Journal of Banking & Finance 33 (2009) 1388–1399

Contents lists available at ScienceDirect

Journal of Banking & Finance

journal homepage: www.elsevier.com/locate/jbf

The wandering weekday effect in major stock markets

John R. Doyle [a,*], Catherine Huirong Chen [b]

[a] Cardiff Business School, Cardiff University, Aberconway Building, Colum Drive, Cardiff CF10 3EU, United Kingdom
[b] Department of Accounting and Finance, Middlesex University, The Burroughs, Hendon, London NW4 4BT, United Kingdom

ARTICLE INFO

Article history:
Received 26 September 2008
Accepted 9 February 2009
Available online 14 February 2009

JEL classification:
G14
G15

Keywords:
Seasonality
Weekday effect
Monday effect
Market efficiency
Stock markets

ABSTRACT

This paper reports a *wandering weekday effect*: the pattern of day seasonality in stock market returns is not fixed, as assumed in the Monday or weekend effects, but changes over time. Analysing daily closing prices in eleven major stock markets during 1993–2007, our results show that the wandering weekday is not conditional on average returns in the previous week (the "twist" in the Monday effect). Nor does it diminish through the period of analysis. The results have important implications for market efficiency, and help to reconcile mixed findings in previous studies, including the reported disappearance of the weekday effect in recent years.

1. Introduction

Seasonality effects in stock markets refer to a diverse set of findings concerning calendar "anomalies" (Thaler, 1987a,b) in the market. Collectively they show that returns are consistently higher on some days of the week, or at some times of the month, or in some months of the year, than others. These patterns are not limited to US equity markets, but appear in futures, Treasury bills, debts and exchange rates, and in non-US countries (Pettengill, 2003).

The efficient market hypothesis (EMH) suggests that all past financial information is already reflected in current stock market prices or returns (Fama, 1970). Therefore, seasonality effects challenge the EMH because they imply that, in the absence of transaction costs, excess returns can be made simply by knowing what day of the week it is, whether it is January, if it is around the turn of the month, and so on. Moreover, any persistence over time of a seasonality effect is an additional threat to EMH, because in the efficient market, once a seasonal inefficiency comes to light it should immediately self-destruct as being part of the newly updated body of information available to the public which prices are supposed to full reflect (EMH/weak). Yet apparently the Monday effect was known to traders as far back as the 1920s (Pettengill, 2003). This article describes and investigates a new and more subtle conception of seasonality which is therefore a new kind of challenge to EMH: the possibility that seasonality is in a continual state of flux, rather than fixed over time.

One frequently tested claim, day seasonality, is that returns stand predictable higher on certain days of the week than on others. Day seasonality has a number of variant formulations. The standard *Monday effect* suggests that Monday's returns are lower than those for Tuesday through Friday (French, 1980; Kamara, 1997); the *weekend effect* examines the difference between returns for Mondays and Fridays alone (Cross, 1973); and the *weekday effect* (also *day-of-week effect*, Ke et al., 2007) is simply that weekdays differ in their expected returns. Being the most general test of day seasonality, the weekday effect is preferable to testing the Monday or weekend effects because it prevents researchers from prematurely committing to an unnecessarily narrow focus and thereby missing important results. Our results support this argument.

However, going beyond the weekday effect, the main innovation in this article is to challenge the assumption of fixity in day seasonality. Previous studies, assuming that seasonality should be steady over time, have presented mixed and inconsistent findings at different sample periods even for the same indices, detailed in Section 2. But we allow that the pattern of day seasonality within a market may shift over time, yet in a manner that is distinguishable from a random process. Thus, "mixed and inconsistent findings" would be the natural state of affairs when testing for fixed seasonality. We call this the *wandering weekday effect* to

* Corresponding author. Tel.: +44 29 2087 5695; fax: +44 29 2087 4417.
E-mail addresses: doylejr@cf.ac.uk (J.R. Doyle), c.chen@mdx.ac.uk (C.H. Chen).

0378-4266/$ - see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.jbankfin.2009.02.002

distinguish it from the previously researched fixed weekday effect. To test the wandering weekday effect we model it as the interaction of the weekday effect with time, and establish that it is present in all the leading stock markets. We also show that the wandering weekday is robust to different formulations, is not driven by market trends (Jaffe et al., 1989), and has not vanished over time, contrary to Kohers et al. (2004).

The wandering weekday is important for several reasons. Looking to future research, it establishes a whole new way that markets can be shown to be inefficient, instantly increasing the vulnerability of EMH. By the same token, it means that any general theory of weekday effects must be able to account for a much more complex set of findings, which makes life difficult for them too. Looking to past research, it helps explain why evidence concerning a (fixed) weekday effect has sometimes been equivocal: different results are to be expected if data have been sampled in different time frames.

The layout of this article is as follows. Section 2 reviews past evidence for seasonality effects. Section 3 describes the sample and models to be run. Section 4 presents the results in four subsections. Section 5 is the discussion.

2. Seasonality in flux

One of the implicit assumptions made in past seasonality research is that seasonality effects are relatively stable through time. The labels on many of these findings emphasize this stability: *The Weekend Effect*, *The Monday Effect, The January Effect*, *The Turn of the Month Effect*. Researchers have acknowledged that seasonality may manifest differently for different markets, and have found *between*-market variations in these effects. For instance, Agrawal and Tandon (1994) found seven markets in their sample exhibited lowest returns on Mondays, as typically found in US data, whereas eight markets had lowest returns on Tuesdays. More recently, Basher and Sadorsky (2006) have also found divergences between day-of-the-week effects in stock markets in emerging economies.

Notwithstanding these studies, which all find some kind of weekday effect in markets, other researchers have found little or no weekday effects: Apolinario et al. (2006) studied fifteen European markets in the period 1997–2004, but found significant weekday effects in only two markets. In their analysis of the Shanghai and Shenzhen markets, Gao and Kling (2005, p. 75) claimed that "the year-end effect was strong in 1991 – but disappeared later". There are different ways to interpret these results. One commonly held view is that the final destination of all seasonality effects should be the null hypothesis. Seasonal effects should not survive public knowledge of their existence, and so will attenuate over time, showing that markets have become more efficient (Kohers et al., 2004).

On the other hand, it is possible that seasonal effects continually evolve. As an example, Mehdian and Perry (2001) found that negative Monday returns pre-1987 had become significant positive Monday returns in the post-1987 period. Evolving seasonality effects may manifest as apparent attenuation at a particular point in time, or when averaged over a period that includes both traditional and reversed Monday effects. Evolving seasonality may therefore present as absence of seasonality. The more general point is that all weekday effects in all stock markets may be in a permanent state of flux so that different researchers looking at the same series may variously report the standard effect, an absence of the effect, a reversal, or a totally new configuration, all depending on the haphazard sampling of time period that they analyse. What might be driving this flux?

One possibility that we will examine in some detail is that the wandering weekday may be driven by the conditional Monday effect, also known as the "twist" in the Monday effect (Jaffe et al., 1989). It has been found that markets on the down-turn exhibit the traditional Monday effect more strongly than markets on the up-turn, whether up-/down-turn is defined at the week level (Jaffe et al., 1989) or much longer (Liano, 1989).

However, it is also clear that the way business was done forty years ago is different from how it is done today, so the conditions that promoted a Monday effect in 1970 may no longer exist today. Settlement procedures change, governments change the days on which they announce key economic indicators (Steeley, 2001), the availability of electronic trading, the changing nature of the weekend, all have the potential to alter the significance of each day of the week. Therefore, many forces may drive the weekday effect into a continually adjusting pattern of changes. In addition, endogenous forces may destabilize the weekday effect. Contrary to the assumption that irrational effects will be automatically traded away once brought to light, there is evidence that markets over-react (De Bondt and Thaler, 1985; Lehmann, 1990), though the success of momentum trading (Antoniou et al., 2007; Asem, 2009) suggests a contrary view. If sufficient people responded to the simple formula of "Buy on Monday sell on Friday", over-reaction to seasonality effects might push Monday returns up beyond equilibrium, leading to a new pattern of seasonality, which would eventually be reacted to, and so on. What would make recursive over-reaction hard to constrain is the difficulty of framing a rational reaction to irrational and erratic tendencies.

3. Hypotheses and methods of analyses

3.1. Fixed day seasonals

Before examining the wandering weekday effect we pause to examine the day seasonals under the assumption that they do *not* vary with time, which is the usual stance taken in the literature. Temporarily laying aside the time dimension allows us to re-create what researchers would have found in this data and the conclusions they would have been forced to draw from it about EMH. This makes it a useful point of reference to judge the benefits of our later analyses of time-varying effects.

Also, the three different formulation of day seasonality are pitted against each other here. We show that the general weekday effect is more sensitive in detecting violations of EMH than the Monday or weekend effect. This superiority of the weekday formulation justifies its later use in more complicated time-varying analyses.

Until fairly recently, the standard way to analyze weekday effects was using OLS regression with daily returns as the dependent and weekday dummy variables as the independent measures. See, for example, Kamara (1997, p. 70). More recently, the ARCH/GARCH family of models (Engle, 1982; Bollerslev, 1986) have become standard. They allow researchers to model variance as conditional on past variance and error, rather than fixed throughout the series, as in regression. A GARCH(p,q) model has p autoregressive lags or ARCH terms, and q moving average lags (GARCH terms). Engle (2001, p. 166) states that "GARCH(1,1) is the simplest and most robust of the family of volatility models," and is the most widely applicable, see also Apolinario et al. (2006). Therefore, we use GARCH(1,1) to impose a standardized analysis across all markets we consider.

Obviously, day seasonality should manifest in serial correlation at lags of order 5, 10, 15, 20, etc. (Copeland and Wang, 1994), which could form the basis for an alternative perspective to that presented here. However, in this article we use ARMA terms as a simple robustness test. If the weekday/wandering weekday is unaffected by the presence or absence of ARMA terms, then the essential properties of day seasonality cannot lie solely within the short-term-memory of our ARMA window, otherwise they would be partialled out by the AR terms. To track serial correlation we used 20 lagged (AR, or autoregressive) terms plus a single moving average (MA) term. The lagged AR terms constitute 4 full weeks of trading days. In the usual notation it was ARMA(20,1). This specification is quite inclusive. To test for fixed day seasonality we use:

$$R_t = b_0 + \sum_{j=2}^{5} B_j Day_j + \sum_{k=1}^{20} \rho_k R_{t-k} + m\varepsilon_{t-1} + \varepsilon_t. \quad (1)$$

R_t are returns at time t, defined as $R_t = \log_e(p_t/p_{t-1})$, where p_t is the closing price of the index at time t; Monday is the base condition for Day dummies; ρ_k are the coefficients on the twenty lagged AR terms; m is the coefficient on the MA term. The error term ε_t is drawn from a normal distribution with variance σ_t which varies over time conditional on past variances according to the GARCH(1,1) formulation. Thus:

$$\varepsilon_t \sim N(0, \sigma_t^2),$$
$$\text{and } \sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2. \quad (2)$$

In Eq. (2), α is the coefficient on the ARCH(1) component, γ is the coefficient on the GARCH(1) component, and ω is the mean-reverting constant.

We define the traditional Monday effect to be that returns on Monday are lower than on other days of the week. There is also the possibility of a revered Monday effect (Monday's returns are higher). Therefore we use 2-tailed testing. Using an explicit notation for B_j *(1 = Mon, 2 = Tue,* etc.), the null hypothesis is therefore:

$$B_{\text{Mon}} = (B_{\text{Tues}} + B_{\text{Wed}} + B_{\text{Thu}} + B_{\text{Fri}})/4.$$

Because Monday is used as the base for the day dummies, $B_{\text{Mon}} = 0$, and the null reduces to:

$$\mathbf{H_01}: B_{\text{Tues}} + B_{\text{Wed}} + B_{\text{Thu}} + B_{\text{Fri}} = 0 \quad \text{(null for Monday effects)}.$$

The weekend effect is that $B_{\text{Mon}} < B_{\text{Fri}}$, but again presuming the possibility of a reversed weekend effect ($B_{\text{Mon}} > B_{\text{Fri}}$), and that Monday is used as the base, the null becomes

$$\mathbf{H_02}: B_{\text{Fri}} = 0 \quad \text{(null for Monday effects)}.$$

The weekday effect is that the returns for different days of the week are not equal. Presuming Monday is the base, so that $B_{\text{Mon}} = 0$, its null hypothesis is

$$\mathbf{H_03}: B_{\text{Tues}} = B_{\text{Wed}} = B_{\text{Thu}} = B_{\text{Fri}} = 0 \quad \text{(null for weekday effect)}.$$

We test **H1**, **H2**, and **H3** using post-estimation Wald tests.

3.2. Wandering weekday

The main innovation in this paper is to model the wandering weekday effect. We analyse this as the interaction of time with weekday. As already argued, the weekday formulation is more flexible than the Monday or weekend formulations. We achieve the same degree of flexibility in modelling time, by treating time as disconnected categories, in the form of year-by-year snapshots, rather than as continuous interval data, as is usual.[1] To be specific, the wandering weekday is tested as the interaction between year dummies and day dummies. It allows us to test a very general form of the hypothesis that weekday effects change over time. The hypothesis anticipates no particular form to the interaction, either generated by theory, expectations from past findings, or data snooping. In order to compare changes in the market we need no prior knowledge to decide on good breakpoints to define a before and an after, and in doing so introduce a subtle source of bias. We therefore preserve a credible Type I error rate. Finally, the generality of the method means that two markets that wander in different ways may still be meaningfully compared as to their propensity to wander.

This method differs in two important ways from those of other researchers who have reported changes in day seasonality. Our time-slice of 1 year is much smaller than multi-year periods used elsewhere (Lakonishok and Smidt 1988; Kohers et al., 2004). A year is the smallest time period that includes an entire financial cycle, all four seasons etc. Second, we use interaction terms to formally test changes in day seasonality across time-slices, rather than merely note that a significant effect in this period is no longer significant in that period. Accumulation of effects across short time-slices will turn out to be crucial for observing the findings that we do.

To summarize, we estimated time effects by dummy variables for year (1993 through 2007) and day-of-the-week effects by dummies for Monday through Friday. We estimated changes in day-of-the-week effects over time by the interaction of year *x* day dummies.

$$R_t = b_0 + \sum_{i=2}^{15} b_i \text{Year}_i + \sum_{j=2}^{5} B_j \text{Day}_j + \sum_{i=2}^{15}\sum_{j=2}^{5} \beta_{ij} \text{Year}_i \times \text{Day}_j + \sum_{k=1}^{20} \rho_k R_{t-k} + m\varepsilon_{t-1} + \varepsilon_t. \quad (3)$$

Terms are as is Eq. (1). Eq. (3) is the same as Eq. (1), but with the additional Year and Year × Day interaction terms. Monday and 1993 are the base condition for the Day and Year dummy sets, respectively. The wandering weekday has the following null hypothesis:

$$\mathbf{H_04}: \beta_{ij} = 0 \text{ jointly for } \quad i = 2, \ldots, 15, \quad \text{and}$$
$$j = 2, \ldots, 5. \quad \text{(null for the wandering weekday)}$$

$\mathbf{H_04}$ implies that, in estimating R_t, no adjustments to the Day coefficients need be made in any Year. In other words, the weekday effect does not vary with time. Rejecting $\mathbf{H_04}$ implies that it does vary with time.

3.3. Challenges to the wandering weekday

3.3.1. Wandering to a halt, or still wandering?

EMH expects that, once known about, seasonality effects should be traded away and disappear over time. As a significant weekday effect moves towards the null hypothesis of no weekday effect, it must obviously change. This change is also a weekday × time interaction, but one that has very different implications from a weekday effect that continues to wander, undiminished over time. To examine whether the weekday effect grinds to a halt (as suggested in Kohers et al, 2004) rather than continues to wander, we run the simple weekday model in Eq. (1) for each year and for each index. We measure the strength of the weekday effect at each year by combining the χ^2s for each of the indices into a combined χ^2 for that year. If the weekday is diminishing to a halt, the χ^2s should also diminish in size over the years, which can be tested by simple correlation.

3.3.2. Conditional Monday

We examine whether the wandering weekday can be explained by up-turns and down-turns of the market. The prece-

[1] The most obvious way would be to use the count of trading days since the start of the series. Thus $t_i = 1, 2, 3, \ldots, 3791$ in the case of DAX. The problem with this approach is that it assumes the wandering weekday will change in a linear fashion with time. This is an unnecessarily constrained view of how the weekday effect will wander. Including a quadratic t_i^2 term is analytically complicated, and still only captures the possibility of a there-and-back movement in weekday effects, rather than the more erratic nature of wandering.

dent for this is the conditional Monday effect (Jaffe et al., 1989). Jaffe et al. defined market down-turns/up-turns by average returns for the previous week, and found that the traditional Monday effect was bigger when the market had experienced a downturn, while in up-turns this effect was much less pronounced, or even reversed. Like the wandering weekday, then, the Monday effect changes over time, prompting the question whether the wandering weekday can be reduced to the conditional Monday. The week-sized effect of the conditional Monday aggregates to a year-sized effect quite naturally. A year that has many poor-return weeks in it would present a clear Monday effect in each week that followed, accumulating to a clear Monday effect across such a year, and so on; and vice versa for good-return years. The weekday effect would be different for good and poor years, and appear in our analyses to be wandering.

To determine whether the wandering weekday is simply the conditional Monday by another name, we need to show that the wandering weekday disappears when it is analysed in conjunction with the conditional Monday (tested as **H8**). On the other hand, if the wandering weekday does not disappear, then it is not driven by market trends. But this only needs to be tested if there actually is a conditional Monday effect present (tested as **H5**), or its variants (**H6**, **H7**).

To formulate the conditional Monday we first define a new variable to be the mean daily returns for week *T*.

$$W_T = (R_{\text{Mon},T} + R_{\text{Tues},T} + R_{\text{Wed},T} + R_{\text{Thu},T} + R_{\text{Fri},T})/5.$$

If a market was closed for part of week *T*, W_T was taken to be the mean of the days for which it was open. If it was not open at all, the means from the previous week were used: $W_T = W_{T-1}$. We use the lagged W_{T-1} as a moderator of the daily returns in week *T*, and introduce the following new terms into Eq. (3):

$$R_t = \langle \text{all terms in equation3} \rangle + \sum_{j=1}^{5} q_j W_{T-1} \text{Day}_j. \tag{4}$$

There are two aims in introducing these terms. First is to replicate the conditional Monday and extend it to the conditional weekend and conditional weekday. These are tested equivalently to the fixed effects in Section 4.1, except that H5 and H6 are directional. The conditional weekend requires that when W_{T-1} decreases, Friday returns should increase relative to Monday. Therefore, q_{Fri} should be less than q_{Mon}. Similarly, according to the conditional Monday, when $W_{T\text{-}1}$ decreases the net of Tuesday, Wednesday, Thursday and Friday should increase relative to Monday, thus enhancing the traditional Monday effect. This means that the average of their *q* coefficients should be less than Monday's. But, consistent with our strategy of general testing to avoid missing results, we can test **H5** and **H6** with 2-tailed tests to cover the possibility of reversals of the conditional effects. Null hypotheses are therefore:

$$\mathbf{H_05}: q_{\text{Mon}} = (q_{\text{Tues}} + q_{\text{Wed}} + q_{\text{Thu}} + q_{\text{Fri}})/4 \quad (\text{null for conditional Monday}),$$

$$\mathbf{H_06}: q_{\text{Mon}} = q_{\text{Fri}} \quad (\text{null for conditional weekend}),$$

$$\mathbf{H_07}: q_{\text{Mon}} = q_{\text{Tues}} = q_{\text{Wed}} = q_{\text{Thu}} = q_{\text{Fri}} = 0 \quad (\text{null for conditional weekday}).$$

Note $W_{T-1} \times$ Day are not a system of dummies so that Monday is not dropped as a base.

The second aim is to determine whether the wandering weekday is still present in the face of the conditional weekday. The null for it has the same form as $\mathbf{H_04}$.

$$\mathbf{H_08}: \beta_{ij} = 0 \text{ jointly for } \quad i = 2, \ldots, 15, \quad \text{and} \quad j = 2, \ldots, 5. \quad (\text{null for wandering weekday}).$$

The logic of using, as a control, the previous week's returns to condition this week's returns is similar to that of Venezia and Shapiro (2007). Their equivalent of W_T was the return from just the last day of the previous week, however.

3.4. Sample and data

Our sample consists of 13 closing price indices from the major markets of USA (NYSE composite, Amex composite, Nasdaq composite), Japan (Nikkei225), UK (FTSE100), Germany (DAX30), France (CAC40) and Hong Kong (Hang Seng composite), where we would expect the markets to run most efficiently. We also include China (Shanghai A Shares, Shanghai B Shares, Shenzhen A Shares, Shenzhen B Shares) and India (Sensex30) as important upcoming emerging markets.

Multiple indices aid in generalisation of the findings, particularly when drawn from developed and developing economies, and prevent data snooping, which has been seen as an endemic problem in seasonality research (Lo and MacKinlay, 1990; Sullivan et al., 2001). Multiple indices within a country (USA and China) are justified by size, but also because specific comparisons between those markets can be made with fewer confounding factors to cloud the issue. For instance, Chan et al. (2004) have documented greater levels of institutional holdings (versus individual) in the NYSE, than in Amex and Nasdaq. If institutional investors trade more efficiently than individual investors (Kamara, 1997), then NYSE should exhibit less strong day seasonal effects than Amex and Nasdaq. A more specific expectation derives from the findings of Venezia and Shapira (2007). They found that "amateurs" traded more heavily than "professionals" on Sunday (the day following the Israeli weekend), with a particular concentration on sell decisions. Since selling drives the market down, the implication is that Amex and Nasdaq, having more amateur investors than NYSE, should exhibit greater Monday effects in particular.

Also, China's stock exchanges both have a system of A shares and B shares.[2] One possibility is that the B shares should be traded more efficiently than their A share counterparts, because of the presumed greater sophistication of foreign investors. Conversely, foreign investors may not have access to the same richness of information that A-share traders have, meaning that B-shares may be traded less efficiently.

All the daily closing price index data were downloaded from Datastream for 1993–2007, inclusive. Unavailability of complete data for China prior to 1993 imposes a limit on how far back in time we go; and for compatibility of analysis we use the same time frame for all markets. The number of returns varied from 3638 (Shenzhen A) to 3791 (DAX). The descriptive statistics for returns are presented in Table 1. Panel A has a full set of descriptive statistics for each weekday for each market. Panel B has mean returns only, but disaggregated by weekday by market by year. It is at this most specific level that the wandering weekday operates. Indices were generally symmetrically distributed (median skew across all indices = −0.02). While the indices also exhibited the usual pattern of fat tails for return distributions, they were not extremely so (median excess kurtosis = 3.82). Nonetheless, we did confirm the most critical results with outlier-robust procedures. Panel C shows mean daily returns, disaggregated by year by market.

[2] A shares are traded by Chinese nationals and, after November 2002, also by a number of selected Foreign Qualified Institutional Investors. B shares may be traded by foreign investors and starting from March 2001 also be traded by Chinese nationals as well, but only with their legal foreign currency accounts.

Table 1
Descriptive statistics of the returns for the 13 indices.

		Mean (×10^6)	Median (×10^6)	s.d. (×10^6)	min. (×10^6)	max. (×10^6)	Skew	Excess kurtosis	*N*
Panel A: Descriptives for markets by weekday									
NYSE	Mon	374	679	9801	−67,911	50,499	−1.08	7.73	711
	Tue	343	390	9414	−39,556	44,795	0.07	3.00	773
	Wed	562	723	8580	−31,669	51,789	0.25	2.86	773
	Thu	63	227	9146	−39,197	47,481	0.11	2.78	759
	Fri	436	824	8959	−52,747	35,077	−0.54	2.81	757
Amex	Mon	1144	993	9969	−68,775	51,177	−0.97	8.52	712
	Tue	599	468	9480	−42,518	48,058	0.16	3.21	768
	Wed	408	479	8830	−28,587	57,668	0.34	3.15	771
	Thu	−232	283	9294	−34,829	46,683	0.10	2.02	758
	Fri	−60	397	9378	−54,766	35,406	−0.69	3.35	756
Nasdaq	Mon	−331	1108	15,847	−89,536	63,536	−0.92	4.49	713
	Tue	−125	508	16,465	−75,065	99,636	0.30	4.53	774
	Wed	1180	2159	15,844	−73,903	132,546	0.45	9.09	774
	Thu	681	1221	15,382	−49,318	85,454	0.32	2.58	759
	Fri	354	1249	15,015	−101,684	75,791	−0.28	6.04	757
Nikkei	Mon	−598	−114	15,919	−72,340	76,605	0.00	2.70	702
	Tue	588	197	12,708	−52,425	42,256	−0.02	0.82	750
	Wed	−145	−61	13,750	−68,645	72,217	0.26	2.51	751
	Thu	320	308	13,567	−59,571	45,840	−0.14	1.34	747
	Fri	−338	−118	13,236	−55,696	60,787	−0.05	2.30	746
FTSE	Mon	234	640	10,881	−55,890	45,279	−0.16	3.52	706
	Tue	78	240	10,298	−58,853	49,301	−0.10	3.30	769
	Wed	−117	220	9907	−49,178	41,089	−0.31	2.13	775
	Thu	279	222	10,694	−48,664	59,026	−0.14	3.60	774
	Fri	616	1264	10,209	−47,410	45,567	−0.36	2.18	761
DAX	Mon	320	902	9640	−57,754	43,798	−0.74	3.72	744
	Tue	−91	495	8945	−68,409	41,731	−1.18	7.90	767
	Wed	400	786	8978	−41,307	40,874	−0.21	2.20	768
	Thu	526	1129	9275	−47,738	44,505	−0.80	4.10	757
	Fri	1161	1818	8311	−45,185	34,754	−0.75	3.54	755
CAC	Mon	228	605	13,655	−60,448	68,009	−0.15	3.13	736
	Tue	345	558	12,861	−76,781	67,267	−0.21	3.99	771
	Wed	−29	452	12,679	−45,075	60,966	−0.09	1.45	769
	Thu	371	497	13,911	−56,272	61,298	−0.13	2.19	763
	Fri	547	585	12,501	−55,492	70,023	0.07	2.60	752
H'Seng	Mon	207	835	18,845	−90,988	13,3954	−0.05	6.13	715
	Tue	619	760	14,059	−14,7347	71,159	−1.36	17.22	752
	Wed	753	624	17,670	−92,854	17,2471	1.03	13.89	751
	Thu	−533	95	15,664	−10,9924	61,958	−0.72	4.70	751
	Fri	1140	566	15,188	−51,084	86,101	0.66	3.81	737
S'zhnA	Mon	876	801	27,509	−105,332	295,777	1.96	21.35	723
	Tue	−73	1408	21,196	−196,323	125,004	−1.70	17.00	729
	Wed	1332	1143	21,403	−147,763	151,718	0.47	8.99	731
	Thu	−974	−901	23,457	−102,336	259,419	1.68	22.73	730
	Fri	1301	1198	20,374	−97,964	110,645	0.32	4.90	725
S'zhnB	Mon	1610	−117	26,104	−105,332	124,655	0.43	4.63	693
	Tue	−791	−45	21,647	−100,722	97,262	−0.19	5.66	720
	Wed	265	−419	21,022	−166,994	95,274	−0.10	9.31	724
	Thu	41	−230	21,885	−87,151	103,378	0.59	4.80	720
	Fri	1515	262	22,059	−159,702	137,981	0.37	9.50	713
S'haiA	Mon	403	319	28,477	−146,005	308,523	1.55	22.01	724
	Tue	−302	1456	21,401	−184,271	116,218	−1.45	13.95	732
	Wed	1815	928	22,581	−117,405	200,777	1.93	18.36	735
	Thu	−786	−599	24,332	−117,928	278,511	1.96	27.06	734
	Fri	1482	365	20,474	−76,166	201,405	1.81	16.59	732
S'haiB	Mon	342	−1318	25,996	−102,917	121,837	0.26	3.56	720
	Tue	−348	−59	21,689	−98,659	115,262	0.38	5.81	727
	Wed	967	−444	21,333	−97,192	94,238	0.30	4.45	734
	Thu	42	−904	22,753	−86,192	95,265	0.61	3.82	731
	Fri	1342	122	20,659	−130,846	94,170	0.19	5.03	727
Sensex	Mon	584	1536	18,802	−118,092	85,915	−0.66	4.46	728
	Tue	64	724	14,468	−74,226	79,311	−0.34	3.51	727
	Wed	1370	997	15,118	−46,224	73,141	0.29	1.36	728
	Thu	576	1135	15,247	−70,033	66,670	−0.13	1.67	733
	Fri	218	918	16,006	−62,986	69,922	−0.02	2.04	723

Table 1 (*continued*)

		NYSE	Amex	Nasdq	Nikkei	FTSE	DAX..	CAC..	Hseng	S'zhnA	S'zhnB	S'haiA	S'haiB	Sensx
Panel B: Mean daily returns (x10^6) for each index and each year, 1993–1999														
1993	Mon	1722	2478	64	−2570	1192	887	861	2163	−2189	4733	−9312	2828	−5297
	Tue	−534	−834	−636	−118	−173	1866	−1037	3158	−2490	1085	−589	42	−755
	Wed	1069	746	2896	−180	2018	−236	998	4492	−1579	−1264	1377	−3333	3648
	Thu	20	−115	230	3771	496	2771	1025	4318	4407	−545	6645	1436	3890
	Fri	−697	−399	105	−186	107	2133	2201	1065	1247	1330	2475	7755	4079
1994	Mon	−152	499	−816	−754	−171	920	−186	−2655	−8053	−842	−2847	−1738	4976
	Tue	−212	−27	−578	905	−302	−1378	457	1988	1831	−3681	216	−3643	−1455
	Wed	381	540	260	561	−928	804	−2133	−302	−2776	−1537	2012	−1769	−3440
	Thu	−591	−426	25	997	−498	47	−1205	−5604	−1750	−2432	−4201	−2165	515
	Fri	−59	508	420	797	−231	−285	−618	−938	−99	−1610	34	−555	3079
1995	Mon	861	1420	−84	−1970	−616	−1120	−2067	−353	−3001	−2001	−2248	−1218	−4542
	Tue	1154	1738	515	2115	−55	1104	1233	1550	−8456	−1735	−5731	−2423	−3185
	Wed	1185	1372	1338	−262	2543	603	3129	1744	1553	−2818	1010	−1590	1718
	Thu	1030	553	2726	751	1100	43	−1133	625	−1149	−945	−789	800	−208
	Fri	1175	822	2058	−448	529	−115	−1531	572	6515	−472	4589	−1214	973
1996	Mon	1176	2142	−449	−2073	125	880	−134	2027	13578	9510	8325	1608	−1958
	Tue	−46	787	−1071	1680	440	−10	2470	2295	−3475	−287	−7109	5619	−2665
	Wed	284	−171	2250	224	−296	1467	−184	1182	8621	−543	6779	1329	4117
	Thu	870	757	1659	−346	601	−28	980	−9	−1614	3546	−3275	−899	1038
	Fri	1223	907	1681	−273	1278	554	987	313	4944	6932	5858	−617	−571
1997	Mon	1426	2565	899	−1241	1215	1206	1331	1194	1992	−1340	2992	176	1761
	Tue	5309	6676	3838	1838	3009	96	3455	−6016	−1389	−10335	−2184	−5773	1942
	Wed	−508	−1843	230	2008	1292	4765	3899	5234	1769	1200	2700	3207	2936
	Thu	−1769	−2446	−1805	−2516	−263	−937	−1972	−7805	−2580	−101	−2101	−2374	−2374
	Fri	702	−396	610	−4854	−931	−843	−1754	3099	3767	2850	4270	1001	−1026
1998	Mon	−327	865	−401	−511	2538	2101	2578	−3325	−1935	−1188	−2037	−3791	4340
	Tue	2528	2038	3364	2152	2943	867	3741	655	−2573	575	−2006	−1364	−3135
	Wed	1362	1500	3945	2160	1189	1286	2123	2450	1964	−5008	1883	−3407	229
	Thu	−2573	−3180	−3297	−3647	−3579	−3191	−4654	−2935	−1179	−7231	−1106	−5633	−1418
	Fri	1996	2099	2880	−1945	−317	31	1590	1902	1944	306	2742	811	−3873
1999	Mon	306	2162	3940	2610	2028	−666	3852	4690	−1189	1455	−1368	1109	5897
	Tue	−3227	−2263	−3327	752	−1856	−555	−1486	253	−776	−8150	−491	−7824	3136
	Wed	1787	1436	5471	−474	−141	−492	−60	−1489	4306	1791	4336	317	2527
	Thu	840	968	1616	3237	1702	2077	3551	3238	−384	10777	595	8093	1182
	Fri	2103	1109	4785	328	1641	585	2396	4132	1273	4270	553	4373	−2513
2000	Mon	2063	3949	−5850	2854	−1802	825	−717	−2430	5211	6706	5095	8108	268
	Tue	801	1052	−1233	−957	−120	307	1430	−76	−223	−4331	−837	−2239	−748
	Wed	−2595	−2115	−10128	−741	−1949	−1364	−5541	−372	997	3810	752	6408	1131
	Thu	1612	−74	4216	−6001	−175	802	2192	−4163	1166	−366	1619	2384	−1844
	Fri	−1471	−4006	2950	−1516	1798	2036	2605	4747	2601	4629	2152	3538	−3496
2001	Mon	−479	−168	−2547	−7195	455	−79	2652	−4021	−4914	2490	−4483	1639	−1440
	Tue	113	414	−2672	1820	−526	−204	−1858	97	3722	7612	3888	6072	1196
	Wed	−1177	−1338	2414	−1761	−1337	−1550	−1696	−952	−2066	−821	−2012	4008	1915
	Thu	1316	1870	4448	641	−595	−674	−739	224	−3749	1535	−3375	178	883
	Fri	−1947	−1758	−6473	442	−1414	987	−3140	−1247	497	3330	834	2062	−6812
2002	Mon	−2006	−1503	−2497	−2604	−2501	−2810	−3867	−913	−2757	−6671	−3073	−5548	−463
	Tue	−3471	−2565	−5348	−2829	−2079	−3131	−1952	464	2463	−985	2910	−1779	−1906
	Wed	2380	2639	4087	−2032	−4041	−2771	−3502	−2712	−2787	−578	−2595	−963	−640
	Thu	−992	−1166	−2376	3446	2863	390	3041	822	645	1389	484	1405	591
	Fri	−314	−508	−1381	−364	107	1189	−1823	−1773	−1778	−594	−1749	−1822	3022
2003	Mon	986	1232	2347	2170	1664	1698	−269	2210	521	2074	1267	−1509	1287
	Tue	1620	1555	4114	1042	−386	−651	−1314	1288	1140	1289	1424	724	2021
	Wed	−591	−1127	−868	1654	−1557	531	−712	302	845	2331	1789	665	2518
	Thu	1706	837	3893	−1088	718	3141	2306	−1237	−1219	1200	−766	67	1223
	Fri	1340	1316	−1412	845	2244	3082	3066	3517	−2266	842	−1766	−1613	3860
2004	Mon	188	136	867	1046	−710	−420	−779	85	−2206	−2648	−2089	−5868	−1235
	Tue	1394	1171	1408	−581	885	783	468	2031	1646	1886	1327	2580	2612
	Wed	436	940	485	744	393	641	758	−116	1185	3683	967	1751	112
	Thu	−187	−453	−678	−1368	340	636	368	−975	−2460	−2997	−2357	−1722	181
	Fri	479	−436	−443	1642	439	1979	543	1438	−1824	−4133	−1192	−3381	676

(*continued on next page*)

Table 1 (*continued*)

		NYSE	Amex	Nasdq	Nikkei	FTSE	DAX..	CAC..	Hseng	S'zhnA	S'zhnB	S'haiA	S'haiB	Sensx
2005	Mon	1111	624	1299	2500	1178	2576	1521	1787	−259	−4202	−716	−5531	2783
	Tue	−915	−1165	−929	1534	1017	800	1300	−979	−568	1390	−1033	1300	457
	Wed	250	−125	−275	696	−1121	−258	−847	−67	3410	1658	2966	3066	1017
	Thu	−10	−812	72	50	−18	165	71	61	−3316	−2477	−2843	−2872	580
	Fri	1003	378	250	2242	2112	2785	2098	178	−1840	1108	−173	−218	2235
2006	Mon	−192	369	−346	−1683	313	−384	−243	−36	6835	8882	7376	7046	−476
	Tue	640	534	44	−1113	−1624	−1549	−1256	−1097	2879	550	3128	203	428
	Wed	1907	1961	2503	−1362	1706	2562	2813	2545	1602	2194	2222	3494	2694
	Thu	1007	673	917	4109	911	2456	1447	2893	113	1678	832	926	2066
	Fri	−196	−613	−1418	1340	669	1738	348	1459	2597	3220	3799	3697	2987
2007	Mon	−1035	371	−1352	166	−1409	−852	−1043	2567	11676	7251	9764	8002	1721
	Tue	7	−32	574	792	−129	214	−493	3687	5373	3380	3090	3854	2614
	Wed	2263	1729	3242	−3214	408	55	482	−654	3062	115	2963	2081	99
	Thu	−1298	−403	−1394	2859	562	−37	−36	2300	−1577	−1605	−1330	1209	2825
	Fri	1251	123	697	−3013	1204	1510	1336	−1020	1922	1146	−417	6239	469

Note that the first five data columns have been scaled by 10^6.

4. Results

Because the conclusions drawn from with-ARMA and no-ARMA analyses are so similar (though with-ARMA results tend to be slightly more powerful), in the text we discuss only the with-ARMA versions unless otherwise stated. Both with-ARMA and no-ARMA analyses are presented in the Tables, however.

4.1. Fixed weekday effects

Table 2 shows that the Monday effect is significant at 5% for only Amex, and the weekend effect is significant for Amex and DAX. Given that thirteen indices have been analysed, the researcher might conclude that finding one or two significant results is not much better than chance. This is confirmed by summing the χ^2s and the *df*s into a combined χ^2 test for the 13 indices. We have: the Monday: $\chi^2(13) = 13.52$, $p > 0.4$; the weekend: $\chi^2(13) = 13.64$, $p > 0.4$. We cannot reject $\mathbf{H_0 1}$ or $\mathbf{H_0 2}$. By failing to find inefficiencies, these results would be taken as evidence supporting EMH across the globe.

A different story emerges from analysing the more general weekday effect. We find results significant at 5% for Amex, Nasdaq and DAX. Combining χ^2s across all indices we find a significant effect for combined $\chi^2(52) = 77.96$, $p = 0.011$. We therefore reject $\mathbf{H_0}$ **3.** Furthermore, no significant results were found for the Monday or weekend effects that were not also found for the weekday effect. Therefore, the omnibus weekday test detected the same effects that the Monday and weekend tests detected, but more besides.

We draw two conclusions. First, seasonality effects still exist to push returns for some days of the week lower than for others, though not necessarily Monday relative to Friday, or Monday relative to the rest of the week. These effects, more evident in some markets than others, must persist long enough to register as time-invariant day-of-the-week differences, certainly long enough to take it outside the ARMA window of 20 lags. Second, the continued existence of relatively stable seasonality effects may have been missed had we taken too narrow a perspective (e.g. testing only for the Monday effect). Analysing for the more general weekday effect, rather than the specific Monday or weekend effects, is not only good statistical practice, but turns out to have been more powerful in rejecting the null of market efficiency.

4.2. Wandering weekday effect

To test H4, the wandering weekday effect, we use Eq. (3). The null is that the weekday effect does not change its pattern significantly over the years of analysis. Obviously, in rejecting $\mathbf{H_0 4}$ we would be undermining the very assumption we made in analysing the fixed weekday effect in (Section 5.1), which is the same assumption tacitly made in previous research. The results for tests of the year × day interaction terms are in Table 3. Most obviously, the wandering weekday is significant at the 1% level for all 13 indices. Therefore we reject $\mathbf{H_0 4}$. The results present a much stronger case against EMH than those from the previous section.

Analyzing the S&P500 from 1980 onwards, Galai et al. (2008) found that outliers in the data tended to mask seasonality effects. However, it is also possible that in other data outliers might actually be *responsible* for (spurious?) seasonality effects that would not be found if outliers were eliminated from the data. Therefore, as a general robustness check, the assumption of Gaussian disturbance terms was relaxed, by repeating the analyses but using the general error distribution (GED). Rather than excluding extremes readings as unlikely to have come from a Gaussian distribution (i.e. treat them as outliers, as in Galai et al.), this approach seeks to incorporate extremes as natural observations from fat-tailed distributions. All results were again significant, the overall level of significance of the GED version (geometric mean probability = $1.26 * 10^{-11}$) being approximately equivalent to the Gaussian version ($5.29 * 10^{-10}$). Furthermore, the ranking of the indices by strength of wandering weekday was roughly as before (Spearman's rank correlation Rho = 0.83).

The interaction of year × day (wandering weekday) is that the pattern of the weekday effect is not fixed but changes over time. Different from the random walk, which has no memory, the weekday effect must have some memory so that it dwells near one pattern long enough to be detected within our one-year time-slices. On the other hand, the wandering weekday does not have the near-perfect memory of the fixed weekday, which is presumed to be stable over time. Therefore, in terms of its memory, the wandering weekday effect lies between the random walk and the fixed week effect. It is transiently stable.

There are several more specific points of interest. First, if the size of the wandering weekday is a sign of market inefficiency, then we can see from Table 3 that the Indian and Chinese markets were generally more inefficient than those in western economies, as anticipated at the outset. Second, the evidence is positive but weak for the greater efficiency of NYSE than Amex and Nasdaq. Recall that NYSE has a greater proportion of institutional investors than the other two. The size of the fixed weekday effect is larger for Amex and Nasdaq than for NYSE, but the size of the wandering weekday effect is greater for Nasdaq than both NYSE and Amex, which are themselves about equivalent. Note

Table 2
Analyses of Monday, weekend and weekday effects, assuming time-invariance.

	No ARMA			With ARMA		
	Monday χ^2 $_{(df=1)}$	Weekend χ^2 $_{(df=1)}$	Weekday χ^2 $_{(df=4)}$	Monday χ^2 $_{(df=1)}$	Weekend χ^2 $_{(df=1)}$	Weekday χ^2 $_{(df=4)}$
NYSE	0.43+	0.20+	2.01	0.45+	0.17+	1.95
Amex	**6.48+**	**6.43+**	**11.32**	**6.34+**	**5.82+**	**11.03**
Nasdaq	0.17−	0.08+	**11.80**	0.19−	0.11+	**13.06**
Nikkei	1.82−	0.24−	4.26	1.81−	0.21−	4.00
FTSE	0.00−	0.94+	3.47	0.00−	1.01+	3.76
DAX	0.68−	**4.89+**	**12.78**	0.64−	**5.14+**	**12.54**
CAC	0.01+	0.23+	1.20	0.01+	0.25+	1.08
Hang Seng	0.34+	0.01+	1.47	0.30+	0.00+	1.47
Shenzhen A	0.54−	0.30−	8.96	0.24−	0.41−	5.76
Shenzhen B	3.07+	0.00+	**10.14**	3.09+	0.01+	8.78
Shanghai A	0.20−	0.01−	6.56	0.12−	0.08−	6.45
Shanghai B	0.07−	0.05+	2.63	0.09−	0.28+	3.08
Sensex	0.22+	0.15+	5.16	0.24+	0.15+	5.00
	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.
NYSE	0.512	0.655	0.734	0.502	0.680	0.745
Amex	**0.011**	**0.011**	**0.023**	**0.012**	**0.016**	**0.026**
Nasdaq	0.680	0.777	**0.019**	0.663	0.740	**0.011**
Nikkei	0.177	0.624	0.372	0.179	0.647	0.406
FTSE	1.000	0.332	0.482	1.000	0.315	0.439
DAX	0.410	**0.027**	**0.012**	0.424	**0.023**	**0.014**
CAC	0.920	0.632	0.878	0.920	0.617	0.897
Hang Seng	0.560	0.920	0.832	0.584	1.000	0.832
Shenzhen A	0.462	0.584	0.062	0.624	0.522	0.218
Shenzhen B	0.080	1.000	**0.038**	0.079	0.920	0.067
Shanghai A	0.655	0.920	0.161	0.729	0.777	0.168
Shanghai B	0.791	0.823	0.622	0.764	0.597	0.545
Sensex	0.639	0.699	0.271	0.624	0.699	0.287
Combined χ^2	14.03	13.53	**81.76**	13.52	13.64	**77.96**
df	13	13	52	13	13	52
Probability	0.372	0.408	**0.005**	0.408	0.400	**0.011**

The daily returns for each stock market in turn, in the period 1993–2007, are estimated by weekday dummies, as in Eq. (1). The error term was modeled by GARCH(1,1). For each index ARMA(20,1) terms were either included (three columns of data on the right), or not (three columns of data on the left). The upper panel contains the χ^2 statistics from post-estimation Wald test, which are conducted to test the following:
H1: Returns on Monday are lower than for the other days of the week (Monday effect, data columns 1 and 4).
H2: Returns on Monday are lower than on Friday (Weekend effect, data columns 2 and 5).
H3: Returns differ between days of the week (Weekday effect, data columns 3 and 6).
The probabilities for each of these χ^2 tests are in the panel below, with 5% significant results in bold. To gauge the overall significance across all 13 indices, χ^2 and degrees of freedom are summed column-wise to give combined χ^2 tests. These and associated probabilities are reported in the last three rows. The plus or minus sign that follows the $\chi^2(1)$ statistics indicates the direction of the effect, with minus indicating that Monday returns were lower, as in the traditional Monday and weekday effects. Note also, $\chi^2(1) = z^2$, so these columns can be turned into z-tests.

Table 3
Wandering weekday effect for 13 indices.

	No ARMA		With ARMA	
	χ^2 $_{(df=56)}$	Prob.	χ^2 $_{(df=56)}$	Prob.
NYSE	97.56	0.0005	117.18	<0.0001
Amex	98.95	0.0004	104.25	<0.0001
Nasdaq	120.36	<0.0001	153.26	<0.0001
Nikkei	77.83	0.0284	90.04	0.0026
FTSE	79.88	0.0198	97.48	0.0005
DAX	91.26	0.0020	118.30	<.0001
CAC	87.36	0.0046	103.28	0.0001
Hang Seng	80.48	0.0177	95.67	0.0008
Shenzhen A	432.02	<0.0001	213.89	<0.0001
Shenzhen B	250.85	<0.0001	282.51	<0.0001
Shanghai A	565.01	<0.0001	153.62	<0.0001
Shanghai B	142.29	<0.0001	162.30	<0.0001
Sensex	128.02	<0.0001	148.76	<0.0001

The daily returns for each stock market in the period 1993–2007 are estimated by weekday dummies, year dummies, and the interaction of day × year dummies as in Eq. (3). As in Table 1, error is estimated by GARCH(1,1), and estimates are repeated both with and without ARMA(20,1). Post-estimation Wald tests are conducted to test:
H4: The year × day coefficients are jointly different from zero.
χ^2s for this test are in data columns 1 (no ARMA in estimation), and 3 (ARMA included), and associated probabilities are in columns 2 and 4, respectively.

also that the specific Monday effect was no more pronounced than the general weekday for Amex and Nasdaq relative to NYSE, as anticipated by our extrapolation of the findings in Venezia and Shapiro (2007). Finally, there is no real support for the contention that Chinese B shares would be traded more efficiently than A shares, or vice versa.

4.3. Challenges to wandering weekday effect

4.3.1. Still wandering

To test whether the weekday effect wanders to a halt or continues to wander, we reran Eq. (1) for each index but for each of the 15 years separately. For these analyses no-ARMA results are presented in Table 4[3].

For each year the combined χ^2 statistic across all indices was used as a simple measure of the strength of the weekday effect present in that year. The results are clear cut. There was no decrease (or increase) in the size of the weekday effect over the period (Spearman's Rho = −0.11 for the correlation of year with size of effect). The same lack of trend was found when the indices were

[3] When ARMA components were modeled, 47 of the 195 GARCHs failed to converge, possibly due to under-constraint in estimating with these additional 21 terms. For this reason, we used no ARMA.

Table 4
Year-by-year weekday effects.

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
NYSE	5.24	1.07	0.12	4.31	7.89	4.24	8.01	**11.10**	2.15	3.36	2.11	1.11	2.61	4.92	7.68
Amex	6.91	0.97	3.71	4.09	**16.98**	3.99	6.13	**11.14**	2.72	2.88	3.93	2.63	2.39	**11.52**	2.69
Nasdaq	9.40	1.69	0.90	6.83	4.18	**10.38**	**9.93**	8.80	3.14	5.45	8.06	1.54	1.96	7.39	7.29
Nikkei	3.38	1.85	1.59	2.55	5.18	8.23	6.70	**13.26**	5.66	5.66	2.04	2.72	5.60	6.38	**10.65**
FTSE	3.62	0.48	6.79	2.44	6.62	3.51	8.04	4.09	0.63	8.78	3.88	1.73	**11.66**	**11.39**	3.22
DAX	5.80	4.93	6.21	3.10	**10.91**	1.97	4.85	3.83	6.98	4.99	4.60	2.27	8.74	**12.78**	0.29
CAC	5.61	2.16	7.26	4.52	8.12	4.00	8.01	**11.40**	4.84	5.66	3.25	0.37	7.03	9.31	3.85
H' Seng	1.86	2.86	1.84	2.36	8.81	2.20	4.13	6.79	1.07	6.73	4.20	3.38	3.26	6.28	**10.13**
S'zhen A	5.34	**15.10**	1.75	5.48	6.90	6.30	4.69	0.94	**13.05**	**11.12**	6.49	4.79	6.06	9.22	8.76
S'zhen B	8.95	0.65	2.54	**12.95**	8.68	**35.32**	**10.10**	3.79	4.31	5.19	0.72	7.20	**12.88**	**23.25**	4.47
S'hai A	5.62	**20.15**	0.59	**13.84**	4.56	6.56	3.90	1.55	**13.63**	**12.94**	5.54	4.83	3.53	9.06	8.18
S'hai B	8.38	5.70	2.83	4.57	3.53	2.82	5.04	2.36	6.77	6.27	3.86	8.76	7.52	7.81	1.31
Sensex	5.49	**11.01**	**12.20**	7.89	2.11	**15.70**	**12.00**	1.38	**9.62**	5.64	0.83	0.82	3.54	0.90	2.08
df	52	52	52	52	52	52	52	52	52	52	52	52	52	52	52
Comb. χ^2	70.1	68.6	48.3	74.9	94.5	105	79.5	67.2	74.6	84.7	38.2	42.2	76.8	120	70.6
Prob.	**0.048**	0.061	0.619	**0.020**	**<0.001**	**<0.001**	**0.008**	0.077	**0.022**	**0.003**	0.923	0.834	**0.014**	**<0.001**	**0.044**
Developed	41.82	16.01	28.42	30.20	**68.69**	38.52	**55.80**	**70.41**	27.19	43.51	32.07	15.75	43.25	**69.97**	45.80
df	32	32	32	32	32	32	32	32	32	32	32	32	32	32	32
Developing	**33.78**	**52.61**	19.91	**44.73**	25.78	**66.70**	**35.73**	10.02	**47.38**	**41.16**	17.44	26.40	**33.53**	**50.24**	24.80
df	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20
Counts															
$p < 0.10$	3	3	1	3	6	4	6	5	3	3	1	1	3	8	4
$p < 0.05$	0	3	1	2	2	3	3	4	3	2	0	0	2	4	2
$p < 0.01$	0	2	0	1	1	2	0	0	1	0	0	0	0	1	0

Each cell in the main 13 indices × 15 years matrix is a separate $\chi^2(4)$ test of the weekday effect for that index in that year. The extent to which weekday effects were present in a particular year is gauged by combining χ^2 (sum of the columns). Note, 10 of the 15 years had significant combined χ^2s and two further were marginally significant. Critical values of χ^2 with $df = 4$ are 7.78 (10% level) and 9.49 (5%). We also show combined χ^2s for developed (first 8 indices) and developing economies (last 5 indices). Significant results (5% level) are in bold.

analysed separately for developed and for developing economies: Rho = −0.28 and 0.18, respectively. Therefore, the wandering weekday is not a weekday effect in 1993 grinding towards a halt in 2007, as in the disappearing weekday scenario painted by Kohers et al. (2004). Instead, the weekday effects are as strong in 2007 as they were in 1993, albeit having different forms. The wandering weekday is still wandering.

4.3.2. Conditional weekday vs. wandering weekday

In this subsection we consider whether the wandering weekday effect can be explained by the moderating effect of market upturns and downturns.

In comparison with Table 2, the results in Table 5 show that Monday/weekend/weekday effects all fare much better when treated dynamically, as conditional on recent movements in the market; and in particular, the Monday and weekend each have nearly as many significant effects for as many indices as does weekday. All three versions of day seasonality are significant when χ^2s are combined over the indices. With ARMA terms included in the model, the χ^2 are 462.9, 385.7, and 597.0, with $df = 13$, 13, 52, respectively. All $p < 0.001$. These results are a comprehensive endorsement of the conditional Monday, generalized to conditional weekend and conditional weekday effects, and across the world's major stock exchanges.

More importantly for the purposes of this article, the wandering weekday effect is still significant for all indices. We conclude that the wandering weekday cannot be reduced to the conditional weekday. In fact, judging by the relative size of the combined χ^2 across the indices, the conditional weekday makes little impression on the strength of the wandering weekday: $\chi^2(728) = 1840.5$ for the wandering weekday when conditional effects are not analysed; and $\chi^2(728) = 1765.4$ when they are. There seems little overlap in the two effects.

The overall conclusion is that there are sources of variation in the weekday effect that are not captured by the conditional weekday, so the latter is not a complete theory. The wandering weekday is still unexplained.

4.4. Trading strategies

Rejecting EMH implies that it should be possible to articulate trading strategies to benefit from excess returns – the equivalent of "buy on Monday, sell on Friday" for the traditional fixed weekend effect. It turns out that the design of our analyses is not optimized for this particular purpose. Nonetheless, the attempt to do so is worthwhile in two ways. It makes more concrete for the reader the transient forms of the weekday effect, and it also points up some minimum requirements in the design of any future attempt to capture time-varying trading rules. The wandering weekday recommends us to replace the assumption of a fixed Monday effect for all markets and for all time with information about weekday effects in a particular market, and at a particular time. As an illustration, the significant χ^2 for Amex in 1997 of 16.98 (see Table 4) tests whether the GARCH regression coefficients are different from each other. But this information alone does not tell us which should be buying or selling days. Instead we need to consider GARCH regression coefficients themselves, the usual form for which is:

$$R_t = 0.002427 + 0.0033889D_{\text{Tues}} - 0.0046587D_{\text{Wed}} - 0.0042178D_{\text{Thu}} - 0.0020189D_{\text{Fri}}. \quad (5)$$

Tuesday through Friday have z-values, respectively, of 1.44, −1.82, −1.79, and −0.9, with 1.39 for the constant. No day has a return that is significantly more (or less) than the base of Monday. Eq. (5) can be re-run, or be re-arranged, to give a different day as the base for the dummies, or with no regression constant so that *all* weekdays are measured relative to zero, as follows:

$$R_t = 0.002427D_{\text{Mon}} + 0.0058159D_{\text{Tues}} - 0.0022317D_{\text{Wed}} - 0.0017908D_{\text{Thu}} + 0.0004081D_{\text{Fri}}. \quad (6)$$

Table 5
Wandering weekday in competition with conditional weekday.

	No ARMA				With ARMA			
	Cond Mon χ^2 $(df=1)$	Cond w-end χ^2 $(df=1)$	Cond w-day χ^2 $(df=5)$	Wand w-day χ^2 $(df=56)$	Cond Mon χ^2 $(df=1)$	Cond w-end χ^2 $(df=1)$	Cond w-day χ^2 $(df=5)$	Wand w-day χ^2 $(df=56)$
NYSE	2.80−	2.12−	**26.99**	**99.22**	1.63−	1.39−	4.40	**118.66**
Amex	0.01−	0.06+	**16.63**	**98.76**	0.19+	0.45+	**26.67**	**103.60**
Nasdaq	**23.9−**	**17.23−**	**29.35**	**120.08**	**20.43−**	**15.78−**	**23.11**	**153.93**
Nikkei	**6.58−**	2.93−	**20.06**	**77.29**	**7.69−**	**3.90−**	**14.65**	**87.96**
FTSE	0.29−	0.13+	**15.45**	**80.93**	0.83−	0.03−	8.24	**96.93**
DAX	**16.28−**	**13.31−**	**21.79**	**88.07**	**6.85−**	**5.08−**	**13.68**	**113.78**
CAC	1.18−	0.16−	**19.30**	**88.71**	1.85−	0.40−	8.58	**103.18**
Hang Seng	**24.53−**	**15.47−**	**31.52**	**78.14**	**11.04−**	**5.44−**	**24.35**	**93.53**
Shenzhen A	**133.38−**	**106.07−**	**142.82**	**298.09**	**124.03−**	**95.39−**	**140.03**	**197.99**
Shenzhen B	**70.43−**	**70.92−**	**77.99**	**234.15**	**48.09−**	**43.49−**	**64.09**	**271.87**
Shanghai A	**147.09−**	**106.83−**	**158.51**	**284.16**	**145.25−**	**105.35−**	**159.13**	**127.05**
Shanghai B	**79.52−**	**64.94−**	**88.20**	**133.20**	**77.60−**	**66.13−**	**92.46**	**155.10**
Sensex	**31.94−**	**29.03−**	**32.44**	**122.69**	**17.39−**	**15.86−**	**17.58**	**141.85**
	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.
NYSE	0.0943	0.1454	**<0.0001**	**0.0003**	0.2017	0.2384	0.4934	**<0.0001**
Amex	0.9203	0.8065	**0.0053**	**0.0004**	0.6629	0.5023	**<0.0001**	**0.0001**
Nasdaq	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**0.0003**	**<0.0001**
Nikkei	**0.0103**	0.0869	**0.0012**	**0.0312**	**0.0056**	**0.0483**	**0.0120**	**0.0041**
FTSE	0.5902	0.7184	**0.0086**	**0.0163**	0.3623	0.8625	0.1435	**0.0006**
DAX	**<0.0001**	**0.0003**	**0.0006**	**0.0040**	**0.0089**	**0.0242**	**0.0178**	**<0.0001**
CAC	0.2774	0.6892	**0.0017**	**0.0035**	0.1738	0.5271	0.1270	**0.0001**
Hang Seng	**<0.0001**	**<0.0001**	**<0.0001**	**0.0270**	**0.0009**	**0.0197**	**0.0002**	**0.0012**
Shenzhen A	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**
Shenzhen B	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**
Shanghai A	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**
Shanghai B	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**
Sensex	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**<0.0001**	**0.0035**	**<0.0001**

Daily returns for each market are estimated using day dummies, year dummies, year × day interaction dummies, and PW × day interaction terms, where PW is the mean return in the previous week for that market index. The PW × day interaction terms capture the conditional effects of recent market swings on day seasonality. GARCH(1,1) estimates the error, and models are run with and without ARMA(20,1) components. Post-estimation Wald tests are run to test:
H5: The conditional effect of market swings on the Monday effect ("cond Mon" in data columns 1 and 5).
H6: The conditional effect of market swings on the weekend effect ("cond w-end" in data columns 2 and 6).
H7: The conditional effect of market swings on the weekday effect ("cond w-day" in data columns 3 and 7).
H8: The year × day coefficients are jointly different from zero ("wand w-day" in data columns 4 and 8).
H8 is the same hypothesis as in **H4**, but now tested in the presence of conditional day seasonal. The upper panel displays the χ^2s for these tests, and the lower panel their associated probabilities (significant ones in bold). The plus or minus sign that follows the $\chi^2(1)$ statistics indicates the direction of the effect, with minus indicating that Monday returns were lower when returns in the previous week were lower, as in the conditional Monday and conditional weekday effects. Note also, $\chi^2(1) = z^2$, so these columns can be turned into z-tests.

Eq. (6) translates into annualized returns for Monday through Friday of approximately 13%, 34%, −11%, −9%, and 2%, respectively, assuming 50 trading days for each weekday[4]. Evidently, during 1997 stocks on the Amex tended to surge ahead on Tuesdays. The day-dummies have z-values of: 1.39, 3.67, −1.19, −1.14, and 0.29 for Monday through Friday, showing that only Tuesday's returns were significantly different from zero ($p < 0.001$, 2-tailed). With hindsight, a successful trading strategy for the Amex investor in 1997 would have been to sell on Tuesdays, all else being equal; and to buy on Wednesdays or Thursdays, but with less assurance that it is a good day to do so (indicated by their smaller z-statistics).

Stepping into the New Year of 1998, and armed with the most up-to-date analyses (Eq. (6)), our investor might apply the same buy-on-Tuesday strategy that would have been good for 1997. But the fact that the weekday effect wanders implies that the usefulness of the information in Eq. (6) will diminish as we move further away from 1997. We get a general idea about the life-expectancy of our estimates in a particular market by the correlation between the coefficients for the weekday returns for this year and the weekday returns for next year. The median of such correlations is just 0.175 across all years and all markets, meaning that typically, only 3% of the variance in next year's coefficients will be explained by this year's. Also, only 59.3% of the correlations were even positive. Therefore, estimates of daily returns made on data from year t will be only slightly informative if used throughout year $t+1$, though presumably better at the beginning of $t+1$ than the end. This lack of carry-over is consistent with the very few fixed weekday effects we have found in earlier analyses.

There are a number of implications for the would-be investor. First, the investor should assess whether the target market has exploitable inefficiency: our results suggest that some markets offer more opportunities than others. Second, because the rules obsolesce, the investor should update his/her estimates not just annually, as in our analyses, but as frequently as possible. Third, given that the pattern of day seasonality changes with time in every market, the estimating method should give greater weight to recent observations in forecasting future patterns. Clearly, one direction for future research is to explore these parameters with trading strategies as the primary focus of interest.

5. Conclusion and discussion

This article makes the case for analyzing day seasonals as time-varying rather than as fixed in time. Doing so reveals new sources of market inefficiency that the standard perspective ignores. When analyzing for fixed seasonality effects among days of the week, and combining over indices, our results show there are no Monday or

[4] Let the annualized ratio of Monday gains $G = \prod_{t=1}^{50} \frac{p_t}{p_{t-1}}$ $(=p_{50}/p_0)$. Then $\ln(G) = \sum_{t=1}^{50} \ln(\frac{p_t}{p_{t-1}}) = \sum_{t=1}^{50} R_t \approx 50 * 0.002427$ from the regression coefficient for Monday in (6). So, $G \approx e^{50*0.002427} \approx e^{0.12135} \approx 1.129$, giving a 13% advance on Mondays.

weekend effects, but there is a significant general weekday effect. This provides evidence for market inefficiency and also demonstrates that analyzing for general weekday effects is superior to the specific Monday or weekend effects. What the weekday effect loses in statistical power over more precise tests, it more than makes up for in capturing more subtle between-weekday variability.

More importantly, we show the wandering weekday effect, which abandons the assumption that a weekday effect is fixed over time, detects previously uncharted inefficiencies. Under this analysis *all* markets are seen to be inefficient, whereas the fixed weekday identified a minority as inefficient. We find these results robustly whether ARMA components are analyzed or not, and whether Gaussian disturbances are assumed or not.

Generally speaking, those markets we expect to be comparatively more inefficient are so: China and India versus the western markets; Amex and Nasdaq versus NYSE. Analyzing the relative efficiencies of markets by these and other means may be a fruitful line of future research, particularly if these could be related to market specific factors that might explain these inefficiencies.

We then establish the credibility of the conditional weekday effect as a potential challenger to the wandering weekday. We show that the average returns of last week, whether positive versus negative, affects the form of between-weekday returns for this week. This effect is present through all markets. If a particular year consists of mostly negative return weeks, while another contains mostly positive return weeks, this alone could drive changes to the weekday effect. However, when pitted in direct competition, the size of the contribution made by the wandering weekday is barely reduced when the conditional weekday is accounted for. The wandering weekday must be capturing sources of day seasonal variability that cannot be explained by short-term rises of falls in the market. Finally, decomposing the wandering weekday effect into its constituent year-weekday effects, we show that size of the weekday effect across the markets in our sample, has not decreased over the years (towards an efficient market). It is as strong now as it was 15 years ago.

Yet these findings contradict the conclusions drawn by Kohers et al. (2004, p. 170): "With improvements in market efficiency over time, the *day-of-the-week effect* may have disappeared in more recent years." This contradiction is particularly surprising because the years they analyse (1990–2002) and several of the markets (USA, Japan, UK, France, Germany, Hong Kong) overlap our own sample. Although Kohers et al.'s sample only included developed economies, the contradiction cannot be attributed to the developing economies in our sample. We found the same lack of trend towards efficiency when both developed and developing economies were examined as separate subsets.

Two more plausible reasons for the discrepancy are first, that we take the entire sample of indices as our ultimate unit of analysis, and combine small weekday effects from each index into annual tests of market efficiency. On the other hand, Kohers et al. take the individual index as their unit of analysis, and do not assess whether the separate small signals from multiple markets add up to a more comprehensive, and therefore sensitive view of market inefficiency.

Second, from analyzing the fixed weekday effect over a 15 year period, our results suggest that its long-term memory may be poor. But analyzing in time-slices of one year (either as year $\times$ day interactions, or as single year weekday effects to be later aggregated) ensures that its memory is checked frequently enough, and over short enough durations, to detect that it must remember. By contrast, Kohers et al. reported 6- and 11-year time-slices. What seems to be important in analyzing modern data is to cast a net with a sufficiently fine mesh.

To conclude, this article reports a wandering weekday effect for the major stock market indices. Our results show that the weekday effect wanders in a way that must lie between a random walk and a fixed (weekday) effect. This finding provides new evidence against the EMH. However, given that we have no universal principle to show us how it wanders (and there may be none), it is difficult to extract excess returns from it. In this way markets, though still demonstrably inefficient, may yet "satisfice" by being efficient enough to discourage the search for anomalous returns.

Acknowledgements

We particularly thank Professor Ephraim Clark for his insightful reading of early drafts of this paper, and the anonymous referees whose criticisms were prompt, constructive, and well-founded.

References

Agrawal, A., Tandon, K., 1994. Anomalies or illusions? Evidence from stock markets in eighteen countries. Journal of International Money and Finance 13 (1), 83–106.

Antoniou, A., Lam, H.Y.T., Paudyal, K., 2007. Profitability of momentum strategies in international markets: The role of business cycle variables and behavioural biases. Journal of Banking and Finance 31 (3), 955–972.

Apolinario, R.M.C., Santanta, O.M., Sales, L.J., Caro, A.R., 2006. Day of the week effects on European stock markets. International Research Journal of Finance and Economics 2, 53–70.

Asem, E., 2009. Dividends and price momentum. Journal of Banking and Finance 33 (3), 486–494.

Basher, S.A., Sadorsky, P., 2006. Day-of-the-week effects in emerging markets. Applied Economics Letters 13 (8), 621–628.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31 (3), 307–327.

Chan, S.H., Leung, W.-K., Wang, K., 2004. The impact of institutional investors on the Monday seasonal. Journal of Business 77 (4), 967–986.

Copeland, L.S., Wang, P., 1994. Estimating daily seasonality in foreign exchange rate changes. Journal of Forecasting 13 (6), 428–519.

Cross, F., 1973. The behavior of stock prices on Fridays and Mondays. Financial Analysts Journal 29 (6), 67–69.

De Bondt, W.F.M., Thaler, R.H., 1985. Does the stock market over-react? Journal of Finance 40 (3), 793–805.

Engle, R.F., 1982. Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50 (4), 987–1007.

Engle, R.F., 2001. GARCH 101: The use of ARCH/GARCH models in applied econometrics. Journal of Economic Perspectives 15 (4), 157–168.

Fama, E., 1970. Efficient capital markets: A review of theory and empirical work. Journal of Finance 25 (2), 383–417.

French, K.R., 1980. Stock returns and the weekend effect. Journal of Financial Economics 8 (1), 55–69.

Galai, D., Kedar-Levy, H., Schreiber, B.Z., 2008. Seasonality in outliers of daily stock returns: A tail that wags the dog? International Review of Financial Analysis 17 (5), 784–792.

Gao, L., Kling, G., 2005. Calendar effects in Chinese stock markets. Annals of Economics and Finance 6, 75–88.

Jaffe, J.F., Westerfield, R., Ma, C., 1989. A twist on the Monday effect in stock prices: Evidence from the US and foreign stock markets. Journal of Banking and Finance 13 (4–5), 641–650.

Kamara, A., 1997. New evidence on the Monday seasonal in stock returns. Journal of Business 70 (1), 63–84.

Ke, M.-C., Chiang, Y.-C., Liao, T.L., 2007. Day-of-the-week effect in the Taiwan foreign exchange market. Journal of Banking and Finance 31 (9), 2847–2865.

Kohers, G., Kohers, N., Pandey, V., Kohers, T., 2004. The disappearing day-of-the-week effect in the world's largest equity markets. Applied Economics Letters 11 (3), 167–171.

Lakonishok, J., Smidt, S., 1988. Are seasonal anomalies real? A ninety-year perspective. The Review of Financial Studies 1 (4), 403–425.

Lehmann, B.N., 1990. Fads, martingales, and market efficiency. Quarterly Journal of Economics 105 (1), 1–28.

Liano, K., 1989. The day-of-the-week effect in stock returns over business cycles. Financial Analyst Journal July–August, 74–77.

Lo, A.W., MacKinlay, A.C., 1990. Data-snooping biases in tests of financial asset pricing models. Review of Financial Studies 3 (3), 431–468.

Mehdian, S., Perry, M.J., 2001. The reversal of the Monday effect: New evidence from US equity markets. Journal of Business Finance and Accounting 28 (7–8), 1043–1065.

Pettengill, G.N., 2003. A survey of the Monday effect literature. Quarterly Journal of Business and Economics 42 (3–4), 121–137.

Steeley, J.M., 2001. A note on information seasonality and the disappearance of the weekend effect in the UK stock market. Journal of Banking and Finance 25 (10), 1941–1956.

Sullivan, R., Timmermann, A., White, H., 2001. Dangers of data mining: The case of calendar effects in stock returns. Journal of Econometrics 105 (1), 249–286.

Thaler, R.H., 1987a. Anomalies – The January effect. Economic Perspectives Summer, 197–201.

Thaler, R.H., 1987b. Anomalies – Seasonal movements in security prices II: Weekend, holiday, turn-of-the-month, and intraday effects. Economic Perspectives Fall, 169–177.

Venezia, I., Shapira, Z., 2007. On the behavioral differences between professional and amateur investors after the weekend. Journal of Banking and Finance 31 (5), 1417–1426.