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Stock market bubble detection based on the price dispersion among similar listed Firms

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Abstract A statistical method is proposed for detecting stock market bubbles that occur when speculative funds concentrate on a small set of stocks. The bubble is defined by stock price diverging from the fundamentals. A firm's financial standing is certainly a key fundamental attribute of that firm. The law of one price would dictate that firms of similar financial standing share similar fundamentals. We investigated the variation in market capitalization among those firms. Even during non-bubble periods, the market capitalization was distributed. The market capitalization distribution grew fat during bubble periods, namely, the market capitalization gap opens up in a small subset of firms with similar fundamentals. This phenomenon suggests that speculative funds concentrate in this subset. We demonstrated that this phenomenon could have been used to detect the dot-com bubble of 1998-2000 in different stock exchanges.

Keywords Stock market · Financial bubble · Nowcast · Power law

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1 Introduction

It is common knowledge in macroeconomics that, as Federal Reserve Board Chairman Alan Greenspan said in 2002, "...it is very difficult to identify a bubble until after the fact; that is, when its bursting confirms its existence." In other words, before a bubble bursts, there is no way to establish whether the economy is in a bubble or not. In economics, a stock bubble is defined as a state in which speculative investment flows into a firm in excess of the firm's fundamentals, so the market capitalization (= stock price $\times$ number of shares issued) becomes excessively high compared to the fundamentals. Unfortunately, it is exceedingly difficult to precisely measure a firm's fundamentals and this has made it nearly impossible to detect a stock bubble by simply measuring the divergence between fundamentals and market capitalization [1–3]. On the other hand, we empirically know that market capitalization and PBR (= market capitalization / net assets) of some stocks increase during bubble periods [4–7]. However, they are also buoyed by rising fundamentals, so it is not always possible to figure out if increases can be attributed to an emerging bubble.

Recently it was reported that real estate bubbles can be detected from increased variability in the prices of houses with similar attributes: the location of the house, the size and floor plan of the house, and so on [8,9]. Similar houses can be regarded as having similar fundamental values. Therefore, increased variation in price among similar houses signify that speculative money beyond the fundamentals is flowing into a subset in the housing market triggering a real estate bubble. By applying the real estate bubble detection approach to stock markets, this paper will propose a statistical method of detecting stock market bubbles from growing disparities in market capitalization between firms that are otherwise similar in industrial sector, size, and other attributes.

There are similar firms in a stock market. The law of one price would dictate that the fundamentals of these firms are comparable. In other words, if the market capitalization of just few firms among similar firms is exorbitantly high, this suggests that the stocks of those firms are overvalued and that a bubble has formed.

A firm's financial standing is certainly a key fundamental attribute of that firm. Our approach will be to first identify another firm in the same industrial sector with similar financial standing by applying the random forest method, then measure the market capitalization difference of the pair of firms. We will then observe the distribution of differences calculated from all the pairs of firms listed on each stock market from year to year. In non-bubble periods, the distribution among firms of similar financial standing is thin because market capitalization remains close to the firms' fundamentals. But if a bubble emerges, speculative funds flow into the stock of a small number of firms and this causes the upper tail of distribution to become fatter than during non-bubble periods. In this paper, by observing the upper tail of distribution we will detect the dot-com bubble of 1998-2000 on nine of the leading global exchanges: NASDAQ, NYSE, London SE, Tokyo SE, Paris SE, Korea

SE, Shanghai SE, Hong Kong SE, and Taiwan SE. Market capitalization and other financial data were obtained from Thomson Reuters Quantitative Analytics. Classification of firms by industrial sector is according to Thomson Reuters two-digit SIC codes.

The rest of the paper is organized as follows. In Section 2, we identify the financial variables and weighting factors that most strongly reflect firms' fundamentals of different industries on the exchanges based on market capitalization and key financial variables during non-bubble periods. In Section 3, we observe differences in market capitalizations between pairs of firms with similar financial variables. Section 4 demonstrates that stock market bubbles can be nowcast by observing the distribution of market capitalization differences between similar firms. And finally, Section 5 is a summary of the paper.

2 Financial variables that reflect fundamentals

In definition of bubble, market capitalization remains close to the firms' fundamentals during non-bubble periods. In order to identify the financial variables that most closely reflect fundamentals, we focus on market capitalization in the years 1997 and 2004 when there were manifestly no stock market bubbles on world exchanges. It is difficult using multiple regression analysis to rank the importance of key financial variables —total assets, net assets, total revenue, operating income, net income, operating cash flow, and number of employees —that reflect the fundamentals. The problem of multicollinearity arises in multiple regression analyses because there is a strong correlation between financial variables [4]. For this reason, we employ a regression tree and random forests which are hardly affected by multicollinearity.

We set logarithmic market capitalization and key financial variables during non-bubble periods to explain variables and explanatory variables. Figure 1 shows a regression tree for electronics firms listed on NASDAQ in 2004. Branching of the tree enable us to visualize net assets as condition, which is a most important explanatory variable. Random forests are an ensemble learning method for regression that operates by constructing a forest or a multitude of regression trees that do not randomly incorporate part of the explanatory variables [10]. Random forests quantitatively rank the importance of the explanatory variables. Figure 2(a) shows a time series of the importance of financial variables for electronics firms listed on NASDAQ from 1995 to 2005. One can see that net assets are critical in almost all of the years covered. The importance of net assets are around 0.5 in 1997 and 2004. Turning to Figure 2(b), this shows the same time series for retailer firms listed on NYSE from 2004 to 2014. For this sector, one can immediately see that both operating and net incomes are predominantly reflected in market capitalization for these firms.

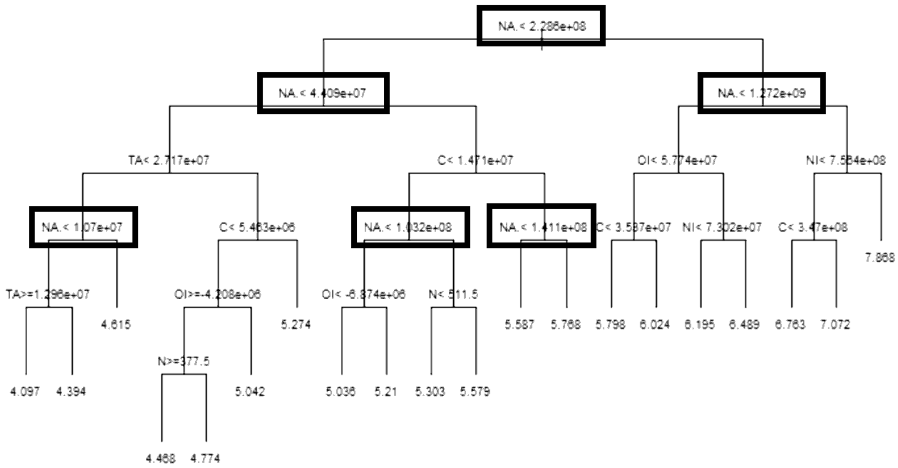

Fig. 1 Regression tree for electronics firms listed on NASDAQ in 2004. The non-explanatory variable is logarithmic market capitalization. Explanatory variables are (TA) total assets, (NA) net assets, (R) total revenue, (OI) operating income, (NI) net income, (C) operating cash flow, and (N) number of employees. Boxes represent branches subject to net assets.

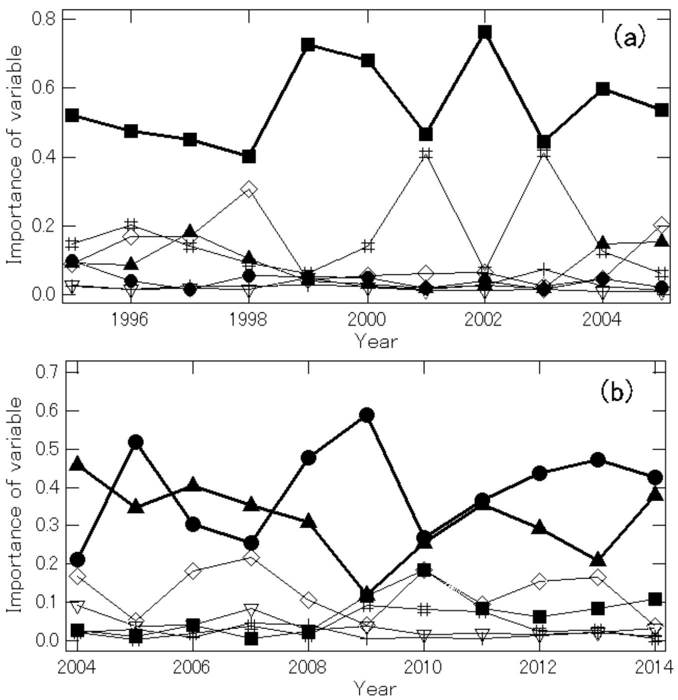

Fig. 2 Importance of financial variables: (a) electronics firms from 1995 to 2005 on NASDAQ, and (b) retailer firms from 2004 to 2014 on the NYSE. (#), (Black square), (+), (Black triangle), (•), (⋄), and (∇) represent total assets, net assets, total revenue, operating income, net income, operating cash flow, and number of employees, respectively.

3 Variation in market capitalization between similar firms

Financial variables of all firms in the same market and industry are ranked from highest to lowest. We depict the reciprocal ranking vector, V_i, of financial standing of firm i as follows,

$$V_i = (v_{TA,i}^{-1}, v_{NA,i}^{-1}, v_{R,i}^{-1}, v_{OI,i}^{-1}, v_{NI,i}^{-1}, v_{C,i}^{-1}, v_{N,i}^{-1}), \tag{1}$$

where $v_{TA,i}$, $v_{NA,i}$, $v_{R,i}$, $v_{OI,i}$, $v_{NI,i}$, $v_{C,i}$, and $v_{N,i}$ are the ranking of firm i for total assets, net assets, total revenue, operating income, net income, operating cash flow, and number of employees, respectively. Firms with better financial standing have a long vector. Based on the estimated importance of financial variables derived in the previous section, we look for firms that have similar important financial valuables from the same industry and market. We define the similarity between firm i and firm j in the same stock market k and industry s as follows,

$$d_{i,j} = U_{k,s} \cdot (V_i - V_j), \tag{2}$$

$$U_{k,s} = (u_{TA,k,s}, u_{NA,k,s}, u_{R,k,s}, u_{OI,k,s}, u_{NI,k,s}, u_{C,k,s}, u_{N,k,s}), \tag{3}$$

where $U_{k,s}$ expresses the vector with elements that are importance of financial variables: total assets, net assets, total revenue, operating income, net income, operating cash flow, and number of employees.

Next, we select firm i_1 to satisfy $d_{i,i_1} = \min\{d_{i,j}\}$ for firm i. Then we also choose the four firms with the 2nd, 3rd, 4th, and 5th smallest similarity for firm i, and calculate an average market capitalization for them, $\overline{m}_i$. If the market capitalization is extremely high with respect to the fundamentals (stock is overvalued) or conversely, discover that the market capitalization is extremely low with respect to the fundamentals (stock is undervalued) for either firm i or firm i_1, we can detect these phenomena by measuring the difference in market capitalization between the firms i and i_1 as follows,

$$\delta m_i = \begin{cases} m_i/m_{i_1} \text{ for } |m_i - \overline{m}_i| \geq |m_{i_1} - \overline{m}_i| \\ m_{i_1}/m_i \text{ for } |m_i - \overline{m}_i| < |m_{i_1} - \overline{m}_i| \end{cases}, \tag{4}$$

where m_i and m_{i_1} are market capitalizations of firm i and firm i_1 with the smallest similarity for firm i, respectively. If $\log \delta m_i \gg 0$, this suggests a high probability that the stock for either firm i or firm i_1 is overvalued. But if $\log \delta m_i \ll 0$, this indicates a strong probability that the stock for firm i or firm i_1 is undervalued.

Figure 3 shows the cumulative distributions of market capitalization differences $\delta m_i \geq 1$ among similar firms listed on NASDAQ. Since the distribution function is always a power law function and independent of timing, one can see that only the slope of distribution varies with time:

$$P_{\geq}(\delta m_i) \propto \delta m_i^{-\beta_t} \text{ for } \delta m_i \geq 1. \tag{5}$$

The slopes, β_t, are 1.5, 1.0, 1.5, and 1.3 for t =1997, 1999, 2004, and 2014, respectively. Such phenomenon is also observed in other stock markets.

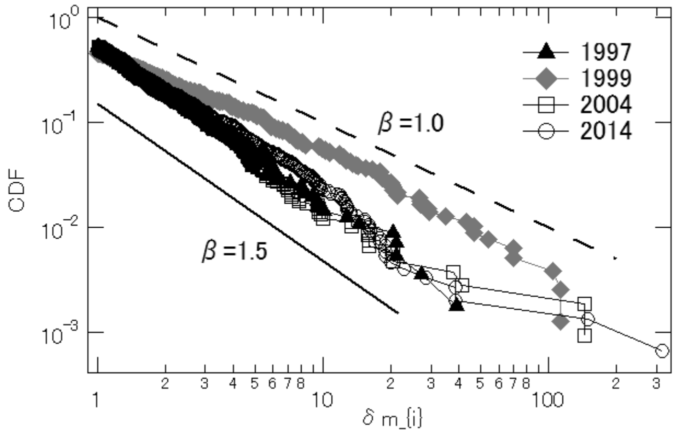

Fig. 3 Cumulative distributions of market capitalization differences $\delta m_i \geq 1$ between similar firms listed on NASDAQ. (Black triangle), (Black diamond), (Square), and ($\circ$) plots represent distributions for 1997, 1999, 2004, and 2014, respectively. The solid and dashed lines show power low slopes, $\beta = 1.5$ and 1.0, respectively.

4 Detecting stock market bubbles: the Dot-com bubble

The dot-com bubble reached its peak toward the end of 1999 as the NASDAQ composite index closed-in on the 5000 mark. Before the bubble in 1997 and after the bubble burst in 2004, the NASDAQ composite index hovered around 2000. Despite the collapse of Lehman Brothers in 2008, NASDAQ has come back and as of 2014 was again approaching 5000. Figure 3 shows distributions of market capitalization differences between similar firms in 1997, 1999, 2004, and 2014. The upper tail of distribution grew fat during the dot-com bubble but after the bubble burst, the distribution fell back to the same level as before the bubble. The fat upper tail is not present in 2014. This means that the sharp rise in market capitalization unrelated to fundamentals that occurred in a relatively small number of firms during the bubble, is not what is happening in 2014. Market capitalization of firms in 2014 is firmly based on fundamentals.

Figure 4 shows time series of distribution's slopes, β_t, for the nine stock exchanges: NASDAQ (1995-2005), NYSE (1995-2005), London SE (1995-2005), Tokyo SE (1999-2005), Paris SE (1998-2005), Korea SE (1999-2005), Shanghai SE (1999-2005), Hong Kong SE (2000-2005), Taiwan SE (2000-2005). The slopes diminished during the dot-com bubble on all of the exchanges, then immediately steepened again after the bubble collapsed. Essentially, this means that market capitalization increases without any accompanying increase in fundamentals for a subset of stocks during bubble periods. Such an aberration can be readily detected by closely monitoring variations in market capitalizations between similar firms.

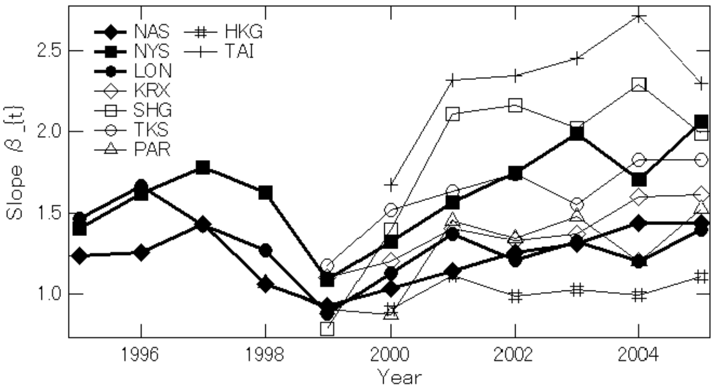

Fig. 4 Distribution's slopes, β_t, of market capitalization differences between similar firms. (Black diamond), (Black square), (•), (◇), (Square), (○), (△), (#), and, (+) represent slopes for NASDAQ, NYSE, London SE, Korea SE, Shanghai SE, Tokyo SE, Paris SE, Hong Kong SE, and Taiwan SE, respectively.

5 Conclusions

The defining characteristic of stock market bubbles is divergent between market capitalization (asset prices) and the fundamentals. A stock market includes many firms in similar industries having similar financial positions. We observed considerable market capitalization variability among firms of similar financial standing. Since fundamentals cannot be accurately estimated from a firm's financial standing alone, the variation in market capitalization among similar firms even under non-bubble conditions must be considered. However, there is significantly greater divergence between market capitalization and fundamentals during bubbles, which opens up far more variation in market capitalization among similar firms. We have demonstrated that this phenomenon could have been used to detect the dot-com bubble of 1998-2000 across several stock markets. While it is difficult to determine if an individual firm or stock is caught up in a bubble, we can detect when a stock market is in the midst of a bubble.

We should note that there are types of bubbles that cannot be detected by the approach outlined here. The method we describe only works when identifying the type of bubble in which a concentration of speculative money flows into a small set of stocks. For example, our method would not work in a situation where speculative funds flow evenly into all stocks so that market capitalization diverges uniformly from fundamentals. In order to detect the formation of this kind of bubble, one would have to have knowledge of speculative money flows between financial markets. This is precisely the challenge that we intend to pursue next: detection of bubbles that arise from the concentration of speculative funds flowing into specific financial markets.

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References

1. Brunnermeier MK (2016) Bubbles. In: Jones G (ed) Banking Crises. Palgrave Macmillan UK, pp 28-36
2. Palan S (2013) A review of bubbles and crashes in experimental asset markets. Jurnal of Economic Surveys 27:570-588
3. Arshanapalli B, Nelson WB (2016) Testing for Stock Price Bubbles: A Review of Econometric Tools. The International Journal of Business and Finance Research 10: 29-42
4. Mizuno T, Ohnishi T, Watanabe T (2016) Power laws in market capitalization during the Dot-com and Shanghai bubble periods. Evolutionary and Institutional Economics Review 13:445-454
5. Kaizoji T (2006) Power laws and market crashes: Empirical laws on bursting bubbles. Progress of Theoretical Physics Supplement 162:165-172
6. Kaizoji T (2006) Precursors of Market Crashes: Empirical laws of the Japan's internet bubbles. European Physical Journal B 50:123-127
7. Kaizoji T, Miyano M (2016) Why does the power law for stock price hold? Chaos, Solitons & Fractals 88:19-23
8. Ohnishi T, Mizuno T, Shimizu C, Watanabe T (2012) Power laws in real estate prices during bubble periods. International Journal of Modern Physics:Conference Series 16:61-81
9. Tay DJ, Chou CI, Li SP, Tee SY, Cheong SA (2016) Bubbles Are Departures from Equilibrium Housing Markets: Evidence from Singapore and Taiwan. PLoS ONE 11:e0166004
10. Breiman L (2001) Random Forests. Machine Learning 45:5-32