Gone Fishin': Seasonality in Speculative Trading and Asset Prices

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Abstract: We develop and test a theory of seasonality in trading activity and asset prices based on heterogeneous beliefs and short-sales constraints. Our theory predicts that trading of all types, including speculative trades, declines when investors are away on vacation but only the prices of those assets with sufficient divergence in opinion will drop at the same time. We test our hypothesis using data from the U.S. and Chinese stock markets. As predicted, we find that turnover in the U.S. stock market drops significantly in the summer (when investors are gone fishin') and that the prices of dot-com and liquid, high turnover stocks are lowest during the summer when compared to other stocks. In China, where investors go on vacation only during the Chinese New Year (January and February), turnover and the prices of speculative stocks bottom out during the first two months of the year. We rule out alternative explanations such as seasonal variations in liquidity.

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1. Introduction

Over the past few years, a sizeable literature has explored the effects of heterogeneous beliefs and short-sales constraints for asset prices. In a static setting, a stock's price will be upwardly biased when there is sufficient divergence of opinion because it will only reflect the valuations of the optimists as pessimists simply sit out of the market instead of short-selling (see, e.g., Miller (1977), Chen, Hong and Stein (2002)). In a dynamic setting, these two ingredients also generate a non-fundamental (or speculative) component in asset prices (see, e.g., Harrison and Kreps (1978), Scheinkman and Xiong (2003)). Investors pay prices that exceed their own valuation of future dividends as they anticipate finding a buyer willing to pay even more in the future. The price of an asset exceeds fundamental value as a result of this resale option. Turnover due to speculative trading emerges naturally in this setting as an important valuation indicator along with standard price-to-fundamental ratios.[1]

In this paper, we develop and test a theory of seasonality in asset prices based on speculative trading due to heterogeneous beliefs and short-sales constraints. The basic premise is that trading of all types, including speculative trades, dry up when investors go on vacation (i.e. gone fishin'). Our theory predicts that the prices of stocks with sufficient divergence of opinion will also drop at the same time. Intuitively, since speculation generates a non-fundamental component in asset prices in the presence of short-sales constraints, periods in which such speculative trades are absent will have less of an upward bias in prices.

[1] For examples of the importance of short-sales constraints for prices, see Chen, Hong and Stein (2002), D'Avolio (2002), Dechow, Meulbroek, Sloan (2001), Jones and Lamont (2002), Lamont and Thaler (2003), Ofek and Richardson (2003) and others.

The predictions are the following. First, there is seasonality in trading activity in that turnover during the period when investors are on vacation (e.g. summer time in the U.S.) is lower than during the rest of the year. This implication is just confirmation of our basic premise that trading of all kinds, whether hedging or speculation, declines when investors are gone fishin'. Second, while trading activity declines for the typical stock, *only* the prices of stocks with sufficient divergence in opinion will bottom out at the same time. Our theory does not have much to say about the seasonality pattern in price for the typical stock. There may be other factors besides our mechanism that generate seasonality in prices. Examples include turn-of-the-year trading for tax reasons or window-dressing (e.g. the January effect) or seasonal variations in sunlight (or weather more generally), which may affect investor mood. Our key prediction is that the prices of speculative stocks will bottom out at the same time as trading activity when compared to the prices of the rest of the market. Third, the documented seasonality in asset prices should not be generated by variations in liquidity along the lines of Amihud and Mendelson (1986) and Vayanos (1998) since there are no transactions costs in the model---only an assumption that investors do not want to short-sell. We think of the short-sales constraints in our model as investors such as mutual funds being reluctant to short-sell as opposed to investors being unable to short a stock.[2] As such, our theory applies to large stocks as well as small ones.

We test our theory using data from the U.S. and Chinese stock markets during the dot-com period of 1992-2003. This setting provides an ideal test of our theory for several

[2] Roughly 70% of mutual funds explicitly state (in Form N-SAR that they file with the SEC) that they are not permitted to sell short (see Almazan, Brown, Carlson and Chapman (2004)). Seventy-nine percent of equity mutual funds make no use of derivatives whatsoever (either futures or options), suggesting that funds are also not finding synthetic ways to take short positions (see Koski and Pontiff (1999)). These figures indicate the vast majority of funds never take short positions.

reasons. First, in the U.S. and most markets in the northern hemisphere, vacation occurs during the summer quarter (the months of July, August and September).[3] But in China, the Chinese take their vacation during the Chinese New Year, which is from late January to late February.[4] As such, we expect trading activity to bottom in the summer quarter in the U.S. but during the first two months of the year in China. Second, focusing on the dot-com period in the U.S provides direct comparability with the results from the Chinese stock market, the data of which is only available beginning in 1992.

Third, during the dot-com period, we know with hindsight that a number of stocks (the dot-com stocks of course) in the U.S. market were highly speculative. And as we describe in detail below, not only do the Chinese take their vacation at a different time of the year than Americans do, China's stock market, with stringent short-sales constraints and many inexperienced investors, provides an ideal venue to study the non-fundamental component in stock prices (see Mei, Scheinkman and Xiong (2004)). As a result, we expect the prices of dot-com stocks in the U.S. to bottom out in the summer when compared to the rest of the market. In contrast, in China, we expect the prices of speculative Chinese stocks to bottom out during the Chinese New Year.[5]

We begin by analyzing seasonality in turnover using data from the U.S. stock market. Consistent with our basic premise, we find that turnover is substantially lower

[3] We have also tried categorizing summer as June, July and August and found a similar dip in trading activity, but we find the most significant summer effect when September is categorized as part of the summer quarter instead of June.
[4] According to CNN.com (January 25, 2005), China's peak Lunar New Year Travel season is the world's biggest annual human migration, with about 2 billion journeys across China beginning in late January through February.
[5] Two markets in the Southern Hemisphere, Brazil and South Africa, have their holidays during the winter months. However, there is not much trading in these markets and so are not as ideal as China as a test of our theory. Other Asian markets such as Taiwan, which also celebrates the Chinese New Year, may provide a better setting to test our theory---however, unlike China, it is not as easy to construct valuation ratios.

during the summer than the rest of the year. This pattern holds when we break our sample into different sub-periods: 1992-2003 and 1961-1991. It also holds across different exchanges (NYSE/AMEX versus NASDAQ) and firm size quintiles. In particular, when we look at dot-com stocks during the period of 1992-2003, provided by Ofek and Richardson (2003), we find a similar seasonal effect.

Having checked that our basic premise holds, we move on to asset prices. Using a stock's market-to-book ratio or price-to-sales ratio as measures of a stock price's non-fundamental component, we find that the typical stock's valuation ratios do not bottom out in the summer quarter, but rather in the fall quarter (consistent with prior studies and the presence of a January effect in stock returns). However, the valuations of dot-com stocks do dip in the summer quarter when compared to the rest of the market.

For the Chinese stock market, we collect data starting in 1992 (the start date of China's stock market) until 2000 on about 82 Chinese stocks that offered two classes of shares: A-shares which could be only held by domestic investors and B-shares which could only be traded by foreigners. Despite their identical rights, A-share prices were on average 420% higher than corresponding B-shares and there was five times more turnover in A-shares (500% per year) than B-shares (100% per year). So the A-B share premium is the perfect way to measure the non-fundamental component in asset prices---we need not rely on valuation ratios as in the U.S. stock market.

Consistent with our theory, we find that the turnover of these Chinese stocks is lowest during the Chinese New Year. Importantly, we also find that the A-B share premium is lower during the Chinese New Year than the rest of the year. These findings in the Chinese market suggest that the seasonal patterns in the U.S. are really due to a gone fishin' effect as opposed to a generic summer effect.

Having established that there is a gone fishin' effect in the market, we then attempt to rule out some alternative hypotheses for our findings. The main alternative is that liquidity is lower when investors are gone on vacation and so prices are lower as a result of higher trading costs. Using various proxies for trading costs in the U.S. such as bid-ask spreads and price impact measures, we find that trading costs do not peak during the summer, when trading activity is at its lowest. As such, liquidity is not likely to be an important determinant of our price findings for the U.S. market. Unfortunately, we do not have information about trading costs for Chinese stocks---but the conjunction of the U.S. findings with these make a strong case in support of our theory.

Through out the paper, we attribute the dip in trading activity and prices in the summer to investors being on vacation. But Wall Street may go on vacation in the summer because there are fewer things to speculate about as a result of Main Street also being on vacation.[6] In other words, there may just be less news to fuel speculation in the summer than in other quarters. We are happy with the broader interpretation that there is less speculation as a result of people more generally being gone fishin' in the summer. The reason being that there simply being less news in the summer would not explain the price patterns without the added ingredient of speculation and short-sales constraints advocated by this paper. In a standard rational asset-pricing model, less news just means less volatility and if anything higher prices in the summer---not lower as we document.

[6] In this paper, we focus on trading activity. We have looked at other types of Wall Street activity such as the number of initial public offerings (IPOs) and frequency of analyst recommendation revisions. We find a similar but less pronounced drop in these activities in the summer, consistent with the idea that the drop in turnover is because Wall Street is on vacation.

However, we decided to see if there is less news and volatility in the summer and do not find evidence that this is the case. So, our effects are unlikely to be driven by seasonality in news and volatility.

Finally, we test an auxiliary implication of our theory---namely that we can identify speculative stocks as liquid stocks with high turnover. We expect these stocks' prices to dip in the summer compared to the rest of the market. While we cannot implement this analysis for the Chinese stock market since there are so few stocks and all of them have high turnover, we can do so for the US stock market. Indeed, a nice feature of using this alternative measure of a speculative stock is that we can go beyond the dot-com period and look to see whether this pattern holds in earlier decades. We find that this is indeed the case: during both the dot-com period and the period of 1961-1991, the prices of large, liquid stocks with abnormally high turnover dip in the summer compared to the rest of the market.

Our paper is related to the literature on seasonality in stock returns. The largest of these is on the January effect: recent losers (especially small stocks) tend to experience fortune reversals in January (hence the January effect) (see, e.g., Dyl (1977), Roll (1983), Keim (1983), Reinganum (1983) and Ritter (1988)). There are several proposed explanations, including window-dressing by institutional investors (Lakonishok, Shleifer, Thaler and Vishny (1991)). More recently, an interesting literature has developed looking at the effect of weather on stock returns (Saunders (1993), Hirshleifer and Shumway (2003) and Kamstra, Kramer and Levi (2003)), though these studies consider different mechanisms, such as mood or risk-taking behavior, for why weather might affect stock returns. Hence seasonal variation in weather leads to variation in stock returns. We take for granted that these factors may affect stock prices. There can also be other seasonal patterns in stock returns (see, e.g., Bouman and Jacobsen (2002)). As we noted above, our theory is mute on seasonal price or return patterns in the market---our identification strategy is to see how speculative stocks' seasonal price patterns differ from the rest of the market.

Our paper proceeds as follows. We develop a stylized model to generate testable predictions in Section 2. We describe the datasets in Section 3 and the main results in Section 4. We consider alternative explanations for our findings in Section 5 and extend our analysis to another measure of speculative stocks in Section 6. We conclude in Section 7.

2. Model

Our model is adapted from Hong, Scheinkman and Xiong (HSX 2004). We consider a single traded asset, which might represent a stock, a portfolio of stocks or the market as a whole. There are infinitely many quarters denoted by $i = 1, 2, 3, ..., \infty$. The asset pays off D_i at the end of each quarter. The D_i's are independent and normally distributed across quarters. Two groups of investors, A and B, trade the asset and investors within each group are identical and risk-neutral. No short-selling is allowed.

Within each quarter *i*, we assume that there are two dates denoted by *(i, 0)* and *(i, 1)*. At the start of each quarter *i*, on date *(i, 0)*, the two groups of investors have the same prior about D_i, which is normally distributed (denoted by $N(0,1/\tau_0)$) with mean zero and precision of belief τ_0. At date *(i, 1)*, they receive two public signals

$$S_i^A = D_i + \varepsilon_i^A, \qquad S_i^B = D_i + \varepsilon_i^B \tag{1}$$

where ε_i^A and ε_i^B are the noises in the signals. These noises are independent and normally distributed (denoted by $N(0,1/\tau_\varepsilon)$) with mean zero and precision τ_ε. We model heterogeneous beliefs as group A over-estimating the precision of signal A as $\phi\tau_\varepsilon$, where ϕ is a constant parameter larger than one. In contrast, group B over-estimates the precision of signal B as $\phi\tau_\varepsilon$.

Let $\hat{D}_i^A$ and $\hat{D}_i^B$ denote the beliefs of group A and B investors, respectively, about D_i after observing the signals given by (1) at date *(i, 1)*. And let $l_i = \hat{D}_i^A - \hat{D}_i^B$ be the difference in opinion regarding D_i between group-A and group-B investors at date *(i, 1)*. It is shown in HSX (2004) that l_i has a Gaussian distribution with a mean of zero and a variance of

$$\sigma_l^2 = \frac{(\phi-1)^2(\phi+1)\tau_\varepsilon}{\phi[\tau_0 + (1+\phi)\tau_\varepsilon]^2}. \tag{2}$$

Notice that when $\phi = 1$, there would be no divergence in opinion among investors (i.e. l_i would always be equal to zero). The variance of the differences in opinion increases with ϕ. Hence, we refer to ϕ as the degree of divergence of opinion about the stock.

Applying Theorem 1 of HSX (2004), we have that the price at the beginning of quarter *i* is given by

$$P_{i,0} = \sum_{m=i}^{\infty} \frac{B_m}{(1+r_Q)^{(m-i)}}, \tag{3}$$

where $B_m = E[Max(l_m, 0)]$ (the expectation is taken with respect to the Gaussian distribution of l_m) and r_Q is the interest rate across quarters. Intuitively, the fundamental component of the price is zero by construction since we assume the mean of the dividends is zero. B_m is the non-fundamental component in asset prices associated with speculation about D_m. Intuitively, with differences of opinion and short-sales constraints, the possibility of selling the shares when other investors have higher beliefs provides a resale option to the asset owners (Harrison and Kreps (1978) and Scheinkman and Xiong (2003)). It represents the option value from selling the asset to investors in the other group when they have higher beliefs.

HSX (2004) also show that the non-fundamental component B_i and the expected turnover rate during a quarter (from date (i, 0) to date (i, 1)) both increase with ϕ, the degree of divergence of opinion about the stock. In other words, turnover is a measure of the degree of divergence of opinion among investors. We will use this result later in identifying high divergence-of-opinion or speculative stocks in Section 6 below.

We now assume that during the vacation quarter (which for the sake of simplicity, we refer to as summer), group A and B investors do not speculate. We can model this in a number of different ways. But probably the easiest way is to assume that the investors do not pay attention to the signals because they are away on vacation. As a result, their beliefs do not differ at date *(i, 1)* if quarter i is a summer quarter and so there is no speculative premium at date *(i, 0)*.

Proposition 1: If investors are not active during a quarter (say the summer) (so that the non-fundamental component of price for the summer is lower than that of the other quarters) then only the price of high-divergence of opinion or speculative stocks (i.e. stocks with $\phi > 1$) *during that quarter is lower than the rest of the year.*

In proving this proposition, we assume that the non-fundamental components of price for the other quarters are similar in magnitude. We will provide additional discussion to this point below (see proof in the appendix).

Another important assumption of our analysis is that we are focusing on short-term speculation of fundamentals within a quarter. This is captured by the assumption of i.i.d. dividends across quarters and these dividends being realized at the end of each quarter. Presumably, investors standing in the spring quarter speculating about information revealed in the summer quarter would also value the resale option less. Hence, our test of Proposition 1 is also a joint test of the assumption of short-term speculation.

Our stylized model also misses a number of other elements of reality which we need to account for in taking it to data. First, the model only allows for one source of turnover due to speculative trading. But in reality, investors will also trade for hedging reasons. Second, there are other reasons for why there might be seasonality in asset prices beyond ours such as the January effect. We are agnostic about other possible sources of seasonality, i.e. our model does not have much to say about price seasonality in the typical stock. Instead, our model predicts that the prices of stocks with sufficiently high divergence of opinion will bottom out in the summer compared to the prices of other stocks.

Hence, a key in testing the model is in identifying speculative stocks. This is why, as we explained in the introduction, we focus on the dot-com period (1992-2003) in the U.S. and Chinese stock markets. It is natural to interpret the dot-com stocks in the U.S. as high divergence-of-opinion stocks. And in the case of China, the Chinese stocks that offered two classes of shares, A-shares which could be only held by domestic investors and B-shares which could only be traded by foreigners, are all highly speculative.

We test the following predictions.

Prediction 1: Trading activity (measured by turnover) should be lowest during the period when investors are gone fishin'---summer quarter in the U.S. and the Chinese New Year or the winter quarter (January and February) in China.

Prediction 2: The valuation ratios (market-to-book and price-to-sales ratios) of dot-com stocks in the U.S. will bottom out in the summer compared to other stocks. In China, the ratio of A-share price to B-share price is lowest during the first two months of the year.

We do not model liquidity effects that might also be present. As such, the following hypothesis is implied by our model:

Prediction 3: The documented seasonal patterns in stock prices are not driven by similar seasonal variations in liquidity.

Finally, our model suggests a natural measure of high divergence-of-opinion or speculative stocks---namely, liquid and high turnover stocks.

Prediction 4: The valuation ratios of speculative stocks in the U.S., defined as liquid, high-turnover stocks, bottom out in the summer compared to other stocks.

The reason is that our model assumes that there are no trading costs (i.e. highly liquid stocks) and stock turnover increases with ϕ, the degree of divergence-of-opinion. A natural proxy for liquidity is the firm size and so large firms with high turnover emerge as natural candidates as speculative stocks.

In the background, we are appealing to limits of arbitrage (see, e.g., Shleifer and Vishny (1997)), for otherwise, arbitrageurs could eliminate any seasonal patterns in prices for high divergence-of-opinion stocks.

3. Data

Our data on U.S. firms come from the Center for Research in Security Prices (CRSP) and COMPUSTAT. From CRSP, we obtain monthly closing stock prices, monthly shares outstanding, monthly share turnover and monthly closing bid-ask spreads for NYSE, AMEX and NASDAQ stocks. From COMPUSTAT, we obtain annual information on a variety of accounting variables. To be included in our sample, a firm must first have the requisite financial data on CRSP and COMPUSTAT. Following other studies using market-to-book ratios, we exclude those firms with one-digit SIC codes of 6, which are in the financial-services industry.

The market equity value of a firm (M), defined as the combined value of all common stock classes outstanding, is taken from CRSP by multiplying monthly closing price and monthly shares outstanding. For the book equity value (B), we use

COMPUSTAT data item 60. Our primary dependent variable is the log of the ratio of market equity to book equity, i.e., Log(M/B). For each month, we take the average daily market value during the month and divide it by the firm's most recently available book value during the previous year to form the market-to-book ratio.[7] We take logs because the raw market-to-book ratio is highly skewed, and the log transformation results in a variable that is much closer to being symmetrically distributed. Alternatively, we can use the book-to-market ratio as the dependent variable, which also leads to results very similar to those we report below, though of course with all of the signs reversed.

We also experiment with an entirely different valuation measure, a firm's price-to-sales ratio. For each month, we take the average daily price during the month and divide it by the firm's sales (item 12) from the end of the previous year.[8] We use the log of price-to-sales, Log(P/S), for the same reasons as for market-to-book ratios. Unfortunately, we cannot use other valuation measures such a firm's cash flow-to-price ratio, because cash-flow and earnings for much of the dot-com stocks were zero during this period. Both Log(M/B) and Log(P/S) are winsorized at the 1% and 99% level.

Our data for Chinese stocks is obtained from Shenzen GTA Information Technology, Inc., which recently reached a cooperative agreement with Wharton Research Data Service (WRDS) to incorporate GTA research databases into WRDS. A number of Chinese companies issued two classes of common shares with identical voting and dividend rights. They are listed on the same exchanges (either Shanghai or Shenzhen stock exchanges). The class-A shares were restricted to domestic residents, while the B-

[7] We have also experimented with using a weighted average of book value from the previous year and the current year book value when it becomes available in forming log(M/B) and obtained similar results.
[8] Again, we have also experimented with using a weighted average of sales from the previous year and the current year in forming price-to-sales ratios and obtained similar results.

shares were confined to foreigners before February of 2001 when domestic residents were allowed to purchase B-shares using foreign currency. We focus our analysis on the period of February of 1992 (beginning of the database) to December of 2000 for these stocks because we will use the ratio of A-share price to B-share price as a measure of the non-fundamental component in price. After 2000, this measure becomes problematic because of the ability of domestic residents to trade B-shares as well as A-shares.

In addition, we obtain from Piqueira (2004) monthly estimates of price impact for each stock, using the Trade and Quote Database (TAQ) for the period of January 1993 to December 2002. The estimates of price impact or cost of trading use the Glosten and Harris (1988) model, which is widely used in the market microstructure literature. Many consider this price impact cost to be a superior measure of the liquidity of a stock when compared to the bid-ask spread. One reason is that the bid-ask spread may overstate the cost of trading since many trades are executed within the spread. Hence, the price impact cost derived from actual trade data gives us a more accurate gauge of actual trading costs faced by traders. We refer the reader to Piqueira (2004) for more details on these estimates.

Finally, we obtain from Chan (2003) data on the days in which there is public news released about a firm. The data is hand collected using the Dow Jones Interactive Publications Library of past newspapers, periodicals, and newswires. But only those publications with over 500,000 current subscribers, daily publication, and stories available over as much of the 1980-2000 period as possible are used to construct the data. Since data retrieval is time consuming and labor intensive, Chan focuses on a random subset of approximately one-quarter of all CRSP stocks. The result is a set of over 4200 stocks, with 766 in existence at the end of January 1980 and over 1500 at the end of December 2000. For each of these companies, Chan hand-collect all dates when the stock was mentioned in the headline or lead paragraph of an article from the sources. The dataset only notes if there was news on a particular day, not how many stories appeared. We refer the reader to Chan (2003) for more details on his database.

Table 1, we report summary statistics that will be helpful in evaluating the economic significance of our findings below. Panel A focuses on turnover in the U.S. market. We report the mean and standard deviation of monthly turnover for different sub-samples. During the period of interest, 1992-2003, the mean monthly turnover is about 0.125 with a standard deviation of 0.527. Not surprisingly, the mean turnover of internet stocks is markedly higher than the rest of the market, with a mean of 0.30 and a standard deviation of 0.449. The mean turnover is lower for NYSE/AMEX stocks (0.082) than NASDAQ stocks (0.150). We also report these figures by firm size. Notice that mean turnover increases slightly with firm size (0.106 for stocks in the smallest quintile compared to 0.141 for stocks in the largest quintile). Moreover, turnover has increased substantially over time. During the period of 1961-1991, the mean turnover is 0.045 (about three times smaller than in the nineties) and the standard deviation is 0.092.

Panel B reports summary statistics for our two valuation ratios in the U.S. market. During the period of 1992-2003, the mean log market-to-book ratio is 0.637 with a standard deviation of 1.312. The mean log price-to-sales ratio is 0.044 with a standard deviation of 1.734. For internet stocks, their log market-to-book and price-to-sales ratios are 0.410 and 1.126 and with standard deviations of 1.813 and 1.824, respectively. The log market-to-book for internet stocks is lower than the rest of the sample because the years 2001-2003 are in the sample. Without these years, internet stocks would have higher mean valuations than other stocks by both metrics. We also report these figures for the period of 1961-1991.

Panel C reports summary statistics for our sample of stocks from the Chinese stock market. The mean monthly turnover of these stocks is 0.490 a month with a standard deviation of 0.574. Turnover is even higher than that observed for internet stocks in the U.S. during the same period. The log of the monthly A-share price to B-share price, which we call the A-B share premium, is 1.223 with a standard deviation of 0.594.

In Panel D, we report summary statistics for bid-ask spreads, price impact costs and volatility of U.S. stocks. The mean monthly bid-ask spread is 0.357 with a standard deviation of 0.6. The mean price impact cost is 0.017 with a standard deviation of 0.029. And the mean monthly volatility, which we measure with daily returns within the month, is 0.03 with a standard deviation of 0.024. And finally, in Panel E, we report summary statistics for the days in a quarter in which a random subset of firms (approximately one-quarter of all CRSP stocks) appears in news headlines. The mean (averaged across stocks) is 5.76 days, with a standard deviation of 6.75 days.

4. Results

A. Seasonality in Turnover of U.S. Stocks

We begin by testing our first prediction---namely, that trading activity or turnover in the U.S. stock market is lower during the summer quarter than the rest of the year. We first calculate for each stock its average turnover in a given quarter by taking the mean of the three monthly turnovers in that quarter. We denote this variable of interest by $\text{TURNOVER}_{i,t}$ for firm i in quarter t. We then implement the following regression specification:

$$TURNOVER_{i,t} = a_0 + a_1{*}SUMMER_t + YEARDUMMIES + STOCKFIXEDEFFECTS. \quad (4)$$

SUMMER is a dummy variable that equals one if stock i's turnover observation is in the summer and zero otherwise. The coefficient of interest is the one in front of the seasonal dummy, which tell us how trading activity differs in the summer compared to the rest of the year.

We focus on this specification because it is our most parsimonious and hence allows us to make the most precise statistical inference possible. The down side is that it does not confirm that summer is lower than each of the other quarters separately. As such, we will also consider a more elaborate specification in which we compare the other quarters to summer to confirm that summer is indeed lower than each of the other three quarters. To this end, we create three new variables, WINTER, SPRING and FALL, which are dummy variables for observations being in the winter, spring and fall quarters, respectively. We then run regression (4) except that we replace SUMMER with the three new variables WINTER, SPRING and FALL. We expect the coefficients in front of these three dummies to be positive.

Note that we also add in year dummies and stock fixed effects. To capture a pure seasonal effect, it helps to include these effects since they control for time trends (turnover has increased significantly over time) and fixed mean differences across stocks (e.g. larger stocks have higher turnover than smaller stocks) that add noise to our measurement of a seasonal effect. We re-run the regressions without year effects and stock fixed effects. For the most part, these additional controls do not significantly change our findings. However, in the case of internet stocks, it does help to add year effects since the turnover of these stocks are significantly larger during the late nineties. Moreover, there are many more internet stocks in the late nineties than in the early nineties, which lead to an unbalanced panel that can magnify the measurement error due to time trends in turnover.

The results are reported in Table 2. Panel A reports the results for regression (4) (comparing summer to the rest of the year) and Panel B reports the results for the more elaborate version of (4), in which we compare the other three quarters to summer. The first row of Table 2 reports the regression results for the period of interest, 1992-2003. The coefficient in front of SUMMER is -0.0133 with a t-stat of -6.12. Since monthly turnover during this period is about 0.12 in our sample, this means that turnover in the summer declines by about 11% relative to the rest of the year---an economically sizeable decline. Notice that the summer quarter is indeed lower than each of the three other quarters. The coefficients in front of WINTER, SPRING and FALL are all statistically significant.

The next row reports the result for only internet stocks during the same period. The coefficient in front of SUMMER is again negative (-0.0354 with a t-stat of -9.65). Since the mean turnover of internet stocks is 0.30, activity drops by about 11.8% during the SUMMER. And again, turnover of internet stocks in the summer is lower than each of the other three quarters.

In the rest of the table, we repeat the same exercises for stocks from different exchanges, across size groups and during the earlier period of 1961-1991. Looking at Panel A, there is a statistically significant drop in activity for each of these cuts. The economic size of the summer dip varies across these cuts (from a maximum of a 16% drop in turnover for Quintile 1 stocks to a minimum of 6.4% for Quintile 4 stocks). The typical sub-sample experiences around a 10% drop in trading activity in the summer. And a quick glance of the Panel B of the table reveals that in each case, this summer effect is statistically significant and is lower than the other three quarter.

Finally, we consider other types of Wall Street activity such as the number of initial public offerings (IPOs) and frequency of analyst recommendation revisions per quarter. We find a similar but less pronounced drop in these activities in the summer, consistent with the idea that the drop in turnover is because Wall Street is on vacation. The summer quarter has about 5.6% fewer IPOs than the rest of the year and 0.5% fewer revisions of analyst recommendations. These results, while statistically and economically weaker than that of trading activity, provide confirmation that Wall Street is indeed on vacation in the summer. We omit these results for brevity but can provide them on request.

B. Seasonality in Valuations of U.S. Stocks

We then test the second prediction of our theory---namely, the valuations of dot-com stocks bottom out in the summer relative to other stocks. The dependent variable is $VALUATIONRATIO_{i,t}$, which can take on one of two values, either Log(M/B) or Log(P/S). It is calculated each quarter by taking the average of either Log(M/B) or

Log(P/S) across the three months within the quarter. The regression specification that we implement is the following:

$$VALUATIONRATIO_{i,t} = b_0 + b_1*DOTCOM_{i,t} + b_2*SUMMER_t*DOTCOM_{i,t} + QUARTERxYEARDUMMIES + STOCKFIXEDEFFECTS\,. \quad (5)$$

SUMMER is the seasonal dummy defined as in (4). DOTCOM equals one if the stock is on the list of dot-com stocks given by Ofek and Richardson (2003) and zero otherwise. The key explanatory variable is the interaction term involving SUMMER and DOTCOM. Our theory predicts that DOTCOM stocks should dip in the summer relative to other stocks---so we expect b_2 to be less than zero. Importantly, in addition to stock fixed effects, we now add in QUARTERxYEARDUMMIES.

The reason we use QUARTERXYEARDUMMIES instead of just year dummies is for obtaining more conservative t-statistics. The QUARTERxYEARDUMMIES take out a common (or market) component in the valuation measures, which may lead to artificially high t-stats. However, the idiosyncratic portion may still be correlated by industries or across time. As such, we cluster the standard errors by the Fama-French (1997) industries. This clustering allows for arbitrary correlation of observations within an industry (but assumes independence across industry clusters) and across time (i.e. allows for arbitrary serial correlation in observations within a cluster). We have also tried a number of alternative ways of calculating standard errors (see below) and conclude that the documented effects are statistically significant.[9]

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[9] When we include only year dummies, we are able to identify a seasonality effect for the typical stock. We find that their valuation ratios bottom in the fall, consistent potentially with the January effect.

As we did for regression (4), we also compare the other three quarters to SUMMER by replacing SUMMER*DOTCOM with WINTER*DOTCOM, SPRING*DOTCOM and FALL*DOTCOM. We expect the coefficients in front of these three variables to be positive.

The results are reported in Panel A of Table 3. In column (1), the dependent variable is Log(M/B). Observe that the coefficient in front of SUMMER*DOTCOM is negative and statistically significant (-0.118 with a t-stat of -5.86). We interpret this finding in the following way. Dot-com stocks have lower valuations in the summer than the rest of the year when compared to the rest of the market, consistent with our theory. The implied magnitude is sizeable in that the market-to-book ratio is about 11% lower in the summer than the rest of the year. In column (2), we compare the other three quarters to the summer. Notice that the coefficients in front of WINTER*DOTCOM, SPRING*DOTCOM and FALL*DOTCOM are each positive and statistically significant, indicating that summer is indeed lower than each of the other three quarters. We also present the results using Log(P/S) instead of Log(M/B) in columns (3)-(4) and find similar results.

In Panel B, we re-run the regressions in Panel A except that we exclude observations from year 2000 and also the two months surrounding the collapse of Long Term Capital (LTCM), the months of August and September in 1998. The motivation for this analysis is two-fold. First, dot-com stocks began their precipitous fall in March 2000, so one might worry that we are capturing the fact that dot-com stocks' valuations were lower at the end of 2000 than in the beginning. Second, we worry about the coincidence of the the collapse of LTCM happening during the summer of 1998. To this end, we only use the valuation ratio for July 1998 in constructing the variable SUMMER for 1998. The results are similar to those in Panels A, suggesting that our findings in Panel A are not driven by either events.

We have also considered a number of additional robustness checks. For instance, we have also added in a dummy variable for firm size (large versus small) and interacted it seasonal dummies. The worry is that DOTCOM might be proxying for firm size and large firms may have different seasonality patterns in price than small firms. But this turns out to not be the case as our results are unaffected by these additional controls.

C. Seasonality in Turnover and Valuations of Chinese Stocks

We next turn out attention to the Chinese stock market and our 82 companies that issued A-B shares during the period of 1992-2000. Since the Chinese New Year takes place only in January and February, we define WINTER to be just January and February. In other words, we look at how the other quarters differ from January and February. The dependent variable is $CHINATURNOVER_{i,t}$, which is the average turnover of Chinese stock i's A-shares in quarter t using the monthly observations in that quarter. We focus on turnover in the A-shares since these are the ones traded only by domestic residents. We then implement the following regression specification:

$$CHINATURNOVER_{i,t} = c_0 + c_1 * WINTER_t + YEARDUMMIES + STOCKFIXEDEFFECTS. \qquad (6)$$

We also include year dummies and stock fixed effects as before. We expect c_1 to be less than zero. As we did for regression (4), we also compare the other three quarters to WINTER by replacing WINTER with SPRING, SUMMER and FALL. We expect the coefficients in front of these three variables to be positive.

The results are reported in Panel A of Table 4. Notice from column (1) that trading activity in winter is lower than the rest of the year.[10] The coefficient in front of WINTER is -0.2218 with a t-stat of -15.30. The mean monthly turnover in China is 0.490. So the average turnover during the Chinese New Year is around 45% lower than the rest of the quarters. This confirms that our basic premise regarding trading activity drying up during vacation periods for the Chinese stock market. Notice from column (2) that when we compare the other three quarters to winter, we find that winter is indeed lower than each of these other three quarters. These findings provide reassurance that our findings regarding trading activity for the U.S. stock market is not due a generic summer effect. Looking at the joint of the U.S. and Chinese results, we conclude that turnover declines when investors are gone fishin'.

In Panel B of Table 4, we re-run the regressions in Panel A except that $CHINATURNOVER_{i,t}$ (turnover in of stock i in quarter t) is calculated using the average daily turnover in a quarter as opposed to the average monthly turnover. The rationale for using daily turnover instead of monthly turnover is that during the Chinese New Year, the Chinese stock markets close for about one week at the end of January. So, monthly turnover during this month may be low simply because of market closure as opposed to investors going away on vacation. By using daily turnover, we can see if trading activity

[10] During the Chinese New Year, the exchanges close for some period of time. However, even when we adjust turnover by the number of trading days each month, a similar seasonal pattern appears.

is genuinely down because of a gone fishin' effect as opposed to a market closure effect. Notice from column (1) that the coefficient in front of WINTER is -0.0064 with a t-stat of -6.72. The mean daily turnover in the sample is 0.022. So turnover is still about 29% higher during the rest of the year than during the beginning of the year. We draw the same conclusion from column (2) in which we compare the other three quarters to WINTER. So we conclude that the findings in Panel A are due to a genuine gone fishin' effect as opposed to a market closure effect.

We have also done a similar analysis using the stocks' B-shares. The results are omitted for brevity. While there is a similar (statistically significant) seasonal pattern, the economic magnitudes are much smaller. This is not too surprising since foreigners who trade the B-shares are most likely ex-patriots living in Asia and they may take vacation during the Chinese New Year (when most of their trading counterparts are also on vacation). However, the vast majority of the turnover is in the A-shares, traded only by residents---so one would expect much more seasonality in the A-share turnover than B-share turnover.

We next turn to valuations of these Chinese stocks. The key prediction of our theory is whether valuations in the Chinese market dip during the winter. Ideally, we would like a set of control stocks much like the rest of the market (or non-dot-com stocks) in the U.S. with which we can compare these speculative Chinese stocks to. In other words, our prediction is that for these 82 (with hindsight speculative) Chinese companies, their A-B share premium should dip in the winter relative to the rest of the Chinese market. Unfortunately, we cannot get comparable valuation ratios for these other companies since there is not sufficient accounting data with which to construct market-to-book ratios. Moreover, there are not many other Chinese companies in the database to begin with. Hence, we hope that our speculative effect is strong enough to show up even in the absence of a market benchmark as there might be other seasonal factors in the Chinese stock market beyond ours. Importantly, we are looking for a dip in the prices of these stocks in January and February, which is quite different from a January effect (when prices are supposed to peak).

To this end, we create a valuation measure of these stocks that is given by the log of a stock's A-share price to its B-share price for each month and we calculate the average A-B share premium within each quarter and denote this by $LOG(A/B)_{i,t}$. We then implement the following regression specification:

$$LOG(A/B)_{i,t} = d_0 + d_1 * WINTER_t + YEARDUMMIES + STOCKFIXEDEFFECTS. \quad (7)$$

where WINTER, defined as in (6). We also include year dummies and stock fixed effects as before. We also re-run (6) in which we replace WINTER by dummies for the other three quarters (SPRING, SUMMER and FALL) so that we can compare summer to these three other quarters.

The results are presented in Panel C of Table 4. Notice from column (1) that the coefficient in front of WINTER is -0.08 with a t-stat of -11.64, indicating that the A-B share premium is lowest during the Chinese New Year (January and February). Comparing the Chinese New Year to the rest of the year, the log of the A-B share premium is about 8% lower during the New Year than the rest of the year. Notice from column (2) that the coefficients in front of the other three quarters are also positive and statistically significant.

D. Robustness Checks: Statistical Inference

In this section, we consider alternative methods of statistical inference. From our perspective, the most persuasive finding is that the China findings are consistent with theory. But we have also tried other methods to calculate t-statistics for the U.S. and China results. First, instead of clustering by industries, we tried to cluster the observations by dot-com stocks versus other industries or non-dot-com stocks and found similar results. Second, we also implement a Fama-MacBeth (1973) (F-M) version of the regression specification in (4)-(7). More specifically, we re-run regressions (4)-(7) (without the stock fixed effects and with the year dummies) year-by-year and take the coefficients from these cross-sectional regressions and average them to get the mean F-M coefficient. We then calculate Newey-West (1987) standard errors using the time-series of these coefficients. With only ten years of data, this approach is problematic. It is basically trying to make an inference using only ten observations---so the central limit theorem is not likely to apply. However, for the sake of completeness, we attempt this anyways. The results are reported in Table 5. Notice that the magnitudes of the coefficients are similar to those obtained using the pooled regressions and all the coefficients are basically statistically significant, supporting the findings in the earlier tables.[11]

[11] The only coefficient that is borderline insignificant is the one in front of daily Chinese turnover, with a t-stat of 1.66.

5. Alternative Explanations

In this section, we consider alternative explanations to our findings in Section 4 (Prediction 3). The main alternative hypothesis is that our findings are driven by the liquidity mechanism described in Amihud and Mendelson (1986) and Vayanos (1998). Specifically, less trading in the summer means that the market is less liquid and so trading costs are higher. As a result, prices of stocks trade lower to reflect the higher costs. To address this hypothesis, we consider two measures of trading cost. The first is bid-ask spreads. We calculate bid-ask spreads at the end of each month for stocks in the U.S. during the period of 1992-2003. Then we create a dependent variable, denoted by $TRADINGCOST_{i,t}$, which is the average of the three monthly bid-ask spreads within a quarter. We also consider an alternative measure of trading cost given by price impact costs for the period of 1993-2002. Similar to bid-ask spreads, we take the average of price impact costs for the three months within a quarter. We implement the following regression:

$$TRADINGCOST_{i,t} = e_0 + e_1 * SUMMER_t + YEARDUMMIES + STOCKFIXEDEFFECTS. \qquad (8)$$

SUMMER is defined as in (4), and year dummies and stock fixed effects are included as before. We also consider the more elaborate specification in which we replace SUMMER with WINTER, SPRING and FALL.

The results are reported in Table 7. Panel A reports the results for trading costs proxied by bid-ask spreads. If the liquidity story is in fact driving our results, we should find bid-ask spreads being the highest during the summer. Instead, we find that bid-ask spreads are actually higher during the rest of the year as opposed to the summer---from column (1), the coefficient in front of SUMMER is -0.0036 with a t-stat of -2.90. Indeed, when we compare the other three quarters to summer (see column (2)), we find that summer actually has lower bid-ask spreads than the winter and spring quarters. In Panel B, we report the results for price impact costs. Here, we find mixed evidence---from column (1), the coefficient in front of SUMMER is 0.0003 but is statistically insignificant (the t-stat is 1.27). We see this more clearly when we compare summer to the other three quarters in column (2). There is no difference between summer compared to winter and spring. We have also experimented with seeing whether the trading costs of dot-com stocks increase in the summer compared to other stocks and do not find that this is the case. We omit these results for brevity. As such, we conclude from Table 7 that seasonal variation in liquidity is not likely to be driving our findings.

As we mentioned in the introduction, we are happy with the broader interpretation that Wall Street may go on vacation in the summer because there are fewer things to speculate about as a result of Main Street also being on vacation. In other words, there may just be less news to fuel speculation the summer than in other quarters. But there simply being less news in the summer would not explain the price patterns since in a standard rational asset-pricing model, less news just means less volatility and if anything higher prices in the summer---not lower as we document. However, we decided to check to see if there was less news and volatility in the summer.

To this end, we create two new dependent variables. $NEWSDAYS_{i,t}$ is the number of days within a quarter that the stock appears in news headlines. $VOL_{i,t}$ is the average monthly return volatility in a quarter, where the monthly return volatility is calculated using daily returns for that month. We implement the same regression as for trading costs, equation (8), except that we replace TRADINGCOSTS with these two new dependent variables.

The results are reported in Table 8. Panel A reports the results for NEWSDAYS. Notice that the coefficient in front of SUMMER from column (1) is -0.082 but is statistically insignificant. Moreover, when we compare the other three quarters to summer in column (2), we find that the coefficient in front of WINTER is actually negative---so that news releases actually bottom out in the winter instead of the summer. However, our measure of news intensity may not adequately capture other sources of public news. So another measure of whether there is seasonal variation in news intensity is to look at return volatility. Panel B reports the results for return volatility. The coefficient in front of SUMMER is -0.0009 and is statistically significant. However, return volatility does not bottom out in the summer. When we compare the other quarters to summer, we find that return volatility is actually somewhat lower in the winter and spring than summer, though the differences are not statistically significant. As such, it does not appear that our findings regarding trading activity and prices are driven by seasonal variation in news or volatility.

6. Alternative Measure of Speculative or High-Divergence-of-Opinion Stocks

Up until this point, we have attempted to test our theory using a natural experiment of sorts, in which we examine the behavior of dot-com stock prices and Chinese stock prices during a very dramatic period in stock market history. In this section, we consider an alternative method to identify speculative stocks---theory predicts that liquid stocks that have high turnover are the ones that are the most likely to have a bubble (Prediction 4). At the end of each year in our sample, we regress a stock's average share turnover during the past six-months (July through December, in log scale) on a stock's market cap (average of the previous year, in log scale) and an indicator for whether the stock is on the NYSE or NASDAQ. A stock is judged to have abnormally high turnover if its residual from this regression is in the top quintile. We will identify stocks at the end of each year as speculative if its residual turnover is in the top quintile and its market capitalization it is in the top-half of the sample (proxy for liquidity), i.e. $SPECULATIVE_{i,t}$ equals one for these stocks and zero otherwise. We can run an analog of the regression given in (2). But we replace the $DOTCOM_{i,t}$ variable by the $SPECULATIVE_{i,t}$ variable. We expect speculative stocks to dip in the summer compared to the rest of the market just like internet stocks. An added benefit of this analysis is that we can extend our analysis to a much longer sample period, from 1962 to 2003.

To this end, we implement the following regression:

$$VALUATIONRATIO_{i,t} = f_0 + f_1 * SPECULATIVE_{i,t} + f_2 * SUMMER_t * SPECULATIVE_{i,t}$$
$$+QUARTERx\ YEARDUMMIES + STOCKFIXEDEFFECTS\ . \qquad (9)$$

SUMMER is defined as in regression (5), and quarter-by-year dummies and stock fixed effects are included in the regression (as in regression (5)). The coefficient of interest is f_2. Our theory predicts that f_2 is negative---i.e. that high turnover stocks bottom out in the summer relative to the market.

The results for the period of 1961-2003 are presented in Table 9. We focus on the interactions of SPECULATIVE with the seasonal dummies. Observe that the coefficient in front of SUMMER* SPECULATIVE is negative and statistically significant (-0.026 with a t-stat of -6.35). Speculative stocks have their lowest valuations in the summer when compared to the rest of the market, consistent with our theory. The implied magnitude is sizeable the market-to-book ratio is about 3% lower in the summer than the rest of the year. We also present the results using Log(P/S) instead of Log(M/B) and find similar results. We have also verified that similar results hold in different sub-periods such as 1992-2003 and 1961-1991 in Panels B and C, respectively. We have also considered the same robustness exercises as described above and find similar results. We omit these results for brevity.

8. Conclusion

We develop a theory of seasonality in trading activity and asset prices based on heterogeneous beliefs and short-sales constraints. Our theory predicts that trading of all kinds, in particular speculative trades, declines for all stocks when investors are away on vacation. However, only the prices of those with large divergence in opinion will drop at the same time. We test our hypothesis using data from the U.S. and Chinese stock markets during the dot-com period of 1992-2003. As predicted, we find that turnover in the U.S. stock market drops significantly in the summer (when investors are gone fishin') and the prices of dot-com stocks are lowest during this quarter when compared to other stocks. In China, where investors go on vacation only during the Chinese New Year (January and February), the turnover and the prices of speculative stocks bottom out during the first two months of the year. We rule out alternative explanations related to seasonal variations in liquidity using various proxies for trading costs. Finally, we use an alternative measure of high divergence of opinion predicted by theory---high turnover stocks instead of dot-com stocks---and find similar results. Our findings indicate that something as mundane as people going on vacation can have significant effects on trading and prices in stock markets.

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Appendix

Proof of Proposition 1: For simplicity, we drop the time index and denote the price at the beginning of each quarter by P_{winter}, P_{spring}, P_{summer} and P_{fall}. Let $WinterB_i$ $SpringB_i$, $SummerB_i$ and $FallB_i$ denote the non-fundamental component in asset price for that quarter in year i (i..e. they correspond to the B_m's in a year). Our main assumptions are the following:

$$WinterB_i = WinterB \quad \forall i \tag{A1}$$
$$SpringB_i = SpringB \quad \forall i \tag{A2}$$
$$SummerB_i = SummerB \quad \forall i \tag{A3}$$
$$FallB_i = FallB \quad \forall i \tag{A4}$$
$$SummerB < SpringB = FallB = WinterB \tag{A5}$$

Let r_A be the interest rate across a year and r_Q be the interest rate across a quarter as before. Then we can express the price in the summer quarter as:

$$P_{summer} = \sum_{i=0}^{\infty} \frac{SummerB}{(1+r_A)^i} + \frac{1}{1+r_Q}\sum_{i=0}^{\infty} \frac{FallB}{(1+r_A)^i} + \frac{1}{(1+r_Q)^2}\sum_{i=0}^{\infty} \frac{WinterB}{(1+r_A)^i} + \frac{1}{(1+r_Q)^3}\sum_{i=0}^{\infty} \frac{SpringB}{(1+r_A)^i}$$

or equivalently,

$$P_{summer} = kSummerB + \frac{1}{1+r_Q}kFallB + \frac{1}{(1+r_Q)^2}kWinterB + \frac{1}{(1+r_Q)^3}kSpringB \tag{A6}$$

where k is a constant greater than one. By analogy, we can express the prices for the other quarters as

$$P_{fall} = kFallB + \frac{1}{1+r_Q}kWinterB + \frac{1}{(1+r_Q)^2}kSpringB + \frac{1}{(1+r_Q)^3}kSummerB \tag{A7}$$

$$P_{winter} = kWinterB + \frac{1}{1+r_Q}kSpringB + \frac{1}{(1+r_Q)^2}kSummerB + \frac{1}{(1+r_Q)^3}kFallB \tag{A8}$$

$$P_{spring} = kSpringB + \frac{1}{1+r_Q}kSummerB + \frac{1}{(1+r_Q)^2}kFallB + \frac{1}{(1+r_Q)^3}kWinterB \tag{A9}$$

It is easy to show that

$$P_{summer} < P_{spring} < P_{winter} < P_{fall} \tag{A10}$$

by using (A6)-(A9) and calculating the differences between adjacent quarters

$P_{summer} - P_{spring}$, $P_{spring} - P_{winter}$, and $P_{winter} - P_{fall}$.

If we drop the assumption about the non-fundamental components being the same across the other quarters (fall, spring and winter), we can still conclude that P_{summer} is the lowest compared to the other quarters under the following two assumptions,

$$\begin{aligned} &SummerB < WinterB + \frac{1}{1+r_Q}\left(SpringB - FallB\right) \\ &SummerB < SpringB + \frac{1}{1+r_Q}\left(SpringB - FallB\right) + \left(\frac{1}{1+r_Q}\right)^2 \left(SpringB - WinterB\right) \end{aligned} \tag{A11}$$

These two assumptions can hold when $SpringB$, $FallB$ and $WinterB$ are similar in magnitudes. However, we will no longer be able to rank the prices in the four quarters without additional assumptions about the magnitudes of the non-fundamental components.

Table 1: Summary Statistics

This table reports various summary statistics. Panel A reports the mean and standard deviation of monthly turnover in the U.S. stock market for various sub-samples: for 1992-2003, by internet stocks from a list provided by Ofek and Richardson (2003), by stock exchanges (NYSE/AMEX and NASDAQ), by firm size quintiles (where Quintile 1 is the smallest to 5 the largest), and for 1961-1991. Panel B reports the mean and standard deviation of valuation ratios in the U.S. (log of market-to-book ratio and log of price-to-sales ratio). Panel C reports mean and standard deviation of monthly turnover and the log of (daily) A share price to B share price (Log(A/B)) for our sample of Chinese stocks. Panel D reports the mean and standard deviation of monthly bid-ask spreads, price impact costs and return volatility. Panel E reports the mean and standard deviation of the number of days a stock is in the news during a quarter (for a random subset of firms from 1980-2000).

Panel A: Turnover in U.S. Market

	Mean	Standard Deviation
1992-2003	0.125	0.527
Internet Stocks	0.303	0.484
NYSE/AMEX	0.082	0.747
NASDAQ	0.150	0.327
Firm Size		
Quintile 1	0.106	0.807
2	0.122	0.339
3	0.141	0.188
4	0.152	0.184
5	0.141	0.182
1961-1991	0.045	0.092

Panel B: Valuation Ratios in U.S. Market

	Mean	Standard Deviation
1992-2003		
Log(M/B)	0.637	1.312
Log(P/S)	0.044	1.734
Internet Stocks		
Log(M/B)	0.410	1.813
Log(P/S)	1.126	1.824
1961-1991		

Log(M/B)	0.411	0.957
Log(P/S)	-0.445	1.399
1961-2003		
Log(M/B)	0.469	1.176
Log(P/S)	-0.175	1.616

Panel C: Turnover and Log of A-B Share Premium in Chinese Market

	Mean	Standard Deviation
Turnover	0.490	0.574
Log(A/B)	1.223	0.594

Panel D: Bid-Ask Spread, Price Impact Cost and Volatility in U.S. market

	Mean	Standard Deviation
Bid-ask spread	0.357	0.600
Price Impact Cost	0.017	0.029
Volatility	0.030	0.024

Panel E: Number of Days in a Quarter a Stock is in the News

	Mean	Standard Deviation
News Days	5.76	6.75

Table 2: Seasonality in Turnover in U.S. Market

This table reports the regression results of each stock's turnover in each quarter (the average of the stock's three monthly turnovers in that quarter) on quarterly dummies, year dummies and stock fixed effects. In Panel A, the quarterly dummy is SUMMER. In Panel B, the quarterly dummies are WINTER, SPRING and FALL These results are reported for regressions done on various sub-samples: for 1992-2003, by internet stocks from a list provided by Ofek and Richardson (2003), by stock exchanges (NYSE/AMEX and NASDAQ), by firm size quintiles (where Quintile 1 is the smallest to 5 the largest), and for 1961-1991. The standard errors are clustered at the industry level (Fama and French (1997)) and adjusted for heteroskedasticity across firms.

Panel A: Summer vs. Rest of the Year

	SUMMER	t-stat
1992-2003	-0.0133	(-6.12)
Internet Stocks	-0.0354	(-9.65)
NYSE/AMEX	-0.0083	(-2.59)
NASDAQ	-0.0163	(-8.03)
Size Quintile 1	-0.0174	(-3.78)
2	-0.0115	(-6.10)
3	-0.0114	(-6.03)
4	-0.0097	(-5.17)
5	-0.0105	(-3.24)
1961-1991	-0.0039	(-7.43)

Panel B: Other Quarters vs. Summer

	WINTER	t-stat	SPRING	t-stat	FALL	t-stat
1992-2003	0.0179	(3.95)	0.0074	(4.28)	0.0146	(6.96)
Internet Stocks	0.0339	(4.68)	0.0229	(2.58)	0.0509	(7.27)
NYSE/AMEX	0.0157	(1.68)	0.0033	(3.49)	0.0057	(7.52)
NASDAQ	0.0190	(6.99)	0.0098	(4.21)	0.0204	(8.04)
Size Quintile 1	0.0268	(2.26)	0.0054	(2.48)	0.0200	(6.40)
2	0.0101	(5.41)	0.0101	(2.30)	0.0145	(6.75)
3	0.0157	(6.97)	0.0082	(3.56)	0.0103	(6.06)
4	0.0132	(4.53)	0.0073	(3.53)	0.0084	(4.57)
5	0.0141	(3.52)	0.0075	(2.36)	0.0100	(3.40)
1961-1991	0.0052	(6.93)	0.0037	(7.23)	0.0029	(6.42)

Table 3: Seasonality in Dot-Com Stock Valuations

This table reports the regression results of each stock's valuation ratio in each quarter (the average of the stock's daily valuation ratios in that quarter) on a dot-com dummy and interactions of the dot-com dummy with various quarterly dummies (SUMMER, WINTER, SPRING, and FALL), quarter-by-year dummies and stock fixed effects. Two valuation ratios, log of market-to-book ratio (Log(M/B)) and log of price-to-sales ratio (Log(P/S)), are considered. Internet stocks are from a list provided by Ofek and Richardson (2003). The standard errors are clustered at the industry level (Fama and French (1997)) and adjusted for heteroskedasticity across firms. Panel A covers the sample period of 1992-2003. Panel B excludes year 2000 and August and September of 1998 (LTCM collapse).

Panel A. Dot-Com Stock Valuations from 1992-2003

	(1) Log(M/B)	t-stat	(2) Log(M/B)	t-stat	(3) Log(P/S)	t-stat	(4) Log(P/S)	t-stat
DOTCOM	-0.140	(-1.01)	-0.258	(-1.89)	-0.020	(-0.12)	-0.141	(-0.84)
SUMMER*DOTCOM	-0.118	(-5.86)			-0.120	(-7.58)		
WINTER*DOTCOM			0.231	(7.47)			0.223	(9.23)
SPRING*DOTCOM			0.069	(3.09)			0.080	(3.73)
FALL*DOTCOM			0.044	(5.46)			0.046	(6.73)

Panel B. Dot-Com Stock Valuations from 1992-2003, excluding year 2000 and LTCM collapse

	(1) Log(M/B)	t-stat	(2) Log(M/B)	t-stat	(3) Log(P/S)	t-stat	(4) Log(P/S)	t-stat
DOTCOM	-0.366	(-3.52)	-0.501	(-4.67)	-0.288	(-1.78)	-0.420	(-2.65)
SUMMER*DOTCOM	-0.133	(-8.08)			-0.131	(-9.36)		
WINTER*DOTCOM			0.232	(7.50)			0.213	(8.10)
SPRING*DOTCOM			0.076	(3.36)			0.082	(3.79)
FALL*DOTCOM			0.085	(7.18)			0.092	(6.32)

Table 4: Seasonality in Turnover in Chinese Market

This table reports the regression results of each stock's (A-share) turnover in each quarter---the average of the stock's monthly (daily for Panel B) turnovers in that quarter---on various quarterly dummies (WINTER, SPRING, SUMMER and FALL), year dummies and stock fixed effects. March is not included in the WINTER quarter. These results are reported for regressions done on the sample of 82 Chinese companies during the period of 1992-2000. The standard errors are clustered at the firm level and adjusted for heteroskedasticity across firms.

Panel A. Monthly Turnover

	(1) Coefficient	t-stat	(2) Coefficient	t-stat
WINTER	-0.2218	(-15.30)		
SPRING			0.3162	(12.77)
SUMMER			0.1648	(9.24)
FALL			0.1878	(8.77)

Panel B. Daily Turnover

	(1) Coefficient	t-stat	(2) Coefficient	t-stat
WINTER	-0.0064	(-6.72)		
SPRING			0.0095	(10.13)
SUMMER			0.0077	(4.75)
FALL			0.0023	(2.21)

Table 5: Seasonality in A-B Share Premium

This table reports the regression results of each stock's A-B share premium in each quarter---the average of log(A-share price/B-share price) using daily closing A-B price pairs---on various quarterly dummies (WINTER, SPRING, SUMMER and FALL), year dummies and stock fixed effects. March is not included in the WINTER quarter. These results are reported for regressions done on the sample of 82 Chinese companies during the period of 1992-2000. The standard errors are clustered at the firm level and adjusted for heteroskedasticity across firms.

	(1) Coefficient	t-stat	(2) Coefficient	t-stat
WINTER	-0.080	(-11.64)		
SPRING			0.048	(6.63)
SUMMER			0.072	(8.09)
FALL			0.118	(13.28)

Table 6: Fama-MacBeth Analogs to Baseline Seasonality Regressions

This table reports the Fama-MacBeth (1973) analogs for the regression specifications (4)-(7). The t-statistics are adjusted for serial correlation using Newey-West (1987).

Panel A. Seasonality in US Stock Market Turnover

	SUMMER	t-stat
1992-2003	-0.0127	(-4.29)
Internet Stocks	-0.0457	(-2.72)
NYSE/AMEX	-0.0082	(-4.11)
NASDAQ	-0.0157	(-4.21)
Size Quintile 1	-0.0180	(-3.28)
2	-0.0122	(-4.88)
3	-0.0110	(-6.40)
4	-0.0094	(-3.76)
5	-0.0090	(-2.86)
1961-1991	-0.0031	(-4.86)

Panel B. Seasonality in Dot-Com Valuations from 1992-2003, excluding year 2000 and LTCM collapse

	(1) Log(M/B)	t-stat	(2) Log(P/S)	t-stat
DOTCOM	0.757	(2.01)	1.568	(7.51)
SUMMER*DOTCOM	-0.090	(-3.57)	-0.113	(-3.67)

Panel C. Seasonality in Monthly Chinese Share Turnover

	Coefficient	t-stat
WINTER	-0.2082	(-4.12)

Panel D. Seasonality in Daily Chinese Share Turnover

	Coefficient	t-stat
WINTER	-0.0058	(-1.66)

Panel E. Seasonality in Chinese A-B Share Premium

	Coefficient	t-stat
WINTER	-0.089	(-2.17)

Table 7: Seasonality in Liquidity in U.S. Market

This table reports the regression results of each stock's liquidity in a quarter (the average of the stock's three monthly closing bid-ask spreads and price impact costs) on various quarterly dummies (SUMMER, WINTER, SPRING and FALL), year dummies and stock fixed effects. The sample period is 1992-2003. The standard errors are clustered at the industry level (Fama and French (1997)) and adjusted for heteroskedasticity across firms.

Panel A: Bid-Ask Spread

	(1) Coefficient	t-stat	(2) Coefficient	t-stat
SUMMER	-0.0036	(-2.90)		
WINTER			0.0152	(8.30)
SPRING			0.0071	(3.81)
FALL			-0.0126	(-13.24)

Panel B: Price Impact Cost

	(1) Coefficient	t-stat	(2) Coefficient	t-stat
SUMMER	0.0003	(1.27)		
WINTER			-0.0002	-0.79
SPRING			-0.0002	-0.87
FALL			-0.0005	-1.83

Table 8: Seasonality in Daily Return Volatility and News

This table reports the regression results of the number of days in a quarter a stock is news headlines and each stock's return volatility in a quarter (the average of the three monthly return volatilities calculated using daily returns within the month) on various quarterly dummies (SUMMER, WINTER, SPRING and FALL), year dummies and stock fixed effects. The sample period is 1980-2000 for a random sub-sample of CRSP stocks for the days in the news regression and the period of 1992-2003 for all stocks for the return volatility regressions. The standard errors are clustered at the industry level (Fama and French (1997)) and adjusted for heteroskedasticity across firms.

Panel A: Days in the News

	(1) Coefficient	t-stat	(2) Coefficient	t-stat
SUMMER	-0.082	(-0.88)		
WINTER			-0.309	(-2.07)
SPRING			0.316	(3.24)
FALL			0.207	(2.42)

Panel B: Return Volatility

	(1) Coefficient	t-stat	(2) Coefficient	t-stat
SUMMER	-0.0009	(-3.47)		
WINTER			-0.0002	(-1.49)
SPRING			-0.0005	(-1.56)
FALL			0.0035	(8.24)

Table 9: Alternative Measure of Divergence of Opinion

This table reports the regression results of each stock's valuation ratio in each quarter (the average of the stock's daily valuation ratios in that quarter) on a dummy for speculative stocks and interaction of the speculative dummy and a SUMMER dummy, along with quarter-by-year dummies and stock fixed effects. (We regress each stock's previous year's July-December average monthly turnover in log scale on its average previous year's market cap in log scale and on a NASDAQ dummy. A stock is classified speculative if the residual turnover is in the highest quintile and if the stock's previous year's average market cap is in the top half using NYSE size cutoff.) Two valuation ratios, log of market-to-book ratio (Log(M/B)) and log of price-to-sales ratio (Log(P/S)), are considered. The sample periods are 1961-2003, 1992-2003 and 1961-1991, respectively for Panel A-C. The standard errors are clustered at the industry level (Fama and French (1997)) and adjusted for heteroskedasticity across firms.

Panel A: Speculative Stock Valuations from 1961-2003

	(1) Log(M/B)	t-stat	(2) Log(P/S)	t-stat
SPECULATIVE	0.137	(5.84)	0.185	(7.54)
SUMMER*SPECULATIVE	-0.026	(-6.35)	-0.029	(-6.01)

Panel B: Speculative Stock Valuations from 1992-2003

	(1) Log(M/B)	t-stat	(2) Log(P/S)	t-stat
SPECULATIVE	0.049	(1.53)	0.147	(4.38)
SUMMER*SPECULATIVE	-0.040	(-5.53)	-0.042	(-4.99)

Panel C: Speculative Stock Valuations from 1961-1991

	(1) Log(M/B)	t-stat	(2) Log(P/S)	t-stat
SPECULATIVE	0.177	(7.33)	0.202	(7.63)
SUMMER*SPECULATIVE	-0.018	(-7.32)	-0.020	(-7.83)