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Gone fishin': Seasonality in trading activity and asset prices

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Abstract

We use seasonality in stock trading activity associated with summer vacation as a source of exogenous variation to study the relationship between trading volume and expected return. Using data from 51 stock markets, we first confirm a widely held belief that stock turnover is significantly lower during the summer because market participants are on vacation. Interestingly, we find that mean stock return is also lower during the summer for countries with significant declines in trading activity. This relationship is not due to time-varying volatility. Moreover, both large and small investors trade less and the price of trading (bid-ask spread) is higher during the summer. These findings suggest that heterogeneous agent models are essential for a complete understanding of asset prices.

JEL classifications: G12

Is stock trading activity important for understanding the formation of expected return? While representative-agent asset pricing models attempt to explain stock returns without trading volume, a growing theoretical and empirical literature indicates that share turnover may play a crucial role in helping us understand asset price movements (see Hong and Stein (2007) for a review). For instance, in asset pricing models featuring heterogeneous beliefs, greater divergence of opinion among investors leads to both higher turnover and higher return in the presence of short sales constraints (see, e.g., Harrison and Kreps, 1978;

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Harris and Raviv, 1993; Scheinkman and Xiong, 2003). In these models, trading volume is informative about return as it is indicative of the degree of speculation in the market. Asset pricing models featuring trading by heterogeneous agents for liquidity rationales generate similar asset pricing implications—increases in liquidity and trading lead to higher prices (see, e.g., Grossman and Miller, 1988).[2] Empirical studies also find interesting joint share turnover and stock return dynamics. Most notably, many studies find that turnover and return are positively correlated contemporaneously using daily or monthly data (see, e.g., Karpoff, 1987) and that past turnover also seems to have forecasting power for future returns (see, e.g., Baker and Stein, 2004; Piqueira, 2005). Nonetheless, it is still unclear whether heterogeneity and trading (be it due to beliefs or liquidity motives) are important determinants of asset price movements.

In this paper, we use seasonality in stock trading activity associated with summer vacation as a source of exogenous variation to study the relationship between volume and return. There is a widely held belief, backed at this point only by anecdotal evidence, that share turnover drops significantly during the summer months when market participants are on vacation, particularly in August and September for stock markets in North America and Europe. The drop in volume is thought to be part of a general slowdown of economic activity in financial markets. To the extent that this is true, we can then better understand the connection between trading volume and asset price by seeing how turnover and return co-vary across summer and non-summer months. For example, if turnover is significantly lower in the summer as is widely believed and that return is also noticeably lower during the summer, this is evidence in favor of trading activity being informative for how asset prices are determined. Our contribution in this paper is to assemble a rich set of facts regarding seasonal variations in not only trading activity and return but also return volatility, bid-ask spread, and investor behavior that allow a better understanding of whether heterogeneity is driving the volume–return relationship in stock markets.

Using share turnover and stock return data from 51 stock markets around the world, we first investigate whether there is a significant summer gone fishin' effect in trading activity. We define summer as the third quarter (July, August, and September) for Northern Hemisphere countries and the first quarter (January, February, and March) for Southern Hemisphere countries. We find that turnover is significantly lower during the summer than during the rest of the year by 7.9% (with a *t*-statistic of 3.34) on average. This effect is larger for the ten biggest stock markets though it is also significant for other countries. As expected, it is more pronounced for European and North American markets than other regions.

Moreover, we confirm the interpretation of the summer turnover dip as a gone fishin' effect by examining the seasonal behaviors of two measures of vacation activity, namely airline passenger travel and hotel occupancy rates. A caveat is that we only have data on these quantities for a small sub-set of countries, mostly those in the largest markets. We find that there is more vacation activity in the summer using both measures. These findings lend additional support to our interpretation that trading volume is lower in the summer because market participants are on vacation.

[2]Other notable theories in which volume is informative about returns include DeLong et al. (1990) (volume can be a proxy of noise trader risk and hence is associated with higher returns) and Campbell et al. (1993) and Wang (1994) (daily returns are more likely to be reversed on high trading volume as volume proxies for liquidity trades).

We then examine whether there is also a gone fishin' effect for mean return. Interestingly, we find that stock returns are lower in the summer than non-summer months. The mean monthly value-weighted market return is lower during the summer than during the rest of the year by 0.90% (with a t-statistic of 2.42). Again, this summer return effect is larger for the top ten markets than for markets outside the top ten and is more pronounced in Europe and North America than in other regions.

Importantly, there is a strong positive correlation between summer turnover dips and summer return dips. For instance, the correlation coefficient for the country-by-country regression estimates of summer turnover effect and summer return effect is 0.405 (with a t-statistic of 3.10). This key finding suggests that the mean return patterns are related to seasonality in turnover. This finding is reminiscent of the positive correlation in turnover and stock return observed in daily and monthly data and is additional evidence that turnover is important for understanding the return formation process.

We perform a number of robustness checks. We show that the seasonality findings are robust to a potential confound with the January effect and other biases pointed out in the related literature (reviewed below). We also check if there is variation in turnover and returns among the other quarters. We compare the summer, winter, and fall quarters to the spring quarter (our reference point) to see if only summer stands out or if winter or fall also differ. Perhaps there is more turnover in winter (independent of the summer effect) because of turn-of-the-year trading effects. To the extent such variation is exogenous, it might further corroborate our thesis that turnover affects returns if we also found significant return differences. There is some evidence that turnover and returns are a bit higher during the winter but these effects are not statistically significant.

Having established the volume–return relationship, we study whether trading volume is genuinely informative about returns as predicted in the heterogeneous agent framework. As such, we turn to examine a main alternative hypothesis—namely, the lower summer return has nothing to do with trading volume but is simply due to lower risk in the summer (as in the representative agent framework). We test this hypothesis by looking at whether stock return volatility (measured using either monthly or daily data) is lower during the summer. We find that volatility is slightly lower in the summer but the effect is statistically and economically insignificant. We also consider other measures of risk, such as fundamental volatility. Using a variety of proxies for fundamentals including data on quarterly GDP growth rates, quarterly earnings per share, and a number of other measures associated with analyst earnings forecasts, we do not find similar summer effects in fundamental volatility. Based on these volatility proxies, the relationship between turnover and mean return during the summer is not due to time-varying risk.

We then investigate the nature of the heterogeneity driving the volume–return relationship by using intraday trading data to see who has actually gone fishin'—retail (small) investors, institutional (large) investors, or both. This helps to distinguish between different heterogeneous models. Moreover, if large traders (and presumably market makers) have gone fishin', we would also expect the price of trading to go up as predicted by heterogeneous agent models of trading based on liquidity motives (Grossman and Miller, 1988).

Using intraday trading data in the sample period of 1993–1999, we identify retail versus institutional investors by trade size. We use the standard assumption that individual investors use small trade size (less than $5,000) and institutional investors use large trade size (over $50,000). We calculate trading activity among these two classes of investors and find a summer dip for both groups. We also find evidence that the price of trading as measured by the bid-ask spread is higher during the summer, consistent with many important traders being gone fishin' (see also Amihud and Mendelson, 1986). These findings provide further support that the summer seasonality in return is related to heterogeneity and trading. We are, however, unable to distinguish between different types of heterogeneous agent models (beliefs vs. liquidity) since these models generate similar predictions.

Our findings contribute to a growing literature that points to the role of trading volume in determining asset prices. In particular, our study is related to two recent studies. The first is by Heston and Sadka (2008), who look at seasonality in individual stock liquidity and returns. The second is by Lamont and Frazzini (2007), who find that stock returns are higher around earnings announcements. Our findings are very similar in flavor to Lamont and Frazzini in that they look at seasonality in trading activity and returns generated by periods of earnings announcements while we look at summer vacation periods. Both studies find a strong positive contemporaneous relationship between trading activity and returns.

Our paper also contributes to the literature on seasonality in stock returns. Among them is the famous "January effect" in which stocks that have suffered recent losses (especially small stocks) tend to experience reversals of fortune at the turn of the year (see, e.g., Dyl, 1977; Keim, 1983; Reinganum, 1983; Roll, 1983; Ritter, 1988; Lakonishok et al., 1991). This literature has expanded in recent years beyond the January effect to consider other forms of seasonality in stock returns (see Saunders, 1993; Bouman and Jacobsen, 2002; Hirshleifer and Shumway, 2003; Kamstra et al., 2003; Cao and Wei, 2005).

Most notably, our paper is related to two very interesting papers by Bouman and Jacobsen (2002) and by Kamstra et al. (2003). Bouman and Jacobsen document that mean return is lower from May to October compared to the rest of the year for a large cross-section of 37 countries. They also attempt to see whether their finding is due to lower trading activity during the May to October period but do not find any evidence. As a result, they argue that their finding is an important puzzle that needs to be understood. Kamstra, Kramer, and Levi argue that seasonal affective disorder (related to a lack of sunlight) increases investor risk aversion and find consistent with their hypothesis that returns are lower during the summer when there is more daylight in a sample of nine countries.

Our finding regarding lower summer returns is related to the findings in these papers. Hence our contribution is really in linking the lower return in the summer to trading volume. Indeed, we show that when one conducts our analysis of turnover using the May to October categorization as in Bouman and Jacobsen (2002), one does not observe a difference in turnover between May to October and the rest of the year. One really needs to focus on a finer analysis at the quarterly level (e.g., summer) to see the connection between trading activity and return. Moreover, our results are robust to dropping the month of September, which Kamstra et al. (2003) argue is the month with the lowest returns. This does not appear to be the case for our sample. The difference here is that we have a much larger sample of 51 countries compared to their nine countries.

The rest of our paper proceeds as follows. We describe the datasets in Section 1 and present our main empirical results and robustness checks in Section 2. In Section 3, we evaluate different explanations for our volume–return findings. Finally, we conclude in Section 4.

1. Data

Our data on the US stock market come from the Center for Research in Security Prices (CRSP). From Datastream, we collect data on the other developed markets, including Australia, Canada, Finland, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, New Zealand, Singapore, Spain, Switzerland, and the United Kingdom. From these two databases, we obtain monthly stock returns, monthly shares outstanding, monthly trading volume (shares traded), and monthly closing bid-ask spreads.[3] Our data on the remaining emerging stock markets come from the Emerging Markets Database (EMDB) provided by Standard and Poor's. From EMDB, we obtain monthly price and dividend data from which we are able to calculate monthly stock returns. EMDB also provides monthly shares outstanding and trading volume. However, it does not provide bid-ask spread information. Accordingly, we locate this information for the emerging markets using Datastream, though it is not available for every market.

The summary statistics are presented in Panel A of Table 1. There are 51 stock markets in our sample. These markets are listed alphabetically by the region or continent to which they belong, where that regional list includes Africa, Asia, Europe, Middle East, North America, Oceania, and South America. For each market, we first report in Column (1) the latitude angle of the country, which is obtained from the CIA Factbook, available online. Countries located on the equator have a latitude angle of 0. The northernmost country in our sample is Finland, with a latitude angle of 64. The southernmost country is New Zealand, with a latitude angle of −41. The country nearest to the equator, i.e., possessing the smallest absolute value of latitude angle, is Singapore, which has an angle of 1.22. The average latitude angle of the countries in our sample is 24. We will use these latitude angles in assigning seasonal dummies.

Columns (2) through (4) of Table 1 describe data on the relative sizes and maturities of the markets in our sample. We report in Column (2) the start and end dates of the data for each country. The country with the earliest start date is the US, beginning in 1962. The countries with the latest start date are Bahrain and Oman in 1999. The largest stock markets in Western Europe and Asia generally have start dates in the early 1970s. This is followed in Column (3) by the time-series average of the number of firms in each stock market (defined as those having price information) in a given month. For the US, the largest market, the average number of firms in a typical month is 5000. The smallest markets in terms of the number of firms are Bahrain and Venezuela, both of which contain an average of 14 firms in a typical month. The typical country in our sample contains about 300 stocks in a given year. In Column (4), we report the total market capitalization of each country in the year 1999. The largest country is the US, with \$14.5 trillion of market capitalization, while Slovakia is the smallest, with only \$0.56 billion. The mean market capitalization of countries in our sample is roughly \$578 billion.

Columns (5)–(7) of Table 1 report the time-series averages of the cross-sectional median, mean, and standard deviation of individual stock turnover in a given month. Share turnover is simply trading volume (shares traded) divided by shares outstanding. The first thing to note is that for most countries, the median and mean are close to each other, and furthermore the numbers look reasonable. For instance, in the US, median turnover is 3.2% per month or about 36% per year, while the mean is 6% per month or about 72%

[3]All prices and returns are expressed in the local currency.

Table 1
Summary statistics.

Panel A presents various summary statistics for each of the 51 countries in our sample along with the (equal-weighted) world averages. Latitude is the latitude angle of a country. Starting-end date is the start-to-end date of the country's sample. No. Firms is the time-series average of the number of stocks in a given month. Market Cap is market capitalization, in billions USD. It is computed using the average of monthly total market capitalization of a country in the year 1999. The average exchange rate between USD and local currency in the year 1999 is used to convert the market capitalization to USD. Median Turnover is the time-series average of the cross-sectional median turnover in a given month. Mean Turnover is the time-series average of the cross-sectional mean turnover in a given month. SD Turnover is the time-series average of the cross-sectional standard deviation of turnover in a given month. Mean Vol is the time-series average of the volatility computed using daily value-weighted market index return in a given quarter (annualized). SD Vol is the time-series standard deviation of the volatility computed using daily value-weighted market index return in a given quarter (annualized). Mean Spread is the time-series average of the cross-sectional mean bid-ask spread as a fraction of stock price in a given month. SD Spread is the time-series average of the cross-sectional standard deviation of spread in a given month. Mean Ret is the time-series average of the cross-sectional mean stock return in a given month. SD Ret is the time-series average of the cross-sectional standard deviation of stock returns in a given month. Panel B of this table summarizes Median Turnover, Mean Turnover, Mean Vol, Mean Spread, and Mean Ret for summer and non-summer months separately.

Region	Country	Latitude (1)	Starting-end date (2)	No. firms (3)	Market cap (4)	Median turnover (5)	Mean turnover (6)	SD turnover (7)	Mean vol (8)	SD vol (9)	Mean spread (10)	SD spread (11)	Mean Ret (12)	SD Ret (13)
Panel A: Summary statistics														
Africa	Egypt	27	1996–2003	58	10.66	0.013	0.027	0.046	0.199	0.066			0.004	0.114
	Morocco	32	1996–2003	18	10.62	0.007	0.009	0.008	0.168	0.188			0.010	0.055
	Nigeria	10	1984–2003	24	1.79	0.001	0.002	0.004	0.106	0.065			0.033	0.096
	South Africa	−29	1992–2003	65	113.51	0.019	0.024	0.021	0.177	0.071	0.074	0.159	0.015	0.110
	Zimbabwe	−20	1975–2003	15	1.17	0.003	0.005	0.006	0.261	0.132	0.048	0.037	0.037	0.161
Asia	China	35	1992–2003	183	138.92	0.084	0.141	0.182	0.303	0.206	0.004	0.009	0.019	0.125
	Hong Kong	22.15	1973–2005	337	424.02	0.018	0.062	0.206	0.225	0.105	0.034	0.046	0.018	0.159
	India	20	1975–2003	62	91.29	0.013	0.048	0.129	0.233	0.074			0.018	0.102
	Indonesia	−5	1989–2003	44	23.39	0.024	0.047	0.072	0.312	0.159	0.113	0.135	0.010	0.153
	Japan	36	1973–2005	1983	3935.68	0.014	1.652	61.518	0.146	0.068	0.031	0.026	0.010	0.117
	Korea	37	1975–2003	78	159.08	0.083	0.129	0.175	0.349	0.147	0.017	0.022	0.017	0.122
	Malaysia	2.3	1984–2003	85	70.14	0.018	0.042	0.075	0.463	2.122	0.038	0.051	0.010	0.109
	Pakistan	30	1984–2003	39	4.20	0.014	0.056	0.117	0.327	0.137			0.017	0.107
	Philippines	13	1984–2003	38	30.96	0.017	0.035	0.051	0.215	0.095	0.141	0.167	0.019	0.140
	Singapore	1.22	1973–2005	154	231.96	0.019	1.835	32.209	0.211	0.104	0.057	0.093	0.011	0.094

Table 1 (*continued*)

Region	Country	Latitude (1)	Starting-end date (2)	No. firms (3)	Market cap (4)	Median turnover (5)	Mean turnover (6)	SD turnover (7)	Mean vol (8)	SD vol (9)	Mean spread (10)	SD spread (11)	Mean Ret (12)	SD Ret (13)
	Sri Lanka	7	1992–2003	44	1.01	0.007	0.014	0.024	0.190	0.133			0.011	0.106
	Taiwan	23.3	1984–2003	76	201.82	0.231	0.317	0.305	0.289	0.121			0.016	0.105
	Thailand	15	1975–2003	30	33.84	0.025	0.053	0.081	0.363	0.185	0.050	0.103	0.014	0.110
Europe	Czech Rep.	49.45	1994–2003	43	9.14	0.004	0.016	0.026	0.243	0.078			−0.002	0.140
	Finland	64	1987–2005	124	215.45	0.065	2.471	25.830	0.260	0.132	0.047	0.064	0.016	0.123
	France	46	1973–2005	559	1237.21	0.007	3.542	103.761	0.190	0.072	0.049	0.094	0.052	1.278
	Germany	51	1973–2005	569	1290.54	0.020	20.321	174.177	0.172	0.086	0.039	0.057	0.009	0.152
	Greece	39	1975–2003	24	78.94	0.015	0.023	0.027	0.282	0.090			0.014	0.094
	Hungary	47	1992–2003	15	11.86	3.993	6.377	6.670	0.292	0.134	0.171	0.335	0.021	0.123
	Italy	42.5	1973–2005	238	585.54	0.028	0.427	5.923	0.203	0.079	0.019	0.032	0.014	0.126
	Netherlands	52.3	1973–2005	219	678.33	0.050	0.617	6.474	0.179	0.097	0.029	0.056	0.010	0.108
	Norway	62	1973–2005	118	57.97	0.034	0.174	0.901	0.171	0.055	0.057	0.094	0.016	0.136
	Poland	52	1992–2003	25	18.90	0.052	0.070	0.058	0.337	0.171	0.084	0.251	0.025	0.126
	Portugal	39.3	1986–1999	18	45.01	0.017	0.024	0.026	0.125	0.061	0.078	0.163	0.024	0.107
	Russia	60	1996–2003	24	20.29	1.661	4.688	10.238	0.523	0.243	0.622	0.491	0.075	0.297
	Slovakia	48.4	1996–2003	16	0.56	0.004	0.032	0.070	0.213	0.060	0.130	0.156	0.058	0.347
	Spain	40	1986–2005	128	327.43	0.048	4.059	41.176	0.168	0.073	0.014	0.020	0.018	0.116
	Switzerland	47	1973–2005	269	726.41	0.037	0.485	2.874	0.165	0.077	0.038	0.089	0.009	0.111
	Turkey	39	1986–2003	39	48.36	0.062	0.129	0.211	0.454	0.142			0.074	0.171
	UK	54	1965–2005	1772	2734.58	0.042	5.591	219.172	0.134	0.062	0.060	0.075	0.016	0.221
Middle East	Bahrain	26	1999–2003	14	5.14	0.003	0.008	0.013	0.097	0.028			0.001	0.070
	Israel	31.3	1997–2003	48	34.06	0.023	0.037	0.050	0.219	0.047			0.008	0.086
	Jordan	31	1978–2003	23	4.62	0.009	0.023	0.038	0.114	0.046			0.008	0.072
	Oman	21	1999–2003	31	3.15	0.007	0.016	0.027	0.116	0.037			0.004	0.102
	Saudi Arabia	25	1997–2003	21	35.46	0.030	0.072	0.108	0.137	0.054			0.008	0.047
North America	Canada	60	1973–2005	1712	574.88	0.013	9.265	136.047	0.119	0.064			0.033	0.594
	Mexico	23	1975–2003	45	93.16	0.014	0.025	0.034	0.256	0.091	0.051	0.095	0.042	0.142
	United States	38	1962–2005	5000	14500.00	0.032	0.060	0.162	0.127	0.060	0.051	0.059	0.013	0.148
Oceania	Australia	−27	1973–2005	578	469.91	0.016	16.443	224.136	0.128	0.062	0.087	0.138	0.032	0.352
	New Zealand	−41	1986–2005	101	22.34	0.009	0.968	9.553	0.150	0.066	0.056	0.105	0.015	0.154

South America	Argentina	−34	1983–2003	25	25.00	0.021	0.048	0.122	0.332	0.126			0.112	0.184
	Brazil	−10	1976–2003	53	104.61	0.013	0.055	0.327	0.321	0.166	0.153	0.239	0.135	0.221
	Chile	−30	1975–2003	30	42.91	0.003	0.005	0.008	0.153	0.059			0.231	0.999
	Colombia	4	1984–2003	21	6.49	0.004	0.009	0.018	0.178	0.069			0.034	0.116
	Peru	−10	1992–2003	32	7.69	0.035	0.049	0.053	0.239	0.092			0.019	0.132
	Venezuela	8	1984–2003	14	4.55	0.007	0.015	0.021	0.327	0.166			0.038	0.136
World Average		24		300	578.52	0.137	1.581	20.854	0.229	0.140	0.066	0.115	0.029	0.185

Region	Country	Median turnover		Mean turnover		Mean vol		Mean spread		Mean Ret	
		Summer	Non-summer	Summer	Non-summer	Summer	Non-summer	Summer	Non-summer	Summer	Non-summer
Panel B: Summary statistics for summer and non-summer months											
Africa	Egypt	0.012	0.013	0.024	0.027	0.198	0.200			0.014	0.001
	Morocco	0.006	0.007	0.007	0.009	0.130	0.181			0.010	0.010
	Nigeria	0.002	0.001	0.003	0.002	0.115	0.103			0.027	0.035
	South Africa	0.018	0.019	0.023	0.024	0.181	0.175	0.074	0.074	0.014	0.015
	Zimbabwe	0.003	0.003	0.005	0.005	0.270	0.259	0.047	0.049	0.050	0.033
Asia	China	0.092	0.082	0.151	0.139	0.351	0.287	0.004	0.004	0.017	0.020
	Hong Kong	0.018	0.018	0.062	0.062	0.220	0.227	0.033	0.035	0.002	0.023
	India	0.012	0.013	0.041	0.050	0.208	0.242			0.022	0.017
	Indonesia	0.027	0.024	0.051	0.045	0.330	0.307	0.114	0.112	0.019	0.007
	Japan	0.013	0.015	1.344	1.751	0.142	0.147	0.029	0.032	−0.008	0.015
	Korea	0.071	0.086	0.116	0.134	0.328	0.355	0.016	0.018	0.000	0.023
	Malaysia	0.018	0.018	0.046	0.041	0.237	0.538	0.038	0.038	−0.003	0.014
	Pakistan	0.008	0.016	0.045	0.060	0.273	0.345			0.008	0.019
	Philippines	0.018	0.017	0.034	0.035	0.208	0.217	0.145	0.139	−0.009	0.028
	Singapore	0.018	0.020	0.066	2.400	0.192	0.217	0.055	0.057	−0.014	0.019
	Sri Lanka	0.007	0.007	0.015	0.014	0.176	0.195			0.020	0.007
	Taiwan	0.208	0.238	0.289	0.326	0.291	0.288			0.003	0.020
	Thailand	0.024	0.026	0.048	0.055	0.387	0.356	0.052	0.049	0.013	0.014
Europe	Czech Rep.	0.002	0.005	0.013	0.017	0.254	0.239			0.011	−0.006
	Finland	0.052	0.069	0.684	3.051	0.247	0.264	0.054	0.044	−0.007	0.023
	France	0.006	0.008	2.478	3.882	0.204	0.186	0.047	0.049	0.008	0.066
	Germany	0.022	0.019	14.415	22.276	0.179	0.170	0.040	0.039	−0.001	0.013
	Greece	0.015	0.015	0.023	0.023	0.307	0.273			0.028	0.009

Table 1 (*continued*)

Region	Country	Median turnover		Mean turnover		Mean vol		Mean spread		Mean Ret	
		Summer	Non-summer	Summer	Non-summer	Summer	Non-summer	Summer	Non-summer	Summer	Non-summer
	Hungary	16.204	0.054	25.888	0.083	0.298	0.291	0.188	0.165	0.011	0.024
	Italy	0.022	0.030	0.550	0.387	0.211	0.201	0.021	0.019	0.006	0.017
	Netherlands	0.046	0.051	0.322	0.711	0.187	0.176	0.027	0.030	−0.007	0.016
	Norway	0.029	0.036	0.131	0.188	0.168	0.172	0.058	0.057	0.006	0.020
	Poland	0.052	0.052	0.065	0.072	0.338	0.337	0.097	0.080	0.007	0.031
	Portugal	0.015	0.017	0.021	0.024	0.129	0.124	0.085	0.075	0.049	0.015
	Russia	0.006	2.195	0.018	6.196	0.506	0.530	0.650	0.612	−0.004	0.101
	Slovakia	0.003	0.005	0.028	0.034	0.197	0.219	0.222	0.100	0.029	0.068
	Spain	0.038	0.051	6.250	3.355	0.176	0.165	0.016	0.014	−0.006	0.025
	Switzerland	0.030	0.039	0.384	0.517	0.192	0.156	0.039	0.038	−0.005	0.013
	Turkey	0.051	0.066	0.100	0.139	0.396	0.473			0.044	0.084
	UK	0.038	0.043	8.481	4.679	0.139	0.132	0.061	0.060	0.007	0.019
Middle East	Bahrain	0.003	0.003	0.008	0.008	0.099	0.096			−0.012	0.006
	Israel	0.020	0.023	0.031	0.038	0.207	0.223			−0.012	0.015
	Jordan	0.007	0.009	0.022	0.023	0.130	0.108			−0.002	0.011
	Oman	0.009	0.007	0.018	0.015	0.092	0.125			0.004	0.003
	Saudi Arabia	0.033	0.030	0.097	0.064	0.139	0.137			0.014	0.005
North America	Canada	0.010	0.013	8.516	9.504	0.110	0.122			0.030	0.035
	Mexico	0.013	0.014	0.024	0.025	0.252	0.258	0.052	0.051	0.034	0.044
	United States	0.030	0.033	0.056	0.062	0.125	0.127	0.052	0.051	0.003	0.017
Oceania	Australia	0.016	0.015	17.022	16.244	0.127	0.128	0.080	0.089	0.062	0.021
	New Zealand	0.008	0.010	0.589	1.100	0.153	0.149	0.055	0.056	−0.002	0.021
South America	Argentina	0.020	0.021	0.034	0.053	0.373	0.318			0.129	0.107
	Brazil	0.014	0.013	0.024	0.066	0.358	0.309	0.148	0.155	0.202	0.113
	Chile	0.003	0.003	0.005	0.005	0.174	0.146			0.049	0.293
	Colombia	0.004	0.004	0.009	0.009	0.157	0.185			0.020	0.038
	Peru	0.036	0.034	0.046	0.049	0.255	0.233			0.026	0.017
	Venezuela	0.007	0.007	0.014	0.016	0.274	0.344			0.043	0.037

per year (similar to figures reported by other studies). However, there are a number of countries, including Japan, Singapore, Finland, France, Germany, Hungary, Russia, Spain, United Kingdom, Canada, and Australia, for which there is a huge disparity between means and medians. For instance, in the case of Germany, the mean turnover is 2000% per month, whereas the median is 2%. While the cross-sectional distribution for turnover is likely to be right-skewed, the sizes of these disparities suggest that they may simply be due to a handful of data errors in each of these countries.[4]

Accordingly, we will work with the log of turnover, which reduces the impact of outliers on our analysis; our results, however, are similar when we use raw turnover. Using logs also aids the interpretation of our seasonal analysis, as it enables us to characterize the percentage difference in turnover between the summer and the rest of the year.

Columns (8)–(9) of Table 1 contain the descriptive statistics on stock return volatility in our sample. In Column (8), we calculate using daily market returns the volatility in each quarter (annualized) and then report the time-series average. The country with the highest individual stock return quarterly volatility is Russia, with a volatility of 52.3% (annualized). The country with the lowest quarterly volatility is Bahrain, which features a volatility of 9.7% (annualized). For the United States, quarterly volatility is 12.7% (annualized). In Column (9), we report for each country the time-series standard deviation of quarterly volatility.

For some of the countries in our sample, Datastream provides us with data on monthly closing bid-ask spreads. Where the data are available, we calculate the time-series average of the cross-sectional mean bid-ask spread as a fraction of the month-ending stock price. This is reported in Column (10) of Table 1. Most of the European countries have a mean bid-ask spread to price ratio ranging between 3% and 10%, which is in the same vicinity as the 5% figure for the US. The time-series average of the cross-sectional standard deviation of bid-ask spreads in a given month for each country is reported in Column (11). Finally, we report the time-series averages of the cross-sectional monthly mean and standard deviation of returns in each country in Columns (12) and (13).

In Panel B of Table 1, we go a step further and report the summary statistics for our four main dependent variables of interest by summer and non-summer months. Note, however, that looking at these quantities country-by-country can be very noisy given that a number of countries in our sample have less than ten years of data. Of particular interest is the difference of turnover across summer and non-summer months for the top ten markets. Fig. 1 plots the summer and non-summer turnovers side by side for the top ten markets. Note here that non-summer turnover is higher than summer turnover for every country except for Germany.

2. Seasonality in share turnover and mean returns

2.1. Seasonality in vacation activity proxies

There is plenty of convincing anecdotal evidence that this is indeed the case in North America and particularly Europe, where many businesses (except exchanges) literally shut down during certain months. Moreover, other studies using data from the World Tourism

[4]We have also experimented with winsorizing extreme observations and obtained similar results.

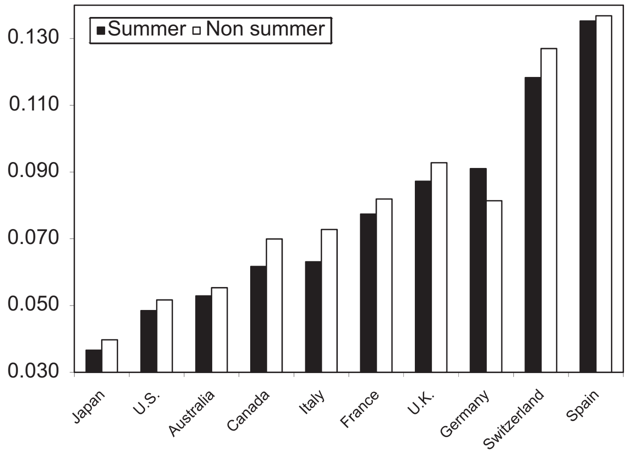

Fig. 1. Turnover in summer and non-summer months. This figure plots the time-series average of average monthly market turnover in summer versus non-summer for the largest ten stock markets (according to the country weighting in the FTSE All-World Index as of June 30, 2006). Market turnover is measured by the value-weighted individual stock share turnover (weighted by the previous month end market capitalization). The sample period for each country is shown in Table 1.

Organization report that summer months feature particularly high air travel volumes in a number of countries, consistent with our interpretation that investors are gone fishin' in the summer.

Nonetheless, to bolster our hypothesis of a gone fishin' effect in trading activity, we seek to establish that vacation activities are higher during the summer for the countries in our dataset. This analysis will be used in our subsequent study of trading activity and returns dip in the summer as stemming from investors going on vacation. We tried but were unable to obtain data from the World Tourism Organization to conduct our own analysis. However, we do have data on hotel occupancy by month for a sample of OECD countries (15 in all) through the publication *Tourism Policy and International Tourism in OECD Member Countries* (1986–1994), and for the US through Travel Industry Indicators (1999–2003). We also obtain data on air travel volume, as measured by number of passengers per month, for a sample of twelve countries, as reported by the major airlines in those countries. We are assuming that hotel occupancy rates and/or number of monthly airline passengers in a country capture when residents of that country go on vacation. This is a big assumption, since the same variables also capture the vacation activity of foreigners within a given country and non-leisure travels. Thus, while we are assuming that these variables are correlated with domestic vacation activity, we acknowledge that they are likely to be noisy proxies. Moreover, the sample sizes are limited, making statistical inference potentially noisy.

With these caveats in mind, Panel A of Table 2 presents the results of a country-by-country regression of the log of the monthly number of airline passengers on a constant, a summer seasonal dummy *SUMMER*, and year dummies. The coefficient in front of *SUMMER* is positive for all countries except for Thailand, and it is statistically significant for half of the countries in the sample. In Panel B of Table 2, we present the results of a

Table 2
Seasonality in measures of vacation activity.

Panel A reports the country-by-country regressions of the log of the monthly number of passengers traveling by air on a constant and *SUMMER*, a summer dummy defined as July–September in Northern Hemisphere countries and January–March in Southern Hemisphere countries. The regressions include year dummies. Panel B reports the country-by-country regressions of the log of the monthly hotel occupancy rate on a constant and *SUMMER*, a summer dummy defined as July–September in Northern Hemisphere countries and January–March in Southern Hemisphere countries. The regressions include year dummies. The *t*-statistics are adjusted for heteroskedasticity.

Region	Country	*SUMMER*	t-stat	Sample period	Data source
Panel A: Country-by-country air travel seasonality regressions					
Asia	China	0.254	2.53	2003–2005	Air China, China Southern Airline
	Hong Kong	0.201	1.16	2003–2004	Cathay Pacific Airline
	Japan	0.139	2.24	2004	All Nippon Airways
	Malaysia	0.054	1.05	2003–2004	Malaysia Airlines
	Singapore	0.028	0.70	2004	Singapore Airlines
	Thailand	−0.019	0.40	2004	Thai Airways
Europe	France	0.103	2.85	2004–2005	Air France
	Germany	0.130	4.94	2000–2005	Lufthansa Airline
	Norway	0.139	1.48	2003–2005	Norwegian Airline
	United Kingdom	0.146	5.61	2000–2005	British Airways
North America	United States	0.090	5.56	1990–2004	US Bureau of Transportation Statistics
Oceania	Australia	0.052	1.77	2002–2004	Qantas Airline

Region	Country	*SUMMER*	t-stat	Sample period
Panel B: Country-by-country hotel occupancy seasonality regressions				
Asia	Japan	0.04	1.63	1984–1991
Europe	Finland	0.15	5.92	1984–1994
	France	0.28	3.26	1994
	Germany	0.41	10.13	1986–1994
	Greece	0.68	6.76	1992–1994
	Italy	0.63	12.63	1984–1991
	Netherlands	0.46	6.03	1988–1992
	Norway	0.28	7.36	1984–1994
	Portugal	0.41	8.82	1985–1993
	Spain	0.37	14.77	1984–1994
	Switzerland	0.49	9.71	1984–1994
	Turkey	0.51	11.46	1984–1994
	United Kingdom	0.40	9.63	1984–1992
North America	Mexico	0.03	0.85	1992–1994
	United States	0.11	3.77	1999–2003
Oceania	Australia	0.04	1.68	1990–1994

regression of the log of the hotel occupancy rate (i.e., the fraction of hotel rooms occupied) by month in each country on a constant, summer seasonal dummy, and year dummies. The coefficient in front of *SUMMER* is positive for all countries and statistically significant for most of these countries, consistent with summer being a time of heightened vacation activity. In sum, these findings are consistent with our interpretation that trading activity is lower in the summer due to investors going on vacation.

2.2. Seasonality in share turnover

We now examine whether there is indeed seasonality in share turnover across the markets in our sample. The dependent variable of interest is $\mathrm{TURNOVER}_{i,t}$ for firm i in month t. We take the log of it to get $LOGTURNOVER_{i,t}$, and then implement the following regression specification country-by-country:

$$LOGTURNOVER_{i,t} = a_0 + a_1 * SUMMER_t + YEARDUMMIES + \varepsilon_{i,t}, \tag{1}$$

where $SUMMER$ is a seasonal dummy variable that equals one if stock i's monthly turnover observation is in the summer quarter and zero otherwise. The coefficient of interest is the one in front of the seasonal dummy, which tells us how trading activity differs in the summer as compared to the rest of the year. Specifically, a_1 is the percentage difference in turnover between summer and the rest of the year. $\varepsilon_{i,t}$ is the error term. Our specification also includes year dummies to control for time trends that otherwise would add noise to our measurement of a pure seasonal effect.[5]

The seasonal dummies for countries in the Northern Hemisphere are assigned in the following manner: winter is January through March; spring is April through June; summer is July through September; and fall is October through December. For countries in the Southern Hemisphere, the seasonal dummies are given by the following: summer is January through March; fall is April through June; winter is July through September; and spring is October through December. This definition of seasonal dummies is used throughout the paper.

For brevity, we report the detailed results of regression (1) for each of the 51 countries in Appendix Table A1. The key finding is that a significant fraction of the countries, particularly those in Europe and North America, have a statistically significant and negative coefficient on the summer dummy variable, implying that turnover is lower during the summer than during the rest of the year. For instance, the coefficient for the US is -0.089 with a t-statistic of 15.22, implying that monthly turnover during the summer is about 8.9% lower than during the rest of the year, an economically significant difference.[6] Indeed, a number of European countries such as France, Spain, and Italy have statistically significant turnover drops near or in excess of 20%. Out of the 51 countries, 38 have a negative point estimate. Under the null hypothesis that the summer coefficient for each country is zero, the regression estimate is normally distributed with mean zero, i.e., the sign of each country's coefficient (either negative or positive) is drawn from an i.i.d. Bernoulli distribution. As a result, the probability of at least 38 countries having a negative

[5]In an alternative specification whose results are not reported in this paper, we also have explored the addition of stock fixed effects, i.e., fixed mean differences across stocks, to this regression. The results from this model were similar to those of the year effects model reported in this paper. One rationale for including stock fixed effects is that larger stocks may have higher turnover than smaller stocks, and the composition of stocks in the market may be changing over time.

[6]For these country-by-country regressions, we cluster the standard errors by industries using the Fama-French (1997) classification for the US stock market and the classification provided by Datastream and EMDB for the other countries. All subsequent country-by-country regressions involving individual stocks utilize the same clustering scheme for standard errors.

coefficient is 0.0003. In other words, our finding is strongly significant. Another way to think about the significance of this finding is to observe that 32 out of the 51 countries have a statistically negative coefficient at the 5% level of significance. This is a much higher fraction than is expected from chance.

In Table 3, we summarize in various ways the summer turnover effects measured in the country-by-country regressions. We begin in Panel A by calculating the average summer

Table 3
Seasonality in share turnover.

Panel A takes the regression coefficients in front of *SUMMER* from Column (1) of the Appendix Table A1 and calculates the equal-weighted world average. Panel B calculates the equal-weighted averages for the largest ten stock markets (according to the country weighting in the FTSE All-World Index as of June 30, 2006) and for the rest of the world, respectively. Panel C calculates the equal-weighted averages for different continents/regions. Panel D calculates the equal-weighted averages for non-tropics and tropics countries, respectively. A non-tropics (tropics) country is one whose absolute value of latitude angle is larger (smaller) than 23.5. Panel E first averages the log monthly share turnover and the vacation measures (log of the monthly number of passengers traveling by air, and log of the monthly hotel occupancy rate) in summer (three-month average) and non-summer (nine-month average) of each year. The resulting panel has two observations in each year (summer/non-summer) of average turnover, air travel, and hotel occupancy. The average share turnover is then regressed country-by-country on average air travel and average hotel occupancy, respectively. The regressions include year dummies. Panel E shows the equal-weighted world average of the regression coefficients in front of the vacation measures (Air or Hotel). The *t*-statistics are adjusted for heteroskedasticity.

	SUMMER	t-stat
Panel A: Equal-weighted world average of summer turnover effect		
World Average	−0.079	3.34
	SUMMER	t-stat
Panel B: Largest 10 stock market and the rest of the world		
Top 10 markets	−0.129	4.47
Rest of the world	−0.067	2.35
	SUMMER	t-stat
Panel C: Summer turnover effect by region		
Africa	−0.073	1.21
Asia	−0.032	0.90
Europe	−0.158	3.03
Middle East	0.015	0.17
North America	−0.135	4.88
Oceania	−0.061	0.99
South America	−0.018	0.57
	SUMMER	t-stat
Panel D: Summer turnover effect for non-tropics and tropics countries		
Non-tropics	−0.120	4.06
Tropics	0.002	0.07
	Turnover	*t*-stat
Panel E: Summer turnover effect and vacation activity		
Air	−3.914	1.79
Hotel	−1.360	2.58

drop across the world. Our hypothesis is that there is a significant summer turnover drop. This is indeed what we find. Across the 51 countries, turnover during the summer is lower by 7.9% (with a *t*-statistic of 3.34) as compared to the rest of the year.[7] In Panel B, we measure the summer turnover effect separately for the largest 10 stock markets and the rest of the world. Anecdotal evidence suggests that the gone fishin' effect in turnover should be bigger for the largest markets of Europe and North America since summer vacation tends to be more important for these countries. This is indeed what we find. Among the largest 10 markets, the summer dip is −12.9% with a *t*-statistic of 4.47. For the rest of the world, the effect is −6.7% with a *t*-statistic of 2.35. So the summer drop in turnover for the largest 10 markets is about twice as large as that of the rest of the world.

In Panel C of Table 3, we regress the 51 country coefficients on the seven continent/region dummies. Among the regions in the Northern Hemisphere, monthly turnover in the summer is lower than during the rest of the year by an average of 13.5% for countries in North America, 15.8% for countries in Europe, and 3.2% for Asian countries, while there does not appear to be a summer effect in trading activity for Middle Eastern countries.[8] Among regions in the Southern Hemisphere, the summer drop in turnover during January through March is 6.1% for countries in Oceania and 1.8% for South American countries, where two of the six countries in South America actually lie north of the equator. For Africa, a region in which two of its countries (South Africa and Zimbabwe) are located in the Southern Hemisphere and the other three lie squarely in the Northern Hemisphere, the average decline is 7.3%. Note there that only Europe and North America exhibit a statistically significant summer turnover drop.

The magnitude of the summer drop in turnover varies across regions for at least a few reasons. The first might simply be measurement error. Europe and North America tend to have the longest histories of data, which allows for a better measure of the effect in these two regions. The other regions in contrast have far shorter data histories and hence are more naturally subject to measurement error.

Another potential reason (though we do not quantitatively prove but rely on anecdotes) is the existence of cultural or religious observances that may exert their own (unmeasured) seasonal effects on trading activity. For instance, summer vacation in Europe is a cultural/societal norm. The absence of a significant summer turnover effect in the Middle East may be due to these countries' major religious holidays of Ramadan and the Islamic New Year, which run through all of October and January, outside of the summer quarter. Citizens of these countries significantly curtail their activities for prayer during these periods. We expect that similar unmeasured seasonal effects due to cultural observances may also exist in Asian countries that celebrate the Chinese New Year from late January through February. Indeed, there are even significant differences in terms of the length and culture of summer vacation between Europe and North America. But these are simply conjectures.

A more refined approach would be to better measure the vacation/holiday periods across these different countries. We do not pursue this path because the data on holidays

[7]Unless otherwise stated, the standard errors reported in the cross-country regressions are adjusted for heteroskedasticity. Though there is not an obvious rationale for it, we have also calculated clustered standard errors and the results are similar. These results can be obtained from the authors. Finally, one may worry about the error-in-variable problem in the second-stage regression. But since the estimates are always on the left-hand side, this is not an issue.

[8]All Asian countries reside in the Northern Hemisphere except for Indonesia, which dips slightly into the Southern Hemisphere.

across many countries are not easy to build. We have tried but were not able to find systematic data on vacation days across countries. As a result, we focus on the summer as an admittedly crude proxy since it is standardized and easily replicable as opposed to holidays that might be more subjective. But we acknowledge that there is nonetheless measurement error with our approach and a more refined approach would likely yield even stronger results.

Another explanation for the observed regional variation in the summer turnover effect is that some regions like Asia, Africa, and Southern America include some countries near the equator, where there is not much seasonal variation in the weather. In the absence of strong seasons, people may spread their vacation activity more uniformly throughout the year, with the summer season conferring no particular advantage of better weather. Accordingly, we expect to find smaller summer drops in trading activity among countries near the equator.

To see if this is the case, we calculate the summer turnover effect by non-tropical versus tropical countries. A country is technically defined as non-tropical if its absolute latitude angle is greater than 23.5. The latitude of the Tropic of Cancer in the northern Hemisphere is 23.5 (and -23.5 is the latitude of the Tropic of Capricorn in the Southern Hemisphere). The results are presented in Panel D of Table 3. For non-tropical countries, the summer dip is 12% with a t-statistic of 4.06. For tropical countries, there is no such seasonal pattern. So it appears that part of the variation in the gone fishin' effect is related to whether a country is located in the tropics. In sum, a number of factors including cultural, religious, and geographical affect the variation in the summer turnover dip across countries.[9]

But even this is by no means perfect. For example, the "gone fishin'" hypothesis seems unlikely to explain the difference in turnover drop between Mexico (-13.1%) and US (-8.9%). Since Mexico is a tropical country, one should expect a weaker turnover effect. Additionally, the summer return effect for Mexico is not significant. This variation may be due in part to measurement error as emerging market countries tend to have more measurement error since their histories of data are shorter.

Finally, in Panel E of Table 3, we take the sample of countries in Table 2 for which we have available data on vacation proxies of air travel and hotel occupancy. For each country, we first compute the average turnover and vacation proxies (using each of the vacation proxies, Air and Hotel) in summer (three-month average) and in non-summer (nine-month average) of each year. The resulting panel has two observations in each year (summer and non-summer) of average turnover, air travel, and hotel occupancy. The average share turnover is then regressed country-by-country on average air travel and average hotel occupancy, respectively. Note that we do not have a very long sample for a number of these countries. As a result, we do not expect to find necessarily statistically significant results. The coefficient in front of Air is -3.91 with a t-statistic of 1.79 and that in front of Hotel is -1.36 with a t-statistic of 2.58. In other words, turnover is lower when there is more vacation activity. This provides a sharper test of our gone fishin' hypothesis.

[9]For the US stock market, we consider other types of Wall Street activity—namely, the number of initial public offerings (IPOs). We find a similar but less pronounced drop in this activity during the summer, consistent with our hypothesis that the drop in turnover is due to Wall Street going on vacation. We omit this result for brevity but can provide them on request.

Table 4
Seasonality in market index returns.

Panel A takes the regression coefficients in front of *SUMMER* from Column (2) of the Appendix Table A1 and calculates the equal-weighted world average. Panel B calculates the equal-weighted averages for the largest ten stock markets (according to the country weighting in the FTSE All-World Index as of June 30, 2006) and for the rest of the world, respectively. Panel C calculates the equal-weighted averages for different continents/regions. Panel D uses the regression estimates in Columns (1) and (2) of the Appendix Table A1 and calculates the correlation coefficient between the summer turnover effect and the summer return effect. Each entry in Panel E is in the form of "x/y, prob = …". "y" is number of countries with negative summer turnover effect and "x" is the number of countries with both negative summer turnover effect and negative summer return effect. "prob" is the probability of observing at least x negative return effect within the y countries that have negative turnover effect, assuming the return effect is i.i.d. across country and has half-half chance of being positive or negative. Panel F first averages the market index returns and the vacation measures (log of the monthly number of passengers traveling by air, and log of the monthly hotel occupancy rate) in summer (three-month average) and non-summer (nine-month average) of each year. The resulting time series has two observations in each year (summer/non-summer) of average index return, air travel, and hotel occupancy. The average index returns (both equal- and value-weighted) are then regressed country-by-country on average air travel and average hotel occupancy observations, respectively. The regressions include year dummies. Panel F shows the equal-weighted world average of the regression coefficients in front of the vacation measures (Air or Hotel). The *t*-statistics are adjusted for heteroskedasticity.

	SUMMER (value-weighted return)	*t*-stat	*SUMMER* (equal-weighted return)	*t*-stat
Panel A: Equal-weighted world averages of summer return effect				
World Average	−0.009	2.42	−0.009	2.16

	SUMMER (value-weighted return)	*t*-stat	*SUMMER* (equal-weighted return)	*t*-stat
Panel B: Largest 10 stock market and the rest of the world				
Top 10 markets	−0.021	6.11	−0.014	1.83
Rest of the world	−0.006	1.39	−0.007	1.57

	SUMMER (value-weighted return)	*t*-stat	*SUMMER* (equal-weighted return)	*t*-stat
Panel C: Summer return effect by region				
Africa	0.001	0.19	0.003	0.85
Asia	−0.012	2.40	−0.012	2.67
Europe	−0.021	2.75	−0.021	2.62
Middle East	−0.009	1.50	−0.011	1.57
North America	−0.011	3.02	−0.010	3.59
Oceania	−0.004	2.33	0.011	0.33
South America	0.021	1.37	0.021	1.33

	value-weighted return	*t*-stat	equal-weighted return	*t*-stat
Panel D: Correlation between summer turnover effect and summer return effect				
Correlation coefficient	0.405	3.10	0.454	3.57

	Value-weighted return	Equal-weighted return
Panel E: Each entry is in the form of "x/y, prob = …". "y" is number of countries with negative summer turnover effect and "x" is the number of countries with both negative summer turnover effect and negative summer return effect. "prob" is the probability of observing at least x negative return effect within the y countries that have negative turnover effect, assuming the return effect is i.i.d. across country and has half-half chance of being positive or negative		
Top 10 markets	9/9, prob = 0.002	9/9, prob = 0.002
Rest of the world	18/29, prob = 0.133	19/29, prob = 0.068
All countries	27/38, prob = 0.007	28/38, prob = 0.003

Table 4 (*continued*)

	Value-weighted return		Equal-weighted return	
	Value-weighted return	*t*-stat	Equal-weighted return	*t*-stat
Panel F: Summer return effect and vacation activity				
Air	−0.083	0.91	−0.529	1.01
Hotel	−0.126	1.08	−0.084	1.87

2.3. Correlation of seasonalities in turnover and returns

Having established a gone fishin' effect in share turnover, we next show that there is also a gone fishin' effect in mean returns. We begin our analysis of seasonality in returns by regressing monthly stock index returns on a summer dummy (which again is defined differently for countries in the Northern versus the Southern Hemisphere). The dependent variable is RET_t, which is the index return of a country in month t. The regression specification that we implement country-by-country is the following:

$$RET_t = b_0 + b_1 \ SUMMER_t + YEARDUMMIES + \varepsilon_t, \tag{2}$$

where $SUMMER$ is a dummy variable that equals one if the index's monthly return observation is in the summer and zero otherwise. As before, the regressions include year dummies to capture time trends in returns. The coefficient of interest is the one in front of the seasonal summer dummy, which tells us how returns differ in this quarter as compared to the rest of the year. ε_t is the error term. We run this model using both equal-weighted and value-weighted stock return indices.

For brevity, we present the detailed country-by-country results for only the value-weighted portfolio in Appendix Table A1, since the results from the regressions using equal-weighted portfolio returns are similar. Like turnover, a significant fraction of the countries have a statistically significant, negative coefficient on the SUMMER dummy variable, implying that return is lower during the summer than during the rest of the year. For instance, the coefficient for the US is −0.011 with a *t*-statistic of 2.37, implying that monthly return during the summer is about 1% lower than during the rest of the year, an economically significant difference. A number of European countries such as France, Spain, and Italy have statistically significant lower monthly returns during the summer of around 3%. Out of the 51 countries, 33 have a negative point estimate. Under the null hypothesis that the summer coefficient for each country is zero, the regression estimate is normally distributed with mean zero, i.e., the sign of each country's coefficient (either negative or positive) is drawn from an i.i.d. Bernoulli distribution. The probability of at least 33 countries having a negative coefficient is 0.034. Though weaker than our turnover results, this finding is still statistically significant. Out of the 51 countries, 19 have a statistically negative coefficient at the 5% level of significance, which is a much higher fraction than is expected from chance.

In Table 4, we summarize in various ways the seasonal effects measured in the country-by-country return regressions. We begin in Panel A by calculating the average summer return effect across the world. Across the 51 countries in our sample, monthly value-weighted market return during the summer is lower by −0.9% with a *t*-statistic of 2.42 as compared to the rest of the year. The corresponding figure for equal-weighted market return is −0.9% with a *t*-statistic of 2.16. At this broad level, it appears that the lower summer turnover is associated with a lower return, which suggests that there might be an interesting link between turnover and return.

In Panel B of Table 4, we measure the summer return effect separately for the largest 10 stock markets and the rest of the world. If there is a link between turnover and return, we would expect the return effect to be stronger for the top 10 markets since the turnover drop is more prominent for these markets. This is indeed what we find. Among the largest 10 markets, the summer return effect is −2.1% with a *t*-statistic of 6.11 using value-weighted returns and −1.4% with a *t*-statistic of 1.83 using equal-weighted returns. For the rest of the world, the corresponding effects are −0.6% with a *t*-statistic of 1.39 for value-weighted returns and −0.7% with a *t*-statistic of 1.57 for equal-weighted returns. The summer drop in return for the largest 10 markets is (similar to the turnover effect) about twice to three-times as large as that of the rest of the world.

In Panel C of Table 4, we regress the 51 country return coefficients on the seven continent or region dummies. Using value-weighted results, we find that the three regions with the strongest return effects are Asia, Europe, and North America. These three regions also have summer turnover drops. The results using equal-weighted returns are similar. The only evidence against our hypothesis is that the Middle East had a non-trivial return effect even though it does not have a significant summer turnover dip. These results are suggestive that turnover and return seasonality are linked.

We turn directly toward establishing this link in Panel D of Table 4, where we calculate the correlation between the coefficients of the summer turnover drop for each country with the coefficients of the summer return drop. Specifically, we take the country-by-country turnover regression coefficients from Column (1) of Appendix Table A1 and calculate their pairwise correlation with the return (both value-weighted and equal-weighted) regression coefficients from Column (2) of Appendix Table A1. The pairwise correlation is 0.405 with a *t*-statistic of 3.10 using value-weighted return and 0.454 with a *t*-statistic of 3.57 using equal-weighted return. In other words, the summer effects of turnover and return are strongly correlated. Another way to confirm this correlation is to look at the number of countries with summer turnover dips that also have a negative summer return coefficient. This is reported in Panel E. For value-weighted returns, it is 27 out of 38 countries (the *p*-value for drawing at least 27 out of 38 is 0.007) and for equal-weighted returns, it is 28 out of 38 (the *p*-value for drawing at least 28 out of 38 is 0.003). These are strong evidence for the correlatedness of the summer effects in turnover and return.

In Panel F of Table 4, we take the sample countries from Table 2 for which we have vacation proxies data. For each country, we first average the market returns and the vacation proxies (using each of the vacation proxies, Air and Hotel) in summer (three-month average) and in non-summer (nine-month average) of each year. The resulting time series has two observations in each year (summer and non-summer) of average market return, air travel, and hotel occupancy. The average market return (both value- and equal-weighted market returns) is then regressed country-by-country on average air travel and average hotel occupancy, respectively. Again, note that we do not have a very long sample for a number of these countries. As a result, we do not expect to find necessarily statistically significant results. For value-weighted returns, the coefficient in front of Air is −0.083 with a *t*-statistic of 0.91 and for Hotel, the coefficient is −0.126 with a *t*-statistic of 1.08. For equal-weighted returns, the corresponding figures are −0.529 with a *t*-statistic of 1.01 and −0.084 with a *t*-statistic of 1.87. All the coefficients have the expected sign and are quite sizeable economically though measurement error leads to statistically insignificant estimates, with the exception of equal-weighted returns and the Hotel proxy. But we take heart in the overall consistency of the results, particularly in conjunction with our earlier analyses.

2.4. Robustness checks

Having established the gone fishin' effects in turnover and returns and their correlatedness, we conduct a number of exercises to verify the robustness of our results.

2.4.1. Removing month of January observations

The first concern is that our findings might be related to the January effect. To this end, we re-run our analyses by dropping the month of January observation. The results are presented in Panel A1 of Table 5. The world average drop in turnover is −6.7% with a *t*-statistic of 2.77. It is slightly smaller than our baseline results in Table 3 but remains economically and statistically significant. The summer return effect is now −0.9% with a *t*-statistic of 2.56 using value-weighted returns, which is similar to our baseline summer

Table 5
Robustness check.

Panel A1 and A2 repeat the country-by-country turnover and return seasonality regressions in Columns (1) and (2) of the Appendix Table A1 except that observations in January (Panel A1) or observations in September (Panel A2) are excluded. The equal-weighted world averages of the coefficients for *SUMMER* are reported in Panel A1 and A2. Panel B of this table repeats the country-by-country turnover and return seasonality regressions in Columns (1) and (2) of the Appendix Table A1 except that it includes both a January dummy and a September dummy. The equal-weighted world averages of the coefficients for *SUMMER* and for the January and September dummies are reported in Panel B. Panel C and D repeat the country-by-country turnover and return seasonality regressions in Columns (1) and (2) of the Appendix Table A1 except that the *SUMMER* dummy is replaced with three quarterly dummies *SUMMER*, *FALL*, and *WINTER*. Panel C and D report the equal-weighted world averages of the coefficients in front of the three quarter dummies. Panel E repeats the country-by-country turnover seasonality regressions in Column (1) of the Appendix Table A1 except that the dependent variable in the country-level regressions is the cross-sectional average (weighted by the previous month end market capitalization) turnover instead of individual stock turnover. Panel E reports the equal-weighted world average of the *SUMMER* coefficients. Panel F repeats the country-by-country turnover and return seasonality regressions for the six-month period from May to October instead of for the summer. Specifically, the country-by-country turnover seasonality regression is the same as that in Panel E of this table except that the *SUMMER* dummy is replaced with a *SELLMAY* dummy, which equals 1 in the six-month period from May to October and 0 otherwise. The country-by-country return seasonality regression is the same as that in Column (2) of the Appendix Table A1 except that the *SUMMER* dummy is replaced with *SELLMAY*. Panel F reports the equal-weighted world averages of the *SELLMAY* coefficients. In Panel G, we first conduct a cross-sectional regression, following Heston and Sadka (2008), of the log of stock turnover in month t on a constant and the log of stock turnover (demeaned of market turnover defined as the equal-weighted average of the log of individual stock turnovers) in month t-12. The cross-sectional regression is done separately for each country and each month. The resulting time-series of regression intercept is then regressed country-by-country on a constant and *SUMMER*, a summer dummy defined as July–September in Northern Hemisphere countries and January–March in Southern Hemisphere countries. The regressions include year dummies. Panel G shows the equal-weighted world average of the coefficients for *SUMMER*. The *t*-statistics are adjusted for heteroskedasticity.

	Turnover	*t*-stat	Return	*t*-stat
Panel A1: Turnover and return regressions without January observations				
SUMMER	−0.067	2.77	−0.009	2.56

Table 5 (*Continued*)

	Turnover	*t*-stat	Return	*t*-stat
Panel A2: Turnover and return regressions without September observations				
SUMMER	−0.075	2.86	−0.006	1.69

	Turnover	*t*-stat	Return	*t*-stat
Panel B: Turnover and return regressions with January and September dummies				
SUMMER	−0.062	2.62	−0.006	1.81
JANUARY	0.117	1.65	0.011	1.98
SEPTEMBER	−0.025	0.88	−0.015	3.29

	SUMMER	t-stat	*FALL*	t-stat	*WINTER*	t-stat
Panel C: Turnover by quarter						
World average	−0.081	2.37	−0.041	1.06	0.036	1.04

	SUMMER	t-stat	*FALL*	t-stat	*WINTER*	t-stat
Panel D: Return by quarter						
World average	−0.0076	1.94	0.0048	1.37	0.0002	0.06

	Summer turnover	*t*-stat
Panel E: Value-weighted market turnover seasonality		
World average	−0.059	3.93

	May–October turnover	*t*-stat	May–October return	*t*-stat
Panel F: May– October turnover effect				
World average	−0.020	1.35	−0.0141	5.92

	Summer turnover	*t*-stat
Panel G: Controlling for Heston and Sadka (2008) calendar effect		
World average	−0.075	3.61

return effect in Table 4. Similar results obtain when we focus on just the largest 10 markets where the summer turnover effect is the most prominent.

2.4.2. Removing month of September observations

Another check we conduct is to see how sensitive our results are to excluding the month of September. The concern here is that Kamstra et al. (2003) find that for their sample of nine countries, the lower returns in the summer were driven by the very poor return during the month of September. Such a result is troubling since September is arguably the tail-end of summer when investors might be back from vacation. Hence, we want to verify that our summer return effect is not being driven only by the month of September. The results are presented in Panel A2 of Table 5. The summer turnover effect is smaller, with a coefficient of −0.075 and a *t*-statistic of 2.86. The summer return effect is also smaller, with a coefficient of −0.006 with a *t*-statistic of 1.69. There is still a sizeable return effect though it is measured less precisely now—significant at the 10% level. Similar results obtain when we focus on the largest 10 markets. As such, it does not appear that the summer effect is only driven by the September monthly observation.

2.4.3. Adding January and September dummies

Rather than dropping these two months of observations, in Panel B of Table 5, we add in both *JANUARY* and *SEPTEMBER* dummies when estimating the coefficient in front of *SUMMER* for both the turnover and return regressions. We find similarly strong results as before. Moreover, we also find that turnover is higher in January as is the return to the market, consistent with our concern earlier about a potential January effect.

2.4.4. Other seasonal variations in turnover and returns

We also look to see if there is variation in turnover and returns among the other quarters. We compare the summer, winter, and fall quarters to the spring quarter (our reference point) to see if only summer stands out or if winter or fall also differ. Perhaps there is more turnover in the winter (independent of the summer effect) because of turn-of-the-year trading effects. To the extent that such variation is exogenous, it might further corroborate our thesis that turnover affects returns if we also found significant return difference.

This approach is better than running our baseline regression but replacing *SUMMER* with a dummy for another quarter. In other words, we can, for instance, compare winter to the other three quarters. However, supposed that the true model is that winter, spring, and fall have a turnover of c but summer has a turnover of $c-x$, where x is the short-fall. If one runs the baseline regression with the *SUMMER* dummy, one would get an accurate estimate of x for the summer short-fall. We would essentially be comparing the summer turnover $c-x$ to the average of turnover in the other three quarters or c, which would give us a difference of $-x$. But note that if we ran the same regression, but say with a *WINTER* dummy, then we might get an effect of $x/3$, or c minus the average of the other quarters $(c+c+c-x)/3$. In other words, if the true model is that there is a summer effect, then we would mechanically find that some of the other quarters have higher turnover.

Indeed, we find for instance that winter is higher than the other quarters, whereas spring and fall are not significantly different from zero. Now some of this might be that there is, say, a distinct winter effect. For instance, there might be lots of portfolio rebalancing at the beginning of the year that can be associated with the January effect as we mentioned earlier. The summer effect might be contaminated by this other effect. On the other hand, it might be the winter effect is there because of the summer effect. As such, a better evaluation of the summer or winter effect is to compare it to either spring or fall, where there is not an ex-ante reason to think there could be an effect.

We find that indeed, there is a slight winter effect but not so different when statistically compared to the other quarters. In contrast, the summer effect is always there. As such, the summer effect is much more pronounced than any of the other three quarters when evaluated individually. In Panel C of Table 5, we show the results for the turnover regression. Observe that only the coefficient in front of *SUMMER* is significant (-0.081 with a t-statistic of 2.37). The coefficients in front of *FALL* and *WINTER* are not significant. In Panel D, we show the result for the return regression. Again, only the coefficient in front of *SUMMER* stands out (-0.76% with a t-statistic of 1.94). The coefficients in front of *FALL* and *WINTER* are again not significant. Overall, there is some evidence that turnover and returns are a bit higher during the winter but these effects are not statistically significant.

Indeed, we have also run additional statistical tests in which we examine whether winter is different from spring and fall and we do not find any evidence of this. In contrast, formal statistical tests comparing summer to spring and fall give strong results in support of our hypothesis.

2.4.5. *Value-weighted market turnover*

Up to this point, we have used individual stock turnover to study turnover seasonality. Alternatively, we can value-weight stock turnover each month to get a market turnover and run a time-series regression of market turnover on the *SUMMER* dummy. We do this in Panel E of Table 5 to see if the results are different. The coefficient in front of *SUMMER* is -0.059 with a t-statistic of 3.93, which suggests that our results are robust to how we measure turnover. Notice that this effect using value-weighted stock turnover is smaller than for the equal-weighted index, suggesting that the gone fishin' effect is stronger for small stocks than large ones.

2.4.6. *Bouman and Jacobsen's "sell in May and go away" effect*

As we stated earlier, our return regression results are similar to Bouman and Jacobsen's (2002) very interesting paper documenting the profitability of a strategy of getting out of the market index in May and coming back into the market after Halloween. The contribution of our paper is to link their return pattern to not only a summer effect but also to turnover. Bouman and Jacobsen argue that they could not find a link of their return pattern to turnover. We argue that part of the reason is that one has to focus more precisely on the summer months. In Panel F of Table 5, we re-do our *SUMMER* analysis by using a dummy for the period of May–October instead. We replicate the Bouman and Jacobsen effect—indeed, the summer return coefficient of -0.0141 with a t-statistic of 5.92 is larger than the baseline magnitude in Table 4, which is on the order of about 1% with a t-statistic of 2.42. So it appears that the "Sell in May and Go Away" effect is not simply our summer effect. However, note that we do not find a turnover effect at all using the coarse grouping of May–October, which would explain why Bouman and Jacobsen could not find the link. In sum, it appears that the summer gone fishin' effect is linked to turnover and is related (but not identical) to the "Sell in May and Go Away" effect.

2.4.7. *Heston and Sadka calendar effect*

Finally, we wonder whether our results might be driven by Heston and Sadka (2008) finding about the idiosyncratic component of stock turnover, i.e., that some stock turnover is higher in certain months and at lags of 12, 24, and 36 months. Though our results are about the common component or market turnover, we nonetheless have concerns about these idiosyncratic dynamics affecting our results.

To address this, we first conduct a cross-sectional regression, following Heston and Sadka (2008), of stock turnover in month t on a constant and the stock turnover (demeaned of market turnover) in month $t-12$. The intercept term is the average turnover of the stocks in month t purged of the autocorrelation at the annual frequency of the idiosyncratic turnover component of stocks. We then conduct our seasonal analysis as before using the constant term or the average market turnover adjusted for this autocorrelation in idiosyncratic turnover. The results are reported in Panel G of Table 5. The results are similar to results in Table 3.

3. Explanations for the joint seasonal patterns in turnover and returns

In this section, we explore a number of potential explanations for the joint seasonal patterns in turnover and returns, with an emphasis on the correlatedness of these patterns across countries. That the turnover pattern is driven by a vacation effect is eminently plausible. The more difficult question to answer is whether the return patterns are also due to this variation in turnover as a result of investors being gone fishin' or whether it is driven by some other seasonalities. We contrast the gone fishin' hypothesis with a representative-agent-based story of time-varying volatility.

3.1. Representative-agent model and seasonality in market return volatility

The time-varying volatility hypothesis is that seasonal variation in volatility drives the seasonal variations in returns. To this end, we attempt to measure seasonal variation in return volatility. For each country, we calculate for each market index i its return volatility in quarter t using the stock index' daily returns in that quarter, denoted by $VOLATILITY_{i,t}$. We then take the log of this to obtain our dependent variable $LOGVOLATILITY_{i,t}$

We implement the following regression specification, country-by-country:

$$LOGVOLATILITY_{i,t} = c_0 + c_1 * SUMMER_t + YEARDUMMIES + \varepsilon_{i,t}, \tag{3}$$

where $SUMMER$ is a dummy variable that equals one if stock i's volatility observation is the summer and zero otherwise. The coefficient of interest is the one in front of the $SUMMER$ dummy, which tells us how stock return volatility differs in the summer as compared to the rest of the year and $\varepsilon_{i,t}$ is the error term. Again, the detailed results of the country-by-country regressions are reported in Appendix Table A1.

The key summary results are presented in Table 6. In Panel A, we calculate the average summer effect for volatility across countries. There is no discernable difference in volatility between summer and the rest of the year.[10] This suggests that our return results are not driven by time-varying volatility. In Panel B, we break down the volatility results for the largest ten stock markets and the rest of the world. We again find no evidence of time-varying volatility. In Panel C, we break down the results by region and find no discernable patterns in volatility across the regions. In conclusion, the seasonal variation in volatility is not driving our turnover and return results since there is not for the most part a significant difference in volatility between summer and the rest of the year.

We have also conducted additional analyses to discern whether there is lower fundamental volatility. The results are omitted for brevity. We use data on quarterly GDP growth rates as a proxy for fundamentals and repeat the same regressions as we did for quarterly return volatility.[11] The GDP data are from the Global Insight database.

[10] The value-weighted world average of summer volatility effect, weighted using the total market capitalization of each country in Table 1, is −0.008 (t-stat 0.71).

[11] The country-by-country fundamental volatility regressions do not include year dummies due to the construction of fundamental volatility using quarterly observations across different years.

Table 6
Summer volatility.

Panel A takes the regression coefficients in front of *SUMMER* from Column (3) of the Appendix Table A1 and calculates the equal-weighted world average. Panel B calculates the equal-weighted averages for the largest ten stock markets (according to the country weighting in the FTSE All-World Index as of June 30, 2006) and for the rest of the world, respectively. Panel C calculates the equal-weighted averages for different continents/regions. The *t*-statistics are adjusted for heteroskedasticity.

	Summer volatility	*t*-stat
Panel A: Equal-weighted world average of summer volatility effect		
World average	−0.003	0.18
Panel B: Largest 10 stock market and the rest of the world		
Top 10 markets	0.016	0.77
Rest of the world	−0.007	0.40
Panel C: Summer volatility effect by region		
Africa	0.038	1.04
Asia	−0.040	1.53
Europe	0.016	0.74
Middle East	−0.027	0.33
North America	−0.051	1.79
Oceania	0.039	1.33
South America	0.023	0.39

To analyze fundamental volatility, we only focus on countries that provide non-seasonally adjusted GDP data. We find that fundamental volatility, as measured by the volatility of quarterly GDP growth rates (calculated using quarterly observations across different years), is smaller during the summer than during the rest of the year but the difference is not statistically significant. We also use the volatility of end-of-the-quarter earnings per share (calculated using the quarterly observations across different years) as a proxy for fundamental volatility. We again find an insignificant summer effect using this proxy.

We also consider more unconventional measures of fundamental volatility associated with analyst earnings forecasts. The analyst forecast data are obtained from the I/B/E/S database. We use the mean analyst earnings forecast error for each quarter, the mean number of analyst earnings forecasts issued in a quarter, and the mean number of analyst earnings forecast revisions as proxies for fundamental variance. In using these latter three proxies, we are implicitly assuming that the higher the fundamental volatility is for a quarter, the higher is the mean analyst forecast error (i.e., more difficult to forecast in a high volatility environment), the more earnings forecasts are issued (i.e., more earnings volatility or news in the economy means more analysts are working and more forecasts are issued) and the more revisions are made in that quarter (i.e., again more volatility or news leads to more updates of their forecasts). The extent to which we are able to interpret these regressions depends critically on these assumptions. We find no discernable gone fishin' effects in fundamental volatility using these proxies.

Finally, we attempt to investigate whether the number of company news stories (another proxy for fundamental volatility) exhibits seasonal variation in the form of a summer drop. We obtain from Chan (2003) data on the days in which there is public news released about a firm. This dataset has been painstakingly collected by hand using the Dow Jones

Interactive Publications Library of past newspapers, periodicals, and newswires. 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. Due to the labor-intensive nature of his data collection, Chan focuses on a random sub-set 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 compiles all dates on which the stock was mentioned in the headline or lead paragraph of an article contained in the Dow Jones library. The dataset only records if there was any news on a particular day, not the number of stories appearing on that day. We refer the reader to Chan (2003) for more details on his database.

From Chan's database, we create the dependent variable $NEWSDAYS_{i,t}$, which represents the number of days within quarter t that stock i appears in news headlines. The mean of this variable (averaged across stocks) is 5.76 days, with a standard deviation of 6.75 days. We then implement the same regression as (1), except that we replace the dependent variable with *NEWSDAYS*. While we do not report the full results for brevity, we note that the coefficient in front of *SUMMER* in this regression is −0.082 but it is statistically insignificant. Thus, it appears that there is only a slight dip in public news in the summer, an effect most likely not large enough to explain our seasonality findings.

3.2. Heterogeneous agent models, trading, and liquidity

While we have ruled out the alternative story of time-varying volatility, it is fair to ask whether there are any additional implications for a gone fishin' or heterogeneous agent hypothesis. Toward this end, we first try to get a better understanding of the nature of the heterogeneity driving the volume–return relationship by using intraday trading data. We want to see who has actually gone fishin'—retail (small) investors, institutional (large) investors, or both? For instance, if only retail investors trade less while large investors continue to trade similarly, this suggests that the heterogeneity behind our findings is along the lines of uninformed or noise traders being on vacation and smart and large investors being in the market. A dichotomy between smart and noise trader fits, in spirit, the models of DeLong et al. (1990). In contrast, if all investors including large ones are trading less in the summer, then models along the lines of Scheinkman and Xiong (2003) that emphasize speculation by investors of divergent beliefs (as opposed to the dichotomy of smart investors predating on noise traders) is more relevant.

Using intraday trading data from the NYSE Trade and Quote database (TAQ), we decompose the US share turnover into three size groups. To identify trades from retail versus institutional investors, we use the standard assumption (see, e.g., Barber et al., 2005; Lamont and Frazzini, 2007) that individual investors use small trade sizes (less than \$5000) and institutional investors use large trade sizes (over \$50,000). As confirmed by Barber et al. (2005), this classification methodology is fairly accurate before 2000, after which decimalization and algorithm trading make it less reliable; hence, our sample period is 1993–1999. For each stock in each month of our sample, we calculate the monthly sum of the dollar volume (sum of all the trades) for three different trade size categories: small is less than or equal to \$5000, large is above \$50,000, and medium is between these two breakpoints. Then we scale these monthly dollar volumes by the stock's previous

Table 7
US Summer turnover effect by trade size and trade direction.

This table decomposes the US share turnover into three size groups and two trade-direction groups using the NYSE Trade and Quote database (TAQ). The size break points are \$5,000 and \$50,000. Buyer or seller initiations are classified using the Lee and Ready (1991) procedure. The regression in Column (1) of the Appendix Table A1 is then repeated for the US for each size or trade-direction group separately, replacing the monthly share turnover with the monthly sum of the dollar volume in the corresponding size or trade-direction group scaled by a stock's previous month-end market capitalization. Panel A and B show the coefficient in front of *SUMMER* for each size and trade-direction group. The sample period is 1993-1999.

	SUMMER	t-stat
Panel A: By trade size		
Large	−0.032	2.69
Medium	−0.034	3.52
Small	−0.038	2.46
Panel B: By trade direction		
Buyer-initiated	−0.038	2.74
Seller-initiated	−0.045	4.19

month-end market capitalization. This replaces the dependent variable in the regression specification (1) for log of turnover.

The results are reported in Panel A of Table 7 for each of the trade size categories. There is equally lower turnover during the summer for each of the size categories. This suggests that all investors appear to be gone fishin,' not just a small group. We then use the methodology in Lee and Ready (1991) to classify trades as buyer versus seller initiated. A trade is classified as buyer initiated if the price is above the mid quote. If the price equals the mid quote, the trade is classified as buyer initiated if the price is above the last trade price. We then calculate trading activity among these two classes of investors as in Panel A and find a summer dip for both buyer- and seller-initiated trades. There seems to be a bit more reduction in the seller-initiated trades but the different is small. Hence, the findings in Table 7 support a gone fishin' hypothesis in which even large traders are away.

This latter finding is interesting since one might expect the summer effect to affect institutional investors less since they presumably are professionals. However, a second thought suggests that this might not be too surprising since retail investors have primary jobs and likely trade as a hobby. They are probably as likely to be able to keep up their trading (perhaps do even more) when they are outside of work. In contrast, institutional investors are always in the market and their primary job is to trade. As a result, the effect of summer on them is more unambiguous than for retail investors. So it is not clear that our gone fishin effect need only apply to retail investors.

This has implications for the price of trading (measured by the bid-ask spread) during the summer. To the extent that many important traders and potential markers are likely gone fishin', bid-ask spreads would be higher in the summer than the rest of the year (Amihud and Mendelson, 1986; Grossman and Miller, 1988). To see if this is the case, we apply our empirical analysis of summer seasonal effects to bid-ask spreads. The only caveat here is that we are only able to get bid-ask spread data for a smaller sample—thirty countries in total. We calculate the trading cost for each stock i in quarter t, denoted by $TRADINGCOST_{i,t}$, as the average of the three monthly bid-ask spreads (as a fraction of price) within that quarter. We take the log of it to get $LOGTRADINGCOST_{i,t}$, and then

Table 8
Summer bid-ask spread.
Panel A takes the regression coefficients in front of *SUMMER* from Column (4) of the Appendix Table A1 and calculates the equal-weighted world average. Panel B calculates the equal-weighted averages for the largest ten stock markets (according to the country weighting in the FTSE All-World Index as of June 30, 2006) and for the rest of the world, respectively. The t-statistics are adjusted for heteroskedasticity.

	Summer spread	t-stat
Panel A: Equal-weighted world average of summer bid-ask spread effect		
World average	0.034	2.24
Panel B: Largest 10 stock market and the rest of the world		
Top 10 markets	0.037	2.30
Rest of the world	0.034	1.59

implement the following regression country-by-country:

$$LOGTRADINGCOST_{i,t} = d_0 + d_1 * SUMMER_t + YEARDUMMIES + \varepsilon_{i,t}, \tag{4}$$

where *SUMMER* is a dummy variable that equals one if stock i's trading cost observation occurs in the summer and zero otherwise. The coefficient of interest is the one in front of the *SUMMER* seasonal dummy, which tells us how trading cost differs in the summer as compared to the rest of the year. $\varepsilon_{i,t}$ is the error term. Again, we report the coefficient in front of *SUMMER* for each country in Appendix Table A1.

The summary results are presented in Table 8. In Panel A, we calculate the average difference in trading cost between summer and the rest of the year from the country-by-country regressions. The bid-ask spreads are higher by 3.4% with a t-statistic of 2.24. In Panel B, we study the bid-ask spread seasonality separately for the largest ten markets and for the rest of the world. In both cases, we see higher bid-ask spreads in the summer, though the effect is less precisely measured outside the largest ten markets. We do not have data on bid-ask spreads for a number of regions and hence omit the region analysis. Nonetheless, the evidence in Table 8 supports the perspective that less participation by all investors results in higher bid-ask spreads or cost of trading.

4. Conclusion

We investigate the joint seasonality in trading activity and asset prices associated with vacation periods, typically the summer months, for many countries. Using data from 51 stock markets, we find strong support for the hypothesis that trading activity falls during the summer because investors are gone fishin'. Interestingly, we also find that mean stock returns are also lower during the summer for countries with significant declines in trading activity. This relationship is not due to time-varying volatility. Moreover, both large and small investors trade less and the price of trading (bid-ask spread) is higher during the summer. These findings suggest that heterogeneous agent models are essential for a complete understanding of asset prices.

Our results fit into the broader research effort to connect trading activity to prices. The positive correlation between trading activity and returns has been documented in other settings. Notably, share turnover was substantially higher during the dot-com period than after the collapse of Internet stock prices. One also observes in the time series of the aggregate market that share turnover and liquidity tend to be higher during periods when the market is doing well. The evidence here provides additional stylized facts that any theory attempting to connect volume and prices now must also explain. This paper also provides important causal evidence for the role of trading activity in influencing asset prices. More generally, this analysis suggests that we need more models that can explain the positive contemporaneous correlation of trading activity and expected returns.

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Appendix. Country-by-country seasonality regressions

Column (1) reports the country-by-country regressions of the log of the monthly share turnover on a constant and *SUMMER*, a summer dummy defined as July–September in Northern Hemisphere countries and January–March in Southern Hemisphere countries (Table A1). The regressions include year dummies. Column (2) reports the country-by-country regressions of the monthly market index (both equal- and value-weighted, only result from value-weighted index is shown) returns on a constant and *SUMMER*. The regressions include year dummies. Column (3) reports the country-by-country regressions of the log of the daily value-weighted market index return volatility in a quarter on a constant and *SUMMER*. The regressions include year dummies. Column (4) reports the country-by-country regressions of the log of the average monthly bid-ask spread as a percentage of stock price in a quarter on a constant and *SUMMER*. The regressions include year dummies. The *t*-statistics are adjusted for heteroskedasticity and correlation within Fama-French 48 industries in Columns (1) and (4), and adjusted for heteroskedasticity in Columns (2) and (3). The *t*-statistics significant at 95% level are marked by *.

Table A1

Region	Country	(1) *SUMMER* Turnover	*t*-stat	(2) *SUMMER* Return	*t*-stat	(3) *SUMMER* Volatility	*t*-stat	(4) *SUMMER* Spread	*t*-stat
Africa	Egypt	−0.154	3.17*	0.006	0.40	−0.006	0.05		
	Morocco	−0.248	5.62*	0.002	0.16	−0.078	0.40		
	Nigeria	0.004	0.07	−0.016	1.98*	0.139	1.02		
	South Africa	−0.066	3.21*	0.007	0.55	0.067	0.68	−0.035	0.48
	Zimbabwe	0.099	2.59*	0.005	0.34	0.069	0.52	0.023	0.51
Asia	China	0.092	4.48*	−0.009	0.23	0.073	0.49	−0.092	1.33
	Hong Kong	−0.025	1.61	−0.025	2.13*	−0.010	0.13	−0.013	1.22

Table A1 (*continued*)

Region	Country	(1) *SUMMER* Turnover	*t*-stat	(2) *SUMMER* Return	*t*-stat	(3) *SUMMER* Volatility	*t*-stat	(4) *SUMMER* Spread	*t*-stat
	India	−0.041	1.32	0.000	0.03	−0.136	1.81		
	Indonesia	0.243	5.77*	0.030	1.58	0.004	0.03	−0.197	1.01
	Japan	−0.039	8.12*	−0.018	1.79	−0.048	1.00	−0.005	0.81
	Korea	−0.184	12.20*	−0.019	1.47	−0.074	1.11	0.103	1.69
	Malaysia	0.029	1.62	−0.027	1.89	−0.015	0.10	−0.029	1.72
	Pakistan	−0.138	3.01*	−0.004	0.31	−0.277	2.29*		
	Philippines	−0.121	2.16*	−0.040	2.56*	−0.023	0.17	0.083	2.94*
	Singapore	0.022	1.00	−0.020	1.89	−0.116	1.61	−0.005	0.39
	Sri Lanka	0.076	2.07*	0.004	0.23	0.033	0.29		
	Taiwan	−0.243	10.72*	−0.024	1.19	−0.006	0.08		
	Thailand	−0.090	2.65*	−0.002	0.14	0.070	0.87	0.080	0.40
Europe	Czech Republic	−0.203	3.73*	0.001	0.06	0.055	0.48		
	Finland	−0.412	12.68*	−0.034	2.64*	−0.052	0.98	0.132	9.14*
	France	−0.197	15.88*	−0.033	3.91*	0.054	0.78	0.057	6.92*
	Germany	−0.058	4.54*	−0.017	2.70*	0.053	0.97	0.064	9.17*
	Greece	−0.076	4.23*	0.016	1.09	0.122	1.48		
	Hungary	0.533	3.81*	−0.021	0.86	0.043	0.32	0.015	0.22
	Italy	−0.240	16.51*	−0.030	2.53*	0.030	0.53	0.082	6.84*
	Netherlands	−0.112	8.48*	−0.029	3.31*	0.050	0.71	0.085	4.26*
	Norway	−0.246	9.13*	−0.027	2.57*	−0.059	0.76	0.110	5.78*
	Poland	−0.169	4.37*	−0.025	0.76	0.139	0.66	−0.013	0.28
	Portugal	−0.013	0.26	0.046	1.38	0.019	0.19	0.130	1.26
	Russia	−0.417	5.22*	−0.105	2.32*	−0.087	0.69	−0.048	0.76
	Slovakia	−0.375	2.41*	0.018	1.18	−0.112	1.44	0.235	1.44
	Spain	−0.277	17.09*	−0.030	3.24*	0.028	0.36	0.099	6.49*
	Switzerland	−0.097	7.92*	−0.036	3.94*	0.136	1.33	0.072	7.97*
	Turkey	−0.216	8.34*	−0.039	1.23	−0.176	2.83*		
	United Kingdom	−0.109	14.55*	−0.015	2.71*	0.026	0.38	−0.003	1.15
Middle East	Bahrain	−0.134	4.67*	−0.017	1.19	0.070	0.48		
	Israel	−0.196	6.86*	−0.025	1.39	−0.069	0.90		
	Jordan	−0.032	0.74	−0.009	1.37	0.180	1.53		
	Oman	0.275	4.02*	0.005	0.25	−0.303	1.72		
	Saudi Arabia	0.164	2.10*	0.003	0.19	−0.013	0.08		
North America	Canada	−0.185	15.33*	−0.018	2.37*	−0.107	1.55		
	Mexico	−0.131	3.51*	−0.005	0.45	−0.023	0.22	0.002	0.03
	United States	−0.089	15.22*	−0.011	2.37*	−0.022	0.53	−0.004	1.06
Oceania	Australia	0.000	0.03	−0.002	0.35	0.010	0.16	−0.033	1.96*
	New Zealand	−0.122	6.15*	−0.005	0.60	0.068	0.91	−0.017	1.05
South America	Argentina	−0.009	0.25	0.028	0.49	0.173	1.51		
	Brazil	0.039	1.83	0.090	2.01*	0.120	0.65	0.156	1.75
	Chile	−0.039	1.20	0.018	1.26	0.124	1.18		
	Colombia	−0.114	1.90	−0.019	1.75	−0.128	1.43		
	Peru	0.093	2.37*	0.009	0.54	0.036	0.28		
	Venezuela	−0.077	2.14*	0.000	0.01	−0.184	2.48*		

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