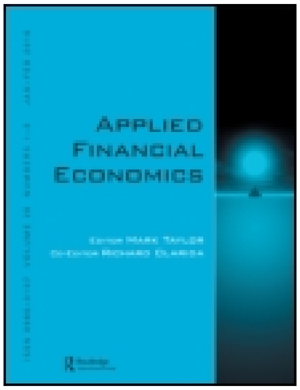

Applied Financial Economics
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/rafe20

Market closings and concentration of stock trading: an empirical analysis

P. V. (Sundar) Balakrishnan [a] , A. Steven Holland [a] , James M. Miller [a] & S. Gowri Shankar [a]
[a] School of Business , University of Washington , Bothell , WA , 98011 , USA

To cite this article: P. V. (Sundar) Balakrishnan , A. Steven Holland , James M. Miller & S. Gowri Shankar (2013) Market closings and concentration of stock trading: an empirical analysis, Applied Financial Economics, 23:17, 1393-1398, DOI: 10.1080/09603107.2013.826873

To link to this article: http://dx.doi.org/10.1080/09603107.2013.826873

Applied Financial Economics, 2013
Vol. 23, No. 17, 1393–1398, http://dx.doi.org/10.1080/09603107.2013.826873

Routledge
Taylor & Francis Group

Market closings and concentration of stock trading: an empirical analysis

P. V. (Sundar) Balakrishnan, A. Steven Holland, James M. Miller*
and S. Gowri Shankar

School of Business, University of Washington Bothell, WA 98011, USA

We adopt a power law framework to measure the concentration of daily trading among the different stocks on the US market. Our analysis of the trends of daily concentration over the last five decades reveals that trading concentration is lower on Mondays and the day after a long weekend. These findings are supportive of the hypothesis that firms manage information release. We also find lower concentration at the end of December and in January. The results are consistent with our expectations for a stock market that comprises multiple groups of traders with unique trading behaviour and timing patterns.

Keywords: trading concentration; power law; weekend effect; Zipf distribution

JEL Classification: G10; H30; D10

The volume of stocks traded on all US stock markets has steadily increased over the last five decades. In 1960, the average daily volume of trading in all the stocks covered in the Center for Research in Security Prices (CRSP) database was 3 million shares with a value of $112 million; by 2010, the average daily volume of trading was 8.4 billion shares valued at $232 billion. Balakrishnan *et al*. (2008) examine whether this extraordinary growth came from a proportionate increase in the volume of all stocks or whether it was due to a disproportionately large increase in a small subset of stocks. They model the distribution of daily trading volume of US stocks from 1962 to 2005 as a power law function and examine its trajectory over time. They document a new phenomenon that the power law exponent steadily increased over that time frame, leading them to conclude that the increase in the daily trading volume was being disproportionately concentrated in a subset of stocks and that trading had become more concentrated over time.

In this article, we employ a similar methodology based on the power law approach to examine, in a finer grained way, the impact of market closings or 'information dams' on the concentration of trading in stocks. Information that could influence stock prices arrives around the clock irrespective of whether stock markets are open or closed. The closing of markets, however, creates an information dam that then releases only when the markets re-open (Tsiakas, 2010). If information arrives for all firms during nontrading hours with some probability, then the odds are that the longer the market closure, the more likely it is that a given stock will have some relevant information arrive. This set of information is 'stored' behind the dam, waiting to be acted on upon the market opening. In this model, we would then expect to see more even daily trading volumes across all stocks – i.e. the concentration of trading will be lower – when the markets re-open after a weekend or a midweek holiday. The release of the information dam might result in even lower concentration after a long weekend.

*Corresponding author. E-mail:jmiller@u.washington.edu

Interestingly, there is also an empirical argument as to how market closings may affect the distribution of trading volumes. There is evidence that individual investors trade more following a weekend (Miller, 1988; Abraham and Ikenberry, 1994). There is also some evidence that institutional traders, on the other hand, trade less on Mondays (Lakonishok and Maberly, 1990). Since individual investors trade more in smaller stocks than institutional investors (Abraham and Ikenberry, 1994), the concentration of stock trading would be expected to be lower following a weekend.

On the other hand, the theory of 'managed information release' would suggest that the trading on any given day is impacted more by the quality of information than the presence/absence or quantity of information. In such a scenario, it is possible that certain types of information are released proactively by managers at particular times. More specifically, it is possible that more of the 'negative' information for stocks is typically released during the start of the weekend by firms to avoid immediate market reactions and to allow its impact to dissipate (Dellavigna and Pollet, 2009). Then, while one would expect concentration to be lower following the weekend, the impact might not be affected by the length (number of days) of the closing.

We next turn our lens to examine whether the concentration of trading changes around the end of December or in January. Keim (1983) and others report that returns on small stocks are abnormally high in January when compared to other months; this has been ascribed to the tax-loss-selling hypothesis, which posits that individual investors prune their portfolios and sell stocks in December to book their tax losses and then re-enter the market in January to re-establish their positions. Based on this, we would expect that trading concentration would be lower towards the end of December since most of the trading is in the smaller, less frequently traded stocks.

Finally, we investigate the changes in concentration around the end of each month, with a special focus on the end of quarters. Mutual funds and other institutional investors tend to trade more at the end of the month and the end of the quarter, both to 'dress up' their periodic performance and to rebalance their portfolios (Lakonishok *et al*., 1991; He *et al*., 2004). Consequently, we expect some of the less frequently traded stocks to register higher volumes in this period, leading to lower concentration in the trading volumes.

To preview our results, we find strong support for the hypothesis that trading concentration is lower on the day following the weekend, whether the weekend is 2 or 3 days long. However, following a midweek holiday, the concentration of stock trading is essentially the same as it would have been without the holiday. Concentration is also lower on 'regular' Tuesdays (i.e. not following a holiday weekend), though not as low as on Mondays or Tuesdays following weekends. Examining the turn-of-the year concentration measures, we find that the concentration of trading is lower during the last few days of a year and higher during the month of January. Trading concentration is also lower in the last 2 days of a quarter.

In the rest of the article, we discuss how we use the power law to measure the concentration of trading and then present our empirical analysis and conclusions.

I. Power Law and Trading Concentration

Many economic variables such as income, wealth, firm size and net income have been modelled using the power law (e.g. Axtell, 2001; Gabaix, 2009). A generalization of the power law applied to any variable that can be ranked by size can be expressed as:

$$(\text{Size}_i) \times (\text{Size Rank}_i)^q = \text{constant} \tag{1}$$

$$\Rightarrow \text{Log(SizeRank)} = (1/q) * \text{Log(constant)} - (1/q) * \text{Log(Size)} \tag{2}$$

The exponent q is specific to the item examined and is known as the power law exponent.

Balakrishnan *et al*. (2008) model the distribution of the trading volumes of individual firms on the US stock markets on each trading day as a power law distribution. The power law exponent, q_t, for each day t is estimated from Equation 3 below.

$$\text{Log}(\text{rank}_{it}) = \alpha_t - \beta_t * \text{Log}(\text{firm trading volume}_{it}) \tag{3}$$

The reciprocal of β_t is the power law exponent for day t. The firm trading volume is a normalized figure computed as (vol_{it}/(average firm volume_t)), where vol_{it} is the daily volume for firm i on day t and average firm volume_t is the average daily volume across all firms on day t. rank_{it} is the rank of the ith firm's trading volume on day t.

Balakrishnan *et al*. (2008), following Naldi (2003), interpret the power law exponent as an indicator of the degree of concentration (or uniformity) in the distribution of trading volumes. A low value for the exponent would mean that trading on day t is not concentrated, but is spread evenly across all stocks, whereas a high value for the exponent would suggest that most trading is concentrated in a small subset of stocks.

As an illustration, consider the distribution of trading volume for a subset of 10 stocks drawn from two different trading days, sorted by individual stock volume, as shown in Table 1.

Table 1. Distribution of trading volumes for a subset of stocks

Day 1			Day 2		
Trading rank	Trading volume	% of total volume	Trading rank	Trading volume	% of total volume
10	63 600	3.45%	10	14 700	0.80%
9	77 300	4.19%	9	26 700	1.44%
8	88 900	4.82%	8	37 600	2.03%
7	99 200	5.38%	7	45 200	2.45%
6	118 800	6.44%	6	69 700	3.77%
56	178 600	9.68%	5	98 690	5.34%
4	205 300	11.13%	4	104 330	5.65%
3	232 400	12.60%	3	246 169	13.32%
2	329 000	17.84%	2	447 029	24.19%
1	451 000	24.46%	1	757 659	41.00%
Total vol	1 844 100			1 847 777	
Average vol	184 410			184 778	

From Table 1, it is evident that though the average volume on the 2 days is comparable, there is a substantial difference in the distribution of trading volume, with trading on Day 2 being more concentrated in the top two or three stocks than on Day 1. To confirm this visual evidence, we use Equation 3 and estimate the power law exponents for the 2 days. The value of the power law exponent for Day 1 is 0.97 and for Day 2 is 1.87. These values confirm the visual evidence that the trading volume on Day 2 is more concentrated in a few stocks than on Day 1.

II. Empirical Analysis

For each trading day from 4 January 1960 to 30 December 2010, we obtain the daily trading volume for all stocks from the CRSP database. We estimate the power law exponent using a maximum likelihood estimation procedure (Naldi and Salaris, 2006) for each trading day for all stocks in each of the stock exchanges – New York Stock Exchange (NYSE), American Stock Exchange (AMEX), NASDAQ – and for the market as a whole.[1] Because of very clear shifts in the data, we use data for AMEX beginning on 2 July 1962 and for NASDAQ beginning on 1 November 1982.[2]

Regardless of whether a time trend is included or not, the augmented Dickey–Fuller and Phillips–Perron tests reject nonstationarity for the estimates of the power law exponents for all stock markets as well as for the NYSE, AMEX and NASDAQ individually. We, therefore, treat all of them as stationary series.

We estimate the trading concentration using the time-series equation below, for the power law exponents estimated for all stocks and each of the three exchanges (NYSE, AMEX, NASDAQ).

$$\begin{aligned}\mathrm{PLE}_t = {} & \beta_0 + \beta_1\,\mathrm{TIME}_t + \beta_2\,\mathrm{WEEKEND}_t \\ & + \beta_3\,\mathrm{LONGWKEND}_t + \beta_4\,\mathrm{MidWkHOLIDAY}_t \\ & + \beta_5\,\mathrm{TUES}_t + \beta_6\,\mathrm{JANUARY}_t \\ & + \beta_7\,\mathrm{LAST6YEAR}_t + \beta_8\,\mathrm{LAST2MONTH}_t \\ & + \beta_9\,\mathrm{FIRST3MONTH}_t + \beta_{10}\,\mathrm{LAST2QTR}_t \\ & + \text{AR terms} + \text{MA terms} + \varepsilon_t \end{aligned} \tag{4}$$

where:

PLE_t = the power law exponent on day t
TIME_t = calendar time (not trading time) for day t (Monday, 4 January 1960 is Day 1, the following Monday is Day 8)
$\mathrm{WEEKEND}_t$ = 1 for the trading day following a 2-day (normal) weekend; 0 otherwise
$\mathrm{LONGWKEND}_t$ = 1 for the trading day following a 3-day weekend; 0 otherwise
$\mathrm{MidWkHOLIDAY}_t$ = 1 for the trading day following a mid-week holiday
TUES_t = 1 for Tuesdays that do not follow a holiday weekend; 0 otherwise
$\mathrm{JANUARY}_t$ = 1 for January; 0 otherwise
$\mathrm{LAST6YEAR}_t$ = 1 for the last 6 trading days of the calendar year; 0 otherwise
$\mathrm{LAST2MONTH}_t$ = 1 for the last 2 trading days of the month; 0 otherwise

[1] Doray and Luong (1995), Naldi and Salaris (2006) and Goldstein *et al*. (2004) show that the maximum likelihood estimate produces a more accurate and robust estimate of the power law exponent and that this has the least variance in comparison to other estimation methods.
[2] On 2 July 1962 the number of stocks in AMEX reported by CRSP increased from 19 to 496 and on 1 November 1982 the number of stocks in NASDAQ reported by C RSP increased from 70 to 2336.

FIRST3MONTH$_t$ = 1 for the first 3 trading days of the month; 0 otherwise

LAST2QTR$_t$ = 1 for the last 2 trading days of the quarter; 0 otherwise

Examination of the time series of the estimated power law exponents suggests that we consider the likelihood of heteroscedasticity and serial correlation from the beginning of the analysis. We adjust the SEs for heteroscedasticity using the Eicker–White method. We estimate ARMAX models, which allow us to model the serial correlation (the ARMA portion of the model), while simultaneously estimating the effects of the variables of interest (the X portion of the model). The desired result is a set of estimated equations with no evidence of serial correlation. In essence, the autoregressive (AR) and moving average (MA) terms are meant to capture much of the influence of any omitted variables.

The results of the time series estimation for all four series (All stocks, NYSE, AMEX and NASDAQ) are presented in Table 2. There is no evidence of serial correlation in any of the reported regressions based on Ljung–Box Q-statistics for up to 30 lags. The coefficients for WEEKEND and LONGWKEND are significantly negative with p-values of essentially zero for all four series, indicating lower concentration of stock trading after weekends. The differences between the two coefficients for each series are insignificant with p-values ranging from 0.35 to 0.87. For all stocks, the power law exponent is 14.5% of its SD of 0.0665 lower following a regular weekend (on Mondays) than the average power law exponent for Wednesdays, Thursdays and Fridays. The results also show that trading after a midweek holiday does not significantly impact trading concentration with p-values ranging from 0.31 to 0.67. Regular Tuesdays have significantly negative coefficients with p-values of essentially zero, indicating lower concentration on Tuesdays than on Wednesdays, Thursdays or Fridays. The coefficients are significantly different from those for WEEKEND with p-values of essentially zero, indicating that concentration

Table 2. Regression results for power law exponents for all stocks, NYSE, AMEX and NASDAQ

We report below the coefficients of the time series regression

$$\mathrm{PLE}_t = \beta_0 + \beta_1\,\mathrm{TIME}_t + \beta_2\,\mathrm{WEEKEND}_t + \beta_3\,\mathrm{LONGWKEND}_t + \beta_4\,\mathrm{MidWkHOLIDAY}_t$$
$$+\beta_5\mathrm{TUES}_t + \beta_6\,\mathrm{JANUARY}_t + \beta_7\,\mathrm{LAST6YEAR}_t + \beta_8\,\mathrm{LAST2MONTH}_t$$
$$+\beta_9\,\mathrm{FIRST3MONTH}_t + \beta_{10}\,\mathrm{LAST2QTR}_t + \text{AR terms} + \text{MA terms} + \varepsilon_t$$

	1 All stocks 1/4/60–12/30/2010	2 NYSE 1/4/60–12/30/2010	3 AMEX 7/2/1962–12/30/2010	4 NASDAQ 11/1/82–12/30/2010
TIME	1.04E-05	8.60E-06	1.29E-05	1.59E-05
	(0.000)	(0.000)	(0.000)	(0.000)
WEEKEND	−9.66E-03	−9.84E-03	−1.32E-02	−9.53E-03
	(0.000)	(0.000)	(0.000)	(0.000)
LONGWKEND	−8.43E-03	−9.58E-03	−9.97E-03	−9.89E-03
	(0.000)	(0.000)	(0.002)	(0.000)
MWHOLIDAY	−1.33E-03	−1.12E-03	2.11E-03	3.84E-03
	(0.437)	(0.570)	(0.668)	(0.306)
TUES	−5.39E-03	−6.19E-03	−6.65E-03	−5.54E-03
	(0.000)	(0.000)	(0.000)	(0.000)
JANUARY	3.90E-03	3.79E-03	1.70E-02	3.47E-03
	(0.008)	(0.040)	(0.000)	(0.143)
LAST6YEAR	−1.97E-02	−1.36E-02	−3.23E-02	−2.76E-02
	(0.000)	(0.000)	(0.000)	(0.000)
LAST2MONTH	−1.77E-03	−8.83E-04	−5.89E-03	−4.56E-03
	(0.035)	(0.394)	(0.023)	(0.001)
FIRST3MONTH	−1.09E-03	−2.58E-03	−1.36E-03	−1.75E-03
	(0.100)	(0.001)	(0.517)	(0.133)
LAST2QTR	−7.48E-03	−6.94E-03	−1.69E-03	−1.25E-02
	(0.000)	(0.000)	(0.725)	(0.000)
CONSTANT	0.729	0.720	0.836	0.720
	(0.000)	(0.000)	(0.000)	(0.000)
AR	3	4	4	4
MA	3	4	3	3
# of observations	12 837	12 837	12 209	7106

The parentheses contain p-values.

Table 3. Regression results for power law exponents for all stocks by decade

We report below the coefficients of the time series regression

$$\text{PLE}_t = \beta_0 + \beta_1\,\text{TIME}_t + \beta_2\,\text{WEEKEND}_t + \beta_3\,\text{LONGWKEND}_t + \beta_4\,\text{MidWkHOLIDAY}_t + \beta_5\text{TUES}_t + \beta_6\,\text{JANUARY}_t + \beta_7\,\text{LAST6YEAR}_t + \beta_8\,\text{LAST2MONTH}_t + \beta_9\,\text{FIRST3MONTH}_t + \beta_{10}\,\text{LAST2QTR}_t + \text{AR terms} + \text{MA terms} + \varepsilon_t$$

	1 All stocks 1/4/1960–12/31/1969	2 All stocks 1/2/1970–12/31/1979	3 All stocks 1/2/1980–12/29/1989	4 All stocks 1/2/1990-12/31/1999	5 All stocks 1/3/2000–12/30/2010
TIME	−1.57E-06	4.51E-06	1.56E-05	1.07E-05	9.50E-06
	(0.757)	(0.261)	(0.000)	(0.047)	(0.194)
WEEKEND	−1.57E-02	−1.14E-02	−4.22E-03	−9.97E-03	−7.15E-03
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LONGWKEND	−1.77E-02	−4.88E-03	−4.99E-03	−1.06E-02	−5.36E-03
	(0.000)	(0.274)	(0.149)	(0.000)	(0.001)
MWHOLIDAY	−8.84E-03	−1.72E-03	6.23E-03	6.73E-03	3.49E-03
	(0.005)	(0.657)	(0.869)	(0.136)	(0.258)
TUES	−7.59E-03	−4.37E-03	−5.50E-03	−5.65E-03	−3.93E-03
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JANUARY	4.07E-03	4.06E-03	1.48E-03	2.76E-03	3.67E-03
	(0.258)	(0.309)	(0.616)	(0.247)	(0.185)
LAST6YEAR	−2.21E-02	−2.18E-02	−1.16E-02	−2.35E-02	−1.75E-02
	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)
LAST2MONTH	−1.88E-03	−1.86E-03	3.13E-03	−3.99E-03	−3.22E-03
	(0.461)	(0.321)	(0.080)	(0.006)	(0.023)
FIRST3MONTH	8.42E-04	−8.06E-04	1.23E-03	−1.28E-03	−4.47E-03
	(0.657)	(0.606)	(0.400)	(0.250)	(0.000)
LAST2QTR	−4.70E-04	−6.56E-03	−1.51E-02	−7.94E-03	−6.68E-03
	(0.904)	(0.058)	(0.000)	(0.003)	(0.017)
CONSTANT	0.761	0.753	0.681	0.698	0.762
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AR	5	3	4	4	4
MA	4	3	3	3	3
# of observations	2489	2526	2528	2528	2766

The parentheses contain *p*-values.

is lower following a weekend than on regular Tuesdays. For all stocks, the power law exponent is 8.1% lower on Tuesdays than the average power law exponent for Wednesdays, Thursdays and Fridays. The coefficient for TIME shows that concentration has increased over time over the sample periods, confirming the results reported in Balakrishnan *et al*. (2008).

We also find other calendar effects on the concentration of trading in stocks. The coefficients for JANUARY are positive and significant, except for NASDAQ, indicating that trading concentration increases in January. For all stocks, the power law exponent is 5.9% of its SD higher in January than the average power law exponent for other months of the year. Concentration is greatly lower in the last few days of a year: for all stocks the power law exponent for the last 6 days of the year is 29.6% of its SD lower than its average for the other days of the year. Concentration is somewhat lower during the last 2 days of a month, but only for NYSE is it also lower in the first 3 days of a month. For all stocks, the average power law exponent is 2.7% of its SD lower during the last 2 days of the month than the average power law exponent for the rest of the month. Concentration is quite a bit lower, except for AMEX if the last 2 days of a month are also the last 2 days of a quarter. For all stocks, the power law exponent is 11.3% of its SD lower during the last 2 days of the quarter than the average power law exponent for other days of the year.[3]

We consider the possibility that the effects of market closings and other calendar effects on the concentration of trading in stocks has been changing over time by estimating separate regression equations for each decade. The results are reported in Table 3. The coefficients for WEEKEND are significantly negative in every decade and generally have gotten smaller in absolute value over

[3] We ran regressions that included other possible calendar effects, including other days of the week, other months, the day before a holiday weekend, the day before a midweek holiday and the first 3 days of a quarter. In general, the coefficients were not statistically significant and the other results were not affected.

time. The coefficients for LONGWKEND are also significantly negative, except in the 1970s and 1980s. As in the regressions above, the coefficients for WEEKEND and LONGWKEND are not significantly different for any decade. Midweek holidays have no significant effect on concentration, except in the 1960s. Concentration is significantly lower on regular Tuesdays in every decade, but not as low as on Mondays except for the 1980s.

Even though January effects are significant for the full sample period, they are not statistically significant for any single decade. Concentration is lower in the last 6 days of the year in every decade. Other calendar effects (last 2 days of the month, first 3 days of the month, last 2 days of the quarter) tend to be more significant in recent decades.

III. Conclusions

We document some empirical regularities in the concentration of trading in stocks over the past five decades. Trading is less concentrated following weekends (regular or long) and somewhat more concentrated on Tuesdays, but less so than on Wednesdays, Thursdays and Fridays. There are other calendar effects associated with the end of the year, month and quarter.

In an earlier study that examines trading volumes and investor participation around market closings, Lakonishok and Maberly (1990) report that the trading volume on Mondays is, on average, 12% lower than the volume on other days. Miller (1988) and Abraham and Ikenberry (1994) find an increase in participation by individual investors and a decrease in institutional trading the day after a market closing. Our finding that trading concentration decreases the day after a market closing is consistent with a market that is comprised of multiple groups of traders, each with unique trading behaviour and timing patterns. We suspect these patterns derive from an inability of traders to react to information releases during market closings and/or the management of information releases on the part of corporate managers. Further research should allow us to more precisely identify causes of these behaviours and timing patterns.

We see this research as another step in modelling the concentration of trading in stocks. We hope this will ultimately lead to a fuller model of stock trading that encompasses returns, volume and concentration.

References

Abraham, A. and Ikenberry, D. L. (1994) The individual investor and the weekend effect, *Journal of Financial & Quantitative Analysis*, **29**, 263–77.

Axtell, R. I. (2001) Zipf distribution of US firm sizes, *Science*, **293**, 1818–20.

Balakrishnan, P. V. (Sundar)., Miller, J. M. and Shankar, S. G. (2008) Power law and evolutionary trends in stock markets, *Economics Letters*, **98**, 194–200.

Dellavigna, S. and Pollet, J. M. (2009) Investor inattention and Friday earnings announcements, *Journal of Finance*, **64**, 709–49.

Doray, L. G. and Luong, A. (1995) Quadratic distance estimators for the zeta family, *Insurance: Mathematics and Economics*, **16**, 255–60.

Gabaix, X. (2009) Power laws in economics and finance, *Annual Review of Economics*, **1**, 255–93.

Goldstein, M. L., Morris, S. A. and Yen, G. G. (2004) Problems with fitting to the power-law distribution, *The European Physical Journal B*, **41**, 255–8.

He, J., Ng, L. and Wang, Q. (2004) Quarterly trading patterns of financial institutions, *Journal of Business*, **77**, 493–509.

Keim, D. B. (1983) Size-related anomalies and stock return seasonality: further empirical evidence, *Journal of Financial Economics*, **12**, 13–32.

Lakonishok, J. and Maberly, E. (1990) The weekend effect: trading patterns of individual and institutional investors, *Journal of Finance*, **45**, 231–43.

Lakonishok, J., Shleifer, A., Thaler, R., *et al*. (1991) Window dressing by pension fund managers, *American Economic Review*, **81**, 227–31.

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

Miller, E. M. (1988) Why a weekend effect?, *Journal of Portfolio Management*, **14**, 43–8.

Naldi, M. (2003) Concentration indices and Zipf's law, *Economics Letters*, **78**, 329–34.

Naldi, M. and Salaris, C. (2006) Rank-size distribution of teletraffic and customers over a wide area network, *European Transactions on Telecommunications*, **17**, 415–21.

Tsiakas, I. (2010) The economic gains of trading stocks around holidays, *Journal of Financial Research*, **33**, 1–26.