the first quarters of previous years, the second quarter only with the second quarters of previous years, and so on.

Our sample covers a 15-year period between 1999 and 2013, but we can only start identifying hot quarters in 2004, since the method needs past five years' data as an input. Furthermore, we take into account the IPO market closures in China, such that past five years' data is based on quarters during which the IPO market was open. Figure 1 illustrates hot quarters (black bars) in China, Hong Kong, and the US between 2004 and 2013. We observe that following the burst of the Dot-com Bubble, there has been a sharp drop in US IPO volume.[6]

[6]See Gao et al. (2013) for a study of the post-2000 IPO market in the US.

Only three quarters in the US are identified as hot between 2004 and 2012, followed by a long hot market in 2013 that emerged after a strong stock market performance in 2012. Overall 6/40=15% of the quarters are hot in the US between 2004 and 2013. Hong Kong is similar to the US, such that 7/40=17.5% of the quarters are hot over the same period. Hot quarters are mainly clustered between the second half of 2010 and the end of 2011. The average monthly market return over the one-year period that precedes this cluster of hot markets is 4.4% compared to an average of 0.7% during the remaining months of the sample period. The last quarter of 2013 is also hot in Hong Kong, which coincides with a period of IPO moratorium in China. In China, 8/40=20% of the quarters are classified as hot. The first hot quarter is the second quarter of 2004, which is the quarter when the SME Board of the SZSE was launched. The Chinese IPO market is also hot in the last quarter of 2009 and throughout 2010, which is mainly driven by the launch of ChiNext Board of the SZSE in late 2009.

[Please insert Figure 1 about here]

Overall, the findings suggest that hot markets emerge in China and Hong Kong at least as often as they do in the US. In both Hong Kong and the US, hot markets follow strong market performance, which is consistent with the theory. However, in China, hot markets tend to coincide with the launches of new market segments, which suggests that they are mostly artifacts of regulatory decision making as suggested by Hypothesis 3b.

3.5 The impact of a hot market on the amount of proceeds raised

There is evidence in the literature that firms raise more equity during hot markets. In particular, Alti (2006) finds that, after controlling for pre-IPO firm characteristics and the value of growth opportunities at the time of going public, hot market IPOs raise substantially higher proceeds than cold market IPOs. We examine whether the US findings extend to China and Hong Kong as well.

The data on firm financials is obtained from Datastream. The set of variables we choose is similar to the sets used by Helwege and Liang (2004) and Alti (2006) and includes variables identified as important drivers of a firm's financing choices in the prior literature (see e.g., Rajan and Zingales, 1995). These variables are defined as follows. $Assets$ and $Sales$ are total assets and net sales respectively. They are measured in millions of yuan (2013 purchasing power) in China and millions of Hong Kong dollars (2013 purchasing power) in Hong Kong. $Profit$ is the profit margin, which is net income divided by net sales. Tan is asset tangibility, which is net plant, property, and equipment divided by total assets. $Debt$ is long-term debt divided by total assets. $MtoB$ is the market-to-book ratio, which is the market value of common equity divided by the book value of common equity. All financials are based on the fiscal year that is prior to the IPO year, except $MtoB$, which is based on the same fiscal year as the IPO year. We follow Baker and Wurgler (2002) and Alti (2006), such that $MtoB$ is set to missing when it exceeds the value of 10. Pro is total proceeds divided by total assets. Finally, our main variable of interest is Hot. It takes the value of one if a firm's IPO took place in a hot quarter and is equal to zero otherwise.

Table 4 provides descriptive statistics for pre-IPO firm characteristics. The distribution of $Assets$ among firms that were listed on main boards of SSE, SZSE, and HKSE is highly skewed. This is mainly driven by IPOs conducted by giant banks such as the Agricultural Bank of China, the Industrial and Commercial Bank of China, and the Bank of China, which are among the largest IPOs in history. ChiNext and GEM attract smaller firms with lower asset tangibility, less long-term debt, and higher market-to-book ratios. The average value of Pro is particularly high for IPOs on the SME Board and ChiNext. Its level is more reasonable for IPOs that take place on the main boards and is more in line with the US evidence provided by Alti (2006).

[Please insert Table 4 about here]

In China, the median value of Pro is 1.33 for IPOs that take place in hot markets and 0.90 for the remaining IPOs. In Hong Kong, the corresponding figures are 0.66 and 0.50 respectively. In both markets, a Wilcoxon-Mann-Whitney test rejects the null hypothesis that the distribution of Pro is the same across hot quarters and the remaining quarters. However, higher values of Pro observed during hot markets can be due to differences in pre-IPO firm characteristics in general, and in growth opportunities (proxied by $MtoB$) in particular. To address this issue, we regress Pro on Hot and control for $MtoB$ and relevant firm characteristics. The results are reported in Table 5. In Models (1) and (2), we regress Pro on Hot and on $MtoB$, respectively. In both China and Hong Kong, the coefficients are positive as expected and are significant at the 5% level or lower. In Model (3), we again regress Pro on Hot, but also control for pre-IPO firm characteristics. In China, the coefficient of Hot remains significant at the 1% level, but in Hong Kong it is no longer significant at the 5% level. Once $MtoB$ is added (Model (4)), the coefficient of Hot loses its significance in Hong Kong, but still remains significant at the 1% level in China. This suggests that the higher level of Pro observed during hot markets in Hong Kong is mainly driven by better growth opportunities firms have during those periods. On the other hand, in China, IPO firms issue more equity in hot markets after controlling for growth opportunities as well as pre-IPO characteristics. In Model (5), we control for the market segment in which the IPO took place. This leads to interesting insights. In China, Pro is higher for firms listed on ChiNext. Furthermore, the interaction variables suggest that IPO firms listed on ChiNext and the SME Board raise more proceeds during hot markets, whereas those listed on Main Boards of the SSE and the SZSE do not. This is consistent with our earlier finding that the two of the hot markets in China coincide with the launches of the SME Board in 2004 and of ChiNext in 2009. A potential explanation is that the overoptimism of investors during those periods helped firms sell equity at higher prices.[7] In Hong Kong, firms that go public on GEM are associated with lower proceeds raised according to Model (5). However, this association is not robust and disappears once industry fixed effects are added in Model (6). In China, the interaction terms remain significant even after controlling for industry.

[Please insert Table 5 about here]

In general, the findings in Table 5 show that Chinese and the US hot markets share the common characteristic that hot market IPOs raise substantially higher proceeds even after

[7] There was press coverage of substantially high amounts of proceeds raised by firms that went public on ChiNext following the launch of this market segment in late 2009. For example, according to a news story ("Shenzhen Tightens ChiNext IPO Rules — Start-Ups' Excess Debut Proceeds for Limited Use", Wall Street Journal, January 7, 2010, p. C2), most of the early IPO firms on ChiNext raised more than double the amount of proceeds they initially planned for.

controlling for other determinants of equity issuance. Surprisingly, Hong Kong is distinct in this sense, such that there is no significant difference between the amounts of proceeds raised by hot market IPOs and the remaining IPOs once growth opportunities and industry factors are accounted for.

4 Conclusion

IPO markets in China and Hong Kong have been growing at a rapid pace in the past 15 years. As a result of their impressive growth over this period, these two major Asian markets have earned their place among the most active IPO markets in the world in terms of the aggregate amount of capital raised and the number of deals completed.

The literature has so far focused largely on underpricing and long-run performance of IPOs in China and Hong Kong. This paper fills a gap in the literature by analyzing IPO waves in these two markets. In particular, we make use of theoretical studies on IPO waves to hypothesize in which ways the IPO cycles in China and Hong Kong are expected to be the same as (or different from) those in the US. We then test our hypotheses using a large sample of IPOs that took place in China and Hong Kong between 1999 and 2013.

Our findings suggest that the nature of IPO activity in Hong Kong has similarities with the US. In particular, Hong Kong's IPO volume is sensitive to changes in market conditions and exhibits strong seasonality. In China, on the other hand, there is no significant relationship between IPO volume and market returns or changes in volatility. This is not surprising given the fact that Chinese regulators continue to have a strong influence on IPO activity in China. The CSRC not only decides which firms go public and when but also exercises power to shut down the IPO market when it deems necessary.

Prior literature reports a lead-lag relationship between IPO initial returns and IPO volume both in the US and UK. In particular, an increase in the average level of IPO initial returns leads to an increase in the future number of IPOs. We find no evidence of such a relationship in China and Hong Kong, which suggests that the relationship is not robust to changes in the institutional framework.

We find that hot markets emerge in both China and Hong Kong. Those in Hong Kong follow strong equity market performance. In contrast, hot markets in China tend to be driven by regulatory choices. In particular, two of the Chinese hot markets coincide with the launch of a new market segment. Furthermore, the fact that the CSRC can suspend IPO activity up to a year or more suggests that a burst of IPOs can lead to a hot market when the IPO market reopens.

There is evidence in the US that IPO firms raise substantially higher amounts of proceeds during hot markets, even after controlling for pre-IPO firm characteristics and growth opportunities. We find that this evidence extends to China. In particular, firms that go public on ChiNext and the SME Board raise significantly more proceeds during hot markets. This is not the case in Hong Kong, such that growth opportunities and industry factors account for the higher amounts of proceeds raised by firms during hot markets. Therefore, while the findings in the US and China are consistent with the market timing hypothesis, results from Hong Kong support the rational explanation that firms raise more proceeds during hot markets as they need more capital to invest in better growth opportunities.

We also observe that IPO markets in Hong Kong and China were less affected by the Global Finance Crisis compared to the US IPO market. In fact, after controlling for various factors, Chinese IPO volume in 2009 was higher compared to other years as ChiNext Board of the SZSE was launched in late 2009. To the extent that changes in IPO volume maintain a low correlation across Western markets such as the US and Asian ones such as China and Hong Kong, IPO volume can be expected to be more robust on a global scale.

Overall, our findings contribute to our understanding of IPO cycles, highlight the characteristics of IPO waves observed in the US that are also present in China and Hong Kong, and demonstrate how IPO activity varies across different regulatory regimes.

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Table 1: Breakdown of IPO volume and IPO initial returns by year and by market

The statistics are based on a sample of 1,665 firms that went public in China, 1,041 firms in Hong Kong, and 2,207 firms in the US and whose shares started trading between 1999 and 2013. Panel A reports the number of IPOs for each year between 1999 and 2013. Panel B reports the mean of the monthly average initial return of IPOs. For IPOs in the US, initial return is $P_1/P_0 - 1$ where P_0 is the offer price and P_1 is the closing price on the first day of trading. For IPOs in China and Hong Kong, initial return is $P_1/P_0 - M_1/M_0$ where M_0 is the level of a market index on the day the offer price is set and M_1 is the level of the same index on the first day of trading. For IPOs in China, depending on the stock, the following indices are used: Shanghai A- or B-Share Index, Shenzhen A- or B-Share Index. For IPOs in Hong Kong, the Hang Seng Index is used.

	China								
		Shenzhen				Hong Kong			
year	Shanghai	M.B.	SME	ChiNext	Total	M.B.	GEM	Total	US
Panel A: IPO volume									
1999	44	50	-	-	94	27	7	34	476
2000	87	51	-	-	138	38	46	84	381
2001	68	0	-	-	68	30	57	87	80
2002	66	1	-	-	67	45	57	102	66
2003	65	0	-	-	65	37	26	63	63
2004	61	1	38	-	100	44	21	65	174
2005	2	0	12	-	14	54	10	64	161
2006	8	0	52	-	60	52	6	58	157
2007	14	0	100	-	114	77	2	79	159
2008	3	0	71	-	74	26	2	28	21
2009	8	0	54	36	98	58	5	63	41
2010	25	0	203	117	345	78	7	85	96
2011	37	0	114	128	279	64	13	77	81
2012	22	0	53	74	149	44	12	56	94
2013	0	0	0	0	0	73	23	96	157
1999-2013	510	103	697	355	1,665	747	294	1,041	2,207

Table 1 - cont'd

	China								
		Shenzhen				Hong Kong			
year	Shanghai	M.B.	SME	ChiNext	Total	M.B.	GEM	Total	US
Panel B: IPO initial returns									
1999	1.01	1.02	-	-	1.02	0.02	0.37	0.05	0.76
2000	1.42	1.45	-	-	1.47	0.10	0.58	0.36	0.49
2001	1.53	-	-	-	1.53	0.03	0.29	0.20	0.13
2002	1.36	0.37	-	-	1.34	0.07	0.11	0.10	0.09
2003	0.75	-	-	-	0.75	0.11	0.18	0.16	0.15
2004	0.72	0.75	0.62	-	0.75	0.08	0.06	0.07	0.13
2005	0.75	-	0.46	-	0.52	0.08	0.09	0.06	0.10
2006	0.35	-	1.06	-	0.92	0.23	0.25	0.23	0.11
2007	1.15	-	1.99	-	1.95	0.19	0.30	0.19	0.17
2008	0.48	-	1.41	-	1.32	0.20	0.22	0.19	0.05
2009	0.37	-	0.65	0.75	0.69	0.06	0.84	0.15	0.13
2010	0.28	-	0.44	0.35	0.40	0.09	0.47	0.11	0.08
2011	0.15	-	0.23	0.26	0.24	0.04	0.18	0.06	0.15
2012	0.24	-	0.17	0.22	0.20	0.03	0.09	0.04	0.17
2013	-	-	-	-	-	0.05	0.97	0.32	0.21
1999-2013	0.82	1.17	0.81	0.30	0.97	0.09	0.32	0.15	0.20

Table 2: Relationship between IPO volume and IPO initial returns

Tests are based on monthly time series of IPO volume and average IPO initial return in China, Hong Kong, and the US between 1999 and 2013. All models are OLS models, except (2) and (6), which are Cochrane-Orcutt models that adjust for serial correlation in error terms. The dependent variable is monthly IPO volume in Models (1)-(4) and monthly average IPO initial return in Models (5)-(8). V_{-i} and R_{-i} are the ith lags of monthly IPO volume and monthly average IPO initial return respectively. $Q1$ ($Q3$) is a dummy variable with a value of one if the month is in the first (third) quarter. d-statistic of a Durbin-Watson test is reported for each model. In Models (3) and (4) ((7) and (8)), p-values of Granger F-tests for the joint significance of R_{-1}, R_{-2}, and R_{-3} (V_{-1}, V_{-2}, and V_{-3}) are reported. Robust standard errors are reported in parentheses. ***, **, and * stand for significance at 1, 5, and 10% levels respectively.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: China				
V_{-1}	0.41***		0.41***	0.41***		−0.01	−0.01	−0.01
	(0.11)		(0.11)	(0.12)		(0.01)	(0.01)	(0.01)
V_{-2}	0.20*		0.21*	0.22*		−0.01*	0.00	0.00
	(0.11)		(0.12)	(0.13)		(0.01)	(0.01)	(0.01)
V_{-3}	0.24**		0.23**	0.23**		−0.01*	−0.00	−0.00
	(0.09)		(0.09)	(0.09)		(0.01)	(0.01)	(0.01)
R_{-1}		0.53	1.26	1.13	0.34***		0.31***	0.31***
		(1.14)	(1.14)	(1.14)	(0.09)		(0.09)	(0.09)
R_{-2}		−2.05**	−1.53	−1.49	0.44***		0.44***	0.44***
		(1.03)	(0.99)	(1.02)	(0.12)		(0.12)	(0.13)
R_{-3}		−0.29	−0.23	−0.07	0.05		0.01	0.01
		(1.03)	(1.13)	(1.15)	(0.10)		(0.10)	(0.10)
$Q1$				−2.11				−0.04
				(1.48)				(0.10)
$Q3$				−0.89				−0.02
				(1.23)				(0.10)
Constant	1.94**	14.83***	2.52	3.03*	0.15**	1.44***	0.35**	0.36**
	(0.74)	(3.48)	(1.57)	(1.69)	(0.07)	(0.22)	(0.15)	(0.15)
Observations	122	115	117	117	125	121	122	122
Adj. R-squared	0.58	0.01	0.58	0.58	0.56	0.05	0.59	0.58
d-statistic	2.04	2.37	2.04	2.06	1.87	2.53	1.85	1.85
Granger F-tests	–	–	0.38	0.46	–	–	0.16	0.18

Table 2 - cont'd

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel B: Hong Kong				
V_{-1}	0.17**		0.11	0.10		−0.00	−0.00	−0.00
	(0.08)		(0.08)	(0.07)		(0.00)	(0.00)	(0.00)
V_{-2}	−0.09		−0.14*	−0.07		0.00	−0.00	−0.00
	(0.08)		(0.08)	(0.08)		(0.00)	(0.00)	(0.00)
V_{-3}	0.22***		0.19**	0.29***		−0.00	−0.00	−0.00
	(0.07)		(0.08)	(0.07)		(0.00)	(0.00)	(0.00)
R_{-1}		2.67	2.87	2.01	0.12		0.12	0.13
		(1.98)	(2.01)	(2.10)	(0.11)		(0.10)	(0.10)
R_{-2}		3.96**	3.60*	2.67	0.22		0.23*	0.24*
		(2.00)	(2.07)	(2.30)	(0.13)		(0.14)	(0.14)
R_{-3}		0.64	0.04	−0.77	0.00		0.01	0.03
		(1.71)	(1.70)	(1.65)	(0.11)		(0.11)	(0.11)
$Q1$				−3.95***				0.07
				(0.80)				(0.05)
$Q3$				−3.38***				0.01
				(0.94)				(0.05)
Constant	4.14***	4.88***	4.18***	5.50***	0.10***	0.15***	0.14***	0.13***
	(0.74)	(0.61)	(0.89)	(0.90)	(0.02)	(0.04)	(0.04)	(0.04)
Observations	177	151	157	157	152	164	152	152
Adj. R-squared	0.05	0.03	0.07	0.19	0.05	−0.02	0.04	0.04
d-statistic	1.94	1.99	1.88	1.99	1.98	2.12	1.99	2.00
Granger F-tests	–	–	0.12	0.49	–	–	0.54	0.31

Table 2 - cont'd

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel C: United States				
V_{-1}	0.60***		0.47***	0.45***		−0.07	0.08	0.05
	(0.13)		(0.15)	(0.15)		(0.17)	(0.19)	(0.19)
V_{-2}	0.05		−0.04	−0.06		−0.03	0.07	0.05
	(0.10)		(0.09)	(0.09)		(0.24)	(0.22)	(0.21)
V_{-3}	0.19*		0.11	0.14		−0.03	0.26	0.26
	(0.12)		(0.09)	(0.09)		(0.13)	(0.20)	(0.20)
R_{-1}		0.21***	0.16*	0.17**	0.58***		0.52***	0.53***
		(0.08)	(0.08)	(0.08)	(0.10)		(0.10)	(0.10)
R_{-2}		0.12	−0.00	−0.00	0.13		0.06	0.08
		(0.08)	(0.09)	(0.09)	(0.15)		(0.15)	(0.14)
R_{-3}		0.11	0.06	0.05	0.13		0.08	0.09
		(0.07)	(0.07)	(0.07)	(0.09)		(0.09)	(0.10)
$Q1$				−3.54**				1.16
				(1.55)				(2.05)
$Q3$				−1.92				3.79
				(1.57)				(2.63)
Constant	1.84**	5.29**	1.76	3.25**	2.39	17.95**	−0.01	−1.13
	(0.84)	(2.15)	(1.16)	(1.55)	(1.58)	(7.53)	(1.84)	(1.81)
Observations	177	142	149	149	143	154	143	143
Adj. R-squared	0.61	0.26	0.63	0.64	0.69	−0.02	0.70	0.70
d-statistic	2.05	1.91	2.00	1.99	1.91	2.37	2.03	2.00
Granger F-tests	–	–	0.00	0.00	–	–	0.17	0.22

Table 3: Relationship between IPO volume and market conditions

Tests are based on monthly time series of IPO volume in China, Hong Kong, or the US between 1999 and 2013. All models are negative binomial regressions. The dependent variable is monthly IPO volume. RM is the monthly market return and RM_{-i} (RM_{+i}) is the ith lag (lead) of RM. σ is the standard deviation of daily market returns in a month. $\Delta\sigma$ is the change in the level of σ between the current month and the previous one and $\Delta\sigma_{-i}$ is the ith lag of $\Delta\sigma$. P/B_{-1} is the price-to-book value of the market index in the previous month. $Q1$ ($Q3$) is a dummy variable with a value of one if the month is in the first (third) quarter. $Y2009$ is a dummy variable that is equal to one if the month is in year 2009. α is the overdispersion paramater, and the likelihood ratio test compares the negative binomial model to a Poisson model. Robust standard errors are reported in parentheses. ***, **, and * stand for significance at 1, 5, and 10% levels respectively.

Model	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: China			
RM_{-1}	−0.23	0.69*	0.73*			0.79*
	(0.57)	(0.39)	(0.41)			(0.41)
RM_{-2}	0.12	0.45	0.51			0.57
	(0.69)	(0.50)	(0.46)			(0.48)
RM_{-3}	0.66	0.94*	0.90*			0.97*
	(0.65)	(0.52)	(0.53)			(0.53)
RM			0.09			0.04
			(0.50)			(0.50)
RM_1			0.03			−0.02
			(0.59)			(0.57)
RM_2			−0.58			−0.67
			(0.52)			(0.55)
RM_3			−0.26			−0.30
			(0.66)			(0.67)
$\Delta\sigma$				−10.44		
				(8.14)		
$\Delta\sigma_{-1}$				−2.96		
				(7.28)		
$\Delta\sigma_{-2}$				18.64*		
				(9.55)		
$\Delta\sigma_{-3}$				12.05		
				(8.89)		
P/B_{-1}					−0.11**	−0.03
					(0.05)	(0.05)
V_{-1}		0.03***	0.03***	0.03***		0.03***
		(0.01)	(0.01)	(0.01)		(0.01)
V_{-2}		0.01**	0.01*	0.02**		0.01*
		(0.01)	(0.01)	(0.01)		(0.01)
V_{-3}		0.02***	0.02***	0.02***		0.02***
		(0.01)	(0.01)	(0.01)		(0.01)
$Q1$		−0.23*	−0.23*	−0.26**		−0.23*
		(0.12)	(0.12)	(0.12)		(0.12)
$Q3$		0.03	0.03	−0.03		0.02
		(0.08)	(0.09)	(0.09)		(0.09)
$Y2009$		0.54***	0.55***	0.48*		0.55***
		(0.19)	(0.20)	(0.25)		(0.20)
Constant	2.47***	1.63***	1.63***	1.68***	2.81***	1.74***
	(0.07)	(0.10)	(0.10)	(0.09)	(0.16)	(0.19)
Observations	140	122	122	122	140	122
Wald p-value	0.751	< 0.001	< 0.001	< 0.001	0.015	< 0.001
Log pseudolikelihood	−477.032	−367.282	−366.477	−367.496	−475.526	−366.267
Likelihood-ratio test of $\alpha = 0$:						
χ^2 value	482.23	51.75	50.17	58.28	463.35	48.89
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

Table 3 - cont'd

Model	(1)	(2)	(3)	(4)	(5)	(6)
			Panel B: Hong Kong			
RM_{-1}	0.22	1.08	0.93			0.77
	(0.93)	(0.93)	(0.96)			(0.95)
RM_{-2}	2.38^{***}	2.43^{***}	2.54^{***}			2.45^{***}
	(0.87)	(0.86)	(0.86)			(0.87)
RM_{-3}	-1.81^{*}	-1.19	-1.29			-1.44
	(1.04)	(0.97)	(0.94)			(0.96)
RM			0.13			0.29
			(0.92)			(0.95)
RM_1			0.85			1.04
			(0.91)			(0.89)
RM_2			-2.21^{**}			-1.98^{*}
			(1.00)			(1.04)
RM_3			0.69			0.92
			(0.91)			(0.97)
$\Delta\sigma$				-12.55		
				(11.24)		
$\Delta\sigma_{-1}$				-26.32^{**}		
				(10.92)		
$\Delta\sigma_{-2}$				-26.30^{*}		
				(13.88)		
$\Delta\sigma_{-3}$				-11.95		
				(12.13)		
P/B_{-1}					0.15	0.18
					(0.17)	(0.19)
V_{-1}		0.03^{**}	0.02^{*}	0.02		0.02
		(0.01)	(0.01)	(0.01)		(0.01)
V_{-2}		-0.01	-0.01	-0.01		-0.01
		(0.01)	(0.01)	(0.01)		(0.01)
V_{-3}		0.06^{***}	0.06^{***}	0.06^{***}		0.06^{***}
		(0.01)	(0.01)	(0.01)		(0.01)
$Q1$		-0.69^{***}	-0.66^{***}	-0.76^{***}		-0.66^{***}
		(0.13)	(0.13)	(0.16)		(0.13)
$Q3$		-0.59^{***}	-0.59^{***}	-0.64^{***}		-0.59^{***}
		(0.16)	(0.16)	(0.16)		(0.16)
$Y2009$		-0.13	-0.12	-0.15		-0.11
		(0.28)	(0.27)	(0.32)		(0.27)
Constant	1.73^{***}	1.57^{***}	1.60^{***}	1.64^{***}	1.50^{***}	1.29^{***}
	(0.06)	(0.13)	(0.14)	(0.13)	(0.31)	(0.36)
Observations	180	177	174	177	180	174
Wald p-value	0.028	< 0.001	< 0.001	< 0.001	0.373	< 0.001
Log pseudolikelihood	-494.512	-466.679	-452.089	-468.617	-498.472	-451.626
Likelihood-ratio test of $\alpha = 0$:						
χ^2 value	230.51	135.42	119.09	141.03	250.53	118.82
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

Table 3 - cont'd

Model	(1)	(2)	(3)	(4)	(5)	(6)
			Panel C: United States			
RM_{-1}	4.74^{***}	4.90^{***}	5.41^{***}			5.43^{***}
	(1.83)	(1.23)	(1.26)			(1.23)
RM_{-2}	5.01^{**}	4.42^{***}	4.59^{***}			4.81^{***}
	(1.96)	(1.18)	(1.09)			(1.13)
RM_{-3}	3.34	2.02^{*}	2.15^{**}			2.46^{**}
	(2.18)	(1.08)	(1.05)			(1.07)
RM			4.15^{***}			4.38^{***}
			(1.24)			(1.21)
RM_{+1}			1.43			1.64
			(1.21)			(1.19)
RM_{+2}			-2.40^{**}			-2.03
			(1.23)			(1.30)
RM_{+3}			-1.59			-1.12
			(1.14)			(1.17)
$\Delta\sigma$				-32.64^{**}		
				(13.64)		
$\Delta\sigma_{-1}$				-34.98^{**}		
				(14.66)		
$\Delta\sigma_{-2}$				-55.07^{***}		
				(12.82)		
$\Delta\sigma_{-3}$				-32.44^{**}		
				(12.98)		
P/B_{-1}					0.59^{***}	0.12
					(0.05)	(0.09)
V_{-1}		0.03^{***}	0.02^{***}	0.03^{***}		0.02^{***}
		(0.01)	(0.01)	(0.01)		(0.01)
V_{-2}		0.00	0.01^{*}	0.01		0.01
		(0.01)	(0.01)	(0.01)		(0.01)
V_{-3}		0.02^{***}	0.02^{***}	0.02^{***}		0.02^{***}
		(0.01)	(0.00)	(0.01)		(0.01)
$Q1$		-0.37^{***}	-0.39^{***}	-0.43^{***}		-0.39^{***}
		(0.12)	(0.11)	(0.13)		(0.11)
$Q3$		-0.28^{**}	-0.22^{*}	-0.46^{***}		-0.20^{*}
		(0.11)	(0.12)	(0.11)		(0.12)
$Y2009$		-0.85^{***}	-0.89^{***}	-0.92^{***}		-0.88^{***}
		(0.25)	(0.26)	(0.33)		(0.26)
Constant	2.39^{***}	1.76^{***}	1.71^{***}	1.85^{***}	0.68^{***}	1.46^{***}
	(0.09)	(0.09)	(0.09)	(0.09)	(0.16)	(0.21)
Observations	180	177	174	177	180	174
Wald p-value	0.005	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Log pseudolikelihood	-629.590	-546.516	-526.592	-548.827	-600.038	-525.898
Likelihood-ratio test of $\alpha = 0$:						
χ^2 value	1,206.87	331.63	238.45	288.70	549.87	222.38
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

Table 4: Descriptive statistics for pre-IPO firm characteristics

The statistics are based on a sample of 1,231 firms in China and 664 firms in Hong Kong that went public between 2004 and 2013. *Assets* and *Sales* are total assets and net sales respectively. They are measured in millions of yuan (2013 purchasing power) in China and millions of Hong Kong dollars (2013 purchasing power) in Hong Kong. $Profit$ is net income divided by net sales. Tan is net plant, property, and equipment divided by total assets. $Debt$ is long-term debt divided by total assets. $MtoB$ is the market value of common equity divided by the book value of common equity. It is set to missing when it exceeds the value of 10. Pro is total proceeds divided by total assets. All financials are based on the fiscal year that is prior to the IPO year, except $MtoB$, which is based on the same fiscal year as the IPO year.

	Assets	*Sales*	$Profit$	Tan	$Debt$	$MtoB$	Pro
Panel A: China							
Main Boards of the SSE and the SZSE							
mean	141,900.10	15,685.59	0.12	0.33	0.08	2.63	0.60
p25	945.03	739.35	0.06	0.15	0.00	1.83	0.32
median	2,170.11	2,122.26	0.10	0.29	0.03	2.33	0.52
p75	6,824.82	6,047.15	0.15	0.51	0.13	3.11	0.80
count	172	172	172	171	172	164	172
SME Board of the SZSE							
mean	1,058.65	1,197.50	0.14	0.30	0.05	3.85	1.11
p25	399.27	356.35	0.08	0.17	0.00	2.54	0.59
median	611.46	631.71	0.12	0.29	0.00	3.49	0.93
p75	1,051.09	1,136.66	0.17	0.40	0.08	4.82	1.44
count	655	655	655	650	655	605	655
ChiNext Board of the SZSE							
mean	401.40	353.86	0.21	0.22	0.03	3.77	2.16
p25	223.53	183.31	0.14	0.10	0.00	2.53	1.29
median	315.85	271.29	0.19	0.20	0.00	3.51	1.86
p75	471.73	421.33	0.27	0.32	0.03	4.56	2.69
count	354	354	353	354	354	306	354
Panel B: Hong Kong							
Main Board of the HKSE							
mean	77,807.17	16,433.15	0.12	0.28	0.08	2.21	0.93
p25	536.81	563.26	0.08	0.09	0.00	1.30	0.25
median	1,334.13	1,139.84	0.14	0.23	0.02	1.99	0.55
p75	5,389.57	3,243.00	0.22	0.42	0.13	2.75	1.05
count	563	564	552	563	559	434	563
GEM Board of the HKSE							
mean	235.94	272.25	0.12	0.17	0.04	2.82	1.21
p25	65.10	65.54	0.07	0.03	0.00	1.68	0.38
median	146.15	149.78	0.14	0.13	0.00	2.33	0.62
p75	247.70	260.44	0.25	0.24	0.01	3.62	1.20
count	95	95	95	95	95	70	95

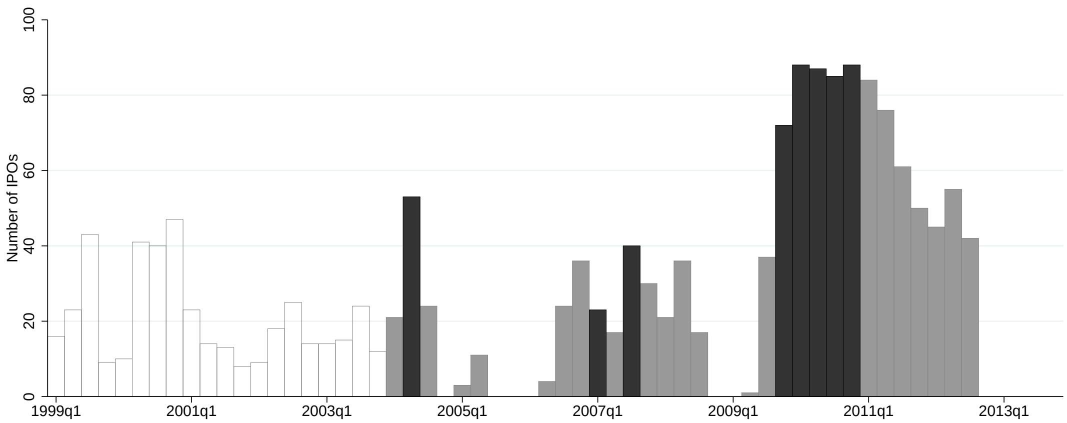
Table 5: The impact of a hot market on the amount of proceeds raised

Tests are based on a sample of 1,231 firms in China and 664 firms in Hong Kong that went public between 2004 and 2013. All models are OLS regressions. The dependent variable is Pro, which is total proceeds divided by total assets. Hot is a binary variable that takes the value of one if a firm's IPO took place during a hot quarter. $Sales$ is net sales measured in millions of yuan (2013 purchasing power) in China and millions of Hong Kong dollars (2013 purchasing power) in Hong Kong. $Profit$ is net income divided by net sales. Tan is net plant, property, and equipment divided by total assets. $Debt$ is long-term debt divided by total assets. $MtoB$ is the market value of common equity divided by the book value of common equity. It is set to missing when it exceeds the value of 10. All financials are based on the fiscal year that is prior to the IPO year, except $MtoB$, which is based on the same fiscal year as the IPO year. $dSME$, $dChiNext$, and $dGEM$ are dummy indicators for firms listed on the SME, ChiNext, and GEM Boards respectively. Model (6) includes industry fixed effects based on 3-digit SIC codes. Robust standard errors are reported in parentheses. ***, **, and * stand for significance at 1, 5, and 10% levels respectively.

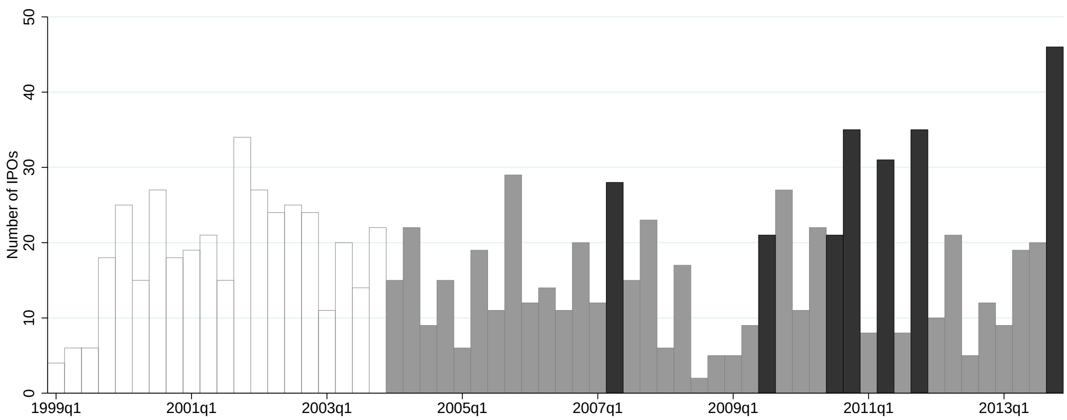
Model	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: China			
Hot	0.57***		0.55***	0.39***	−0.07	0.06
	(0.06)		(0.05)	(0.05)	(0.08)	(0.07)
$Hot \times dSME$					0.41***	0.26***
					(0.10)	(0.09)
$Hot \times dChiNext$					0.99***	0.94***
					(0.14)	(0.15)
$MtoB$		0.17***		0.04**	0.02	0.02
		(0.02)		(0.02)	(0.02)	(0.02)
$\ln(Sales)$			−0.23***	−0.19***	−0.11***	−0.02
			(0.02)	(0.02)	(0.02)	(0.03)
$Profit$			4.27***	4.36***	3.99***	4.89***
			(0.37)	(0.39)	(0.36)	(0.42)
Tan			−0.78***	−0.71***	−0.45***	−0.45**
			(0.15)	(0.15)	(0.14)	(0.21)
$Debt$			−1.43***	−1.39***	−1.26***	−1.01***
			(0.30)	(0.30)	(0.27)	(0.32)
$dSME$					0.04	0.02
					(0.06)	(0.07)
$dChiNext$					0.33***	0.25***
					(0.08)	(0.10)
Constant	1.10***	0.68***	2.22***	1.84***	1.17***	0.34
	(0.03)	(0.07)	(0.19)	(0.21)	(0.21)	(0.52)
Observations	1,181	1,041	1,174	1,035	1,035	1,035
Adj. R-squared	0.07	0.08	0.45	0.47	0.54	0.58

Table 5 - cont'd

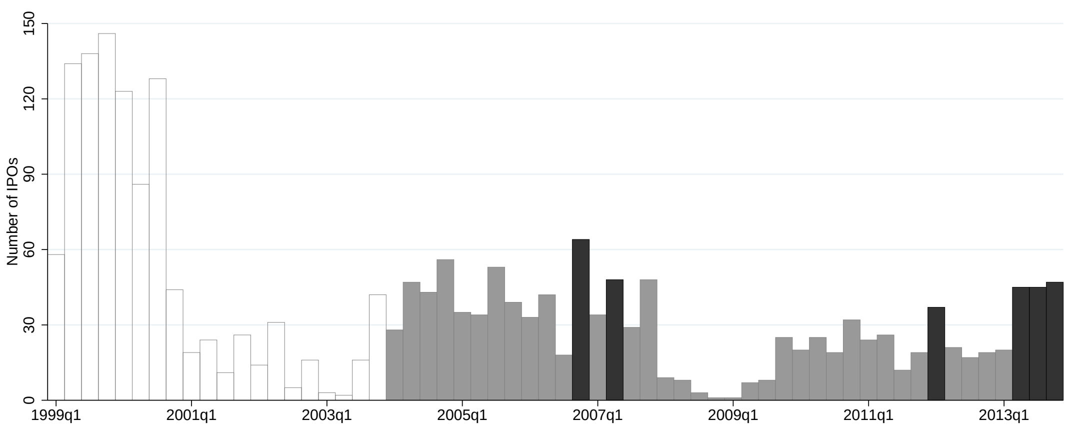
Model	(1)	(2)	(3)	(4)	(5)	(6)
			Panel B: Hong Kong			
Hot	0.26**		0.21*	0.19	0.31**	0.12
	(0.13)		(0.12)	(0.16)	(0.16)	(0.18)
$Hot \times dGEM$					−1.06*	−0.91
					(0.57)	(0.82)
$MtoB$		0.38***		0.37***	0.41***	0.38***
		(0.08)		(0.08)	(0.08)	(0.10)
$\ln(Sales)$			−0.20***	−0.21***	−0.27***	−0.25***
			(0.04)	(0.06)	(0.06)	(0.08)
$Profit$			0.06	0.03	0.04	0.06*
			(0.06)	(0.06)	(0.06)	(0.03)
Tan			−0.53**	−0.28	−0.33	−0.01
			(0.25)	(0.25)	(0.26)	(0.47)
$Debt$			−0.13	−0.48	−0.59	−0.22
			(0.47)	(0.52)	(0.52)	(0.72)
$dGEM$					−0.24	−0.11
					(0.34)	(0.61)
Constant	0.89***	0.12	2.40***	1.66***	2.02***	2.07**
	(0.07)	(0.15)	(0.36)	(0.42)	(0.43)	(0.81)
Observations	658	500	643	488	488	487
Adj. R-squared	0.00	0.10	0.07	0.16	0.18	0.16



(a) China



(b) Hong Kong



(c) United States

Figure 1: **Hot markets in China, Hong Kong, and the US.** Hot quarters (black bars) are identified between 2004 and 2013. The quarters between 1999 and 2003 (empty bars) are not classified as the method needs past five years' data.